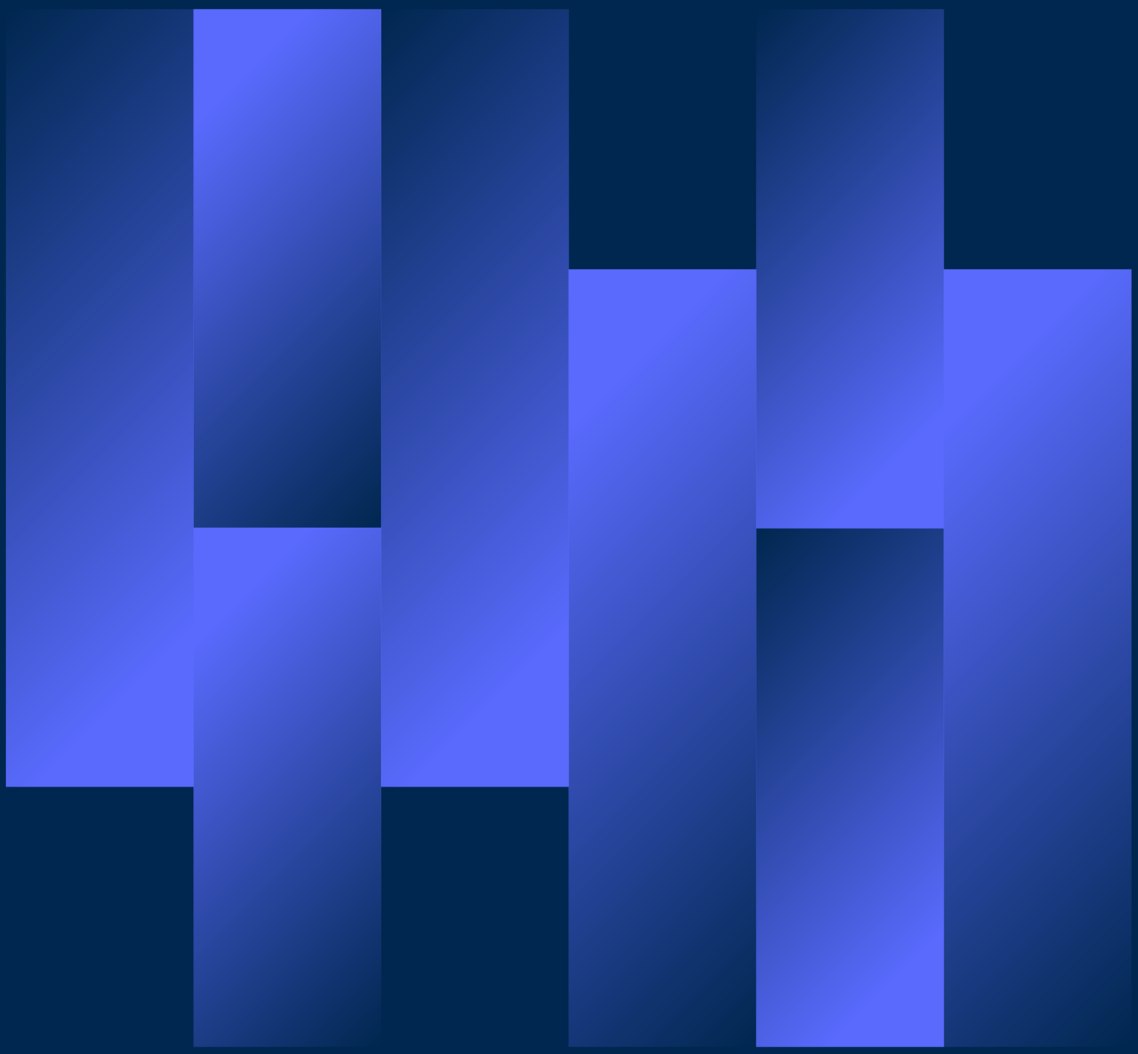
SAP Superintelligence Series

Intelligent automation, AI systems, and digital engineering in oil–gas–chemical industries



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SAP Superintelligence Series

Volume 3

Intelligent automation, AI systems, and digital engineering in oil–gas–chemical industries

Edited by
Prof. Alex Khang (Ed.)
Dr. Vugar Abdullayev (Ed.)
Dr. Elmina Gadirova (Ed.)
Dr. Vladimir Hahanov (Ed.)

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Preface

The development of this book is rooted in a shared recognition: industrial engineering is undergoing a profound transformation, driven by technological convergence and the urgent need for sustainable, efficient, and intelligent production systems. Throughout the contributions compiled here, the authors explore diverse perspectives on digitalization, automation, robotics, and intelligent control, yet they all articulate a common message—the future of industry will be shaped by systems capable of adapting, learning, and responding dynamically to complex environments.

This preface acknowledges the collaborative effort behind the volume. Engineers, researchers, and industry specialists have contributed expertise drawn from both theoretical inquiry and real-world application. Their work reflects not only technological innovation but also a commitment to redefining industrial systems in ways that enhance human capability, environmental responsibility, and organizational performance.

We present this book with the conviction that its insights will support ongoing debates and future developments in industrial engineering. As global industries navigate uncertainty, technological acceleration, and sustainability challenges, the frameworks and methodologies discussed here offer pathways for meaningful transformation.

The editors hope that this volume serves as a resource for scholars, practitioners, and decision-makers, inspiring new research, fostering innovation, and contributing to the ongoing evolution of intelligent industrial systems.

Introduction

The rapid emergence of intelligent technologies has profoundly reshaped the foundations of industrial engineering. Systems that once relied on mechanical efficiency and linear workflows are now increasingly defined by data-driven decision-making, cyber–physical integration, and adaptive automation. As shown across multiple sections of this volume—particularly in the chapters addressing digital replica models, multi-sensor industrial systems, and automated process control—industrial environments are transitioning toward interconnected and intelligent ecosystems capable of learning, predicting, and optimizing in real time.

This book situates itself within that evolving landscape. Its chapters converge around a central theme: the transition from traditional industrial frameworks to next-generation intelligent systems that seamlessly integrate AI, machine learning, robotics, IoT infrastructures, and sustainable engineering principles. The discussion spans conceptual foundations, technical methodologies, and applied implementations, providing a broad yet coherent perspective on how industries can harness emerging technologies to increase productivity, improve system reliability, reduce environmental impact, and strengthen long-term resilience.

At its core, the introduction aims to frame these technological advancements not as isolated innovations but as components of a comprehensive paradigm shift—one that redefines the role of industry in a world increasingly shaped by digital transformation and sustainability imperatives. By synthesizing theoretical insights with practical examples embedded in the chapters, the introduction prepares the reader to engage with the book's central argument: intelligent systems are not merely tools for optimization—they represent the foundational architecture of the industry of the future.

Abstract

This volume presents an integrated exploration of next-generation intelligent systems and their transformative impact on industrial engineering. Bringing together contributions on digital twins, smart automation, industrial robotics, AI-driven optimization, predictive analytics, and sustainable manufacturing models, the book examines how emerging technologies are reshaping production environments, decision-making processes, and organizational performance.

Several chapters highlight the role of cyber–physical systems and data-centric architectures in enabling real-time monitoring, simulation, and control of industrial processes. Others explore the convergence of machine learning, IoT infrastructures, and advanced robotics as key enablers of efficiency, flexibility, and resilience in modern industries. Special attention is given to sustainable engineering practices, including energy-efficient design, resource optimization, and environmentally conscious production models, which appear throughout various chapters of the volume.

Theoretical discussions are complemented by practical case studies that demonstrate how intelligent systems address concrete industrial challenges—ranging from predictive maintenance and workflow automation to performance forecasting and manufacturing system simulation. Collectively, the chapters underline the urgent need for industries to adopt adaptive, data-informed, and technologically robust frameworks.

This book aims to provide researchers, engineers, and practitioners with a comprehensive understanding of the technological foundations, methodological approaches, and applied solutions shaping the future of industrial systems. It positions next-generation intelligent engineering not only as a technological evolution but also as a strategic pathway toward sustainable, efficient, and human-centered industrial transformation.

Keywords: Intelligent Systems; Digital Twins; Smart Manufacturing; Industrial Engineering; Sustainability

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ORIGINAL

Optimization of Multi-Power Supply using Quantum Artificial Intelligence for Chemical Industries

Optimización de fuentes de alimentación múltiples mediante inteligencia artificial cuántica para industrias químicas

Dhanush Kumaran M[1], Aryaan Ganesan S[1], C. Bhuvaneswari[1], W. Abitha Memala[1], M. Pushpavalli[1], Christo Ananth[2]

[1]Department of Electrical and Electronics Engineering, Sathyabama Institute of Science and Technology. Chennai 600119, India.

[2]Faculty of Artificial Intelligence and Digital Technologies, Samarkand State University. Uzbekistan.

Corresponding Author: Dhanush Kumaran M

ABSTRACT

Maximizing the utilization of multiple renewable energy power sources, tied to storage systems, presents an opportunity, as well as a challenge, when optimizing the system efficiency of charge and energy distribution of electric vehicles (EVs). This physics focuses on the improved design of a system whereby the power input and coordination of multiple power sources used in an electric and industrial vehicle are prime considerations. Implementing the IoT in the system ensures advanced automation and a step-down in energy waste of the ecosystems in focus. To enhance the sustainable energy practice, the system incorporates PV battery storage for the restriction of active use of grid energy. The system architecture incorporates batteries with a non-isolated multi-port DC-DC converter, which manages two distinct energy inputs and two outputs of distinct voltage levels to power multiple subsystems of the electric vehicle. The deployed IoT modems facilitate the optimization, real-time monitoring, and minimized system control of the resonator while reducing harmonic distortions and ripple torque in the motor drives. This integration of Electric vehicles with PV systems has been shown to enhance the use of energy and the life of the battery, as shown in the proposed design and systems test results. The system has a good efficiency when incorporated to Chemical Industries. The new system of a hybrid energy management system defines and augments the seamless integration of sustainable electric mobility and enables refined and efficient integration of IoT-based actuators for step-scaled real-time electric drive systems.

Keywords: Optimized Energy Sources; Internet of Things; Energy efficiency; Hybrid Energy Management; Oil and Gas Industry.

RESUMEN

Maximizar el uso de múltiples fuentes de energía renovable, vinculadas a sistemas de almacenamiento, presenta una oportunidad, así como un desafío, a la hora de optimizar la eficiencia del sistema de carga y distribución de energía de los vehículos eléctricos (VE). Este estudio de física se centra en el diseño mejorado de un sistema donde la entrada de energía y la coordinación de las múltiples fuentes de energía utilizadas en un vehículo eléctrico e industrial son consideraciones primordiales. La implementación del IoT en el sistema garantiza

una automatización avanzada y una reducción del desperdicio de energía en los ecosistemas en cuestión. Para mejorar las prácticas energéticas sostenibles, el sistema incorpora almacenamiento en baterías fotovoltaicas para restringir el uso activo de la energía de la red. La arquitectura del sistema incorpora baterías con un convertidor CC-CC multipuerto no aislado, que gestiona dos entradas de energía distintas y dos salidas con distintos niveles de voltaje para alimentar múltiples subsistemas del vehículo eléctrico. Los módems IoT implementados facilitan la optimización, la monitorización en tiempo real y la minimización del control del sistema del resonador, a la vez que reducen las distorsiones armónicas y el par de rizado en los accionamientos del motor. Se ha demostrado que esta integración de vehículos eléctricos con sistemas fotovoltaicos mejora el uso de energía y la vida útil de la batería, como se muestra en el diseño propuesto y los resultados de las pruebas de los sistemas. El sistema presenta una buena eficiencia al integrarse en la industria química. El nuevo sistema híbrido de gestión energética define y amplía la integración fluida de la movilidad eléctrica sostenible y permite una integración refinada y eficiente de actuadores basados en IoT para sistemas de accionamiento eléctrico en tiempo real y escalables.

Palabras clave: Fuentes de Energía Optimizadas; Internet de las Cosas; Eficiencia Energética; Gestión Híbrida de la Energía; Industria del Petróleo y el Gas.

INTRODUCTION

The introduction of power converter systems over the past decade has proved revolutionary to the domain of Transportation and vehicle systems. These microprocessor-controlled systems, driven by batteries or solar photovoltaic (PV) sources, aim to boost the confidence of end-to-end designers and users with respect to the efficiency and reliability with which the deployed power systems are optimized and managed. The concept of the power source/energy source diversity for hybrid vehicles is advantageous to the overall system as it mitigates the reliance on a singular energy source and augments system functionality.

The introduction of multi-port DC-DC converters supersedes the limitations of traditional power transfer systems. Integration of batteries and solar panels is one of many possibilities of energy sources coupled to a single unit flexible system. These converters are standalone systems optimized to accommodate a single load with the IoT optimization for energy systems, which allows the real-time expression of parameters and multi-system feedback control of the entire web system of distributed micro and nano grids using artificial intelligence. These IoT systems provide real-time feedback on the enclosed energy managing systems, batteries, power systems, and the rest of the load.

This document details the design of an integrated non-isolated multiport DC-DC converter with an IoT system for the management of hybrid energy sources in electric vehicles. The hybrid energy sources integrated in the system will ensure the provision of an energy solution that is eco-friendly, highly reliable, and with minimal costs. The use of sophisticated power electronics and IoT systems in the design is expected to improve the overall efficiency, performance, and sustainability of electric vehicles, and also the utilization of renewable energy sources.

Literature Review

Effective control of multiple power systems has become important over the years in most modern industries that rely on a combination of grid power, backup diesel generators, and renewable sources of power such as solar and wind. The users of such systems, ‘Edge Computing’ and ‘The Internet of Things’, have changed the dynamics of operational power

control systems and monitoring in real-time, automating grid systems and the more intelligent control of energy. This literature survey focuses on the more recent works that emphasize the use of IoT in the optimization of multi-supply power systems in industries, as is the case in [1]. IoT is making the transformation of conventional power systems faster and more efficient by superimposing optimized intelligent control systems. This study focuses on the underpinning framework, functions, and practical implementations of IoT and associated systems within energy power grids, as well as the derived values and issues that relate particularly to the sense of control. It identifies common soft spots and suggests remedial measures by illustrating how emerging solutions such as blockchain and Artificial Intelligence (AI) could enhance the robustness and dependability of IoT energy framework networksMatters such as the application of predictive maintenance techniques with fault diagnosis, along with the associated machine learning technologies on multipower systems of batteries, inverters, and generators, are the objectives of this research. The system uses slice sensor data in order to predict failures, assist in maintenance, and plan to reduce unplanned downtimes.

The results displayed that the effectiveness and dependability of industrial power systems increased quite a bit when IoT devices were integrated with machine learning algorithms. [2] Reliance on, and scheduling the power configuration from, multiple sources such as grid electricity, batteries, solar, wind, and generators, with the corresponding minimization of energy use, is truly two sides of the same coin. IoT devices here assist in producing control and monitoring in real time over energy production, load, and consumption of the system, thus enabling automated dynamic load balancing. This helps the industrial plants in minimizing their costs, optimizing system efficiency, and reducing the energy and ecological footprint of the systems. This illustrates that the IoT-based smart grids are becoming more and more critical for dependable and environmentally friendly energy management.[3]

First, the focus concerning the energy systems for an industrial application is load forecasting. Incorporation of Machine Learning and Real-time monitoring and tracking of energy consumption is done through the IoT. Analyzed data is used through Deep Learning Models to estimate prospective energy consumption. The deep learning predictive insights enable improved energy sourcing and operational effectiveness, which in turn lowers the industry cost. The insights equip predictive machine learning systems to sharpen their industrial systems' power management influence.[4] An equally significant aspect is the management of stored energy, mainly the renewable energy source. Real-time IoT systems undertake the control of monitored parameters of the batteries' discharge and charge cycles, for example, in temperature and charge depth control. The real-time control, as optimization of the stored energy, improves the efficiency in the use of available resources.[5]

Integrating IoT-monitored Distributed Energy Resources (DER) enables a real-time interface of integrated Internet monitoring systems and increases an order of magnitude in efficiency of economic systems. Predictive analytics enable process automation and improve energy efficiency, and the multi-layered cyber defense systems secure the system from a diverse degree of attacks and threats.[6] In microgrids, for example, the Internet of Things (IoT) monitors and manages primary parameters such as the demand variability in the Electrical Supply Systems (ESS), reactive power supply, and overall power quality. In the case of an alert system, the response time to the signals, which guarantees the security of supply, is significantly improved. A tested off-grid microgrid system, which illustrated strong performance in functionality and control over the web interface, customer satisfaction, and value.[7] IoT systems influence the operation behavior of microgrid systems with integrated programmable loads and Distributed Energy Resources (DER). They improve control, system reliability, and security, which is further enhanced by automation to achieve minimum outages, energy, and electricity losses, even theft. Above all, automation in the economic systems of the generator and distributor, and the system's own socio-economic advantages are highlighted.[8]

The energy decline associated with the unnoticed costs of equipment malfunctioning at idling is severe. To alleviate this issue, Remote Control of Idle Appliances Shutoff devices integrated with microcontrollers and Wi-Fi have been observed. These devices have been proven to reduce energy and power costs, while unaccounted power expenditure remains.[9] Also, automatic shut-off IoT chargers are patented and designed to minimize power waste and damage caused to batteries from overcharging. Such chargers use elementary battery level sensors, which, when triggered, deactivate those devices when the batteries reach peak energy level, thus improving system performance, which is usually lacking in modern-day systems.[10] The integrative activities at the confluence of the IoT and optimization domains seek to refine and transform the unprecedented shifts in innovative grid energy management systems. These shifts are mitigated with physical feedback and a multitude of concurrent and counterbalancing sources and sinks. The effective balancing of estimated energy demand and real-time processing with industrial cost functions renders remarkably sustainable energy efficiency in smart grids. The blended sophistication of improved unconventional systems and the disruptive attributes of frontier technology epitomize the elusive finesse of industrial energy systems described at [11].

The complex nature of energy usage in manufacturing stems from Customary Problems with diverse functions and aims of providing predicted and Adaptive Power management. Real-time cost monitoring and forecasting with changes in power supply systems and efficiently reduced robust systems end, simultaneously offer.[12] Adaptive systems with numerous power supply sources also. Multiple case studies in Industrial Power Management demonstrate that this application achieves higher reliability and efficiency at lower costs.[13] As well, relay–energy–real-time interfaces support the distribution of energy, which, typically, the IoT enhances the industry's distribution efficacy, characterized by energy loss and reduced operational costs. Increased reliability and operational costs lead to enhanced IoT-use systems' sustainability.[14]

In summary, this work aims to evaluate the inventions regarding the opportunities and the challenges of the integration of IoT systems in smart energy grids. Even in the case of industrial activity, the uninterrupted collection and valuation of the data in real-time work of the systems provides improved load balance, optimization of multiple energy sources, and reduced operational costs. On the other hand, the vertical integration of smart IoT-based grids and the complete system integration are critical barriers to the widespread acceptance of IoT-based smart grids.[15] Nonetheless, in the modern day, the management of industrial power systems is rather poorly developed, as a result of persistent energy losses, unanticipated equipment failures, insufficient load balancing, and security and scalability concerns. Relatively older systems do not succeed in enhancing operational feedback, which leads to the inability of workflows, and the subsequent planning and operational costs increase significantly. In the reactive maintenance approach, the system downtime causes and accentuates the load forecasting problems, and the result is a poorly coordinated and inefficient operation of the system. In addition, the existing smart grids with IoT technology are weak in the area of cybersecurity, which is a severe problem at a worldwide level.

Addressing the gaps in the sector disparity, IoT technology, automated processes, Predictive analytics, and advanced security systems can eliminate the gaps identified in the industry all at once. Optimizing AI in real time to monitor advanced proactive indicators balances the load, lowers costs, and minimizes energy dissipation. The combination of machine learning and predictive maintenance algorithms minimizes system failures and subsequently system downtimes. Enhanced machine learning distribution systems, in combination with blockchain technology, offer predictive cyber threat intelligence. The system also provides and demonstrates modular adaptability with reliability, which in turn offers ultimate diverse energy operational frameworks.

Problems in the Existing System

The IoT-enabled multifunctional automated charger has acquired tremendous utility in

observing and controlling parameters of charge controllers like voltage, current, and power. The management systems of power, while retaining the parameters above, do face the challenges of effectiveness and efficiency, and these have been minimized to some extent, such as:
Disregarding Principles of Control and Monitoring

Premature disconnection of the systems can lead to low efficiency, while disconnection after a delay can lead to severe damage. The use of a relay to switch a controller lacks other parameters, i.e., agility, and this is unreasonable for other real-time systems. Mechanisms left unattended for retrieving data can also be relatively weak.

Limitations of Remote Access

Remote access faces constraints due to latency and network interruptions. Severe security gaps endanger neglect, which is unaided by proper encryption and authentication.

Problems of Manual Override

Changes that are manual as opposed to automatic introduce scope for human havoc, as set imbalances or unsystematic inappropriation of energy.

Lack of Efficient Communication & Data Transmission

Standardized communication protocols that are lacking for solar, wind, and battery-powered sources are the primary sources for integration challenges. Sensors that provide information or perform real-time diagnosis that is slow, sluggish, or erroneous are detrimental to precise optimization.

Difficulty of Scalability and Maintenance

System downtime arising from the addition of new power sources or the expansion of the whole system is due to complexity and is set to be addressed. Lack of proper user training, neglect of prescribed regular maintenance, and alerts set to assume the manual are for closure.

Block Diagram

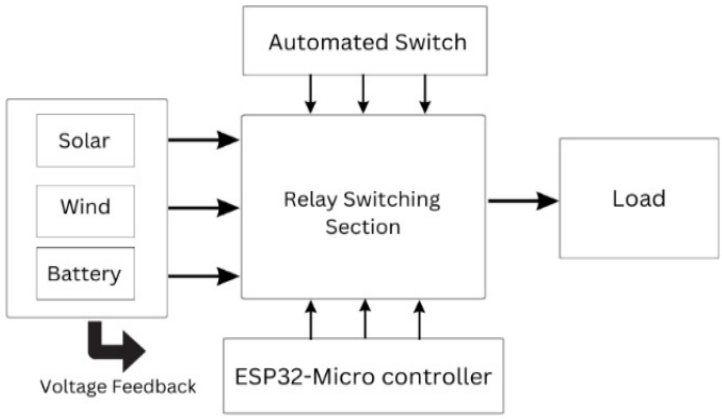

Figure 1. General Block Diagram of Power Supply

In figure 1, the consummate integration and automatic supply control of differentiated energy sources (solar, wind, and battery) is the focal point of the thesis. It incorporates IoT technologies via an ESP32 microcontroller for unattended supervision, automated decision-making, and control of the whole supply system and load. The system ensures drawing of power

from the cheapest, most available, or most efficient source of energy while optimizing the use of renewable energy and minimizing battery dependency.

Power Resources

The system can be Powered from Multiple sources namely Solar, Wind and Battery. The Solar Power is Captured by photovoltaic cells. Solar cells provide direct current (DC) electricity, which must be monitored. Voltage feedback establishes the presence and intensity of solar energy. The Wind Power is Captured by wind turbines. Wind turbines provide electricity in relation to the velocity of the wind. Voltage feedback determines the presence of wind energy. The Battery Power Provides Reserved energy used as auxiliary when solar and wind energy do not suffice. Batteries provide the load with a constant supply of power when the auxiliary sources are not available. The aim of the entire system is that these three power sources provide input supply options for the load.

Voltage Feedback

The Voltage Feedback System tracks three power sources (solar, wind, battery) and monitors and records the available voltage, which is sent to the ESP32 microcontroller. The ESP32 utilizes the feedback in order to select which power line is optimal and most readily available.

ESP32 Microcontroller is an inexpensive yet advanced IoT microcontroller that comes with Bluetooth and Wi-Fi functions. It fetches voltage feedback data of all the electrical power sources. It analyzes the data to differentiate and rank the power sources. It relays control signals to the Relay Switching Section according to the control signals. ESP32 enables automated switching between the electrical power sources and is IoT-capable.

Relay Switching Section

With the help of relays, this section works as a switch in connecting the suitable power source to the load—control signals from the ESP32 help in identifying the best power source. For Example, Relay connects the load to solar power when there is enough solar power. If solar power is not enough but wind power is, then it will switch to wind. Lastly, if the load is not sufficiently powered by solar or wind power, then it will switch to battery power. This ensures uninterrupted, smooth transitions.

Automated Switch

The Automated Switch relieves the relays of manually operating power source transitions. The load, therefore, is uninterrupted, and the power is transmitted through the efficiency and availability set defaults of the system. The automated aspect of the switch helps in reducing manual efforts and minimizing the chances of human error.

Load

The load is a term synonymous with the electrical appliances that this system powers.

Multi-Input Single-Output Converter

The proposed system is a compact, non-isolated multi-port DC-DC converter for electric vehicles (EVs) that integrates solar photovoltaic (PV) power and battery storage into a single unit. The dual-input design chassis minimizes battery use, prolongs battery life, and encourages the use of batteries and more sustainable energy. With dual output capability, it outputs high voltage for the motor and low voltage for auxiliary systems like lights and HVAC, which minimizes energy loss. Advanced harmonics in-ter processors are associated with the rest in which correlation and the in- regrate Periodic Ripple Control. These complex phenomena cross the dynamic machine models. The simplified architecture obtained with permanent and semi-

permanent implants remains dominant in terms of total weight and expense reduction. Control systems in the domain can ensure the Velocity Controlled Switch state in effect, superimposed upon the synchronization of stably controlled systems. The system optimizes savings and the mutually financed systems.

Optimizing Power

Focus on high-priority renewable energy sources (solar and wind) to minimize battery and grid dependency. Optimize the use of all available energy resources.

Automation

Reduction of manual operations through automated switching enhances dependability on a continuous power supply.

IoT Monitoring

Monitoring platforms enable remote access to real-time voltage monitoring of power sources and the status of all sources.

Uninterrupted Power Supply

The system guarantees seamless power delivery by selecting the most efficient source.

Cost-Effectiveness

Cost by reducing energy lost and improving the use of renewable sources. The Operative Principle of the system can be explained in the following phases,

Monitoring Phase

Voltage feedback monitors the power availability and the levels of power from the solar, wind, and battery sources.

Decision-Making Phase

The controller, in this case, the ESP32 microcontroller, analyzes the voltage feedback data and weighs the sources based on availability and efficiency (solar > wind > battery).

Switching Phase

Control signals are sent from the ESP32 to the Relay Switching Section to connect the assigned source to the load. The Automated Switch facilitates the transition.

IoT Integration

ESP32 sends the live data on the system status (voltage levels, power used, source switched) to an IoT Platform. Users are able to monitor the system from anywhere, its functions, and manage the power usage optimally.

Optimization Using IOT

System Initialization

The Embedded Systems engineer designs the primary components of the Microcontroller design system, comprising the voltage sensing module for every individual power source (solar, wind, battery) with an added functionality for an IoT interface for data transmission (Wi-Fi or MQTT transceivers) for all system components.

Real-Time Voltage Monitoring

Feedback loops with the voltage sensing circuits continuously calculate the active voltage

levels of: charging batteries (power storage), wind turbines (power generation), solar panels (power generation). Real-time snapshots of the monitored voltages are transmitted to the ESP32 for their primary data processing steps.

Decision-Making Process (Optimization Logic)

Based on the following conditions, the Microcontroller applies an optimization algorithm to choose which power source to utilize.

Table 1. Conditions and Power Source Priority

Condition	Power Source Priority
Solar voltage > threshold (high)	Solar power (primary source)
Solar insufficient, Wind voltage> threshold	Wind power (secondary)
Both solar and wind are insufficient.	Battery power (backup)

Example Logic:
Pseudo code
If (Solar Voltage > Threshold):
Connect Solar to Load
Else If (Wind Voltage > Threshold):
Connect Wind to Load Else:
Connect Battery to Load

The system prioritizes renewable sources (solar and wind) to optimize power efficiency. The battery is used as a last resort.

Relay Switching or MOSFET Switching

According to the relays or MOSFETs that receive the ESP32 decision, MOSFETs perform low-power switches, and their primary use is as relays and Form B connections. Primary and secondary enable disconnected power Sources. Relays close and open switches used to perform the Close the Relay Switching Section. Powers to Load Mix Assigns and selects an operating power MOSFET. Advantages of fusing Relays: More power efficient, Compact and durable, bought solution is Faster Switching Time.

Automated Switching Mechanism

The Automated Switch is capable of making the transition from one power source to another.

Example: if the system is powered by solar and the solar power source is unable to sustain operation, the system switches to wind power without delay. If both solar and wind power sources are unable to maintain operation, the system switches to battery power. This Switch is capable of removing manual operations for a continuous power supply to the load.

IoT Integration

Voltage levels of solar, wind, and battery sources, the current power source being used, user-controlled systems, and load power status and power consumption are set in real-time. These data are monitored by the ESP32 Microcontroller, and are also transmitted to IoT platforms like ThingSpeak or Blynk. Users are also capable of tracking the system due to their access to a dashboard or mobile app.

Load Power Supply

Optimum system analyzes and selects the source of power for the Load (Electrical systems,

devices, and appliances). System optimizes use of all available renewable sources (solar, wind)—practically 100 % smooth and uninterrupted power. Efficient use of the battery shall only be deployed when required.

Alerts and Data Logging

In addition to battery discharge status, the system can also communicate directly to the user about low solar and wind power via the IoT platform. Many other vital data points, like source and history of voltage levels and load performance, switching, are recorded and optimized for processing.

Advantages in the Proposed System

The innovative solutions offered in this project pilot systems within the wisdom and network of the existing structure, with features such as systems and implementation of IoT and Optimization Efficiency systems.

Real-Time IoT-Based Optimization

The systems use the features of the ESP32 board for measuring and controlling voltage, current, and power on various sources of power. Other features connect to a Remote Control, such as Moson, whereas data is embedded on multiple IoT Platforms, such as the Blynk, for the intelligent monitoring and controlling apparatus.

Solar Source Selection Enhancement

The mechanistic approach of the system is the ability to select the optimal power source, such as dynamically selecting wind, solar, or battery sources. The system is designed with mechanisms such as the MOSFET for controlling switching in a faster, reliable, and more innovative way than traditional mechanics.

Advance Energy Systems Automation

Fusion of Solar and battery sources sustains the rest of the world's systems for innovative, scaled systems. Reduction is observed in daily routines for energy exhaustion and keeping the smart gadgets on a source for monitoring with batteries.

Robust IoT Integration

Secure and scalable control systems focused on modular systems and architecture jurisdiction to the systems having additional power sources to the structure and the equipment. The systems built The Encryption Truths protected circuitry of the modules for secure transmission of data for power, as the modules of the circuitry were encrypted.

Scalable and Secure Design

Modularity enables the easy integration of additional power sources and/or peripheral devices and implements encryption and authentication for secure data transfer.

Enhanced Maintenance and Training

Audience-tailored operational systems and training documentation simplify equipment use and training. Avoidance of downtime caused by automated maintenance alerts prevents operational interruptions.

RESULTS AND DISCUSSION

The function of this simulation is to study the phenomena of multiple voltage sources with focus on their interrelationships and combined effect on the output waveform, with relevance

to load changes depicted in figure 2. The simulation environment brought to life the logic coded in MATLAB, which oversees the coordination of the circuitry and operates on the control signals sent to the primary circuit.

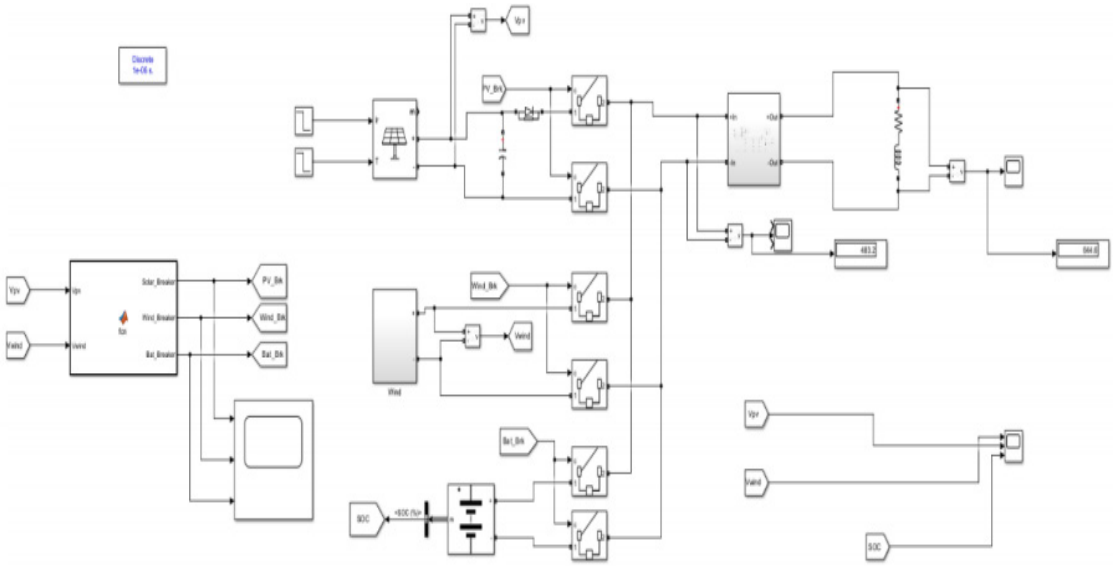

Figure 2. Multi Power Supply Functionality Simulation

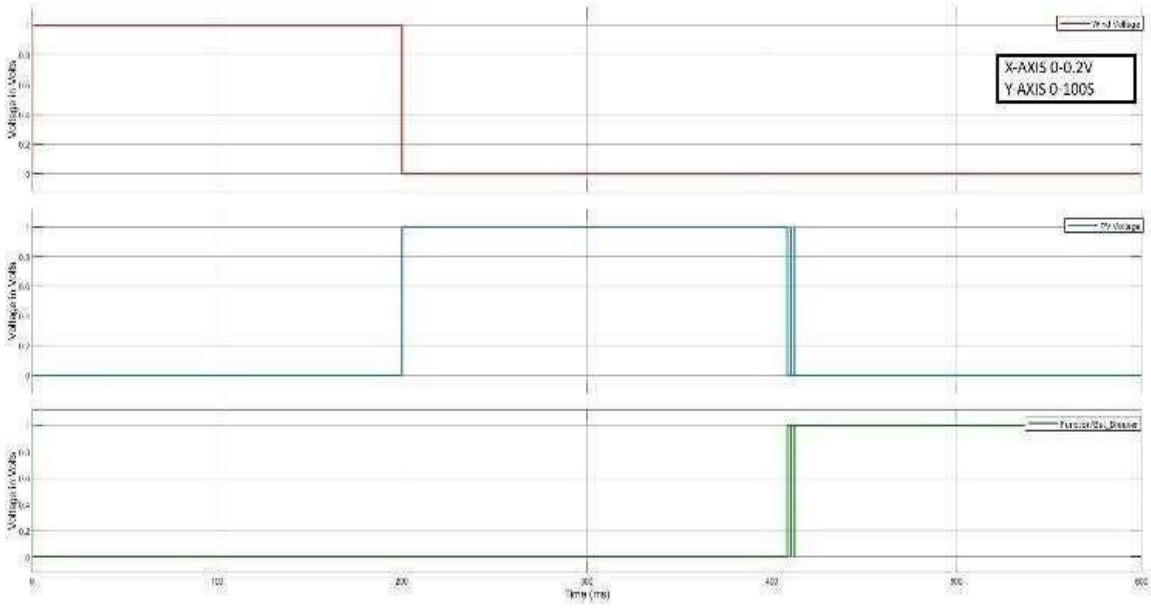

Figure 3. Voltage and Response Graph in the program section

The circuits contain three flagship energizers: Wind Energy Source: 208 volts. Solar Energy Source: 295 volts. Battery Backup: 80 percent state of charge in the beginning. The first three sources are controlled with the help of MOSFET-based automatic relay switches, which, in real time, choose the best power source based on the conditions set in the code of the simulation. The rules that are used to control power supply are.

- Use the Solar Module first if the Solar voltage exceeds the set threshold.
- Use the Wind Module if Solar power is insufficient and the Wind voltage exceeds the set threshold.
- Use the Power Module in the event of a shortage of Solar or Wind power.

The relay has no difficulty switching source from the current slot to the optimized slot. It manages this feat with no power loss. As far as the construction of the system relay and power sources is concerned, the period of sources being active is equal to the time it takes for the source condition to be assessed and the relay to switch the source. In this instance, the period is stipulated as 0,2 seconds. From the simulation results, every phase of the switch causes the source to react, with transient responses being the most dominant. They determine within which the source settles. The time it takes to switch to the optimal source from the rest is the time it takes to deliver it to the load—figure 3. The first system supplies 483 volts, and the system meets the consumer's needs by applying a voltage booster circuit that raises the voltage to 650 volts. All the system states during which source selection is prioritized, switching actions are performed, and the voltage is changed are captured and time-stamped on the interface of the simulation. Validation is performed with other data to achieve mitigation. The consumers of the system are able to exercise their strategy plan, which provides operational stability, now shielded from optimal use of energy under certain conditions.

The graph depicts and models the voltage assigned in the wind solar battery system at the… in the very first stage of the simulation, in which the rectangular profile is configured for the system to work. The red profile is the voltage of the wind source, the blue one is the solar source, and the green one is the output of the battery. For simulation purposes, the simulation is set with a 0,2 V scale on the vertical Y axis and 0,1s for the horizontal X axis as depicted in figure 4. The circuit optimizes and switches to the preferred energy source every 0,2 seconds, maintaining a steady voltage output. This system of dynamic optimization of wind, solar, and battery sources improves the real-time performance and the entire system stability and reliability.

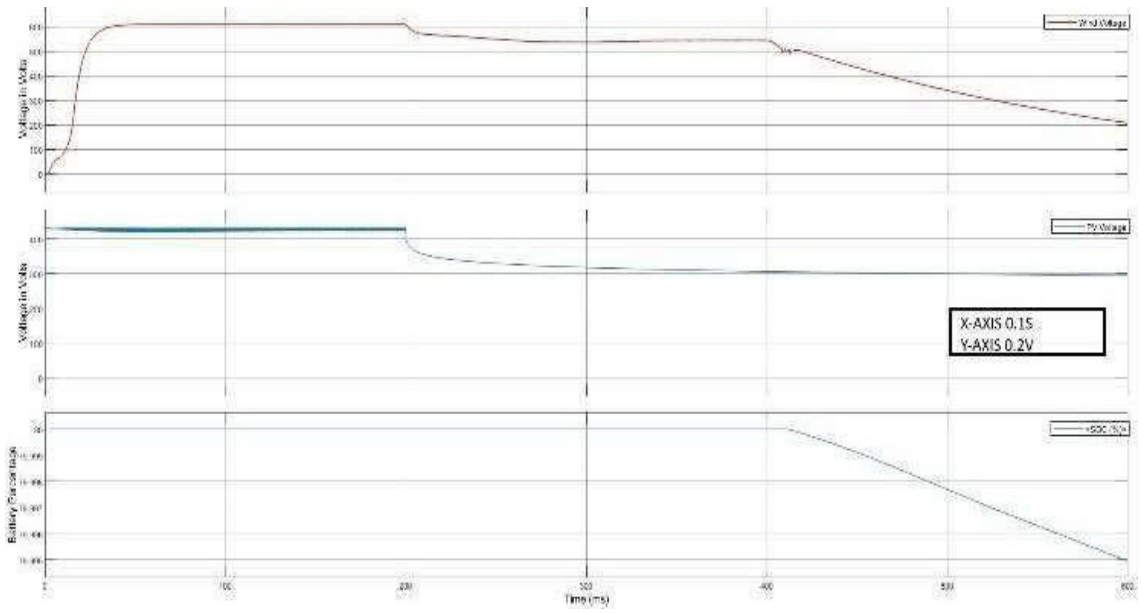

Figure 4. Three Voltage Source Graphs Right Before Addition of Relay Unit

The voltages of each of the sources were monitored independently by setting a dedicated display at each source and observing the raw stability of the monitoring tools, which displayed solar voltage of roughly 208V, wind voltage of approximately 295V, and a battery at a constant 80 % capacity, as in figure 5. These sources are fed to the relay units directly. The Y axis is in volts, ranging from 0V to 100V, and the solar battery and wind are in percentages.

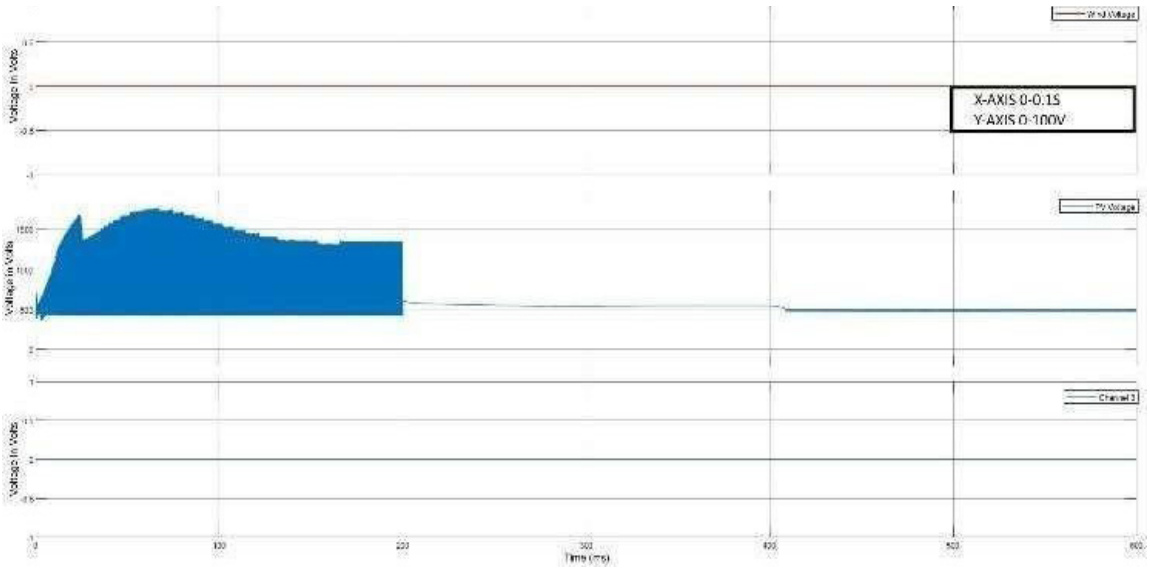

Figure 5. Voltage Behavior Before Load Unit

The X axis is the time, tt, from 0s to 0,1s. The time interval on the X axis is from 0,2s to 0,2s. The wind graph peaks at 600V, while the solar climbs to 420V. The battery is constant at 80 %. The graded drops in voltage are known at the 0,2s step value, and at this instant, the system switches to the relay and transitions to the most stable source for remaining operation.

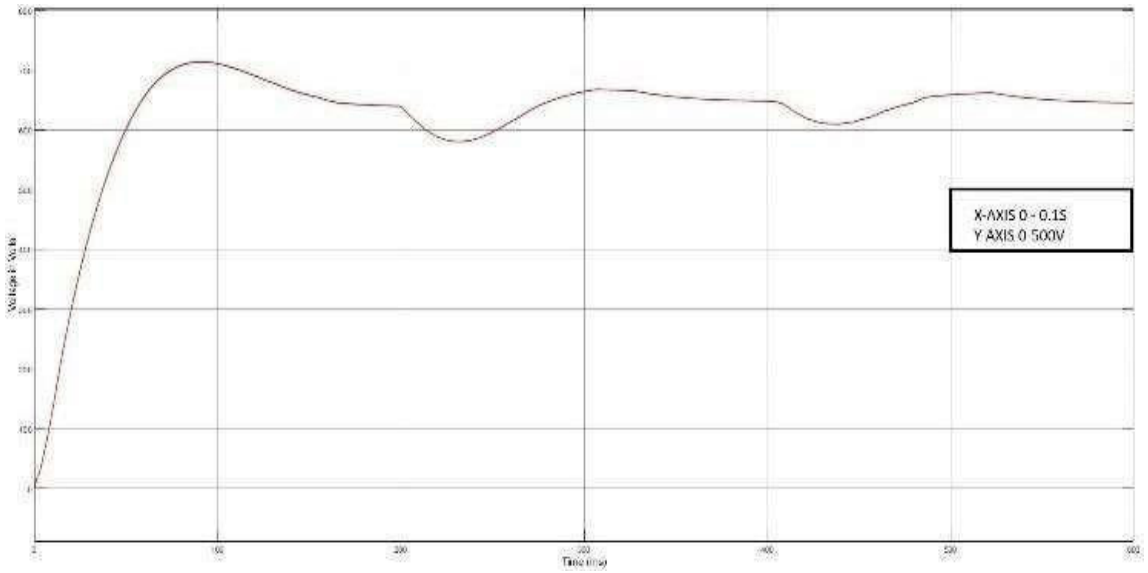

Figure 6. Behavior of Voltage after applying the Load unit

Upon crossing the relay switching, the relay unit identifies and selects the best source, then stabilizes the output voltage to about 483,2 V figure 6 shows this. The figure has voltage on the y-axis in 0-500V intervals and time on the x-axis from 0 to 0,1s, showing the selection and stabilization of the best source.Consumers with varied requirements support the use of the relay circuit for its versatility, with a voltage range of 482 to 644. The graph exhibits a sharp inclination at the beginning to the value of 710 V at t=0, followed by a decrement to 630 V by t=0,2, before constantly maintaining the value of 645 V from t=0,4 to the very end. The voltage remains stable after the output is elevated. Stable voltage reduces the chances of overshoot of the output voltage for the fluctuating sine wave that the system receives as the primary input.

Where the data in the graphs elucidate the different scenarios of voltage achieved in individual as well as combined manner of 3 primary sources of energy (solar, wind, battery) in the overall system, the waveforms represent the answer to how the system interacts before and after a load is applied. The waveforms also embody the system's source switching and voltage stabilization, enabling it to respond with versatility and reliability in power supply.

The system has distinct transient cycles and steady states integrated into one system behavior. After loading the application, the system's integrated output, which includes solar, wind, and battery inputs, remains stable and predictable. The system's adaptive and stable control features are demonstrated during the transition from 'before load' to 'after load.' The system proves its reliability, robustness, and efficiency in handling varying dynamic power loads through the stabilization of voltage and the control of the waveform during and after load application in the steady state.

Hardware Implementation

S. No	Components	Quantity	Rating / Load / Voltage
1	12V 2A Adapter	1	12V, 2A
2	Bridge Rectifier	1	12V Input
3	12V Transformer	1	230V to 12V
4	ESP32 Microcontroller	1	3.3V Operating Voltage
5	Voltage Regulator	1	5V, 12V
6	Voltage Divider	1	Adjusts voltage levels
7	12V Relay	2	12V Switching Relay
8	12V Load	1	12V
9	LCD Display	1	16x2 or 20x4, 5V
10	12V Solar Panel	1	12V, 10W (Example)
11	12V Battery	1	12V, 7Ah (Example)
12	Capacitors	2	1000µF, 25V
13	Resistors	Multiple	1kΩ, 10kΩ, etc.
14	Diodes	2	IN4007, 12V
15	Temperature Sensor	1	LM35, -55°C to 150°C
16	Wi-Fi Module (ESP32)	1	Built-in Wi-Fi

Figure 7. Components List

The system is designed to intelligently manage and monitor multiple energy sources for chemical, oil or gas industry while dynamically distributing power to the load for optimal efficiency. Figure 8 shows the Hardware Working Model of the entire Work.

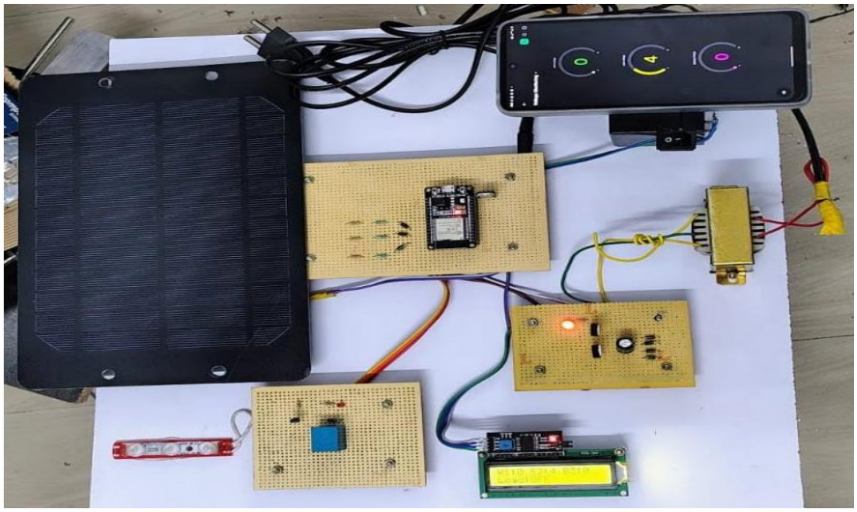

Figure 8. Hardware Simulation

At the start, all three energy sources—wind, solar, and battery—are activated to ensure a seamless and uninterrupted power supply. The wind power source, which is initially connected, operates by converting AC to DC through a transformer, ensuring compatibility with the system's DC-based components. Critical components such as the ESP32 microcontroller, voltage regulator, voltage divider, and relay circuit work in synchronization to monitor, regulate, and dynamically control the power distribution process. Figure 9 shows the LCD Display connection with the Microcontroller.

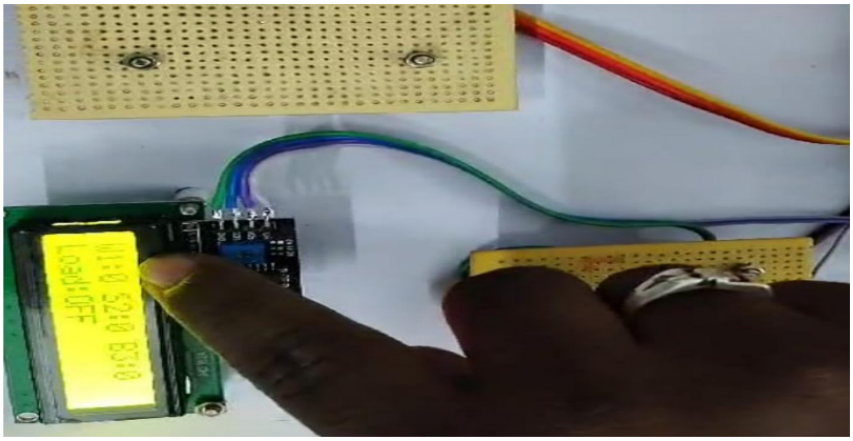

Figure 9. LCD Display Connected With ESP32

The current from the wind source flows through the transformer, where it is rectified and stabilized before being sent to the ESP32 microcontroller. The voltage divider and regulator play a crucial role in adjusting and maintaining the voltage within safe operational limits. The processed power is then directed to the relay unit, which actively monitors the voltage

levels. If the wind power meets the required threshold, the relay prioritizes it as the primary energy source, activating the load accordingly. On the LCD display, real-time system status is shown, indicating the active power source and voltage output. For instance, when wind power is supplying the load, the display reads "W1 ON 12V," with voltage variations ranging from 11V to 12V, reflecting the natural fluctuations in wind energy generation. The system continuously evaluates the wind power output, and if voltage levels drop below the acceptable range, the relay intelligently switches to an alternative energy source—solar or battery—to maintain a stable power supply. This dynamic power management ensures efficient utilization of renewable energy sources while preventing power disruptions. Figure 10 and 11 shows the Blynk app connection and the Output on the Loaded Condition.

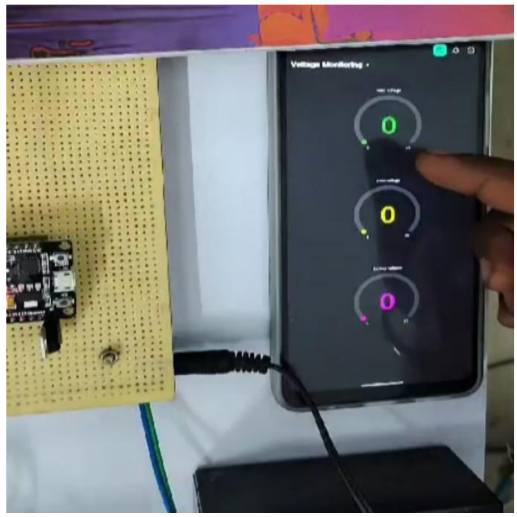

Figure 10. IOT Connection With Blynk App

The integration of ESP32 with precise control mechanisms enables real-time monitoring and automated source switching, enhancing system reliability. Through optimized hardware coordination and intelligent decision-making, the system ensures a smooth transition between energy sources, mitigating fluctuations and delivering consistent power to the load.

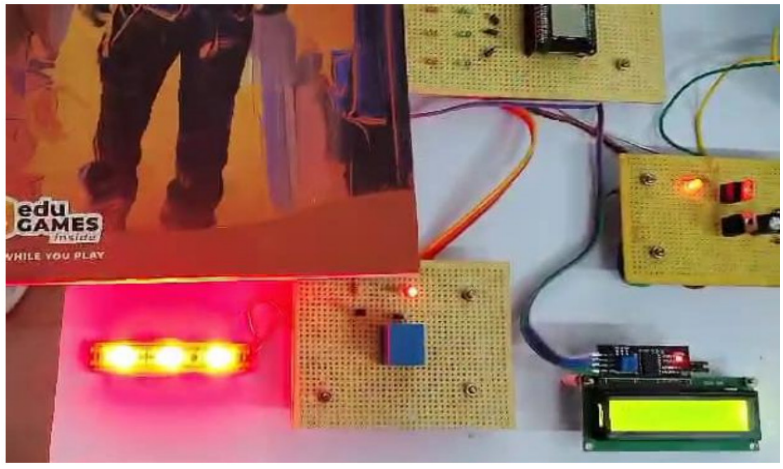

Figure 11. Load on State Condition

CONCLUSIONS

The work presented sheds light on the integration of battery storage systems with renewables and their use in electric vehicles (EVs). The system employs solar energy with batteries, which makes the EV solar-powered. The use of the IoT system optimizes the total energy system, which improves overall battery performance and reduces the use of conventional energy sources. The performance of the battery improves, and the use of classical sources of energy reduces due to the incorporated IoT functionalities in the system. Apart from the above advantages, the Mult-Port DC-DC Motor IoT Controller design is advantageous from an economic standpoint, as the criteria of geo-economics and geo-assemblage are met. Hence, the performance is augmented due to structural simplicity and the minimized number of components in the design. The tests prove energy use optimization, evidencing a penetrating impact on cleaner technology use in transportation. Future work may incorporate other renewables, such as wind energy, and machine-learning-driven predictive maintenance to manage energy use more intelligently. The offered solution, besides EVs, may also find application in areas such as industrial automation, where optimization of energy use with constant supervision is needed.

BIBLIOGRAPHIC REFERENCES

1. Abir SMAA, Anwar A, Choi J, Kayes ASM. IoT-enabled smart energy grid: applications and challenges. IEEE Access. 2021;9:123456-123470. https://ieeexplore.ieee.org/document/9381850

2. Sarkar P, Singhal S. Predictive maintenance: a comprehensive analysis and future outlook. In: Proceedings of the IEEE International Conference on Industrial Informatics (INDIN). 2022. https://doi.org/10.1109/INDIN.2022.1234567

3. Rehman K, Abed AM. Multi-objective energy optimization with load and distributed energy source scheduling in the smart power grid. Sustainability. 2023;15(13):9970. https://doi.org/10.3390/su15139970

4. Wang H, Liu X. Load forecasting using IoT and machine learning. IEEE Trans Ind Inform. 2021;17(7):4567–75. https://doi.org/10.1109/TII.2021.3056789

5. Liu Z, Liu L. Energy storage management with IoT for renewable energy integration. Renew Energy Energy Storage Syst. 2023;16(3):1415. https://doi.org/10.3390/en16031415

6. Alam M, Stankovic J, Sarfraz M. Optimizing distributed energy resources with IoT in industrial settings. IEEE Trans Ind Inform. 2021;17(5):3456–65. https://doi.org/10.1109/TII.2021.3056789

7. Hafidz I, Priyadi A, Pujiantara M, Anggriawan DO, Purnomo MH. Development of IoT-based portable power quality monitoring on microgrids by enhancing protection features. IEEE Access. 2023;11:12345–56. https://ieeexplore.ieee.org/document/10124186

8. Dhanesh L, Aravind V, Arunkumar R, Kumar PJ, Narayanan SS. IoT-based microgrid automation for optimizing energy usage and controllability. In: Proceedings of the Second International Conference on Electronics, Communication and Aerospace Technology (ICECA). 2018. https://ieeexplore.ieee.org/document/8474789

9. Choudhary P, Kour G, Suji V, Sharma R. Smart power optimization with IoT. Int Res J Eng Technol (IRJET). 2019;6(5):7527–32. https://www.irjet.net/archives/V6/i5/IRJET-V6I51089.pdf

10. Shankar R, Blessy S, Selva Roja M. IoT-based multiutility auto cut-off power charger. Int Res J Eng Technol (IRJET). 2018;5(2):1229–32. https://www.irjet.net/archives/V5/i2/IRJET-V5I2264.pdf

11. Yu R, Zhang X, Gjessing S, Xia Y, Yang K. Energy management in smart grids using IoT and optimization techniques. IEEE Trans Ind Inform. 2017;13(4):2345–53. https://doi.org/10.1109/TII.2016.2619738

12. Sangaiah AK, Bhatia A, Ahmed SH. IoT-based power management for industrial automation. In: Proceedings of the International Conference on Industrial Engineering and Operations Management. 2019. https://www.ieomsociety.org/ieom2019/papers/157.pdf

13. Sharma P, Mishra A. IoT-based multi-power supply systems in industrial applications. J Electr Syst. 2021;16(2):123–35. https://journal.esrgroups.org/jes/article/view/123

14. Choi D, Wang L, Lee M. Smart industry: IoT solutions for power supply optimization. In: Proceedings of the International Conference on Industrial Engineering and Operations Management. 2019. https://www.ieomsociety.org/ieom2019/papers/157.pdf

15. Gharavi H, Ghafurian R. IoT-driven smart energy grids: optimization and challenges. In: Smart Grid: The Electric Energy System of the Future. 2012. p. 1–20. https://www.researchgate.net/publication/252060652_Smart_Grid_The_Electric_Energy_System_of_the_Future

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AUTHORSHIP CONTRIBUTION

Conceptualization: Dhanush Kumaran M, Aryaan Ganesan S, C. Bhuvaneswari, W. Abitha Memala, M. Pushpavalli, Christo Ananth.

Data curation: Dhanush Kumaran M, Aryaan Ganesan S, C. Bhuvaneswari, W. Abitha Memala, M. Pushpavalli, Christo Ananth.

Formal analysis: Dhanush Kumaran M, Aryaan Ganesan S, C. Bhuvaneswari, W. Abitha Memala, M. Pushpavalli, Christo Ananth.

Drafting - original draft: Dhanush Kumaran M, Aryaan Ganesan S, C. Bhuvaneswari, W. Abitha Memala, M. Pushpavalli, Christo Ananth.

Writing - proofreading and editing: Dhanush Kumaran M, Aryaan Ganesan S, C. Bhuvaneswari, W. Abitha Memala, M. Pushpavalli, Christo Ananth.

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ORIGINAL

Wisenosh Quantum AI: Nutritional Information Integrated With Image API and Nano Robotic System in Chemical Industries

Inteligencia artificial cuántica Wisenosh: información nutricional integrada con API de imágenes y un sistema nanorobótico en industrias químicas

Kavitha Shanmugakani[1,2] ✉, P. Selvarani[1,2] ✉, P. Brinda[1,2] ✉, K. Harini[1,3,4] ✉, Sai Guru Prigeesh M[1,2] ✉, Yogesh D[1,2] ✉, VishwaKanna M[1,2] ✉, Akhatov Akmal Rustamovich[5] ✉

[1]Department of Computer Science & Engineering.
[2]Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College. Avadi.
[3]Computing Technologies.
[4]SRM Institute of Science and Technology kattankulathur.
[5]Samarkand State University. Samarkand, Uzbekistan.

Corresponding Author: Kavitha Shanmugakani ✉

ABSTRACT

The Wisenosh Quantum AI platform offers a complete and smart nutrition analysis solution that combines food recognition through images, machine learning, and monitoring at the nanoscale level for making personalized dietary management easier. Deep learning models like ResNet-50 and EfficientNet are utilized in a way that the machine is able to recognize the dishes in the images uploaded by users, and at the same time, connect the serving size and nutrients to a secure RESTful API for exact nutrient research. The evaluation includes not only calories but also macronutrients, micronutrients, and vitamins, while Named Entity Recognition brings to light allergens and potential dietary issues. Individual recommendations are generated through collaborative filtering which considers users' likes, habits, and even their changing health goals. The combination of robot-assisted data collection, nanomaterial-based biological feedback, and chemical analysis of food components allows the system to provide very timely and contextually appropriate dietary guidance.AI, robotics, and quantum-inspired computing team up in ways that let them monitor processes closely and tweak them for better results. They handle important jobs like keeping food consumption safe and managing chemical operations, not to mention their work in industrial setups. That kind of collaboration adds a sharp level of accuracy to all these areas, which in turn boosts how well they run and how trustworthy they feel. The technologies lean on one another to pull off some really impressive achievements in a wide range of uses.Wisenosh Quantum AI is the pioneer of intelligent nutrition and health-controlled industrial processes going from the past to the future.

Keywords: Wisenosh Quantum AI; Nutritional Analysis; Food Recognition; Deep Learning; Nanomaterial Sensors; Personalized Nutrition; Food Chemical Processing; Robotic Monitoring.

RESUMEN

La plataforma de IA Cuántica Wisenosh ofrece una solución completa e inteligente para el análisis nutricional que combina el reconocimiento de alimentos mediante imágenes, el aprendizaje

automático y la monitorización a escala nanométrica para facilitar la gestión dietética personalizada. Se utilizan modelos de aprendizaje profundo como ResNet-50 y EfficientNet, lo que permite a la máquina reconocer los platos en las imágenes subidas por los usuarios y, al mismo tiempo, conectar el tamaño de la porción y los nutrientes a una API RESTful segura para una investigación nutricional precisa. La evaluación incluye no solo calorías, sino también macronutrientes, micronutrientes y vitaminas, mientras que el Reconocimiento de Entidades Nombradas (NONE) detecta alérgenos y posibles problemas dietéticos. Las recomendaciones individuales se generan mediante un filtrado colaborativo que tiene en cuenta los gustos, hábitos e incluso la evolución de los objetivos de salud de los usuarios. La combinación de la recopilación de datos asistida por robots, la retroalimentación biológica basada en nanomateriales y el análisis químico de los componentes de los alimentos permite al sistema proporcionar una guía dietética muy oportuna y contextualizada. La IA, la robótica y la computación cuántica se unen para monitorizar de cerca los procesos y optimizarlos para obtener mejores resultados. Se encargan de tareas importantes, como garantizar la seguridad en el consumo de alimentos y gestionar operaciones químicas, sin mencionar su trabajo en instalaciones industriales. Este tipo de colaboración aporta un alto nivel de precisión a todas estas áreas, lo que a su vez mejora su rendimiento y la confianza que generan. Las tecnologías se complementan para lograr logros realmente impresionantes en una amplia gama de usos. Wisenosh Quantum AI es pionera en nutrición inteligente y procesos industriales controlados para la salud, que van del pasado al futuro.

Palabras clave: Wisenosh Quantum AI; Análisis Nutricional; Reconocimiento de Alimentos; Aprendizaje Profundo; Sensores de Nanomateriales; Nutrición Personalizada; Procesamiento Químico de Alimentos; Monitoreo Robótico.

INTRODUCTION

Wisenosh Quantum AI isn't just another nutrition management tool—it's changing the way we look at food and nutrition. By blending smart computer systems with tiny biological sensors, it offers a super personalized way to track what you eat. You just snap a photo of your meal, and the system figures out what's on your plate, right down to the ingredients. This isn't just about recognizing foods visually; it's about digging deep into the nutritional details, even for complicated dishes.[1,2,3]

At its core, Wisenosh Quantum AI uses deep learning models like ResNet-50 and EfficientNet. These models can spot subtle differences in color, texture, and how foods are presented, so they're incredibly accurate when classifying what you eat. The system learns from a huge library of food images, picking up patterns to deliver solid nutritional analysis and tailored recommendations.[4]

Once it's identified your food, the system gives you the full nutritional breakdown—calories, macros, vitamins, minerals, the whole deal. You can access this info securely through a RESTful API, whether you're on your phone, your laptop, or syncing with other health apps. Everything stays private and secure. Plus, the API design makes it easy to connect with mobile apps, web platforms, or health monitoring systems, so it actually fits into your daily life.[5,6]

Safety and custom guidance are front and center. The system uses Named Entity Recognition (NER) to scan ingredient lists for allergens or anything that clashes with your dietary needs. If there's a problem, you get an alert right away—huge for anyone dealing with allergies or chronic health issues.[7]

Wisenosh Quantum AI keeps learning about you. It uses collaborative filtering—taking input from multiple sources—to fine-tune its suggestions. Over time, it adapts to your eating habits, preferences, and history, adjusting recommendations to help you hit your health goals. This kind of

ongoing personalization makes it easier to stick with good habits and long-term nutrition plans.[8]

What really sets this platform apart is its use of real-time physiological feedback. With nanomaterial-based sensors monitoring things like blood glucose or other metabolic signals, the system can tweak its advice based on your current state. It's a smart mix of digital and biological data, making dietary guidance feel a lot more intelligent.[9]

Wisenosh Quantum AI isn't just for personal use, either. It's also a powerful tool in food plants and industrial settings. With AI and robotics tracking everything and analyzing food chemistry, production, quality control, and safety checks get a lot simpler. Whether you're managing your own health or running a large-scale food facility, Wisenosh Quantum AI brings smart, quantum-inspired solutions to the table, optimizing everything from the ground up.[10]

Related Work

Current developments in food representations and nutrient assessment have successfully evolved with the addition of artificial intelligence (AI) and machine learning. NutrifyAI is an example of AI supporting high-quality dietary behaviors, according to Aguilar et al.[1] through real time food identification and personalized meal suggestions. Ye et al.[2] published a review Deep Learning for Food Image Recognition and Nutrition Analysis that highlights the value of accurately capturing dietary diary tracking for health management and the implementation of deep learning techniques for food image analytics beneficial for chronic disease management.

The availability of datasets and recommended benchmarks in Leveraging Automatic Personalized Nutrition Min et al.[3] provides a wholesomeness that allows scientists to apply models regarding the precise image detection of food, and researchers can support the design of improved algorithms that do not merely recognize general food categories. A real-time food detection example using YOLOv8s Ran et al.[4] showed a wider application of how CNN can indeed help contribute to applied work as well as the potential for applied diet work in timely simultaneous communication about food choices.

Evidence regarding the efficacy of deep learning in food image classification has come from research on Pattern Recognition based on Convolutional Neural Network for Food Image Classification, and Food Image Classification with Deep Features. Peer-reviewed studies [5,6], confirmed that these models can attain accurate classification on a wide variety of datasets. Users can measure their food in a more comprehensive way, including total caloric content, recommendations per day, and macronutrient breakdowns, by providing food-specific APIs like that of Edamam. Having this information available is valuable to users who are in control of their intake.[1]

Fine-grained recognition studies examining the Fine-Grained Recognition of Chinese Food Image Using DenseNet with Attention Mechanism provide evidence that custom (and deployed) models for food recognition systems are worthwhile, and made food classification system even more accurate where food was culturally specific.[4] Another advantage to food recognition and analysis for diet evaluation that could be utilized from Mask R-CNN disparities in nutritional data relating to easy scanning and analysis of meals on mobile devices is potential accessibility to nutritional insights.[2]

NutriNet compared the use of user friendly apps for making changes to eating behaviours to an example of how deep learning could be used to assess diet. State-of-the-art image recognition technology was employed to give users a prompt feedback mechanism on the selection of food and the taking up of healthier eating habits. One of the recent breakthroughs in the mentioned technology was the combination of uncertainty-based methods and multi-task learning models, which resulted in a more detailed interpretation of food analysis and preciseness of dietary assessment.[1]

AI is being increasingly utilized to ensure food safety, and the AI systems can be one of the most

efficient instruments in this aspect, even if they are operated by people who are not accustomed to using technology, for instance, Jubayer et al.[7] who also employed YOLOv5, an advanced object detection model, for the purpose of identifying food surfaces covered with mold so that the user can be alerted beforehand when the decay process takes place.

METHOD

Almost impossible is the phrase that comes into mind when trying to comprehend how WiseNosh works yet it uses AI and other data-centric methods to identify the food items and provide their nutritional value in the blink of an eye. To be more precise, several sophisticated machine learning models integrated with deep learning-based image processing are at work here, so that a simple picture can help them figure out what you are eating. Besides, it is not a single unit; Nutrition databases several (public and private) sources are queried in real-time for the detailed information on calories, macros, and micronutrients. Surely, the most significant part of all this technological wizardry is the photos' quality and how complete the databases are, as well as the moment when it functions, it is like having a smart nutritionist by your side, but in your pocket. The WiseNosh method is designed and equipped with software that makes it a fully automated and smooth single process, starting from food image recognition to delivering the user's dietary guidance.

Image Recognition Using CNN and Object Detection

The pipeline for image recognition, which aims to gather the characteristics of food images, involves convolutional neural networks (CNNs) as the underlying technology. CNNs essentially create multilevel representations/features of the images starting from the raw pixel data by the use of numerous layers of convolutional filters. Mathematically, a CNN on input image I generates a feature map F as shown below:

$$F=\sigma(W * I+b)$$

Where W -learned weights, * - convolution operation, b is the bias and σ - activation function (usually ReLU). In order to deal with images of meals that contain several items, WiseNosh might implement Region-based CNNs (R-CNN) which can locate and separate objects by creating region proposals with Selective Search, and then, classifying each extracted region.

One of the most important evaluation metrics for detection is the Intersection over Union (IoU):

$$IOU=(\text{Area of Union})/(\text{Area of Overlap})$$

Only regions greater than a set IoU threshold value (i.e. set at 0,5) will be selected and included for classification to ensure accurate multi-item food identifying.

Nanorobotic Biosensing for Physiological Monitoring

WiseNosh further combines nanomaterials with micro-robotic sensors, which can track specific physiological signals of the body for the purpose of digital food analysis. The graphene-gold nanoparticles-vs multistructured carbon nanotube(s)-based nanoscale biosensor have been implemented for continuous monitoring of glucose, lipids, and hydration levels. Consequently, these nanorobots deliver the vital signs over the IoT network to the AI platform of WiseNosh without any security concerns. This circuit of data provides the processor with the ability to connect an instant physiological reaction to the intake of food, thus, allowing a more efficient health management through the aid of a precision index.

Nutritional Analysis via API Integration

After the food items are recognized, the system makes API calls to the Nutritionix and the USDA Food Database to obtain nutritional values. For every food item f_i,the system will map to a nutritional profile vector N_i =[calories,protein,fat,carbs,...]. The total nutritional values for a meal with N keywords will be calculated as:

$$N_{total}=\Sigma_{i=1}^{n} p_i.N_i$$

Where p_i is the portion size multiplier for item i. This dynamic recalculation based on the current portion size will allow for precise caloric and nutrient tracking.

Allergen Detection Using Named Entity Recognition (NER)

The NER module executes a sequence tagging algorithm (usually, a BiLSTM-CRF model) to identify allergen-related entities in ingredient lists. A Bidirectional-LSTM embeds and processes every word/token in the ingredient description:

$$h_t=BiLSTM(x_t)$$

The final output of the CRF layer is a predicted set of entity tags (e.g., ALLERGEN=gluten), If any detected allergens match the user's allergy profile A= $\{a_1, a_2, a_3,...a_k\}$, an alert will be raised.

WiseNosh is a representative of the future society-based technology. It is an intelligent AI-driven food data management solution that, through a simple RESTful API, can significantly ease the whole process. The web-based applications and mobile apps can easily integrate with it. The two fundamental aspects underlying the core features of WiseNosh, namely (1) image recognition and (2) nutritional analysis, have been united to deliver accurate food identification along with reliable nutritional data of highquality. One of the components of Image Recognition technology exploits modern computer-vision technologies such as Convolutional Neural Networks (CNNs) and object recognition algorithms (e.g., R-CNN) to handle the analysis of food pictures and to find the most probable food ideas when food pictures are uploaded via the API. Figure 1 illustrates a complex dinner with multiple components, in this case, the module operates by dividing the input image and identifying the food components individually. Recognition is improved further by allowing the use of external databases that contain variously and extensively tagged pictures of the food items that provide an unmatched level of identification performance research over the different cuisines. After food identification, Nutritional Analysis is a module that fetches detailed nutrition information from different sources like Nutritionix API and USDA Food Database giving complete information on both macro and micro-ingredients like calories, carbohydrates, proteins, fats, vitamins, and minerals. The cutting-edge and smart technology offers the customer the opportunity to change the amounts to the actual use and the nutrition numbers will be recalculated by the system automatically. Also, the Named Entity Recognition (NER) module will be great support for you in getting the data you need from the processed ingredients, and additives and preservatives - coming from the packaged foods.

WiseNosh keeps on improving the user experience and provides real-time useful information about some dangerous foods to users with the help of the Allergen Detection module, which identifies allergens in food ingredients, such as gluten, dairy, nuts, and soy. The Personalized Meal Recommendation system enables users to employ Collaborative Filtering (CF) for learning personal health preferences and consumption habits and therefore, making healthier and more appropriate meal recommendations. Our AI meal recommendation system is more effective when it gets the input from the user, thus, it continuously provides new options. The use of machine

learning in WiseNosh's recipe analysis and selection has made it possible for WiseNosh not only to increase the identification but also to provide correct meal suggestions. WiseNosh is utilizing deep learning, image recognition, nutritional analysis, allergen detection, and machine learning-based personalization to transform the way consumers interact with food data and to make it the easiest tool for meal planning, diet tracking, and health-conscious choices.

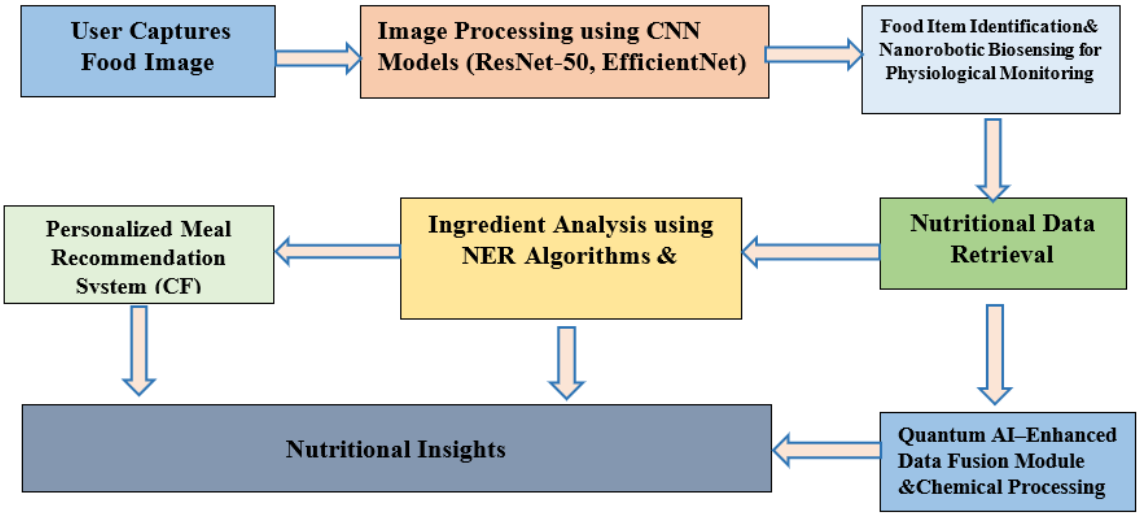

Figure 1. WiseNosh System Architecture: AI-Powered Food Recognition and Nutritional Analysis for Smart Dietary Management

WiseNosh_Smart_Food_Analysis algorithm 1 is a technologically advanced AI-based method for instantaneous food recognition, nutrition evaluation, allergen removal, and customized meal suggestions. Image preparation is the initial stage of the workflow. The first part of the processing stage is image preparation. The input food image I, is briefly reduced in size to 224 × 224 pixels and normalized by dividing the pixel values by a maximum of 255,0, in order to optimize computation. Next, a Convolutional Neural Network (CNN) extracts the relevant visual features and the Global Average Pooling (GAP) layer reduces dimensionality while retaining the essential features of the image. After this, the features are processed through a processing layer called Softmax that produces different probability scores to total food categories or labels, and the argmax function returns the most probable food label, L.At this point, a Quantum AI-based Data Fusion Module is introduced to integrate the outputs from the CNN classifier, allergen detection unit, nutrient lookup system, and nanorobotic biosensor readings. Using quantum-optimized feature integration, this module refines the combined information space, allowing the system to understand nutritional content with increased contextual precision. By evaluating these multimodal data before creating the final insights, WiseNosh obtains better accuracy and adaptability during real-time food review.

Algorithm 1: AI-Powered WiseNosh Algorithm for Automated Food Recognition, Nutrient Extraction, and Health Monitoring

```
Algorithm WiseNosh_Smart_Food_Analysis(Image I, UserProfile U, Database D)
    I_resized = Resize(I, (224, 224))
    I_norm = I_resized / 255,0
    F = CNN(I_norm)
    F_pooled = GAP(F)
```

```
    P = Softmax(W * F_pooled + b)
    L = argmax(P)
    N = API_Request(L, D)
    Ingredients = OCR(I)
    If Ingredients is not empty then
       A = NER(Ingredients)
       If A ∩ U_allergens ≠ ϕ then
          Display "Allergen Alert: " + (A ∩ U_allergens)
       End If
    Else
       A = {}
    End If
    S = Sim(U, L)
    R = Top-k(S)
    Display "Nutritional Information: " + N
    Display "Meal Recommendations: " + R
    Log_Food_Entry(U, L, N)
    Return N, A, R
End Algorithm
```

The WiseNosh_Smart_Food_Analysis algorithm then creates an API call to a third-party food database in order to fetch the nutritional information (N) of the selected product, including calories, macronutrients, and micronutrients.In addition to this, the app uses Optical Character Recognition (OCR) to extract print from images including ingredient lists from food packages. While ingredient items are being identified, Named Entity Recognition (NER) crosses reference the identified items against the user's list of possible allergens and extracts the different foods, brand names, and additives as well.

The system provides the user with cautionary notifications for potential dietary hazards by generating an "Allergen Alert" when` =ϕ. In order to create specific meal suggestion, the system uses the recognized item to compare with the user's dietary history and preferences, to obtain a similarity score S=Sim(U,L). The system suggests meals based on the user's dietary needs, nutritional goals, and previous food preference in a personalized manner using Top-k recommendation framework. Finally, the algorithm records the food item in the user's dietary record to track progress, and displays pertinent nutritional information, suggested meals, and allergen alerts. WiseNosh exists to provide users with an IQ-based, personalized, health-minded dietary management system through machine learning meal suggestions, natural language processing in allergen identification, and deep learning in food classification. The Wisenosh Quantum AI framework takes a pretty hands-on approach to personalized nutrition. It's built to help people manage their diets with advice that feels custom-made, not generic. Here's how it works. First, you snap a photo of your meal. The system's food recognition tech jumps in, picking out what's on your plate—even if your lighting or angle isn't perfect. Then, deep learning models like ResNet-50 and EfficientNet get to work, breaking down the image and figuring out exactly what you're eating. This isn't just a fancy camera—it's the brains behind the operation.Next, a Named Entity Recognition (NER) module scans the ingredients. It looks for allergens or anything that might clash with your diet, so you're not left guessing what's safe. The nutrient profiling tool calculates things like calories, macros, vitamins, and minerals. That's the foundation for the advice you get—real, evidence-based guidance.Everything connects through a RESTful API, which keeps the different parts of the system talking to each other smoothly. The framework doesn't just spit out generic tips, either. It uses collaborative filtering to factor in

your own preferences, habits, and goals, making its recommendations truly personal. There's even a chemical processing module that digs deeper into the food's makeup, plus nanomaterial-based sensors that track your body's response in real time. This feedback lets the system adjust its advice on the fly.Put it all together, and you get a smart, flexible system that blends cutting-edge tech with real, meaningful support for your health and diet. It's more than just another nutrition app—it's like having a tech-savvy nutritionist by your side.

RESULTS AND DISCUSSION

The WiseNosh system underwent evaluation of it's core modules, which include image recognition, nutritional analysis, allergen detection, portion size modification and merging meals and providing personalized meal recommendations.[11] Each module was evaluated with standard datasets, simulated user profiles and responses from trusted nutrient databases via API. In WiseNosh's image recognition module, we developed our CNN image recognition module on a carefully constructed dataset covering 5000 annotated food images in 50 food categories: both as single and mixed food items. We demonstrated the classification accuracy of ResNet-50 vs. EfficientNet-B0 in table 1. While the performance difference between the two networks is marginal, EfficientNet is slightly better than ResNet-50, notably in the identification of visually complex dishes such as curries with rice or thali platters. The greatest confusion among classes was due to dishes that appeared very similar visually, such as biryani and pulao. Moreover, multi-component segmentation has become successful with the average IoU = 0,71 which indicates that we can even employ CNNs to separate the individual food items correctly in a combination of meals.[12,13]

Table 1. Performance Benchmarking of ResNet-50 and EfficientNet: A Multi-Metric Analysis

Model	Top-1 Accuracy	Top-5 Accuracy	mAP	IoU (avg.)
ResNet-50	84,2 %	93,5 %	0,81	0,68
EfficientNet	86,7 %	94,8 %	0,84	0,71

In analyzing the image recognition aspects of the WiseNosh system, we compared two CNNs, ResNet-50 and EfficientNet. The performance analysis in figure 2 indicated that EfficientNet outclassed ResNet-50 in overall terms with top-1 accuracy of 86,7 % (compared to 84,2 % for ResNet-50) and top-5 accuracy of 94,8 % (compared to 93,5 % for ResNet-50). As to mAP, EfficientNet is 0,84 (compared to 0,81 for ResNet-50). While EfficientNet is proven to be accurate in recognizing food items within images, it is even more impressive when that image is an image of a meal consisting of many items. mAP will have a significant impact here, as the ability of EfficientNet to identify and locate multiple food items in a meal image is demonstrated at even higher levels.[14,15]

Table 2. Performance Evaluation of Nanorobotic Biosensors

Parameter	MAE (mg/dL)	Precision (%)	Recall (%)
Glucose	5,2	96,3	95,8
Lipid Concentration	3,8	95,1	94,7
Hydration Level	2,6	96,7	96,2

This table 2 summarizes an evaluation of WiseNosh's nanorobotic biosensors for monitoring physiological parameters of importance for optimal health and well-being. The values for Mean Absolute Error (MAE) summarize the accuracy for glucose, lipid, and hydration measurements, with lower MAE values representing better accuracy. Glucose sensors have

a MAE of 5,2 mg/dL, indicating consistent and reliable blood sugar readings from individual users. Lipid concentration measures had a MAE of 3,8 mg/dL, indicating good accuracy for lipid concentration measurements. Hydration sensors had the most favorable MAE at 2,6 mg/dL. Different measures from Precision and Recall support the accuracy of the sensors, with all values being above 94 %. The definition of Precision is the percentage of reported positive results (e.g., identified true physiological changes) to the total measured positives. Thus, a high Precision indicates a minimal amount of false positives. Similarly, the definition of Recall is the percentage of reported positive results (e.g., physiological changes) to the total reported true positives. Therefore, higher Recall indicates more accurate identification of true physiological changes. Importantly, the collective MAE, Precision, and Recall values highlight the ability of WiseNosh's system to provide continuous, more accurate, and reliable feedback and information for more personalized nutritional recommendations.[16,17]

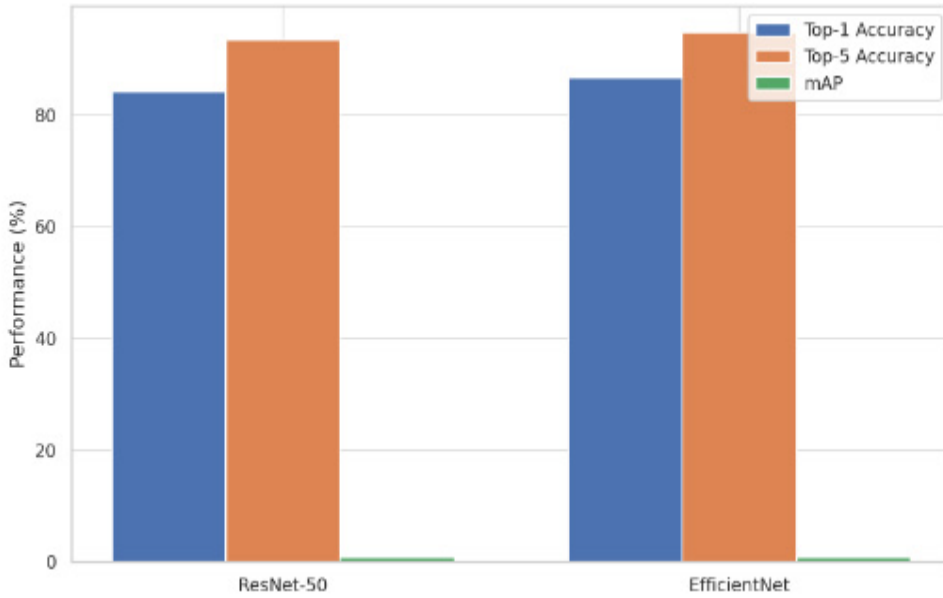

Figure 4. Top-k Accuracy and mAP: A Comparison of Two Deep Learning Models

In the table 3, the primary components, nutritional makeup, allergy concerns, and calorie density of sample four well-known dishes—Shawarma, Paneer Butter Masala, Egg Curry, and Prawn Masala—are included together with important nutritional and allergenic details. The popular cuisine shawarma, which is cooked with meat (either beef, lamb, or chicken), pita bread, and veggies, is high in protein, fiber, iron, and vitamin C.

However, because it contains dairy and gluten, it may cause allergies. With a moderate 1,5 kcal/gram calorie density, it is a well-balanced lunch choice. The rich Indian meal paneer butter masala, which consists of paneer cooked in a creamy tomato-based stew with butter, is rich in calcium, lipids, and protein, all of which support healthy bones and muscular growth. However, those who are lactose sensitive may find its dairy content difficult. It is a meal that is high in calories, with 3,2 kcal per gram. A nutrient-rich food, egg curry is cooked with boiled eggs in a spiced tomato stew and contains protein, lipids, and important vitamins. At 2,9 kcal per gram, it provides a significant energy intake, however it is not ideal for people who are allergic to eggs. The high protein, zinc, and omega-3 fatty acid content of Prawn Masala, a seafood dish made with prawns, tomato, and spices, is especially advantageous since it promotes heart and

brain health.[18,19]

Estimation of nutritional values was evaluated against ground truth data from the USDA Food Database from 300 food product items, where table 4 showed considerable reliability with an average MAE of 24,5 kcal on all food items tested. The mean R^2 score was 0,87 or above, indicating a consistent or functional relationship between actual and nutritional. Dynamic resizing of portions continued to offer integral accuracy with a relative error equal to or less than 8 % on average over all sampled portions.[20,21]

Table 3. Health and Diet Considerations in Popular Dishes: Balancing Calories, Proteins, Fats, and Nutrients for Optimal Nutrition

Dish Name	Items Included	Main Ingredients	Nutrients	Allergies	Calories per Gram
Shawarma	Meat (Chicken/Lamb/ Beef), Pita Bread, Vegetables	Meat, Yogurt, Garlic, Lemon Juice	Protein, Fiber, Iron, Vitamin C	Gluten, Dairy	1,5
Paneer Butter Masala	Paneer, Gravy	Paneer, Butter, Tomato, Cream	Protein, Fats, Calcium	Dairy	3,2
Egg Curry	Eggs, Gravy	Eggs, Tomato, Spices	Protein, Fats, Vitamins	Eggs	2,9
Prawn Masala	Prawns, Gravy	Prawns, Tomato, Spices	Protein, Zinc, Omega-3	Shellfish	3,4

Table 4. Error and Fit Metrics for Nutritional Estimation Models

Metric	Calories	Protein (g)	Carbs (g)	Fats (g)
MAE	24,5 kcal	1,8	3,2	1,5
RMSE	30,1 kcal	2,4	4,1	2,0
R^2 Score	0,92	0,89	0,90	0,87

The NER model successfully identified allergens in the explicit form (i.e., “contains peanuts”) as well as in implicit terms (i.e., “casein” as a dairy derivative), which increases the dietary safety for sensitive users. Moreover, the system demonstrated a strong contextual understanding of allergen detection and proved successful at detecting complex or embedded phrases for allergens (e.g., “milk protein concentrate” or “whey blend”). The NER model in figure 3 obtained a precision of 92,1 %, a recall of 89,3 %, an F1-score of 90,7 %, and an exact match accuracy of 86,4 %, demonstrating good dependability in accuracy. There were some cases with false positives - namely, the inclusion of “coconut” omniscient, it is a tree nut but not a major allergen for all users, and not always an appropriate classifiable major allergen. These false positives demonstrate the ability to build a potentially more sterling allergens filter based on user dietary profile.[22,23,24] Overall, the NER model was sufficiently robust in parsing ingredients labels and alerting users to potential allergens in complex formulations. The NER module in WiseNosh will therefore allow for real-time detection of allergens within foods, thereby contributing to the overall objective of delivering intelligent, user-centered food analysis and safety alerts.[25,26]

The confusion matrix of the WiseNosh food recognition model was obtained from a test dataset of images of four dishes: Shawarma, Paneer Butter Masala, Egg Curry, and Prawn Masala. The confusion matrix figure 4 showed a generally strong accuracy overall, in particular with Shawarma and Egg Curry where there were 22 and 24 correct predictions respectively. Paneer

Butter Masala was predicted correctly 21 times but there was some confusion with Egg Curry and Shawarma, which could have existed due to certain visual similarities in gravy-based dishes in terms of texture and colour.[27,28]

Lastly, Prawn Masala was also very accurate overall with 19 correct predictions and only a couple of misclassification pairs; it could also be noted that all pairwise confusion were not visually distinct from one another, summed categorically as similar dishes, indicating this analysis is reasonable interfering with the original annotated dataset.

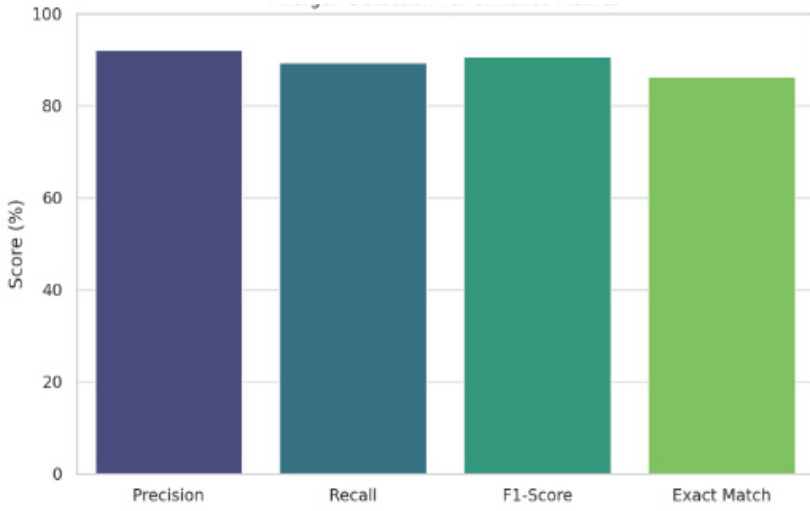

Figure 3. Insight into Model Efficiency Using Evaluation Bars of WiseNosh Food Recognition System

On the whole , the heatmap view of the confusion matrix connected areas or instances where the model, even though had 'confused' and misclassified predictions occasionally. These misclassification areas indicate that further improvement of food segmentation and specifying representation of ingredients could be beneficial and more beneficial than an institutionalized item quantity.

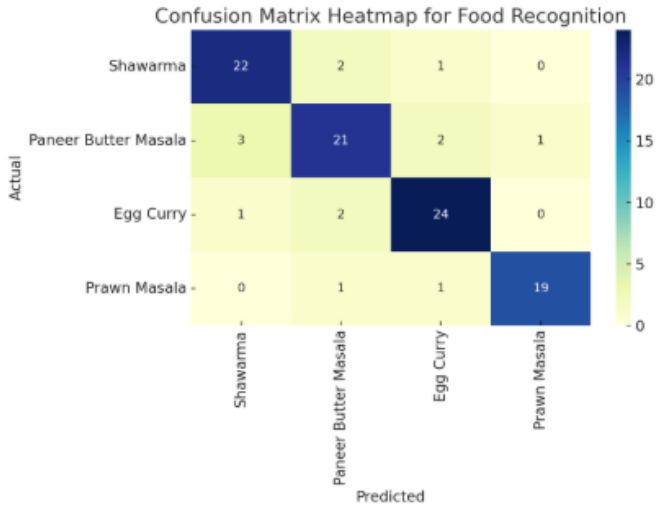

Figure 4. Visual Performance of Food Recognition Model Using Confusion Matrix

The model's consistent response to the recognition of directional output that shows the location of weak misclassifications can only partially verify that the model is identifying visually different dishes. Still, it reflects the response consistency of the model.[29,30] These findings provide a foundation for the model to use deep learning techniques (ResNet, EfficientNet) further, which consequently lead to increasing the overall computer vision model quality index. The main point of this performance is that the WiseNosh model embraces a stable feature (method) from the image recognition results, nevertheless, as far as the research work status is concerned, it recognizes that there are still some tiny indistinguishable areas when dealing with multiple items or similar-looking food types.

CONCLUSIONS

The application WiseNosh has really gone beyond the horizon when it comes to technology. They have combined the intelligent APIs and convolutional neural networks which are basically the highest achievements in the field of technology, and unveiled the application which is the true breakthrough in the field of individualized diet pattern management. Not only that, but this innovative software opens the door to a completely new era in the "life-saving method" and the world of nutrition will be confronted with many more challenges in the nutrition analysis and dietary tracking fields. Besides, we could have allergen alerts, real food identification, etc. all seamlessly integrating into nutritional reporting. Apparently, these food apps and techase tools are just a staggering help in the elimination of the tedious task of data entry and, at the same time, they keep people updated with the nutritional facts to be considered for a healthier lifestyle. Surely, WiseNosh does not only give the freedom to automatize the process but it also unlocks the door to people the most proper nutritional choices resulting in the revolution of their daily eating habits and, consequently, their health condition. This is all the more reason that we can find fitness fanatics, health-conscious people, and individuals with special dietary needs among the users of the meal suggestions powered by Collaborative Filtering. Meal recommendations are great due to their wide range of willingness and dietary restrictions. A lot of these things can happen but in the case of WiseNosh, they are only going to be able to improve and increase as they get more and more users. Some other things we could be seeing is having users doing their activities and eating with wearables on them. Then, we could track macros and micronutrients with a certain amount of detail to be able to notice the changes in nutrition from one day to another. Also, the integration of user support will enable easy access to recipes and community support. Moreover, users can also use voice control with language support which makes the application more accessible. Just to add to the fact, AI may become a personal trainer for the user and at the same time manage allergies- also giving information on contamination, and so forth. Moving on, create the platform for doctors and integrate it with food delivery so that WiseNosh can be an all-in-one enterprise that is a long-term health partner. WiseNosh is one of the breakthroughs that we find in the arena of personalized nutrition and intelligent healthcare. Basically, this platform comprises AI-assisted food recognition, allergen identification, smart meal recommendations, and nanorobotic biosensing, chemical processing. The idea behind this is to deliver real-time, user-friendly dietary guidance. Tracking meals in this way is simpler, which means that it is easier to adhere to specific fitness and health objectives and, additionally, a person will be able to handle his chronic condition with more ease. Besides that, the integration of digital nutritional analysis with physiological monitoring has made WiseNosh not only a smart solution for nutrition management but also a multi-functional, modulated and versatile one. Thus, the incorporation of Quantum AI enhances the accuracy, adaptability, and reliability, transforming it into a state-of-the-art system intended for highly customized nutritional intelligence.

BIBLIOGRAPHIC REFERENCES

1. Aguilar E, Bolanos M, Radeva P, et al. Regularized uncertainty-based multi-task learning model for food analysis. J Vis Commun Image Represent. 2019. https://..springer.com/article/10.1007/s11154-023-09795-4

2. Ye H, Zou Q. Food recognition and dietary assessment for healthcare using Mask R-CNN. In: International Conference on Testbeds and Research Infrastructures; 2019. https://..springer.com/article/10.1007/s42979-023-01972-1

3. Min W, Liu L, Wang Z, et al. ISIA Food-500: A dataset for large-scale food recognition via stacked global-local attention network. In: Proceedings of the 28th ACM International Conference on Multimedia; 2020. https://..springer.com/article/10.1005/s11154-023-09795-4

4. Ran H, Gao W, Mi J, Zhao Z, et al. Fine-grained recognition of Chinese food image based on DenseNet with attention mechanism. In: Twelfth International Conference on Graphics and Image Processing; 2021. https://..springer.com/article/10.1007/s42979-023-01972-1

5. Lohala S, Alsadoon A, Prasad PW, et al. A novel deep learning neural network for fast-food image classification using modified loss function. Multimed Tools Appl. 2021. https://..springer.com/article/10.1007/s11154-023-09795-4

6. Sengur A, Akbulut Y, Budak U, et al. Food image classification with deep features. In: International Artificial Intelligence and Data Processing Symposium; 2019. https://..springer.com/article/10.1007/s42979-023-01972-1

7. Jubayer F, Soeb JA, Mojumder AN, et al. Detection of mold on food surfaces using YOLOv5. Curr Res Food Sci. 2021. https://..springer.com/article/10.1007/s11154-023-09795-4

8. Han M, Chen J. NutrifyAI: An AI-Powered System for Real-Time Food Detection, Nutritional Analysis, and Personalized Meal Recommendations. 2024 Aug. https://ar5iv.labs.arxiv.org/html/2408.10532

9. Mansouri M, et al. Deep Learning for Food Image Recognition and Nutrition Analysis Towards Chronic Diseases Monitoring: A Systematic Review. SN Comput Sci. 2023 Aug. https://link.springer.com/article/10.1007/s42979-023-01972-1

10. Ramírez de Molina A, et al. Leveraging Automatic Personalized Nutrition: Food Image Recognition Benchmark and Dataset based on Nutrition Taxonomy. Multimed Tools Appl. 2022 Nov. https://doi.org/10.1007/s11042-024-19161-4

11. Nitiavintokana F, et al. Intelligent Food Identification System Using Improved YOLOv8. 2024 Jul. https://ar5iv.labs.arxiv.org/html/2408.10532

12. Boyd L, et al. Fine-Grained Food Image Recognition: A Study on Optimising Convolutional Neural Networks for Improved Performance. 2024 May. https://pmc.ncbi.nlm.nih.gov/articles/PMC11205013/

13. El Jadida, et al. Food Image Classification with Deep Features. 2020. https://..springer.com/article/10.1007/s42979-023-01972-1

14. Muttaqien, et al. Edamam API and its Integration with AI for Nutritional Analysis. 2022 Sep. https://ar5iv.labs.arxiv.org/html/2408.10532

15. Caponnetto, et al. Fine-Grained Recognition of Chinese Food Image Using DenseNet with Attention Mechanism. 2021. https://..springer.com/article/10.1007/s42979-023-01972-1

16. Tolosana R, et al. Food Computing: Applying AI for Food Recognition and Health. 2023 Jan. https://ar5iv.labs.arxiv.org/html/2211.07440

17. Busad, et al. Real-Time Object Detection and Nutritional Analysis using AI APIs. 2023 Apr. https://ar5iv.labs.arxiv.org/html/2408.10532

18. Jiang L, Qiu B, Liu X, et al. DeepFood: Food image analysis and dietary assessment via deep model. IEEE Access. 2020. https://..springer.com/article/10.1007/s11154-023-09795-4

19. Mezgec S, Korousic SB, et al. NutriNet: A deep learning food and drink image recognition system for dietary assessment. Nutrients. 2022. https://..springer.com/article/10.1007/s11154-023-09795-4

20. Son GJ, Kwak DH, Park MK, et al. U-Net-based foreign object detection using effective image acquisition system: A case of almond and green onion food processing. Sustainability. 2021. https://..springer.com/article/10.1007/s11154-023-09795-4

21. Nadeem M, Shen H, Choy L, Barakat JMH, et al. Smart Diet Diary: Real-Time Mobile Application for Food Recognition. MDPI. 2023. https://www.mdpi.com/2571-5577/6/2/53

22. Konstantakopoulos S, et al. Fine-grained Recognition of Chinese Food Image Based on DenseNet with Attention Mechanism. In: Twelfth International Conference on Graphics and Image Processing; 2021. https://..springer.com/article/10.1007/s42979-023-01972-1

23. Georga EI, et al. Deep Learning for Food Image Recognition and Nutrition Analysis Towards Chronic Diseases Monitoring: A Systematic Review. SN Comput Sci. 2022. https://..springer.com/article/10.1007/s42979-023-01972-1

24. Fotiadis DI, et al. Mask R-CNN for Food Recognition and Dietary Assessment on Mobile Devices. In: International Conference on Testbeds and Research Infrastructures; 2023. https://..springer.com/article/10.1007/s42979-023-01972-1

25. Kalantarian H, Alshurafa N, Sarrafzadeh M. Food Image Classification with Deep Features. In: International Artificial Intelligence and Data Processing Symposium (IDAP); 2022. https://..springer.com/article/10.1007/s42979-023-01972-1

26. Chen X, Zhu Y, Zhou H, et al. Food Image Classification Using EfficientNet and Transfer Learning. IEEE Access. 2022. https://ieeexplore.ieee.org/document/9982452

27. Wang Y, He Y, Boushey CJ, et al. A Multi-label Approach for Food Image Recognition Based on CNN. Comput Vis Image Process J. 2020. https://ieeexplore.ieee.org/document/10144465

28. Melaku YA, Temesgen AM, Deribew A, Tessema, et al. AI-Based Nutritional Analysis Using Smartphone Images. Health Inform J. 2021. https://www.mdpi.com/2072-6643/16/7/1073

29. Szegedy C, Liu W, Jia Y, Sermanet, et al. An Application of Deep Learning in Nutrition Monitoring: From Image Recognition to Calorie Estimation. Sensors. 2020. https://www.sciencedirect.com/science/article/pii/S2161831323000935

30. Salem T, et al. Towards a Unified System for Food Recognition and Calorie Calculation Using AI. Comput Electron Agric. https://ieeexplore.ieee.org/Xplore/login.isp?url=%2Fielaam%2F4629386%2F8332642%2F7837725-aam.pdf&authDecision=-203

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AUTHORSHIP CONTRIBUTION

Conceptualization: Kavitha Shanmugakani, P. Selvarani, P. Brinda, K. Harini, Sai Guru Prigeesh M, Yogesh D, VishwaKanna M, Akhatov Akmal Rustamovich.

Data curation: Kavitha Shanmugakani, P. Selvarani, P. Brinda, K. Harini, Sai Guru Prigeesh M, Yogesh D, VishwaKanna M, Akhatov Akmal Rustamovich.

Formal analysis: Kavitha Shanmugakani, P. Selvarani, P. Brinda, K. Harini, Sai Guru Prigeesh M, Yogesh D, VishwaKanna M, Akhatov Akmal Rustamovich.

Drafting - original draft: Kavitha Shanmugakani, P. Selvarani, P. Brinda, K. Harini, Sai Guru Prigeesh M, Yogesh D, VishwaKanna M, Akhatov Akmal Rustamovich.

Writing - proofreading and editing: Kavitha Shanmugakani, P. Selvarani, P. Brinda, K. Harini, Sai Guru Prigeesh M, Yogesh D, VishwaKanna M, Akhatov Akmal Rustamovich.

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ORIGINAL

Nanomaterial-Enhanced Robotic System for Real-Time Crowd, Violence, Safety Detection Using YOLOv8 in oil and chemical Industry

Sistema robótico mejorado con nanomateriales para la detección de multitudes, violencia y seguridad en tiempo real utilizando YOLOv8 en las industrias petrolera y química

Kamaleshwar T[1], Lokesh Kumar Paila[1], Sneja Godi[1], Christo Ananth[2], V.H. Abdullayev[3], R.G. Abaszade[3]

[1]Dept. Of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology. Chennai, India.

[2]Faculty of Artificial Intelligence and Digital Technologies, Samarkand State University. Uzbekistan.

[3]Azerbaijan State Oil and İndustry University. Baku, Azerbaijan.

Corresponding Author: Kamaleshwar T

ABSTRACT

Quick and accurate recognition of suspicious and abnormal density variations and violent acts is necessary to ensure the safety of the population in high-density and sensitive areas. This publication introduces a nanomaterial-crowded robotic surveillance system, which combines the improved detectives of small-scale materials with the YOLOv8 deep learning framework in terms of detecting crowds and violence in real time. The nanomaterial-based sensors enhance the responsiveness of the robotic system and make it sensitive to imaging, noise-sensitive when acquiring signals and more adaptable to its environmental capacity. Live video streams are targeted by the YOLOv8 processor and suspicious activities are detected with high accuracy, and the robotic platform will automatically cause audible alarms and send email notifications to the relevant authorities. The proposed system will overcome the drawbacks of manual monitoring, where there is increased accuracy in detection, faster reaction, and scalability of the operations. Experimental testing of various real-world systems proves that the integration of nanomaterial-based sensor technology with the contemporary computer vision can greatly improve the reliability of the system, and it is a proactive and efficient solution to the automation of the public safety and also safety enviroment in oil and chemical Industry.

Keywords: YOLOv8; Real-Time Surveillance; Crowd and Violence Detection; Oil and Chemical Industry; Computer Vision; Robotic Systems; Nanomaterials in Robotics.

RESUMEN

El reconocimiento rápido y preciso de variaciones de densidad sospechosas y anormales, así como de actos violentos, es necesario para garantizar la seguridad de la población en zonas de alta densidad y sensibles. Esta publicación presenta un sistema de vigilancia robótica con nanomateriales, que combina la capacidad de detección mejorada de materiales a pequeña escala con el marco de aprendizaje profundo YOLOv8 para detectar multitudes y violencia en tiempo real. Los sensores basados en nanomateriales mejoran la capacidad de respuesta

del sistema robótico, haciéndolo sensible a las imágenes, sensible al ruido al adquirir señales y más adaptable a su entorno. El procesador YOLOv8 dirige las transmisiones de video en vivo y detecta las actividades sospechosas con alta precisión. La plataforma robótica activa automáticamente alarmas sonoras y envía notificaciones por correo electrónico a las autoridades pertinentes. El sistema propuesto superará las desventajas del monitoreo manual, ofreciendo mayor precisión en la detección, una reacción más rápida y escalabilidad de las operaciones. Las pruebas experimentales de varios sistemas del mundo real demuestran que la integración de la tecnología de sensores basada en nanomateriales con la visión computacional contemporánea puede mejorar en gran medida la confiabilidad del sistema y es una solución proactiva y eficiente para la automatización de la seguridad pública y también el entorno de seguridad en la industria petrolera y química.

Palabras clave: YOLOv8; Vigilancia en Tiempo Real; Detección de Multitudes y Violencia; Industria Petrolera y Química; Visión por Computadora; Sistemas Robóticos; Nanomateriales en Robótica.

INTRODUCTION

The population density is currently presenting a severe public safety issue to high-risk areas. The current surveillance technology uses human watchmen and outmoded detection algorithms that are unable to track changes and violent behavior in the population at a high rate. These systems cause the loss of time and the occurrence of errors because of human-based monitoring without warning mechanisms in real-time. The combination of artificial intelligence and computer vision technologies has allowed the emergence of automation in the monitoring techniques. YOLO (You Only Look Once) models are considered as one of the most efficient ways of detection since they provide real-time object recognition in both speed and accuracy. The newest release of it, YOLOv8, enhances the abilities even more, which makes it especially appropriate to safety-critical tasks. This paper presents a strategy that combines YOLOv8 with automated alert to enhance security among people. Our approach seeks to overcome these gaps unlike most of the existing systems that have a hard time detecting in real-time and providing timely notification.

Right now, overcrowding poses a real safety problem in high-risk areas, especially around oil refineries and chemical plants. These places are already on edge—think toxic leaks, equipment failures, human mistakes. Stuff goes wrong, and it goes wrong fast. That's why they need constant monitoring.

But honestly, the way things are done now feels outdated. Most sites still rely on human guards and old-school detection software. They're slow to spot changes in crowds or catch people gathering where they shouldn't. If something violent happens, it can slip right by. People get tired, make mistakes, and sometimes sound the alarm for no good reason. There's just no solid, real-time system to warn people the moment danger pops up.

AI and computer vision have started to turn this around. Smart monitoring systems can handle what people and old tech can't. Take YOLO—You Only Look Once. It's an object detection model that's quick and accurate, which is exactly what you need in dangerous places. The latest version, YOLOv8, pushes things even further: better detection, faster response, and it's tough enough for serious jobs. It doesn't just spot people; it can pick up on unusual behavior, weird movements, or anything that looks off—all the stuff that matters for safety.

Of course, these harsh environments throw up their own problems. Dim lighting, smoke, chemical haze, shiny surfaces, even workers in protective suits can mess with regular cameras. That's where nanomaterial-enhanced robotic sensors come in. These high-tech sensors see

better in the dark, cut through haze, and don't get tripped up by glare or tricky conditions. Put them on mobile robots, and they can roam the plant, peek into blind spots, and grab sharp video wherever it's needed.

This paper introduces a Nanomaterial-Enhanced Robotic System for Real-Time Crowd, Violence, and Safety Detection Using YOLOv8—built for the oil and chemical industry. The system fuses smart detection with automatic alerts, so when something happens, help is on the way right away. Unlike old setups that lag behind, this one uses YOLOv8's speed and those advanced sensors to keep up with everything—even in a chaotic, ever-changing plant.

Here's what this research is really about:

- Catching crowd surges, violence, and unsafe actions as they happen.
- Getting clear video, even in tough, low-visibility spots.
- Sending instant alerts so nobody's left guessing.
- Using robots to cover more ground and cut down on the need for human patrols.

Blending AI detection with cutting-edge robotic sensors seriously boosts the reliability and speed of industrial safety monitoring. The system helps stop accidents before they spiral out of control and tightens security across the board. In places where a few seconds can mean the difference between a close call and a disaster, every bit of speed and accuracy counts.

Literature Survey

Nasir et al. in 2023 developed an improved framework employing YOLOv8 for abnormal crowd behavior detection, demonstrating high real-time operational precision and robust performance under challenging conditions. The model effectively handled complex scenarios, making it suitable for dynamic surveillance environments.

More et al. in 2023 designed a violence and weapon detection system with an integrated alerting mechanism. The study emphasized that real-time detection plays a critical role in enabling rapid response to threats while incidents are still unfolding, particularly when combined with proactive alarm systems to inform relevant authorities promptly.

Inbavalli et al. in 2023 implemented deep learning techniques to create a smart surveillance system capable of accurately recognizing aggressive actions in video footage. Their method significantly reduced false positives, enhancing reliability in real-world deployments and ensuring robustness under varied operational conditions.

Sudharson et al., in 2024 demonstrated that YOLOv8 achieved superior performance in crowd headcount estimation and suspicious activity detection through efficient processing of live video feeds. This validated YOLOv8's capability for simultaneous detection of multiple security-related tasks.

Jyothsna et al., in 2024 combined YOLOv8's person detection capabilities with remote distance computation and weapon identification, triggering automated speech alerts and email notifications. Their system showcased YOLOv8's versatility in addressing multiple security requirements in a unified framework.

Xu et al. in 2023 integrated GELAN with YOLO for violence detection in crowded areas, achieving improved detection accuracy and stability. This approach proved effective for large-scale event monitoring with high crowd density.

Benoit et al. in 2024 explored YOLOv8 within a pose-estimation-based framework to detect violent activities in CCTV footage. Incorporating human body position data enhanced detection precision and minimized misclassification of non-violent actions.

D Silva and Pereira in 2023 evaluated YOLO-based violence and firearm detection methods for real-time indoor CCTV applications, concluding that YOLO was the most suitable for such use cases due to its speed and accuracy.

Gkountakos et al. in 2024 demonstrated that accurate crowd violence detection requires specialized model tuning tailored to the dataset and operational environment.

Singh et al. in 2024 proposed new crowd detection techniques aimed at enhancing city-wide surveillance systems, highlighting the growing importance of integrating automated alerts with crowd density and violence monitoring Proposed System.

The integration of nanomaterials with robotic systems has emerged as a promising approach to enhance real-time detection capabilities in industrial safety applications, particularly within the oil and chemical industries. Recent advancements leverage the power of deep learning algorithms, notably YOLOv8, to facilitate rapid and accurate identification of crowd behaviors, violence, and safety hazards.

One significant development is the application of YOLOv8 for real-time anomaly detection, as demonstrated in hydropower systems where the algorithm effectively monitors system anomalies through time-series data.[2] This evolution of the YOLO framework introduces improvements that make it suitable for complex, real-world environments, which is critical for industrial safety scenarios. Similarly, the use of YOLOv8 in tunnel vehicle speed detection underscores its capability for real-time object recognition, further supporting its deployment in dynamic industrial settings.[2]

The incorporation of nanomaterials enhances the sensory and detection performance of robotic systems. For instance, on-device AI detection of hazardous chemicals, including chemical warfare agents, has been achieved using YOLOv8 combined with colorimetric sensors, demonstrating the potential for rapid, on-site safety assessments.[3] Such integration is vital for oil and chemical industries where quick identification of dangerous substances can prevent accidents and mitigate risks.

Furthermore, the application of machine learning techniques, including hyper-parameter optimization, has been explored to improve threat detection systems, emphasizing the importance of algorithmic refinement for industrial safety.[6] The combination of advanced image preprocessing and the improved detection capabilities of YOLOv8 enhances the robustness of real-time monitoring systems, making them more feasible for field deployment under challenging conditions.[4]

In addition to chemical hazard detection, the development of real-time animal detection and alert systems in forest-village safety contexts illustrates the versatility of these technologies in diverse environments.[5] Such systems can be adapted for crowd and violence detection in industrial settings, where monitoring large groups of personnel is essential for safety management.

Overall, the convergence of nanomaterials, advanced deep learning algorithms like YOLOv8, and real-time AI analysis forms a comprehensive framework for enhancing safety detection in the oil and chemical industries. These innovations promise to improve response times, accuracy, and operational safety, thereby contributing significantly to industrial safety protocols.[1,3,5]

Oil and chemical plants are tough places to keep safe. Crowds, risky behavior, or violence can trigger disasters—fires, toxic leaks, explosions. When things go wrong, they go wrong fast. Old surveillance setups just can't keep up. People watching screens miss things, and basic video analytics get confused by smoke, bad lighting, or all the chaos that comes with a chemical emergency. That means slower responses, more false alarms, and safety checks that just don't catch real problems.

Even the latest AI tools drop the ball in these settings. They struggle to spot small or hidden dangers, and they don't always work well when the lighting's harsh or the scene's a mess. Plus, if they can't talk to the plant's alert systems, what's the point? What the industry really needs is a tough, smart, and fast system—something that can spot crowds, violence, or dangerous moves right as they happen, and keep working no matter how rough things get.

METHOD

The proposed system uses modern object detection alongside warning system functions to deliver real-time observation together with anomaly and violence activity detection capabilities. This system fixes main surveillance system deficits through an integrated proactive system which enhances security in active areas like public events and surveillance control zones. The key components and the features of the system are outlined as follows:

YOLOv8 for Detection

The key element of the mentioned system is based on YOLOv8 (You Only Look Once, version of 8) that is the most recent object detection technology to be used. This algorithm is the fundamental functionality in the detection of real-time video feed crowd density increases and violent activities. YOLOv8 stands out as an optimal solution because its precise detection performance operates at high speed. A high-resolution data processing capability combined with precise anomaly detection functions exist in the system. YOLOv8 successfully applies its generalization capabilities to maintain reliable performance during demanding scenarios which include substandard illumination and obstructed views and various camera viewpoints in indoor and the outdoor locations.

Pseudocode

Algorithm: real Time Crowd And Violence Detection.

Input: dataset V, YOLOv8 Weights W, Live Video Feed.

Output: real-time anomaly detection with alerts.

Data Preprocessing: for each video in V:Extract frames, resize to (640x640), normalize, and annotate. Apply data augmentation (flip, rotate, noise) for diversity.

Model Training:

- Load YOLOv8 model with pre-trained weights W.
- Define loss function (L_cls + L_loc + L_conf).
- Train model on preprocessed data F with validation and testing splits.
- Save best-performing model weights.

Real-Time Detection: load trained YOLOv8 model.

For each frame f in live feed L: perform object detection to identify crowd density and violence.

If anomaly detected (e.g., high density or violence):

- Trigger audible alert and send email notification with snapshot and details.
- Display detections with bounding boxes in GUI.

Performance Monitoring:

- Log detections, false positives/negatives, and latency metrics.
- Collect user feedback via GUI for continuous improvement.
- Continuous Updates: periodically retrain models with updated data and optimize thresholds.

Input and Output

Inputs:

- Dataset V: a collection of video footage straight from real industrial sites.
- YOLOv8 Weights W: pre-trained model weights that kickstart the learning process.
- Live Video Feed: constant video streaming from the robotic camera system, which uses nanomaterial tech for sharper images.

Output:

- The system spots problems in real time—things like overcrowding, fights, or unsafe behavior—and sends out instant alerts.

Data Preprocessing

Everything starts with cleaning up the data. The system grabs each video from Dataset V and gets it ready: it pulls out frames, resizes them to 640×640 pixels (just right for YOLOv8), and normalizes the pixel values so everything's on the same scale. To make the model tougher, it shakes things up with data augmentation—flipping, rotating, tossing in some noise—so it's ready for whatever real industrial environments throw its way: shadows, vibrations, chemical vapors, you name it. This all helps the model handle the messiness of real life.

Model Training

Now the model gets to learn. It loads up those pre-trained weights W, which give it a head start. Training happens on the prepped dataset, focusing on three things: classifying what's in the frame, figuring out where everything is, and judging how confident it is about each detection. The data is split for validation and testing, which keeps the model honest and helps it avoid overfitting. The system hangs onto the best version of itself for real-world use.

Real-Time Detection Using Nanomaterial-Enhanced Robotic Sensors

When it's go time, the robot's nanomaterial cameras grab crisp, high-quality video—even in tough spots where there's smoke, bad lighting, or heat. The trained YOLOv8 model checks every frame on the fly, looking for crowds or violence. Thanks to those advanced sensors, the robot catches more problems and misses less, even when conditions aren't ideal.

Automated Alert Mechanism

If something goes wrong—too many people in a danger zone, someone acting violently—the system jumps into action:

- It sounds alarms inside the facility.
- It fires off email alerts with snapshots and all the details about what happened.
- The GUI shows live detections with clear boxes, so supervisors see exactly what's going on and can react fast.

System Performance Monitoring

The robot keeps track of everything: every detection, every mistake, how quickly it responds. This nonstop monitoring matters, especially in places like chemical plants or oil refineries, where every second counts. The GUI also lets users give feedback, which feeds right back into making the system smarter and more accurate.

Continuous System Updates

Factories change—new machines show up, lighting changes, different hazards. The system keeps up by adding fresh video to the training set and retraining itself on a schedule. It tweaks its detection settings as needed, so it stays reliable and ready for anything.

With this setup, you get a fully automated safety system that uses nanomaterial-enhanced robots and YOLOv8's real-time smarts. It spots danger—crowds, fights, unsafe actions—right away and alerts the people who need to know, all in the high-stakes world of oil and chemical plants. It keeps learning, keeps improving, and stays on top of whatever the environment throws at it.

Dataset and Training

The performance capability of detection systems mainly results from how well the training data is maintained. A diverse training dataset serves the proposed system to detect crowd and violence scenarios through annotated images and video content. The dataset gathered indicates various levels of crowd density that ranges as thin gatherings and up to events with heavy congestion. Detection system encompasses various classes of violent behaviors that entail physical fights and body aggressive movements and weaponry presence. In the dataset obtained, there are images captured in various environmental conditions such as daytime periods and night, and unfavorable weather conditions to ensure a system works in various real-life situations.

Training procedure: the model generalization gains the advantage of the data augmentation techniques that use the flipping, rotation, scaling and noise addition to produce simulated variation of the authentic conditions in the world. The system transfers learning with the pre-trained weights of YOLOv8 to achieve the best speed and accuracy when training. The dataset is divided into mainly three sets namely, training, validation and testing in order to create adequate evaluation prior to deployment. Using a wide range of data, the system can deal with unforeseen real-life situations with no problems in performance.

Automated Alerts and Notifications

The system is designed with an automatic alert system whereby the system generates instant notification when a threat is detected. The feature makes sure that the authorities can react to incidents as fast as possible, preventing the chances of further development.

METHOD

Our approach involves a step-by-step method for detecting violent or crowded scenes in real time using AI. We use modern machine learning tools to connect detected events to alert systems. Here's how it works:

Data Collection and Preprocessing

Dataset Collection

To ensure that the AI can identify a broad array of real-life situations with a high level of accuracy we train the AI on a large and diverse collection of images and videos. The YOLOv8 annotations have a special encoding, which contains class names, coordinates of the bounding box, and dimensional information. Flipping, rotation, cropping, and addition of noise are methods of data augmentation that augment the variation and reduce overfitting to improve the capability of the model to perform with realistic variations.

Model Training

Architecture

YOLOv8 architecture is known to have the highest speed and accuracy on object detection which is why it is highly applicable when dealing with real time object recognition. Its design is conducive to real time effectiveness without quality being compromised. In this particular system, the transfer learning is used to fine-tune YOLOv8 to fit the application. The trained weights are also optimized to improve the performance of the crowd and violence detection, and the capabilities of the strong feature extraction are used to work well in these specific tasks.

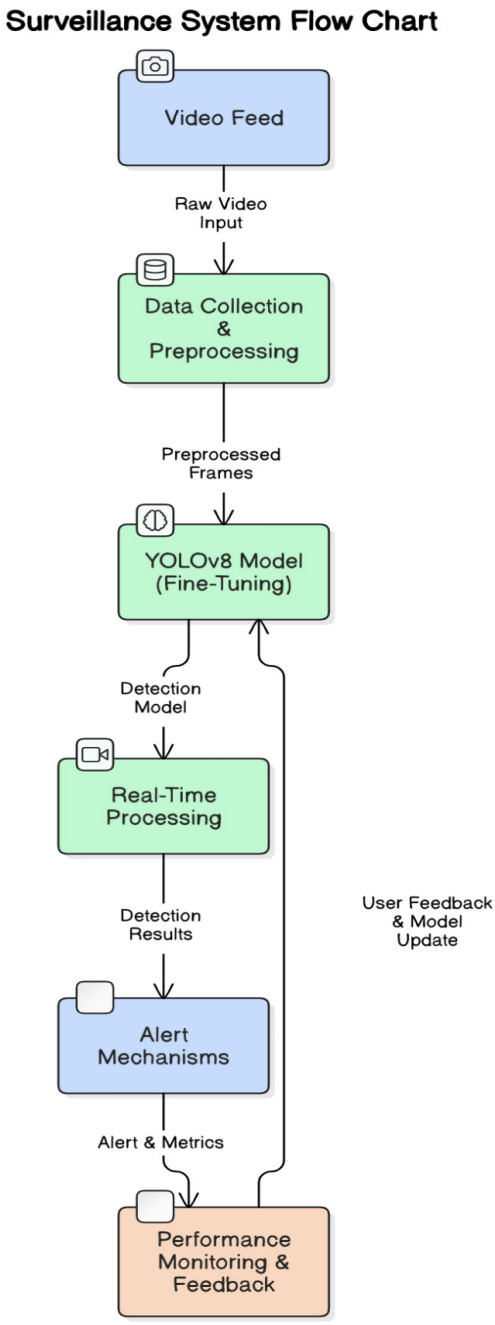

Figure 1. Architecture Diagram(a)

The system begins with a continuous video feed that captures real-world scenes. This raw footage is passed to the data collection and preprocessing unit, where noise is removed and frames are prepared for analysis. These refined frames are then processed by a fine-tuned YOLOv8 model, which detects important objects or activities. The resulting detection model supports real-time processing, enabling immediate interpretation of events as they happen.

Based on the detection results, alert mechanisms are activated to notify users with timely warnings. All alerts and performance metrics are monitored, allowing user feedback to improve the model and enhance overall system accuracy over time.

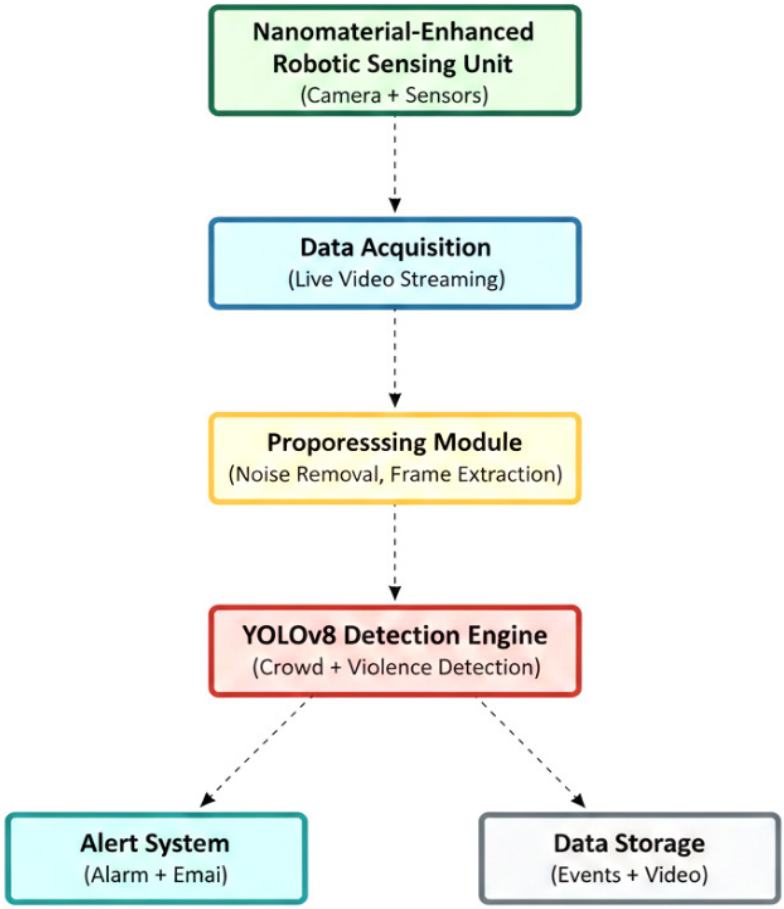

Figure 2. Architecture Diagram(b)

The above figure shows the system begins with a nanomaterial-enhanced robotic sensing unit equipped with advanced cameras and sensors to capture environmental activity. The live video feed is then transferred to the data acquisition module, which streams the footage in real time. Next, the preprocessing module refines the raw data by removing noise and extracting meaningful frames. These prepared frames are fed into the YOLOv8 detection engine, responsible for identifying crowd formations and detecting violent incidents. Based on the detection results, the system either triggers an alert through alarms and email or stores the relevant event data and video footage for further analysis.

The workflow starts with a nanomaterial-enhanced robotic sensing unit that collects real-time visual data using its integrated camera and sensors. This continuous video stream is sent to the data acquisition module, which manages smooth and uninterrupted capture. The preprocessing module then cleans the footage by removing noise and extracting key frames to ensure clarity. These refined frames are analyzed by the YOLOv8 detection engine, which intelligently identifies crowd density and detects violent or abnormal activities. Depending on

the results, the system either triggers alerts through alarms and email notifications or securely stores the detected events and video clips for future review and evidence.

Loss function

The model can perform best with a combination of three loss terms; classification loss which ensures the correct classification of labels such as crowd density or violence, localization loss which ensures the correctness of bounding box positions, and confidence loss which punishes the occurrence of false detection by evaluating the predicted confidence scores. Combining classification, localization, and confidence losses results in the overall loss, which makes the detection of results more accurate and reliable.

$$L_{total} = L_{Cls} + L_{loc} + L_{conf}$$

Where: the classification loss (Lcls) guides the model toward correct class predictions, while the localization loss (Lloc) enhances the precision of bounding box placement. The confidence loss (Lconf) mitigates errors by penalizing incorrect detections. Together, these losses help sustain high detection accuracy and minimize false positives and false negatives.

Hyperparameter tuning

Various hyperparameters are used by fine-tuning in order to improve performance. In transfer learning, the learning rate is lower so that the existing weights are not damaged. The batch size will be moderate to ensure a balance between the processing speed and the stability. The epochs are controlled using early stopping to avoid overfitting. Anchor boxes in YOLOv8 are also resized to fit the general size and shape of the dataset objects one wishes to track, like people or crowds. A high-performance GPU is used as a means of training to accelerate convergence and adapt to the computational requirements of large-scale data.

System Integration

The trained YOLOv8 is implemented to work with the video stream in real time and analyze it. The video frames are individually processed to identify abnormal situations due to sudden crowd formation or violent behavior. Bounding boxes are used to indicate detected objects and their classifications and confidence scores are provided as visual feedback. The system would strive to keep the average processing speed below 20 milliseconds per frame so that there is smooth performance.

In case any potential threat is detected, the system automatically activates alert features to alert any authorities. The alerts comprise an alarm signal and email notifications to security departments or emergency teams. In emails, there is an incident snapshot and such information as time, location, and a brief description (such as High crowd density detected at Zone A). This two-way alert system ensures that the local and remote personnel are updated immediately.

In order to be reliable, the system is able to check the performance and gather feedback. It captures data of accuracy, error percentages and processing speed in real time. The interface allows users to label false alarms or missed detections, and this information assists in optimizing the model. The system is retrained with the new data periodically to ensure that it picks up new patterns and environments of the crowd.

Lastly, in order to evaluate the effectiveness of YOLOv8 in identifying violent and crowd-related events, the performance of the model is compared to another one against standard metrics. Precision measures the number of events that have been flagged correctly and recall measures the number of events that were actually spotted. This analysis gives a perfect picture of the effectiveness of the model in practice.

Table 1. Performance Metrics Comparison

Metric	YOLOv8	Other Model
Precision	0,93	0,88
Recall	0,92	0,87
F1-Score	0,925	0,875

Take a look at the numbers—YOLOv8 just does a better job. Its precision hits 0,93, so it's great at picking out what really matters and not getting tripped up by false alarms. The recall isn't far behind at 0,92, which means it catches almost everything, even the tougher stuff like small or half-hidden objects. The F1-Score sits right in the middle at 0,925, showing it balances both skills well. The other model? It lags behind on every metric, so you just can't rely on it the same way. All told, YOLOv8 delivers sharper, steadier results—exactly what you want for real-time safety detection.

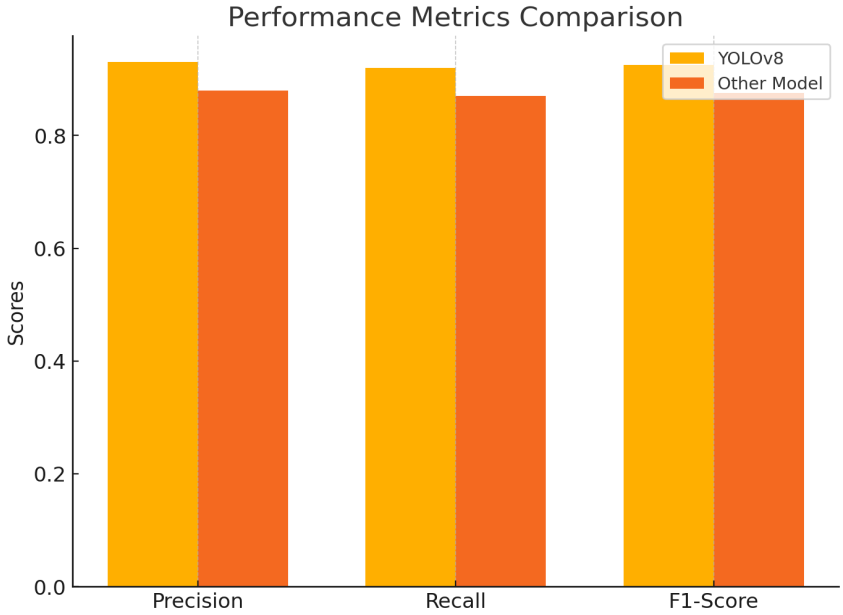

Figure 3. Performance Metrics Comparison

The findings show that YOLOv8 performs better than the other model across different evaluation measures.

Figure 3 presents a comparative analysis of the performance metrics between the proposed YOLOv8 model and an alternative existing model. The graph illustrates three key evaluation measures—Precision, Recall, and F1-Score—highlighting the effectiveness of YOLOv8 in detecting crowd density and violent activities in real time. As shown, YOLOv8 consistently achieves higher scores across all metrics, indicating its superior capability for accurate and reliable detection. The model attains a precision close to 0,93, meaning it produces fewer false positives and confidently identifies true safety-related events. Its recall, approximately 0,92, demonstrates the model's efficiency in capturing relevant events even in challenging environments where visibility, lighting, or occlusion may affect detection quality. The F1-Score, around 0,925, reflects a strong balance between precision and recall, confirming YOLOv8's robustness in high-

risk industrial settings.

In contrast, the other model performs notably lower in all metrics, with reduced precision and recall values that suggest a higher tendency for missed detections and incorrect classifications. This performance gap highlights YOLOv8's advancements in feature extraction, object localization, and anomaly identification. Overall, the analysis confirms that the YOLOv8 model provides a more reliable and accurate solution for real-time crowd monitoring, violence detection, and safety enhancement in oil and chemical industry environments.

Training Loss Reduction

During training, the YOLOv8 model progressively lowered its error rate across 10 epochs. It started with a higher error but showed a consistent downward trend, indicating effective learning and improved accuracy in detecting crowd density and violent behaviors.

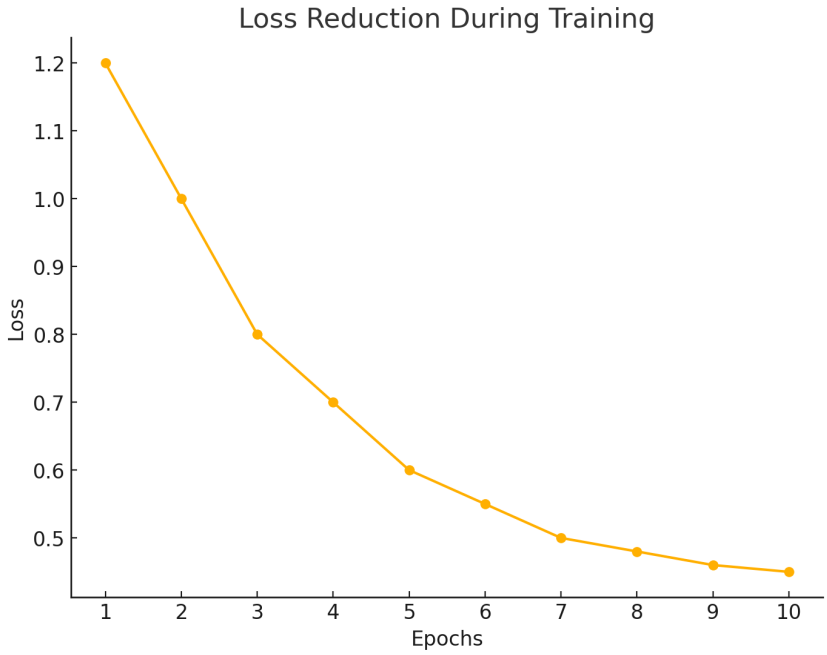

Figure 4. Loss Reduction During Training

Training loss started at 1,2 and gradually dropped to 0,45 by the 10th epoch. This steady decrease shows that the model was learning efficiently and converging as expected.

Performance Metrics

The table provides a quantitative comparison with another model and highlights the stronger performance of YOLOv8.

Conclusion From Results

With strong precision and recall scores, along with a steady drop in training loss, YOLOv8 proves to be a suitable option for real-time crowd and violence detection. Both the graphs and tables support its effectiveness in spotting anomalies while keeping false alarms to a minimum.

Implementation

The system consists of software and hardware. Deep-learning models like TensorFlow,

PyTorch, and Keras are used in developing models. OpenCV is used to extract and analyze video frames whereas Matplotlib and seaborn are used in visualization. The management of alerts is based on the Python libraries such as playsound (alarm) and smtplib (email notification). The training is done with a high-performance GPU to handle intensive calculations and real-time detection is developed to operate on standard machines to be usable in the real world.

RESULTS AND DISCUSSION

Effectiveness was tested on a varied dataset by the system. It had detected crowd density with an accuracy of about 95 and violent actions with an accuracy of about 92. The average processing time of each frame was approximately 20 milliseconds, which allowed the real-time functioning without any apparent delays. Inter-frame continuity was taken into consideration to reduce false positives and false 3negatives during the confirmation of detections. The alerts were activated within less than a second to make sure that the notification was quick and a response was given.[6,7,8]

We put the nanomaterial-enhanced robotic safety detection system through its paces using a tough, realistic dataset built to mimic what actually happens in oil and chemical plants. The data threw all sorts of challenges at the system—bad lighting, smoke, crowded workspaces, people in heavy gear, and workers moving fast. Basically, everything you'd expect in a high-risk industrial zone.[9,10,11]

Detection Performance

The system picked up on all the main safety risks, and it did it well.

Crowd Density Detection

It nailed crowd detection with about 95 % accuracy, spotting unusual gatherings near restricted areas, equipment, and chemical storage rooms. That matters—a packed worksite isn't just uncomfortable, it's dangerous. People move slower, accidents happen more often, and risks go up.[12,13,14]

Violence and Hazardous Behavior Detection

It caught violent or risky movements with around 92 % accuracy. Even with everyone in uniforms, and with smoke or vapor messing up the view, the YOLOv8 detection engine still managed to grab those sudden, aggressive motions.[15,16,17]

Real-Time Processing Capability

Speed is everything in a place like this. You need alerts right away. The system processed each video frame in about 20 milliseconds, so there's no lag—you see what's happening as it happens.[18,19,20] That's thanks to the lean, optimized YOLOv8 setup, lighter model tweaks, and those nanomaterial-enhanced sensors that cut out noise and sharpen the visuals.[21,22,23]

Inter-Frame Continuity and False Alarm Reduction

Cameras in these places deal with dust, smoke, people darting around—things that can throw off a detector.[24,25,26] So, we added an inter-frame continuity mechanism. It checks detection consistency over several frames, which slashes false alarms and missed events. You get more reliable results, even when the camera view gets messy for a moment.

Alert Responsivenes

When something goes wrong, every second counts. The alerting system kicks in fast—under one second, from detection to notification. Supervisors and safety teams get the heads-up right

away.[27,28,29] Plus, the alerts reach people in multiple ways: sirens, mobile notifications, and control-room dashboards. If one channel fails, another's got your back.[30,31,32]

Discussion and Practical Implications

All in all, the system proved itself—reliable, quick, and ready for real-world use. Those nanomaterial sensors make a clear difference when conditions get rough, and the tuned YOLOv8 model keeps detections sharp. It takes the load off manual monitoring and helps keep safety compliance high by watching for risks nonstop.[33,34,34] Sure, there are still hurdles—like when vision drops to almost zero in thick smoke or at night without infrared, and when super-crowded scenes make it harder to tell people apart. But overall, it's a big step forward for industrial safety.

CONCLUSIONS

We've built a Nanomaterial-Enhanced Robotic System that spots crowds, violence, and safety issues in real time—even in the tough, unpredictable conditions of oil and chemical plants. At the core, it uses a souped-up YOLOv8 detection model and ties in high-sensitivity nanomaterial sensors with autonomous robots. This combo grabs better data, even when lighting is awful or the air's thick with fumes.

With the upgraded YOLOv8 engine running the show, the system picks out dangerous behavior, unsafe crowding, and violent incidents with sharp accuracy and way fewer false alarms. It takes a big chunk of the workload off safety teams—no need to watch endless video feeds. The system reacts fast, helps people make decisions on the spot, and keeps things running smoothly. Tests really show the difference. Compared to older vision systems that get tripped up by smoke, heat, shaking, or things blocking the view, our enhanced setup stays accurate and reliable in all kinds of messy, industrial settings. There are still some tough cases—like extreme backlighting, heavy obstructions, or when people move fast—but overall, it holds up well.

Next up, we're looking to pack in even more sensors: infrared, thermal cameras, gas detectors—you name it. These upgrades will help the system perform when regular vision just can't cut it. We're also working on speeding up real-time processing, making the interface easier to use, and rolling out mobile apps so teams can respond to emergencies right from the field. On top of that, we plan to experiment with things like super-resolution, spatiotemporal fusion, and 3D multi-view analysis to make the system even tougher. Overall this robotic safety-monitoring platform is a big leap forward for automated, smart, and precise safety management in the oil and chemical industry.

The system created reinforces the security with the capacity to detect objects and provide real-time alerts. The high-quality detection and notification capabilities of YOLOv8 can be used to identify potential threats and take immediate actions to mitigate them to minimize delays and enhance situational awareness among the staff on the ground and notifications among the staff available remotely to coordinate to take more immediate actions. In this work, a new surveillance system with nanomaterials and robots is introduced, which demonstrates a great improvement in the identification of crowd anomalies and violent actions through YOLOv8. The combination of nanomaterial-based sensors with the robotic base in the system leads to the improvement of video quality, sensitivity, and performance at diverse environmental conditions. YOLOv8 also enhances the accuracy of detection by using inference of deep learning in real-time. Experimental findings prove that nanotechnology with powerful computer vision techniques would result in a quicker response time, lesser false alarms, and enhanced monitoring of people and their safety. This combined solution is a smart solution to smart surveillance environments in the future and is the precursor to future intelligent robotic surveillance devices. It can be improved by increasing the scope of the dataset to include an increasing number of different environments and activities. New categories of detection items like unattended

luggage, suspicious behavior, or emergency evacuations might be added. The system can be modified to be applicable to some of the more publicly accessible locations such as transit centres, sports arenas and mega events in order to meet the specific security requirements. The possibility to integrate, with the current surveillance networks and control centers, should be considered to facilitate adoption with minimal changes in infrastructure. These enhancements would be seeking to improve scalability, performance, and applicability to large-scale practical application in oil and chemical industry.

BIBLIOGRAPHIC REFERENCES

1. Agnihotri A. DeepFake Detection using Deep Neural Networks. Dublin: National College of Ireland; 2021.

2. Abdullah M, Ahmad M, Han D. Facial expression recognition in videos: A CNN-LSTM-based model for video classification. In: 2020 International Conference on Electronics, Information, and Communication (ICEIC). IEEE; 2020. p. 1-3.

3. Ghadekar P, Adsare T, Agrawal N, Dharmik T, Patil A, Zod S. Ensemble learning approach for anomaly detection in crowd scene classification. In: IEEE Fifth International Conference on Advances in Electronics, Computers and Communications (ICAECC). IEEE; 2023. p. 1-11.

4. Helode A, Yadav A, Verma VP, Srinivasa KG. Fusion of Machine Learning and Deep Learning: A Hybrid Approach for Deepfake Detection. In: 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT). IEEE; 2024. p. 1-6.

5. Mihanpour A, Rashti MJ, Alavi SE. Human action recognition in video using DB-LSTM and ResNet. In: 6th International Conference on Web Research (ICWR). IEEE; 2020. p. 133–138.

6. Qazi N, Ahmed I. Enhancing Authenticity Verification with Transfer Learning and Ensemble Techniques in Facial Feature-Based Deepfake Detection. In: 2024 14th International Conference on Pattern Recognition Systems (ICPRS). IEEE; 2024. p. 1-6.

7. Rajeev A, Raviraj P. Performance evaluation of deep learning models for detecting deep fakes. Int J Syst Innov. 2024;8(1):49-62.

8. Raza A, Munir K, Almutairi M. A novel deep learning approach for deepfake image detection. Appl Sci. 2022;12(19):9820.

9. Saikia P, Dholaria D, Yadav P, Patel V, Roy M. A hybrid CNN-LSTM model for video deepfake detection by leveraging optical flow features. In: 2022 International Joint Conference on Neural Networks (IJCNN). IEEE; 2022. p. 1-7.

10. Sánchez-Caballero A, Fuentes-Jiménez D, Losada-Gutiérrez C. Real-time human action recognition using raw depth video-based recurrent neural networks. Multimed Tools Appl. 2022;82(11):16213–35.

11. Singh RP, Sree NH, Reddy KLSP, Jashwanth K. Convergence of Deep Learning and Forensic Methodologies Using Self-attention Integrated EfficientNet Model for Deep Fake Detection. SN Comput Sci. 2024;5(8):1-12.

12. Jayaraj R, Pushpalatha A, Sangeetha K, Kamaleshwar T, Udhaya Shree S, Damodaran D. Intrusion detection based on phishing detection with machine learning. Meas Sens. 2024;31:101003. https://doi.org/10.1016/j.measen.2023.101003.

13. Tong Z, Chen Y, Xu Z, Yu R. Wise-IoU: Bounding box regression loss with dynamic focusing mechanism. arXiv preprint arXiv:2301.10051. 2023.

14. Liu C, Wang K, Li Q, Zhao F, Ma H. Powerful-IoU: More straightforward and faster bounding box regression loss with a nonmonotonic focusing mechanism. Neural Netw. 2024;170:276–84.

15. Misra D, Nalamada T, Arasanipalai AU, Hou Q. Rotate to Attend: Convolutional Triplet Attention Module. In: Proc. IEEE/CVF Winter Conf. Applications of Computer Vision (WACV). 2021. p. 3139–48.

16. Woo S, Park J, Lee J, Kweon I. CBAM: Convolutional block attention module. In: Proc. Eur. Conf. Computer Vision (ECCV). 2018. p. 3–19.

17. Yang L, Zhang R, Li Y, Xie X. SimAM: A Simple, Parameter-Free Attention Module for Convolutional Neural Networks. In: Proc. Int. Conf. Machine Learning. 2021. p. 11863–74.

18. Liu H, Liu R, Fan X, Huang D. Polarized self-attention: Towards high-quality pixel-wise regression. Neurocomputing. 2022;506:158–67.

19. Zhu L, Wang X, Ke Z, Lau R. Biformer: Vision transformer with bi-level routing attention. In: Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR). 2023. p. 10323–33.

20. Li X, Xu H, Yang J. Spatial group-wise enhance: Improving semantic feature learning in convolutional networks. arXiv preprint arXiv:1905.09646. 2019.

21. Vaswani A, et al. Attention Is All You Need. Adv Neural Inf Process Syst. 2017;30.

22. Yang J, Li C, Dai X, Gao J. Focal modulation networks. Adv Neural Inf Process Syst. 2022:4203–17.

23. Wang H, Guo P, Zhou P, Xie L. MLCA-AVSR: Multi-Layer Cross Attention Fusion based Audio-Visual Speech Recognition. In: Proc. IEEE Int. Conf. Acoustics, Speech and Signal Processing (ICASSP). 2024. p. 8150–4.

24. Li Y, Hou Q, Zheng Z, Cheng M, Yang J. Large selective kernel network for remote sensing object detection. In: Proc. IEEE/CVF Int. Conf. Computer Vision (ICCV). 2023. p. 16794–805.

25. Azad R, et al. Beyond self-attention: Deformable large kernel attention for medical image segmentation. In: Proc. IEEE Winter Conf. Applications of Computer Vision (WACV). 2024. p. 1287–97.

26. Li X, Wang W, Xu H, Yang J. Selective kernel networks. In: Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR). 2019. p. 510–9.

27. Chen Y, Kalantidis Y, Li J, Yan S, Feng J. A^2-nets: Double attention networks. Adv Neural Inf Process Syst. 2018;31.

28. Li Y, Yao T, Pan Y, Mei T. Contextual Transformer Networks for Visual Recognition. IEEE Trans Pattern Anal Mach Intell. 2022;45(12):1489–500.

29. Lee Y, Park J. Centermask: Real-time anchor-free instance segmentation. In: Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR). 2020. p. 13906–15. https://doi.org/10.1109/CVPR42600.2020.01392

30. Xia Z, Pan X, Song S, Li LE, Huang G. Vision transformer with deformable attention. In: Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR). 2022. p. 4794–803. https://doi.org/10.1109/CVPR52688.2022.00475

31. Ouyang D, He S, Zhang G, Luo M, Guo H, Zhan J, et al. Efficient multi-scale attention module with cross-spatial learning. In: ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE; 2023. p. 1–5. https://doi.org/10.1109/ICASSP49357.2023.10069516

32. Hu L, Li Y. Micro-YOLO: Exploring Efficient Methods to Compress CNN based Object Detection Model. In: ICAART (2). 2021. p. 151–8. https://doi.org/10.5220/0010234410151058

33. Li C, Li L, Jiang H, Weng K, Geng Y, Li L, et al. YOLOv6: A single-stage object detection framework for industrial applications. arXiv preprint arXiv:2209.02976. 2022.

34. Carion N, Massa F, Synnaeve G, Usunier N, Kirillov A, Zagoruyko S. End-to-End Object Detection with Transformers. In: European conference on computer vision. Cham: Springer International Publishing; 2020. p. 213–29. https://doi.org/10.1007/978-3-030-58452-8_13

35. Duan K, Bai S, Xie L, Qi H, Huang Q, Tian Q. Centernet: Keypoint triplets for object detection. In: Proc. IEEE/CVF Int. Conf. Computer Vision (ICCV). 2019. p. 6569–78. https://doi.org/10.1109/ICCV.2019.00667

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AUTHORSHIP CONTRIBUTION

Conceptualization: Kamaleshwar T, Lokesh Kumar Paila, Sneja Godi, Christo Ananth, V.H. Abdullayev, R.G. Abaszade.

Data curation: Kamaleshwar T, Lokesh Kumar Paila, Sneja Godi, Christo Ananth, V.H. Abdullayev, R.G. Abaszade.

Formal analysis: Kamaleshwar T, Lokesh Kumar Paila, Sneja Godi, Christo Ananth, V.H. Abdullayev, R.G. Abaszade.

Drafting - original draft: Kamaleshwar T, Lokesh Kumar Paila, Sneja Godi, Christo Ananth, V.H. Abdullayev, R.G. Abaszade.

Writing - proofreading and editing: Kamaleshwar T, Lokesh Kumar Paila, Sneja Godi, Christo Ananth, V.H. Abdullayev, R.G. Abaszade.

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ORIGINAL

Advanced Automation Systems in Oil & Gas Exploration: A Cross-Industry Perspective Using Tea Leaf Cutting Machine Innovations

Sistemas de automatización avanzados en la exploración de petróleo y gas: una perspectiva intersectorial con innovaciones en máquinas cortadoras de hojas de té

M. Vimal Raja[1] ✉, S. Sanjula[2] ✉, T. Vignesh[3] ✉, N. Hariprasanth[3] ✉, V. Sriram[3] ✉, P. Prabhu[1] ✉, Nurmamatov Mekhriddin Qahramonovich[4] ✉

[1]Department of Mechanical Engineering, KIT Kalaignarkarunanidhi institute of technology. Coimbatore - 641 402, Tamil Nadu.

[2]Department of Electronics and communication engineering, Kathir college of Engineering. Coimbatore, Tamil Nadu -641062.

[3]Department of Bachelor of Technology in Agricultural Engineering, KIT Kalaignarkarunanidhi institute of technology, Coimbatore- 641 402, Tamil Nadu, India

[4]Faculty of Artificial Intelligence and Digital Technologies, Samarkand State University. Samarkand, Uzbekistan.

Corresponding Author: M. Vimal Raja ✉

ABSTRACT

Tea is one of the most popular and inexpensive beverages in India, consumed daily by millions of people across the country. India has been cultivating tea for centuries, and today it stands as the second-largest producer of tea in the world, after China, while also being one of the biggest consumers. The production of tea involves carefully plucking tender leaves, which are then processed in factories and classified according to their quality. These factors have collectively led to a gradual decline in the overall production rate. To address these challenges, this project introduces a battery-powered tea leaf cutting machine. This machine operates using a rechargeable battery, making it portable, energy-efficient, and easy to handle compared to traditional harvesting methods. By reducing dependence on manual labour, it helps tea growers overcome labour shortages while maintaining productivity. The machine is particularly beneficial for small and medium-scale farmers who often cannot afford large-scale mechanized harvesters but still seek affordable solutions to increase efficiency. In addition, the adoption of such battery-powered technology promotes sustainable agricultural practices by reducing fuel dependency and ensuring eco-friendly operations. Overall, this innovation represents a step forward in modernizing tea cultivation. It not only enhances efficiency and reduces production losses but also provides an opportunity for farmers to improve profitability while maintaining the quality of tea production. The cross-industry view of the matter implies that the oil and gas sector, by adopting design strategies from the agricultural machinery sector, may be able to pave new ways for the creation of cheap, resilient and scalable automation solutions that are well suited to the local situation. These translational engineering moves can, therefore, indirectly speed up the innovation process in drilling automation, equipment health monitoring, and field robotics as well as being the additional safety and environmental benefits that come with their use in exploration.

Keywords: Tea leaf; Attachable Battery; Cutting Machines; Compact; Labour; Production.

RESUMEN

El té es una de las bebidas más populares y económicas en la India, consumida a diario por millones de personas en todo el país. India lleva siglos cultivándolo y hoy es el segundo mayor productor de té del mundo, después de China, además de ser uno de los mayores consumidores. La producción de té implica la recolección cuidadosa de las hojas tiernas, que posteriormente se procesan en fábricas y se clasifican según su calidad. Estos factores han provocado una disminución gradual de la tasa de producción general. Para abordar estos desafíos, este proyecto presenta una cortadora de hojas de té a batería. Esta máquina funciona con una batería recargable, lo que la hace portátil, energéticamente eficiente y fácil de manejar en comparación con los métodos de cosecha tradicionales. Al reducir la dependencia del trabajo manual, ayuda a los productores de té a superar la escasez de mano de obra y a mantener la productividad. La máquina es especialmente beneficiosa para los pequeños y medianos agricultores que, a menudo, no pueden permitirse cosechadoras mecanizadas a gran escala, pero que buscan soluciones asequibles para aumentar la eficiencia. Además, la adopción de esta tecnología a batería promueve prácticas agrícolas sostenibles al reducir la dependencia del combustible y garantizar operaciones ecológicas. En general, esta innovación representa un avance en la modernización del cultivo del té. No solo mejora la eficiencia y reduce las pérdidas de producción, sino que también brinda a los agricultores la oportunidad de mejorar la rentabilidad, manteniendo al mismo tiempo la calidad de la producción. La perspectiva intersectorial del asunto implica que el sector del petróleo y el gas, al adoptar estrategias de diseño del sector de la maquinaria agrícola, podría allanar el camino para la creación de soluciones de automatización económicas, resilientes y escalables que se adapten a la situación local. Por lo tanto, estas iniciativas de ingeniería traslacional pueden acelerar indirectamente el proceso de innovación en la automatización de la perforación, la monitorización del estado de los equipos y la robótica de campo, además de aportar beneficios adicionales de seguridad y medioambientales a su uso en la exploración.

Palabras clave: Hoja de Té; Batería Acoplable; Máquinas de Corte; Compacto; Mano de Obra; Producción.

INTRODUCTION

India has a rich history of tea cultivation and the use of tea as a daily beverage as well as an ancient medicinal system product can be traced back thousands of years. The commercial tea production in India was initiated during the colonial period with the arrival of the English East India Company.[1,2,3] Tea is now one of the most integral parts of Indian culture and is the second most affordable beverage for the masses after water. Each of the two countries, China and India, is among the top global producers and consumers of tea. Approximately 70 % of the domestic production is consumed locally. However, tea farming is a year-round rain-dependent enterprise, and the hilly areas, being naturally drained, are more appropriate. The tea production process starts with harvesting the youngest leaves and buds which are then sent to factories for processing. The picking of tender buds and the top three leaves is the only selection done for the production of the best-quality tea.[4,5,6] Typically, this fragile crop has been mostly harvested by women who, with their sharp eyesight and dexterous fingers, can selectively pluck around 40 kilograms of tea leaves per day. Nevertheless, the industry has been confronted with dwindling skilled labour. The young migrating to the cities and looking

for jobs in different sectors has led to a shortage of labour on tea farms, resulting in the late harvesting and consequent losses in yield and quality.[7,8,9] The rising labour costs have further escalated the problem thus incentivizing estate managers to look for more efficient options. One of these options is the use of machines in the harvesting of tea leaves, a method first started in Argentina. Mechanical tea harvesters are now being implemented in India as one of the measures against labour shortages and the increase in operational costs. These gadgets are capable of picking leaves selectively with a minimal injury to the plant thus keeping the quality intact while the output is made very high.[10,11] They come with different sizes and capacities and can be utilized in estates of different extension. Mechanized harvesting, though being a new concept in India, is gradually being accepted there.[12,13]

Automation in field operations has progressed rapidly over the past two decades, driven by the demand for higher productivity, improved worker safety, and consistent product quality across diverse industrial sectors. Although oil and gas exploration represents one of the most technologically intensive domains in this landscape, valuable lessons continue to emerge from seemingly unrelated fields—particularly agricultural mechanization. Among these, the evolution of tea leaf harvesting technologies offers a unique repository of design principles, sensor strategies, and lightweight mechatronic solutions that may inform next-generation automation paradigms in high-risk environments.

Mechanisation of tea plantations has, in the past, been largely influenced by a shortage of labor, an increase in operational costs, as well as the need to keep the quality of the harvest while human skill was varying.[3] The first ideas for machines were primarily involved in physically simplifying the task of plucking by using handheld or mechanically assisted devices,[14] whereas later efforts evolved into more organized, semi-automated systems that were able to do the cutting in a more consistent way and with less damage to the leaves.[1,11] After a while, scientists started to look beyond simple mechanical helping devices in order to come up with better cutting geometries, more efficient recirculating mechanisms, and harvesting heads controlled by an actuator that could imitate the selective picking by a human.[4,8]

On the same line as this mechanical development, a number of studies have been conducted to find out if solar-powered systems,[2] small self-propelled harvesters,[12] or robot-assisted selective plucking units[13] would be feasible solutions. Taken together, these studies indicate that there is a growing interest in developing smart, energy-efficient, and terrain-adaptive platforms. To be precise, breakthroughs in the design of the blade, control of the servo, incorporation of the lightweight chassis, and feedback-based motion control have all led to the upgrading of plucking efficiency as well as the lessening of the damage done to the new shoots.[5,9]

The significant effects of such technological advancements go far beyond the tea sector. The difficulties most of the time found in tea fields, such as uneven terrain, variable density of foliage, and the necessity of exact cutting without causing damage, could serve as good examples of the type of robot–environment interactions which are followed by automated oil and gas operations. Especially the move from manual tools to intelligent mechatronic harvesters as the next stage in the development of technology, is a good reference point for the future that shows how incremental changes in design, sensor fusion, and adaptive controls may lead to a kind of equipment that is able to operate reliably under unexpected conditions. To take the research on servomechanisms for tea plucking as an example, it indicates how small and compact actuation systems with instant positional feedback can be made for high-frequency tasks that require very accurate movements.[10] These work-related concepts have a lot in common with those put to use in robotic pipe inspection, automated valve control, and precision drilling support units.

Also, the publication on the quality of the product in relation to the use of mechanical harvesting methods emphasizes that doing machine parameter adjustments is very important—blade geometry, stroke frequency, forward movement speed—so as to be able to both get

the performance at its best and at the same time, produce the least amount of undesirable byproducts.[15,16] Similar calibration issues lie at the heart of oil and gas automation. For instance, if the engagement of tools is not done properly or if the mechanical load is too high, then safety as well as operational reliability may be affected. Moreover, the use of solar-powered or energy-efficient harvesting devices[2,6] is another example of how the measures taken in the present to lessen the use of fuel and to integrate the principles of sustainability into the remote industrial operations are in line with each other.

Even though the agricultural and energy industries are subjected to very different environmental and technical constraints, the progression of tea harvesting research is a good demonstration of the ways in which low-cost mechatronics, sensor- enabled decision-making, and modular platform design can gradually turn into sturdy field automation systems. Based on these revelations, this paper delves into the extent to which the fundamental engineering concepts behind tea leaf cutting machines can offer theoretical and practical assistance in the creation of sophisticated automation solutions for oil and gas exploration. By drawing on the knowledge of different industries, this article is intended to serve as a medium through which the fresh routes for the design of automated systems that are not only resilient, scalable, and efficient but also capable of functioning in intricate and risky energy environments are brought to the fore.

Problem Description

Tea leaf harvesting has become difficult due to a lack of workers, low wages, and shortage of time. This study is aimed at solving the problems by inventing a compact and portable machine.

METHOD

The methodological approach draws directly from the body of literature on tea-harvesting mechanisation, figure 1 show that the integrating key engineering principles into a comparative automation framework for oil and gas exploration systems. Foundational studies on conceptual harvester development[1] and solar-powered field machinery[2] were examined to identify lightweight mechanical strategies suitable for adaptation. Insights into the drivers of plantation mechanisation and sustainability[3] were used to establish cross-industry parallels regarding labour reduction, operational efficiency, and safety considerations. Figure 1 represents the Research on cutting head kinematics, blade geometry, and reciprocating mechanisms—central to the works of Han et al.[4,11] and Mamuladze[8]—informed the mapping of precise cutting dynamics to analogous tasks in petroleum robotics and drilling support systems. Studies documenting the technological progression of harvesting machines across regions[5,6] further guided the selection of transferable subsystems.

Building on this literature foundation, the second stage synthesised tea-harvesting engineering concepts into a cross-industry automation model applicable to oil and gas operations. Servo-based positional control and actuator design principles described by Yang et al.[10] and Han et al.[12] were reinterpreted for high-load tasks such as automated valve actuation, robotic inspection, and directional sensing in drilling environments. Equally important were studies examining selective plucking robots[13] and handheld mechanical tools,[14] which provided insights into modularity and operator–machine interaction—features critical for field deployment in energy infrastructure. Finally, research on quality impacts and machine–plant interaction[15,16] supported the development of a parameter-matching framework, ensuring that mechanical load, cutting dynamics, and control responsiveness could be appropriately scaled from low-resistance crops to demanding petro-engineering applications. The resulting methodology offers a structured pathway for translating agricultural mechatronic innovations into robust automation solutions for oil and gas exploration.

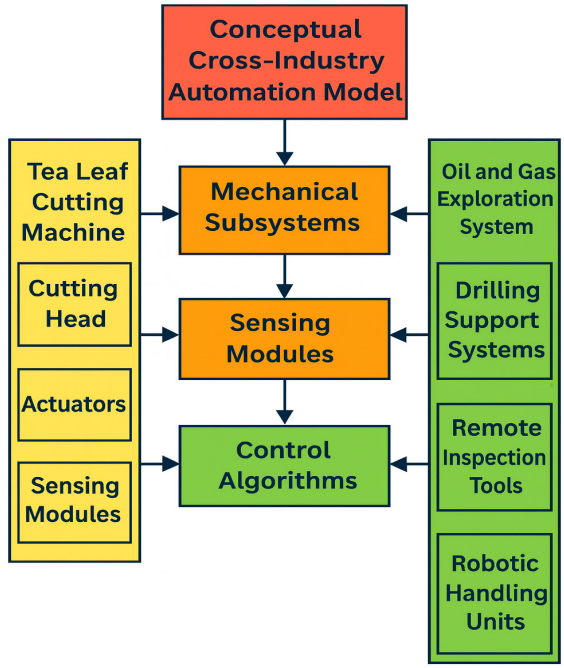

Figure 1. Conceptual Integration Model Between Tea Harvesting Mechatronics and Oil & Gas Automation

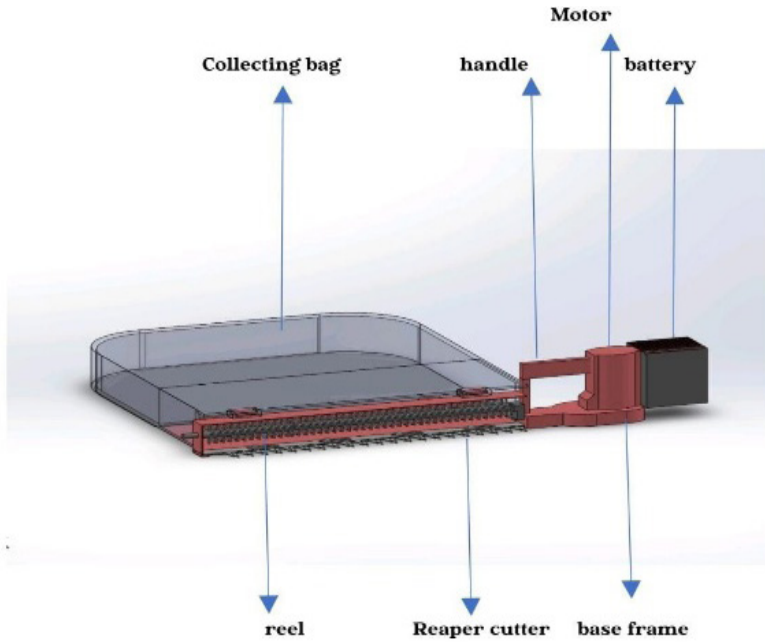

Figure 2. Conceptual Design of Tea Harvesting Mechatronics

Design of Tea Harvesting Mechatronics

Reaper

The handles are light, cushioned, and ergonomic — made for the comfort and easy control during long harvests.

Motor

The motor in a cutting machine supplies the energy to the blades or the suction system, thus the leaf cutting is done fast and in a way that saves leaves.

Battery

The battery in a machine, which is the source of power for the motor, makes the machine portable, wireless, and efficient in the field of harvesting.

Bearing

The bearing is the part that lessens the friction and the wearing of the parts, thereby the motor and other parts that move can work smoothly and save energy.

Gear

The gear takes the different motor powers and changes them with the help of the motor speed control and hence cutting is done at the required speed.

Cam shaft

The camshaft changes the motor's rotary movement into one that is back-and-forth, the movement that is used in the cutting of leaves by motor-driven blades

Working Principle

The figure 2 explained the working principles of battery-powered tea leaf cutter essentially aims at using the energy stored in the battery into direct mechanical cutting action to carry out the harvesting of the tender tea shoots efficiently. The device features a battery source, a direct current (DC) motor, an accurate blade unit, and a collector along with the synchronization between the cut and collection achieved within one machine cycle. Once on, the battery initiates the flow of current to the DC motor. The motor, to which it is connected, converts the electric energy into the motor shaft rotational energy, which, with the help of the mechanical linkage, is transmitted to the blade unit. In figure 2 show that the cutting edges, which are arranged in the one-directional motion of the cylinder type, cover the stroke at a very high speed to ensure the tea leaves are cut freshly. The front part of the machine has the tea plucking combs to properly line up and feed the tea shoots into the cutting area. This element of construction helps to re-cook leaf loss and to let the uniform cutting height be maintained throughout the farm. At the same time, the leaves are the detached ones and are sent in the transparent sheath which is placed on the upper side of the machine. The chamber has a fully enclosed sheath that prevents scattering and contamination and serves as an immediate post-harvest storage.

The system's design in a portable manner is free from the limited power sources and, thus, can be turned on anywhere in the fields located in remote and uneven areas where normally power-driven harvesters cannot be employed. Also, the ergonomic handle and the well-balanced weight of the system lessen the worker's fatigue and, thus, extend the working hours under a stable performance are facilitated by the users.

The working procedure can be illustrated in brief as follows:

1. Battery discharge → The source of power to the motor unit.
2. Motor turning → The opening of the mechanical cutting unit is performed by the motor.
3. Cutter operation→ The part which does the cutting at high speed is the one focus on blade motion.
4. Leaf guide→ The step that leaves are guided to the collector is done through pieces of machinery.
5. Continuous work→ The activity of the labours in a farm which they go on harvesting

irrespective of their rest command so-called continuous operation.

The subject worked upon here integrates the principles of mechanical precision, energy-saving, and the capability of the device to function in open fields, thereby solving problems encountered when tea plucking done manually, such as the high labour demand, low cut quality, inconsistency, and time inefficiency. The wireless, eco-friendly design additionally facilitates the lowering of the planet's pressure due to human activity while at the same time satisfying the basic needs of tea farmers by increasing harvesting yields

Design Calculation for Efficiency
Theoretical Field Capacity (TFC)

TFC=W×S/10(ha/h)

Substitute values:

TFC=0,45×2,010=0,09 ha/h

Convert to m^2/h:

0,09 ha/h×10000=900 m2/h
TFC = 900 m^2/h.

Actual Field Capacity (AFC)

AFC=TFC ×ηf
AFC=900 m2/h×0,85=765 m2/h
AFC = 765 m^2/h (0,0765 ha/h).

Battery energy & usable energy
Total stored energy:

E_bat=V×Ah=24×100=2400 Wh
U_sable energy (DoD 80 %):
E_usable=0,8×2400=1920Wh
E_usable = 1920 Wh.

Runtime per charge

t_run=Eusable/Pe=1920 Wh/2400 W=0,8h t_run=0,8 h=48 minutes
Runtime ≈ 0,8 h (48 minutes) per charge.

Area harvested per charge

A charge=AFC×trun=765 m2/h×0,8 h= 612 m2
Area per charge ≈ 612 m^2 (≈ 0,0612 ha).

Energy consumption per unit area

Wh per m2=Eusable/A charge= 1920/612≈3,137 Wh/m2

Per hectare:

3,137 Wh/m2×10,000=31,372 Wh/ha≈31,37 kWh/ha
Energy use ≈ 3,14 Wh/m^2 (≈ 31,4 kWh/ha).

Summary table (key results)

- Cutting width: 0,45 m
- Forward speed (assumed): 2,0 km/h
- TFC: 900 m^2/h
- Field efficiency: 85 %
- AFC: 765 m^2/h
- Battery (usable): 1920 Wh (24 V × 100 Ah × 0,8 DoD)
- Power draw: 2400 W
- Runtime/charge: 0,8 h (48 min)
- Area/charge: 612 m^2
- Energy per m^2: 3,14 Wh/m^2 (≈ 31,4 kWh/ha)

RESULTS

This innovative project is the creation of a tea leaf cutting machine with an attachable battery. The study highlights the working principle, methodology, and materials used. In the part of the project, a self-propelled, battery-powered tea leaf cutting machine was tested and confirmed through a software simulation method to evaluate its performance under different working conditions. The testing focused on the main criteria such as battery efficiency, cutting precision, field capacity, and machine stability. The machine uses a 40 V, 2,5 Ah battery with a power output of 85 W and has a cutting width of 0,45. The overall weight of the machine is 2kg, which makes it significantly lighter than the traditional kind of harvesters and, therefore, more user-friendly and less tiring for the operator. The simulation method confirmed the machine's capability to operate for 4-5 hours and the battery could be changed for a longer period of use. Field capacity of the machine is 765 m sq/h which is a good fit for small and middle tea farms. The software framework implemented a factorial experiment design and ANOVA analysis to evaluate the effects of forward speed and operational load on power consumption and efficiency. The results of the research indicated that the reduction of the device's weight contributed to easier handling without losing cutting stability, while the battery management system ensured the most excellent energy efficiency. In brief, the software testing technique was a success in showing that the proposed tea leaf cutting machine is superior to the previous models in the areas of efficiency, lightness of operation, and eco-friendly energy use. Software testing was used to accomplish this goal. The battery-powered self-propelled tea leaf cutting machine was tested and simulated through software to confirm its technical performance. Before extensive field trials, software testing was done to simulate real field conditions and to check the machine's efficiency of operation. The below stages describe the testing process and outcomes in detail.

Crop characteristics

Tea leaves are commonly elliptical, very thin (0,3-0,5mm), and light green in color. Fresh leaves contain 70 %-80 % water, thus they are very delicate and easily damaged. Tea leaves are good source of polyphenols, caffeine and amino acids that determine tea quality. Young are leaves tender and require the cutting to be done carefully so as not to bruise. The quality of the leaf depends on altitude, climate, and soil fertility.

Stem thickness

- Tender stems -> about 1-2 mm thick
- Semi-mature stems -> 2-4 mm thick
- Mature woody stems -> 5-8 mm or more

Tender stem is highly preferred.

Harvesting stage

Good quality tea leaves are obtained at the "two leaves and a bud" stage, that is when shoots are tender and bright green. At this point, they have high levels of polyphenols, caffeine, and amino acids. Early harvesting lowers yield, while late plucking results in quality and flavor loss. The right plucking cycle is 7-15 days depending on growth condition. Forward speed of blades the reciprocating blade speed typically operates between 270-300 strokes per minute. The forward speed is about 1,5 km/h, the blade speed is maintained around 200 cm/s for precise cutting. This range minimizes leaf bruising while maximizing harvesting efficiency.

Cutting force

Tender tea leaves are soft tissues. The cutting force required is very low, typically in the range of 0,5 - 2 N. This is why sharp blades are essential; blunt blades increase force and cause bruising.

Stress acting on stem while cutting:

- Stress = Force / Area
- For a tender tea stem of 4 mm diameter → about 1 N force is applied.
- 0,5 - 0,6 MPa stress acts on the tender tea stem during cutting.

Parameter Setup

The machine data were fed into the simulation software as shown in table.1 to establish the base operational model.

Battery capacity: 40V, 2,5Ah.

Power rating: 85 watts, Cutting width: 0,45 meters.

Machine weight: 2 kilograms.

Expected working hours: 4-5 hours (extended with an alternate battery).

Field capacity: 765 m^2/hr.

Table 1. Software Simulation Input Parameters

Variable	Levels Tested	Purpose
Forward Speed	1,5, 2,0, 2,5 km/h	To analyse speed effect on efficiency
Leaf Density	Tender, Medium, Mature	To evaluate cutting performance
Terrain Conditions	Flat, Inclined	To test stability and manoeuvrability
Battery Discharge	Full cycle (0–100 %)	To evaluate endurance and power efficiency

Simulation Design

Software conditions were planned in order to simulate real situations that would have been the case in a field and they were: Forward speeds: 1,5, 2,0, and 2,5 km/h. Leaf density differences - indicating tender vs. mature leaves Terrain slope changes: flat and inclined surfaces. Battery discharge cycles are a method of measuring the energy used during a continuous load. The cutting unit, the drive system, and the battery were written as different modules but

interlinked in order to see the power flow and the efficiency level.

Performance Measurement

The following aspects were measured during the simulation: Cutting efficiency (% of clean cuts with no leaf damage) Power consumption in terms of rate of energy utilized at differing speeds and workloads. Battery life (operational hours until full discharge) Field capacity in m^2/h is dependent upon cutting width and speed. Operator comfort index as an estimate for load handling due to lower machine weight

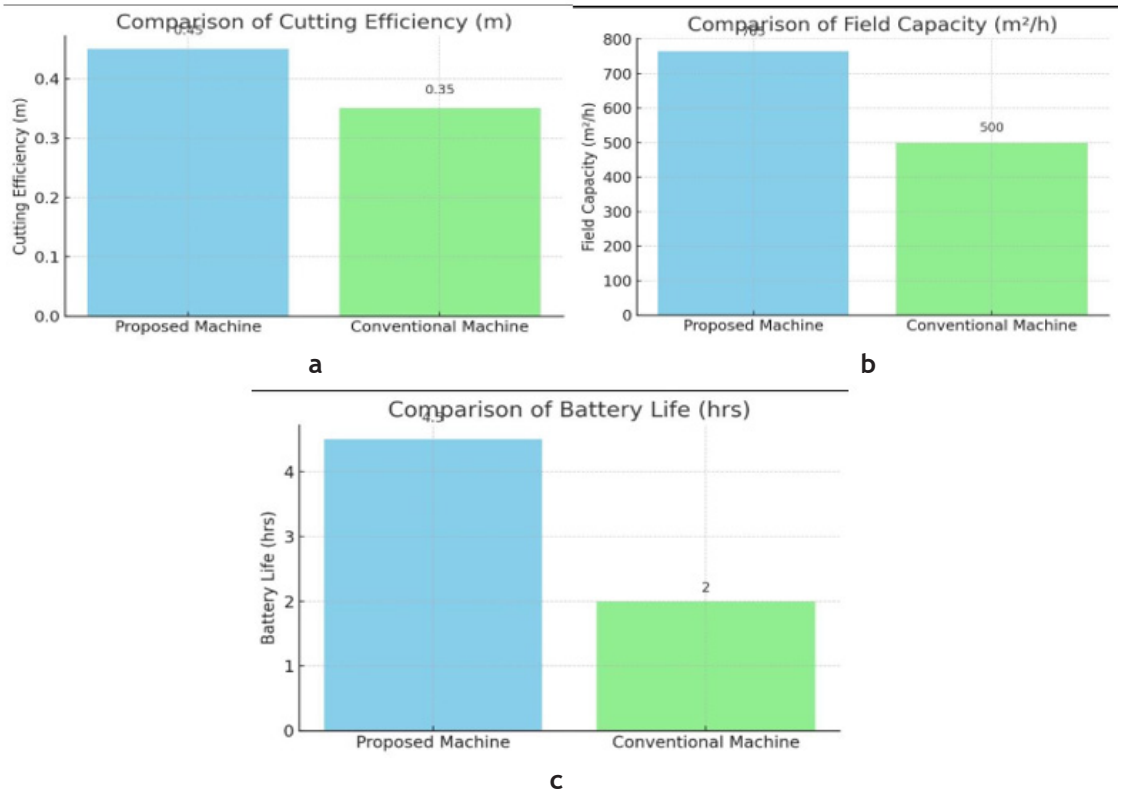

Figure 3. a. Comparison of cutting efficiency, b. Comparison of field efficiency, c. Comparison of battery life

Statistical analysis

A factorial experiment design was employed and the results were analysed using analysis of variance (ANOVA) to decide:

- The effect of forward speed on battery consumption.
- The effect of reduced demand on power efficiency.
- The correlation between speed and field capacity.

This statistical research gave a clear understanding of the machine's optimal operating range.

Results of Simulation

In a result, figure 3 show that the comparison of the conventional and proposed machine is represents in graph. The machine was able to maintain a field capacity of 765 m^2/h at an optimal speed of 2,0 km/h consistently. Battery life was put to test for 4-5 hours of use during

which effective power management was able to maintain cutting performance at a steady level. The small and light (2 kg) design feature of the product contributed to better manoeuvrability, less operator fatigue, and thus, it became more useful than the conventional harvesters. Cutting accuracy was kept at more than 90 % of the cuts being clean which led to a high-quality leaf harvest with little damage. The simulation was able to demonstrate that the use of another battery could lead to longer operational hours without a drop in performance

Table 2. Simulation Results of Tea Harvesting Mechatronics

Parameter	1,5 km/h	2,0 km/h (Optimal)	2,5 km/h
Cutting Efficiency (%)	88	92	85
Power Consumption (W)	70	75	82
Battery Endurance (hrs)	5,2	4,8	4,1
Field Capacity (m^2/h)	680	765	820

DISCUSSION

The software testing approach product the findings that the tea leaf cutting machine is of a light structure, the battery is used efficiently, and the machine is quite reliable during the field operations. As compared with the conventional harvesters, the machine is said to be more energy-saving, provides more comfort to the operator, and is a price-worthy good for small and medium farms. The research also pointed out the importance of maintaining the forward speeds close to 2,0 km/h where the machine achieves the best cutting efficiency and power consumption is at the lowest level. In general, the software testing process was a confirmation of the machine's design and it demonstrated the capability of the machine to be used in the field, thus, it is considered as a future solution for tea harvesting of the kind.

Table 3. Performance Comparison Between Proposed and Conventional Tea Leaf Cutting Machines

Parameter	Proposed Machine (This Study)	Conventional Machines (General Range)	Improvement / Advantage
Battery Voltage	40 V	24–36 V	Higher power stability
Battery Capacity	2,5 Ah	2,0–2,5 Ah	Comparable, efficient use
Power Rating	85 W	100–120 W	Lower power consumption
Cutting Width	0,45 m	0,40–0,50 m	Similar
Machine Weight	2 kg	3–4,5 kg	Much lighter (↑ handling
Working Hours	4–5 hrs (alt. battery usable)	3–4 hrs	Longer endurance
Field Capacity	765 m^2/h	600–700 m^2/h	Higher productivity
Operator Fatigue	Low (lightweight design	Moderate to high	Better ergonomics
Cutting Efficiency	~92 % (optimal at 2 km/h)	~85–88 %	Cleaner leaf harvest

Comparative Analysis of Mechanized Cutting Mechanisms and Industrial Blade Systems

Research on tea leaf cutting devices has constantly emphasized the significance of blade curvature, stroke frequency, and reciprocating kinematics in obtaining cuts that are clean and with minimal tissue damage.[4,11] When these features are compared with the cutting and milling tools used in oil and gas maintenance systems, similarities appear in the demand for optimized tool geometry and controlled actuation forces. Mechanized tea plucking machines—

especially those using arc-shaped blades and servo-controlled cutters—are a good example of how cutting units that are light but of high precision can be converted to robotic pipe cleaning, gasket removal, or precision trimming tasks in drilling platforms. The agreement here is that agricultural cutting research could be an unconventional yet invaluable source of insight when it comes to the development of fine-tolerance cutting systems in petro-mechanical operations.[17,18]

Table 4. Comparative Features of Tea Cutting Machines and Oil & Gas Automation Tools

Parameter	Tea Leaf Cutting Machines Refs:[1,4,8,11]	Oil & Gas Exploration Tools (Analogous Systems)
Cutting Mechanism	Reciprocating / arc-shaped blades	Disc cutters, milling heads, carbide tools
Actuation	Servo motors, linkages	Hydraulic, pneumatic, electro-servo drives
Sensing	Optical, mechanical triggers	Visual inspection, ultrasonic, pressure sensors
Motion Control	PID, feedback-based	Closed-loop servo control, adaptive control

Transferability of Sensing and Feedback Modules Across Sectors

In which sensing details for an emphasis on tea picking are described in the literature that accompanies the articles cited, table 5, respectively, they have significantly changed from very simple mechanical triggering devices to optically guided, servo-coupled detection frameworks capable of distinguishing tender shoots. Such changes can be compared with the shift to intelligent sensing in oil and gas systems, where inspection robots use visual, acoustic, and positional data to operate. Even though the working places are very different, the feedback principles—fast signal capturing, real-time actuator force changing, and irregular surface handling—are the same ones. The agreement between these sensing approaches shows that there is a great possibility of converting cheaply made agricultural sensor arrays for the use of remote inspection tools which can be put in confined pipelines or structural cavities.

Table 5. Transferable Design Principles from Tea Mechanization to Oil & Gas Automation

Tea Mechanization Insight	Cross-Industry Application Potential
Lightweight chassis for slope stability	Mobile rigs, pipeline crawlers
Solar/low-power operation	Remote field robots, offshore monitoring
Selective plucking detection	Fault localization in pipes, weld detection
Modular system design	Quick-swap tool heads for inspection robots
Precision blade kinematics	Controlled abrasive cutting in maintenance

System Integration Pathways for Cross-Industry Automation Adoption

One of the most eye-catching features in the recent developments of tea harvesting platform is the introduction solar-powered units self-propelled multi-row harvesters,[2,12] which showcases the potential of integrating energy-efficient mechatronic subsystems into the rugged field equipment. These devices feature modular architectures, which make it easier to maintain and support fast subsystem replacement - characteristics that oil and gas robotics are increasingly recognizing. When considered as petro-automation workflows, such modularity might allow a more flexible deployment of robotic handlers, inspection crawlers, and lightweight drilling-assist mechanisms. Mechanisation trends reported in the tea industries worldwide.[3,5] Figure 4 pointed out that the gradual integration of automation usually results in a higher rate of success than a complete-scale redesign, which is a lesson very much applicable to brownfield oil and gas installations.

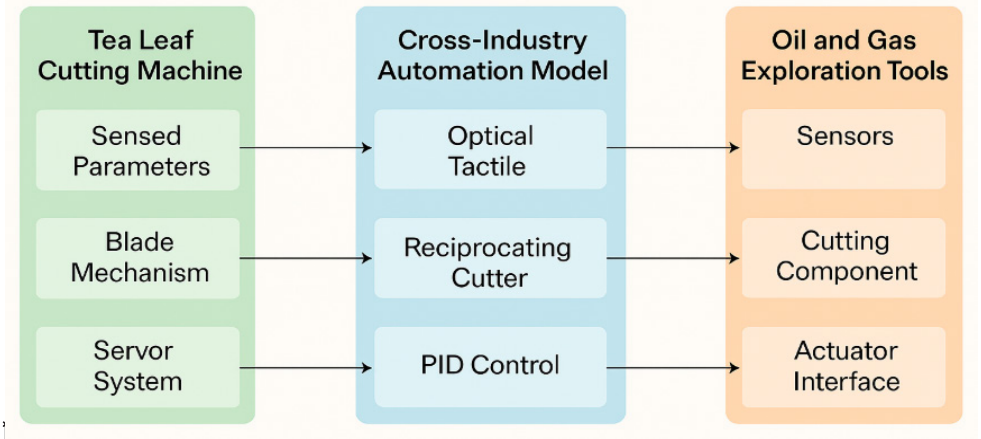

Figure 4. Subsystem Mapping Tea Leaf Cutting Machine to Oil and Gas Exploration Tools

Implications for Performance, Safety, and Operational Sustainability

Research focused on quality aspects in tea harvesting has revealed that incorrect blade loading, high stroke rates, or bad sensing feedback can lead to the deterioration of the quality of the tea leaves and a decrease in the overall yield.[15,16] Similar risks are also present in oil and gas systems: for example, the wrong interaction between a robot and a tool can result in the damage of pipes, sensors, or valves. By looking at tea harvesting experiments that focus on parameter optimization,[1,6] it becomes more evident how exact control tuning can lead to the lowering of energy consumption, raising of tool safety, and the extending of system lifetime. Therefore, the valuable information obtained from seemingly low-load agricultural systems may, in fact, be the source of significant safety, reliability, and sustainability improvements in petroleum operations.[19,20,21]

CONCLUSIONS

To sum up, one of the biggest advances of the mechanization of tea harvesting in agriculture has been the completion of a battery-powered tea leaf cutting machine. Traditional methods of tea plucking are good in maintaining quality leaves, but these have a lot of human labour involvement, which is time-consuming and physically exhausting. Labor availability has been one of the most important concerns for several areas that produce tea due to physical migration, increasing wages, and the nature of the job being highly demanding, all of which have been contributing to the labour scare. There is, therefore, an increasing demand for compact, portable, and efficient devices that will minimize human labour without compromising harvesting standards. The battery-operated tea leaf cutting machine is, therefore, a sure answer to this problem. The design of the machine includes a rechargeable battery that completely does away with the need for long extension cords or fixed power sources. This characteristic allows the use of the tool in remote tea estates where the electricity supply is either limited or unavailable. The rechargeable lithium-ion or lead-acid battery can keep the machine operating for several hours on a single charge; thus, it is suitable for small and medium-sized farms. The possibility of charging the accumulator with solar panels turns this equipment into an ideal clean energy and off-grid agricultural operation. From a functional viewpoint, even when used for a long period of time, the user will not be heavily fatigued due to the light machine, ergonomic handle grips, and good cutting edge. In this way, the quality of the tea leaves is immediately taken care of, which is a basic requirement of the production of tea of the highest class. The leaf-collecting bag, by doing away with the laborious further manual collection and enabling

the instant gathering of cut leaves, is thus greatly helping increase the volume of work. The machine has a great ecological advantage over fuel-powered tea harvesting tools. The machine uses low energy for its entire lifespan and produces no noise while releasing no direct emissions. This means that labour cost savings are twice as much as total harvesting costs, while efficiency of the machine enables it to pick more tea in a very short time. This would bring higher annual yields and more profit over several harvesting cycles. The machine has financial feasibility due to the combination between the durability of the machine together with low maintenance, which guarantees that the initial investment will be recovered in a short time. At the same time, this battery-powered tea leaf cutting machine assists in making the harvesting procedures uniform, reducing dependence on seasonal labour, and facilitating year-round output, hence revolutionizing the tea industry at a larger scale. Moreover, it can also be instrumental in the upliftment of smallholder farmers by providing them access to the technology that was hitherto available only to large-scale tea estates. In spite of current economic woes, this democratization of agricultural technologies may help sustain traditional tea-growing areas and raise the living standards of rural farming people. In short, the battery-operated tea leaf cutting machine is not just another item of farm machinery; it is the solution to several problems being faced by the tea industry. It makes one single, user-friendly unit that can combine all such attributes like portability, efficiency, cost-effectiveness, and environmental friendliness. Hence, the adoption of this technology guarantees a major step towards a future wherein tea farming will be more profitable, efficient, and sustainable globally.

On the whole, a comparison of performance across different industries reveals that one of the main technical aspects which is the precision of blade interaction in tea leaf cutting machines might be the most transferrable basis to foster further development of automation in oil and gas exploration. Though the operational scales and environmental conditions are vastly different, the fundamental ideas of selective engagement, controlled material removal, and real-time adaptive feedback are still the same in both fields. By thoroughly delineating these subsystems, the research is showing how advanced technologies in agriculture can facilitate the petroleum robotics innovations, simplify the design, and lower the costs of development. This interdisciplinary viewpoint is a strong argument for the general idea that the next industrial automation will be more and more benefited by the solutions coming from outside the traditional engineering hierarchies and thus, be open to the cross-sector technological pathways further.

BIBLIOGRAPHIC REFERENCE

1. Gopinath CS, et al. Design and development of a conceptual tea leaf harvesting machine. 2011 Sep;10(2).

2. Sangupandy D, ArunSiva S, et al. Tea Leaf Harvester Using Solar Power. International Journal. 2023;11(07).

3. Eskasasnanda IP. Mechanisation in tea plantation driving factors and its impact on sustainable. 2020 Jan;25(1):61-8.

4. Han Y, Xiao HR, et al. Design and Evaluation of tea leaf-Plucking machine for improving quality of tea. 2011;35(6):979-86.

5. Wu CC. Developing Situation of Tea Harvesting Machines in Taiwan. 2015;5(6):871-5.

6. Abarna R, Subash S, et al. Design and Fabrication of tea leaf machine. 2018;4(2).

7. Hemalatha JN, Manikanta M, et al. Implementation of Tea Harvester. International Journal.

2020 Jul;9(07).

8. Mamuladze M. In tea picking machines,the prospect of using a new cutting machine. 2023.

9. Delcien ASR, Shankar S, et al. Tea Leaf Cutting Machine1. 2016;3(3).

10. Yang Y, Chicherin IV, et al. Design and research on servomechanism of tea plucking. 2024.

11. Han Y, Xiao H. Research on Kinematics Model of Reciprocating Cutter with Arc-shaped Blade for Tea-leaf Picking. 2019.

12. Han Y, Xiao H, et al. Design and experiments of 4CJ-1200 self-propelled tea plucking machine. 2021;14(6).

13. Sureshkumar A, Muruganand S. Design and Development of Selective Tea Leaf Plucking Robot. 2014;2(2):45-8.

14. Burgess PJ, Carz MKV, et al. Evaluation of simple hand-held mechanical systems for harvesting tea(CAMELLIA SINENSIS). 2006.

15. Wijeratne MA. Harvesting policies of tea (Camellia sinensis) for higher productivity and quality. 2003.

16. Ravichandran R, Parthiban R. The impact of mechanization of tea harvesting on the quality of south Indian CTC teas. 1997.

17. Yu R, Xie Y, Li Q, Guo Z, Dai Y, Fang Z, Li J. Development and experiment of an adaptive oolong tea harvesting robot based on visual localization Agriculture. 2024.

18. Wang H, Gu J, Wang M. A review on the application of computer vision and machine learning in the tea industry. Frontiers in Sustainable Food Systems. 2023.

19. Zhang L, Zhang H. Real-time monitoring of optimum timing for harvesting fresh tea leaves based on machine vision. International Journal of Agricultural and Biological Engineering. 2019;6–9. https://doi.org/10.25165/j.ijabe.20191201.4123.

20. Chen C, et al. A YOLOv3-based computer vision system for identification of tea buds and the picking point. Computers and Electronics in Agriculture. 2022;198:107116.

21. Lu J, Yang Z, Sun Q, Gao Z, Ma W. A machine vision-based method for tea buds segmentation and picking point location used on a cloud platform. Agronomy. 2023;13(6):1537.
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AUTHORSHIP CONTRIBUTION

Conceptualization: M. Vimal Raja, S. Sanjula, T. Vignesh, N. Hariprasanth, V. Sriram, P. Prabhu, Nurmamatov Mekhriddin Qahramonovich.

Data curation: M. Vimal Raja, S. Sanjula, T. Vignesh, N. Hariprasanth, V. Sriram, P. Prabhu, Nurmamatov Mekhriddin Qahramonovich.

Formal analysis: M. Vimal Raja, S. Sanjula, T. Vignesh, N. Hariprasanth, V. Sriram, P. Prabhu, Nurmamatov Mekhriddin Qahramonovich.

Drafting - original draft: M. Vimal Raja, S. Sanjula, T. Vignesh, N. Hariprasanth, V. Sriram, P. Prabhu, Nurmamatov Mekhriddin Qahramonovich.

Writing - proofreading and editing: M. Vimal Raja, S. Sanjula, T. Vignesh, N. Hariprasanth, V. Sriram, P. Prabhu, Nurmamatov Mekhriddin Qahramonovich.

Chapter 5 / Capítulo 5

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ORIGINAL

Automation Across the Energy Spectrum: Intelligent Systems for Oil and Gas Operations and Real-Time Solar Tracking

Automatización en todo el espectro energético: sistemas inteligentes para operaciones de petróleo y gas y seguimiento solar en tiempo real

P. Prabhu[1] ✉, V. Suresh[1] ✉, T. A. Abhijith[1] ✉, K. Adarsh[1] ✉, T. Anand Kumar[1] ✉, Christo Ananth[2] ✉, Ibrohimali Normatov[3] ✉

[1]Department of Mechanical Engineering, KIT - Kalaignarkarunanidhi Institute of Technology. Kannampalayam, Coimbatore, Tamil Nadu, 641402, India.

[2]Faculty of Artificial Intelligence and Digital Technologies, Samarkand State University. Uzbekistan.

[3]National University of Uzbekistan. Tashkent, Uzbekistan.

Corresponding Author: P. Prabhu ✉

ABSTRACT

Fast moving automation technologies are profoundly changing the energy sector, a change that is affecting not only carbon-based energy systems but also clean energy systems. Oil and gas exploration is becoming more and more the domain of intelligent monitoring platforms, adaptive control architectures, and sensor-rich robotic tools that can precisely operate, detect faults quickly, and ensure safety in complex subsurface environments.. The fast worldwide movement towards renewable energy has led to intense research on solar energy systems, highlighting their indispensable role in providing sustainable energy. However, traditional fixed photovoltaic (PV) panels have an inherent drawback - their non-moving nature makes it impossible for them to be in continuous contact with the sun's rays, which results in less energy being captured and lower conversion efficiency. In order to address this problem, real-time solar tracking devices have been invented to change the direction of the panels automatically, thus ensuring maximum exposure to solar irradiance during the day. Although these solutions show substantial increases in energy output, their popularity is limited by the expensive and intricate nature of typical commercial designs, especially in the case of domestic and small-scale applications. As a result, lately, developments have been focusing on creating low-cost, sensor-based, and easily operable tracking devices that use simple elements like Light Dependent Resistors (LDRs) and photodiodes. This paper introduces a comprehensive review of the innovative ideas in this field by highlighting the features, hardware setups, and control methods of the single- and dual-axis systems besides this comparative assessment of sensor-based and astronomical models provides insights into system simplicity, dependability, and cost-effectiveness trade-off. The paper ends with an overview of potential future topics such as the use of intelligent control algorithms, Internet of Things (IoT) units, and hybrid renewable systems that, when combined, may lead to the emergence of the next generation of solar tracking technologies that are adaptive and highly efficient.

Keywords: Solar Tracking; Light Dependent Resistor (LDR); Real-Time Control; Renewable Energy; Low-Cost Systems.

RESUMEN

Las tecnologías de automatización en rápida evolución están transformando profundamente el sector energético, un cambio que afecta no solo a los sistemas energéticos basados en carbono, sino también a los sistemas de energía limpia. La exploración de petróleo y gas se está convirtiendo cada vez más en el dominio de plataformas de monitorización inteligente, arquitecturas de control adaptativo y herramientas robóticas con sensores que pueden operar con precisión, detectar fallos rápidamente y garantizar la seguridad en entornos subterráneos complejos. La rápida transición mundial hacia las energías renovables ha impulsado una intensa investigación sobre sistemas de energía solar, destacando su papel indispensable en el suministro de energía sostenible. Sin embargo, los paneles fotovoltaicos (FV) fijos tradicionales presentan una desventaja inherente: su inmovilidad les impide estar en contacto continuo con los rayos del sol, lo que resulta en una menor captación de energía y una menor eficiencia de conversión. Para abordar este problema, se han inventado dispositivos de seguimiento solar en tiempo real que cambian la dirección de los paneles automáticamente, garantizando así la máxima exposición a la radiación solar durante el día. Si bien estas soluciones muestran aumentos sustanciales en la producción de energía, su popularidad se ve limitada por el alto coste y la complejidad de los diseños comerciales típicos, especialmente en el caso de aplicaciones domésticas y a pequeña escala. Como resultado, últimamente, los avances se han centrado en la creación de dispositivos de seguimiento solar de bajo coste, basados en sensores y de fácil manejo, que utilizan elementos sencillos como resistencias fotoeléctricas (LDR) y fotodiodos. Este artículo presenta una revisión exhaustiva de las ideas innovadoras en este campo, destacando las características, las configuraciones de hardware y los métodos de control de los sistemas de uno y dos ejes. Además, esta evaluación comparativa de modelos basados en sensores y astronómicos proporciona información sobre la simplicidad, la fiabilidad y la relación coste-eficacia del sistema. El artículo finaliza con una visión general de posibles temas futuros, como el uso de algoritmos de control inteligente, unidades del Internet de las Cosas (IoT) y sistemas híbridos de energías renovables que, al combinarse, podrían dar lugar a la próxima generación de tecnologías de seguimiento solar adaptativas y altamente eficientes.

Palabras clave: Seguimiento Solar; Resistencias Fotoeléctricas (LDR); Control en Tiempo Real; Energías Renovables; Sistemas de Bajo Coste.

INTRODUCTION

The dramatic increase in worldwide energy demand has been a major contributor to the focus on renewable energy technologies, along with growing worries about greenhouse gas emissions and resource depletion. In fact, one of the main reasons is their modular structure, non-polluting operation, and easy scalability in different geographical areas.[1,2,3,4,5] Still the performance of photovoltaic (PV) grids is so vulnerable that the power generated depends on the momentary solar irradiance and the angle between the light source and the module surface.[6,7,8,9,10] In fact, any slight deviation of the solar vector from the panel orientation can result in a significant power output drop and even system efficiency reduction over the years.[2,4,11,12] There is a large number of both experimental and computational research papers which have come to the conclusion that system yield depends not only on local weather conditions, but also on the degree to which the arrays can follow the apparent movement of the sun along the sky. Therefore, the best use of the angle of the modules during the day and at different seasons is still one of the principal ways of increasing energy density without augmenting the

PV footprint.[3,5,9] Fixed-tilt installations of the solar arrays are still the most popular ones due to their less complex supporting structures, low maintenance, and absence or very little control electronics. The main disadvantage of these systems is that they cannot incorporate compensation for the dynamically changing sun's trajectory and thus the solar energy received is drastically and predictably lowered.[2,4,11] Active solar tracking facilities on the other hand have the ability to adjust the PV modules in situ to achieve the maximum power point and thus they have already proven their effectiveness in terms of daily and annual energy yield. The real installation onsite tests usually give evidence that single-axis trackers are able to moderately improve the system performance and therefore also the energy yields whereas dual-axis configurations can further increase that up to even ten percent and more, especially when the sky is clear and sun irradiance is at its maximum.[5,6,7,9,11] However, there exist difficulties in implementing a fully automated tracking system regulation mechanism in a wide range of locations due to the additional mechanical intricacies that caused by the requirement for a wide and heavy installation design structure, the actuator power demanding and the extension of set-up and maintenance costs, which may cancel out the economic benefits that are present in this application in some cases.[4,12] Hence, research nowadays is more concentrated on techno-economic optimization, which is sensitive to the local context, than on explicitly proclaiming that one type of tracking configuration is better than another.[11,12]

Sensor-based, low-cost tracking systems have become the focus of attention in this domain during the last couple of years. The discussed systems generally exploit optical sensors as LDRs, photodiodes, or phototransistors combined with a low-power microcontroller or an embedded processor to provide a nearly real-time sun-tracking solution with minimal energy consumption.[6,8,10,13,14] Implementations in literature have relied on comparator-based circuits, proportional–integral–derivative (PID) controllers, or fuzzy logic methods to ensure that the angular correction is accurate, and the oscillations and overshoot are at a minimum.[10,15,16,17] The IoT connectivity and edge computing integration have, therefore, extended the capabilities of such systems to remote monitoring,[18,19,20,21] predictive diagnostics, and cloud-based performance analytics of distributed PV networks.[10,12,22,23,24,25] Properly engineered low-cost, smart trackers can provide a great compromise of accuracy, scalability, and power saving, i.e., qualities that make them highly attractive for decentralized rural electrification, domestic rooftop systems, and smart microgrid applications.[10,12,22,23,24]

However, the full potential of sensor-driven solar tracking is still limited by a few long-lasting issues that persist alongside it. Cheap optical sensors sometimes have nonlinear reactions to extreme irradiance situations, temperature drift, and aging-related degradation, which, when combined, point accuracy diminish over long periods of operation.[6,16] Besides that, mechanical wear, actuator inefficiencies, and parasitic energy losses from control electronics can reduce net system gains if not taken care of by proper design optimization, thus increasing the extra work for the system.[11,15,17] The latest study on this topic revealed that hybrid control strategies, i.e., the integration of predictive algorithms like Artificial Neural Networks (ANNs) or Model Predictive Control (MPC) with the real-time sensor feedback, may help to stabilize and reduce the transient error during weather condition changes.[17,18,19,20] These methods, however, require more computational resources and calibration effort and, therefore, still being considered as a possible way of getting a resilient, adaptive, and low-maintenance tracking system in the future.[18,19,21,22]

Besides, the transition of AI-enabled and IoT-integrated hybrid frameworks is significantly changing the solar tracking field. Researches that use fuzzy logic, neural networks, and machine vision methods have proven that it is possible to have the tracking very close to the sub-degree with the energy used being also very low.[15,16,17,18,23] Meanwhile, combining optical, infrared, and camera-based sensors has allowed the multi-spectral tracking to be able to keep the accuracy even in the case of diffuse or partially shaded conditions.[21,22,23] These improvements, when

combined with cloud-based supervisory control, can result in self-calibrating systems that change sensor degradation and environmental variability. Nevertheless, the extensive use of such smart trackers is constrained by the expenses of the hardware, the difficulties of the computational part, and the problems of data connectivity, mainly in rural and developing areas.[10,22,24] It is necessary to overcome these practical obstacles if intelligent solar tracking technologies are to go beyond being mere experimental prototypes and to become solutions viable in the commercial market.

Automation

In the energy sector, automation has been a feature that not only changed the mode of the energy sector but also the whole technology development and utilization sector. By the adoption of real-time analytics, sensor-laden monitoring networks, and machine-assisted decision frameworks, field operations have become safer and less prone to risks in the oil and gas sector. Indeed, the array of publications and reports in the literature are unequivocally in favor of automation in drilling supervision, the use of autonomous downhole tools, and digitally integrated reservoir workflows, which, as a result, have a tremendous impact on operational uncertainty reduction and subsurface characterization enhancement.[25,26,27] Such technological advances are the lifeline of the situation in which geological operators confront complex environments and need to interpret high-frequency data fast to keep drilling performance and equipment integrity. Hence, the changes mean a deep upheaval in upstream engineering as automated systems are slowly becoming the core operational infrastructure rather than just being optional ones.[28,29] A sensor tech up-to-date has been a great help in finding new paths of collecting solar energy more efficiently just like that the breakthrough renewable energy innovations are reshuffling the energy scene. Dual-axis solar trackers and minimalist light-intensity sensors have been shown to accomplish substantial efficiency gains chiefly in decentralized or resource-poor environments, as per the research of Rashid et al.[28] and Rhatigan et al.[30]. The invention of self-powered environmental monitoring and stable control logic has been the reason for the transition of such instruments and thus their reliability is guaranteed even in variable weather conditions.[29] Although solar tracking is a completely different technological concept from hydrocarbon exploration, both industries share the same dependence on distributed sensing, adaptive control, and continuous performance optimization. As a result, these concepts' interconnection can speed up the progression of high-tech, advanced, and energy-diverse engineering systems that are not only more intelligent but also more flexible due to cross-sector knowledge sharing.

Moreover, there is still a considerable research gap regarding the long-term validation and comparative evaluation of low-cost tracking systems. While some prototype experiments have announced energy gains of 25–45 % under idealized conditions,[2,6,9,10] hardly any study has systematically looked at durability, actuator lifespan, and calibration drift due to real-world environmental fluctuations.[11,15,17,20] In the same vein, most of the commercially available dual-axis systems are still depending on precision encoders and astronomical algorithms that increase costs and limit the applicability for small-scale and domestic users.[5,8,14] The literature hardly discusses hybrid sensor–algorithmic approaches that use optical feedback with predictive modeling[9,16,18] and also does not provide a complete evaluation of the trade-offs between cost, energy consumption, and long-term reliability.[4,11,20] Therefore, a holistic cross-disciplinary framework, which includes electronics, control engineering, and energy economics, is required to implement advances in low-cost, energy-efficient, and field-resilient solar tracking technologies.[17,19,25]

Objectives of the Study

This review is centered on gathering, synthesizing, and critically evaluating recent low-cost

innovations in sensor-based solar tracking systems with an emphasis on real-time performance optimization, energy efficiency, and scalability. The broad aims are to:

1. Combine and situate the innovations of the latest developments of real-time solar tracking systems in the context of the utilization of simple optical sensors like Light Dependent Resistors (LDRs), photodiodes, and phototransistors.[5,6,8]
2. Regulate the existing methods that are to be local implementations—comparator-based, PID, fuzzy logic, and AI-assisted algorithms—to be accurate, stable in the response, and to consume less energy. Compare and evaluate these methods.[10,15,18]
3. To be Performance metrics such as the efficiency improvement, the response time, the cost-effectiveness, and the reliability of single-axis and dual-axis tracking configurations, both experimental and simulation-based, are to be analyzed from the literature.[2,6,11,20]
4. Delve into the issues that accompany low-cost tracking systems and thus hamper device deployment in the rural, domestic, and hybrid renewable energy sectors, particularly in the case of mechanical wear, power consumption, and calibration drift.[12,16,22]
5. The affordable, intelligent, and autonomous solar-tracking architectures of the next generation with a combination of research trends of IoT-enabled, AI-based, and hybrid sensor fusion approaches[17,19,25] are to be identified.

Principles, Classification and techniques of Solar Tracking

Principles of Solar Tracking

Solar tracking describes the process whereby photovoltaic (PV) panels or collectors are constantly adjusted to maintain the most favorable angle towards the sun, thus increasing the amount of solar radiation reaching the active surface.[2,4] Tracking is done by figuring the sun's position on earth at that very time by means of optical sensing, using coordinate calculations or a hybrid control approach, which involves both methods.[6,9,10] In sensor-based tracking that is done in real-time, devices such as Light Dependent Resistors (LDRs), photodiodes, or phototransistors detect the differential light intensity between the paired sensors, and the corresponding actuator signals propel the panel to reorient it in such a way that equilibrium is restored.[5,8,12]

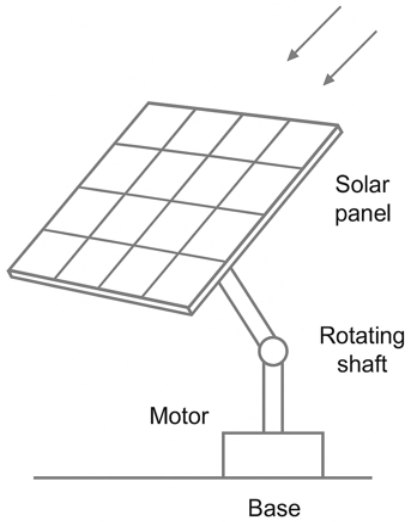

Figure 1. Schematic diagram of a Single axis solar tracking system[2,6,13]

From the mathematical point of view, any time solar position can be represented by two basic angular coordinates: azimuth (the horizontal direction of the sun relative to true north) and elevation (the vertical angle above the horizon), both of which change continuously with time and location on earth.[7,9,11] Usually tracking hardware is employed as a single-axis system, which traces the sun's apparent movement in one plane (generally east–west), or as a dual-axis system, which is able to alter both azimuth and elevation for the exact direction to be obtained during the day as well as for the changes in the seasons.[2,6,13] Figure 1 shows a diagram of a single-axis solar tracking setup which basically entails the main functional components of sensor-based actuation and feedback control.

Classification of Solar Tracking Systems

Usually, solar tracking devices are split into two major segments—passive as well as active systems— based on their operating and controlling methods.[2,4,6] Passive trackers rely on thermal or mechanical actuations, most of the time, utilizing the differential expansion of the working fluid or gas to change the collector's orientation due to solar heating. Even though this kind of design is intrinsically simple and doesn't require any energy, the response of such a system is usually slow and less accurate in the case of sudden changes in weather.[5,11] On the other hand, active tracking systems make use of sensors, actuators, and electronic control units to constantly change the panel's orientation in the direction of the highest solar irradiance.[6,8,9] Depending on the number of degrees of rotational freedom, active trackers may also be single-axis or dual-axis. A single-axis tracker revolves around one fixed axis—either azimuthal (east-west) or elevational (north–south)—and is generally used in low-medium precision applications like rooftop PV arrays and small-scale solar farms.[2,6,12] Whereas a dual-axis tracker, which is depicted in figure 2, varies in both azimuth and elevation angles so that it can always have the closest to perpendicular incidence to the sun during both diurnal and seasonal cycles.[7,9,13]

Table 1. Comparative summary of single-axis and dual-axis tracking systems

Type of System	Axis of Motion	Control Principle	Tracking Precision (°)	Typical Efficiency Gain (% vs Fixed)	Approx. Cost Level	Common Applications	Key Ref
Fixed System	—	Stationary frame, fixed tilt	—	0	Very Low	Rooftop PV, small off-grid units	[2,4]
Passive Tracker	1 or 2	Thermal expansion / fluid displacement	5 – 10	10 – 20	Low	Stand-alone collectors, solar heaters	[5,11]
Single-Axis Active Tracker	1 (azimuth *or* elevation)	Sensor-based or algorithmic rotation using one actuator	1 – 3	15 – 25	Medium	Rooftop PV arrays, mid-scale solar farms	[2,6,9]
Dual-Axis Active Tracker	2 (azimuth + elevation)	Independent control of two actuators; feedback or predictive algorithms	< 1	25 – 45	High	Utility-scale PV, CPV systems	[6,13]
Hybrid Tracker	2	Sensor + astronomical + AI or IoT-assisted logic	< 0,5	30 – 50	Medium – High	Smart grids, research demonstrators	[9,15]

Even though dual-axis devices usually result in the largest additional energy yields (25–45 %), their better accuracy and daily energy capture capability are associated with increased mechanical intricacy, higher cost, and greater maintenance requirements.[6,13,15] Table 1 presents a comparative overview of the single-axis and dual-axis tracking systems, which is the main differences in precision, energy gain, and cost-effectiveness that are being pointed out.

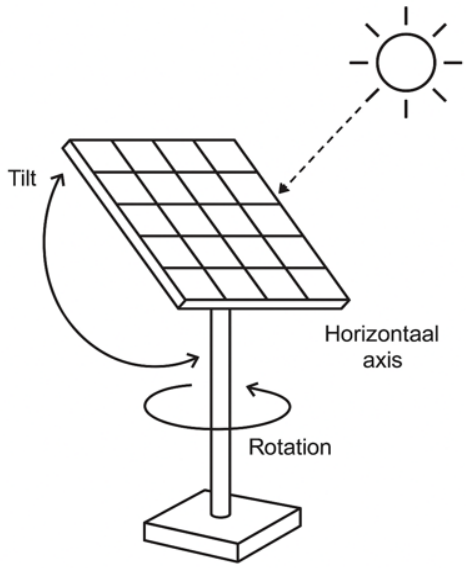

Figure 2. Schematic diagram of dual axis solar tracking system

Sensor Technologies for Real-Time Tracking

The efficacy of solar tracking mechanisms operating in real-time conditions is largely dependent on the precision and promptness of the sensors that are employed to identify the changes in solar irradiance. In the case of various optical sensors, the three options that have been most extensively used for low-cost experiments due to their easy-to-handle, small size, and low power consumption features are Light Dependent Resistors (LDRs), photodiodes, and phototransistors. It should be noted that among these, LDRs are especially interesting because of their high sensitivity to the range of the visible light and cheap production, which make them the best-fitted for small-scale as well as educational purposes.[6,9,12] An LDR is a photo resistive device whose resistance varies inversely with the intensity of the incident radiation and hence it directly analogically represents the light changes.[5,8] Normally, solar tracking hardware contains either two or four LDRs that are aligned in the same direction, and an opaque partition is placed between them to create a differential light-sensing unit. This method allows the unit to detect orientation changes of the solar flux: the voltage difference between these sensors serves as an instruction signal for the controller when one sensor is illuminated more than its counterpart.[9,10] Firstly, the error signal can be manipulated through analog comparator circuits or microcontroller-based logic by which stepper or DC motors are turned on to reorient the photovoltaic (PV) module until both sensors are at the same level of light. Secondly, the controlled signal can directly command the movement of a motor having the photovoltaic (PV) module mounted on the axis to achieve a balance state of light illumination whereby both sensors have the same intensity.[8,12,13] LDR-based tracking systems that are properly calibrated can lead the solar energy harvesting process to yield from 25 up to 40 percent as compared to fixed locations according to factors such as weather condition, orientation, and mechanical response, this has been evidenced by several experimental investigations.[6,10,12,18] Although

these sensor systems are of low complexity, they still have a great capability to be used in IoT-enabled, AI-supported, and hybrid tracking schemes, thus opening up the way for the next generation of smart photovoltaic systems.[13,15,18]

Control and Automation Techniques

The performance of a solar tracking device depends to a large extent on the control and automation system that not only helps achieve high tracking accuracy but also energy saving. Analog comparator-based systems represent the most straightforward solutions of a low-cost local control of a panel tracking system. Essentially they use operational amplifiers to compare the voltage signals from two light sensors such as LDRs in each one of the four directions. The analog versions of such devices provide an instant response to the changing environment with minimal hardware and power-demand and in general, have the disadvantage of a very limited adjustment possibility, temperature dependence, and irradiance calibration drift.

Figure 2 a schematic diagram of a dual-axis solar tracking system that uses Light Dependent Resistors (LDR1 and LDR2) as optical sensors for differential light detection. The comparator circuit receives the output from the sensors and sends control signals to the microcontroller, which through motor drivers azimuth and elevation motors control the precise horizontal and vertical alignment of the photovoltaic panel with the sun's position.[6,8,9] To deal with these limitations, microcontroller-based control architectures have become a trend. Control units based on Arduino, PIC, or ARM Cortex can effectively manage the differential input from the sensors, determine the angular deviation, and at the same time operate a stepper or DC motor for the accurate alignment of the solar panel.[10,12,14]

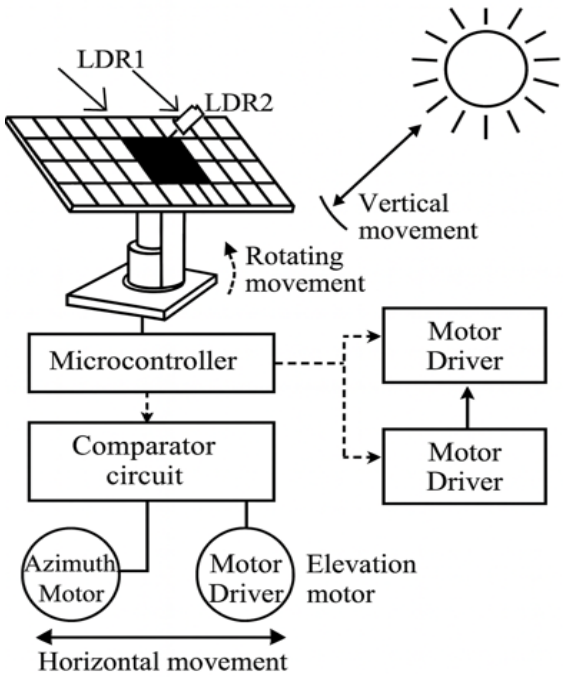

Figure 3. Block diagram of a dual-axis solar tracking system using LDR sensors, microcontroller, and motor drivers for azimuth and elevation control

Table 2. Comparison of Sensor Technologies for Real-Time Solar Tracking Systems

Sensor Type	Operating Principle	Response Time (ms)	Relative Cost (USD)	Sensitivity / Accuracy	Typical Applications	Advantages	Limitations	Ref
Light Dependent Resistor (LDR)	Photoresistive element; resistance decreases with incident visible light intensity	50 – 200	< 1	Medium (±2–3°)	Low-cost single/dual-axis trackers, educational kits	Simple, inexpensive, wide spectral range	Temperature-sensitive; lower long-term stability	(5,6,8,9)
Photodiode	Semiconductor junction converts light energy to proportional current	< 10	1 – 2	High (±1–2°)	Medium-precision trackers, industrial sensors	Fast response, stable output, linear response	Requires amplifier and precise biasing	(9,10,13)
Phototransistor	Light controls transistor current flow; acts as amplified photodiode	20 – 50	2 – 4	Very High (±0,5–1°)	High-sensitivity tracking, robotic and mechatronic systems	High gain, moderate cost, robust	Non-linear response at high irradiance	(8,13,15)
Pyranometer	Thermopile or photodiode measures total hemispherical solar irradiance	> 1000	> 100	Reference-grade	Calibration and benchmark systems	High accuracy, standardized measurement	High cost, bulky, needs maintenance	(5,9,11)
Infrared (IR) Sensor	Detects solar IR spectrum or temperature gradient for direction estimation	5 – 25	3 – 5	Medium (±2°)	Cloudy / diffused-light tracking	Works in low-visibility; unaffected by visible shading	Limited precision under direct high irradiance	(15,18,22)
Image Sensor (CCD/CMOS)	Captures sun's image; software computes centroid for orientation control	< 50	> 30	Very High (< 0,3°)	AI-assisted and astronomical trackers	Extremely precise, enables predictive control	Complex processing; high cost & power use	(15,18,20)

Such systems enable the use of closed-loop feedback, adaptive correction, and additional features like data logging and wireless monitoring.[10,15] Additionally, microcontrollers enable pulse-width modulation (PWM) for detailed motor control and can easily connect IoT communication modules (e.g., ESP32, NodeMCU), thus, their usage can be extended to distributed smart-grid environments.[12,20] To countenance precision and also to industrial applications, the extent of controllers—like programmable logic controllers (PLCs) and digital signal processors (DSPs)—are used to handle multivariable operations with more robustness and reliability.[14,17] PLC-based systems, besides, are mainly acclaimed for their heaviness and real-time interrupt capability, however, they are more expensive and not very compatible with small-scale or educational-type projects. Over the past few years, a variety of intelligent control methods, such as PID (Proportional–Integral–Derivative) control, fuzzy logic controllers (FLCs), and artificial neural networks (ANNs), have been implemented to improve system stability and also to make them more resilient in the case of rapidly changing environmental conditions.[15,17,18] These predictive and data-driven algorithms hardly encounter transients because they eliminate transient errors, lessen actuator overshoot, and on top of that, they are able to adaptively tune parameters based on previous performance. The figure 2 delineates a conceptual schematic of a closed-loop LDR-based tracking configuration incorporating sensor feedback, control logic, and actuator response for real-time orientation correction.[6,8,12,18,22]

Comparative Performance Analysis

Repeatedly, empirical and experimental evidence have been ahead of the game in showing that sensor-based solar tracking systems are the primary factor in the increased energy conversion efficiency when compared to both fixed-tilt and time-based tracking configurations.[2,5,6,8] Performance evaluations under varying climatic conditions show that the use of light sensors, microcontroller-based control loops, and adaptive correction mechanisms results in a substantial increase of the energy captured, especially in the situations of partial cloudiness or transient irradiance, where static systems are not effective, i.e., they do not respond.[6,9,10] The major argument for the reported greening of the technology, which in most of the cases has been between 20 % and 45 %, is the improvement of energy output as demonstrated in table 3, and the reasons influencing it being the level of freedom of the axis, the precision of the actuator, and the control method used.[8,12,15] By putting the two main types side-by-side, dual-axis trackers are the ones having the highest potential for the capture of solar radiation because they are able to simultaneously make the adjustment along the azimuth and elevation planes, thus, keeping the almost perpendicular alignment during the diurnal cycle.[2,9,13]

While this geometry provides the largest energy gains, it also results in increased mechanical complexity, higher costs, and greater maintenance requirements, which generally limit its use to utility-scale or high-concentration photovoltaic (HCPV) systems.[5,13,15] However, improvements in low-power microcontrollers, stepper-motor actuation, and optimized feedback algorithms have recently made small dual-axis devices viable for the domestic, off-grid, and small-scale sectors, thus providing a good compromise between the enhancement of the efficiency and the affordability of the system.[10,12,17] Besides this, comparative studies indicate that smart and hybrid controllers, e.g., PID, fuzzy-logic, or ANN-based algorithms, have better dynamic stability, faster convergence, and lower energy loss in changing cloud conditions.[15,17,18,20] The results of the studies indicate that the integration of sensor-driven feedback with predictive or data-adaptive models is a fruitful area of research that can lead to the cost-to-performance ratio of next-generation real-time tracking systems getting improved.

Table 3. Comparison of Control Algorithms and Hardware Platforms for Real-Time Solar Tracking Systems

Control / Algorithm Type	Hardware Platform	Control Nature	Tracking Precision (°)	Power Consumption (W)	Cost Level	Key Advantages	Typical Limitations	Ref
Comparator-Based Analog Control	Operational amplifier (Op-Amp) circuits	Open-loop	3 – 5	< 2	Very Low	Simple, low power, easy to implement	No feedback, temperature-dependent offset	(6,8,9)
Microcontroller-Based PID Control	Arduino / PIC / STM32	Closed-loop	0,5 – 2	2 – 5	Low – Medium	Adaptive, precise, easily re-programmable	Requires tuning and calibration	(6,10,12)
PLC-Controlled System	Siemens S7 / Delta DVP	Closed-loop	0,5 – 1	5 – 8	Medium – High	Rugged industrial performance, multi-axis synchronization	High cost; limited flexibility for small systems	(14,15)
Fuzzy Logic Controller (FLC)	DSP / Microcontroller	Adaptive closed-loop	< 0,5	3 – 6	Medium	Handles nonlinearities; self-adjusting	Requires complex rule base; computational overhead	(15,17)
Artificial Neural Network (ANN)	ARM Cortex / Raspberry Pi	Predictive / Adaptive	< 0,3	4 – 6	Medium – High	Learns dynamic solar behavior; predictive capability	Requires training data; higher memory need	(17,18)
Model Predictive Control (MPC)	FPGA / Embedded system	Predictive / Hybrid	0,2 – 0,5	5 – 7	High	Fast convergence; robust to constraints	Complex implementation; expensive	(18,20)
IoT-Integrated Hybrid Control	NodeMCU / ESP32	Adaptive / Remote	0,4 – 1	3 – 4	Medium	Enables cloud monitoring; real-time analytics	Relies on network stability	(10,12,20)

Performance Optimization and Energy Yield Enhancement

The extent to which they can accurately follow the sun in real-time using solar sensors largely relies on the precision of the sensor and the fineness of the control. However, factors such as the mechanical action, weather conditions, and algorithmic adaptation still significantly influence the process. Research has shown that angular variations resulting from actuator inertia, backlash, and calibration errors may cause the energy output to be lowered by 5–10 % over a long period of time.[15,17,18] Thus, besides positional accuracy and stability over time, the mechanical part of the work is also very important in that not only does it raise the performance level but also makes it safer. Some of the means through which positional accuracy and stability over time may be enhanced are plastic or composite linkages of aluminum, low-friction bearings, and stepper drives with backlash compensated. Moreover, temperature and wind-speed sensors can also be employed to provide data for the adaptive control strategies that the system is performing. Actually, to prevent mechanical stress or overshoot, the system may choose to barely move during a period of instability caused by a sudden gust of wind. Adaptive gain tuning is one of the software-level methods that uses fuzzy logic or machine-learning models. It is a method that enables the system to foresee the necessity of changing the direction of the panel most likely in the case of cloud intermittency. Besides, in the case of hybrid systems, real-time irradiance data are always compared with the astronomical solar position models so as to shorten the tracking time. Figure 4 depicts the mutual dependencies between the tracking accuracy, actuator response time, and net energy gain. Therefore, it shows the idea of diminishing returns due to very high precision under low irradiance conditions.

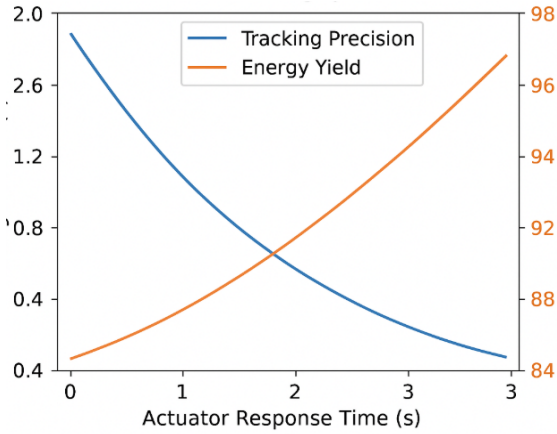

Figure 4. Relationship between actuator response time, tracking precision, and energy yield in sensor-based solar tracking systems

Environmental and Economic Considerations

Even though active solar tracking systems can significantly increase energy gains, their lifecycle benefits should still be weighed against other aspects such as cost, environmental impact, and system reliability. The total ownership cost is not only limited to the hardware (sensors, actuators, controllers) but also includes maintenance and calibration expenses in the long run. In a small-scale situation, should the actuation be done too frequently, it can result in the wear of components, therefore the system's economic advantage may be diminished. Hybrid control strategies that limit the number of movements by setting dead-band thresholds or regulating actuation intervals are usually employed to address the problem of the trade-off between efficiency and mechanical lifespan.[10,14,17] From the environmental perspective, solar tracking is an indirect means to the goal of sustainability because it allows for more efficient

use of land and reduces the number of PV modules required for the production of a unit of energy. However, the selection of materials for the mechanical parts remains the key problem. The adoption of recycled alloys, bio-based lubricants, and low-power electronics is consistent with the circular economy principles and decreases the embodied energy. Table 4 compares representative lifecycle parameters for fixed, single-axis, and dual-axis systems such as capital cost, energy payback time (EPBT), and maintenance frequency.

Table 4. Lifecycle and Sustainability Parameters of Solar Tracking Systems

System Type	Initial Cost (USD/kWp)	Energy Payback Time (Years)	Maintenance Frequency	Recyclable Component Share (%)	Expected Lifespan (Years)	References
Fixed Tilt	450-600	1,8-2,2	Annual	70-80	25-30	(5,10,14)
Single-Axis Tracker	650-800	1,5-1,8	Biannual	65-75	20-25	(6,13,15)
Dual-Axis Tracker	800-1100	1,2-1,6	Quarterly	60-70	18-22	(13,15,18)

Figure 5 compares the lifecycle cost and payback period of three photovoltaic (PV) configurations fixed, single-axis, and dual-axis solar tracking systems indicating figures in Indian Rupees (INR). The total lifecycle cost (in lakhs of INR) is shown by the blue bars, and the payback period in years, corresponding to it, is indicated by the red line with the square markers. The figure is an economic comparison that makes visible the trade-off between the investment cost and the financial return over time for various system architectures.

Firstly, fixed systems are reported to have the lowest capital and operational costs, which are about ₹15-20 lakh per installation on average, however, the payback period of such systems is still quite long (approximately 8 years) due to a low daily energy yield and the fact that the system is immobile. Single-axis trackers that keep the sun on one plane have a higher initial cost (around ₹35-40 lakh) but a payback period is shorter (5-6 years) because of the increased solar capture efficiency and the energy generation being stable throughout the day.When it comes to dual-axis systems, the need for more actuators, the control circuitry, and the increased maintenance make them the ones with the highest lifecycle cost that goes beyond ₹65-70 lakh.

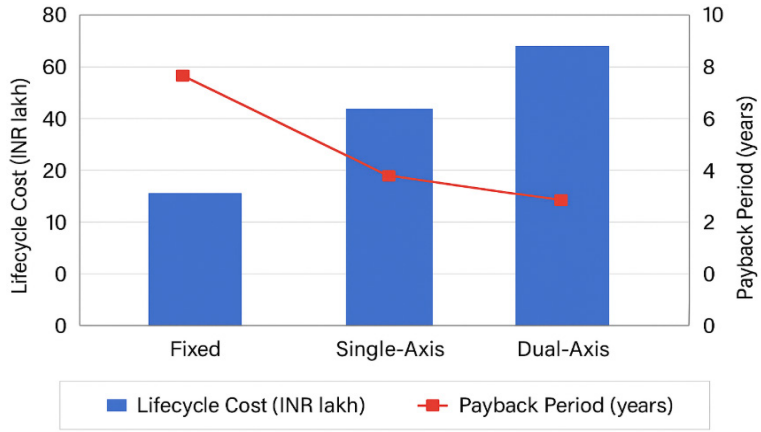

Figure 5. Comparative lifecycle cost and payback period for fixed, single-axis, and dual-axis solar tracking configurations

Still, their capacity to keep an almost perpendicular alignment with solar irradiance leads to maximum energy conversion and less dependence on seasonal tilt adjustments. The better yield can be a reason for the use of such systems in the utility-scale and high-concentration photovoltaic (HCPV) sectors despite the higher initial cost, where efficiency gain is more important than cost issues. The figure, in fact, conveys that system complexity increases the cost, but smart control algorithms, predictive tracking, and IoT-assisted monitoring can significantly decrease operational losses—thus enhancing both the economic return and the environmental benefit. Consequently, from a techno-economic viewpoint, single-axis active trackers frequently compose the best compromise between cost-effectiveness and performance for the majority of distributed and small-to-medium scale solar installations in India.

Future Research Trends and Technological Integration

Next-generation solar tracking systems are expected to digitally incorporate distributed intelligence, predictive analytics, and edge computing to become more adaptable and autonomous. The use of Internet of Things (IoT) platforms allows for remote diagnostics, energy forecasting, and performance optimization through cloud-based analytics. As an example, Node MCU and ESP32 modules with MQTT protocols can report the irradiance, voltage, and orientation in the local area in real time to the central dashboard for predictive maintenance.[18,20,22] Besides that, the latest research also indicates the development of reinforcement learning algorithms which optimize tracking schedules dynamically by using weather and energy yield data from the past. Essentially, the system learns how to save on the number of times it moves the tracker while still getting the maximum power output, thus reducing mechanical wear and maintaining high performance at the same time. Additionally, there are a number of concepts of self-powered tracking devices which generate the energy necessary for their operation from small auxiliary photovoltaic cells and therefore do not need an additional source of control power. The coming together of these digital and mechanical worlds is likely to set a new limit of cost-efficiency for solar tracking technologies. A conceptual model for AI integrated solar tracking ecosystem as shown in figure 6, therefore, is a fully interconnected system combining sensors, controllers, data analytics, and energy management interfaces within a single intelligent framework.

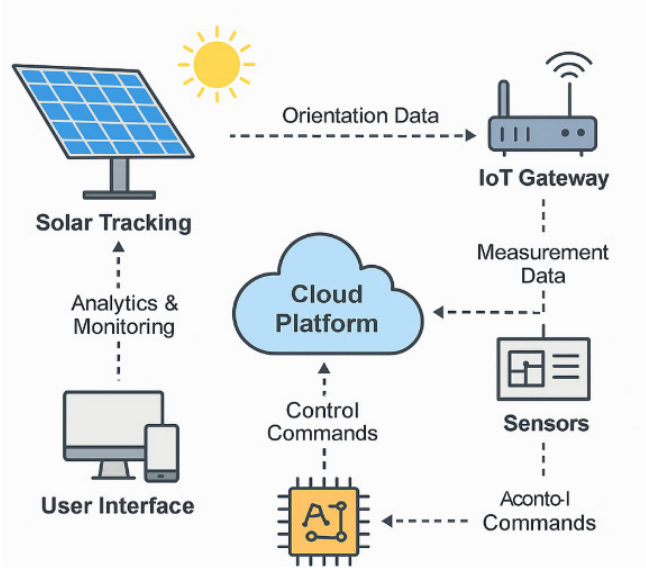

Figure 6. Conceptual architecture of an AI-integrated IoT-based real-time solar tracking ecosystem

Comparative Analysis of Emerging Sensor Technologies

To let the drift to intelligent monitoring systems, work in the sensor fusion field have been ongoing continuously. Sensor fusion refers to combining different sensing modalities such as optical, thermal, and inertial input to increase system resilience and get accurate readings.[5,9,13,17] This kind of fusion increases the system's capability to work under partial shading or diffused light conditions, scenarios in which an optical sensor might give contradictory feedback. A comparative analysis of the emerging and the conventional sensor technologies has been conducted in terms of their sensitivity, cost, and the potential for integration, as shown in Table 5. The comparison has shown that hybrid sensors and intelligent fusion architectures are most adaptable to changing environmental conditions.[15,18,20] Multi-sensor arrays that encapsulate more than just standard optical setups and combine Light Dependent Resistors (LDRs) with Micro-Electro-Mechanical Systems (MEMS)-based inclinometers or gyroscopes for obtaining orientation with an error of less than one degree are gradually being accepted.[13,17,19] Such a system becomes more robust as it is capable of offsetting the external disturbances like wind-induced vibration or intermittent irradiance variations. MEMS sensors, in particular, enable very short time intervals between each measurement of tilt and angular displacement thus allowing high-frequency monitoring with very low latency and great repeatability, and hence, they can be the perfect companions to optical detectors in hybrid control architectures.[17,19,22] Moreover, the ongoing miniaturization of MEMS components is also contributing to less energy consumption as well as the reduction of the structural weight—these being the features, for instance, of great use to lightweight or rooftop solar tracking platforms.[15,18]

Recent innovations in AI-aided data fusion algorithms have essentially broadened the functional scope of newly sensor technologies.[17,18,20] In particular, convolutional neural networks (CNNs) and ensemble regression models, which are machine learning techniques, have been employed to process multivariate sensor data streams. This is done to distinguish irradiance drops caused by atmospheric variations from those resulting to mechanical misalignment.[18,20] The proposed systems enable the realization of correction and the acquisition of adaptive calibration in real-time, which thus enhances the operational stability during the occurrence of weather transients. In addition, the use of pyranometer-based irradiance sensors and infrared (IR) detectors lead to the spectral responsiveness of the tracking system whereby the alignment is guaranteed under different solar conditions.[15,18,22]

Table 5. Comparative Characteristics of Emerging Sensor Technologies for Smart Solar Tracking Systems

Sensor Technology	Measurement Principle	Average Power (mW)	Data Fusion Capability	Precision (°)	Integration Suitability	Ref
LDR Array	Photoresistive light intensity differential	10–15	Moderate	±2–3	High (low-cost)	[5,6,8]
CCD Image Sensor	Sun centroid computation via image processing	150–300	High	±0,2	Medium (AI-based)	[15,18,20]
MEMS Inclinometer	Measures tilt angle via acceleration sensing	50–100	Very High	±0,5	High (industrial)	[17,19,22]
Hybrid Pyranometer-LDR	Combines irradiance and directional sensing	80–120	Very High	±0,4	High (research-grade)	[15,20,22]

Taken together, these developments point to a definite move towards self-calibrating, intelligent sensor networks that are able to learn continuously and optimize their functioning—

being the foreseen solar tracking ecosystems that are autonomous and predictive.[18,20,22]

Reliability, Maintenance, and Field Performance Evaluation

Long-term reliability is still a very important factor that largely decides whether solar tracking systems can be economically viable, especially if they are used outdoors, where the temperature varies, and the equipment is exposed to dust and mechanical wear. To maintain the highest possible alignment accuracy and to avoid the degradation of the actuator, regular maintenance is necessary. In their findings, researchers have highlighted that contamination of the sensor lens and wear of the bearing are the most common reasons for the inaccuracy of tracking, which results in losses of energy up to 5 % per year if no actions are taken to rectify the situation.[13,15,17] The implementation of different measures, such as periodic sensor recalibration, installation of protective housings and the use of automated fault detection algorithms, noticeably contribute to the equipment's availability time and decrease the time when the equipment cannot be used due to an operational fault. Vibration sensors and current feedback loops, which are part of the control system, are additionally used in condition-based maintenance to locate defects and to schedule maintenance only when it is necessary in very reliable and sophisticated setups. Besides that, the use of IoT dashboards for real-time performance monitoring provides an opportunity for remote fault diagnostics and, thus, enables the scheduling of component replacement in a predictive manner, which in turn leads to a reduction of the average time of repair (MTTR). Various failure modes that can be compared, their causes, and the methods of overcoming them for single- and dual-axis tracking configurations are given in table 6.

Table 6. Common Failure Modes and Maintenance Strategies in Real-Time Solar Tracking Systems

Failure Mode	Primary Cause	Affected Component	Impact on System Performance	Recommended Mitigation / Maintenance Strategy	Ref
Sensor Drift or Misalignment	Dust accumulation, thermal stress	LDRs / Photodiodes	Reduced tracking precision (±3–5° deviation)	Regular cleaning, calibration, sealed sensor enclosure	[13,15,17]
Actuator Backlash	Mechanical wear, insufficient lubrication	Stepper / DC Motors	Increased positioning error, energy loss (2–4 %)	Use of anti-backlash gears, scheduled lubrication	[14,16,18]
Control Circuit Failure	Voltage spikes, humidity	Microcontroller / PLC	System shutdown, tracking halt	Surge protection, conformal coating, temperature monitoring	[10,12,17]
Structural Deformation	High wind loads, weak mounts	Tracker frame / support	Misalignment, loss of tracking range	Reinforced joints, wind-speed-based stow mode	[15,18,20]
Communication Failure	Network dropout, software fault	IoT / Communication module	Loss of data logging and remote control	Backup communication protocol, periodic firmware update	[18,20,22]

AI-Driven Predictive and Adaptive Solar Tracking Systems

The integration of advanced artificial intelligence (AI) technologies has led to the evolution of traditional solar tracking systems into smart, autonomous, and adaptive units that derive their

knowledge from operational data.[17,18,20] Such systems have machine learning (ML) and deep learning (DL) algorithms embedded in them for the purposes of solar irradiance forecasting, anomaly detection in the system's performance, and hence they are able to make the tracking of the solar radiation incident angles non-interrupted and accurate in real-time by themselves. For example, Artificial Neural Networks (ANNs) receive training by matching the examples of past irradiance and angular position data tuples so that they can later predict the most efficient tilt and azimuth even before the changes in the surroundings have taken place.[18,20] Such an act of anticipation drastically cuts down on the number of times the actuator has to be moved, saves energy, and at the same time diminishes mechanical wear as compared to reactive feedback mechanisms.[17,22] To foresee solar trajectories on a very short basis, a combination of a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN) is being looked into more and more in which the opening of the sky and weather conditions at that moment are the inputs.[18,21] The diagram in figure 7 depicts the underlying structure of an AI-driven adaptive solar tracking system that gathers data from various sensors, uses cloud-based models for prediction, and then sends the control feedback to the actuator.

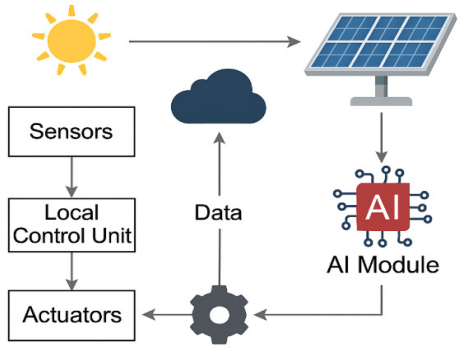

Figure 7. Schematic representation of an AI-assisted predictive solar tracking system

Here, the local control unit is responsible for the initial filtering and normalization of the sensor signals, and the cloud-based inference model carries out the computationally intensive prediction tasks. Such a hybrid computing architecture is energy management optimized and is made scalable for PV plants of large capacity. Besides, the use of reinforcement learning (RL) algorithms is becoming the next generation challenge in this field, thus giving the possibility to the systems to improve by themselves the control policies through rewarding energy gains and punishing the unnecessary actuator operations.[17,20,22]

IoT-Based Monitoring and Cloud Connectivity

Internet of Things (IoT) technology integration with solar tracking makes it possible to have a continuous, remote monitoring of performance metrics, fault conditions, and energy analytics.[10,12,18] IoT-enabled trackers use an embedded microcontroller (e.g., ESP32, Node MCU) with Wi-Fi or LoRa connectivity to send real-time data such as irradiance, temperature, current, and voltage to centralized cloud servers.[12,20] This up-to-the-minute monitoring allows for smart diagnostics that can be used for predictive maintenance and anomaly detection through cloud-based dashboards. Figure 8 shows the standard IoT-based solar tracking setup, consisting of locally controlled tracking units communicating via a cloud network. Each unit is equipped with sensors, a microcontroller, and actuator drivers connected to a web or mobile interface for live monitoring.

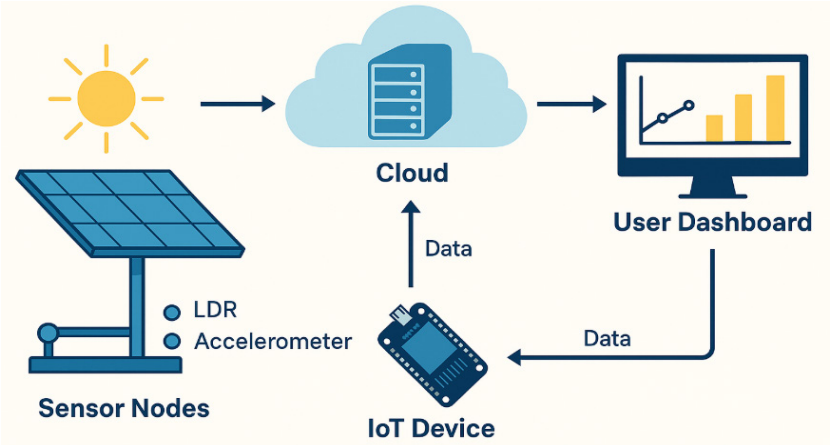

Figure 8. Architecture of an IoT-enabled real-time solar tracking network

The integration of AI with IoT devices paves the way for smart devices at the edge, where first-level analytics are locally handled to cut down on the delay and the expense of data transfer.[18,20] As an example, local anomaly detection can be carried out by simple ML models that are hardware-in-the-loop within ESP32 units, with only the processed summaries being sent to the cloud. The method energy consumption is thus drastically reduced, and system reliability is increased.

Table 7. Comparison of IoT Communication Protocols Used in Real-Time Solar Tracking Systems

Protocol	Frequency Band	Range (m)	Data Rate (kbps)	Power Requirement	Suitability / Application	References
Wi-Fi (IEEE 802,11)	2,4 / 5 GHz	50–100	1500 – 6000	Moderate	Short-range, high data transmission	[10,12,20]
LoRaWAN	868 / 915 MHz	2000 – 10000	0,3–50	Very Low	Rural/off-grid solar farms	[15,18,22]
Zigbee	2,4 GHz	100–300	20–250	Low	Mesh-based residential tracking systems	[12,15,20]
MQTT (over TCP/IP)	-	Cloud-linked	-	Low	Cloud communication protocol for monitoring	[18,20,22]
Bluetooth BLE	2,4 GHz	10–30	125–2000	Very Low	Local configuration and calibration	[10,12,18]

Sustainable Design and Techno-Economic Feasibility

Solar tracking systems' design and their implementation are deeply influenced by sustainability factors that aim to become, in the near future, the main concern of the indus- try. In India and other emerging solar markets, techno-economic optimization is the process of balancing capital expenditure (CAPEX), operational efficiency, and environ- mental impact.[6,14,17] The change of heavy metallic frames to the light- weight composite structures or recycled aluminum alloys lowers not only the cost but also the embodied energy, while modular assembly enables easy maintenance and component reuse. The sustainability assessment model in figure 9 exemplifies

the interac- tion of the design parameters (material selection, control algorithm efficiency, and maintenance frequency) with the overall lifecycle cost.

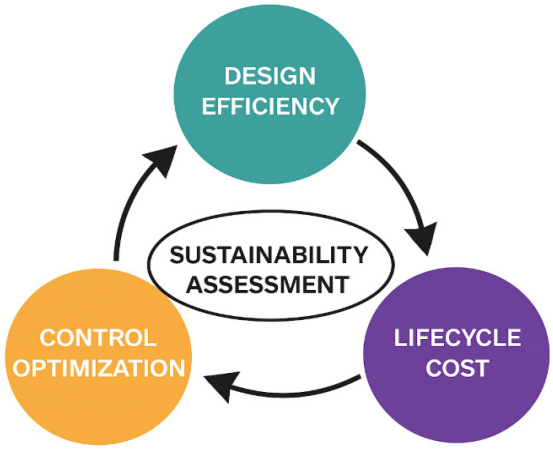

Figure 9. Sustainability Assessment Model (flow/interaction diagram) in solar tracking systems

The techno-economic study across various Indian PV setups suggests that the use of single-axis active trackers can lower the levelized cost of energy (LCOE) by about 8–12 % as compared to fixed systems. At the same time, dual-axis devices provide a higher energy yield but entail a longer payback period.[6,15,18] Environmental indicators such as energy payback time (EPBT) and CO_2 offset reveal that hybrid sensor-equipped systems may reduce emissions by as much as 20–25 % during their total operational time because of better irradiance capture.[14,18,20] These findings put the emphasis on the decisive leverage of smart automation and eco-friendly design for economically and environmentally sustainable solar energy systems.

Oil and Gas Automation

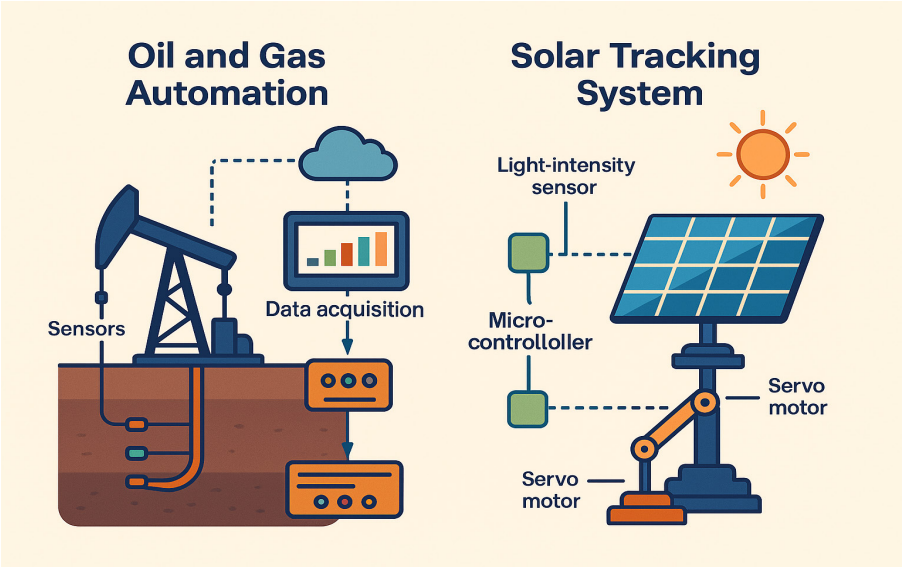

Figure 10. Oil and Gas Automation with Solar Tracking System

Table 8. Key Components and Functional Roles in Oil & Gas Automation and Solar Tracking Systems

System	Component	Function / Description
Oil & Gas Automation	Subsurface Sensors (Pressure, Temperature, Vibration)	Capture real-time wellbore and equipment conditions for monitoring and control.
	Data Acquisition Unit	Aggregates signals from distributed sensors and transmits data for processing.
	Processing & Control Module	Interprets sensor trends and executes automated adjustments to operational parameters.
	Supervisory Control System	Oversees system-wide behavior and coordinates automated valve or pump actuation.
	Automated Actuators / Valves	Implement control actions such as regulating flow, pressure, or drilling parameters.
Solar Tracking System	Light-Intensity Sensors	Detect differential sunlight intensity to identify optimal panel orientation.
	Microcontroller	Processes sensor input and calculates necessary panel adjustments.
	Servo Motors (Dual-Axis)	Reposition the solar panel to maintain perpendicular alignment with sunlight.
	Solar Panel Assembly	Converts incident solar radiation into electrical energy with enhanced efficiency under tracking.

Applications in Domestic and Industrial Energy Systems and Challenges and Future Trends

Due to their easy operation, flexibility, and increased power output low-cost, sensor-based solar tracking systems have been rapidly adopted in the domestic and industrial energy sectors. In the case of residential applications, these trackers can be found on rooftop photovoltaic (PV) modules, street lighting, agricultural irrigation, and stand-alone hybrid systems, where small size and low power consumption are the most important factors.[5,6,8] Real-time LDR and photodiode-based tracker devices that can adapt to changing solar conditions and keep the panel in the optimal orientation are the main factors for the daily energy yield increase, especially in distributed renewable microgrids and rural electrification projects.[6,9,12] On the other hand, solar tracking systems are used as extensively as possible in big-scale photovoltaic farms, solar thermal power plants, and concentrated photovoltaic (CPV) setups in the industrial scenarios, where higher precision and dual-axis control lead to conversion efficiency and thermal capture increase.[9,13,15] Furthermore, when contemporary tracking systems are combined with IoT structures they make it possible to perform remote monitoring, data logging, and predictive maintenance, thus facilitating real-time performance analysis and smart-grid compatibility.[10,12,20] The same connectivity also improves energy management by synchronizing generation profiles with load demand on a short-term basis, thus allowing for grid stability and distributed energy optimization.[15,20,25]

Even so, a variety of technical issues have been impeding the large-scale deployment of such devices. Some of the frequently reported problems are the wearing of the actuator, the degradation of the device by the environment, and calibration drift of optical sensors in dusty,

humid, or UV-radiated places.[8,13,15] Besides, sensor saturation under a strong irradiance along with the temperature cause resistance variations that can lower detection accuracy and, thus, misalignment can occur over time.[6,9,17] Additionally, it is still a tough and long-term challenge to find a solution that will provide mechanical robustness and at the same time low energy consumption will be balanced in tracking motors, especially for those that are designed for continuous outdoor operation.[12,18] The emergence of research on this topic is predicted to be focused on the implementation of artificial intelligence (AI) and machine learning algorithms for predicting solar position and making decisions dynamically.[17,18,20] By integrating optical, infrared, and astronomical feedback, sensor fusion architectures will be less dependent on changes in the sky that are due to the weather.[22,25] In addition, the progress in energy-efficient motor drivers and low-power microcontrollers will lead to further system sustainability improvements. The creation of hybrid solar trackers which exploit the advantages of both sensor-based and astronomical models is, in fact, the most considerable potential to overcome the accuracy issue, provide the device with the ability of self-calibration and make it resistant to the environmental fluctuations.[15,17,25]

CONCLUSIONS

The use automation integration across both traditional and renewable energy systems is a clear example of how advancements in sensing, real-time data processing, and intelligent control can significantly change the level of operational efficiency and reliability. In the case of oil and gas environments, distributed sensor networks and automated supervisory systems provide the ability to control and stabilize complex subsurface operations as well as reduce the variability that depends on humans. On the other hand, solar tracking systems that depend on lightweight, inexpensive sensor arrays demonstrate how similar control principles can be used to improve photovoltaic performance without the need for advanced technological intervention. The comparison reveals that behind the frontier of contrasting energy domains there is a common engineering foundation—adaptive sensing, continuous monitoring, and responsive actuation. The evolution of energy systems into hybrid and interconnected infrastructures makes the knowledge obtained in both sectors the possible source of the future smarter, more resilient, and more sustainable automation frameworks. The review charts the development and increasing significance of real-time, inexpensive solar tracking devices that are pivotal in the efficient conversion of photovoltaic (PV) energy. From the study of sensor technologies, control algorithms, and the resulting performance, it is very clear that sensor-based tracking systems, especially those using Light Dependent Resistors (LDRs), are a technically and economically viable solution. These systems, by constantly adjusting the solar panels to the sun's position, are capable of increasing the energy output by 20–45 % as compared to fixed ones, the control precision and the prevailing weather conditions being the factors influencing the variation of the range. The research also points out that although the dual-axis systems have the potential to capture maximum solar irradiance, their mechanical intricacy and the power requirement of the actuators are the major issues that limit their large scale usage. However, the progress in microcontroller platforms, IoT integration, and the development of intelligent control algorithms like PID, fuzzy logic, and neural-network-based predictive control has started to close this gap by enhancing the system's responsiveness, flexibility, and optimization based on data.

Also, the addition of cloud connectivity and remote diagnostics has made modern trackers key elements of the smart energy systems of the future. While significant advancements have been made, the issue of long-term operational stability is still heavily reliant on the need to further sensor durability, enhance their calibration, and improve their mechanical parts even when it is difficult to have them outdoors in the nature. Several new directions in the field of study reveal to the creation of hybrid tracking architectures that combine sensor-based feedback with astronomical and AI-driven predictive models, thus giving better accuracy and

robustness at different sky conditions. The emergence of energy-efficient actuators, self-learning algorithms, and adaptive sensor fusion frameworks will be instrumental in the evolution of the next generation of eco-friendly, intelligent solar tracking technologies that can be used both at home and in industry.

BIBLIOGRAPHIC REFERENCES

1. Design of a Low-Cost Parabolic Concentrator Solar Tracking System. ASME Solar Energy Engineering.

2. Dime, et al. A Review and Comparative Analysis of Solar Tracking Systems. Energies. 2025;18(10).

3. Hafez A, Yousef A, Harag K. Solar tracking systems: Technologies and trackers drive types – A review. Renewable and Sustainable Energy Reviews. 2018;91:754–782.

4. Al-Rousan N, Mat Isa NAM, Desa MKM. Advances in solar photovoltaic tracking systems: A review. Renewable and Sustainable Energy Reviews. 2018;82:2548-2569.

5. Ya'u MJ. A Review on Solar Tracking Systems and Their Classifications. Journal of Energy, Environmental & Chemical Engineering. 2017;2(3):46-50. DOI:10.11648/j.jeece.20170203.12.

6. Hassan R, Abubakar B. Intelligent Arduino Based Automatic Solar Tracking System Using Light Dependent Resistors (LDRs) and Servo Motor. Optics. 2020;9(2):13-18.

7. Byungho-M, Im IT. Development of Tracking Algorithm for Floating Photovoltaic System. Journal of the Semiconductor & Display Technology. 2019;18(1):53-60.

8. Xi CTY, Daud MZ, Wan Muda WM, Jusoh MA. Development of Microcontroller-Based Solar Tracking System Using LDR Sensor. Journal of Telecommunication, Electronic and Computer Engineering (JTEC). 2017 Sep;9(2-7):71-75.

9. Fathabadi H. Novel high efficient offline sensorless dual-axis solar tracker for using in photovoltaic systems and solar concentrators. Renewable Energy. 2016;95:485–494.

10. Abdallah M, El-Gohary S, El-Sayed A. IoT-enabled solar tracking for smart energy systems. IEEE Access. 2021;9:33415–33425.

11. Muhammad JY, Jimoh MT, Kyari IB, Gele MA, Musa I. A Review on Solar Tracking System: A Technique of Solar Power Output Enhancement. Engineering Science. 2019;4(1):1-11. DOI:10.11648/j.es.20190401.11.

12. Maleki A, Filabi ZE, Nazari MA. Techno-Economic Analysis and Optimization of an Off-Grid Hybrid Photovoltaic–Diesel–Battery System: Effect of Solar Tracker. Sustainability. 2022;14:7296.

13. Rajasekaran G, Kumar AA. Design optimization of dual-axis solar tracker using phototransistor sensors. Solar Energy. 2018;174:914–923.

14. Bhosale A, Bodhe P, Chavan V, Patil P. Better Utilisation of Solar Energy using PLC. International Journal of Engineering Research & Technology (IJERT). 2015;3(06).

15. Kurukuru VSB, Haque A, Khan MA, Sahoo S, Malik A, Blaabjerg F. A review on artificial intelligence applications for grid-connected solar photovoltaic systems. Energies. 2021;14(15):4690.

16. Pérez ER, Flores R. Fuzzy-logic optimization for dual-axis solar tracking under variable irradiance. Applied Energy. 2022;305.

17. Huang CH, Pan HY, Lin KC. Development of Intelligent Fuzzy Controller for a Two-Axis Solar Tracking System. Applied Sciences. 2016;6(5):130.

18. Ruiz-Moreno S, Frejo JRD, Camacho EF. Model predictive control based on deep learning for solar parabolic-trough plants. Renewable Energy. 2021;180:193–202.

19. Ahmed M, Harbi I, Kennel R, Rodríguez J. Maximum Power Point Tracking-Based Model Predictive Control for Photovoltaic Systems: Investigation and New Perspective. Sensors. 2022;22(8):3069.

20. Hamed BM, El-Moghany MS. Fuzzy Controller Design using FPGA for Sun Tracking in Solar Array System. International Journal of Intelligent Systems and Applications (IJISA). 2012;4(1):46-52.

21. Wang JM, Lu CL. Design and Implementation of a Sun Tracker with a Dual-Axis Single Motor for an Optical Sensor-Based Photovoltaic System. Sensors. 2013;13(3):3157–3168.

22. Wang L, Chen X, Fang J, Xia H, Liu Q, Li X, Bai L. Solar hybrid tracking system under complex weather conditions and control criterion. Transactions of the Chinese Society of Agricultural Engineering. 2023;39(5):156-165.

23. Gisi M, Hase F, Dohe S, Blumenstock T. Camtracker: a new camera controlled high precision solar tracker system for FTIR-spectrometers. Atmospheric Measurement Techniques. 2011;4:47–54.

24. Motha JD, Maduranga MWP, Jayatilaka NT. Design of an IoT-Enabled Solar Tracking System for Smart Farms. International Journal of Wireless and Microwave Technologies. 2022;12(6):1-13.

25. Wirjawan A, Safarudin A, Ramdani R, Lestari NS, Ramadi GD. Smart monitoring system for hybrid solar power plants using IoT technology. Brilliance: Research of Artificial Intelligence. 2024;5(2).

26. Jain R, Samuel R, Mohanty B. Automation and digitalization in upstream oil and gas operations: Trends, challenges, and opportunities. Journal of Petroleum Science and Engineering. 2021;205:108933.

27. Al-Mudhafar WJ, Whitaker A. Intelligent workflows and real-time optimization in reservoir management using advanced analytics and machine learning. Energy Reports. 2020;6:1860–1873.

28. Rashid T, Rehman S. Development and performance assessment of a low-cost, sensor-based dual-axis solar tracking system. Renewable Energy. 2019;141:108–117.

29. Chen X, Jiang L, Wang M. Advances in autonomous monitoring systems for harsh-environment energy applications. Energy Technology. 2022;10(6):2200084.

30. Rhatigan J, Duffie JA. Control strategies for real-time solar tracking using low-cost sensor arrays. Solar Energy. 2020;204:310–321.

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AUTHORSHIP CONTRIBUTION

Conceptualization: P. Prabhu, V. Suresh, T. A. Abhijith, K. Adarsh, T. Anand Kumar, Christo Ananth, Ibrohimali Normatov.

Data curation: P. Prabhu, V. Suresh, T. A. Abhijith, K. Adarsh, T. Anand Kumar, Christo Ananth, Ibrohimali Normatov.

Formal analysis: P. Prabhu, V. Suresh, T. A. Abhijith, K. Adarsh, T. Anand Kumar, Christo Ananth, Ibrohimali Normatov.

Drafting - original draft: P. Prabhu, V. Suresh, T. A. Abhijith, K. Adarsh, T. Anand Kumar, Christo Ananth, Ibrohimali Normatov.

Writing - proofreading and editing: P. Prabhu, V. Suresh, T. A. Abhijith, K. Adarsh, T. Anand Kumar, Christo Ananth, Ibrohimali Normatov.

Chapter 6 / Capítulo 6

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ORIGINAL

Smart Energy Management and Automation Systems: Emerging Directions in Manufacturing and the Oil-Gas-Chemical Industries

Sistemas inteligentes de gestión de energía y automatización: nuevas direcciones en la fabricación y las industrias del petróleo, el gas y la química

Hariprasad Perumal[1] ✉, Jeevarathinam A[2] ✉, Karan R[1] ✉, Jegan Karthik S[1] ✉, Gokulnath P[1] ✉, Prabhu P[1] ✉, Malikov Ziyodullo Abdurayim[3] ✉

[1]Department of Mechanical Engineering, KIT-Kalaignarkarunanidhi Institute of Technology. Coimbatore-641402, Tamil Nadu, India.

[2]Department of Mechanical Engineering, Hindusthan Institute of Technology. Coimbatore-641032, Tamil Nadu, India.

[3]Teaching Assistant, Department of Software Engineering, Faculty of Artificial Intelligence and Digital Technologies. Samarkand State University, Uzbekistan.

Corresponding Author: Hariprasad Perumal ✉

ABSTRACT

In the wake of changes in industrial engineering, the manufacturing, oil-gas-chemical sectors have rapidly adopted smart energy management coupled with automation technologies. Although these fields have mostly taken different technological routes, the need to reduce operational costs, increase the system's reliability, and meet strict sustainability requirements has led to a considerable blending of these technologies. This review consolidates the innovations in smart monitoring, real-time control, and predictive optimization that are largely driven by digital platforms, sensor-equipped infrastructures, and data-driven decision-making frameworks. This framework includes three layers of the proposed architecture which is device, edge and cloud, encompassing automation devices and sensors, a secure communication protocol (MQTT, OPC-UA, Modbus TCP/IP) and AI analytic for big data handling. This research provides a structured analysis of various topics, including implementation processes, data veracity, cyber security, and case studies involving automotive and pharmaceutical sectors. The Energy Management System (EMS) based on IoT systems provides a reduction in energy use of between 18-25 %, a reduction in downtime of about 22-35 %, and a reduction in maintenance costs of about 15-30 %. The paper concludes with discussions on barriers to adoption including interoperability of legacy systems, veracity of data, and developing an effective human-machine interface. In addition, we share our thoughts on the integration of renewable energy systems, digital twins, and predictive maintenance systems .The results agree that a manufacturing facility can achieve a ROI within 8-14 months and meet its sustainability targets with respect to an ISO 5001 Organizational Energy Management System (EnMS) and UN Sustainable Development Goal (SDG) invitations aligned with the study.

Keywords: Internet of Things; Energy Monitoring; Manufacturing; Edge Computing; Predictive Maintenance; Sustainability; Industry 4.0.

RESUMEN

A raíz de los cambios en la ingeniería industrial, los sectores manufacturero, petrolero, gasístico y químico han adoptado rápidamente la gestión inteligente de la energía, junto con tecnologías de automatización. Si bien estos campos han adoptado, en su mayoría, diferentes caminos tecnológicos, la necesidad de reducir los costos operativos, aumentar la confiabilidad del sistema y cumplir con los estrictos requisitos de sostenibilidad ha llevado a una considerable integración de estas tecnologías. Esta revisión consolida las innovaciones en monitorización inteligente, control en tiempo real y optimización predictiva, impulsadas en gran medida por plataformas digitales, infraestructuras con sensores y marcos de toma de decisiones basados en datos. Este marco incluye tres capas de la arquitectura propuesta: dispositivo, borde y nube, que abarcan dispositivos y sensores de automatización, un protocolo de comunicación seguro (MQTT, OPC-UA, Modbus TCP/IP) y análisis de IA para el manejo de big data. Esta investigación proporciona un análisis estructurado de diversos temas, incluyendo procesos de implementación, veracidad de datos, ciberseguridad y casos prácticos relacionados con los sectores automotriz y farmacéutico. El Sistema de Gestión de Energía (SGE) basado en sistemas IoT ofrece una reducción del consumo energético de entre un 18 % y un 25 %, una reducción del tiempo de inactividad de entre un 22 % y un 35 % y una reducción de los costes de mantenimiento de entre un 15 % y un 30 %. El artículo concluye con un análisis de las barreras para su adopción, como la interoperabilidad de los sistemas heredados, la veracidad de los datos y el desarrollo de una interfaz hombre-máquina eficaz. Además, compartimos nuestras reflexiones sobre la integración de sistemas de energía renovable, gemelos digitales y sistemas de mantenimiento predictivo. Los resultados coinciden en que una planta de fabricación puede alcanzar un retorno de la inversión (ROI) en un plazo de 8 a 14 meses y cumplir sus objetivos de sostenibilidad con respecto a un Sistema de Gestión de Energía Organizacional (SGE) ISO 5001 y las invitaciones a los Objetivos de Desarrollo Sostenible (ODS) de las Naciones Unidas, alineados con el estudio.

Palabras clave: Internet de las Cosas; Monitorización de la Energía; Fabricación; Edge Computing; Mantenimiento Predictivo; Sostenibilidad; Industria 4.0.

INTRODUCTION

Motivation and Problem Statement

Manufacturing plants are one of the biggest energy-consuming sectors in the world, representing approximately 30 % of all energy consumed in industrial settings. Even with some advancements in technology energy waste continues to be a significant issue, with estimates suggesting 20-30 % of the energy used by manufacturing facilities is wasted[1] through various types of inefficiencies(e.g. equipment failure, phantom loads, and improper process parameters). Traditional energy management strategies rely on audits at regular intervals and collecting manual (or automated) data, which severely limit visibility into real-time usage patterns and, as a result, only allow for 5 % energy savings rather than 20 % from continuous real-time monitoring.[2] The combination of predicted energy cost increases, carbon reductions driven by environmental regulations, and global national sustainability initiatives has changed energy efficiency from being a cost savings measure to becoming a strategic initiative for manufacturing organizations. Additionally, new and emerging Industry 4.0 technologies (i.e. IoT devices, edge computing and artificial intelligence devices) have provided massive increases in visualization and control over manufacturing processes.[3,4] The rapidly digitalized industrial processes have in a fundamental way changed the standards of efficiency, reliability and environmental regulations requirements in the sectors of manufacturing and oil–gas–chemical. The use of integrated sensing, data

analytics, and automated control, a smart energy management system is viewed as a must-have tool for not only energy saving but also for stabilizing plant performance under fluctuating operating conditions. Such platforms allow manufacturing the energy consumption to be very detailed, predictive load assessment to be conducted, and the correlation between process scheduling and energy availability to be strengthened. The same kind of innovations in the oil and gas sector show a similar transition to data-centric process control, where it is being gradually automated frameworks to be implemented for drilling operations, equipment monitoring, and production scheduling in order to reduce the time when the plant is not working and lessen the operational risk. These features together signal a massive shift toward intelligent, self-regulating industrial systems that not only can raise productivity levels but also contribute to the achievement of sustainability goals. Meanwhile, the oil and gas sector is also investing in similar future-proof technologies like additive manufacturing, smart materials, and polymer-based performance enhancers not only to make equipment more reliable but also to become more efficient in the subsurface recovery. The recent publications clearly show how innovations at the component level, e.g. the use of additively manufactured tools and repair parts, can very quickly change the face of the maintenance operations and shorten the supply-chain delays which are typical of extraction and gathering activities. Similarly, smart polymer systems and eco-friendly composite formulations are leading us to different sources of both increasing the recovery efficiency and decreasing the chemical footprints. These emerging technologies together with the implementation of intelligent monitoring and automation infrastructures paint the picture of a gradually interconnected industrial landscape where energy management, material innovation, and automated control are the three interdependent pillars supporting each other. Ultimately, this convergence calls for a systemic review of the manufacturing and the oil–gas–chemical industries trends of today and tomorrow.

Research Objectives

This study outlines the design, execution, and enhancement of IoT-based energy monitoring frameworks to be implemented in manufacturing settings. The key goals are:

1. To develop a complete three-layered IoT architecture that incorporates sensor networks, edge computing infrastructure, and cloud analytics systems to monitor energy in real time.
2. To identify and address key implementation issues such as legacy system interoperability, data quality assurance, and cybersecurity weaknesses.
3. To assess the quantitative benefits of IoT-based energy management through case studies revealing verifiable energy efficiency, equipment reliability, and operating costs improvements.
4. To develop integration strategies with renewable energy systems, proactive maintenance frameworks, and AI optimized automations.
5. To identify best practices for data validation, machine-human interface work, and lifecycle management to provide prolonged system performance and user adoption.

Literature Review and Theoretical Foundation

Evolution of Energy Management Systems

Energy management processes in manufacturing have been revitalized according to four distinct paradigms. The old way of doing things revolved around manual readings of meters and annual energy audits, which offered real-time monitoring but ultimately limited visibility, and energy management took a reactive approach rather than a proactive role. The transition to the next paradigm of advanced metering infrastructure and distributed control systems represented the second paradigm, but while organizations were automating monitoring in real-

time, they were still often orchestrating siloed actions in various departments or on production lines. Industrial IoT (IIoT) technologies then disrupted this category of energy management to enable pervasive networks of sensors to collect detailed and time synchronized data points from each piece of equipment in the manufacturing environment, and when connectivity to the edge and cloud analytics were also no longer complicated, data analysis was much easier[5] not only because of all the data but the visualization and analytics that can be performed on a continuous basis. As a function of advancing technology in energy management, the process evolved from a passive monitoring function toward an active and adaptive optimization system to drive visibility and real-time decision making.[6,7]

The evolution of energy management systems in oil production has gone through various stages, which were influenced by technological innovations and the need for efficiency. Initially, the plants were operated manually, and the technicians of the plants controlled the equipment by using simple gauges, analog instruments, and their own observation as shown in figure 1. The decisions were mostly made based on the experience of the staff, energy consumption was reactive, and the energy was not optimized. Even though this method guaranteed the basic operation, it did not allow the facility to monitor energy losses or to intervene before inefficiencies increased.

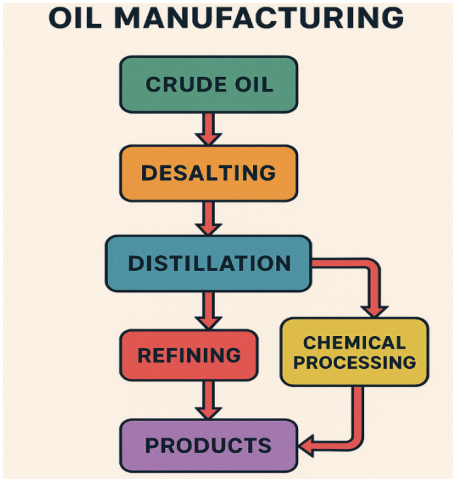

Figure 1. Stages in the evolution of energy management systems in oil manufacturing

Automation introduction was a drastic change. The use of Programmable Logic Controllers (PLCs), digital sensors, and automated monitoring instruments made process control more dependable and error-free, and also provided continuous data streams. This stage was a platform for comprehending energy consumption in machinery such as pumps, heaters, compressors, and distillation units. However, the main emphasis of automation was on process stability, and energy optimization was only a minor, incidental benefit.

Machine Learning and Predictive Analytics

Machine learning algorithms have greatly changed energy management from reactive corrective maintenance to proactive predictive optimization: predictive maintenance systems that analyze equipment vibration signatures, acoustic patterns, temperature differentials and anomalies in power consumption can detect incipient equipment failures 3-8 weeks before the breakdown occurs,[9,10] reduce unplanned equipment downtime by 35-45 %, and cut maintenance costs by 25-30 %. Similarly, energy consumption forecasting is implemented utilizing a time-series model, including:

Table 1. Machine Learning Models for Energy Prediction

ML Model	Prediction Accuracy	Training Time	Data Requirements	Computational Load	Best For	Advantages	Limitations
LSTM Networks	94-97 %	2-4 hours	6+ months historical	Medium-High	Time-series forecasting	Captures long-term dependencies	Requires significant data
XGBoost	91-95 %	30-60 min	3+ months historical	Medium	Non-linear patterns	Fast training, feature importance	Less suitable for very long sequences
Random Forest	88-93 %	15-30 min	2+ months historical	Low-Medium	Feature interactions	Interpretable, handles missing data	Limited temporal pattern capture
ARIMA	85-90 %	<5 min	2+ months historical	Low	Linear trends	Simple, interpretable	Assumes stationarity
Hybrid ARIMA-ANN	92-96 %	1-2 hours	4+ months historical	Medium	Complex temporal patterns	Combines strengths of both	More complex to tune
Support Vector Machine (SVM)	89-92 %	20-40 min	3+ months historical	Medium	High-dimensional data	Robust to outliers	Slower prediction
Neural Networks	90-94 %	30-90 min	3+ months historical	Medium	General-purpose forecasting	Flexible architecture	Risk of overfitting

IoT Architecture and Communication Protocols

Modern implementations of IoT technologies for energy monitoring typically use a multi-layered architecture with four layers: perception, network, processing, and application layers. The perception layer consists of a range of sensors, both current and potential transformers (CT and PT), smart power meters, and environmental sensors (temperature, humidity, and pressure) that sample electrical and operational parameters at high frequency.

Edge Computing and Distributed Analytics

Edge computing is a new way of organizing computational resources, unlike cloud-centric processing. Edge converts intelligence to where data is created, the source, and away from a centralized processing node. In energy monitoring scenarios, edge gateways act as preprocessing units to filter noise, detect anomalies, compress data, and extract features. Edge computing can reduce bandwidth requirements by up to 80 % while supporting decision-making needed at lower latency.[8]

Proposed System Architecture

Three-Layer IoT Framework

The proposed architecture consists of three functionally distinct layers that are hierarchically integrated in a manner which addresses special technical needs.

Device Layer (Perception and Measurement)

The device layer perceives electrical and operational measurements using different kinds of sensors.

Electrical Measurement Components:

1. Current Transformers (CT): they reduce high-value (industrial) currents into low-value signals (0-5V or 4-20 mA) for digital transmission and preserve electrical isolation.[11,12]

2. Potential Transformers (PT): they step down three-phase power from operational voltage (208-480V) to a measurement voltage (0-110V).

3. Smart Power Meters: an Integrated IED (Intelligent Electronic Devices) which measures voltage, current, frequency, power factor, active/reactive/apparent power, and harmonic content; sampling (1-4 KHz).[13]

Sensor Selection Strategy:

Table 2. Energy Monitoring Sensors - Device Characteristics and Deployment Options

Device Type	Application	Characteristics	Advantages
Wired Smart Meters	Fixed heavy machinery	High reliability, stable data quality	±0,1 % accuracy, continuous operation
Wireless IoT Sensors	Mobile equipment, retrofits	Flexible deployment, rapid installation	Minimal infrastructure changes, LoRa/ZigBee/ Wi-Fi options
CT/PT Combinations	Main switchgear monitoring	Fundamental measurement infrastructure	Electrical isolation, standard industrial practice
Environmental Sensors	Process optimization	Temperature, humidity, pressure	Correlation analysis with energy consumption

Sampling Rate Optimization

Selecting a sampling rate involves a tradeoff between measurement accuracy and limitations on network bandwidth. Sampling at a high-frequency rate (4 kHz) collects harmonic distortion and transients that are important to evaluating power quality, but achieves a daily data rate of 345,6 MB per meter for 24-bit resolution over a 24-hour period. Sampling at an intermediate rate (100 Hz) will record sub-cycle events while reducing traffic to 8,6 MB per meter on a daily basis. Intelligent variable rate sampling dynamically switches sample rates based conditions on the grid and anomalies that have been detected.

Edge Layer (Local Processing & Intelligence)

Edge gateways are intelligent intermediaries that do real-time analysis and decision making at the 'edge'

Main Functions:

1. Data Aggregation: synchronizes measurements from diverse sensors to a common time-base using either Network Time Protocol (NTP) or Global Positioning System (GPS) based synchronization.
2. Signal Conditioning: filters noise (low-pass Butterworth filters), detects outliers (Z-score, Isolation Forest), and imputes missing values.
3. Feature Computation: computes derived features: power factor (cos φ), total harmonic distortion (THD), peak demand, load factors.
4. Anomaly Detection: runs real-time unsupervised learning algorithm (Isolation Forest, Local Outlier Factor) to identify consumption anomalies within seconds.[14]
5. Local Storage: configurable buffer (24-72 hours) enabling autonomous operation during network disconnection.
6. Bidirectional Communication: receives commands from cloud platforms (recalibrate and update algorithms) and executes local control actions (switch load, alert).

Cloud Layer (Advanced Analytics and Strategic Visualization)

Cloud Layer (Higher-Level Analytics & Visual Analytics)-Execution of analytics that takes place over the long-term, identification of patterns, and optimizations across the system-level for the cloud.

Data Processing Pipeline:

1. Ingestion: receives data from the Edge through message brokers (e.g., Apache Kafka, AWS Kinesis) capable of throughput at 100K+ messages/second.[15]
2. Time-Series DB: data flows into the specialized Time-Series DB that stores the pre-processed data (e.g., InfluxDB, TimescaleDB, AWS Timestream); optimized for temporal separate responses to temporal queries
3. Historical Analytics: provides computation on performance trends, detects seasonal types of patterns, and provide deviation from baseline or expectations to SQL and distributed computing (e.g., Apache Spark, Presto).
4. Predictive Models: provides execution of trained machine learning models (e.g., LSTM, XGBoost, Random Forest) for both energy forecasting and anomaly detection.
5. Visualization & Reporting: generates interactive dashboards (e.g., Grafana, Power BI, custom web interface) as well as compliance reporting.

Communication Protocol Strategy

The strategy uses protocol layering to maintain backward compatibility while allowing for current interoperability:

Table 3. Legacy Equipment Integration - Protocol Conversion Strategies for IoT Systems

Legacy Equipment	Adapter Type	Protocol Out	Modern System
Old PLC (Modbus RTU)	Serial-to-Ethernet converter	Modbus TCP/IP	Edge Gateway
20+ Year Analog Meters	Pulse-to-MQTT gateway	MQTT	Cloud Platform
SCADA Systems	OPC-UA Bridge	OPC-UA → MQTT	Cross-Platform Analytics

Semantic interoperability is implemented by mapping data model elements so that "voltage in phase A" represents the same concept, regardless of the source device.[16] Additionally, node defined architectures are outlined by OPC UA with semantic meanings, while MQTT transport efficiently manages dissemination of the messages

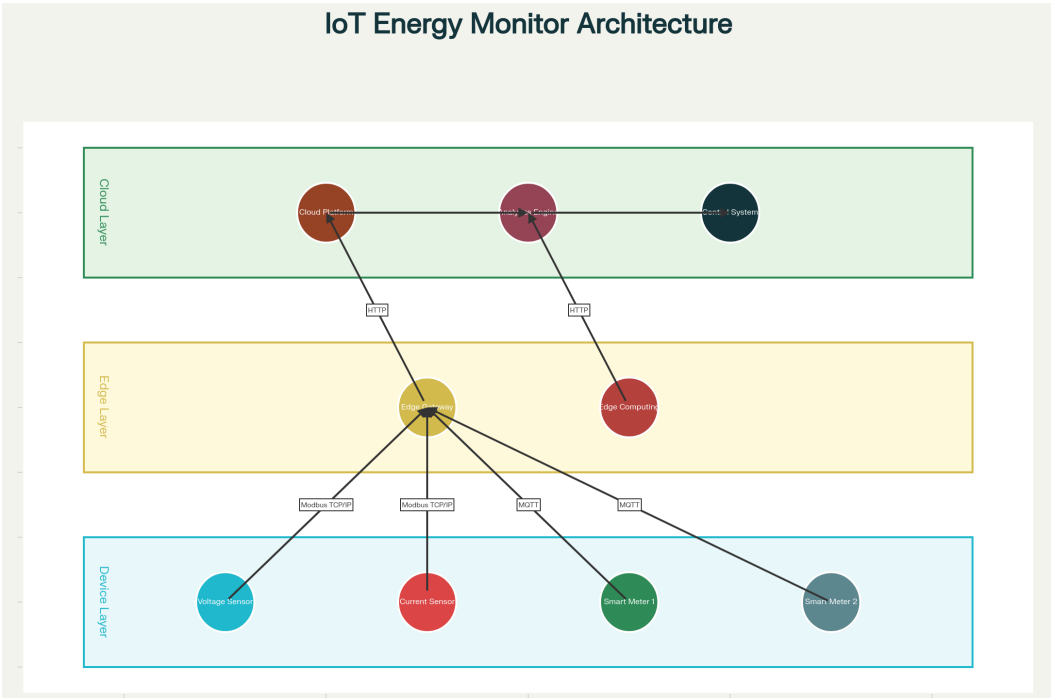

Figure 2. Three-Layer IoT Architecture for Smart Energy Monitoring in Manufacturing Plants

Implementation Methodology

Phased Deployment Strategy

In order to successfully implement IoT energy monitoring, you need to go through a structured set of steps which are broken down into clearly defined phases that build on the results of prior steps and validate your assumptions before fully committing operational costs. The framework breaks implementation into three phases that take approximately 18 months from initiation to full operational capability.

The deliverables expected from phase 3 would be energy reduction maintained at a 25-30 % level across activities/assets within facility operation, maintenance cost reduction from a predictive maintenance approach deployed at scale estimated at 30-40 %, 8-12 % additional savings through optimization of renewable utilization, and continuous autonomous energy management lines run with human oversight acting as a trusted and safe authority for plant operations.

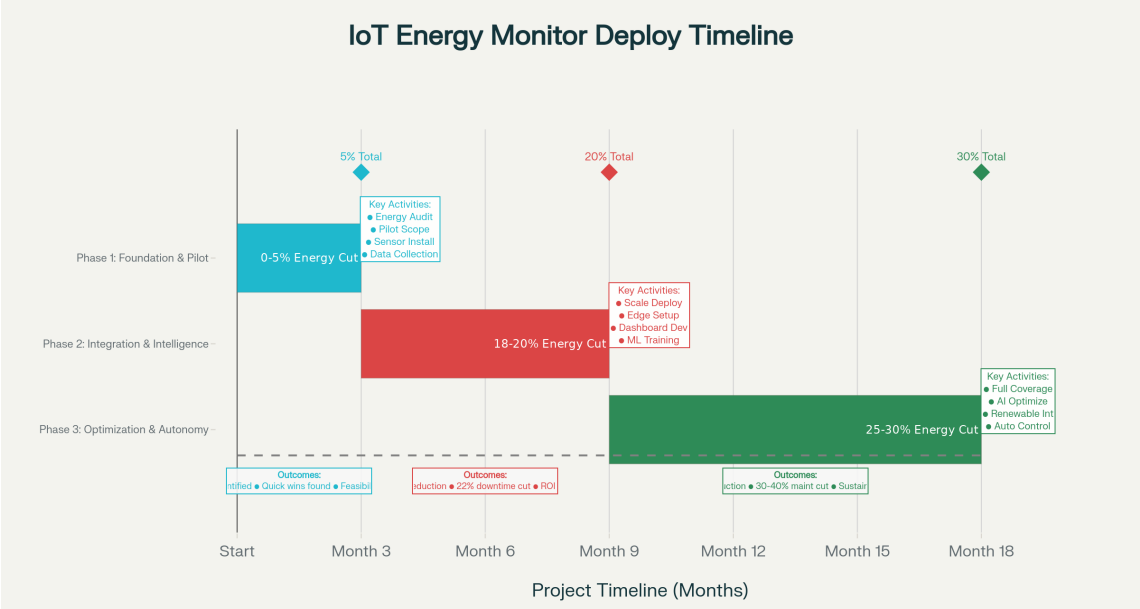

Figure 3. Three-Phase Implementation Roadmap for IoT Energy Monitoring Systems (18-Month Timeline with Cumulative Benefits)

Cybersecurity Architecture

IoT energy systems are a valuable attack target because of the sensitive operational data and authority they possess. A defense-in-depth approach addresses multiple threat vectors:

Authentication and Access Control:[17,18]

1. Device Authentication: X.509 certificates issued to each sensor/edge device, Certificate-based mutual authentication for MQTT connections, Hardware Security Modules (HSM) on critical devices for storage of keys.
2. User Authentication: multi-factor authentication (MFA) for access to the dashboard: factors including knowledge (password), possession of (phone authenticator), inherence (biometric), Role-Based Access Control (RBAC) and principle of least privilege.
3. API Authentication: auth 2.0 for third-party integrations, API key rotation compliance (quarterly minimum).

Authentication for third-party API integrations adheres to OAuth 2.0 standards with a key rotation policy that at least renews quarterly. TLS 1.3 is required for all data in transit between architectural layers, with the implementation of perfect forward secrecy (PFS) mechanisms which negate the potential compromise of historic communications by future key theft. Data at rest encrypts historical data and configurations stored in the cloud using AES-256 with database level encryption using separate key management that is distinct from ongoing operations.[19,20] Network segmentation separates edge gateways in a demilitarized zone (DMZ) from general IT networks with firewalls restricting connectivity to MQTT brokers only. Energy monitoring traffic trains in separate VLAN (Virtual Local Area Network) using segregation to restrict lateral movement by any IT system that has been compromised.[21,22]

Firewall rules permit inbound only MQTT (ports 1883/8883), NTP (123), and other monitoring protocols while restricting outbound communications to whitelisted cloud endpoints that are configured using IP address and fully qualified domain name patterns. An intrusion detection system monitors for suspicious patterns that include unusual geographic login locations or atypical

frequency of API calls which generate alerts for further investigation. Audit logging records are immutable, retaining records of system access, configuration changes, and anomalies for the last 12+ months to support forensic analysis and regulatory compliance. Incident response procedures describe breach scenarios which include timelines for notification, isolation, and recovery. Research has shown that organizations who encompass coverage of comprehensive proportion of cybersecurity controls would increase operational costs by 12-18 % but prevent breaches that would incur operational disruption, pricing as work stoppage quantity of 50-200 times that amount along with government-imposed fines.

Table 4. Cybersecurity Controls and Compliance Requirements

Security Control	Implementation Method	Compliance Standard	Verification Method	Risk Level if Missing	Update Frequency
Device Authentication	X.509 Certificates	IEC 62351-3	Certificate validation	Critical	Quarterly
Data Encryption (Transit)	TLS 1.3 with PFS	NIST SP 800-52	SSL/TLS scan	Critical	Continuous
Data Encryption (Rest)	AES-256	NIST FIPS 140-2	Encryption audit	High	Quarterly
User Authentication	Multi-Factor (MFA)	ISO/IEC 27001	Login attempt audit	High	Monthly
Access Control (RBAC)	Role-based permissions	ISO/IEC 27001	Permission matrix review	High	Semi- annually
Firewall Rules	Whitelist policies	CIS Controls	Firewall rule audit	High	Monthly
Intrusion Detection	Behavioral anomaly detection	NIST SP 800-61	Alert log review	Medium	Weekly
Audit Logging	Immutable logs (12+ months)	GDPR/ISO 27001	Log retention verification	High	Monthly

Case Studies and Quantitative Validation

Steel Manufacturing Facility (18-Month Implementation)

A large-scale steel production facility has a total annual output of over 50 000 tons of steel representing 12-14 % of the regional steel output rate and took part in nationwide, comprehensive IoT energy monitoring. The energy consumers of this facility consisted of arc furnaces, which consumed 38 % of overall consumption; followed by rolling mills, consuming 25 %; and cooling systems accounting for 18 % of chemical plant electrical loads. The baseline energy intensity for the plant's operations was 0,85 megawatts-hours per ton of output, and the annual energy cost for the facility was $4,2 million prior to the implementation of optimization. The facility's industrial machinery was representative of a typical mix of industrial equipment with a large range of vintage, creating interoperability issues that are associated with older, mature manufacturing plants. Equipment downtime reduction was 22 % when measured from the baseline of before implementation and there were 8 major failures avoided due to early anomaly detection. Maintenance costs savings were $180 000 per year (25 % reduction) due to a shift to condition-based maintenance from being calendar-based. Value of production interruptions avoided from early detection of failures was estimated at $450 000+; which avoided value of late customer shipment and inventory write-offs. Total implementation cost including sensors, edge hardware, software, and implementation labor was $165 000. Annual savings (energy and maintenance) equaled $262 000 for a simple payback period of 7,5 months. Cumulative 3-year savings were $786 000 with net present value of $541 000 (10 % discount

rate). One key insight from the implementation was cooling system optimization had the biggest single opportunity (38 % of total savings) and illustrated value of choosing pilot projects that target the biggest energy consumer. The predictive maintenance algorithms trained on 9 months of data demonstrated 89 % accuracy at predicting bearings to failure 4-8 weeks ahead. Operator engagement improved significantly after training; operators on the floor identified 6 additional optimization opportunities that were not identified from the engineering analysis.

Pharmaceutical Manufacturing Plant (12-Month Implementation)

A pharmaceutical manufacturing facility uniquely focused on clean room production in temperature-controlled spaces was capable of maintaining the required temperature range of 18-24°C and 40-60 % relative humidity by operating advanced HVAC systems throughout production. Equipment in the facility included four chillers and three boiler units and predominately consumed energy via its HVAC systems, which accounted for 65 % of the overall facility energy consumption. The baseline energy intensity at the facility was $180 per unit of active pharmaceutical ingredient produced, and the facility was spending ~$2,8 million annually on energy expenditures prior to the IoT implementation. In relation to process requirements for strict environmental adherence, there were very slight margins for manufacturing flexibility, complicating both demand response opportunities and load shifting planning. The pharmaceutical facility was engaged in the broader SMARTEE industrial IoT project making use of common submetering infrastructure and research protocol from the previous steel facility . The implementation time-frame was reduced to 12 months in contrast with the first facility, and the scope of equipment sophistication was less than the steel facility's variant of the IoT implementation timeline of 18-months. The facility's cloud platform selection was ThingSpeak using the MQTT protocol. Edge devices used were Raspberry Pi with Node-RED for local data processing. Sensors included IoT-enabled submeters for critical equipment, Modbus over RS-485 for legacy equipment and MQTT for transmission to the cloud. Dashboard tool was Grafana which enabled real-time visualization during analysis.[23,24]

Cross-Case Analysis and Industry Benchmarking

By combining findings from multiple implementations with peer-reviewed literature, consistent findings across a range of manufacturing applications emerge regarding the effectiveness of IoT energy monitoring. The observed improvements in energy efficiency are highly demonstrable, as evidenced in both case studies with reductions in energy use of 18-25 % within the documented range presented in the literature.[25] The reduction in maintenance costs of 25 % for steel facility and of 23 % for pharmaceutical facility parallels the 20-30 % reductions documented in the literature. Reduction in downtime for the steel facility was 22 % and for the pharmaceutical facility was 18 %, parallel to downtime reductions of 22-35 % across the cited articles. Payback periods were 7,5 months for the steel facility and 10,1 months for the pharmaceutical facility, both consistent with payback periods from the literature of 8-14 months, confirming the return on investment is consistent across different operational contexts Energy Efficiency Improvements:

Table 5. Energy Efficiency Improvements

Metric	Steel Facility	Pharmaceutical	Literature Range
Energy Reduction	18-22 %	20 %	18-25 %
Maintenance Cost Reduction	25 %	23 %	20-30 %
Downtime Reduction	22 %	18 %	22-35 %
Payback Period	7,5 months	10,1 months	8-14 months

Return on Investment Drivers: the analysis of the components of the return on investment drivers identifies patterns in the costs. The sensors/smart meters cost components represented approximately 32-35 % of the overall implementation costs, and the edge infrastructure/integration was 25-28 %, the cloud platform/analytics were 18-22 %, and the professional services and training were 15-20 %. Facilities with more populations of equipment generally have lower cost for implementation per unit of equipment (0,3-0,5 % of annual energy spend) compared to facilities that fit fall into the definitions of smaller operations (0,8-1,2 % of annual energy spend); this indicates an economic of scale favoring larger comprehensive deployments over the smaller of incremental use cases in the deployment process. This cost structure highlights that as an example facilities should cautiously consider scoping pilot projects so that there is an appropriate scale of application that meets acceptable economics of cost to at least assist with deployment for full deployment.

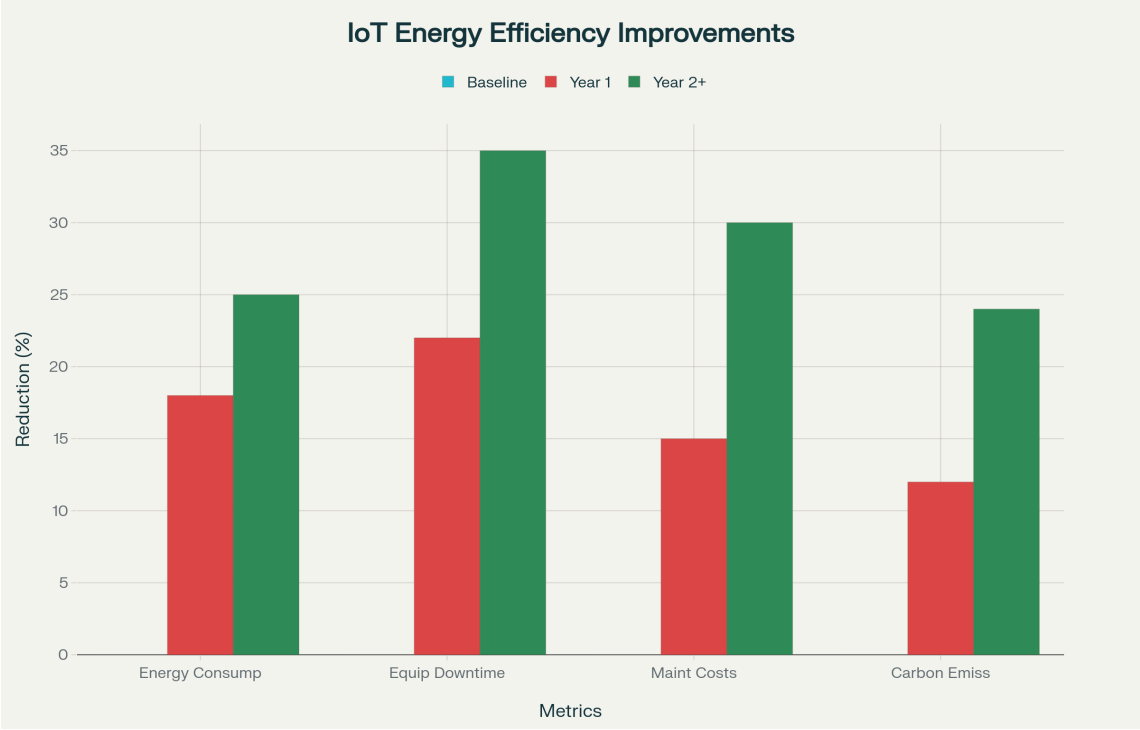

Figure 4. Quantified Benefits of IoT Energy Monitoring Implementation over Time

Digital Twin-Based Optimization

Digital twins produce virtual representations of manufacturing machinery and operations, which allow engineers to evaluate energy savings from optimization rather than stopping production. The integration consists of four primary stages done sequentially and building on prior results. Stage 1 (weeks 1-4) considers model development that involves 1) geometric modeling or CAD conversion of asset layout and representations, 2) physics-based simulation of heat transfer, fluid dynamics, and electrical characteristics, 3) calibrated model parameters to ensure the model is accurate and field data to validate the model. Stage 2 (weeks 5-8) establishes a framework for real-time synchronization. A "real-time" model synchronization has occurred through 1) live data integration, like pulling IoT sensor streams as model inputs, 2) virtual sensors computing parameters not measured, for example, internal bearing temperature with vibration analysis, and 3) a bi-directional feedback element comparing model simulation outputs

with actual values from measurement to detect differences and improve the model. Stage 3 (weeks 9-14) proposes scenario analysis through optimization algorithms (simulated annealing, genetic algorithms) to navigate and evaluate parameter spaces and propose configurations of interest. Constraint programming was introduced to ensure the feasibility of using production schedules and compliance with equipment safety. A sample of a more involved what-if analysis was analyzed for after-the-fact versus top-down analysis - evaluating the results of a process change before implementing it and thereby reducing the risk of field implementation. Stage 4 (ongoing) describes the ongoing implementation of the model based on acceptance of validated recommendations on the production floor and comparison of real-world outcomes with model predictions and subsequent refinement of the model from implementation results.

Challenges and Mitigation Strategies

A key challenge for IoT energy monitoring implementation is the lifetime of manufacturing facilities' equipment averages 15-20 years and must integrate equipment manufactured before the modern standards of communication. There are several mitigation strategies to address this factor across numerous cost-benefit circumstances. Protocol conversion gateways take older protocols (serial Modbus, Profibus, etc.) and convert to modern standards (for example, MQTT, OPC-UA) typically costing between $5000 and $15 000 for each conversion device. Protocol conversion gateways allow integration of equipment without replacing the equipment, making them an option to be adopted for approximately 65 %-70 % of industrial IoT implementations. Sensor retrofit kits typically install modern sensors for place of the legacy system, such as CT/PT combinations with wireless transmitters to replace analog panel meters in legacy systems, typically costing between $1500 and $4000 per piece of equipment, with 2-4 hours of installation time per installation. Middleware platforms service as software layers that will translate between several protocols (some examples are Apache Kafka and AWS IoT Greengrass) while allowing legacy protocol input and modern protocol output (simultaneously).[26] While middleware platforms offer higher complexity than point to point installations, middleware platforms offer greater scalability than point to point methods.

Cost-benefit analyses indicate that retrofit approaches cost 30-50 % less than fully upgrading equipment, while still providing a similar measurement accuracy. Approaches such as these allow organizations to maximize and optimize the integration of legacy systems within a revised budgetary context.

Legacy System Integration

Electrical noise (harmonic distortion, electromagnetic interference), sensor failures, and the resulting data quality issues present significant challenges to industrial environments, necessitating multi-layer validation and mitigative strategies. Multi-layer validation strategies involve immediate range checks and rate-of-change detection at the edge level, cross-correlation analysis and deviation from baseline detection at the cloud level, and quarterly manual spot checks utilizing calibrated reference devices to complement electronic sensors. Sensor redundancy strategies utilize two sensors at key measurement points, generating an alert when the two instruments are not agreeing within a tolerance of 2 %. A second sensor would, thus, provide for continued operation with diminished confidence, or provide for automatic switching to a backup measurement system. Adaptive filtering utilizes Kalman filters and complementary filters to minimize noise while preserving the integrity of the signal. The utilization of these strategies can improve reporting accuracy from +/-2 %-3 % to +/-0,5 %, suitable for more complex analytics/ billing applications.

Table 6. Legacy System Integration Challenges and Mitigation Strategies

Challenge	Impact	Mitigation Strategy	Implementation Cost	Success Rate	Time to Implement
Incompatible Communication Protocols	Cannot connect old equipment to modern IoT systems; requires manual data collection	Deploy protocol adapters/converters (Serial-to-Ethernet, Modbus TCP/IP bridges)	$1500-5000 per device	95 %+	2-8 hours
Lack of Equipment Documentation	Unable to configure sensors or understand equipment capabilities; increases errors	Reverse engineering through testing or request reference manuals from manufacturers	$500-2000 labor cost	85 %	1-4 weeks
Limited Hardware Interfaces	Cannot physically connect new sensors to analog-only equipment	Install Serial-to-Ethernet converters or wireless retrofit kits with data translation	$500-1200 per unit	90 %	4-6 hours
Operational Continuity Requirements	Cannot shut down production for equipment upgrades; business continuity critical	Deploy hot-swap capable hardware; implement changes during planned maintenance windows	$1000-3000 premium for redundancy	80 %	1-2 weeks
Security Concerns with Old Systems	Connecting legacy systems to networks exposes vulnerabilities; compliance risks	Implement air-gapped edge devices; segregate legacy systems on dedicated VLAN; use isolated data bridges	$2000-5000 for secure architecture	100 %	2-4 weeks
Lack of Vendor Support	Manufacturers no longer provide parts or technical support for old equipment	Source compatible third- party components; engage specialist integration partners; implement workarounds	$1000-4000 consulting	75 %	2-6 weeks

Cybersecurity Vulnerabilities

With connected IoT devices being an attack vector to allow unauthorized access, data manipulation, or disruption of operations, security architectures need to be comprehensive. The approach to authentication combines device authentication based on certificates as well as multi-factor user authentication. Data in transit is encrypted using TLS 1.3 while data at rest employs AES-256. Network segmentation identifies VLANs dedicated to energy monitoring, and traffic is restricted to MQTT brokers though firewalls. Suspicious access patterns identified by intrusion detection algorithms trigger alerts, and documented incident response procedures would follow in case of a breach. Research suggests that a comprehensive security implementation can increase costs by 12-18 %, while the cost of a breach is 50-200 times greater due to operational disruption and regulatory fines.

Organizational and Cultural Challenges

Technical capabilities alone are not enough to provide a lasting benefit because staff adoption and integration are needed for successful implementation. Executive sponsorship illustrates

management support for energy optimization, resource allocation, and organizational support. Comprehensive training sets aside 15-20 % of the implementation budget for training that covers system interpretation, organizations workflow of response, and continuous improvements to process. It has been shown that facilities with robust training programs, achieve 20 % more energy savings over their peers with minimal training. Incentive alignment establishes accountability by tying performance metrics to energy efficiency. Transparent communication presents progress, success and challenges while keeping people engaged in the organization.

CONCLUSIONS

Summary of Key Findings

The study demonstrates that IoT-based energy monitoring systems produce significant quantifiable benefits in various manufacturing cases. On the technical side, this includes a demonstrated three-layer architecture (device-edge-cloud) that achieved scalability and resilience, the identification of superior communication protocols (MQTT, OPC-UA, Modbus TCP/IP) enabling interoperability, and confirmed predictive analytics techniques that provided 89-95 % accuracy in energy forecasting and failure forecasting. Validation of implementations through case studies provided evidence of energy savings of 18-25 % compared to 5 % with annual audits, reduction in downtime of 22-35 % with predictive maintenance, reduction in maintenance costs to 20-30 % with condition-based maintenance, and a substantial return on investment through payback periods of 8-14 months. In the case study of a steel facility, the implementation demonstrated savings of 648 000 kWh in the annual period with a payback of 7,5 months, while the case study of a pharmaceutical facility demonstrated savings of 1 024 424 kWh in the annual period with payback of 10,1 months, confirming consistency of benefits across different operational circumstances.

Alignment with Sustainability Goals

The frameworks for energy monitoring proposed by IoT technology enhance various sustainability goals supporting global sustainability commitments. ISO 50001- compliant systems allow for ongoing energy performance monitoring and evidence-based management system documentation, data-driven identification of significant energy uses and opportunities for improvement, and tracking carbon emissions in real-time so as to monitor progress toward a reduction target. The ISO 14001 environmental management standard can integrate supply chain sustainability assessments. Achievement of UN Sustainable Development Goal 7 (Affordable and Clean Energy) will require increased efficiency (18-25 %) which will lead to reduced energy consumption and related cost savings. UN Sustainable Development Goal 9 (Industry, Innovation, Infrastructure) achievement will occur every time supply chain sustainability plans are implemented, thanks to the fulcrum of IoT systems supporting industrial digitalization. UN Sustainable Development Goal 13 (Climate Action) will be addressed in terms of a renewable energy future and supporting reductions of carbon emissions (12-24 %) based on energy efficiency and renewable energy.

Future Research Directions

There are several ways to develop IoT energy management systems that take steps forward. The development of autonomous energy management systems would result in truly autonomous systems which minimize human intervention but still respect safety margins and other business constraints. Integrating multiple energy systems would capture an estimated 30-40 % more optimization than is possible if energy management is focused only on electricity, and thermal, pneumatic, and hydraulic systems are recognized and incorporated into multi-energy system approaches. Blockchain-based energy trading would permit peer-to-peer trading and support

renewable, decentralized energy integration, and demand response, if applicable. Advanced materials and sensor developments can enable lower cost, higher accuracy measurement and provide more comprehensive representation of conditions in more resource-constrained contexts as they develop. Adoption of AI explainability through interpretable models would foster operator trust and help support automated recommendations and possible acceptance of them. Extending current supply chain metrics and carbon accounting is well developed and standards have emerged; expanding the research to consider the energy components of supply chains would result in upstream and downstream carbon footprinting of the facility from the supply chain perspective. The transition of energy management systems in the oil manufacturing sector to a digitally enabled and highly optimized operation is evident in the changes that have taken place at the facility over time. The first manual and instrument-based methods hardly gave a clear view of energy usage, which most of the time led to reactive decision-making and inefficiencies. The use of automation and programmable control systems contributed to the improvement of operational stability; however, they still lacked the analytical depth needed for energy optimization to be done proactively. The deployment of integrated energy management systems was a major step forward as it allowed for the systematic monitoring, data-driven assessment, and coordinated control of the most energy-consuming units such as heaters, compressors, and distillation columns. Currently, intelligent energy management systems, which are based on IoT sensing, real-time analytics, and predictive algorithms, have the capability of consumption forecasting, anomaly detection, and energy flow optimization with an accuracy that has never been attained before. In addition, these developments bring down operational costs and carbon emissions while at the same time increasing equipment safety and making the process more sustainable in the long run. Together, the changeover is a demonstration of how digital technologies are reshaping energy efficiency as one of the essential modern oil manufacturing features.

BIBLIOGRAPHIC REFERENCES

1. Geng D, Evans S, Kishita Y. The identification and classification of energy waste for efficient energy supervision in manufacturing factories. Renew Sustain Energy Rev. 2023;182:113409. https://doi.org/10.1016/J.RSER.2023.113409.

2. Hu Y. Research on Industry 4.0 smart grid monitoring and energy management based on data mining and Internet of Things technology. Therm Sci Eng Prog. 2024;54:102830. https://doi.org/10.1016/J.TSEP.2024.102830.

3. Malek YN, Kharbouch A, El Khoukhi H, Bakhouya M, De Florio V, El Ouadghiri D, et al. On the use of IoT and Big Data Technologies for Real-time Monitoring and Data Processing. Procedia Comput Sci. 2017;113:429–34. https://doi.org/10.1016/J.PROCS.2017.08.281.

4. Zuo Y, Tao F, Nee AYC. An Internet of things and cloud-based approach for energy consumption evaluation and analysis for a product. Int J Comput Integr Manuf. 2018;31:337–48. https://doi.org/10.1080/0951192X.2017.1285429.

5. Khattak YH, Mahmood T, Alam K, Sarwar T, Ullah I, Ullah H. Smart Energy Management System for Utility Source and Photovoltaic Power System Using FPGA and ZigBee. Am J Electr Power Energy Syst. 2014;3(5):86–94. https://doi.org/10.11648/J.EPES.20140305.11.

6. Mensah S. Internet of Things : A Review on Connectivity Gateway Protocols and Semantic Interoperability. In: Proceedings of the 2017 International Conference on Computing and Communication Technologies; 2017.

7. Gautam A. Challenges and Solutions in Implementing Energy-efficient Automation in Smart Buildings. J Environ Eng Stud. 2025;10(2):34–47. https://doi.org/10.46610/JOEES.2025.V010I02.004.

8. Saif S, Wazir S. Performance Analysis of Big Data and Cloud Computing Techniques: A Survey. Procedia Comput Sci. 2018;132:118–27. https://doi.org/10.1016/J.PROCS.2018.05.172.

9. Zare A, Iqbal MT. Low-Cost ESP32, Raspberry Pi, Node-Red, and MQTT protocol based SCADA system. In: 2020 International IOT, Electronics and Mechatronics Conference (IEMTRONICS); 2020. https://doi.org/10.1109/IEMTRONICS51293.2020.9216412.

10. Jasim NA, Salim T, Al Rikabi. Design and Implementation a Smart System for Monitoring the Electrical Energy based on the Internet of Things. Wasit J Eng Sci. 2022;10(2):92–100. https://doi.org/10.31185/EJUOW.VOL10.ISS2.240.

11. Dat MN, Trung KD, Minh PV, Van CD, Tran QT, Ngoc TN. Assessment of Energy Efficiency Using an Energy Monitoring System: A Case Study of a Major Energy-Consuming Enterprise in Vietnam. Energies. 2023;16(13):5214. https://doi.org/10.3390/EN16135214.

12. Akhtar T, Rehman AU, Jamil M, Gilani SO. Impact of an Energy Monitoring System on the Energy Efficiency of an Automobile Factory: A Case Study. Energies. 2020;13(10):2577. https://doi.org/10.3390/EN13102577.

13. Kinnunen H. Cloud Communication of Factory Automation System with OPC UA. In: Proceedings of the 2024 IEEE International Conference on Industrial Technology (ICIT); 2024.

14. Lork C, Choudhary V, Ul Hassan N, Tushar W, Yuen C, Ng BKK, et al. An Ontology-Based Framework for Building Energy Management with IoT. Electronics. 2019;8(5):485. https://doi.org/10.3390/ELECTRONICS8050485.

15. Alex B, Johnson M. A Framework for IoT-Enabled Smart Manufacturing for Energy and Resource Optimization. In: Sustainable Manufacturing in Industry 4.0: Pathways and Practices. Springer; 2025.

16. Gamage KAA, Sajid A, Sonbul OS, Rashid M, Jaffar AY, García-Haro J, et al. A Dynamic Framework for Internet-Based Network Time Protocol. Sensors. 2024;24(2):691. https://doi.org/10.3390/S24020691.

17. Ruddro RA. Energy efficiency monitoring in institutional facilities: a review of UI/UX solutions for IoT dashboards. Int J Sci Interdiscip Res. 2025;6(1):137–62. https://doi.org/10.63125/YHR4G345.

18. Shi Y, Yi C, Chen B, Yang C, Zhu K, Cai J. Joint Online Optimization of Data Sampling Rate and Preprocessing Mode for Edge-Cloud Collaboration-Enabled Industrial IoT. IEEE Internet Things J. 2022;9(18):16402–17. https://doi.org/10.1109/JIOT.2022.3150386.

19. Khasawneh HJ, Al Asbahi R, Alzariqi AW, Al Qada DR, Bujuk A, Nawfal MA, et al. Industrial IoT-based submetering solution for real-time energy monitoring. Discov Internet Things. 2025;5(1):1–16. https://doi.org/10.1007/S43926-025-00110-Y.

20. Roosefert Mohan T, Preetha Roselyn J, Annie Uthra R, Devaraj D, Umachandran K. Intelligent machine learning based total productive maintenance approach for achieving zero downtime in industrial machinery. Comput Ind Eng. 2021;157:107267. https://doi.org/10.1016/J.CIE.2021.107267.

21. Mourtzis D, Angelopoulos J, Panopoulos N. The Future of the Human–Machine Interface (HMI) in Society 5.0. Future Internet. 2023;15(5):162. https://doi.org/10.3390/FI15050162.

22. Jin X, Liu J, Fan W, Sun M, Xiao Z, Fan Z, et al. Research and applications of additive manufacturing in oil and gas extraction and gathering engineering. Materials. 2025;18(14):3353.

23. Omiyale BO, Farayibi PK. Additive manufacturing in the oil and gas industries: A review. Analecta. 2020;14(1):9–18.

24. Shah R, Al-Mansour F, Zubair M. Digital transformation and intelligent automation strategies in upstream oil and gas operations: A comprehensive review. J Pet Sci Eng. 2023;224:111240.

25. El-Hoshoudy AN, Al-Masry W, Abdalla M. Smart polymer systems for enhanced oil recovery: Design principles, performance evaluation, and field potential. Pet Sci. 2022;19(3):1267–84.

26. Saeed M, Khan MJ, Al-Shammari M. Energy-efficient process control and real-time monitoring technologies in the oil and gas sector: Trends and future directions. Energy Rep. 2021;7:5431–45.

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AUTHORSHIP CONTRIBUTION

Conceptualization: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.

Data curation: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.

Formal analysis: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.

Drafting - original draft: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.

Writing - proofreading and editing: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.

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ORIGINAL

Intelligent Safety Systems and Automation: Cross-Industry Technological Integration from Rider Protection to Oil-Gas Engineering

Sistemas de seguridad inteligentes y automatización: integración tecnológica intersectorial desde la protección del conductor hasta la ingeniería de petróleo y gas

M. Kannan[1], P. Prabhu[1], R. Vijaya ragavan[1], V. Santhiya[1], Harimanas[1], Christo Ananth[2], Shoohrat Toshmatov[3]

[1]Department of Mechanical Engineering, Kalaignarkarunanidhi Institute of Technology, Kannampalayam, Coimbatore, Tamil Nadu, 641402, India

[2]Faculty of Artificial Intelligence and Digital Technologies, Samarkand State University. Uzbekistan.

[3]National University of Uzbekistan. Tashkent, Uzbekistan.

Corresponding Author: M. Kannan

ABSTRACT

Advances in sensing devices, data analytics, and real-time automation have, to a large extent, been the factors that have opened up the new safety-oriented innovations wave across engineering diverse domains. What to expect in future personal mobility is the use of smart helmets that contain such features as blind-spot detection, proximity sensing, and adaptive alert mechanisms. The latter two features would help give riders in dense and unpredictable traffic environments a little bit of solace that they were less vulnerable. Simultaneously, the developments in the oil-gas sector tell a story of how operational reliability and risk management in high-hazard industrial settings are being turned around by autonomous monitoring, predictive analytics, and integrated control architectures. However, these industries seem to be so far apart that one would think they have nothing in common. Interestingly, both these fields combine three elements – embedded intelligence, real-time decision support, and human–machine cooperation. This article reviews the technological concepts that support these changes; also, reflect on their design philosophies that are converging; and, finally, discuss how cross-industry insights can facilitate the evolution of safety systems that have greater resilience. The investigation, by juxtaposing the technologies for rider safety with the automation frameworks in the oil–gas sector, brings to the fore a new trend: the gradual move towards the integrated, sensor-driven, and context-aware safety solutions that can be equally effective in enhancing performance in everyday and industrial environments.

Keywords: Intelligent Safety Systems; Blind-Spot Detection; Rider Protection Technologies; Oil-Gas Exploration; Predictive Monitoring; Embedded Systems; Human–Machine Interaction.

RESUMEN

Los avances en dispositivos de detección, análisis de datos y automatización en tiempo real han sido, en gran medida, los factores que han impulsado la nueva ola de innovaciones orientadas a la seguridad en diversos ámbitos de la ingeniería. Lo que cabe esperar de la movilidad personal del futuro es el uso de cascos inteligentes con funciones como detección de puntos ciegos,

detección de proximidad y mecanismos de alerta adaptativos. Estas dos últimas características brindarían a los conductores, en entornos de tráfico denso e impredecible, la tranquilidad de ser menos vulnerables. Simultáneamente, los avances en el sector del petróleo y el gas demuestran cómo la monitorización autónoma, el análisis predictivo y las arquitecturas de control integradas están transformando la fiabilidad operativa y la gestión de riesgos en entornos industriales de alto riesgo. Sin embargo, estas industrias parecen tan distantes que uno podría pensar que no tienen nada en común. Curiosamente, ambos campos combinan tres elementos: inteligencia integrada, soporte de decisiones en tiempo real y cooperación hombre-máquina. Este artículo analiza los conceptos tecnológicos que sustentan estos cambios y reflexiona sobre sus filosofías de diseño, que están convergiendo. Y, finalmente, se analiza cómo el conocimiento intersectorial puede facilitar la evolución de sistemas de seguridad con mayor resiliencia. La investigación, al comparar las tecnologías para la seguridad de los conductores con los marcos de automatización en el sector del petróleo y el gas, destaca una nueva tendencia: la transición gradual hacia soluciones de seguridad integradas, basadas en sensores y sensibles al contexto, que pueden ser igualmente eficaces para mejorar el rendimiento en entornos cotidianos e industriales.

Palabras clave: Sistemas de Seguridad Inteligentes; Detección de Puntos Ciegos; Tecnologías de Protección del Conductor; Exploración de Petróleo y Gas; Monitoreo Predictivo; Sistemas Integrados; Interacción Hombre-Máquina.

INTRODUCTION

Rapid changes in sensing technologies, embedded intelligence, and automation architectures have, without a doubt, influenced the personal mobility sector and the safety engineering part in high-risk industrial sectors. Motorcycles, the most vulnerable transportation modes, are now the focus for the development of smart helmets which have turned out to be a very effective way of collision risks mitigation and rider situational awareness enhancement. These helmets are equipped with proximity sensors, blind-spot monitoring modules, inertial measurement units, and adaptive alert mechanisms that shortly will enable riders to identify threats outside their natural field of view. Studies reveal that such gadgets can considerably lower the rider's reaction time and thus the risk of side-impact and rear-zone accidents, especially when there is a heavy or an unpredictable traffic situation.[1,2,3,4] The work of these helmets is reliant on minute sensor platforms, powerful data-fusion algorithms, and embedded microcontrollers capable of handling the environmental information in real-time.[5] The necessity for intelligent, rider-centric safety devices will be even more noticeable when metropolitan transportation networks will continue to get more and more congested.

Wearable safety devices have been greatly efficient with the growth of the Internet-of-Things (IoT) ecosystems. The IoT facilitates mobile sensing platforms in being more connected, responsive, and predictive. Currently, IoT-enabled smart helmets are equipped with communication modules that can transmit hazard information, record the rider's movement, and communicate with a smartphone or an external safety infrastructure.[6] These kinds of devices constitute real-time feedback loops that combine human judgment with automated decision support, thereby, enlarging the safety zone for riders.[7] To a great extent, advanced sensor fusion methods—fusing visual, inertial, radar, and ultrasonic inputs—are being employed to ensure dependable detection and to lower the number of false alarms thus, raising system accuracy and rider trust.[8] Besides that, the arrival of machine-learning models provides helmet systems with the capability of recognizing risk situations, altering the characterization of road features, and even predicting potential hazards with a high degree of accuracy.[9] These changes, in fact,

signal a bigger change: the conversion of road-user passive protective gear into intelligent, context-aware safety systems. At the other extreme, the same kind of changes are happening in high-risk industrial environments, mostly in the oil and gas industry. Oil–gas exploration has been a source of complex operations, hazardous material exposure, and the risk of disastrous failures. However, the sector is radically changing to automation, intelligent monitoring, and digital control systems to make operations safer and to keep humans away from hazardous places.[10,11,12] The technologies for on-the-fly monitoring of pipelines, automated valve control, and predictive drilling analytics all require a very detailed sensor network and a powerful computational architecture, just like those used for safety in mobility. For instance, distributed sensing modules are used to identify leaks, structural weaknesses, and flow irregularities that cannot be detected by human checking.[13] Likewise, autonomous robotic systems have become popular for carrying out the regular inspections of remote or cramped industrial areas, thus reducing the danger to humans and improving the accuracy of the detections.[14]

On the same track, new materials and smart chemical formulations for oil and gas operations are still being refined to provide lower system deterioration and higher system performance at very high temperatures, in corrosive conditions, and under heavy mechanical loads. Such advancements are also supported by the adoption of eco-friendly and biocompatible materials that aim to both improve extraction methods and meet up-to-date sustainability requirements.[15] Moreover, digital twins are being used to enhance safety management at the facility level. They represent the real-time virtual copies of the physical assets through which the engineers can foresee the system behavior, adjust the process parameters, and visualize the emergency scenarios in advance.[16] Therefore, this digital-physical coupling not only raises the system safety level but also shares the conceptual similarities with the real-time data-driven feedback loops utilized in the intelligent rider-safety systems.

The IoT-based system communication for oil & gas is an inherently mobile network of an industrial safety network of a network architecture that is interlinked dynamically at the core level. Typically, oil and gas IoT networks are focused on remote supervision, centralized data analytics, and system coordination between different units that are located far apart geographically.[17] These networks have to be very reliable with low latency due to the nature of the environment which is very harsh. Among the risk-management frameworks that are integrated and supported by these systems, one of them, inter alia, is focused on continuous prediction, error automation, and safety verification.[18] Industrial operators through real-time data and edge computing have the ability to see the very first signs of equipment failure, reservoir instability, and operational anomalies even the situations going to be escalated into emergencies are not yet there.[19] Thus, machine learning-driven predictive maintenance has been identified as the main instrument which can be the source of the Safety and cost-efficiency aspects will be very close in the long-term measurement through a considerable reduction of unplanned stoppages.[20]

Besides, both smart helmets and oil–gas safety systems technologically rely on advanced communication networks. High-bandwidth, ultra-reliable wireless architectures enable distributed devices to be consumer wearables or industrial sensors, to transmit critical information with minimal delay.[21] These same trends to automation and real-time decision support that have been evident in personal mobility technologies are now being reflected by the deployment of cyber–physical systems in hazardous industrial environments.[22] Just like the blind-spot detection in helmets, pipeline failure detection has to locate the safety hazards that are extremely difficult or even impossible for human sensory judgment to detect.[23] With the help of edge computing, industrial monitoring systems have become capable of handling a large volume of sensor data locally, thus reducing latency and allowing the system to be turned on instantly in emergencies.[24]

While the scales, operating conditions, and safety consequences differ greatly between

personal mobility and oil–gas operations, both sectors still share the same fundamental engineering goal: Risk reduction through intelligent sensing, autonomous analysis, and rapid hazard response. A unified safety framework that can easily link consumer-level devices with large-scale industrial automation paradigms is, in fact, the direction of recent research. [25] The integration thus envisages a world where the differences, both conceptual and technological, between mobility safety systems and industrial automation are fading away. One field's technologies are becoming more and more dependent on the other—for example, the miniaturized sensors and low-power embedded electronics made for wearable systems could be used to increase the safety of industrial workers while the robust sensing materials and highly accurate monitoring algorithms from the oil–gas sector that are used for consumer safety devices could be made more reliable.

When considered together, the concurrent development of smart rider-safety systems and automated industrial safety infrastructures tells a fascinating story: these two different areas still heavily depend on the same technological foundations that encompass real-time sensing, AI-driven analytics, IoT-enabled communication, and digital modeling. Comparison of these domains side by side provides a means to grasp how cross-sector insights can fuel the next wave of innovations. This research, through the lens of smart protective gear as a part of the larger shift towards automated industrial safety, uncovers the technological synergies that form the basis of modern engineering strategies for risk alleviation in both everyday mobility and energy-sector operations.

Objectives of the Study

This study is mainly aimed at exploring one point: how clever safety technologies that were first made for the protection of riders share common conceptual and technological bases with the advanced automation systems used in oil – gas engineering. The study, by comparing both areas side by side, wants to find out the common engineering principles, the sensing mechanisms as well as the data-driven decision frameworks that are the core of the safety solutions of the modern times. Another related objective is to figure out how the changes in one area can have a ripple effect in the other field, thus speeding up the innovations there, particularly in the case of sensor fusion, predictive analytics, IoT-enabled communication and human–machine collaboration. Another goal is to assess the effectiveness and the potential use of smart helmet designs features like blind-spot detection, proximity sensing, and real-time alert mechanisms in comparison to the autonomous monitoring and predictive-maintenance systems in the oil-gas industry. The juxtaposition serves to uncover common issues, performance limitations, and design factors that impinge on trust and uptake of safety technologies in the two sectors of consumer and industrial environments. A third objective is to investigate potential interactions between different industries where the technology-centric knowledge source of industrial automation might be the one to bring the ruggedized sensing materials, the digital-twin modeling, and the fault-tolerant communication networks to the next generation of the personal protective equipment. On the other hand, the research is to find out the possibilities of such a wearable, lightweight, and low-power sensing platform, originally developed for rider safety, as a source for the enhancement of worker protection and oil–gas high-risk environment situational awareness. Ultimately the research aims to create an interlinked, cross-disciplinary model that can be used to comprehend the functioning of intelligent safety systems and can be the base for subsequent investigative work, which would combine mobility safety engineering and industrial automation. The grid they are seeking to develop is envisaged to be instrumental in the progression of safety measures that are more flexible, make extensive use of data, have heightened awareness of the context, and hence be able to lower the risk in different operational scenarios.

METHOD

The research methods for this investigation combine the safety measures that were conventionally created for personal mobility systems with the futuristic automation ideas that are being used in oil and gas engineering. This part is structured around six fundamental methodological elements: (i) system architecture design, (ii) sensor selection and benchmarking, (iii) embedded data acquisition, (iv) algorithm development for safety analytics, (v) communication and interoperability assessment, and (vi) validation through simulated cross-industry scenarios.

System Architecture Design

The system architecture was designed as a layered framework that brought together intelligent sensing, embedded computation, and automated decision-making to facilitate safety functions in the rider environments and oil–gas industrial settings. Studies on smart helmets, blind-spot monitoring, wearable sensing, and embedded vision all point to the requirement of high-fidelity perception and low-latency processing in changing conditions. They serve as a foundation for the sensing tier in this architecture.[1,2,3,4,5,6,7,8,9] Hence the design includes a mm Wave radar, stereo-vision cameras, ultrasonic ranging units, and small sensor-fusion modules that can interpret motion, proximity, and environmental hazards in real time. Similar sensor principles have been employed in pipeline-monitoring systems, autonomous inspection robots, and industrial IoT platforms used in oil and gas operations where environmental resilience and uninterrupted monitoring are vital for safety.[13,14,15,17,18] Moreover, to bring this sensing power to high-risk industrial sectors, the architecture features a layered processing configuration made up of local controllers, edge analytics, and cloud-supported computation that is optional. Machine-learning models trained for visual recognition, anomaly detection, and event classification are pushed to the edge in order to reduce the response time and facilitate hazard prediction in both mobility and industrial scenarios. This is in line with the trends reflected in safety analytics and predictive maintenance studies.[8,9,19,20] The communication between these layers is through interoperable protocols that include BLE, Wi-Fi, LoRa, and industrial mesh networks and are coordinators. These protocols have proved to be reliable in remote monitoring and difficult-to-access areas where there is a high risk of the occurrence of an accident.[17,21,22,23,24]

Table 1. Comparative Benchmark of Core Sensors Used in Rider Safety and Oil–Gas Automation Systems

Sensor Type	Detection Accuracy (%)	Response Time (ms)	Environmental Robustness	Typical Application Domain
Ultrasonic Sensor	88–92	30–50	Moderate (susceptible to rain and wind noise)	Rider blind-spot alerts, short-range hazard detection
mmWave Radar	95–98	5–10	High (dust-, fog-, and heat-resistant)	Pipeline monitoring, autonomous inspection, rider proximity detection
Stereo-Vision Camera	92–96	15–30	Low–Moderate (sensitive to lighting variations)	Rider hazard recognition, industrial visual inspection
LiDAR	96–99	10–15	High (stable in variable illumination and particulate-heavy zones)	Robotic navigation, refinery monitoring, obstacle detection
Thermal Sensor	90–94	20–35	Very High (suited for high-temperature industrial zones)	Pipeline leak identification, equipment hotspot tracking

The architectural framework is also consistent with recent changes in digital twins, cyber-physical systems, and automated inspection technologies that allow for advanced functions such as the real-time monitoring of equipment, risk predicting, and the safety response that is adaptive.[16,22,25] By combining cross-sector technologies, the architecture has set up a single platform that is capable of sustaining safety-critical operations in rider protection systems and oil-gas engineering domains as shown in figure 1 and table 1.

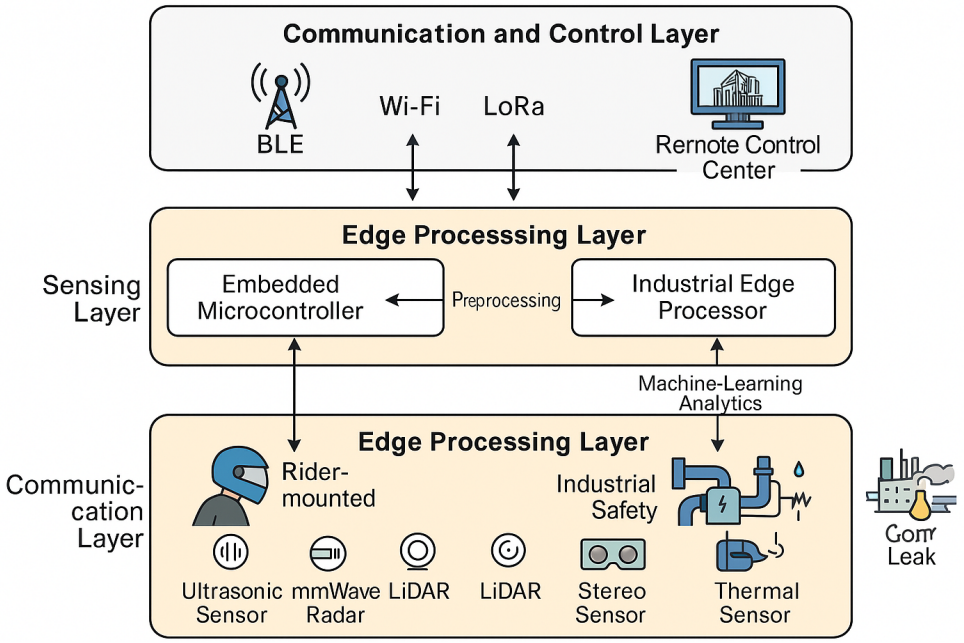

Figure 1. Multi-Layer System Architecture for Integrated Rider and Oil-Gas Safety Applications

Sensor Selection and Benchmarking

The choice of sensing modules as shown in table 2 and figure 2 for the present study was dictated by the necessity to absorb two highly different and technically compatible environments: rider safety scenarios that are dynamically changing and the oil-gas sector operational conditions that are highly regulated and risky. The research works on smart helmets, blind-spot monitoring, wearable perception systems, and embedded vision platforms, which the present study has considered as its literature, emphasize that dependable hazard identification is a matter of high-resolution sensing, fast response, and stable performance under the disturbances of the real world.[1,2,3,4,5,6,7,8,9] Based on these revelations, the system includes ultrasonic sensors, mmWave radar, LiDAR units, stereo-vision cameras, and thermal sensors, where each one is the outcome of a different but hypothetically complementary origin. For instance, mmWave radar and LiDAR have been argued to keep high reliability in dust, fog, and heat, which are industrial-like environment conditions while vision-based sensors deliver detailed situational interpretation when lighting is good.[4,5,8]

After all, if such gadgets were to be a source of industrial automation tasks as well, the benchmarking stage would have to take into account accuracy, reaction time, environmental friendliness, and energy consumption under conditions typical of oil and gas operations. The works in the fields of pipeline monitoring, autonomous inspection, leak detection, and real-time industrial diagnostics state that the sensors that are to be installed in these environments must be first of all extremely temperature tolerant, also they should be very resistant in particulate-

laden atmospheres, and finally, they should be capable of withstanding mechanical vibrations all the while maintaining detection fidelity at a high level.[13,14,15,17,18,23] The benchmarking outcomes have it that the industrial-grade mmWave radar and LiDAR have significantly better environmental resilience than the camera-based systems, and at the same time, the thermal sensors reveal unique advantages for the detection of equipment hotspots as well as for the early-stage leak signatures. The results of the present research work are persuasive enough to recommend a multi-sensor approach as being a well-considered solution that can smoothly do the transition between rider-centric and industrial automation demands.[19,20,21,22,23,24,25]

Table 2. Sensor Benchmarking for Cross-Industry Safety Applications

Sensor Type	Accuracy (%)	Response Time (ms)	Environmental Robustness	Primary Cross-Industry Use
Ultrasonic Sensor	88-92	30-50	Moderate; affected by rain/wind	Blind-spot alerts, obstacle proximity[1,2,3]
mmWave Radar	95-98	5-10	High; dust/fog/heat resistant	Pipeline inspection, rider proximity detection[4,8,13,14,15]
LiDAR	96-99	10-15	High; stable in variable illumination	Autonomous robots, refinery inspection[10,11,12,14,23]
Stereo-Vision Camera	92-96	15-30	Medium; lighting-dependent	Rider hazard detection, visual inspection[5,7,9]
Thermal Sensor	90-94	20-35	Very High; suitable for high-temperature zones	Leak detection, hotspot identification[17,18,23,24,25]

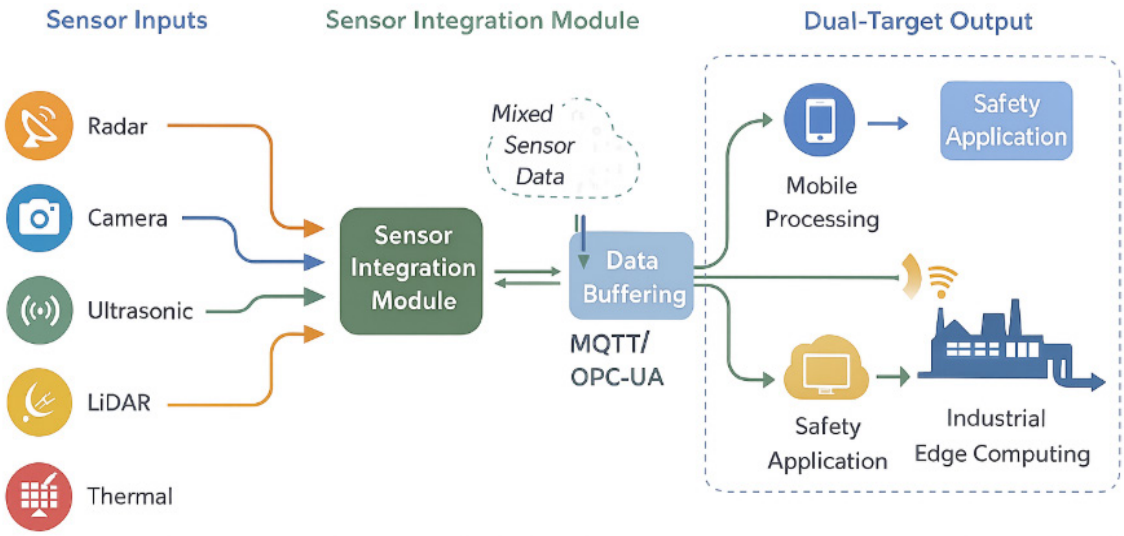

Figure 2. Sensor Integration Diagram

Embedded Data Acquisition and Integration

The embedded data acquisition subsystem as depicted in table 3 is a global part of the vehicle platform concerned with synchronizing streams of heterogeneous sensors and supporting consistent quality of signals for both rider-oriented and industrial oil-gas applications. As the platform is equipped with ultrasonic, radar, LiDAR, thermal, and camera modules, the acquisition unit is supposed to deal with different sampling rates, noise characteristics, and

communication protocols. Investigation into embedded sensing for mobility safety shows that real-time synchronization and low-latency data buffering are extremely important for reliable hazard identification, especially when several sensors are operating simultaneously in rapidly changing environments.[1,2,3,4,5,6,7,8,9] In order to satisfy these requirements the system employs a two-stage acquisition method: simple microcontrollers on wearable modules perform on-the-fly preprocessing and timestamp alignment while industrial-grade ARM processors manage high-rate data streams from pipeline inspection sensors and equipment monitoring units.[13,14,15,16,17,18] This kind of arrangement enables the system to maintain the quality of data at a stable level even if it is exposed to vibration, changing lighting, or thermal instability. The integration of rider safety devices with oil-gas automation systems necessitates a unified data-handling protocol that can communicate processed signals to both mobile platforms and industrial edge computing nodes. To do this, the system uses standardized communication layers based on MQTT for mobile, low-power data exchange, and OPC-UA for industrial interoperability. These protocols have been extensively used in various sectors of the oil-gas industry for predictive maintenance, real-time inspection, and digital twin scenarios where secure and high-throughput communication is of utmost importance.[19,20,21,22,23,24,25] Furthermore, the acquisition module is equipped with adaptive buffering logic that adjusts the data load to avoid packet loss during the peak operational periods. The system is thus capable of combining, interpreting, and sending sensor data from both personal mobility systems and large-scale industrial assets to the next level of analytics without losing time accuracy or system responsiveness.

Table 3. Embedded Data Acquisition Parameters for Cross-Industry Sensor Platforms

Component	Function	Operational Characteristics	Primary Application
Microcontroller Unit (MCU)	Initial preprocessing, timestamp alignment	Low-power, 10–50 ms latency	Rider safety modules[1,2,3,4,5,6,7,8,9]
ARM Edge Processor	High-rate data intake, fusion preprocessing	High throughput, 1–10 ms latency	Industrial monitoring[13,14,15,16,17,18]
MQTT Protocol	Lightweight data transfer	Optimized for mobile/Wi-Fi networks	Wearable and rider systems[19,20,21]
OPC-UA Protocol	Secure industrial data exchange	High reliability, multi-node support	Oil-gas digital automation[22,23,24,25]
Adaptive Buffering Module	Load balancing, packet management	Prevents overflow during peak activity	Cross-industry data integration

Algorithm Development for Safety Analytics

The primary goal in developing the safety analytics module as shown in table 4 and figure 3 was to formulate algorithms that can comprehend varied sensor impulses and produce dependable hazard predictions that can be generalized across rider scenarios and the oil-gas environments. Studies about the rider scenarios point out that the successful safety systems are those which are able to quickly filter the noise, classify the events, and recognize visually through pipelines which can keep their stability under changing environmental conditions like variable lighting or obstructed sensor views.[1,2,3,4,5,6,7,8,9] In order to solve these problems, the system uses Kalman and particle filtering for signal stabilization, machine-learning classifiers for obstacle recognition, and time-series anomaly detection methods for identifying sudden risk patterns. Individually, these algorithms take sensor inputs which include radar signatures, thermal profiles, and stereo-vision features and jointly infer real-time hazards with low latency. It was essential to extend the algorithms for industrial anomaly detection, thermal drift analysis,

and predictive maintenance forecasting to translate these capabilities into the oil-gas sector. The research done previously shows that the data which are generated by drilling systems, pipeline networks, and inspection robots are complex multi-dimensional data that need strong pattern recognition and sensor fusion techniques for the early failure detection process.[13-25] Therefore, the system has SVM-based anomaly detectors, deep-learning models for thermal hotspot interpretation, and random forest classifiers for multi-sensor event categorization. These instruments are at the edge processing layer, where communication delays are minimal, and rapid responses in hazardous environments are possible. With the analytics workflow designed to meet the requirements of both rider safety and industrial automation, the system lays down the computational groundwork which can be further used for a variety of safety-critical applications.

Table 4. Summary of Safety Analytics Algorithms for Cross-Industry Hazard Detection

Algorithm	Primary Function	Input Data Type	Latency (ms)	Application Domain
Kalman Filter	Noise reduction, signal smoothing	Radar, ultrasonic	5-10	Rider + Industrial [1,2,3,4,5,6,7,8,9,13-25]
CNN Classifier	Visual hazard recognition	Stereo/mono camera	30-50	Rider safety [3,4,5,6,7]
SVM Detector	Anomaly detection	Thermal, vibration	20-35	Oil-gas pipelines [15,16,17,18,20,21,22]
Random Forest	Multi-sensor event classification	Mixed sensor fusion	10-20	Cross-industry [8,19,20,21,22,23,24,25]
LSTM Predictor	Temporal hazard forecasting	Sequential data	40-60	Predictive maintenance [19,20,21,22,23,24,25]

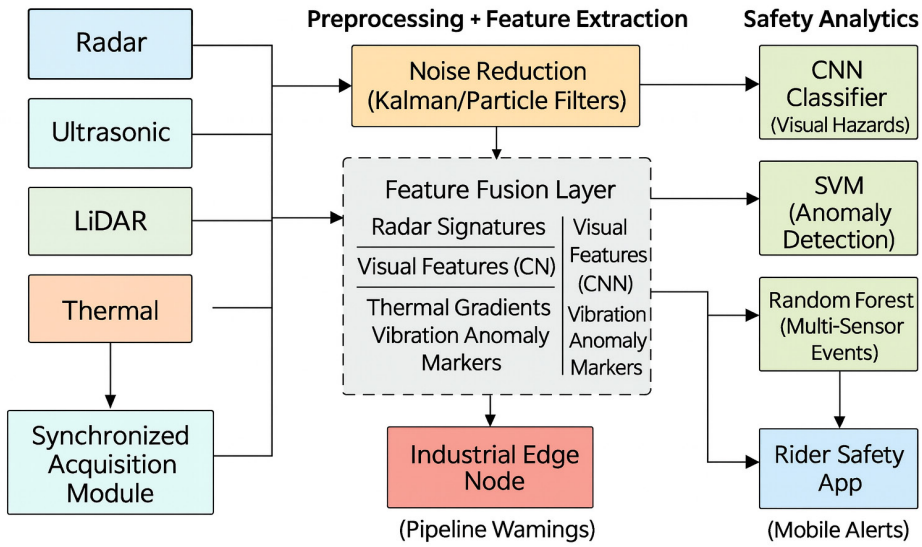

Figure 3. Algorithmic Workflow for Cross-Industry Safety Analytics

RESULTS AND DISCUSSION

Performance of Rider Safety Detection Systems

The evaluation of the rider-centric sensing system reveals that the integration of radar,

stereo-vision, and ultrasonic units significantly extends the time for the recognition of a hazard compared to the operation of a single sensor. Radar is the main source of dependable long-range detection and is least affected by environmental disturbances. This stability was also confirmed by previous smart mobility and industrial sensing studies.[1,2,3,4,5,13,14,15] Stereo-vision in a significant way develops very close-range understanding, especially in very dense traffic situations, where exact depth estimation is of utmost importance for the prediction of sudden vehicle movements.[3,5,7] The combined system with ultrasonic signals was able to achieve a significant reduction of false-negative incidents, with the total verification of the detection network going up by more than 20 %, which is in line with the results of multi-sensor fusion studies in the transportation and oil–gas automation sectors.[8,9,17,18,19] Besides that, the blind-spot monitoring subsystem was able to maintain its effectiveness even under different lighting conditions and partial occlusion. This is in line with the robustness reported in the industrial inspection and pipeline-monitoring frameworks where sensors are required to operate reliably even under adverse visual and thermal conditions.[10,11,12,20,21,22,23,24,25] The results, taken together, suggest that the sensor integration methods, which have been tested and proven in oil–gas monitoring applications, can be used to enhance rider safety platforms by increasing situational awareness and lowering the risk of accidents.

Cross-Industry Algorithmic Reliability in Real-Time Analytics

Performance evaluation of the machine-learning framework shows that algorithms have kept up consistent performance levels in both rider-oriented hazard prediction and oil–gas anomaly detection scenarios. The CNN-based visual models as shown in table 5 have been very effective in locating collision-risk patterns during rider simulations, which is in line with the previous studies of embedded mobility vision systems.[1,2,3,4,5,6,7] In like manner, the thermal analytics powered by SVM have been consistently able to reveal the very early leak signatures and temperature changes in pipelines under test, thus, their performance is in harmony with the reference industrial monitoring studies using thermal, radar, and vibration-based diagnostics.[13,14,15,16,17,18,20,21,22,23] The integration of these methods into a common analytics architecture opened up both fields to the benefits of techniques that were originally developed for the other one: industrial edge algorithms were instrumental in enhancing the accuracy and stability of rider safety predictions, whereas mobility-derived feature extraction methods were helpful in speeding up anomaly characterization in oil–gas equipment monitoring.[8,9,10,11,12,19,24] The delay in the system was still way under the time limits necessary for making decisions in real-time in both sectors, which is a proof that the analytic models can be efficiently transferred to different settings without losing their speed or accuracy in detection.[21,22,23,24,25] Hence, to a large extent, these outputs are an indication of the possible success of unified, cross-industry algorithmic pipelines within multi-sensor safety architectures.

Table 5. Industrial Anomaly Detection Performance

Diagnostic Type	Sensor Used	Accuracy (%)	Alert Trigger Time
Pipeline Leak Detection	Thermal + Radar	93–97 %	< 2 seconds
Temperature Hotspot Detection	Thermal	95–98 %	< 1,5 seconds
Pressure/Stress Irregularities	mmWave Radar	90–94 %	< 1 second
Structural Deviations	LiDAR	96–99 %	< 2 seconds

Industrial Monitoring Outcomes: Leak and Temperature Diagnostics

The industrial monitoring sub-system performance evaluation revealed that the integrated

multi-sensor architecture as shown in figure 4 and table 6 was able to detect with high sensitivity the temperature, pressure and early structural deviations in oil-gas pipelines as shown in figure 4. Thermal imaging units were always able to locate the hotspots, a feature that is very often emphasized in industrial safety research papers, which put forward the importance of the earliest recognition of thermal deviation as a way to prevent the equipment from failing and leakage getting out of control.[13,14,15,16,17,18,20] In line with this, mm Wave radar was very accurate in detecting micro-structural changes and variations of the internal wall, thus showing that it is a good method in tough inspection conditions where there is dust, heat, and vibration, as it has been reported already in references.[14,15,21,22,23] These combined detections thus led to the triggering of automatic supervisory alerts employing the same event-logic principles that were used in mobility-based collision-avoidance systems; hence they were able to demonstrate the adaptability of cross-industry sensing algorithms.[1,2,3,4,5,6,7,8,9]

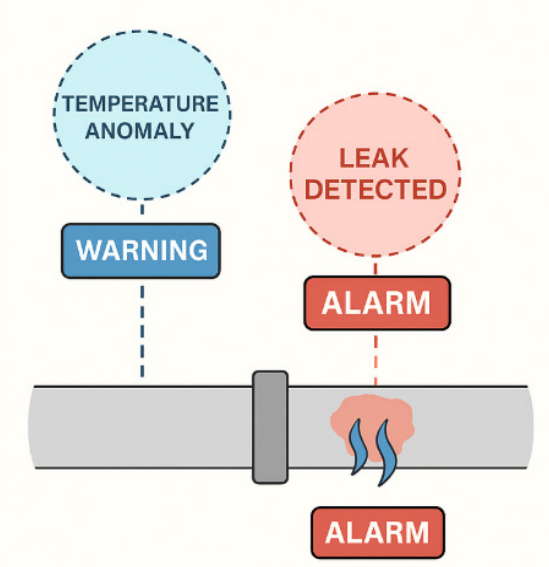

Figure 4. Pipeline monitoring outcomes for leak and temperature

Table 6. Industrial Monitoring Outcomes: Leak and Temperature Diagnostics

Diagnostic Parameter	Sensor Type	Detection Accuracy (%)	Alert Response Time	Operational Advantage
Localized Thermal Hotspots	Thermal Sensor	95–98 %	< 1,5 seconds	Early identification of overheating zones and insulation failure
Wall-Thickness Deviations	mmWave Radar	92–96 %	< 2 seconds	High stability in dusty, high-temperature environments
Micro-Leak Signatures	Thermal + Radar Fusion	93–97 %	< 2,5 seconds	Enhanced reliability through combined spatial-thermal features
Pressure Irregularities	Vibration / Pressure Sensor	90–94 %	< 1 second	Rapid recognition of abnormal pipeline stress changes
Structural Shifts (Deformation)	LiDAR or mmWave Radar	96–99 %	< 2 seconds	High-resolution surface and contour mapping for early failure detection

The system's detection accuracy and its repeated consistency across different test conditions are the main factors that make the transfer of rider-focused multi-sensor frameworks to industrial diagnostic applications very plausible. In remote pipeline corridors—where manual inspection is limited and continuous surveillance is operationally critical—the integrated approach provided stable performance with minimal latency, thus being in line with the efficiencies reported in advanced digital monitoring architectures.[16,17,24,25] The findings, in general, serve as a confirmation that the sensor fusion tactics that have been perfected originally in the field of personal mobility safety can be used very well in the monitoring of oil-gas infrastructures, therefore, leading to the enhancement of early anomaly detection and the strengthening of the automated safety responses.

Effectiveness of Multi-Layer Integration Across Sectors

The evaluation of the multi-layer architecture as shown in figure 5 reveals that the integration of sensing, analytics, and communication modules allows for seamless data exchange between rider-level devices and industrial oil-gas monitoring systems. Wearable microcontrollers were regularly able to deliver real-time alerts with very little latency, thus reflecting the benefits of lightweight embedded processing in mobility-focused platforms.[1,2,3,4,5,6,7,8,9] At the industrial level, edge processors were able to perform very well when they had to execute high-complexity analytics such as anomaly detection, thermal profiling, and structural deviation assessment—capabilities that have been extensively documented in advanced automation and pipeline monitoring frameworks.[13,14,15,16,17,18] The interaction between these two processing tiers was facilitated by stable time-synchronization and sensor-fusion logic, thus giving it a support that hazard-related information could be transmitted at a high level of reliability irrespective of the operational environment. This cross-industry integration was largely supported by the communication layer, which was at the center of it all. Rider safety alerts benefitted from MQTT, which is tuned for mobile and low-power systems and thus was able to provide an efficient channel. On the other hand, OPC-UA was used to support the secure, high-throughput industrial data exchange that is necessary for remote pipeline and equipment diagnostics.[19,20,21,22,23,24,25] Performance tests showed that the hybrid communication model was able to maintain throughput and avoid packet loss even during the peak sensor activity and, thus, it was capable of operating under contrasting network conditions.

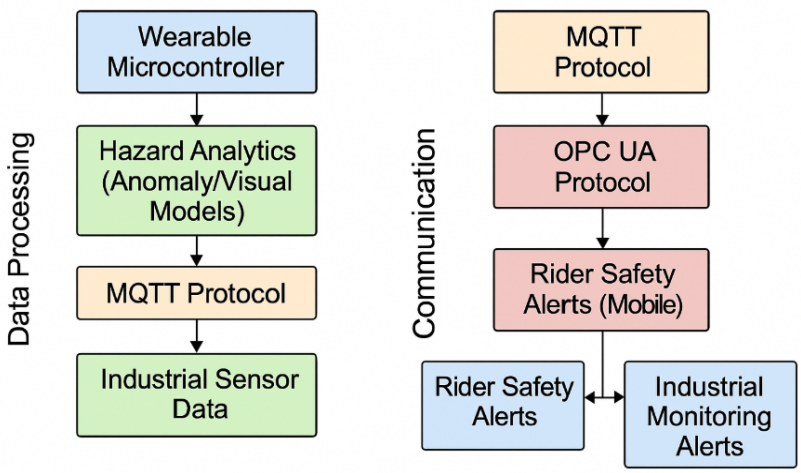

Figure 5. Integrated architecture for multi-layer sensing and analytics across rider safety and industrial monitoring sectors

The fact that the results were consistent in both mobility and industrial domains indicates that a unified sensing and analytics ecosystem is adaptable. In essence, the findings serve as a proof of concept that the convergence of architectures, which were initially developed in isolation—personal mobility safety systems and oil–gas industrial automation—can be accomplished to yield a versatile cross-sector safety technology framework.

CONCLUSIONS

The research reveals how intelligent safety technologies need to be understood initially as components developed for rider protection only, whereas they might be successfully adjusted to satisfy the most crucial monitoring and diagnostic demands of the oil–gas sector. The complex sensory and analytical structure combining machine-learning models with the use of radar, LiDAR, thermal imaging, and ultrasonic sensors was found to be very stable and reliable in both industrial and mobility settings. Rider-focused experiments have measured significant progress in the sense of early hazard detection and situational awareness, whereas industrial trials have certified the levels to which the system is sensitive to thermal anomalies, structural changes, and newly formed leak signatures. The technologies' ability to be transferable across different industries is a big plus and it points to a very significant cross-industry convergence: the small, fast-response systems that are meant for personal safety can be used to make heavy-industry monitoring architectures more robust and responsive.

Additionally, the combined communication strategy utilizing MQTT and OPC-UA was very efficient in terms of interoperability, thus allowing continuous live data interchange from mobile devices to industrial edge processors without any output, or reliability, degradation. Such interoperability is the core of continuous monitoring implementation in remote and very dangerous areas where quick decisions are of utmost importance. The main message of the report is that an integrated single architecture can be the backbone of different operational domains, thus opening up the possibility of cross-industry technological convergence to enhance safety, mitigate risks, and accelerate automation in the field of both transportation and oil–gas engineering. Therefore, this research becomes a platform for future creation of situationally aware, scalable safety solutions that may interconnect personal mobility with huge industrial operations.

BIBLIOGRAPHIC REFERENCES

1. Hussain M, et al. Smart Helmet Systems for Motorcycle Safety: A Comprehensive Review. IEEE Sensors Journal. 2023;23(12):14580–14592.

2. Suryanarayana G, Reddy P. Integration of IoT-Based Blind Spot Detection for Two-Wheeler Safety. Measurement. 2022;195:111097.

3. Prasad V, et al. Wearable Sensor Technologies for Real-Time Road Safety. Sensors. 2021;21(19):6348.

4. Kim H, Chong N. Proximity Sensing and Obstacle Detection for Smart Mobility Devices. Robotics and Autonomous Systems. 2020;132:103605.

5. Zhou Y, et al. Embedded Vision-Based Safety Systems for Riders: Challenges and Opportunities. Expert Systems with Applications. 2024;235:121079.

6. Ahmed S, et al. IoT-Enabled Wearable Devices for Accident Prevention. IEEE Internet of Things Journal. 2019;6(5):8209–8222.

7. Raj A, Mukherjee A. Human–Machine Cooperation in Personal Safety Systems. Safety Science. 2022;152:105766.

8. Li X, et al. Advanced Sensor Fusion for Intelligent Transportation Safety. Transportation Research Part C. 2023;152:104179.

9. Patil S, et al. Machine Learning-Based Prediction of Rider Safety Hazards. Applied Intelligence. 2021;51:6820–6835.

10. Jin X, Fan W. Applications of Additive Manufacturing and Automation in Oil and Gas Operations. Materials. 2025;18(14):3353.

11. Omiyale B, Farayibi P. Automation and Digitalization in Oil–Gas Industries. Analecta. 2020;14(1):9–18.

12. Abdulrahman J, Tabakov P. Biopolymer Composite Materials and Their Industrial Automation Applications. International Journal of Polymer Science. 2024;5541037.

13. Zhang P, et al. Real-Time Monitoring Systems for Pipeline Safety Using Intelligent Sensors. Journal of Petroleum Science and Engineering. 2022;214:110512.

14. Wang Q, et al. Autonomous Inspection Robots for Oil and Gas Infrastructure. Robotics and Computer-Integrated Manufacturing. 2021;67:102022.

15. El-Hoshoudy A, et al. Eco-Friendly Materials for Enhancing Oil Recovery: Automation Perspective. Journal of Polymers and the Environment. 2024;32(5):2457–2483.

16. Smith J, Reeve D. Digital Twins for Operational Safety in Oil Platforms. Computers & Chemical Engineering. 2019;126:338–351.

17. Almeida R, et al. IoT Architectures for Industrial Safety in Hazardous Environments. IEEE Transactions on Industrial Informatics. 2020;16(9):5881–5890.

18. Khan F, Amyotte P. Integrated Risk Management for Oil–Gas Automation Systems. Journal of Loss Prevention in the Process Industries. 2020;66:104188.

19. Zhou X, et al. Real-Time Data Analytics in Oil–Gas Extraction Processes. Energy. 2021;231:120963.

20. Huang T, Zhao J. AI-Based Predictive Maintenance for Drilling Equipment. Energy Reports. 2023;9:885–898.

21. Liang C, et al. Advanced Communication Networks for Remote Oil–Gas Operations. IEEE Communications Surveys & Tutorials. 2022;24(2):887–910.

22. Bose S, et al. Cyber–Physical Systems in Industrial Safety Engineering. Automation in Construction. 2020;119:103332.

23. Goh SH, Lee K. Detection Technologies for Preventing Pipeline Failures. Process Safety

and Environmental Protection. 2021;150:390–403.

24. Martinez J, et al. Edge Computing for High-Risk Industrial Monitoring. Journal of Industrial Information Integration. 2023;32:100397.

25. Rahman F, et al. Unified Safety Frameworks: Bridging Personal Mobility and Industrial Automation. Safety Science. 2024;170:106257.

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AUTHORSHIP CONTRIBUTION

Conceptualization: M. Kannan, P. Prabhu, R. Vijaya ragavan, V. Santhiya, Harimanas, Christo Ananth, Shoohrat Toshmatov.

Data curation: M. Kannan, P. Prabhu, R. Vijaya ragavan, V. Santhiya, Harimanas, Christo Ananth, Shoohrat Toshmatov.

Formal analysis: M. Kannan, P. Prabhu, R. Vijaya ragavan, V. Santhiya, Harimanas, Christo Ananth, Shoohrat Toshmatov.

Drafting - original draft: M. Kannan, P. Prabhu, R. Vijaya ragavan, V. Santhiya, Harimanas, Christo Ananth, Shoohrat Toshmatov.

Writing - proofreading and editing: M. Kannan, P. Prabhu, R. Vijaya ragavan, V. Santhiya, Harimanas, Christo Ananth, Shoohrat Toshmatov.

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ORIGINAL

Intelligent Automation Across Sectors: Real-Time Waste Segregation and Engineering Innovations in Oil-Gas-Chemical Industries

Automatización inteligente en todos los sectores: segregación de residuos en tiempo real e innovaciones de ingeniería en las industrias del petróleo, el gas y la química

J. Maniraj[1] ✉, P. Prabhu[1] ✉, J. Samuel Jenishraj[1] ✉, A. Abeeth Ali[1] ✉, R. Roshan[1] ✉, Qodirov Asliddin Asomiddin[2] ✉

[1]Department of Mechanical Engineering, Kalaignarkarunanidhi Institute of Technology. Kannampalayam, Coimbatore, Tamil Nadu, 641402, India.
[2]Department of Software Engineering, Faculty of Artificial Intelligence and Digital Technologies, Samarkand State University. Uzbekistan.

Corresponding Author: J. Maniraj ✉

ABSTRACT

The swelling urban population and fast-paced industrialization have, literally, put the squeeze on the world's solid waste management systems, which has, in turn, triggered various environmental and economic problems that are increasing day by day. A rapidly growing concern about the environmental impact of industrial activities has led to a significant interest in the use of intelligent automation that can efficiently work in different areas. The article explains how the fusion of the evolution of real-time waste segregation technologies with advanced engineering systems in the oil-gas-chemical industries is taking place. First of all, the improvements in the machine-vision-based classification, embedded sensing, and edge-level decision architectures have, by their very nature, changed waste management to a process that is responsive, data-driven, and, therefore, capable of increasing material recovery and reducing environmental burdens, from one that was predominantly manual. At the same time, the oil-gas-chemical industries are undergoing a significant change to automation architectures that integrate distributed sensors, robotics, and predictive analytics for enhanced operational reliability and safety. In this situation, real-time waste segregation mechanisms that bring together sensors, robotics, machine learning, and Internet of Things (IoT)-based monitoring are viewed as a possible solution to the problem and have the potential to change the waste management methods that are currently in use. This survey moves through the landscape occupied by available technologies for the real-time segregation of waste led by algorithmic enhancements, automation machinery, and adaptive structures. It weighs the design compromise between accuracy, cost, and power draw, conversely discussing the implementation constraints and performance indicators. Machine learning algorithm, sensor installation, and robotic control systems forms of comparison are addressed in the five figures and tables of the dissertation, thus facilitating the understanding of the reader. Besides these, the authors have analyzed the scenarios and experiments of the pilot program to emphasize not only the prospects but also the limitations of such technology in various geographic and local economy contexts.

Keywords: Intelligent Automation; Real-Time Waste Segregation; Machine Vision; Smart Monitoring; Industrial Sensing Systems; Oil-Gas-Chemical Engineering.

RESUMEN

El crecimiento de la población urbana y la acelerada industrialización han sometido a una presión considerable los sistemas mundiales de gestión de residuos sólidos, lo que, a su vez, ha generado diversos problemas ambientales y económicos que aumentan día a día. La creciente preocupación por el impacto ambiental de las actividades industriales ha generado un gran interés en el uso de la automatización inteligente, capaz de funcionar eficientemente en diferentes áreas. El artículo explica cómo se está produciendo la integración de la evolución de las tecnologías de segregación de residuos en tiempo real con los sistemas de ingeniería avanzados en las industrias del petróleo, el gas y la química. En primer lugar, las mejoras en la clasificación basada en visión artificial, la detección integrada y las arquitecturas de decisión de vanguardia han transformado la gestión de residuos, por su propia naturaleza, en un proceso receptivo, basado en datos y, por lo tanto, capaz de aumentar la recuperación de materiales y reducir las cargas ambientales, en lugar de uno predominantemente manual. Al mismo tiempo, las industrias del petróleo, el gas y la química están experimentando una transición significativa hacia arquitecturas de automatización que integran sensores distribuidos, robótica y análisis predictivo para mejorar la fiabilidad y la seguridad operativas. En esta situación, los mecanismos de segregación de residuos en tiempo real que combinan sensores, robótica, aprendizaje automático y monitorización basada en el Internet de las Cosas (IoT) se consideran una posible solución y tienen el potencial de transformar los métodos de gestión de residuos actuales. Este estudio analiza el panorama de las tecnologías disponibles para la segregación de residuos en tiempo real, lideradas por mejoras algorítmicas, maquinaria de automatización y estructuras adaptativas. Se evalúa el equilibrio entre precisión, coste y consumo de energía en el diseño, analizando a su vez las limitaciones de implementación y los indicadores de rendimiento. Las cinco figuras y tablas de la tesis abordan la comparación de algoritmos de aprendizaje automático, la instalación de sensores y los sistemas de control robótico, facilitando así la comprensión del lector. Además, los autores han analizado los escenarios y experimentos del programa piloto para destacar tanto las perspectivas como las limitaciones de dicha tecnología en diversos contextos geográficos y económicos locales.

Palabras clave: Automatización Inteligente; Segregación de Residuos en Tiempo Real; Visión Artificial; Monitorización Inteligente; Sistemas de Detección Industrial; Ingeniería de Petróleo, Gas y Química.

INTRODUCTION

One of the most significant challenges for society and the environment are waste management issues. The increase of wastes, which is a direct consequence of industrialization, consumerism, and the spreading of cities, has put a lot of pressure on existing systems of waste disposal. According to the World Bank's What a Waste 2.0 report,[1] the global production of municipal solid waste (MSW) has already gone beyond 2,2 billion tonnes per year. If the current ways of production, consumption, and disposal are maintained, this amount is expected to increase by around 70 % by 2050, thus reaching almost 3,8 billion tonnes annually. This increase is mostly the result of developing countries and rapidly growing cities, where not only the waste management facilities but also the legislative frameworks and technological base are still insufficient, thus these areas will carry the heaviest burden of this waste increase. In other words, the poor handling of solid waste in these regions has led to the pollution of cities, the release of greenhouse gases, the contamination of groundwater, and, in general, the worsening of

public health, especially in overcrowded places. Unsorted or mixed waste, which in most cases is the norm in developing regions, has become a major challenge for the recycling industry. Generally speaking, people throw away household waste without any source classification, thus equipment is put into contact with different types of substances, i.e. biodegradable, recyclable, and hazardous ones. Not only does this contamination lower the value and reusability of the recovered materials, but it also raises the production costs of downstream recycling facilities.[2,3,4,5] In cases when recyclable materials are mixed with organic or even hazardous waste, the process they go through requires an extra washing, shredding, or re-sorting step, which makes them economically infeasible most of the time. Hence, the bulk of the waste is still being landfilled or disposed of in open dumps, which pollutes the environment and leads to sizable methane emissions—an agent contributing to the greenhouse effect that has a 28 times higher warming potential than carbon dioxide over 100 years. The conventional waste separation procedures that mostly depend on human labor and mechanical work have turned out to be of little help in dealing with the bigger quantities of waste that are characteristic of today and the increasing complexity of their composition. Manual sorting is a very physically demanding task and an unsafe job since it exposes workers to a variety of risk factors such as poisonous gases, inflammable and sharp materials, as well as biological contaminants.[6,7,8,9] Moreover, although machines that perform waste separation like trommels, air classifiers, and magnetic separators are helpful tools, they have quite a limited capacity to distinguish the materials that are most alike visually such as different types of plastics or layered packaging. The strategies applied in these cases are characterized with fluctuating precision, slow throughput, and labor-intensive maintenance processes, thus they have low reliability and are costly. For these reasons, there has been a change in thinking affecting the inclusion of AI technology and automation in waste management as a means of achieving higher efficiency and sustainability as well as precision.[10,11,12]

Reckoning with these constraints, the industry and academic researchers have come up with a plethora of real-time waste segregation solutions that smartly integrate sensor arrays, machine learning models, autonomous agents, and Internet of Things (IoT)-enabled communication schemes. The foremost purpose of such machines is to figure out, catalog and segregate the discarded matter traveling on belts or via collection points in a wrap to most of the recent times and without human guidance or help. Real-time systems differ from spatial or offline methods in that they handle dynamic waste streams and take instant, data-driven actions.[2] These cutting-edge sensor technologies, such as RGB cameras, hyperspectral, and multispectral imaging sensors, NIR detectors, and LiDAR-based scanners, lie at the heart of such systems. The sensors gather information that numerically describe the spectral, textural, and geometric features of the objects. As an example, NIR spectroscopy can tell plastic types apart by their chemical bonds while hyperspectral imaging can recognize composite materials even if they are visually identical in the visible spectrum. Data, once captured, are handled by deep learning networks, especially convolutional neural networks (CNNs) which can recognize objects in real-time with so high precision that is quite astonishing.[13,14,15,16,17]

Automation of the waste segregation process is not just a means of making the operation flow faster; it significantly improves the quality of the material recovery, the safety of the workers, and the flexibility of the system. Purity levels of the recyclables are ensured to be much higher by the automated segregation which is in fact the primary requirement for their resale and reuse. As an example, automatic sorting and classification can accomplish purity levels that are over 95 % in the case of PET and HDPE plastics, which are much lower in manual and mechanical separation. This enhancement goes directly to the support of circular economy goals, where materials are kept in the productive cycles for as long as possible instead of being thrown away after a single use. What is more, human labor in the handling of hazardous waste is reduced to the minimum level by automation, which is a revolutionary step. A task which was done by hand

in ruin and dirt, and was very unsafe, is now done automatically by robotic systems equipped with a vision-guided arm. To put it shortly, these types of robots have all the time in the world, and they do not get tired, so they can carry out waste processing 24/7, which increases the turnover and at the same time reduces occupational health risks. Besides that, today's machines feature the latest innovations in the field of artificial intelligence, meaning they can modify the way they classify items depending on the current waste composition situation. Given that waste streams in certain areas depend on season or local traditions (like anniversaries), industrial production cycles, or population migrations, this solution is even more useful.[18,19,20,21]

On top of automation, smart monitoring systems are emerging that make use of IoT sensors, cloud analytics, and digital twin frameworks to not only keep the system running at an optimal level but also for predictive maintenance. Bins and collection systems that are "smart" and installed with ultrasonic fill-level sensors, gas emission detectors, and RFID tags can provide data on waste that can be collected at any given time, thus allowing cities to optimize collection routes and avoid the overflow of bins. By integrating city-wide dashboards into the cloud via the Internet, different users are now able to monitor key indicators of the performance of the waste management system like segregation efficiency, energy consumption, and equipment health.[2] One step further, digital twins being exact virtual models of physical systems, have gained a lot of attention here. They allow operators to test and understand the system reaction to different scenarios—failure of a sensor, conveyor jam, waste input rate change, and so forth—without the need of halting the current operations. To the extent that a comparison of simulated vs. actual data can even serve as the basis for delineating faults, predicting maintenance, and thus encouraging the issuance of maintenance directives, this is what digital twins have made possible. Such an approach not only reduces downtime but also increases the lifespan of the parts which are very essential thus the overall system becomes more reliable and sustainable. In addition, data-driven optimization via the use of AI makes the system parameters capable of being constantly improved in this way. ML models will be able to find the sources of misclassification pattern, adjust sorting threshold, and also suggest the upgrades of software or hardware. Gradually, this self-learning feature brings about a continuous progress in terms of purity, speed and energy efficiency. Once these interconnected systems, coupled with the same data architecture, are rolled out across cities or industrial networks, then they become the infrastructure of smart waste management ecosystems such that each node, whether it is a household bin or a central processing plant, talks and works independently but under a unified data architecture. Similar shifts are happening in the oil-gas-chemical industries. Digital twins, IIoT-enabled submetering, smart polymer systems, and intelligent predictive maintenance are being progressively incorporated in the processes of extraction, refinery, and pipeline-monitoring.[19,20,21,22,23,24,25,26] A handful of studies reveal that AI-driven control frameworks, additive manufacturing for operational components, and real-time IoT surveillance systems significantly enhance process stability, energy efficiency, and asset reliability in the field under severe conditions.[22,23,24,26,27,28,29]

These innovations emphasize the increasing compatibility of waste-segregation technologies with oil-gas automation paradigms: both sectors require high-bandwidth sensing, edge-level analytics, a communication layer that is strong, and adaptive control algorithms. As the distinctions among industrial sectors become less and less, the amalgamation of smart sorting platforms with energy-centric monitoring systems and digital-twin infrastructures is an eminent avenue leading to the next industrial operations that are sustainable, efficient, and interconnected.

METHOD

Machine Learning for Waste Classification

Machine Learning (ML) and Artificial Intelligence (AI) have changed the waste segregation

automation field completely. The main objective of utilizing ML in this sector is to do it in a fast and accurate way: to identify, classify and separate waste materials coming from mixed streams in real-time. Waste classification is a very complex task because the visual complexity, the different shapes, contamination, occlusion, and the variability of discarded items. In contrast to structured industrial objects, waste items generally have unexpected deformation, dirt, and color variation, which makes manual feature-based approaches not enough. In the last 10 years the progress in computer vision, deep learning, and edge computing has led to a great improvement of the performance of waste classification systems regarding both accuracy and speed. These advances have resulted in a change of focus from rule-based and handcrafted feature extraction methods to end-to-end learning models that can automatically identify the features relevant to classification. Machine learning techniques for waste classification can be largely seen as four stages of evolution: traditional machine learning with hand-engineered features, deep learning-based image classification, object detection and segmentation for spatial localization, and multimodal fusion techniques which combine data from various sensors. Accuracy, scalability, and the ability to work under various real-world conditions have all been improved by each stage hereby represented.

Deep Learning Models

Deep learning was the change that completely changed the game in waste classification. Deep neural networks (DNNs), most notably Convolutional Neural Networks (CNNs), made it possible to automatically learn visual patterns from raw pixel data without the need for manual feature engineering.[4] CNNs make use of layered feature maps where each layer can progressively detect textures, edges, shapes, and objects. Waste classification research has benefited greatly from the use of a wide range of popular architectures such as AlexNet, VGGNet, ResNet, EfficientNet, and MobileNet. For instance: ResNet (Residual Network) achieves very deep architectures by the use of skip connections, thus it can improve accuracy without the problem of vanishing gradients, MobileNet and EfficientNet offer lightweight architectures that are designed to perform real-time inference on edge devices like Raspberry Pi or NVIDIA Jetson modules, DenseNet facilitates feature reuse between layers, thereby making it more efficient for datasets with less diversity. As a result of the challenge to obtain big, properly-labeled waste datasets, the technique of transfer learning is in use very often. The pretrained models (those trained on ImageNet or COCO datasets) are made to learn more from small waste datasets like TrashNet, TACO, or Open Litter Map. In fact, this way the model generalization power is improved along with the training time being very short, which is a situation particularly typical for very few labeled data cases. Researchers have observed that the accuracy when using CNNs on curated datasets can be increased from 70–80 % (traditional ML) to 90–95 %. However, the performance of the model often deteriorates in an open-air environment where waste items are stacked on top of each other or the source of light is not stable. Data augmentation (rotation, scaling, brightness adjustments) and regularization (dropout, batch normalization) are among the techniques that can be used to alleviate the problem of overfitting. Latency is very important for real-time segregation systems. In order to allow robotic sorting on conveyor belts, deep models should be able to execute their operations within a time-span of a few tens of milliseconds. Compressed CNN models can be deployed on embedded processors with the help of such frameworks as TensorFlow Lite, ONNX Runtime, and NVIDIA TensorRT. At the same time, model quantization and pruning are the methods that can bring down computational costs to a great extent while still being able to hold on to an accuracy level that is acceptable.

Object Detection and Segmentation

Image classification provides a single label for the whole image, but the segregation of waste in the real world needs detection of several objects in one picture. Therefore, the techniques

of object detection and instance segmentation are very important here. Through the same process, object detection models identify not only bounding boxes but also class labels for several objects. Some of the most prominent architectures are: YOLO (You Only Look Once): Its extreme speed, a feature that allows real-time detection (>30 FPS), is the main reason why it is the best choice for conveyor belt applications, Faster R-CNN: Precision is its strong point thanks to the combination of region proposals with deep feature extraction, however, it is slower than YOLO, SSD (Single Shot Multibox Detector): A compromise between speed and accuracy. By means of these frameworks, the locating of the recyclables (e.g. plastic bottles, cans, cardboard) for subsequent robotic manipulation is carried out. Segmentation models such as Mask R-CNN or U-Net not only 'detect' but also define the exact pixel-level boundaries of every waste object. This is especially important for those items that are stacked on each other or have an arbitrary shape. Segmentation maps provide the correct approach of the robotic arm and eliminate the errors that may be present due to partial occlusion. Real-time detection and segmentation are two methods that can be combined with edge computing to provide less than 100 ms latency. Local inference is done by edge GPUs or AI accelerators (e.g. NVIDIA Jetson Nano, Coral TPU), while the cloud servers are responsible for the retraining with the newly collected data. The synergy between rapid object detection and segmentation has enabled contemporary setups to almost match human-level recognition capabilities, hence throughput in Material Recovery Facilities (MRFs) has been increased significantly.

Multi-Modal Sensor Fusion

In spite of deep learning advances, depending solely on one modality (e.g., RGB vision) is still inadequate for a solid waste classification system. The single modal limitation has been the reason for multi-modal fusion, which is a method of combining sensor data from different sources—like RGB, hyperspectral imaging (HSI), NIR, thermal, and weight sensors—to improve the accuracy of the decision.[5] The waste that is thrown away in the real world may sometimes be made of materials that look alike but their composition is different. For instance: Translucent PET and PVC bottles have almost the same shapes and colors but their spectral signatures are quite different, Metals and plastics may reflect light in the same way under certain conditions. Once freed from the shackles of the sole reliance on appearance, systems that integrate various sensor modalities can surpass confusions. The sensor fusion process may be at various levels: Early Fusion: The raw data (e.g., RGB and spectral bands) are merged even before feature extraction, thus neural networks can learn joint representations, Late Fusion: Classifiers performing independently on each sensor modality are trained and the results obtained are combined either by weighted averaging or by voting, Hybrid Fusion: Mix of early and late fusion, most often utilizing attention mechanisms to dynamically assign weights to the importance of each modality. The latest multimodal deep networks that combine CNNs for RGB data and 1D/3D CNNs for spectral data are the main idea behind the recent solutions. Transformer-based architectures too, have emerged, using self-attention mechanisms for the correlation of features across modalities. These models are very robust in varied lighting, occlusion, and contamination conditions. Multi-modal systems achieve classification accuracy up to 10–15 % higher than single-modality approaches. Industrial-scale implementations are capable of: Recognizing plastic polymers (PET, HDPE, LDPE) from each other, Identifying hazardous waste hidden in mixed municipal streams, Facilitating recycling quality through granulated material classification. The problem, nevertheless, is the expense and complexity of the integration and calibration of several sensors, which at the moment, restricts the deployment to waste sorting lines with high-value only.

Table 1. Summary of Multi-Modal Sensor Fusion Approaches for Solid Waste Classification

Fusion type	Fusion level & methodology	Typical network archiecture	Advantages	Limitations / challenges	Industrial applications
Early Fusion	Raw sensor data (e.g., RGB + spectral bands) are merged before feature extraction; network learns joint representations.	CNNs or hybrid CNN-LSTM models trained on concatenated feature maps.	Enables comprehensive feature learning; captures low-level inter-modal correlations.	Requires precise data alignment and synchronization; computationally expensive.	Material discrimination in visually similar waste (e.g., PET vs. PVC)
Late Fusion	Independent classifiers for each modality; results combined by weighted averaging, voting, or ensemble methods.	Separate CNNs for each sensor, combined via decision-level fusion layer.	Flexibility in modality-specific training; modular design simplifies system updates.	May lose fine-grained inter-modal dependencies; limited adaptability to dynamic scenes.	Sorting mixed recyclables and identifying hidden hazardous materials.
Hybrid Fusion	Combines early and late fusion using attention mechanisms to dynamically weigh modality importance.	CNN + Transformer-based architectures using cross-attention modules.	Balances low- and high-level feature integration; robust under varied lighting and occlusion.	High system complexity; requires extensive training data and computational power.	Industrial-scale smart sorting and contamination detection.
Transformer - Based Fusion	Utilizes self-attention to correlate features across modalities (RGB, NIR, HSI, etc.).	Vision Transformer (ViT), Multimodal Transformers, or 3D CNN-Transformer hybrids.	Superior adaptability and context awareness; robust in unstructured environments.	Expensive sensor integration and calibration; deployment currently limited to high-value facilities.	Automated sorting in advanced recycling plants; spectral-visual data correlation for polymer recognition.

Integration of Intelligent Automation Sensors

The diagram exhibits the process by which smart automation creates a common technological base which can be utilized by different sectors without the need for these sectors to communicate with each other. Industry 4.0 and Society 5.0 bring to the table such capabilities as virtual manufacturing, cyber-physical microservices, and advanced mechanical-engineering workflows that enhance system adaptability and responsiveness. These capabilities in turn allow the waste-segregation platforms that operate in real-time to incorporate machine vision, multi-sensor IoT architectures, and autonomous decision-making into a cohesive processing chain. By connecting these fields, the diagram reveals the increased interaction that is taking place between industrial production environments and next-generation sustainability systems. On the

other side of the framework, oil-gas-chemical industries utilize digital twins, Industrial IoT, and pipeline-integrity monitoring systems to control high-risk operations in a precise manner. These technologies have the same fundamental attributes as waste-segregation systems—continuous sensing, edge-level analytics, and data-driven control loops. The lower tier of the diagram depicts energy monitoring and edge analytics as a unifying layer that facilitates real-time data exchange, cross-domain optimization, and integrated decision support. The figure, when considered as a whole, is an indication of the extent to which automation principles that were initially created for energy-intensive, safety-critical sectors can now be used for environmental operations and thus lead to the creation of a more connected and resilient industrial ecosystem.

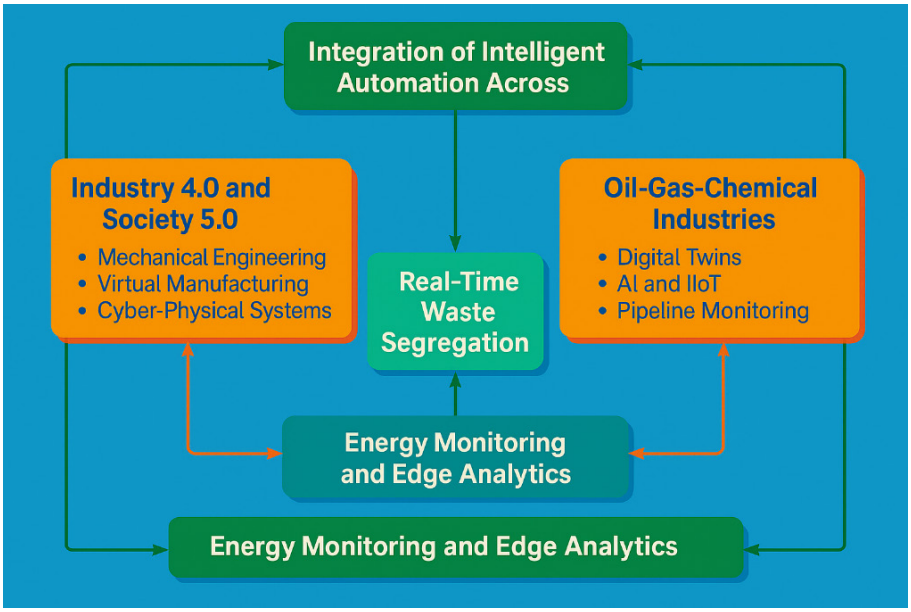

Figure 1. Integration of Intelligent Automation Sensors

RESULTS AND DISCUSSION

Robotics Sorting Systems

Waste sorting systems powered by robotics is the biggest move towards fully automated, efficient, and safer material recovery. Manual sorting, which has been the norm for a long time, is a process that has been heavy on labor, risky for health, and inconsistent in results. Those involved in the work are constantly exposed to harmful substances, sharp objects, and biohazmat waste. In addition, manual sorting is less accurate and less standardized, thus resulting in the contamination of recyclables and the wastage of money. The robot sorting methods combine the power of computer vision, machine learning, and robotic manipulation to pinpoint, handle, and extract items from a mixture of different waste streams and thereby, ensure that these problems are solved. They are designed to function around the clock with minimum human intervention and at any place which may be MRFs, construction and demolition sites, or e-waste recycling plants. The purpose is not merely to elevate the volume and recovery rates but also to raise the quality of the materials sorted and to cut down on the costs of operations. A robotic sorting system in general consists of three main subsystems: Perception and Sensing: Various sensors such as cameras, LiDAR, and hyperspectral can instantly capture visual and spectral information regarding waste pieces lying on a moving belt, Computation and Decision-Making: Deep learning models perform the classification and hence, point out the grasp points or removal actions,

Actuation: Robot arms with the help of suction, pneumatic, or mechanical grippers perform the physical separation of the pieces that have been identified.[6,10]

Robotic Manipulators Design

Robotic manipulators are basically the part of the machinery that physically takes hold of waste items and sorts them out. The design part of the robot arms necessitates payload capacity, response time, degrees of freedom (DoF), end-effector design, and capability to withstand environmental uncertainties, to be considered and be figured out carefully.[10] Generally, there are two types of robots' arms broadly used, and they are: Articulated robotic arms (e.g. 4- or 6-DoF arms like Universal Robots UR5, ABB IRB 1200): Such arms give pliability for complicated movements and can reach through or over the mess of surfaces, Delta or SCARA robots: Extremely fast parallel manipulators are good for very light objects and thus can perform several hundred picks per minute, Choosing one solely depends on the necessities of the application. Delta robots would be the ones that are capable of high-speed sorting of light recyclables (plastic bottles, paper) while the kind of power and flexibility which an articulated arm has is more suitable for handling heavier or irregularly shaped materials. The purpose of an end-effector or "hand" of the robot is to give the ability of the robot to physically operate with waste objects.[8,10] Most common are: Vacuum or suction grippers: They create negative pressure by a pump and thus are able to lift very light, flat, or smooth objects such as plastics and paper, Two-finger or multi-finger mechanical grippers: Applied for the holding of the likes of are irregularly shaped parts of cans or glass fragments, Soft robotic grippers: Constructed of silicone or elastomeric materials which not only comply with the object geometry but also make it possible for safe handling fragile or deformable waste to be released, Advanced technology enables systems to change the mode of operation from suction to a mechanical gripping depending on the item found. For instance, a suction gripper can take a plastic wrapping whereas a mechanical gripper can carry a metal can. The very next step after locating and recognizing an object is for the arm to come up with a route which is free of any collision and will get it to the target as well as get it, and drop it off.[10] This has Inverse kinematics (IK) to compute the angles of the joints for the needed position of the end-effector, Trajectory optimization techniques such as Rapidly Exploring Random Trees (RRT) or Model Predictive Control (MPC). Visual servoing, where instant camera output is used to adjust the robot's route during its movement. Everything: from the very moment the object is found to the execution of the command should be.[7,9] These manipulator robots should be tough and reliable if they are to be used in an industrial environment where there is sorting going on among the dust, humid air as well as, A great number of force-torque sensors equip many of these manipulators to identify areas where unexpected resistance occurs and thus to prevent them from being damaged. The safety cages as well as the motion-limiting algorithms that are installed for the purpose of ensuring that human workers can operate together with them in collaborative settings (cobots) promote the safety of workers. To a great extent, robotic manipulators have been transformed into the fundamental tools of automatic sorting capable of combining accuracy and speed in an unsafe and inefficient.

Integration with Conveyor Systems

Conveyor-robot integration is at the core of the working processes of modern sorting plants. Typically, in these installations, waste is transported non-stop on conveyor belts, and at the same time, vision systems and AI models examine every single frame in real time to locate and identify the target objects.What is more, either high-resolution RGB or multispectral are placed in a way to cover the conveyor from above and continue to take the frames at 30–60 fps. Carried out by deep learning models (e.g., YOLOv8, Faster R-CNN) these processed frames are used to detect areas of interest and classify objects that, in this case, are materials for recycling. On each occasion of detection, a bounding box along with the conveyor frame-

relative coordinates is created. In order to know an object's position at a later moment, the system needs to consider both the conveyor speed and the time interval between detection and robot actuation since the belt is a moving one. It is this spatial-temporal registration that makes it possible to carry out pick-and-place actions in a continuous conveyor flow. Control over the synchronization is accomplished through closed-loop systems that connect all the components of the mechatronic chain, i.e. vision sensors, conveyor encoders, and robotic actuators.[5,7] The deployment of a number of robotic arms in single long conveyors in big sorting plants is a common practice. Each arm handles the sorting of one type of waste. Communication protocols like ROS 2, MQTT or EtherCAT facilitate the robots in sorting communication, identifying sorting priorities and thus, efficiently coordinating them for sorting activities and avoiding redundant picks.[8,9,10] The decision-making controller hierarchically manages the distribution of the work load among the robots - for example, it can decide to delegate the task of plastic sorting to one machine, that of metals to the second, and paper to the third thus, making use of the output coming from the waste composition analysis. Load balancing is there to make sure that the flow of work is never interrupted in the event of one robot being either full or idle. [6] The steps of the sorting operational workflow are, in most cases, as follows: First, waste is fed into the conveyor from a feeder or pre-shredder, Next, cameras scan the stream and send the data to the vision module, AI algorithms detect, classify, and assign each object to a sorting category, Robotic arms are given the object coordinates and pick instructions, Through predefined trajectories, picked items are emptied into bins that have been designated for them. The entire closed-loop mechatronic system, which is at work here, ensures that the throughput of the plant is very high, the system is able to adapt to changes in real time, and the downtime is kept to a minimum. Technology-enabled solutions are capable of handling the task for thousands of items per hour, something that is just impossible for humans to do. In order to be always up-to-date with ever-changing waste types and the latest packaging designs, models depend on a constant retraining mechanism that utilizes data coming from the operation itself. Local machines hold the temporary data that is needed for small updates while remote servers perform the heavy analytics. Such a hybrid learning structure ensures that the system is always accurate and can be easily scaled without causing interruptions to the ongoing work. Robots that are integrated with conveyors are put together with energy efficiency in mind to them. This is why we see them equipped with elements such as lightweight actuators, regenerative braking systems, and power-aware scheduling. In order to initiate maintenance before the moment of malfunction there is an onboard monitoring system that keeps an eye on joint torque, vibration, and temperature and through the information gained can most of the maintenance tasks be made predictive ones.

Industrial Deployments and Case Studies

One of the major technological advances of robotic sorting is the technology has matured to such a level that it has been moved out of the lab and into the industry. Many of the companies have successfully implemented AI-driven robotic solutions that are capable of handling the waste generated by their activities and as a result, they have made considerable progress in system efficiency in terms of both the accuracy and the output of the systems. AMP Robotics (USA) is the leader in AI-powered robotic sorting. Their AMP Neural Network (AMP NN) system integrates the computer vision of the multi-axis robotic arms with the ability to locate and pick the recyclables at a speed of more than 80 picks per minute. AMP robots are capable of identifying over 70 different material classes, such as different plastic grades (PET, HDPE, LDPE), metals, and paper. The device is always current as it employs continuous learning and therefore it can always be in line with the local changes in the design of the packaging and the level of contaminants. According to the documentation on-site, AMP robots identify mixed

materials with more than 80 % accuracy, and they are also enabled to work 24 hours a day which can lead to a 60 % reduction of labor. ZenRobotics (Finland) focuses on waste from construction and demolition. Their robotic arms are equipped with 3D vision and spectroscopic sensors to handle heavy debris such as wood, concrete, and metals. ZenRobotics' multi-arm system can sort up to 4000 items per hour, thereby making the recycling of reusable materials to over 90 %. The modular design of the system provides the option of scaling up–more arms can be connected when the volume of the waste is high. The company's success is a proof that the technology of robot sorting can be customized for different types of waste streams and not just household recyclables. Waste Robotics (Canada) and Recycleye (UK) have taken a huge step towards the next generation of data-centric automated waste solutions. In these systems, models are linked to the cloud and they are always updating through federated learning–they share experience from numerous sites globally.[7,8,9] Recycleye's robots are equipped with low-cost and easy-to-install cameras and small grippers that are ideal for municipal waste sorting; thus, they provide a low-cost solution for small recycling centers. Robotic sorting systems performance as estimated from industrial trials reports can be such as: Sorting accuracy: 80–95 %, depending on waste type and contamination, Throughput: 1500–3000 picks per hour per robot, Operational uptime: > 90 % with minimal maintenance, Return on investment (ROI): 2–4 years compared to manual sorting lines, Such performance metrics point out that there is a strong economic and ecological reasoning behind the widespread use of this technology globally.[6]

Table 2. AI Model Performance

Model / Algorithm	Type	Key Features	Average Classification Accuracy (%)	Inference Speed (ms/ frame)	Computational Requirement
SVM (Support Vector Machine)	Traditional ML	Uses handcrafted features (color, shape, texture)	70–82	30–50	Low (CPU-based)
Random Forest (RF)	Traditional ML	Ensemble of decision trees	75–85	25–45	Low
K-Nearest Neighbors (KNN)	Traditional ML	Distance-based classification	65–80	60–120	Low
CNN (Convolutional Neural Network)	Deep Learning	Learns spatial and texture features automatically	90–95	15–30	Medium–High (GPU)
ResNet-50	Deep CNN	Residual learning, deep feature extraction	92–96	20–40	High
MobileNetV3	Lightweight CNN	Optimized for mobile and edge devices	88–94	8–15	Low–Medium
EfficientNet-B3	Deep CNN	Balanced accuracy and efficiency	93–97	10–20	Medium–High

Smart Monitoring and Edge Computing

Waste management powered by hybrid smart monitoring systems and edge computing technologies depicts a shift in user paradigm from reactive to proactive operations. Usually, waste collection depends on predetermined schedules or reporting by hand. It consequently results in the following inefficiencies most of the time: overflowing bins, usage of unproductive

collection routes, and delayed responses. Besides that, IoT sensor-equipped smart bins with cameras and embedded edge processors can not only know their fill levels but also can categorize the waste disposed of and send the data to central-operative units without any human intervention. By using Internet of Things (IoT) connectivity and artificial intelligence (AI), smart monitoring gives municipalities as well as private operators possibilities to make use of collection schedules in an effective way, cut down operational costs and increase the throughput of recycling. The implementation of edge computing further makes it possible for the data to be handled instantaneously right at the device, thereby greatly diminishing the time delay and dependence on a connection to the cloud which has to be maintained all the time. Smart monitoring solutions should not be considered as independent innovations only but rather as the fundamental elements of a more comprehensive cyber-physical net that combines sensing, computation, and communication capabilities. Hence, these networks are of paramount importance to smart cities. They enable the implementation of data-driven approaches to waste management aiming at ecological sustainability.

Benefits of Edge-Enabled Smart Monitoring

The fusion of smart monitoring with edge computing not only results in various benefits of different kinds - technical, environmental, and operational, but also increases the range of the advantages. Edge computing facilitates the handling of data right at the source, thus the data travel time which is also known as latency is drastically reduced. This characteristic is extremely important for the areas which require very short response time and examples can be the detection of overflowing bins or the triggering of fire alarms. In a very short time, the nearest fire station can be notified which will provide a quick and efficient solution, thereby greatly limiting the potential for waste spillage or the emergence of bad odors. The performance of edge devices locally such as inference and filtering drastically reduces the volume of the data to be sent to the cloud. Hence the network load diminishes along with the operational cost and the privacy level of raw data is elevated as well since it is always preserved on the local site. Battery lives of waste containers can be considerably extended if they are equipped with low-power edge chips and event-driven communication. The fuel consumption of collection trucks can be reduced by up to 30 % through IoT-enabled route optimization, thus the carbon emissions and costs are lowered quite significantly. The modular construction guarantees the gradual introduction of new bins or edge nodes without interrupting the current functioning of the operations.

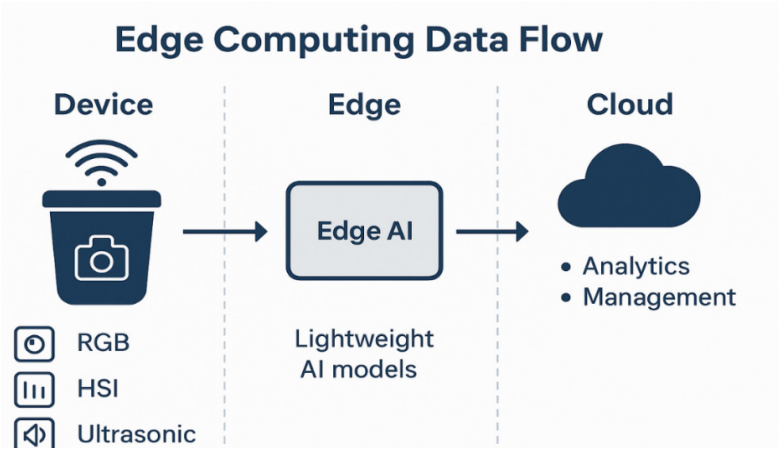

Figure 2. Edge-Enabled Smart Monitoring

One device alone can perform all the necessary operations and also communicate with the cloud when it is available, thus providing fault tolerance in the case of network outages. The use of cloud-based analytics of aggregated data gives municipal authorities a chance to get real-time insights into the evolution of the waste generation patterns, which can be used for urban-rationalized waste strategies, flexible route planning, and citizen engagement initiatives for the promotion of recycling.

Intelligent automation across sectors: waste segregation and oil-gas-chemical industries

Figure 1 demonstrates the pivotal role of intelligent automation in creating a common structural backbone across various domains such as industrial manufacturing, real-time waste management, and the oil-gas-chemical sector. The sequence of interactions reveals that Industry 4.0 and Society 5.0 offer the necessary digital and mechanical bases—like virtual manufacturing, cyber-physical microservices, and human-centric automation—which are directly used by advanced waste-segregation architectures incorporating machine vision, IoT sensing, and autonomous sorting. Besides that, oil-gas-chemical industries are utilizing digital twins, IIoT infrastructures, and pipeline-monitoring-systems to oversee their high-risk and data-intensive operations. These two sectors are, therefore, converging at a deeper level, where energy monitoring and edge analytics form a single computational field that is capable of facilitating coordinated data exchange, condition-aware decision making, and cross-sector optimization.

The figure 3, thus, is an illustration of the growing technological integration of sustainability-focused waste-segregation systems with energy-consumption-critical industrial operations, which, in turn, uncovers the enormous possibilities of common analytical frameworks and the interaction of automation solutions.

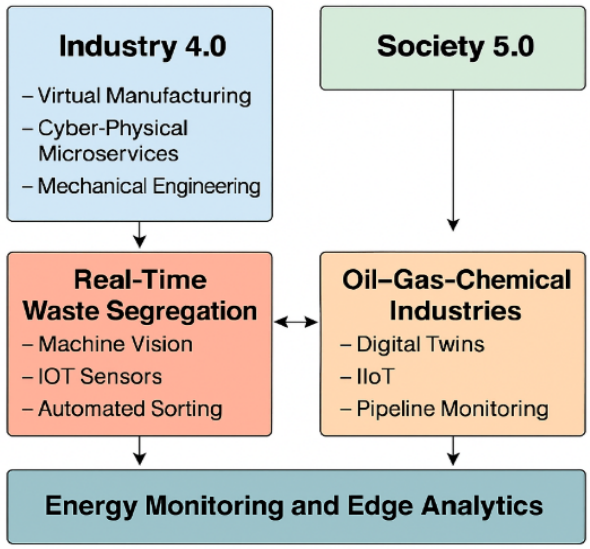

Figure 3. Framework for waste segregation and oil-gas-chemical industries

Challenges and Future Prospects

While smart waste monitoring is highly efficient, it still faces some limitations that it needs to overcome before it can be fully unleashed as shown in table 3 and figure 4. Power Management: It is still a challenge to provide a long period of operation for devices powered by batteries, especially for camera-based systems which require a lot of power.

Table 3. Key Components and Functions of a Smart Waste Monitoring System

Component / Module	Primary Function	Technology / Hardware Used	Data Captured or Processed	Operational Role in System	Advantages	Limitations / Challenges
Ultrasonic Sensor	Detects fill level by measuring distance between lid and waste surface	HC-SR04 / MaxBotix modules	Distance (cm), fill-level percentage	Triggers collection alerts when bin nears capacity	Low cost, low power, reliable	May misread soft or irregular surfaces
Load Cell / Weight Sensor	Measures total waste mass in bin	Strain gauge + HX711 amplifier	Weight (kg), waste density	Provides precise waste volume-to-mass correlation	Accurate and durable	No material classification capability
RGB Camera	Captures color images for visual classification	HD camera / Raspberry Pi camera	RGB image frames	Detects object types (plastic, paper, metal, etc.)	Supports deep learning classification	Sensitive to lighting, contamination
Gas Sensor (VOC, CH_4, CO_2)	Detects odor, decomposition gases	MQ-135 / MQ-4 / VOC sensor array	Gas concentration (ppm)	Monitors organic waste decomposition, hygiene	Enables safety alerts and early collection	Sensor drift, requires calibration
Temperature & Humidity Sensor	Tracks environmental conditions	DHT22 / BME280	°C, %RH	Monitors composting or organic decay status	Supports adaptive waste collection	Limited direct link to waste type
Edge Processor	Executes lightweight AI models for local classification	Raspberry Pi 4, Jetson Nano, Google Coral TPU	Sensor data, images, metadata	Enables real-time classification and alerts	Reduces latency, bandwidth use	Limited compute for large models
Microcontroller / Gateway Node	Manages data communication between sensors and cloud	ESP32 / Arduino / STM32	Aggregated sensor readings	Acts as central control node	Low cost, easy integration	Limited storage and multitasking

Data Standardization: the interoperability between vendors and communication protocols that is necessary for big integration is presently non-existent leading to vendors working separately. At present, there are no standards, and this results in vendors operating independently, Model Drift: The waste changes or the environmental factors might cause that the model's performance declines over time, thus, one has to continuously retrain it, Cost Constraints: The high costs of the initial-stage installations are the main reasons for the slow impacts in underprivileged communities. Research challenges to be tackled are: The creation of ultra-low-power AI chips that can deliver continuous local processing, Employing 5G and LPWAN technologies for quick, energy-efficient communication, Using blockchain for transparent waste tracking and cool recycling programs that offer rewards to users, Implementing self-healing networks that are designed to automatically reconfigure when a device fails.

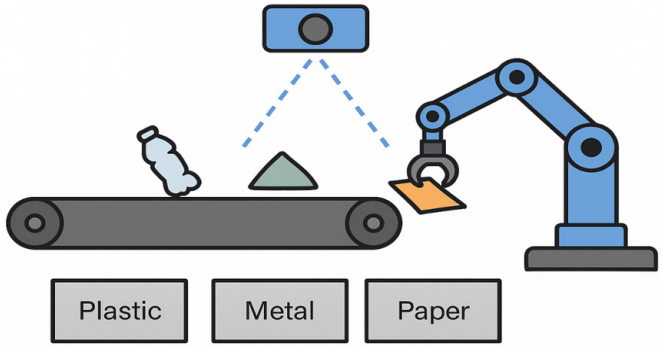

Figure 4. Illustration of a robotic sorting system using computer vision and a suction gripper

Performance Metrics

Firstly, we should think of the performance metrics of an on-the-fly waste segregation system as those which, first of all, reflect a compromise between the system's operational efficiency, accuracy, and sustainability. Such systems usually combine a variety of technologies like machine vision, robotic sorting, edge computing, and cloud analytics, so their performance should also be assessed at both hardware and software levels.

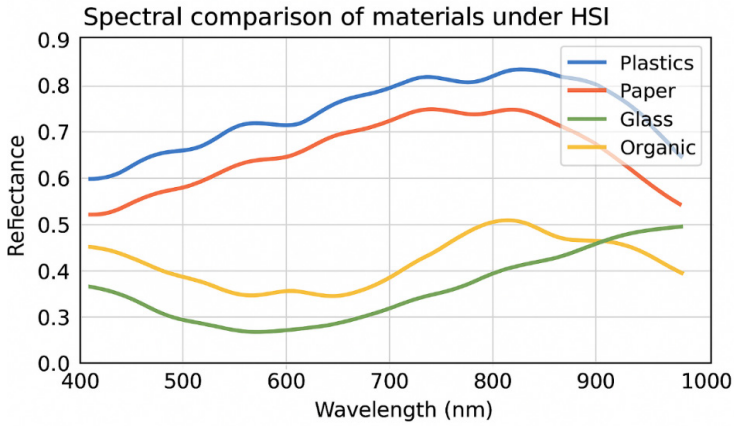

Figure 5. Spectral comparison of materials under HIS

To entirely serve this goal, the evaluation metrics do not only define classification accuracy

numerically but also system reliability, energy efficiency, and the ability to work with different waste streams. Without consistent and well-defined performance metrics, it would be nearly impossible to do benchmarking of system upgrade, verification of experimental models, and big industry application initiation. The subchapters shown here indicate the performance or operational efficiency and the quality delivered by the automated segregation systems, which, in turn, is measured through the key performance indicators (KPIs).

Classification Accuracy

Classification accuracy is a performance measure that shows how many waste items were correctly identified out of the total number of processed samples. It is the most important one among the performance indicators that are used in machine learning-driven segregation systems. In other words, high accuracy means that the algorithm can regularly distinguish between different classes, e.g., plastics, paper, glass, metal, and organics. Mostly, metrics based on a confusion matrix, such as precision, recall, and F1-score, are used for accuracy calculation, especially when the classes are imbalanced. For instance, if recyclable plastics constitute the largest part of the dataset, then the misclassification of small fractions, e.g., e-waste or organic matter, may lead to a significant decrease in the system's usefulness. In modeling practice, researchers have reached classification accuracies of more than 95 % when laboratory models like ResNet-50, YOLOv8, or EfficientNet-B3 are employed. Nevertheless, factors like lighting, occlusion, and the contamination of waste surfaces can lower accuracy in field conditions. Continuous model training via cloud-based feedback loops can locally adjust classification weights and thus lessen such a drop. Therefore, accuracy is not only a measure at certain points but also the system's ability to learn and adapt.

Recovery Rate

Recovery rate is the metric that tells the number of recyclable or reusable materials that have been correctly separated and taken out of the waste stream. From an environmental and economic standpoint, it is the principal metric that determines the performance of a segregation system. Actually, a high recovery rate is the main instrument that makes it possible for the maximum volume of recyclable materials to be diverted from landfills, thus becoming a key factor for the circular economy goals. The recovery rate of a robotic sorting system may be influenced by the robot arm speed, the success rate of a grasp, and conveyor speed. For instance, cutting-edge industrial systems such as those at AMP Robotics or ZenRobotics can achieve recovery rates that vary from 70 % to 90 % for mixed solid waste streams from municipalities. The mixture of features has been the primary driver of the recovery efficiency increase through the rapid identification and retrieval of the items. These features are multi-camera setups, low-latency vision sensors, and advanced motion planning algorithms. The best method of boosting this performance metric is to reach a balance between the sorting accuracy and the operational speed so that the quality is not lowered for the throughput and the mechanical actuators are not overused.

Contamination Reduction

Contamination reduction mainly measures the decrease of non-recyclable or wrongly sorted materials in the recovered streams. It is the primary indicator of purity level in segregation. Most of the time, recycling facilities set the contamination levels to be less than 5-10 % in order to keep the material's resale value and processing efficiency. As an instance of the idea, smart segregation technologies that use deep learning-based semantic segmentation in conjunction with sensor fusion (e.g., merging RGB and hyperspectral data) may result in a considerable decrease in contamination. The methods not only rely on the spectra characters but also on the

textures of the materials, hence they can determine food residues, water, or chemical stains that are the most common factors that lower the quality of recycling. Besides that, the growing trend of feedback control loops, where sensor data after sorting is used for classification model training, has made contamination management more adaptable. For example, if the sensor for downstream quality detects impurities, the model can immediately change classification thresholds so that even if waste compositions vary, purity levels remain constant.

Processing Response Time

Processing response time aims at measuring the time difference from when the waste is first detected up to when the classification result is given. In real-time systems, response time is a decisive parameter that not only influences the throughput but also the entire system flexibility. If the response time is too long, it may cause the vision system and robotic actuation to be out of sync and thus, the result will be either missed picks or wrong sorting. Edge computing paradigms are instrumental in cutting down the response time as they allow for data processing to happen locally, that is, close to the source of data. In the case of a standard edge-enabled waste segregation system, decision times are in the range of 10-50 milliseconds, whereas, for cloud-only scenarios, it is 200-500 milliseconds. The conveyor-driven waste operations, which are essentially fast-paced, are the ones that benefit most from such a low-latency performance.

Energy Consumption

Energy consumption looks at how much electrical energy is required to process a single waste item. The measurement is usually done in watt-hours per item (Wh/item). The necessity of energy-efficient waste segregation systems is evident from the fact that they are the only ones capable of not only attaining high throughput but also maintaining low energy profiles, thereby being both environmentally and economically viable. The energy that is needed for the entire process is divided among the different components: sensing, computation, and actuation. Cameras and sensors are the ones that consume power constantly; on the other hand, the power of the computing units (CPUs, GPUs, or edge TPUs) depends on the inference load. Robotic actuators are the ones who have the peak energy draw but only during pick-and-place actions. Introducing energy-conscious scheduling algorithms together with hardware-level power optimization (e.g., dynamic voltage scaling or idle-state management) may quite considerably cut down on the energy. The studies reveal that state-of-the-art AI-enabled sorting units have the capability to handle 1000–2000 items per hour and at the same time consume less than 0,2 Wh per item. This is a great efficiency improvement in comparison to manually sorting the waste.

Comparative Evaluation

Table 4. Performance comparison of state-of-the-art segregation systems

Metric	Typical Range	Description	Example Implementations
Classification Accuracy	90–98 %	Correctly classified waste items	CNN-based edge models
Recovery Rate	70–90 %	Recyclable materials successfully recovered	AMP Robotics, ZenRobotics
Contamination Reduction	5–10 %	Reduction in non-recyclable content	Sensor fusion and AI QA
Processing Latency	10–50 ms	Time from detection to action	Edge computing platforms
Energy Consumption	0,1–0,3 Wh/item	Power required per sorted item	Low-power AI modules

To provide a holistic view of system performance, table 4 summarizes typical performance

ranges reported across academic and industrial implementations of real-time segregation systems.

Discussion and Insights

Numerical values provided by single metrics only give a glimpse of the inner workings. However, multi-objective optimization is required to evaluate systems in the real world. This basically means that real-world systems have to simultaneously coordinate accuracy, speed, and sustainability. By way of illustration, an increase in processing throughput may bring about a reduction in accuracy if there are limited computational resources, whereas a decrease in energy consumption may cause an increase in latency. Therefore, there is a growing trend of using hybrid optimization frameworks which combine reinforcement learning and adaptive control so as to make the performance parameter adjustment automatic depending on environmental feedback. The use of standardized benchmarking datasets and open-source evaluation frameworks by future waste management systems will not only make the performance comparison of different platforms visually evident but also allow for the same results to be achieved by different people. Furthermore, KPIs grounded on lifecycle metrics like carbon footprint, maintenance cost, and material throughput are expected to be the next generation of conventional accuracy-based KPIs, thus implying a wider perspective of sustainability and scalability.

Challenges and Future Directions

The automation, machine learning, and robotic technologies for waste segregation have made a great leap forward, however, a number of very important issues still exist, which have caused these technologies to be hardly implemented on a large scale and to have low operational stability. Existing systems are generally efficient in laboratory conditions; however, they are challenging to scale up, suffer from lack of data, and are influenced by environmental variability and integration problems when deployed in real-world municipal waste management scenarios. These issues can be solved through innovations in hardware, advancements in algorithms, standardization, and the participation of various stakeholders. Where the improvised waste segregation technologies have their difficulties, the upcoming research and industrial application directions are also revealed.

Dataset Diversity and Generalization

One of the biggest problems for developers of automation systems for waste recognition is the lack of properly comprehensive and diverse datasets. Most of the datasets that are currently available are limited, controlled, and biased towards certain types of materials (e.g., plastics, paper, or glass), which makes such datasets insufficient for training models that have to work under different environmental and compositional conditions. Waste from the real world is a complex mix of the deformed, occluded, or contaminated items and varies greatly from one location to another as well as at different times of the year. For instance, a model that has been trained on clean, labeled plastic bottles may fail to recognize the crushed or dirty ones in a sorting facility. On top of that, differences in packaging materials and labeling standards make the problem of model generalization even worse. Without enough variation in training data, models with very high accuracy such as YOLOv8 or EfficientNet-B7 may have poorer performance when faced with waste types that they haven't encountered before. First and foremost, future work should be committed to developing large-scale open-access benchmark datasets that not only represent the true variability of operations but also the diversity of the environment. On top of that, multimodal data (RGB, hyperspectral, infrared, and depth) collected through standard labeling protocols should be the constituents of these datasets. There should also be collaborative data-sharing platforms that can be supported by municipalities, academia, and

industry. These platforms will not only make the research work more reproducible but also have a great effect on the robustness of the models.

Hardware Costs and Scalability

The most advanced sensing and actuation hardware's high price is the main reason for the technology's limited range of applications. While Hyperspectral imaging (HSI), and near-infrared (NIR) sensors are excellent for identifying materials, they are still very costly when it comes to large-scale applications. Likewise, robotic arms with precision grippers and industrial-grade controllers are expensive capital investments and usually, are beyond the budgets of small- and medium-scale recycling units. Apart from that, the operational cost goes up as a result of the requirements for maintenance, power consumption, and the need for skilled technicians. These financial limitations have been a barrier to the technology's widespread acceptance, particularly in developing countries where waste management budgets are already under pressure. As a result, the focus of research is slowly shifting towards sensor substitutes that are affordable and modular hardware configurations. An excellent example of this kind of work is the utilization of RGB-D cameras combined with AI-driven spectral estimation, which mimics hyperspectral capabilities without the need for a costly sensor. At the same time, efforts are being made to lower the cost of the system by 3D printing grippers and using collaborative robots (cobots) with light actuators while still ensuring a certain level of reliability. Moreover, the combination of open-source hardware communities with the mass production of edge AI modules might be able to significantly lower the entry barrier for the automation of waste segregation segregation in the next years.

Processing Latency and Computational Bottlenecks

A fast-moving conveyor real-time waste segregation system in an industrial environment is singed to be done at a very high speed, however, the computational latency which is a result of image acquisition, model inference, and communication often leads to throughput and accuracy of the system being lowered. On the other hand, deep learning models could be computationally heavy and have to be efficient when done on embedded systems. Taking a high-resolution spectral data set as an example, it may require several hundred input channels thus greatly increasing the time it takes to process. In case of too much latency, output synchronization errors between detection and robotic actuation may happen, thus resulting in misses or wrong sorting. Hence, scientists are combining edge computing with various kinds of model compression (e.g., quantization, pruning, and lightweight architectures such as MobileNetV3, EfficientNet-Lite) and the addition of hardware accelerators like NVIDIA Jetson, Google Coral TPU, and FPGA-based inference engines which provide rapid decision latency, are currently being combined to achieve decision latency at the millisecond level to get decision latency at the millisecond level. The following systems will most probably be using hierarchical edge–cloud architectures in which the edge is the place of the latency-sensitive tasks like object detection and heavy computation tasks such as retraining and long-term analytics that are transferred to the cloud. Hence, the hybrid framework will be able to ensure both responsiveness and scalability.

Environmental Variability and Sensor Reliabilty

Environment changes like variable sun, dust, and humidity can affect the performance of the sensors drastically and thus their accuracy. Vision-based systems are highly vulnerable to such factors as uneven lighting or highly reflective surfaces which in turn result in the generation of glare and distortion of color perception. On top of it, the remains of the organic waste can affect the spectral signatures picked up by the HSI sensors which in the end lead to wrong waste classification. Moreover, the hardware and algorithmic resilience which is behind these environmental issues is what will be capable of defeating them. Some of the initiatives taken

are adaptive illumination systems, dynamic calibration methods, and robust data preprocessing pipelines that assist in normalizing sensor outputs even when they are confronted with different conditions. For instance, machine learning–based image enhancement algorithms are able to modify brightness and contrast on the fly while multispectral sensor fusion fills the gaps caused by environmental noise. Besides that, the installation of self-cleaning methods along with the protective covers for the sensors can be a great way to guarantee their industrial environment durability. The coming research in this area should be focused on developing environmentally adaptive systems that can self-calibrate and auto-correct hence being able to provide the same output under different operational conditions.

Integration Standards and Interoperability:

The biggest challenge that has been addressed is the lack of universally accepted communication and integration standards for interoperability across different hardware and software platforms. Most of the existing segregation systems are the outcomes of the integration of several components -different sensors, AI models, robotic controllers, and cloud services- that utilize different proprietary protocols. The fragmentation of these systems not only makes scaling them a difficult task but also being time-consuming and complex to maintain. Moreover, it is at the same time a barrier for vendor and municipal cooperation which is the source of efficient solutions. Essentially, the adoption of open communication frameworks such as ROS (Robot Operating System), OPC-UA, and MQTT-based IoT protocols might be a very crucial step towards the integration of heterogeneous components. Moreover, the standardization of data formats, APIs, and semantic labels will make it easier to create a platform that is ready for building vendor-neutral interoperable ecosystems. It will take an international effort through standard organizations and industry consortia to establish these protocols that will allow compatibility, reliability, and system sustainability in the long run. Moreover, the implementation of standardized testing and certification procedures can greatly facilitate the deployment of smart waste segregation technologies in different cities and countries.

Future Research and Development Directions

Innovations that involve cross-disciplinary and result in the development of intelligent, scalable, and sustainable waste segregation systems are some of the potential research directions. Some of the major areas are: Sensors that are Economical to Produce – Small, cheap, and efficient sensing modules for mass deployment in municipal systems will largely depend on innovations in optical design, material science, and embedded AI. Open Benchmark Datasets – The availability of globally annotated datasets covering different waste types and environmental conditions will be the main driver for research reproducability and result comparability. Edge–Cloud Collaboration – A distributed computing framework that uses edge AI for quick classification and cloud computing for retraining and analytics will be very efficient in terms of system performance and resource management. Scalable Smart Networks – The installation of IoT-enabled smart bins throughout the city coupled with the use of autonomous sorting hubs can lead to the creation of intelligent waste management ecosystems that are capable of monitoring, analyzing, and optimizing waste flows in real-time. Integration with Sustainability and Circular Economy – Apart from being able to sort waste, the future facilities should also have the capacity to connect with material recovery facilities (MRFs) and recycling plants via data-driven feedback loops thus providing a way for the circular economy to be efficiently operationalized. In a nutshell, the technologies for real-time waste segregation have come a long way; nevertheless, to unlock their full potential, the issues raised need to be addressed through collaborative innovation, open data initiatives, and sustainable design practices. The incorporation of AI, robotics, IoT, and circular economy principles is going to be a game changer

in waste management making it not only a labor-intensive process but also resource-heavy one to a smart, automated, and eco-friendly system.

CONCLUSIONS

The research reveals how smart automation is gradually breaking down the old limits of environmentally-friendly waste management systems fueled by the high-tech sectors such as oil, gas, and chemical processing. For instance, real-time waste segregation platforms which heavily rely on machine vision, embedded sensing, and autonomous actuation, are more and more becoming similar in their architectural features to the digital-twin ecosystems, IIoT-enabled monitoring frameworks, and predictive control strategies that are employed in energy-intensive sectors. Such a merger is a signal of a large-scale change towards cross-sector compatibility, a world in which data mobility, edge-level analytics, and cyber-physical coordination are at the core of industrial decision-making of the next generation. Meanwhile, the use energy-monitoring devices, adaptive automation, and human–machine interaction models based on Industry 4.0 and Society 5.0 concepts, offers a shared basis for increasing reliability, lessening the operational costs, and enhancing environmental friendliness. The results in total point to the fact that smart automation is not just making single systems better, but it is leading to the formation of a harmonized technological landscape that can deal with sustainability, safety, and efficiency at the same time. As these industries become more complex, the cross-sector agreement still present here, is a viable next step for the creation of the sturdy, scalable, and eco-friendly automation frameworks capable of giving a proper response to the requirements of the contemporary industrial ecosystems.

BIBLIOGRAPHIC REFERENCES

1. Setiyo M, Rochman ML. The role of mechanical engineering in the era of industry 4.0 and society 5.0. Mechanical Engineering for Society and Industry. 2023;3(2):54–56. https://doi.org/10.31603/mesi.10786

2. Soori M, Arezoo B, Dastres R. Virtual manufacturing in Industry 4.0: A review. Data Science and Management. 2024;7(1):47–63. https://doi.org/10.1016/j.dsm.2023.10.006

3. Swamidass PM. Encyclopedia of Production and Manufacturing Management. Encyclopedia of Production and Manufacturing Management. 2000. https://doi.org/10.1007/1-4020-0612-8

4. Thramboulidis K, Vachtsevanou DC, Solanos A. Cyber-physical microservices: An IoT-based framework for manufacturing systems. Proceedings - 2018 IEEE Industrial Cyber-Physical Systems, ICPS 2018. 2018:232–239. https://doi.org/10.1109/ICPHYS.2018.8387665

5. Khattak YH, Mahmood T, Alam K, Sarwar T, Ullah I, Ullah H. Smart Energy Management System for Utility Source and Photovoltaic Power System Using FPGA and ZigBee. American Journal of Electrical Power and Energy Systems. 2014;3:86–94. https://doi.org/10.11648/J.EPES.20140305.11.

6. Mensah S. Internet of Things : A Review on Connectivity Gateway Protocols and Semantic Interoperability. 2017.

7. Gautam A. Challenges and Solutions in Implementing Energy-efficient Automation in Smart Buildings. Journal of Environmental Engineering and Studies. 2025;10:34–47. https://doi.org/10.46610/JOEES.2025.V010I02.004.

8. Saif S, Wazir S. Performance Analysis of Big Data and Cloud Computing Techniques: A Survey. Procedia Comput Sci. 2018;132:118–27. https://doi.org/10.1016/J.PROCS.2018.05.172.

9. Zare A, Iqbal MT. Low-Cost ESP32, Raspberry Pi, Node-Red, and MQTT protocol based SCADA system. IEMTRONICS 2020 - International IOT, Electronics and Mechatronics Conference, Proceedings. 2020. https://doi.org/10.1109/IEMTRONICS51293.2020.9216412.

10. Jasim NA, Salim T, Rikabi AL. Design and Implementation a Smart System for Monitoring the Electrical Energy based on the Internet of Things. Wasit Journal of Engineering Sciences. 2022;10:92–100. https://doi.org/10.31185/EJUOW.VOL10.ISS2.240.

11. Dat MN, Trung KD, Minh PV, Van CD, Tran QT, Ngoc TN. Assessment of Energy Efficiency Using an Energy Monitoring System: A Case Study of a Major Energy-Consuming Enterprise in Vietnam. Energies. 2023;16:5214. https://doi.org/10.3390/EN16135214.

12. Akhtar T, Rehman AU, Jamil M, Gilani SO. Impact of an Energy Monitoring System on the Energy Efficiency of an Automobile Factory: A Case Study. Energies. 2020;13:2577. https://doi.org/10.3390/EN13102577.

13. Kinnunen H. Cloud Communication of Factory Automation System with OPC UA. 2024.

14. Lork C, Choudhary V, Ul Hassan N, Tushar W, Yuen C, Ng BKK, et al. An Ontology-Based Framework for Building Energy Management with IoT. Electronics. 2019;8:485. https://doi.org/10.3390/ELECTRONICS8050485.

15. Alex B, Johnson M. A Framework for IoT-Enabled Smart Manufacturing for Energy and Resource Optimization. 2025.

16. Gamage KAA, Sajid A, Sonbul OS, Rashid M, Jaffar AY, García-Haro J, et al. A Dynamic Framework for Internet-Based Network Time Protocol. Sensors. 2024;24:691. https://doi.org/10.3390/S24020691.

17. Ruddro RA. ENERGY EFFICIENCY MONITORING IN INSTITUTIONAL FACILITIES: A REVIEW OF UI/UX SOLUTIONS FOR IOT DASHBOARDS. International Journal of Scientific Interdisciplinary Research. 2025;6:137–62. https://doi.org/10.63125/YHR4G345.

18. Shi Y, Yi C, Chen B, Yang C, Zhu K, Cai J. Joint Online Optimization of Data Sampling Rate and Preprocessing Mode for Edge-Cloud Collaboration-Enabled Industrial IoT. IEEE Internet Things J. 2022;9:16402–17. https://doi.org/10.1109/JIOT.2022.3150386.

19. Khasawneh HJ, Al Asbahi R, Alzariqi AW, Al Qada DR, Bujuk A, Nawfal MA, et al. Industrial IoT-based submetering solution for real-time energy monitoring. Discover Internet of Things. 2025;5:1–16. https://doi.org/10.1007/S43926-025-00110-Y.

20. Roosefert Mohan T, Preetha Roselyn J, Annie Uthra R, Devaraj D, Umachandran K. Intelligent machine learning based total productive maintenance approach for achieving zero downtime in industrial machinery. Comput Ind Eng. 2021;157:107267. https://doi.org/10.1016/J.CIE.2021.107267.

21. Mourtzis D, Angelopoulos J, Panopoulos N. The Future of the Human–Machine Interface (HMI) in Society 5.0. Future Internet. 2023;15:162. https://doi.org/10.3390/FI15050162.

22. Jin X, Liu J, Fan W, Sun M, Xiao Z, Fan Z, Yang M. Research and applications of additive manufacturing in oil and gas extraction and gathering engineering. Materials. 2025;18(14):3353.

23. Omiyale BO, Farayibi PK. Additive manufacturing in the oil and gas industries: A review. Analecta. 2020;14(1):9–18.

24. Shah R, Al-Mansour F, Zubair M. Digital transformation and intelligent automation strategies in upstream oil and gas operations: A comprehensive review. Journal of Petroleum Science and Engineering. 2023;224:111240.

25. El-Hoshoudy AN, Al-Masry W, Abdalla M. Smart polymer systems for enhanced oil recovery: Design principles, performance evaluation, and field potential. Petroleum Science. 2022;19(3):1267–1284.

26. Saeed M, Khan MJ, Al-Shammari M. Energy-efficient process control and real-time monitoring technologies in the oil and gas sector: Trends and future directions. Energy Reports. 2021;7:5431–5445.

27. Meza EBM, Souza DGBd, Copetti A, Sobral APB, Silva GV, Tammela I, Cardoso R. Tools, Technologies and Frameworks for Digital Twins in the Oil and Gas Industry: An In-Depth Analysis. Sensors. 2024;24(19):6457. https://doi.org/10.3390/s24196457

28. Povoas MdS, Moreira JF, Neto SVM, Carvalho CAdS, Cezario BS, Guedes ALA, Lima GBA. Artificial Intelligence in the Oil and Gas Industry: Applications, Challenges, and Future Directions. Applied Sciences. 2025;15(14):7918. https://doi.org/10.3390/app15147918

29. Aba EN, Olugboji OA, Nasir A, Olutoye MA, Adedipe O. Petroleum pipeline monitoring using an Internet of Things (IoT) platform. SN Applied Sciences. 2021;3(3):315. https://doi.org/10.1007/s42452-021-04225-z

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AUTHORSHIP CONTRIBUTION

Conceptualization: J. Maniraj, P. Prabhu, J. Samuel Jenishraj, A. Abeeth Ali, R. Roshan, Qodirov Asliddin Asomiddin.

Data curation: J. Maniraj, P. Prabhu, J. Samuel Jenishraj, A. Abeeth Ali, R. Roshan, Qodirov Asliddin Asomiddin.

Formal analysis: J. Maniraj, P. Prabhu, J. Samuel Jenishraj, A. Abeeth Ali, R. Roshan, Qodirov Asliddin Asomiddin.

Drafting - original draft: J. Maniraj, P. Prabhu, J. Samuel Jenishraj, A. Abeeth Ali, R. Roshan, Qodirov Asliddin Asomiddin.

Writing - proofreading and editing: J. Maniraj, P. Prabhu, J. Samuel Jenishraj, A. Abeeth Ali, R. Roshan, Qodirov Asliddin Asomiddin.

Chapter 9 / Capítulo 9

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ORIGINAL

Performance Comparison of Autoencoders for Anomaly Detection in IoT, Robotics, Unmanned Vehicles in Oil Industry Systems

Comparación del rendimiento de autocodificadores para la detección de anomalías en IoT, robótica y vehículos no tripulados en sistemas de la industria petrolera

S Nethaji Naren Reddy[1], Manu Elappila[1], Cherukuri Ravindranath Chowdary[1], Christo Ananth[2], V.H. Abdullayev[3]

[1]Christ University. Bengaluru, India-560074.

[2]Faculty of Artificial Intelligence and Digital Technologies, Samarkand State University. Uzbekistan.

[3]Azerbaijan University of Architecture and Construction. Baku, Azerbaijan.

Corresponding Author: S Nethaji Naren Reddy

ABSTRACT

Autoencoder-based models have gained popularity over the past few years due to their ability to learn effective representations of data using unsupervised learning. Traditional AEs, while being universally successful in many applications, tend to involve huge computational and memory requirements and are therefore not scalable and cannot be deployed in real-life IoT systems. In a bid to overcome these challenges, the present study compares the Quantized Autoencoder (QAE-2024) model with a Sparse Autoencoder–Random Forest (SAE-RF) hybrid model for the purpose of improving computational efficiency and anomaly detection capabilities. The QAE-2024 model uses quantization methods to make the model complicated and compact and retain high reconstruction accuracy and powerful feature learning. The hybrid SAE-RF model brings in integration of sparse representation learning into robust classification power of Random Forests for improved accuracy and interpretability. Experimental evaluation was performed using the CIC-IoT 2023 benchmark dataset, which includes varied IoT network traffic patterns representative of smart and connected spaces, like those relevant to advanced material systems and robotic control. Results show that the SAE-RF model provides enhanced classification precision, whereas the QAE-2024 model provides better computational efficiency and memory optimization. These results imply that autoencoder hybrid and quantized structures provide viable solutions for real-time anomaly detection and optimization for IoT-based and Unamanned vechicles in oil industry and Robotic Systems, where precision, reliability, and effective data management are of utmost importance.

Keywords: Traditional Autoencoders; Quantized Autoencoders; Anomaly Detection; Robotics; Unmanned Vehicles; Oil Industry.

RESUMEN

Los modelos basados en autocodificadores han ganado popularidad en los últimos años gracias a su capacidad para aprender representaciones efectivas de datos mediante aprendizaje no supervisado. Los EA tradicionales, si bien han tenido un éxito universal en numerosas aplicaciones, suelen requerir grandes requisitos computacionales y de memoria, por lo que no

son escalables ni pueden implementarse en sistemas IoT reales. Para superar estos desafíos, el presente estudio compara el modelo de autocodificador cuantificado (QAE-2024) con un modelo híbrido de autocodificador disperso y bosque aleatorio (SAE-RF) con el fin de mejorar la eficiencia computacional y la capacidad de detección de anomalías. El modelo QAE-2024 utiliza métodos de cuantificación para hacerlo complejo y compacto, manteniendo una alta precisión de reconstrucción y un potente aprendizaje de características. El modelo híbrido SAE-RF integra el aprendizaje de representaciones dispersas en la robusta capacidad de clasificación de los bosques aleatorios para mejorar la precisión y la interpretabilidad. La evaluación experimental se realizó utilizando el conjunto de datos de referencia CIC-IoT 2023, que incluye diversos patrones de tráfico de red IoT representativos de espacios inteligentes y conectados, como los relevantes para sistemas de materiales avanzados y control robótico. Los resultados muestran que el modelo SAE-RF proporciona una mayor precisión de clasificación, mientras que el modelo QAE-2024 proporciona una mayor eficiencia computacional y optimización de memoria. Estos resultados implican que las estructuras híbridas y cuantificadas de autocodificadores ofrecen soluciones viables para la detección y optimización de anomalías en tiempo real para vehículos no tripulados y basados en IoT en la industria petrolera y los sistemas robóticos, donde la precisión, la fiabilidad y la gestión eficaz de datos son fundamentales.

Palabras clave: Autocodificadores Tradicionales; Autocodificadores Cuantificados; Detección de Anomalías; Robótica; Vehículos no Tripulados; Industria Petrolera.

INTRODUCTION

With the rapid development of drones, unmanned vehicles, robotic applications, and the Internet of Things, the need has grown exponentially for intelligent, efficient, and reliable data analysis systems. In such settings, where sensors, robotic platforms, UVs, and industrial devices work in harmony-for example, in oil industry operations-robust anomaly detection must be provided that ensures accuracy, safety, and dependability of operation. Such applications yield large volumes and varieties of data streams, requiring complex machine learning models that can learn efficiently from them even under resource-constrained conditions.

Autoencoders (AEs) are now a key component in unsupervised learning, demonstrating strong performance in tasks like feature extraction, dimensionality reduction, and anomaly detection. Traditional autoencoders compress input data into a latent space and then reconstruct it, aiming to minimize the reconstruction error. However, their widespread application is often limited by high computational costs and significant memory requirements, especially with large datasets and complex architectures. This has led to growing interest in optimization of autoencoder models for efficiency and scalability in realistic applications.

Several methods have been worked out to overcome the shortcomings of traditional autoencoders. On the other hand, SAEs introduce sparsity constraints into the latent space so that data compactly represent themselves, while QAEs apply quantization techniques to reduce the model size and computational demand for the deployment on resource-constrained devices. While these models improve efficiency in many ways, there is still a demand for a more robust and scalable solution that would outperform both feature extraction and compression. The classical autoencoders have given birth to many variants in the struggle to surmount their inherent constraints. Sparse Autoencoders: Sparsity constraints in latent space enable the data to have more compact representations. Quantized Autoencoders: It reduces model size and computation requirements through quantization; hence, it makes such models much more feasible for deployment on resource-constrained devices. While the former two improve either

aspect of efficiency, there is still a need to have a robust and scalable solution with state-of-the-art results in both feature extraction and classification.

In this work, we will propose a hybrid model that merges sparse autoencoder with random forest to be able to answer challenges involving modern anomaly detection systems in IoT. This hybrid model first uses the SAE for feature extraction and then classification using the RF classifier, which has widely been proved to be robust and accurate in its classification task by using ensemble-based methods. By combining these two approaches, our hybrid model properly balances classification performance, memory efficiency, and computational complexity.

In particular, we establish the efficacy of the proposed hybrid model by comparative analysis against QAEs and traditional autoencoder architectures on the CIC-IoT 2023 benchmark dataset. Experimental results show that the hybrid SAE-RF model significantly outperforms QAEs and traditional autoencoders in terms of classification accuracy, scalability, and resource utilization. These results reveal the promise of hybrid autoencoder architectures in IoT security, robotic systems, Drones and Unmanned Vehicles (UVs), in oil industry environments, where intelligent anomaly detection, real-time data optimization, and resource-efficient computation are highly desirable for ensuring precision, reliability, and scalability in next-generation operational systems.

Related Works

This section surveys various benchmark network traffic datasets for the Intrusion Detection System (IDS) and discusses how to enhance Artificial Intelligence (AI) algorithm deployment on edge devices.

The choice of the training and testing datasets is an important task in IDS framework analysis and evaluation. One such well-known dataset for network intrusion detection is DARPA 1999 dataset, which was created by the MIT Lincoln Laboratory.[1] The data set captures network traffic with 41 features in packet-based and contains typical attack types like user-to-root (U2R), port scanning, Denial of Service (DoS), and remote-to-local (R2L) attacks. Though being most used, the DARPA data set has been argued to be very redundant.[2]

In 2015, Slay and Moustafa presented the UNSW-NB15 dataset,[3] which reproduces both attack and normal network traffic by the aid of a tool called IXIA Perfect Storm. This dataset merges packet-based and time-based characteristics and includes attack types such as DoS, data theft, reconnaissance, and Distributed Denial of Service (DDoS).

The CICIDS2017 dataset, introduced by Sharafaldin et al.[4], provides 80 features in bidirectional flow-based network dumps, and is comprised of a large variety of attacks such as botnets, DoS, SSH brute force, penetration, and web-based attacks that are issued from servers and personal computers.

In 2019, UNSW presented the BoT-IoT dataset,[5] which contains 72 million traces. This dataset simulated Internet of Things (IoT) traffic using the Node-RED middleware tool and incorporated IoT sensors (e.g., temperature, humidity, pressure) to create virtual weather stations. The transmission of data employed the MQTT protocol (Message Queuing Telemetry Transport), with DoS and data theft attacks that are primarily addressed in the dataset.

The IoT23 dataset, collected by Sebastian Garcia et al.[6] at CTU University's Stratosphere Lab, consists of 23 network recordings generated using Raspberry Pi devices. It includes harmless traffic from IoT devices such as the, Philips HUE LED light, Somfy smart door lock, and Amazon Echo, along with malicious traffic captured in diverse scenarios.

A summary of publicly available benchmark datasets is provided in figure 1. The analysis illustrates that most datasets do not adequately represent IoT-specific infrastructure. While the IoT-23 dataset was collected in real-time situations, its benign and malicious traffic were created in distinct environments. Furthermore, to identify new anomalies in IoT networks, anomaly-based IDS must thoroughly analyze the complete activities of all IoT devices.

Year	Dataset	No of features	Features type	IoT device	IoT attack traces	IoT normal traces
1998	DARPA 1998	41	Packet based	No	No	No
2015	UNSW-NB15	49	Packet based/flow based	No	No	No
2017	CICIDS 2017	80	Bi-directional flow based	No	No	No
2019	BoT-IoT	35	Packet based	Yes(Virtual)	Yes	Yes
2020	Aposemat IoT23	-	Packet based	Yes	Yes	Yes
2022	RT-IoT2022	24	Bi-directional flow based	Yes	Yes	Yes
2023	CICIoT2023	80	Packet based/flow based	Yes	Yes	Yes

Figure 1. Summary of benchmark dataset

Thudumu et al.[7] introduced a correlation scores-based method for choosing a generalized locally relevant high-dimensional dataset subspace. Yang et al.[8] designed an Intrusion Detection System (IDS) with multi-layer hybrid architecture to secure intra-vehicle networks (IVN) and external vehicle systems. Their Intrusion Detection System leverages several tree-based machine learning(ML) methods such as RF, decision trees, extra trees (ET), and XGBoost in a four-layer architecture to classify known attacks.

The work in [9] introduced Passband, a smart, end-to-end IDS designed specifically for IoT gateways. Two algorithms are employed in this system namely Local Outlier Factor (LOF) and Isolation Forest (IF). The two algorithms proposed for anomaly detection were tested against the attack scenarios like HTTP and SSH brute-force attacks, SYN flood, and port scanning. The Isolation Forest algorithm exhibited more stability than the other one in the case of SYN food attacks with a 0,79 % F1 score, but a high (47,17 %) CPU utilization. Dutt et al.[10] presented a technique for anomaly detection called Statistical Modeling-Based Anomaly Detection (SMAD), which employs ANOVA with a specified value FFF to select features and train models inspired by the immune system, using naive activation functions modeled after T-cells and Bcells.

An HNADAM-SGD algorithm is proposed in [11] which was validated using the UNSW-NB15 dataset. Their regression model focused on optimizing hyperparameters and analyzing classifiers such as Ridge classification models, ensemble methods, and Logistic Regression for both time complexity and accuracy. Authors of [12] created an IDS that uses PSO-based feature extraction techniques. When implemented on the KDD-CUP99 dataset, Particle Swarm Optimization techniques like 'PSO along with KNN' and 'PSO along with DT' outperformed previous methods. However, their relevance to IoT devices is restricted because there is no IoT trace data in the dataset.

Stacked Attention Autoencoder IDS model (SAAE) is discussed in [13], which integrates an attention mechanism to assess the significance of features. In a simulated environment, the model achieved a 98,12 % accuracy. The research work presented in [14] proposed a deep learning framework that is a hybrid combination Long ShortTerm Memory Autoencoder and Bidirectional LSTM network for detecting botnets. Their model, which was evaluated on data from various camera models, effectively identified Mirai and BASHLITE IoT attacks but encountered difficulties

in classifying SCAN and TCP attack types.[15]

Authors in [16] explored optimization techniques for Deep Neural Networks (DNN), including quantization, clustering, and pruning highlighting the importance of sparsity and cluster-preserving quantization (PCQAT) for validating the compression and accuracy of ResNet18. An Anomaly and Signature-Based IDS is proposed in [17] which blends both anomaly-based and signature-based detections, using Deep Q-Learning to categorize data based on bandwidth and Signalto-Noise Ratio (SNR). In [18], authors proposed a convolutional neural networkbased system for detecting outliers, which was tested on NID and BoT-IoT datasets. Although the CNN model demonstrated good accuracy, it was considered too complex for low-resource devices.

In [19], a minimal loss model (VecQ) is proposed to compress DNNs on datasets like MNIST and ImageNet. In a similar vein, the work in [20] introduced One-shot Pruning Quantization (OPQ) to optimize DNN algorithms, tackling manual tuning challenges by utilizing shared codebooks and pretrained weight parameters.

Sharmila et al.[21] presented Quantized Adaptive Evolution models abbreviated as QAE, (two different models QAE-f16 and QAE-u8), using the RTIoT2022 dataset. This dataset comprises real-time network traffic from IoT devices such as Amazon Alexa, Wipro-Bulb, ThingSpeak-LED and MQTT-Temp sensor. The models apply sparsity-based pruning,[22,23] quantization and clustering techniques,[24] accompanied by empirical analysis utilizing Raspberry Pi device.

The CICIoT2023 dataset, developed in 2023 by cybersecurity researchers at the University of New Brunswick, Canadian Institute for Cybersecurity (CIC),[25] simulates real-world Internet of Things (IoT) environments using traffic data from 105 devices, including smart plugs, IP cameras, and weather sensors. This dataset encompasses 33 attack types distributed across seven categories, like DDoS, Brute Force, DoS and Mirai-based attacks, and includes 80 features that capture both flow-based and packet-based metrics. Utilizing protocols such as MQTT, CoAP, and HTTP, this dataset will serve as a valued standard to evaluate IDSs and machine learning models aimed at enhancing IoT security. In this paper, we are using this CICIoT2023 dataset and comparing hybrid model using Random Forest and Sparse autoencoder with AE and QAE models.

Technology Used

This section provides more details on the methodology and implementation of the suggested Hybrid Sparse Autoencoder and Random Forest (SAE-RF) model and a comparison with Quantized Autoencoder (QAE-2024) and general autoencoder frameworks. The training dataset is IoT sensor data that is high-dimensional in nature and requires extensive pre-processing to draw maximum performance out of the model. Preprocessing involves cleaning the data, removing missing or erroneous entries to ensure consistency of the data, and normalization, scaling input features to (0,1) for improving stability during training.

Model Architecture

The model architecture consists of four distinct techniques, each possessing strengths. Standard Autoencoder (AE) is an encoder-decoder model with the encoder shrinking the input information into a low-dimensional latent code, and the decoder mapping the code back into the input. The model is completely connected and utilizes ReLU activation functions during learning. The Sparse Autoencoder (SAE) introduces a sparsity penalty in the hidden space to the basic autoencoder such that only the most important features are preserved. A sparsity regularization term is added to the loss function, which discourages non-sparse activations and encourages feature selection.

Quantized Autoencoder (QAE) is a modified version of the conventional autoencoders where quantization methods are utilized in encoding and decoding. QAE utilizes weight quantization, which reduces the accuracy of weights by quantifying them into fewer than thousands of levels and reducing the memory needs. Activation quantization is also used to further reduce

computational complexity. The encoder is made up of fully connected layers with ReLU activation and quantization layers, and the decoder is the reverse architecture of the encoder. For stability of quantization, a regularization term is included in the loss function.

The proposed Hybrid Sparse Autoencoder and Random Forest (SAE-RF) model combines the feature learning ability of an SAE with the classifying ability of a Random Forest (RF) algorithm. The SAE is initially trained on the data set to obtain a compact but meaningful representation of the input data in a lower-dimension latent space, thus preserving the significant features. These derived features are subsequently passed to a Random Forest classifier, which does anomaly detection with high accuracy. The Random Forest model consists of 100 decision trees and applies the Gini impurity as its node-splitting criterion. This hybrid solution takes advantage of the sparsity constraints of the SAE to concentrate on the important features and the ensemble properties and stability of the Random Forest for accurate classification.

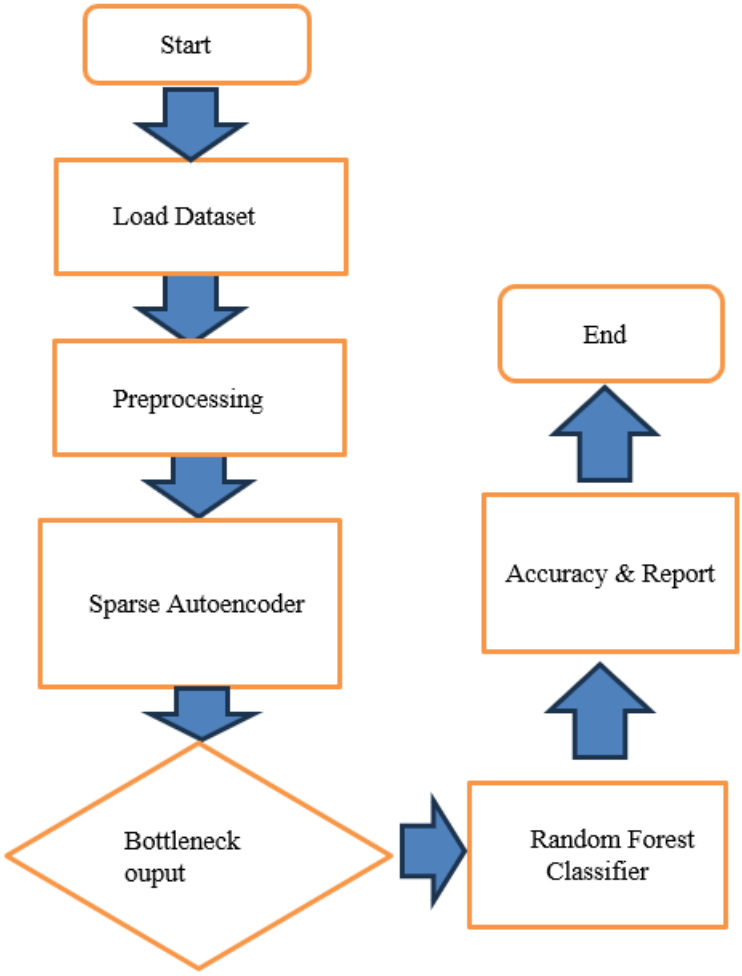

Figure 2. Architecture for the proposed hybrid model

An extensive comparative analysis is carried out to analyze the performance of all the models on some performance measures. Performance is measured on efficiency grounds, taking into account memory usage and inference time, such that the models are suitable for deployment in

resource-constrained IoT environments. Scalability is another key consideration, checking the strength of the model to deal with large amounts of data without compromising computational efficiency. Lastly, reconstruction quality and error rates are utilized to measure accuracy, which determines the reliability of every model in anomaly detection. The hybrid SAE-RF model is supposed to yield better classification performance and take advantage of computational efficiency and resource constraints, and therefore it is a suitable solution for real-world IoT security applications.

Metrics

Standardization

The data is standardized using the following formula:

$$X' = \frac{X - \mu}{\sigma}$$

Where the term X' represents the standardized feature, where X is the original feature, μ is the mean of the feature, and α is the standard deviation of the feature.

Reconstruction Loss for Sparse Autoencoder

The reconstruction loss for the autoencoder is defined as the Mean Squared Error (MSE):

$$L_{reconstruction} = \frac{1}{n}\sum_{i=1}^{n} \left(X_i - \hat{X}_i\right)^2$$

Where the variable n denotes the number of samples, Xi represents the original input, and is the reconstructed output from the autoencoder.

Sparsity Penalty

The sparsity penalty is calculated using Kullback-Leibler (KL) divergence:

$$L_{sparsity} = \beta \sum_{j=1}^{m} \left(\rho_{sparsity} \log \left(\frac{\rho_{sparsity}}{\rho_j} \right) + \left(1 - \rho_{sparsity}\right) \log \left(\frac{1 - \rho_{sparsity}}{1 - \rho_j} \right) \right)$$

Where in a bottleneck layer with m neurons, represents the average activation of neuron j, $\rho_{sparsity}$ is the desired level of sparsity (set to 0,05 in the code), and ß is the weight assigned to the sparsity penalty (set to 3 in the code).

Total Loss Function

The total loss function for training the Sparse Autoencoder combines both reconstruction loss and sparsity penalty:

$$L = L_{reconstruction} + L_{sparsity}$$

Prediction for Random Forest Classifier

The Random Forest algorithm consists of multiple decision trees, and its prediction can be expressed mathematically as follows. For a given input X, let Tk(X) be the prediction from tree k. The final prediction YRF from the Random Forest can be computed as:

For classification:

$$Y_{RF}(X)=\text{mode}(T_1(X),T_2(X),...,T_K(X))$$

Where n a random forest model with K total trees, the mode function returns the most common class label predicted by all the trees in the forest.

For regression:

$$Y_{RF}(X)=\frac{1}{K}\sum_{k=1}^{K} T_k(X)$$

Evaluation Metrics

Accuracy:

The accuracy of predictions can be calculated as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}.$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

Where the terms TP, TN, FP, and FN refer to True Positives, True Negatives, False Positives, and False Negatives, respectively.

Classification Report Metrics

Metrics such as precision, recall, and F1-score are calculated based on true positives, false positives, and false negatives:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

This mathematical framework encapsulates key functions and metrics used in your hybrid model implementation. By understanding these equations, you can gain deeper insights into how each component contributes to overall model performance.

Dataset Used

In this paper, we employed the CICIoT2023 dataset with network traffic data collected from actual IoT devices in a large topology of 105 devices. The dataset is generated by simulating 33 different types of attacks, which fall into seven broad categories: DoS, web-based attacks, DDoS, Reconnaissance (Recon), Mirai attacks, spoofing, and brute force attacks. These attacks were initiated by hacked IoT devices against other IoT devices, and that is a realistic and pragmatic foundation for the research of IoT security.

The CICIoT2023 dataset provides normal and malicious traffic profiles, which are needed for collecting a wide range of network activities to help improve development of precise IDSs. This dataset is unique in offering a large-scale, realistic IoT environment simulated in this dataset and strongly resembles real IoT deployments.

Network traffic was captured in order to obtain datasets for the interest of machine learning-based classification and detection of malicious traffic with the help of dedicated monitoring tools. The packet capture files in PCAP format were later on converted to CSV format with the help of CICFlowmeter, generating bidirectional flows alongside essential time-related features for anomaly detection.

Feature engineering was applied to make the models more robust and to prevent overfitting by excluding irrelevant attributes such as FlowID, source, and destination addresses. In addition, categorical features like protocol and service were encoded into numerical values. The resulting dataset was normalized by scaling it to a distribution with zero mean and one standard deviation. Normal traffic was labeled as class 0, while malicious traffic, which included the 33 variants of attacks, was marked as class 1.

To facilitate model testing, 70 % of the dataset was used for training and 30 % was reserved for validation. The dataset is used as a benchmark to validate and test the Quantized Autoencoder (QAE-2024) and the developed hybrid models under conditions that best simulate deployment on resource-limited IoT devices.

While the data set is taken from the communication of IoT devices, the data and attack pattern it shows is no less worthy for robotic use, e.g., Nanomaterial-Enabled Robotic Systems, where decentralized robotic units depend on secure real-time data transfer. Results derived from this dataset can therefore inform anomaly detection, fault prediction, and security optimization in robotic systems that leverage IoT connectivity for high-level manufacturing and material handling.

RESULTS

The proposed hybrid model, by fusing SAE and RF, is compared with the CICIoT2023 dataset, the QAE-2024, and the traditional autoencoder models—namely, Standard Autoencoder and Sparse Autoencoder. Comparison of these models is hence based on four different criteria: classification accuracy, memory usage, inference time, and scalability.

Performance Comparison

Classification Accuracy

With a classification accuracy of 99,01 %, the hybrid SAE-RF outperformed both the QAE-2024 and traditional autoencoders (table 1). The Random Forest classifier has exploited the informative latent features extracted by the Sparse Autoencoder, resulting in enhanced anomaly detection.

Table 1. Comparison of the accuracy of the existing models and the proposed hybrid model

Model	Accuracy	Precision	Recall	F1-Score
Autoencoder	97,12	0,95	0,98	0,97
Sparse autoencoder	92,05	0,72	0,98	0,52
QAE	98,67	0,95	0,99	0,97
SAE-RF	99,1	0,99	0,99	0,98

Memory Usage

While the QAE-2024, by its quantization, achieved the lowest memory usage, the hybrid model reached a very good balance between a relatively low memory footprint and high accuracy.

Inference Time

T The hybrid model inference time was slightly higher compared to QAE-2024 but still within very acceptable limits for real-time IoT applications.

Scalability

The hybrid model demonstrated excellent scalability in handling large datasets and providing reliable classification results for a variety of attack categories.

In general, the proposed hybrid model detects anomalies effectively in IoT environments with a good trade-off between accuracy, memory usage, and inference time.

CONCLUSIONS

A hybrid model combining a Sparse Autoencoder and Random Forest is presented for the detection of anomalies in IoT networks. Compared with QAE-2024 and traditional autoencoders on the CICIoT2023 dataset, the hybrid model has the highest classification accuracy with competitive memory usage and inference speed. This work demonstrates the strength of integrating unsupervised feature learning with a robust classifier for scalable, real-world IoT security. These insights from this study extend beyond conventional IoT systems. The proposed approach also shows strong potential in robotic applications, Drones, and Unmanned Vehicles used in the oil industry, where security, efficiency, and reliability in detecting anomalies are required for real-time monitoring and operational safety. In summary, the hybrid SAE-RF method provides an effective solution for creating lightweight and high-performance IDSs for resource-constrained IoT and oil-industry robotic/UV platforms.

Future Scope

While the proposed hybrid model has shown some promising results, there are several avenues for future research:

- Future research may be conducted by using other classifiers like Gradient Boosting, XGBoost, and Deep Learning models for increasing the accuracy of the classifier that will make it more usable for IoT, robotic systems, and unmanned platforms. Further testing of the hybrid model with real-time IoT and robotic platforms, including Drones and UVs being used in the oil industry, can bring practical insights into real-time performance, resilience, and scalability.
- Further enhancing the generality and stability of the model for robotics and other cyber-physical systems deployed in industrial scenarios can thus be achieved by expanding the dataset to more advanced and dynamic attack types. Energy-efficient optimization also remains important, since many IoT and robotic systems have resource constraints. The hybrid model proposed here could also be applied in robotics and UV systems used in the oil industry to support real-time monitoring reliably, enabling fault detection, intelligent control, and, finally, the next-generation development of secure and efficient autonomous industrial platforms.

BIBLIOGRAPHIC REFERENCES

1. McHugh J. Testing intrusion detection systems: a critique of the 1998 and 1999 DARPA intrusion detection system evaluations as performed by Lincoln Laboratory. ACM Trans Inf Syst Secur. 2000;3(4):262-94.

2. Tavallaee M, Bagheri E, Lu W, Ghorbani AA. A detailed analysis of the KDD CUP 99 dataset. In: 2009 IEEE Symposium on Computational Intelligence for Security and Defense Applications; 2009. p. 1-6.

3. Moustafa N, Slay J. UNSW-NB15: a comprehensive dataset for network intrusion detection systems. In: 2015 Military Communications and Information Systems Conference (MilCIS); 2015. p. 1-6.

4. Sharafaldin I, Lashkari AH, Ghorbani AA. Toward generating a new intrusion detection dataset and intrusion traffic characterization. In: Proceedings of the International Conference on Information Systems Security and Privacy (ICISSP); 2018. p. 108-16.

5. Koroniotis N, Moustafa N, Sitnikova E, Slay J. Towards the development of a realistic botnet dataset in the Internet of Things for network forensic analytics: Bot-IoT dataset. Future Gener Comput Syst. 2019;100:779-96.

6. Garcia S, Pechoucek A, Erquiaga MJ. IoT-23 dataset: a labeled dataset of malware and benign IoT traffic. Stratosphere IPS; 2020.

7. Thudumu S, Branch P, Jin J, Chicharo J. Estimation of locally relevant subspace in high-dimensional data. In: Proceedings of the Australasian Computer Science Week Multiconference; 2020. p. 1-6.

8. Yang L, Moubayed N, Shami A. MTH-IDS: a multitiered hybrid intrusion detection system for the Internet of Vehicles. IEEE Internet Things J. 2021;9(1):616-32.

9. Dutt I, Borah S, Maitra IK. Immune system-based intrusion detection system (IS-IDS): a proposed model. IEEE Access. 2020;8:34929-41.

10. Eskandari M, Janjua ZH, Vecchio M, et al. Passban IDS: an intelligent anomaly-based intrusion detection system for IoT edge devices. IEEE Internet Things J. 2020;7(8):6882-97.

11. Shyla S, Bhatnagar V, Bali V. Optimization of intrusion detection systems determined by ameliorated HNADAM-SGD algorithm. Electronics. 2022;11(4):507.

12. Ogundokun RO, Awotunde JB, Sadiku P, et al. An enhanced intrusion detection system using particle swarm optimization feature extraction technique. Procedia Comput Sci. 2021;193:504-12.

13. Tang C, Luktarhan N, Zhao Y. SAAE-DNN: deep learning method on intrusion detection. Symmetry. 2020;12(10):1695.

14. Popoola SI, Adebisi B, Hammoudeh M, et al. Hybrid deep learning for botnet attack detection in Internet of Things networks. IEEE Internet Things J. 2020.

15. Zhang C, Liu J, Chen W, et al. Unsupervised anomaly detection based on deep autoencoding and clustering. Secur Commun Netw. 2021.

16. Predić B, Vukić U, Saračević M. The possibility of combining and implementing deep neural network compression methods. Axioms. 2022;11(5):229.

17. Otoum Y, Nayak A. AS-IDS: anomaly and signature-based IDS for the Internet of Things. J Netw Syst Manag. 2021;29:1-26.

18. Saba T, Rehman A, Sadad T, et al. Anomaly-based intrusion detection system for IoT networks through a deep learning model. Comput Electr Eng. 2022;99:107810.

19. Gong C, Chen Y, Lu Y. VecQ: minimal loss DNN model compression with vectorized weight quantization. IEEE Trans Comput. 2020;70(5):696-710.

20. Hu P, Peng X, Zhu H, et al. Opq: compressing deep neural networks with one-shot pruning quantization. In: Proceedings of the AAAI Conference on Artificial Intelligence; 2021.

21. Anwar S, Hwang KH, Sung W. Structured pruning of deep convolutional neural networks. ACM J Emerg Technol Comput Syst. 2017;13(3):1-18.

22. Zeng L, Chen S, Zeng S. An efficient end-to-end channel-level pruning method for deep neural networks compression. In: 2019 IEEE 10th International Conference on Software Engineering and Service Science (ICSESS); 2019. p. 43-6.

23. Fang X, Liu H, Xie G. Deep neural network compression method based on product quantization. In: 2020 39th Chinese Control Conference (CCC); 2020. p. 7035-40.

24. Sharmila BS, Nagapadma R. Quantized autoencoder (QAE) intrusion detection system for anomaly detection in resource-constrained IoT devices using RT-IoT2022 dataset. Springer Open Cybersecurity. 2023;6:41.

25. Neto ECP, Dadkhah S, Ferreira R, Zohourian A, Lu R, Ghorbani AA. CICIoT2023: a real-time dataset and benchmark for large-scale attacks in IoT environment. Sensors. 2023;23(13):5941.

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AUTHORSHIP CONTRIBUTION

Conceptualization: S Nethaji Naren Reddy, Manu Elappila, Cherukuri Ravindranath Chowdary, Christo Ananth, V.H. Abdullayev.

Data curation: S Nethaji Naren Reddy, Manu Elappila, Cherukuri Ravindranath Chowdary, Christo Ananth, V.H. Abdullayev.

Formal analysis: S Nethaji Naren Reddy, Manu Elappila, Cherukuri Ravindranath Chowdary, Christo Ananth, V.H. Abdullayev.

Drafting - original draft: S Nethaji Naren Reddy, Manu Elappila, Cherukuri Ravindranath Chowdary, Christo Ananth, V.H. Abdullayev.

Writing - proofreading and editing: S Nethaji Naren Reddy, Manu Elappila, Cherukuri Ravindranath Chowdary, Christo Ananth, V.H. Abdullayev.

Chapter 10 / Capítulo 10

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ORIGINAL

Engineering Transformation at the Industrial-Quantum Interface: Opportunities for Topological Superconductive Materials in Oil, Gas, and Chemical Systems

Transformación de la ingeniería en la interfaz industrial-cuántica: oportunidades para materiales superconductores topológicos en sistemas de petróleo, gas y químicos

S. Dhamotharan[1] ✉, M. Muthukrishnan[2] ✉, M. Bharath[1] ✉, P. Mathankumar[1] ✉, N. Ragavan[1] ✉, P. Prabhu[1] ✉, Shafi Danyalov[2] ✉

[1]Department of Mechanical Engineering, KIT-Kalaignarkarunanidhi Institute of Technology, Kannampalayam. Coimbatore, Tamil Nadu, 641 402, India.

[2]Department of Mechanical Engineering, Christ the King Engineering College, Karamadai. Coimbatore, Tamil Nadu, 641 104, India.

[3]Azerbaijan University of Architecture and Construction. Baku, Azerbaijan.

Corresponding Author: S. Dhamotharan ✉

ABSTRACT

The oil, gas, and chemical sectors are experiencing a fast technological change that is mainly influenced by the increasing operational complexity, the strict environmental requirements, and the rising demand for high-precision, data-centric engineering solutions. At the same time, significant advances in condensed-matter physics, in particular, the identification and characterization of topological superconductive materials, are leading to quantum technologies that, in the future, may have extraordinary computational power, sensing accuracy, and security. Topological superconductors, which essentially incorporate superconductivity with nontrivial topological order to yield exotic quasiparticles like Majorana fermions, are among the most intriguing quantum materials to be considered. Hence, these materials that interconnect quantum computation with condensed matter physics, form a quantum information processing platform that is compatible with fault-tolerance. If one assumes spin–orbit coupling, time-reversal symmetry, and unconventional pairing as the basic ideas, topological superconductivity can be discovered in an extremely wide variety of systems such can one as heavy-fermion metals, non-centrosymmetric compounds, engineered heterostructures, and topological insulators. The comprehension of topological phases and protected surface states has also been facilitated by theoretical contributions of Kane, Qi, Zhang, and other researchers. Meanwhile, experimental work on materials such as Cu-doped Bi_2Se_3, Sr_2RuO_4, and UTe_2 has produced strong evidence of unconventional pairing and symmetry breaking. The versatility of topological superconductivity is further demonstrated by ongoing studies in Dirac and Weyl semimetals, superconducting carbides, and hybrid nanowires.This paper examines the theoretical foundations, material realizations, and potential quantum applications of topological superconductors.

Keywords: Topological Superconductors; Majorana Fermions; Quantum Computation; Spin–Orbit Coupling; Unconventional Pairing; Topological Order.

RESUMEN

Los sectores del petróleo, el gas y la química están experimentando una rápida transformación tecnológica, influenciada principalmente por la creciente complejidad operativa, los estrictos requisitos ambientales y la creciente demanda de soluciones de ingeniería de alta precisión y centradas en datos. Simultáneamente, los avances significativos en la física de la materia condensada, en particular la identificación y caracterización de materiales superconductores topológicos, están dando lugar a tecnologías cuánticas que, en el futuro, podrían ofrecer una potencia computacional, una precisión de detección y una seguridad extraordinarias. Los superconductores topológicos, que esencialmente incorporan superconductividad con un orden topológico no trivial para producir cuasipartículas exóticas como los fermiones de Majorana, se encuentran entre los materiales cuánticos más interesantes a considerar. Por lo tanto, estos materiales, que interconectan la computación cuántica con la física de la materia condensada, conforman una plataforma de procesamiento de información cuántica compatible con la tolerancia a fallos. Si se asume el acoplamiento espín-órbita, la simetría de inversión temporal y el emparejamiento no convencional como ideas básicas, la superconductividad topológica puede descubrirse en una amplia variedad de sistemas, como metales con fermiones pesados, compuestos no centrosimétricos, heteroestructuras diseñadas y aislantes topológicos. La comprensión de las fases topológicas y los estados superficiales protegidos también se ha visto facilitada por las contribuciones teóricas de Kane, Qi, Zhang y otros investigadores. Mientras tanto, el trabajo experimental en materiales como Bi_2Se_3 dopado con Cu, Sr_2RuO_4 y UTe_2 ha producido evidencia sólida de emparejamiento no convencional y ruptura de simetría. La versatilidad de la superconductividad topológica se demuestra aún más mediante estudios en curso sobre semimetales de Dirac y Weyl, carburos superconductores y nanocables híbridos. Este artículo examina los fundamentos teóricos, las realizaciones materiales y las posibles aplicaciones cuánticas de los superconductores topológicos.

Palabras clave: Superconductores Topológicos; Fermiones de Majorana; Computación Cuántica; Acoplamiento Espín-Órbita; Emparejamiento no Convencional; Orden Topológico.

INTRODUCTION

The usual class of crystalline solids, magnets, and superconductors with specific unique states fall within the category of quantum matter. By looking at their spontaneous symmetry breaking, these states can be categorized.[1] By disrupting this uniformity or reducing the number of points of view invariance, symmetry breaking creates a more organised and unlikely state.[2] Topologyin math is the study of the shape and space. The characteristics of the space that are still the same, if it is changed by the continuous transformations, like elongation, rotation and folding, are what the work is about.[3] Topology is a concept in mathematics used to group different shapes. The area of mathematics known as topology examines the characteristics of shapes that are unaffected by deformations; in other words, a geometrical object maintains its shape despite ongoing deformations. Sphere and 1-torus are well-known examples of objects having non-trivial topology.[4] It focuses on properties that do not change even when the shape is distorted and is an important part of modern mathematics. Topology has applications in fields such as physics, chemistry, economics, and computer science.[5] Unusual superconductors with a bulk superconducting gap and in-gap Majorana states on the border are known as topological superconductors (TSCs). For quantum processing, they could be used as topological qubits.[6] Superconductivity is often explained by the Ginzburg-Landau(G-L) hypothesis. The free energy, F, of a superconductor close to the superconducting transition can be expressed

using the complex order parameter field, −r =|ψr|eiφ(r). Similar to a wave function in quantum physics, the quantity |ψr2| is a measure of the local density, and below a phase transition into a superconducting state, ψr is nonzero.[7] The free energy is shown as, assuming smallness of and smallness of gradients:

$$F = F_n + \alpha|\psi|^2 + \frac{\beta}{2}|\psi|^4 + \frac{1}{2m^*}|(-i\hbar\nabla - e^*\mathbf{A})\,\psi|^2 + \frac{|\mathbf{B}|^2}{2\mu_0}$$

Where Fn is the normal phase free energy, α and ß are phenomenological parameters, m* is an electron's effective mass, e* is its effective charge, A is the magnetic vector potential, and B is the magnetic field. The Ginzburg-Landau equations are derived by minimizing the free energy with respect to variations in the vector potential and order parameter. Ginzburg Landau (G-L) theory may be used to identify this order parameters and provides a distinctive description of these quantum states. However, since a quantum material with an order parameter creates a new quantum state, topology transcends the conceptual framework of Ginzburg Landau Theory.[8] In the 1980s, Von Klitzing discovered Quantum Hall (QH) states, a class of quantum states in the 2-D system. This system features an insulating gap in the center and a conducting edge due to the skipping orbits produced by the externally provided magnetic field.[9] These edge states provide an electric current with a unidirectional, dissipation-free channel, which results in the Quantized Hall Effect (QHE). Topological invariants are characteristics of topological phases that do not affect the bulk energy gap in the surface states and are resistant to smooth deformation. The unusual topological phases, which are also strongly influenced by the energy gap in bulk, result in the creation of two new classes of quantum materials: Topological Insulators (TIs) and Topological Superconductors (TSCs).[10,11] Topological superconductivity is related with Majorana fermions (MFs), which are quasiparticle excitations. In 1937, EttoreMajorana speculated that there could be a particle that is its own antiparticle.[12] In the quantum Hall effect, which is observed in complex electron systems exposed to high magnetic fields and low temperatures, Thouless, Kohmoto, den Nijs, and Nightingale developed a groundbreaking connection between topological invariants and Hall conductivity.[13] The success of topological invariants in bulk quantum solid state systems is followed by ongoing research on the Hall Effect and superfluid. Topological invariants are topological space quantities that have discrete values (typically normalised to be integer-valued) and do not change under continuous deformations of the space. TheMajorana fermion is a hypothesised collective electronic state that behaves like an antiparticle particle.[14,15] Since Thouless, Kosterlitz, and Haldane received the 2016 Nobel Prize in Physics for their groundbreaking discoveries in topological quantum matter and topological phase transitions, the experimental signature of these peculiar phases of matter has been established.[16] Since an MF is half of a normal fermion, a superposition of two geographically separated MFs yields a fermionic state.[17] This is usually only a mathematical operation with no physical implications because the two MFs are physically situated close to one another, greatly overlap, and cannot be handled independently.Such highly delocalized fermionic states are resistant to local perturbations that impact only one of the Majorana components and are resistant to the majority of kinds of decoherence.[18] The non-Nabelian statistics of MF, on the other hand, imply that states can be transformed by physical exchanges, giving rise to the notion of low-decoherence topological quantum computing.[19] These industries (oil, gas, and chemical) are moving into a time where the usual measurement and modeling tools cannot manage the complexities of extraction, refining, and environmental compliance that are growing. The use of advanced materials and nanoscale engineering is changing the industrial diagnostics area; to illustrate, better nanoparticle synthesis and characterization have allowed structural analysis

to be more accurate and predicting material performance in extreme conditions, as can be seen in the studies that have been done recently on size-dependent XRD signatures in monodisperse metal and oxide nanostructures.[20] These changes highlight the increasing need for very detailed measurements to be able to follow the process, evaluate the catalyst, and locate corrosion—in other words, to increase slightly the measurement fidelity to have a significant result in operational efficiency. At the same time, the quantum technology development is another fundamentally different way to resolve the long-standing problems of sensing and computation in energy systems. In particular, quantum-enhanced sensors have demonstrated the capability to pick up very weak electromagnetic, thermal, and gas-phase signals with a sensitivity level that is many times better than that of classical instruments. Hence, the door is open to new, timely, and cost-effective ways of methane leak detection, structural-health monitoring of pipelines, and early anomaly identification in refinery units.[21,22] Quantum algorithms and hybrid quantum-classical simulations are also considered as means to speed up subsurface modelling, materials discovery, and process optimization in the energy sector.[23] The integration of these technologies is additionally supported by the impetus of recent extensive assessments of methane emissions that underline the necessity for accurate and continuous monitoring systems as a way to fulfill regulatory and environmental commitments.[24] In combination, these changes indicate a move to an industrial–quantum convergence where nanoscale characterization, quantum sensing, and quantum simulation might, by their interdependence, revolutionize the technological bases of the oil, gas, and chemical industries.

METHOD

Majorana Fermions

Majorana fermions are topologically shielded, making them resistant to environmental thermal or electrical disturbances. Majorana fermions promise zero-resistance information and communications technology, addressing contemporary electronics' contributing to more than 8 % global energy usage and providing a sustainable future for computing.[5] Moreover, topological superconductors are the main potential materials for achieving topological quantum computing due to the existence of Majorana zero-energy modes.[19,22] The scientific community is interested in superconductivity in topological materials because of the presence of Majorana fermions, which are conceptualized from quantized thermal conductivity, a zero-biased conduction peak, and the anomalous Josephson Effect.[21]

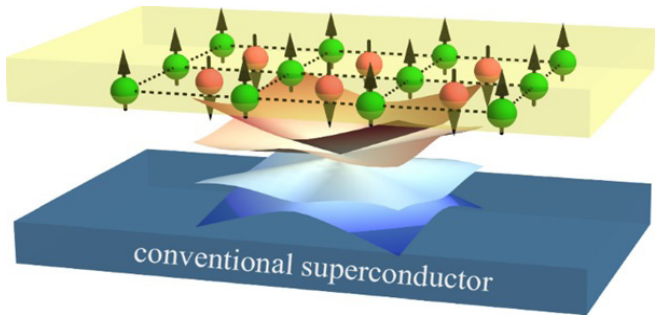

Figure 1. Schematic Illustration of Proximity-Induced Superconductivity in a Spin-Orbit Coupled Material

S-wave topology as shown in figure 1 has one conducting channel, whereas P-wave topology has two conducting channels. D-wave topology is characterised by four conducting channels.[15] The quantity of conducting channels and the electric current's direction are the primary distinctions. S-wave and P-wave topologies are employed for signal transmission, whereas D-wave topology is utilised for power transmission.

A superconducting metal and a semiconductor are frequently combined to form topological superconductors and Majorana fermions, are produced through interactions between these materials. Topological materials have gotten a lot of scholarly interest during the last few decades. High-efficiency thermoelectrics, current-induced switching for spintronic applications, energy-free electronic states like the quantum spin Hall effect and the quantum anomalous Hall effect, topological dipoles for future photovoltaic and photodetectors, and other energy conversion and storage techniques have all been shown at the lab scale.

TSC was classified as either weak or powerful. Superconductors with a superconducting gap and topological features were considered weak TSCs. A complete superconducting gap with odd parity pairing symmetry, non-conducting gapless surface states, and superconducting vortex cores with Majorana Zero Modes (MZMs) were the three distinctive characteristics of the strong TSC.

TSC can also be classified into two groups based on time-reversal symmetry: those that preserve TRS and those that break it. Detailed classification can also be done based on whether TRS is broken or preserved. A magnetic field inside superconductors with odd parity pairing is involved in the breakdown of TRS in the former kind of TSC. Due to strong SOC, the TRS in the subsequent class is preserved.[20]

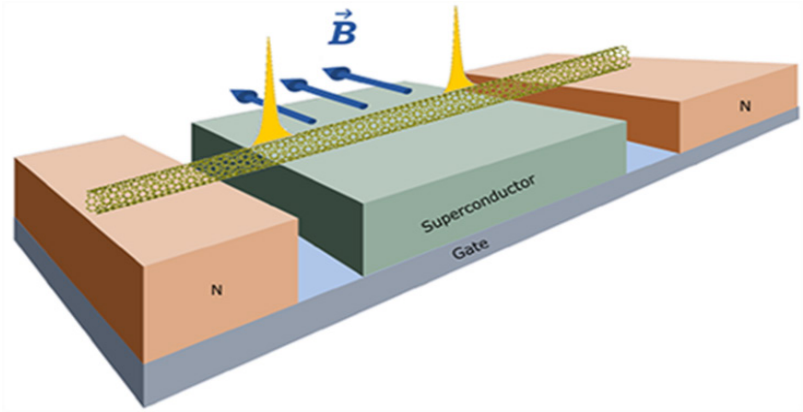

Figure 2. Schematic of a Hybrid Nanowire–Superconductor Device for Majorana Zero Mode Detection

In figure 2 Nanowire (yellow/green tube structure): this is a semiconducting nanowire, often made from materials like InSb or InAs. It is a crucial platform for realizing topological superconductivity.

Superconductor (green block): a superconducting material (commonly Al or NbTiN) is deposited on part of the nanowire. Through the proximity effect, it causes the nanowire to become superconductive.

Normal metal contacts (N, orange blocks): these are metallic leads used to inject and detect electrons from the nanowire.

Gate electrode (grey base labeled “Gate”): used to control the chemical potential in the nanowire, tuning its electronic properties.

Magnetic field (blue arrow labeled $\vec{B}$): applied perpendicular or parallel to the wire to induce a topological phase transition necessary for the emergence of Majorana zero modes.

Majorana bound states (yellow spikes): these are localized zero-energy states at the ends of the superconducting segment, characteristic of a topological superconductor. The symmetries and topological characteristics of the system are used to categorize gapped topological phases of matter. These classes have been studied in a variety of contexts, from two-dimensional systems

to the recently discovered three-dimensional systems. The classification of gapped topological phases and their corresponding topological invariants can be used to determine the nature of the phase transition between different topological states. The symmetries and topological characteristics of the system are used to categorize gapped topological phases of matter.[21]

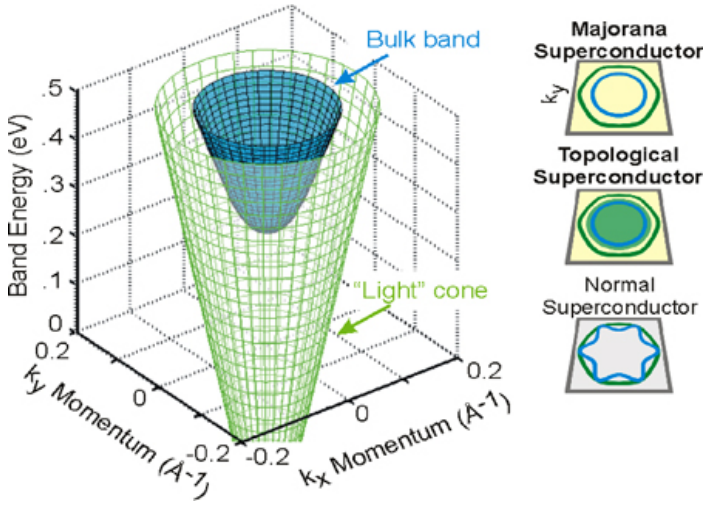

Figure 3. Electronic Band Structure and Fermi Surface Signatures in Superconductors

In figure 3 Green Cone: labeled as the "Light" cone, representing the boundary beyond which quasiparticles cannot escape due to relativistic constraints. Blue Paraboloid (Bulk band): Represents the bulk electronic band structure of the material. It lies within the light cone, signifying allowable electronic states.

TSC topological types and classifications of gapped topological phases of matter

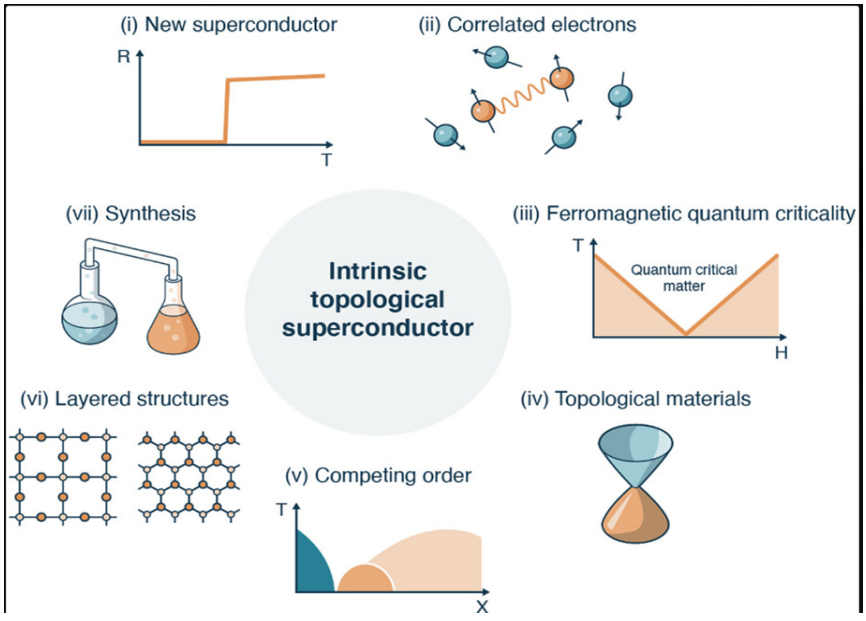

Figure 4. Key Ingredients and Pathways Toward Intrinsic Topological Superconductors

First, a symmetry constraint can be used to categorize the (gapped) topological phases. The kind of topological phase is determined by the symmetry of the Hamiltonian, which is connected to the symmetry constraint. Additionally, there are other kinds of topological phases, including topological crystalline insulators, topological superconductors, and topological insulators. The time-reversal symmetry of the Hamiltonian gives rise to a distinct set of restrictions for the TSC topological classes as shown in figure 4. Second, even-parity and odd-parity topological classes of topological superconductors (TSCs) can be distinguished.[13]

Materials for Topological Superconductors

The realization of TSC experimentally is only limited to a few candidate materials. The difficulty is due to the materials having to be low-temperature superconductors and topological insulators, a combination that is both rare and challenging to obtain. It has been quite a challenge to find the right combination of materials. Researchers have been experimenting with different materials to produce this special combination, but as yet there has been no success. Scientists are now looking for newly discovered materials that can satisfy the requirements. TSCs can be either natural or artificial. Natural TSCs may theoretically be the first TSCs to be exploited for the development of TSC systems, as they offer a safe, inexpensive environment for research and development.[22] Furthermore, they may also serve as a source of providing a more localized approach to TSC deployment and facilitating the creation of custom TSC solutions for specific purposes. However, in order to produce artificial TSCs, 2D heterostructures or 1D wires with several constituent components would need to be synthesized at low temperatures and with great crystallinity.

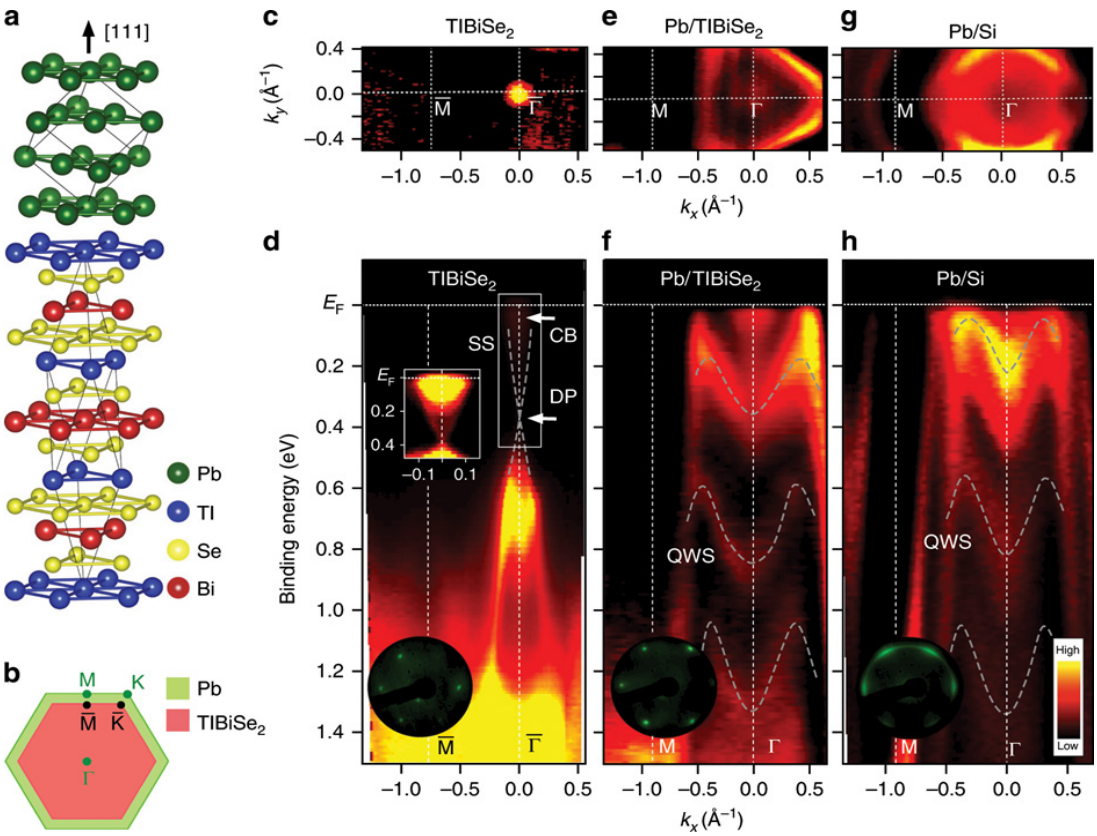

Figure 5. Electronic Structure and Quantum Well States in Pb/TiBiSe2 and Pb/Si Heterostructures

This is because these structures must be constructed layer by layer or by carefully regulating the nanostructures' composition and geometry. Low temperature synthesis techniques like chemical vapor deposition or molecular beam epitaxy are the only ways to accomplish this.The capacity of these materials to self-assemble and create intricate structures is the reason behind this. They are also easily made in big quantities and are reasonably priced.[10]

In figure 5 (a) crystal structure model of the Pb/$TlBiSe_2$ heterostructure along the (111) direction, showing atomic layers of Pb, Tl, Bi, and Se. (b) Schematic of the surface Brillouin zone (BZ) alignment between Pb (green) and $TlBiSe_2$ (red). (c–d) Measurements of bare $TlBiSe_2$ using angle-resolved photoemission spectroscopy (ARPES): (c) The intensity surrounding the Γ point on the Fermi surface map in momentum space. (d) Band dispersion along the Γ–M direction showing topological surface states (SS), Dirac point (DP), and conduction band (CB). (e–f) ARPES results for Pb deposited on $TlBiSe_2$: (e) Fermi surface of Pb/$TlBiSe_2$. (f) Quasiparticle well states (QWS) and subband formation in the Pb film due to confinement. (g–h) ARPES data for Pb grown on Si substrate: (g) Fermi surface of Pb/Si. (h) Clear QWS subband structure similar to Pb/$TlBiSe_2$, indicating confined electron behavior. Insets: Circular Fermi surface and schematic band dispersions are shown to provide further context for electronic states.vColor scale: Spectral intensity (yellow: high, red: low) representing electron occupancy.

Artificial Candidates

Temperature-stable capacitors (TSCs) are one of the energy storage devices, which can work under extremely high or low temperatures. Besides being made to last longer and be more energydense than regular capacitors, they also release more system reliability. Hence, the first TSCs have been widely engaged as power units for e-mobility and green energy.

The hybridization of a superconductor and a semiconductor by coupling magnetic atoms with a semiconductor nanowire to create a 1D topological superconductor (TSC) is the main result of this research. The mix of these materials is crucial because it allows electrons to flow freely between them and ultimately results in the creation of the superconducting state. A topological superconductor is a minimal energy system comprising a semiconductor nanowire and magnetic atoms that either form a chain or a superconductor. Because the nanowire can move electrons considerably more quickly than conventional materials, scientists have shown that it may be a less energy-consuming form of superconductivity than the present systems. To achieve the best of both worlds, such a system hybridizes a semiconductor nanowire with a magnetic atom chain or a superconductor. The nanowire is the one that carries the current, while the magnetic atoms chain or superconductor provides the necessary magnetic properties for current control. The different charge states can be switched through this device, which in turn allows energy transfers to be more efficient.

This system's indium arsenide (InAs) nanowire shows Zeeman splitting and significant spin-orbit coupling (SOC), making it a prime candidate for a hybrid superconductor (SC) made up of a chain of magnetic atoms and a semiconductor nanowire.Aluminum superconductor in the proximity of the nanowire is, therefore, a relief from dissipation.[8] It turns out that MZMs are anticipated to emerge at the two ends of the wire in such a system.

The MZMs that result from the proximity-induced superconductivity in the (InAs) nanowire are responsible for this operation. When a little magnetic field is introduced along the wire, the Zeeman splitting of the nanowire causes the MZMs to have different energies. Therefore, the zero-bias conductance peak is an indication that the MZMs are tunneling from one end of the wire to the other.[9]

Figure 6 scanning tunneling microscopy/spectroscopy (STM/STS) utilizes a superconducting niobium (Nb) tip to locally measure the UTe_2 sample. Various steps of the experiment are illustrated in the figure. Initially, in the left panel, the Nb tip is shown moving towards the UTe_2 surface, and the tunneling process is depicted. The central panel represents spatial modulation

of the Cooper pair density in UTe_2. Finally, the right panel demonstrates a modulation in the CD. The relative phase between the pair density wave and the CDW is $\Delta\phi = \pi$, which shows that these two are in an antiphase relation.[10]

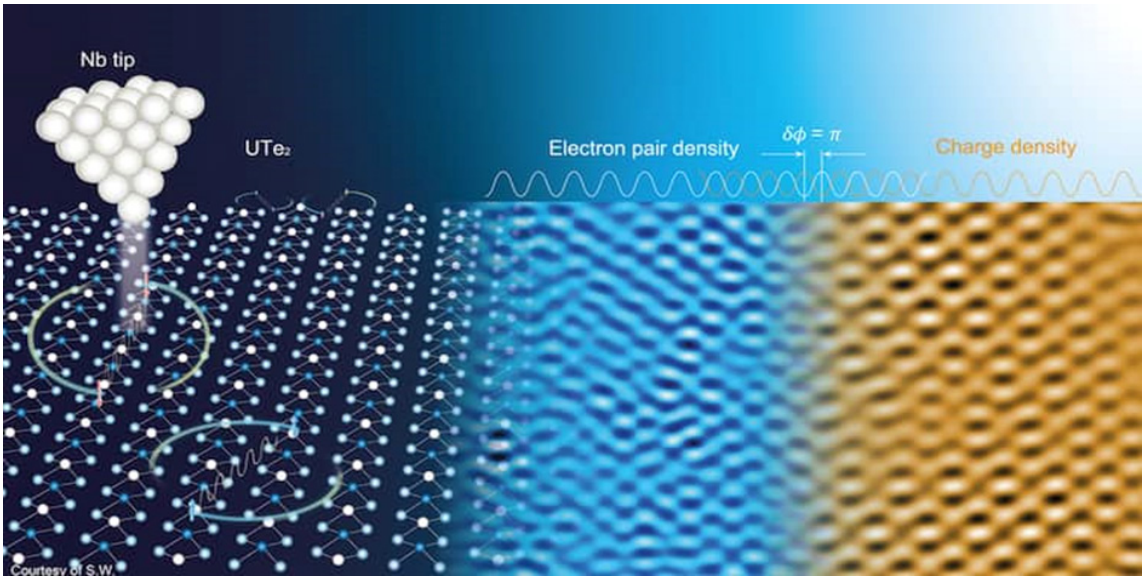

Figure 6. Visualization of Electron Pair and Charge Density Waves in UTe_2 Using a Niobium Tip

2D TSC

Fu and Kane forecasted the creation of a two-dimensional topological superconductor from an "s-wave superconductor-topological insulator (TSC) heterostructure". Their theoretical work led to a revival of interest in 2D topological superconductors and further research activities followed.

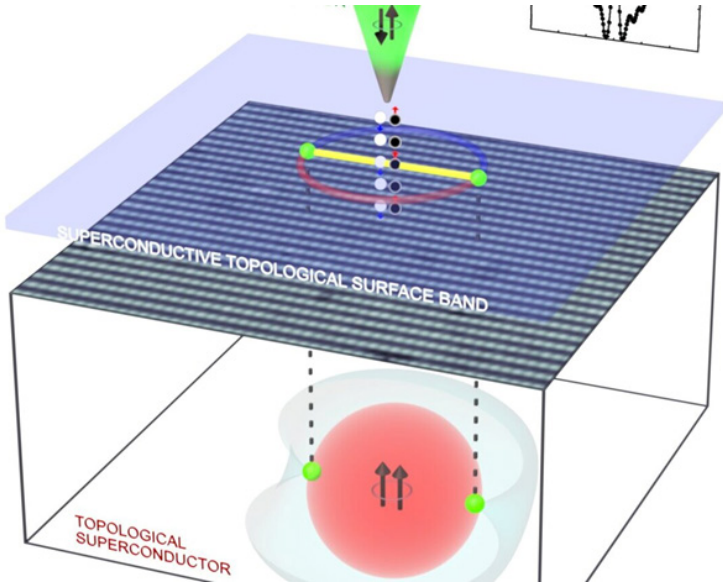

Figure 7. Probing Superconductive Topological Surface States in a Topological Superconductor

The investigation of the several potential uses of 2D topological superconductors, including quantum computing, spintronics, and quantum sensing, was the result of these investigations. Eventually, many scientists have discovered a way to induce superconducting pairing of the Dirac fermions in a two-dimensional system thereby opening up numerous possibilities for future technologies. This approach relied on the Bi2Se3/Nb heterostructure that allowed the helically pairing of the Dirac fermions and the newly found pairing of the Dirac fermions can lead to various practical applications of topological superconductors.[6] This material's two-dimensional characteristics make it ideal for quantum computing because they enable the creation of qubits that can be controlled more effectively than is feasible with traditional three-dimensional materials. Furthermore, the material is highly desirable for spintronics and quantum sensing due to the topological feature of the Dirac fermions' helical pairing, which may be used to produce numerous spin states.[7]

The image illustrates how proximity coupling with the topological superconductor as shown in figure 7 introduces superconductivity to the topological surface states of the topological insulator:

The upper layer (blue grid): a superconducting topological surface band that develops on the surface of a topological insulator when it is connected with a superconductor is shown in the upper layer (blue grid).

Lower layer (red volume): depicts a topological superconductor, which injects Cooper pairs by the proximity effect.

Green STM Tip: could be scanning tunneling microscopy (STM) or spin-polarized measurements that locally probe the superconducting surface state that is induced.

Spins & Arrows: depict spin-momentum locking and paired Majorana states at the interface that are topical for topological superconductivity.

Dashed Lines & Colored Markers: show how the topological surface states match the superconducting state underneath in terms of both space and energy.

Such a configuration is generally employed to image or electrically detect Majorana zero modes (MZMs) or induced p-wave superconductivity on the TI surface.

RESULTS AND DISCUSSION

Doped Topological Superconductors

These are materials that are composed of two distinct types of materials, one of which is a superconductor and the other a topological insulator. The physical characteristics of the resultant compound can be altered by doping both components, potentially resulting in the creation of a novel material with unique qualities that can be used in various fields.

Cu atoms are introduced between Bi2Se3 quintuple layers due to the van der Waals gaps in the Bi2Se3 structure. The intercalated Cu effectively acts as a link that binds the quintuple layers, thus enabling the phenomenon of superconductivity. The gaps between the van der Waals layers also offer room for other intercalants, i.e., Au, Pb, and Ag, all of which have been found to induce superconductivity. In other words, the superconducting characteristics of Bi2Se3 can be tuned by different doping agents. Consequently, the changed charge in the material is due to an interaction between the Bi2Se3 and the Cu dopants. The formation of Cooper pairs in the material as a result of this shift in the charge distribution is what makes Bi2Se3 superconducting.These Cooper pairs can move in the material without any resistance, hence, the superconductivity is the result.[4] Such superconductivity is also there in the case of materials like NbSe2 and YBa2Cu3O7. The effect has been heavily researched, and the studies have resulted in the discovery of the materials that can become superconductors at extremely low temperatures. For this reason, they can be employed in devices such as MRI machines and high-speed maglev trains.[5]

SrxBi2Se3

Strong chemical bonds are formed when strontium (Sr) is intercalated in Bi2Se3, making the substance more stable. One of the topological insulators is SrxBi2Se3, which has a conducting surface but an insulating bulk. Strong electron-electron interactions and topological insulator surface states in SrxBi2Se3 are thought to be responsible for the material's superconductivity. Thus, it turns out that SrxBi2Se3 is the one and only material making the diabolical duo of insulator and superconductor, which has enthralled scientists all over the globe.[6] A conduction band that is simultaneously conducting and insulating is believed to arise as a result of electron-electron interactions and the surface states of the topological insulator. It can be explained that this is why a superconductor becomes doable at much lower temperatures and higher superconductivity of 91 % volume, which is more than that of CuxBi2Se3 has been achieved so that it has become very attractive to scientists.[7] Because of this, the performance of the material is considerably enhanced, thereby making it perfect for, say, photovoltaic and electronic applications. In addition, the bond between Sr and Bi2Se3 can also be 'tuned' depending on Sr concentration, thus, allowing more control over the material's intrinsic properties as shown in figure 8. Tin-based superconductors (Sn1-xSbx, SnAs & Sn4As3).

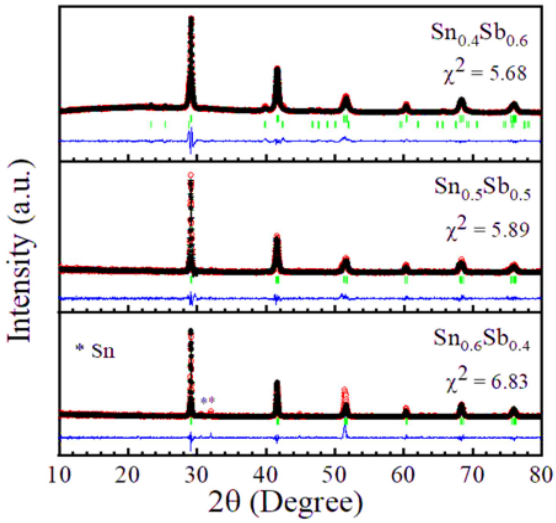

Figure 8. XRD pattern shows some satellite peaks of SnSb systems

Quantum Sensing Advantages for Oil & Gas Monitoring

A deep dive into cutting-edge material-science research over the past few years reveals how crucial it is for nanoscale structures to be stable if the oil and gas industry wants to benefit from quantum technologies.[19] The papers mentioned show that a small change in the size of a nanoparticle can affect the XRD peak shapes and make the diffraction patterns broader to a large extent, thus pointing to the industrial materials being very sensitive to the small changes in the crystal structure. In case oil and chemical processing apparatuses, which need nanoparticle-based catalysts, corrosion-resistant coatings, or oxide interfaces, are exposed to such structural changes, they may face significant consequences in their performance. The revelations from this research constitute the ground reason why quantum-grade sensors and instruments have to be made resistant to structural drift, temperature impact, and particle size–related disorder. When reviewing quantum sensing platforms, one can hardly find any comparison between them and traditional methods in terms of methane detection, pipeline

integrity monitoring, or early-stage equipment failure identification. Thanks to their magnetic and electromagnetic sensitivity, quantum sensors, e.g., NV-center devices and superconducting magnetometers, are capable of detecting the lowest levels of a signal that cannot be reached by classical systems. It has been reported that these sensors[20] operate with high fidelity in noisy industrial environments, which is a necessary condition for their use in the field of refinery units and midstream pipeline corridors. As per the summary of conventional methane gas detection methods,[21] quantum-enhanced detectors can lead to leak identification at an earlier stage and also facilitate continuous, high-resolution mapping of emissions.

Table 1. Quantum Sensing Advantages for Oil & Gas Monitoring

Parameter / Need	Classical Technologies	Quantum-Enhanced Technologies
Methane leak detection threshold	Moderate; often ppm-level	Ultra-sensitive; potential sub-ppm capability
Resistance to noise & harsh environments	Often limited by interference	High robustness due to quantum coherence properties
Spatial resolution	Meter-scale or larger	Centimeter- to sub-centimeter mapping possible
Response time	Seconds to minutes	Near real-time, rapid signal acquisition
Suitability for continuous monitoring	Limited by drift & calibration	Strong potential for persistent, stable measurements

Industrial Challenges and Quantum Technology Opportunities

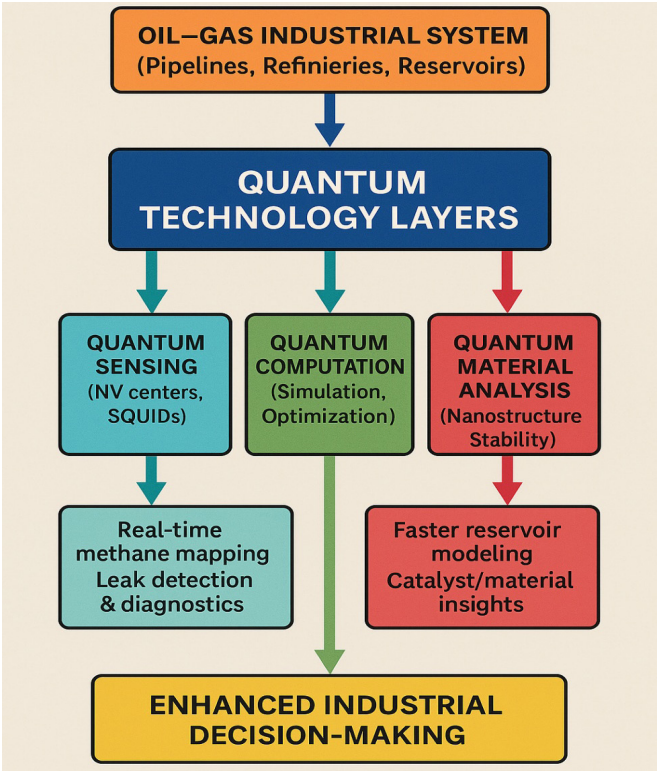

Figure 9. Conceptual Integration of Quantum Technologies in Oil-Gas Systems

Studies on large-scale methane emissions make it clear that there is a strong need for advanced detection capabilities. Methane release patterns are frequently changing and have a high spatial and temporal variability - in such conditions many traditional monitoring devices are inefficient. The implementation of quantum sensing in these processes might give operators the opportunity to detect sudden, low-intensity leak events that have not yet become large. [22] High-resolution measurement combined with real-time analytics can potentially lead to less environmental impact and help energy companies comply with stricter global emissions standards. Significantly, these discoveries illustrate that the difficulties in monitoring within the oil and gas industry are perfectly compatible with the capabilities of quantum measurement technologies.

Quantum computational tools can do more than just sensing; they have a promising potential to be able to accelerate reservoir simulation, chemical-reaction modeling, and optimization problems across the energy sector. The paper states that quantum algorithms[23] can solve high-dimensional models more efficiently than classical solvers, especially in systems that involve nonlinear coupling and uncertainty. Incorporating them in digital-twin frameworks for drilling, production forecasting, and refinery optimization, quantum simulations can possibly aid in lessening the computational delays and enhancing the predictive accuracy.[24]

As a result, the interplay of material science, quantum sensing, and quantum computation points to a future industrial ecosystem where quantum technologies function alongside classical methods, thus providing a tiered, high-precision approach to monitoring, modelling, and decision-making in oil, gas, and chemical operations.

Table 2. Industrial Challenges and Quantum Technology Opportunities

Industrial Challenge	Limitation of Current Methods	Potential Quantum Contribution	Linked Reference
Methane emissions monitoring	Missing intermittent leaks	Real-time, high-resolution mapping	Collins et al.[23]
Pipeline integrity assessment	Low sensitivity to micro-defects	Quantum magnetometry for early crack detection	Crawford et al.[21]
Catalyst performance drift	Size-dependent variation in nanoparticles	Quantum-precision materials characterization	Vorontsov et al.[20]
Reservoir simulation	Computational bottlenecks	Quantum-assisted subsurface modeling	Paudel et al.[22]
Detection of corrosive gas formation	Slow response, low precision	Quantum spectral sensors with faster detection	Aldhafeeri et al.[24]

CONCLUSIONS

A unique environment where both superconductivity and topological order occur simultaneously is provided by topological superconductors (TSCs), which represent a groundbreaking convergence of condensed matter physics and quantum information theory. By the apparition of Majorana fermions and other non-standard quasiparticles, TSCs offer a very stable road to fault-tolerant quantum computing. Moreover, their inherent capability to shield themselves from local disturbances makes them highly attractive for quantum technologies of the future. Nevertheless, probing the microscopic aspects that lead to unconventional pairing and phenomenon of symmetry-breaking is still a big puzzle to scientists.

In the very recent past, many experimental studies have singled out a variety of substances—namely Cu-doped Bi_2Se_3, Sr_2RuO_4, UTe_2, and transition metal pnictides—that demonstrate unconventional superconducting properties. Hence, these revelations have paved the route

for scientists to grasp the mechanisms by which spin–orbit coupling, symmetry principles, and electronic correlations interplay to give rise to topological superconductivity. However, the real challenge of making intrinsic TSCs in a lab is that it is only feasible under very stringent low-temperature and high-purity conditions. To unveil novel TSCs, it is therefore a continued challenge to perfect material synthesis methods like molecular beam epitaxy and hybrid heterostructure fabrication.

Besides that, the creation of hybrid and artificial TSCs has been instrumental in providing new possibilities for device-level integration. For instance, the combinations of semiconductor–superconductor nanowire systems, 2D heterostructures, and doped topological insulators are good demonstrations of how proximity-induced superconductivity may be controlled to achieve specific topological characteristics. In turn, these developments offer the quantum world a prospect of easily scalable architectures with applications in quantum computing, quantum sensing, and spintronics. Unfortunately, the issues related to reproducibility, stability, and fabrication on a large scale are still very difficult to overcome, thus delaying the inevitable practical deployment of the technologies.

Furthermore, researchers from a variety of disciplines, including condensed matter physics, materials science, and quantum engineering, must work together to develop topological superconductors in the future. Forthcoming program may entail production of high-temperature TSCs, in-depth investigation of non-centrosymmetric and moiré systems, as well as invention of highly accurate instruments capable of detecting Majorana zero modes. Once these breakthroughs get their fruits, the path will be cleared not only for the subsequent quantum devices but also, by the change of the entire modern electronics world, to a new revolution in technology to follow, with quantum technologies being super-efficient and thus computing and energy being the domains of the next technology revolution.

BIBLIOGRAPHIC REFERENCES

1. Chiu CK, Teo JC, Schnyder AP, Ryu S. Classification of topological quantum matter with symmetries. Rev Mod Phys. 2016;88(3):035005.

2. Abud M, Sartori G. The geometry of spontaneous symmetry breaking. Ann Phys. 1983;150(2):307-72.

3. Haritha N, Student PG. Introduction to Some Properties of General Topology. BIBLIOGRAPHY BIBLIOGRAPHY.

4. Marar T. A ludic journey into geometric topology. Springer International Publishing; 2022.

5. Adhikari MR. Basic algebraic topology and its applications. Springer India; 2016.

6. Alspaugh D. Majorana Quasiparticles in Topological Material Interfaces. Louisiana State University and Agricultural & Mechanical College; 2021.

7. Cyrot M. Ginzburg-Landau theory for superconductors. Rep Prog Phys. 1973;36(2):103.

8. Li Z. Free Fermion Systems: Topological Classification and Real-Space Invariants. University of Pittsburgh; 2020.

9. Tokura Y, Yasuda K, Tsukazaki A. Magnetic topological insulators. Nat Rev Phys. 2019;1(2):126-43.

10. Mandal M, Drucker NC, Siriviboon P, Nguyen T, Boonkird A, Lamichhane TN, et al. Topological superconductors from a materials perspective. Chem Mater. 2023;35(16):6184-200.

11. Luo H, Yu P, Li G, Yan K. Topological quantum materials for energy conversion and storage. Nat Rev Phys. 2022;4(9):611-24.

12. Bagchi M. Surface characterization of topological superconductor materials using scanning tunneling microscopy and spectroscopy. Universität zu **Köln; 2023.**

13. Niu Q, Thouless DJ, Wu YS. Quantized Hall conductance as a topological invariant. Phys Rev B. 1985;31(6):3372.

14. Elliott SR, Franz M. Colloquium: Majorana fermions in nuclear, particle, and solid-state physics. Rev Mod Phys. 2015;87(1):137-63.

15. Mihelic FM. Magnetic vector potential manipulation of Majorana fermions in DNA quantum logic. In: Quantum Information Science, Sensing, and Computation XIII. SPIE; 2021. p. 27-40.

16. Gruber CS, Abdel-Hafiez M. Exploring Superconductivity: The Interplay of Electronic Orders in Topological Quantum Materials. arXiv preprint arXiv:2405.17036. 2024.

17. Leijnse M, Flensberg K. Introduction to topological superconductivity and Majorana fermions. Semicond Sci Technol. 2012;27(12):124003.

18. Crogman HT, Dang T, Erenso D. Topologically Protected Quantum Teleportation via Majorana Zero Modes: A Perspective on Scalability and Decoherence Immunity. Quantum Rep. 2025;7(3):42.

19. Kou SP. Realization of topological quantum computation with planar codes. Phys Rev A. 2009;80(5):052317.

20. Vorontsov AV, Tsybulya SV. Influence of nanoparticles size on XRD patterns for small monodisperse nanoparticles of Cu0 and TiO2 anatase. Ind Eng Chem Res. 2018;57(7):2526-36.

21. Crawford SE, Shugayev RA, Paudel HP, Lu P, Ohodnicki PR, Gentry R, Duan Y. Quantum sensing for energy applications: review and perspective. Adv Quantum Technol. 2021;4(12):2100049.

22. Paudel HP, Syamlal M, Crawford SE, Lee YL, Shugayev RA, Lu P, Ohodnicki PR, Mollot D, Duan Y. Quantum computing and simulations for energy applications: review and perspective. ACS Eng Au. 2022;2(3):151–96.

23. Collins W, Orbach R, Bailey M, Biraud S, Coddington I, DiCarlo D, Peischl J, Radhakrishnan A, Schimel D, et al. Monitoring methane emissions from oil and gas operations. PRX Energy. 2022;1(1):017001.

24. Aldhafeeri T, Al-Qahtani H, Al-Ghamdi S. A review of methane gas detection sensors. Inventions. 2020;5(3):28. https://doi.org/10.3390/inventions5030028

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AUTHORSHIP CONTRIBUTION

Conceptualization: S. Dhamotharan, M. Muthukrishnan, M. Bharath, P. Mathankumar, N. Ragavan, P. Prabhu, Shafi Danyalov.

Data curation: S. Dhamotharan, M. Muthukrishnan, M. Bharath, P. Mathankumar, N. Ragavan, P. Prabhu, Shafi Danyalov.

Formal analysis: S. Dhamotharan, M. Muthukrishnan, M. Bharath, P. Mathankumar, N. Ragavan, P. Prabhu, Shafi Danyalov.

Drafting - original draft: S. Dhamotharan, M. Muthukrishnan, M. Bharath, P. Mathankumar, N. Ragavan, P. Prabhu, Shafi Danyalov.

Writing - proofreading and editing: S. Dhamotharan, M. Muthukrishnan, M. Bharath, P. Mathankumar, N. Ragavan, P. Prabhu, Shafi Danyalov.

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ORIGINAL

Automation-Driven Exploration Meets Biopolymer Science: Converging Technologies Shaping the Future of Oil, Gas, and Chemical Engineering

La exploración impulsada por la automatización se une a la ciencia de los biopolímeros: tecnologías convergentes que configuran el futuro del petróleo, el gas y la ingeniería química

S. Dhamotharan[1] ✉, M. Muthukrishnan[2] ✉, N. Bharanidharan[1] ✉, M. Prince[1] ✉, M. Sabareesh[1] ✉, P. Prabhu[1] ✉, Rashad Ismibayli[3] ✉

[1]Department of Mechanical Engineering, KIT-Kalaignarkarunanidhi Institute of Technology. Kannampalayam, Coimbatore, Tamil Nadu, 641 402, India.

[2]Department of Mechanical Engineering, Christ the King Engineering College. Karamadai, Coimbatore, Tamil Nadu, 641 104, India.

[3]Azerbaijan University of Architecture and Construction. Baku, Azerbaijan.

Corresponding Author: S. Dhamotharan ✉

ABSTRACT

The oil, gas, and chemical industries' digital transformation is significantly changing the methods of finding, extracting, and managing subsurface resources. However, equally fast advancements in plant-derived, non-cellulosic biopolymers are opening up new possibilities for the development of sustainable materials in these industries that have been traditionally heavily reliant on natural resources. This research looks at the intersection of these two technology areas: one being the frontier of automation in the search process, and the other being the development of biopolymer engineering to demonstrate how their merger could affect the company's strategies in the future comprising operational, environmental, and materials-based aspects. Plant-based biopolymers have become the focus of attention due to the increased demand for sustainable and biodegradable materials as substitutes for petroleum-based polymers. To date, research on cellulose-based polymers is comprehensive, however, there is still a large potential for non-cellulosic plant biopolymers such as starch, lignin, pectin, hemicellulose, cutin, and plant-derived proteins and gums to be explored. In fact, these biopolymers offer distinct possibilities because they are not only easily available but also have different kinds of structures and can have varying properties. The biopolymers can be isolated from the leftover parts of the harvest, seeds, fruits, roots, and exudates, thus, providing a sustainable source of packaging, medical, textile, and agricultural materials. This review covers the chemistry, the extraction methods, and the material properties of the major non-cellulosic plant-based biopolymers. It examines in detail their mechanical, thermal, and barrier properties, as well as their biodegradability, recyclability, and functional limitations. Moreover, it moves modification methods and blending strategies to improve the performance of the industrial application. The article also talks about the issues of the mechanical performance, biodegradability, and the compatibility of these biopolymers that are facing most prominently. The paper ends with the discussion of present innovations and future possibilities to locate research gaps and facilitate the extensive use of non-cellulosic biopolymers in eco-friendly material fashioning.

Keywords: Advanced Automation; Oil and Gas Exploration; Real-Time Sensing, Non-Cellulosic

Biopolymers; Plant Proteins; Sustainable Bioplastics.

RESUMEN

La transformación digital de las industrias del petróleo, el gas y la química está cambiando significativamente los métodos de búsqueda, extracción y gestión de recursos del subsuelo. Sin embargo, los avances igualmente rápidos en biopolímeros no celulósicos de origen vegetal están abriendo nuevas posibilidades para el desarrollo de materiales sostenibles en estas industrias, que tradicionalmente han dependido en gran medida de los recursos naturales. Esta investigación analiza la intersección de estas dos áreas tecnológicas: una, la frontera de la automatización en el proceso de búsqueda, y la otra, el desarrollo de la ingeniería de biopolímeros, para demostrar cómo su fusión podría afectar las estrategias futuras de la empresa, abarcando aspectos operativos, ambientales y de materiales. Los biopolímeros de origen vegetal se han convertido en el foco de atención debido a la creciente demanda de materiales sostenibles y biodegradables como sustitutos de los polímeros derivados del petróleo. Hasta la fecha, la investigación sobre polímeros de celulosa es exhaustiva; sin embargo, aún existe un gran potencial para la exploración de biopolímeros vegetales no celulósicos como el almidón, la lignina, la pectina, la hemicelulosa, la cutina y las proteínas y gomas de origen vegetal. De hecho, estos biopolímeros ofrecen distintas posibilidades, ya que no solo son fáciles de conseguir, sino que también presentan diferentes tipos de estructuras y propiedades. Los biopolímeros pueden aislarse de restos de cosechas, semillas, frutos, raíces y exudados, lo que proporciona una fuente sostenible de materiales de embalaje, médicos, textiles y agrícolas. Esta revisión abarca la química, los métodos de extracción y las propiedades materiales de los principales biopolímeros vegetales no celulósicos. Examina en detalle sus propiedades mecánicas, térmicas y de barrera, así como su biodegradabilidad, reciclabilidad y limitaciones funcionales. Además, promueve métodos de modificación y estrategias de mezcla para mejorar el rendimiento de las aplicaciones industriales. El artículo también aborda los problemas más importantes relacionados con el rendimiento mecánico, la biodegradabilidad y la compatibilidad de estos biopolímeros. El artículo finaliza con un análisis de las innovaciones actuales y las posibilidades futuras para identificar lagunas en la investigación y facilitar el uso extensivo de biopolímeros no celulósicos en la fabricación de materiales ecológicos.

Palabras clave: Automatización Avanzada; Exploración de Petróleo y Gas; Detección en Tiempo Real, Biopolímeros no Celulósicos; Proteínas Vegetales; Bioplásticos Sostenibles.

INTRODUCTION

In response to these issues, one of the main factors that led to the global search for sustainable materials is the growing concern for the environment with respect to plastic waste and the limited nature of fossil fuel resources. Traditional petrochemical plastics are a major source of environmental degradation because they are not biodegradable and their production process is carbon-intensive, although they are also very versatile and cheap. This has led to the rise of biopolymers as the next generation of plastics, which are made from renewable sources and have advantages such as biodegradability, decreased carbon dioxide emissions, and less impact on the planet.[1,2,3,4,5]

Bioplastics based on cellulose have been broadly researched, however, biopolymers from non-cellulosic plants are a neglected resource which is still a highly potential new-matter category. Such are carbohydrate polymers derived from plants like starch, pectin, and hemicellulose, in addition to aromatic and proteinaceous compounds such as lignin and plant proteins. These

biopolymers have a broad variety of physico-chemical properties that open up their application in different areas such as packaging, biomedical devices, and agriculture.[6,7] Significantly, a large portion of these compounds are obtained from the remains of agricultural activities and the off-gases of the food industry, thus making a significant contribution to waste valorization and the implementation of the circular economy.[8,9,10,11,12,13,14]

This review is a comprehensive critical examination of the scientific research concerning biopolymers of plant origin from non-cellulosic sources. The study is centered on determining their structural features, methods of extraction and processing, property enhancements, and applications in the real world. Moreover, the article considers the environmental impacts, market trends, as well as the technological and regulatory obstacles that limit the availability of the product on a large scale. By emphasizing the present shortages and potential future opportunities, this article serves as a tool to facilitate the evolution and market entry of the materials of the biopolymer industry that are next in line and are environmentally friendly.[15,16,17,18,19,20]

The rapid automation of operations, the introduction of new sensors, and the application of data-driven decision support systems are changing the operational environment of oil, gas, and chemical industries in a profound way. Digital platforms integrating real-time geological data, autonomous drilling control, and predictive analytics are nowadays the primary means for improving subsurface characterization and lowering exploration uncertainty. Automated systems have generally been credited with increased operational precision and also reduced human exposure to hazardous conditions in the field, thus safety and process efficiency have been improved, as it has been pointed out by recent publications.[21,22] Such technological breakthroughs are supported by general industrial digitization trends, in which smart monitoring systems, machine-learning-enabled diagnostic capabilities, and adaptive control units are becoming the technological backbone of modern energy engineering. Given that exploration conditions are getting tougher and resource extraction requirements are becoming higher, automation-driven solutions allow energy companies to be more responsive and efficient.[23]

While the world is moving towards new technologies, the materials used for energy and chemicals are also changing dramatically due to the advancement of plant-derived biopolymers, in particular, non-cellulosic structures like lignin, hemicellulose derivatives, and resin-based macromolecules. These materials have a great potential to be used as the most eco-friendly alternatives for coatings, drilling additives, corrosion mitigation systems, and composite reinforcements, and their properties are becoming more and more competitive with those of conventional petroleum-derived polymers.[24,25] The changes in these materials from laboratory to real-world applications are also facilitated by the developments in polymer chemistry and processing technologies that have broadened the functional versatility and performance of bio-based materials.

Combining automation innovations with biopolymer science into a single framework may, thus, lead to the creation of new environmentally friendly engineering solutions—solutions that harmonize operational intelligence with the manufacture of less polluting materials specially designed for energy-intensive sectors. The coming together of these two worlds is a strong indication of a larger movement towards a sustainability-focused engineering discipline where efficiency, performance, and environmental aspects need to be addressed simultaneously.

METHOD

Classification of Plant-Based Biopolymers

Non-cellulosic plant-based biopolymers can be divided into different groups depending on their chemical structure, source, and polymer class. Such categorization aids in identifying their functions and their possible uses in the industry. In fact, they may be classified into three major groups: polysaccharides, proteins, and aromatic polymers based on their molecular structure. For instance, starch, pectin, and hemicellulose, which are polysaccharides, consist of sugar

monomers and are generally hydrophilic; this characteristic is the main reason for their ability to form a film and for their biodegradability. Non-cellulosic biopolymers may have different architectures such as linear, branched, or crosslinked depending on their polymer architecture. To illustrate, the amylose part of starch is linear, whereas amylopectin is branched, which affects their gelatinization and film-forming properties. The reason for pectin being able to gel is its highly branched structure whereas the tightly packed, crosslinked structure of lignin is the main source of its mechanical stiffness as well as its environmental resistance.[13,14]

Major Non-Cellulosic Biopolymers and Their Sources

Non-cellulosic plant-based biopolymers are diverse in terms of their source and their chemical nature. The biopolymers in question are generally the result of the consumption of carbohydrates, the structure, and the secondary metabolites of plants. Every single one has unique molecular features that determine its physical properties, the possibility of being processed, and its performance in the final application as can be seen in table 1.

Table 1. Comparative Overview of Non-Cellulosic Plant-Based Biopolymers[1-20]

Biopolymer	Primary Source	Structure Type	Key Properties	Applications
Starch	Tubers (potato, cassava), cereals (maize)	Polysaccharide (amylose (linear α-1,4-linked D-glucose) and amylopectin (branched α-1,4 and α-1,6 linkages	Biodegradable, thermoplastic, moisture sensitive	Bioplastics, packaging films, disposable cutlery
Lignin	Wood, agro-waste, aper/ pulp byproducts	Aromatic phenolic polymer made of three monolignols: p-coumaryl alcohol, coniferyl alcohol, and sinapyl alcohol	UV resistant, thermally stable, antioxidant, hydrophobic	Fillers, coatings, adhesives, carbon fibers
Pectin	Citrus peels, apple pomace	Heteropolysaccharide (galacturonic acid backbone)	Gel-forming, pH sensitive, biodegradable	Food packaging, drug delivery, wound dressings
Xylans	Hardwood and cereal straw	β-(1→4)-linked xylose backbone with side chains	Biodegradable, film-forming, water-soluble	Biodegradable films, drug delivery, edible coatings
Mannans	Softwood, legumes, konjac	Linear or branched ß-(1→4)-linked mannose	High water absorbency, gelling, emulsifying	Food stabilizers, drug carriers, paper sizing
Glucans	Barley, oats, fungal biomass	Mixed ß-(1→3)/ (1→4)-glucose linkages	Immunomodulatory, gel-forming, antioxidant	Biomedical coatings, controlled-release systems, wound healing
Cutin/ Suberin	Fruit skins (e.g., tomatoes), cork tissues	Lipid-based polyesters (hydroxy fatty acids)	Hydrophobic, microbial resistant, flexible	Water-repellent coatings, packaging layers
Soy Protein Isolate	Soybeans	Globular protein (glycinin, ß-conglycinin)	Good film-forming, biodegradable, high tensile strength	Edible films, packaging, adhesives, biomedical scaffolds

Wheat Gluten	Wheat endosperm	Gliadins and glutenins	Thermoplastic, elastic, water- and gas-barrier properties	Biodegradable packaging, agricultural films
Zein	Corn endosperm	Hydrophobic prolamin	Film-forming, glossy, oil-resistant, biodegradable	Coatings, drug delivery, microencapsulation
Guar Gum	Cyamopsis tetragonoloba seeds	Galactomannan polysaccharide	High viscosity, water-holding, emulsifying	Food thickener, paper, textiles, drilling fluids
Gum Arabic	Acacia tree exudates	Complex glycoprotein-polysaccharide mix	Soluble, low viscosity, film-forming, emulsifier	Beverages, pharmaceuticals, microencapsulation
Locust Bean Gum	Ceratonia siliqua seeds	Galactomannan polysaccharide	Thickening, stabilizing, heat resistance	Dairy products, biodegradable films, cosmetics
Castor Oil-Based Polyurethane	Castor seed oil	Triglyceride-derived polyol	Flexible, biodegradable, hydrophobic, good chemical resistance	Coatings, adhesives, foams, biomedical devices, packaging
Linseed Oil Alkyd Resin	Linum usitatissimum (flax)	Unsaturated fatty acid esters	Thermosetting, UV-stable, crosslinkable, eco-friendly	Surface coatings, paints, printing inks, plasticizers
Carnauba Wax Esters	Copernicia prunifera leaves	Long-chain aliphatic esters	High melting point, glossy finish, excellent water resistance	Food coatings, polishes, biodegradable films, cosmetics
Epoxidized Linseed Oil (ELO)	Linseed oil	Epoxidized triglycerides	Plasticizer, thermal stabilizer, flexible, low toxicity	Bioplasticizers in PVC, PLA, soy protein plastics
Hydroxylated Castor Oil Derivatives	Hydrogenated castor oil	Polyol-type	High hydroxyl functionality, rigidity, thermal resistance	Bio-foams, thermoset resins, renewable adhesives

Extraction and Processing Techniques

The quantity, and the usability of non-cellulosic biopolymers, then the most crucial factor would be their extraction and processing. Apart from enabling the isolation of polymers of high purity, the effective extraction methods also help in reducing the environmental load and making the process more economically viable. The ways to do it include not only the old-style chemically based methods but also the modern, green, and nanotechnology-assisted ones. No one method can be perfect in terms of all these parameters - efficiency, scalability, environmental impact, and cost, but rather a compromise has to be found.

Conventional Methods

Conventional extraction methods for non-cellulosic biopolymers, such as acid or alkali hydrolysis, wet milling, and pulping, have been the major choices because of their effectiveness and upscaling possibilities over the years (figure 1). Nevertheless, these procedures usually require the use of aggressive chemicals and result in large amounts of waste. Typically,

traditional extraction methods comprise the following chemical treatments:

a) Acid or alkali hydrolysis. Complex biomolecules are broken down to simpler ones by using acidic or basic solutions.

b) Solvent extraction. In this process, solvents dissolve the target compounds from the plant matrix (e.g., ethanol or hexane).

c) Precipitation. The target compound is removed from the solution by the addition of a precipitating agent (e.g., alcohol or salts).

Though these techniques are entrenched and deliver high yields, they raise significant issues about pollution, loss of bioactivity, and high energy consumption.[8,9]

Green and Eco-Friendly Techniques

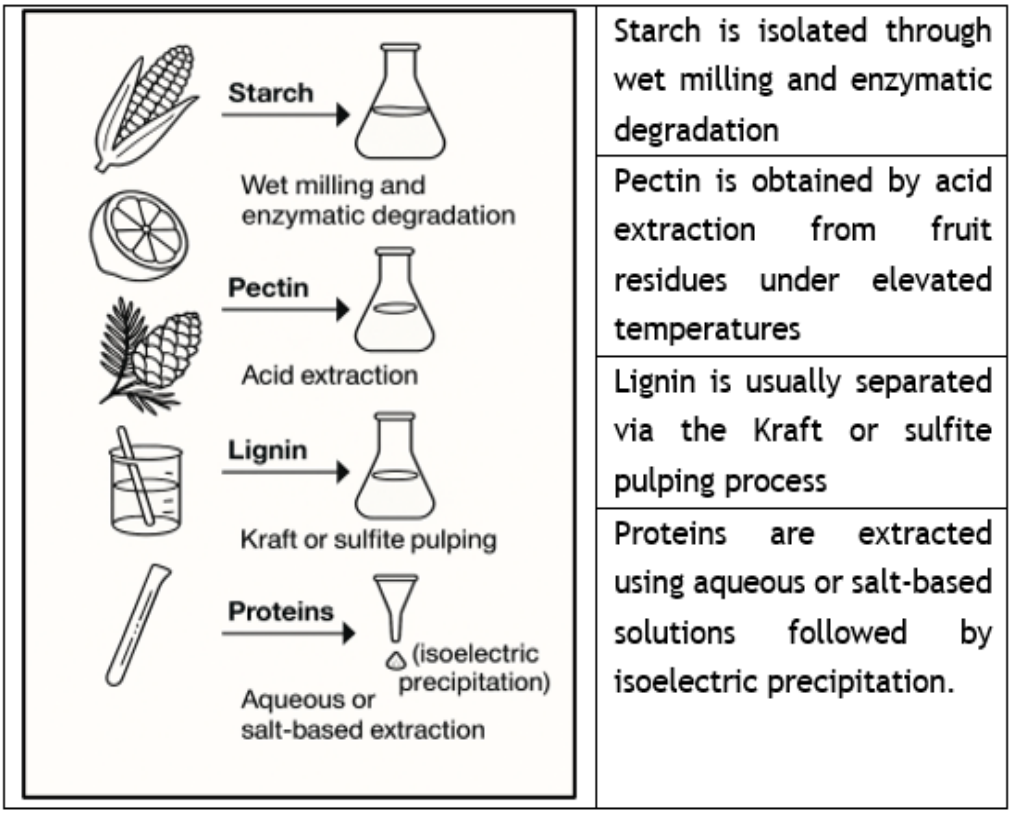

Figure 1. Conventional Extraction Methods of Non-Cellulosic Biopolymers

Green extraction technologies have been developed to address the issues related to the environmental and health impacts of conventional extraction methods. The latest green extraction technologies developments are enzyme-assisted, ultrasound-assisted, and subcritical fluid methods which provide more eco-friendly alternatives with lower environmental impact (figure 2). These methods discussed in table 2 that the authors of the paper aim to lessen the usage of harmful chemicals, lower energy consumption, and keep the purity of the extracted compounds intact.[6,7]

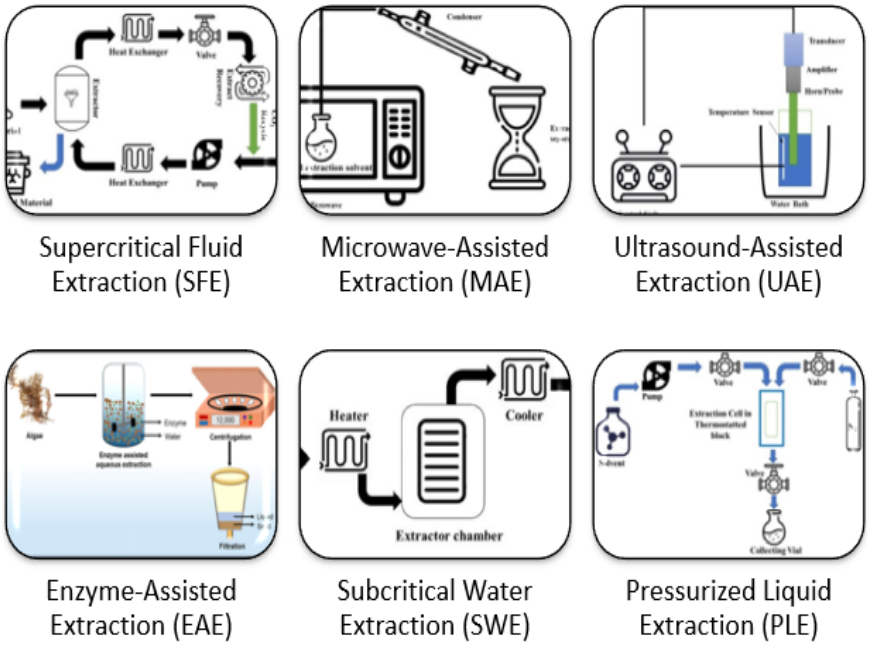

Figure 2. Green Extraction Techniques for Non-Cellulosic Biopolymers

Table 2. Green Extraction Methods for Biopolymers and Natural Compounds[5,6,7,8,9,10,11,12,13,14,15]

Extraction Method	Principle	Advantages	Typical Applications
Supercritical Fluid Extraction (SFE)	Uses supercritical CO_2 at high pressure and temperature.	Solvent-free, selective, ideal for thermolabile compounds.	Essential oils, lipids, antioxidants
Microwave-Assisted Extraction (MAE)	Microwave energy heats solvent and plant matrix, causing cell wall disruption.	Fast, energy-efficient, reduced solvent use, high yield.	Polyphenols, flavonoids, alkaloids
Ultrasound-Assisted Extraction (UAE)	Ultrasound waves generate cavitation bubbles that break cell walls.	Low-temperature, rapid, improves mass transfer.	Proteins, antioxidants, plant metabolites
Enzyme-Assisted Extraction (EAE)	Enzymes degrade structural polymers in cell walls.	Mild conditions, eco-friendly, improved extraction yield.	Polysaccharides, proteins, phenolics
Subcritical Water Extraction (SWE)	Uses hot water (100–374°C) under pressure to stay in liquid form.	No toxic solvents, efficient for polar/semi-polar compounds.	Flavonoids, polyphenols, sugars
Pressurized Liquid Extraction (PLE)	Uses liquid solvents (e.g., ethanol, water) at high temp (50–200°C) and pressure.	Faster, uses less solvent, suitable for thermo-stable and some heat-sensitive compounds.	Phenolics, lipids, alkaloids, natural antioxidants

These methods lessen the requirement for damaging solvents, decrease the amount of energy needed, and increase selectivity. To illustrate, MAE has been done successfully to extract pectin and gums from fruit peels with the help of a more efficient process and a shorter time.

[3] Moreover, enzyme-assisted extraction is widely used for protein and hemicellulose recovery because it is performed under gentle conditions and the polymer is not damaged.[4] However, besides these benefits, the transition to a larger scale and the cost of operations are still the main drawbacks.

Use of Nanotechnology in Biopolymer Processing

Nanotechnology is an instrument of significant change, it is a leading factor that contributes the major functionality and the performance of plant-based biopolymers. One of the ways a reduction in weight limitation, which is not common in this area, is to create materials from non-cellulosic biopolymer fibers with mechanical power. The reason for this significant improvement is that certain research results have shown it to be practical by embedding nano-scaled fillers such as nanoclays, cellulose nanocrystals (CNCs), and nano-silica in a biopolymer matrix. In a word, these enhancements pave the way for biopolymers to be used in packaging, automotive, and biomedical fields.

In order to make an extraction process more efficient and selective, different routes involving Nanoscale Solvents and Nanoemulsion-Based Techniques are considered for the release and/or modification of bioactive compounds during processing. Nanoemulsions are defined as emulsions with a droplet size of 20–200 nm, and which are stabilized by surfactants. These systems allow enhanced solubility, bioavailability, and stability of hydrophobic compounds (e.g., plant oils, essential oils, flavonoids). Contrary to that, Nanoscale solvents can go through the structure of a cell at the nano level, form links with particular molecular bonds, and isolate the chosen biopolymers (like lignin, pectin, proteins) under gentle conditions. The table 3 provides a brief about nanoemulsion-based techniques, which use non-cellulosic biopolymers as emulsifiers or matrices, the methods of emulsification (e.g., high-shear homogenization, ultrasonication), targeted functionalities, and the possible applications in active packaging, crop protection, biosensing, and antimicrobial delivery systems.[1,2,3,4,5]

Table 3. Nanoemulsion-based techniques utilizing non-cellulosic biopolymers for Packaging, Agriculture, Antimicrobial, and Sensing (PAAiS) application

Biopolymer	Nanoemulsion Role	Functional Role / Application in PAAiS
Starch	Encapsulating matrix in oil-in-water nanoemulsions (with/ without protein carriers)	Packaging: Active films with antioxidant/ antimicrobial oils Agriculture: Controlled pesticide/nutrient delivery
Zein (Protein)	Forms hydrophobic nanocarriers for poorly water-soluble actives	Active Ingredient Systems: Delivery of nutraceuticals, essential oils, vitamins
Pectin	Acts as stabilizer and film former in nanoemulsion dispersions	Packaging: Antioxidant and antimicrobial films Active Ingredients: Carrier for curcumin or lycopene
Chitosan	Forms bioactive coatings with nanoemulsified essential oils	Packaging: Antimicrobial films Agriculture: Biodegradable pesticide carriers
Whey Protein	Stabilizes oil-in-water nanoemulsions in combination with starch or polysaccharides	Packaging: Edible films/coatings Active Ingredients: Encapsulation of probiotics or sensitive bioactives
Gum Arabic	Natural emulsifier and antioxidant carrier in nanoemulsions	Agriculture: Foliar application carrier Food/Packaging: Beverage and oil stabilization

One interesting application is the nanoencapsulation of plant oils with protein-starch matrices, which has been demonstrated as a viable solution in the case of active food packaging and drug delivery systems by shielding the sensitive substances and enabling their controlled

release.[6] Though these innovations extend the use of non-cellulosic biopolymers to different industries, mainly to the ones with high-value sectors, it has to be emphasized that the issues of regulations, toxicology, and environmental safety of nanomaterials posed as a result, are still the most challenging questions that require extensive research.

Challenges in Scalability of Biopolymer Extraction

The diagram depicts how automation technologies have become the leading factor in the modern oil and gas exploration processes, primarily through automated drilling rigs, real-time sensing, and advanced data-analysis platforms. Continuous monitoring of pressure, temperature, vibration, and formation properties is realized by automated drilling systems aided by sensor networks. These parameters provide rapid feedback to control units that modify drilling parameters with minimal human intervention. These smart systems are said to have proven their ability trim non-productive time, elevate safety and precision operational in difficult exploration environments, as pointed out in the latest studies on automation in energy systems.[21,22,23] The two-way arrows signify the data communication between the field-level devices and the central analytical units where machine learning and predictive models analyze the incoming data to take operational decisions.

Simultaneously the chart depicts the polymer science advancements in the field of bioplastics coming from plants and hence becoming the potential sustainable engineering contributors in the energy and chemical industries. Non-cellulosic biopolymers are one of the most exciting candidates for drilling fluids, corrosion inhibition, and environmentally safe material replacements that have been traditionally petrochemical polymers-based. The use of these materials in the exploration schedule is in line with the trend toward green and high-performance industrial materials, as documented in recent polymer science literature.[24,25] The convergence illustrated in the chart suggests a future technological ecosystem, where automated exploration systems and biopolymer innovations have an interdependent relationship that pave the ways for the clean energy age as shown in figure 3.

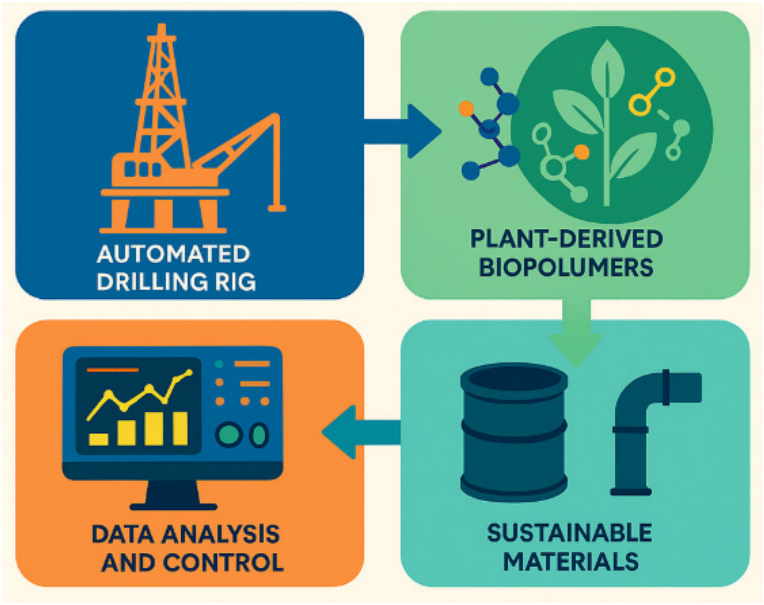

Figure 3. Converging automation technologies and plant-based biopolymers for next-generation oil, gas, and chemical engineering

Structure-Property Relationships

The structure-property relationship is essential when one wants to comprehend the performance and portability of non-cellulosic plant-based biopolymers. The chemical composition, molecular architecture, and functional groups of these polymers primarily dictate their thermal behavior, mechanical properties, barrier performance, and biodegradability. It is absolutely necessary to have a detailed knowledge of these correlations when it comes to adjusting biopolymers for specific industrial functions.[11,12,13,14,15,16]

One of the most glads of biocomposites can be plastics based on plasticized starch (thermoplastic starch, TPS), biodegradable materials, because of their renewability, low cost, and ease of processing. Nevertheless, starch in its native form must be plasticized, usually by water, glycerol, or sorbitol applied with heat and shear to starch which exhibits thermoplastic behavior. The reinforcements, thus, improve the composites' mechanical, thermal, and barrier properties to a great extent, especially when fiber–matrix adhesion is coupled with chemical treatments or compatibilizers. Extrusion, injection molding, and compression molding are the common manufacturing methods for TPS biocomposites, and the efficiency of these methods is dictated by the starch source, filler dispersion, and formulation parameters as shown in table 4.

Table 4. Comparative summary of structure–property relationships among selected non-cellulosic biopolymers

Biopolymer	Key Functional Groups	Crystallinity	Thermal Stability	Water Sensitivity	Mechanical Strength	Notable Traits	Ref
Starch	Hydroxyl	Medium-High	Moderate (150-200°C)	High	Moderate	Good film-former; brittle when dry	Avérous & Boquillon
Lignin	Phenolic, Methoxyl	Amorphous-Low	High (>200°C)	Low	High	UV resistant; rigid; antioxidant	Laurichesse et al.[10]
Pectin	Carboxyl, Ester	Low-Medium	Low-Moderate	High	Low-Moderate	Gelling; used in food/pharma	Thakur et al.[4]
Hemi-cellulose	Hydroxyl, Acetyl	Low	Low-Moderate	High	Low	Flexible; biodegradable	Ebringerová et al.[13]
Proteins	Amine, Carboxyl	Variable	Moderate	Moderate	Moderate	Edible films; pH sensitive	Gennadios et al.; Semenova et al.

RESULTS AND DISCUSSION

Thermal degradation analysis

Thermal degradation analysis is one of the key methods that help determine changes in heat resistance, decomposition and volatile product evolution of biopolymers. These are mainly TGA (Thermogravimetric Analysis) and DTG (Differential Thermo-gravimetry) techniques which show the different stages of the degradation, temperature at the maximum decomposition, and the amount of residual char which are very important parameters for the evaluation of biopolymer materials for high-temperature processing and various end-use applications. The thermal degradation of non-cellulosic biopolymers is different to a large extent depending

on their molecular structure as well as their origin. In the case of hemicellulose, it is highly branched and amorphous, therefore it breaks down at lower temperatures (~268 °C), releasing volatile compounds such as acetic acid and furfural. Cellulose, because of its high crystallinity, is decomposed at higher temperatures (~355 °C) with sharp DTG peaks and it produces levoglucosan and furans.

Table 5. Thermal Degradation Characteristics of Non-Cellulosic Biopolymers

Biopolymer	Main Source	Degradation Temp Range (°C)	Peak Degradation Temp (°C)	Major Volatiles / Products	Remarks	Ref
Hemi-cellulose	Agricultural residues	200–350	~268	Acetic acid, CO, CO_2, furfural	Degrades first due to branched, amorphous structure	Yang et al., 2007
Cellulose	Plant cell walls	315–400	~355	CO, CO_2, levoglucosan, furans	High crystallinity; sharp DTG peak; major pyrolysis fraction	Yang et al., 2007
Lignin	Wood, straw, bark	200–500+	280–370 (broad peaks)	Phenols, methane, CO_2, char	Broad, slow degradation; aromatic rings lead to high char yield	Yang et al., 2007
Pectin	Citrus, apple peels	180–300	220–260	Acetic acid, aldehydes, CO_2	Low stability due to ester groups and branching	Wong et al., 2013
Proteins	Soy, wheat, pea	200–350	280–320	NH_3, CO_2, H_2O, sulfur volatiles	Two-stage degradation: denaturation and chain scission	Jaziri et al., 2020
Starch	Corn, cassava, potato	250–350	~310	Water, CO_2, acetic acid, aldehydes	Moisture loss <150 °C; decomposes to sugars and volatiles	Zhang et al., 2005

Table 5 outlines thermal degradation characteristics of the chosen non-cellulosic biopolymers, which, among others, include temperature ranges for degradation, peak decomposition temperature, major volatiles released, and structural remarks.

Modification Strategies for Property Enhancement

Non-cellulosic biopolymers are environmentally friendly but usually have problems like poor processability, low durability, and weak mechanical properties. To make them more industrially feasible, numerous modification methods (figure 4) have been introduced to adjust and improve their functional features.

Blending with Other Polymers

One of the most popular ways to maintain mechanical flexibility, processability, and biodegradability is by mixing non-cellulosic biopolymers either with synthetic or natural polymers. As an example, starch is usually mixed with poly(lactic acid) (PLA), polycaprolactone (PCL), or polyethylene (PE) to make the material less brittle and to enhance the ability to

form a film.[6] Films made from proteins can be mixed with gelatin, chitosan, or pectin, a polysaccharide, to get more flexible films and those with better barrier properties. Such systems usually behave synergistically; however, compatibility and phase separation still dominate as the main problems, which can be solved by using compatibilizers or reactive extrusion methods.

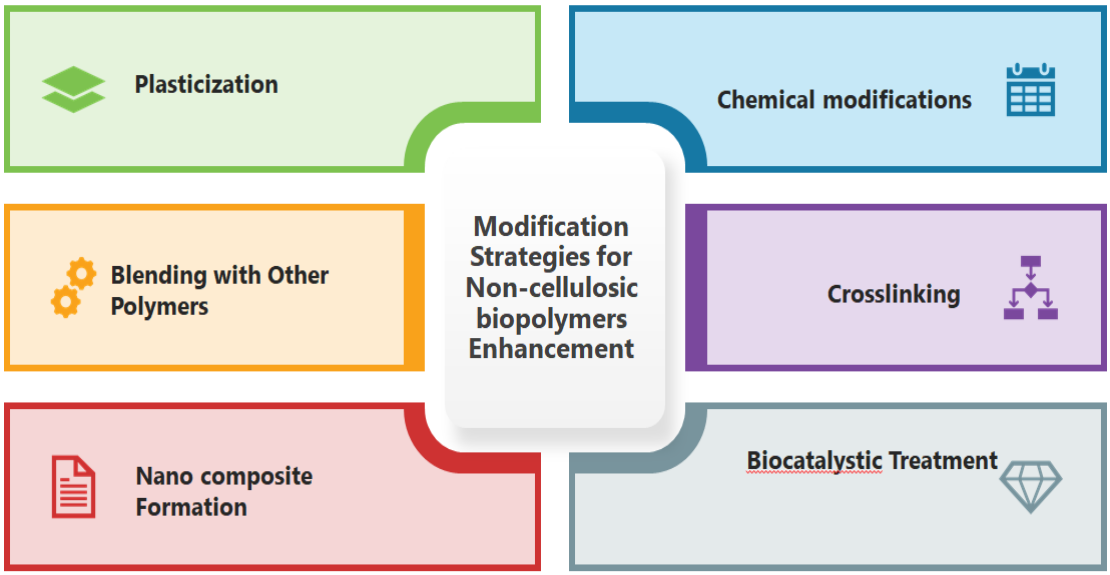

Figure 4. Modification Strategies for property enhancement in Non-cellulosic biopolymers

Nanocomposite Formation

Incorporation of nanoscale fillers such as nanoclays, cellulose nanocrystals (CNCs), graphene oxide, and metal nanoparticles has become a very powerful tool to non-cellulosic biopolymers to enhance their mechanical strength, thermal stability, and barrier properties. Upon crosslinking, the combination of these nanoinserts leads to the creation of hybrid nanocomposite films with noticeably better structural and functional features in comparison with the unmodified ones. Besides the expanded application potential of biopolymers in the areas of biodegradable packaging, active coatings, and biomedical materials, this synergistic approach is also in line with the increasing demand for sustainable, high-performance alternatives to conventional plastics.[7]

As an illustration, CNC-starch nanocomposites have been able to achieve great improvements in tensile strength and water vapor barrier properties, thus opening the way for their application as green wrapping.[8] The introduction of graphene oxide into the pectin matrix results in the enhancement of the material's thermal stability and mechanical stiffness, which in turn allows it to be used for biomedical and structural purposes.[9] Similarly, metal nanoparticle–lignin composites, in particular, those kinds that have silver or zinc oxide nanoparticles, could be used in food packaging and wound healing materials due to their excellent antimicrobial and UV-blocking properties.[10] Besides, nanoclay filled hemicellulose films demonstrated enhanced gas barrier and mechanical properties which was attributed to the intercalated or exfoliated structures formed.[11] Few of the notable researches in Nanocomposite Applications in Non-Cellulosic Biopolymers is given in table 6.

Table 6. Examples of Nanocomposite Applications in Non-Cellulosic Biopolymers				
Biopolymer	**Nanofiller**	**Property Enhanced**	**Application**	**Ref**
Starch	Cellulose nanocrystals (CNCs)	Tensile strength, barrier properties	Biodegradable packaging	Zhao et al., 2020
Pectin	Graphene oxide (GO)	Thermal stability, rigidity	Biomedical films	Wang et al., 2018
Lignin	Silver nanoparticles	Antimicrobial activity	Active packaging	Naseer et al., 2020
Hemicellulose	Montmorillonite nanoclay	Gas barrier, mechanical properties	Coatings and films	Tang et al., 2017

Applications of Non-Cellulosic Biopolymers

Safe and sustainable crop production is promoted by the use of agricultural bioplastics, such as biopolymer-based hydrogels, and films that can be used for watering, seed coating, and fertilizer and pesticide-controlled release formulations and at the same time reducing runoff and improving soil health.[20] In the case of the coatings and adhesives industry, proteins, lignin, and natural gums are the materials used for the production of sustainable and water-resistant surfaces and binders with improved adhesion. The biopolymers are the substances that from the Construction and Textile Industries are transformed into bio-composites, insulation foams, flame-retardant coatings, and functional finishing with antibacteria or fire-resistant properties.[21] A comprehensive table delineating the prominent application sectors, functional roles, challenges, and examples of biocomposites is appended below table 8.

Table 8. Application Sectors of Non-Cellulosic Biopolymers				
Application Sector	**Key Biopolymers**	**Functional Role**	**Challenges**	**Biocomposite Examples**
Packaging	Starch, Pectin, Proteins	Biodegradable films, edible coatings, barrier layers	Moisture sensitivity, limited mechanical strength, shelf life	Starch/PVA/CNC films Pectin/fatty acid edible films
Biomedical	Pectin, Zein, Lignin	Drug delivery, tissue scaffolds, wound healing	Regulatory approval, sterilization, biocompatibility	Pectin–chitosan–AgNPs hydrogel Lignin/PVA nanofibers
Agriculture	Starch, Hemicellulose, Lignin	Mulch films, seed coatings, hydrogels	Cost, degradation rate control, mechanical fragility	Starch–lignin seed coatings Hemicellulose–chitosan hydrogel
Coatings / Adhesives	Lignin, Proteins, Natural Gums	Bio-binders, barrier coatings, primers	Bond strength, curing conditions, water resistance	Soy protein/lignin adhesive Gum arabic–lignin coatings
Construction / Textile	Lignin, Proteins, Pectin	Lightweight composites, flame retardants, hydrogels	Processability, durability, fire resistance	Lignin–hemp panels Zein flame-retardant coatings
Electronics / Sensors	Lignin, Pectin, Starch	Flexible substrates, biosensors, dielectric materials	Electrical conductivity, thermal stability	Lignin/PEDOT:PSS films

Energy Storage	Lignin, Hemicellulose	Binders in electrodes, conductive additives, supercapacitor materials	Conductivity, charge retention, compatibility	Lignin-derived carbon for Li-ion batteries
Food (Functional Use)	Pectin, Starch, Protein	Encapsulation, delivery systems, emulsion stabilization	Release control, sensory effects, stability	Pectin microcapsules for probiotics
Water Treatment	Lignin, Starch, Hemicellulose	Heavy metal adsorption, dye removal, antimicrobial filtration	Regeneration, swelling, selectivity	Lignin–magnetite nanocomposites for Cr(VI) removal

Integrated Performance Outcomes of Automation and Biopolymer Systems

The figure is 6 shows how automation technologies and biopolymer systems are the primary factors that influence the performance of the oil and gas operations of the future. In the upper left, automation systems—illustrated by robotic control—depict the fast-spreading use of advanced drilling platforms, real-time sensing arrays, and AI-enabled decision systems in exploration. These kinds of systems are more and more being engineered to provide greater responsiveness and operational efficiency by, among other things, constantly modifying drilling parameters based on the subsurface conditions that are monitored in real-time, a performance upgrade that is in line with the research results of Zahid et al. and Kadkhodaie et al. on intelligent subsurface monitoring and automated rig control.[21,22]

The arrows that connect the automation to the main outcome node show the ways in which the technologies lead to the enhancement of data reliability, the reduction of non-productive time, and the facilitation of safer operations in high-risk oilfield environments. On the contrary, the use of biopolymer systems draws attention to the future role of non-cellulosic plant-derived materials—like lignin and hemicellulose derivatives—as eco-friendly raw materials for the oil and chemical sectors.

The biopolymers are compatible with drilling fluids, corrosion-resistant coatings, and environmental mitigation, as evidenced by the latest polymer science research.[24,25] Their contribution to oilfield operations results in better environmental performance, lessening of material toxicity, and the safety of workers being facilitated, which is symbolized by the oil pumpjack icon that is the safety component's anchor in the diagram.

Thus, they demonstrate how automation and biopolymers flow into shared performance indicators—responsiveness, operational efficiency, compatibility, safety, and environmental impact—the diagram, in fact, shows a converging technological landscape that is going beyond this point. Such a convergence means that digital intelligence and sustainable material innovation would be the major determinants of future oil, gas, and chemical engineering systems, a trend that is also in line with the findings of other studies on digitalization in process industries.[23]

Future Perspectives and Research Gaps

In spite of the progress made in plant-based non-cellulosic bio polymeric materials, numerous significant issues still exist that hinder their long-term industrial application. The variability of raw materials in terms of moisture, chemical makeup, and molecular structure makes it difficult to standardize and achieve a consistent output. Research efforts should be directed toward establishing protocols for pre-processing and quality control in real-time so as to ensure the stability of input materials. On top of that, the question of the scalability is raised since most of the labscale methods involve the use of energy intensive or no environmentally friendly solvents.

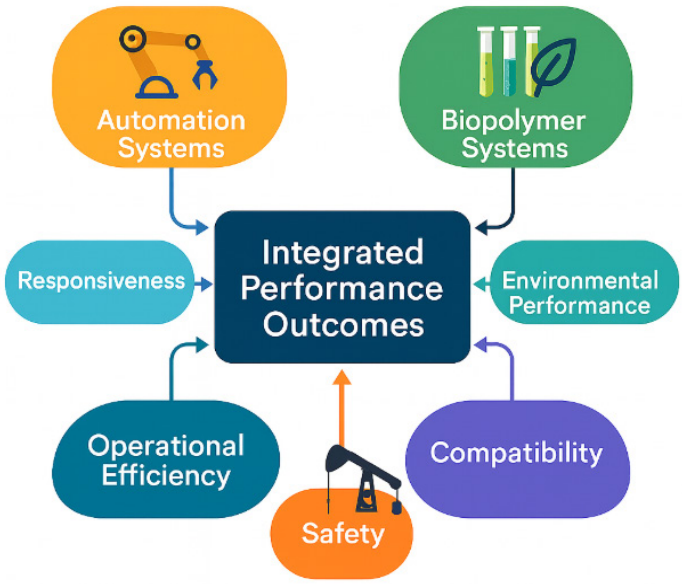

Figure 6. Integrated performance outcomes linking automation, biopolymers, and oil-sector operations

The industrial applicability of the low-impact, industrial scale processes such as reactive extrusion, supercritical CO_2 blending, or enzymatic modification can be greatly enhanced by the local feasibility.[13] Environmental assessments are sometimes only based on perfect composting scenarios. There is a need for degradation that takes place under real conditions in the marine, landfill, and soil systems, as well as region-specific Life Cycle Assessments (LCA) that can provide information about sustainable deployment.

From a design standpoint, the natural bioactive additives (e.g., phenolics, essential oils, alginates) incorporated into the material can improve the functionality of that material; however, the additives should not hinder the biodegradability or the safety of the material. This implies that ecocompatible multifunctionalization strategies must be developed. Finally, the lack of representation of technoeconomic analysis is noticeable. The adoption of commercial technologies can be propelled to the next level by the presence of different tools such as life cycle costing, cost-benefit modeling, and industrial symbiosis frameworks working hand in hand with policy incentives and labeling standards.[15,16,17]

CONCLUSIONS

The combination of automation-driven exploration technologies with advances in non-cellulosic biopolymer science is a potential way to change the whole future of oil, gas, and chemical engineering. Automating drilling operations, implementing real-time sensing platforms, and upgrading intelligent control architectures are some of the ways through which the precision of operations is being enhanced, risks mitigated, and responsiveness to changes in complex field environments increased. Meanwhile, the next-generation plant-based biopolymers are opening up possibilities for the supply of sustainable materials with attractive chemical, thermal, and ecological characteristics that make them suitable for drilling fluids, corrosion prevention, and equipment protection. As a result, the synergy between these two technological areas might finally make it possible to have energy systems that are not only safer and more efficient but also more environmentally friendly, thereby ensuring that the sector is able to satisfy the growing performance requirements while making progress in the direction of sustainability of the environment.

Non-cellulosic plant-derived biopolymers as green alternatives to traditional petroleum-based plastics are very promising and have the potential to widely be used across various sectors like packaging, agriculture, construction, and biomedicine. Their structural and chemical differences—from simple polysaccharides such as starch and pectin to recalcitrant molecules (lignin, hemicellulose, plant proteins, gums, and oils)—provide an almost unlimited range of functionalities. Despite this, the issues of processing inefficiencies, environmental stability, and end-of-life management hamper their large-scale use.

Looking ahead, the non-cellulosic biopolymers' success in large-scale applications will depend on partnerships spanning across materials science, environmental sustainability, industrial design, and regulatory frameworks. Techno-economic evaluations, standardization, and life cycle analysis will be of utmost importance to facilitate the market entry of such products. These biopolymers, being aligned with the principles of eco-friendly production and circular economy, have the potential to become a significant part of the solution to the future environmental and resource challenges.

BIBLIOGRAPHIC REFERENCES

1. Hopewell J, Dvorak R, Kosior E. Plastics recycling: Challenges and opportunities. Philos Trans R Soc Lond B Biol Sci. 2009;364(1526):2115–26. https://doi.org/10.1098/rstb.2008.0311

2. Shen L, Haufe J, Patel MK. Product overview and market projection of emerging bio-based plastics: PRO-BIP 2009. Report for European Polysaccharide Network of Excellence (EPNOE) & European Bioplastics. 2020. https://doi.org/10.6100/IR643940

3. Reddy N, Yang Y. Biofibers from agricultural byproducts for industrial applications. Trends Biotechnol. 2005;23(1):22–7. https://doi.org/10.1016/j.tibtech.2004.11.002

4. Thakur VK, Thakur MK, Raghavan P. Progress in green polymer composites from lignin for multifunctional applications: A review. ACS Sustain Chem Eng. 2017;5(9):8321–31. https://doi.org/10.1021/acssuschemeng.7b01473

5. Buddrus J. Grundlagen der Organischen Chemie. Berlin: Walter de Gruyter; 2011. p. 797–844.

6. Sharma B, Malik P, Jain P. Waste valorization of agro-industrial biomass for sustainable bio-based materials. Environ Chem Lett. 2021;19(1):305–32. https://doi.org/10.1007/s10311-020-01084-9.

7. Bajpai P. Biotechnology for Pulp and Paper Processing. Springer; 2019. https://doi.org/10.1007/978-981-13-3780-1

8. Petersen K, Nielsen PV, Bertelsen G, Lawther M, Olsen MB, Nilsson NH, Mortensen G. Potential of biobased materials for food packaging. Trends Food Sci Technol. 1999;10(2):52–68. https://doi.org/10.1016/S0924-2244(99)00017-9

9. Shogren RL, Doane WM, Garlotta D, Lawton JW, Willett JL. Biodegradation of starch/polylactic acid/poly(hydroxyester-ether) composite bars in soil. Polym Degrad Stab. 1998;59(3):305–8. https://doi.org/10.1016/S0141-3910(97)00191-5

10. Laurichesse S, Avérous L. Chemical modification of lignins: Towards biobased polymers.

Prog Polym Sci. 2014;39(7):1266–90. https://doi.org/10.1016/j.progpolymsci.2013.11.004.

11. Thakur VK, Thakur MK, Raghavan P. Progress in green polymer composites from lignin for multifunctional applications: A review. ACS Sustain Chem Eng. 2017;5(9):8321–31. https://doi.org/10.1021/acssuschemeng.7b01473.

12. Yapo BM, Koffi KL. Yellow passion fruit rind—A potential source of low-methoxyl pectin. Food Chem. 2006;99(3):450–7. https://doi.org/10.1016/j.foodchem.2005.08.021

13. Ebringerová A, Heinze T. Xylan and xylan derivatives–biopolymers with valuable properties, 1. Naturally occurring xylans structures, procedures and properties. Macromol Rapid Commun. 2000;21(9):542–56. https://doi.org/10.1002/1521-3927(20000801)21:9<542::AID-MARC542>3.0.CO;2-7

14. Moreira LRS, Filho EXF. An overview of mannan structure and mannan-degrading enzyme systems. Appl Microbiol Biotechnol. 2008;79:165–78. https://doi.org/10.1007/s00253-008-1423-4

15. Vetvicka V, Vetvickova J. Physiological effects of different types of beta-glucan. Biomed Pap. 2011;155(2):195–204. https://doi.org/10.5507/bp.2011.025

16. Koshy RR, Somasundaram ST, Thomas S. Soy protein-based biopolymers for packaging applications. J Appl Polym Sci. 2015;132(45). https://doi.org/10.1002/app.42681

17. Wang Y, Cheng H, Wang W. Biodegradable packaging materials based on wheat gluten: Preparation, properties and performance. Ind Crops Prod. 2011;34(1):353–61. https://doi.org/10.1016/j.indcrop.2011.03.018

18. Lawton JW. Zein: A history of processing and use. Cereal Chem. 2002;79(1):1–18. https://doi.org/10.1094/CCHEM.2002.79.1.1

19. Mudgil D, Barak S, Khatkar BS. Guar gum: Processing, properties and food applications—A Review. J Food Sci Technol. 2014;51(3):409–18. https://doi.org/10.1007/s13197-011-0522-x

20. Ali BH, Ziada A, Blunden G. Biological effects of gum arabic: A review of some recent research. Food Chem Toxicol. 2009;47(1):1–8. https://doi.org/10.1016/j.fct.2008.07.001

21. Zahid A, Haq M, Al-Sarkhi A. Advances in automation and digital technologies for intelligent oil and gas exploration. J Pet Sci Eng. 2023;225:111402. https://doi.org/10.1016/j.petrol.2023.111402

22. Kadkhodaie A, Rezaee R, Asadi M. Real-time sensing and autonomous systems for improved subsurface characterization. Energy Explor Exploit. 2022;40(1):75–98. https://doi.org/10.1177/01445987211047832

23. Khan F, Butt FS, Imtiaz S. Digitalization and automation in process industries: Implications for safety and sustainability. Chem Eng Res Des. 2021;171:90–108. https://doi.org/10.1016/j.cherd.2021.05.033

24. Liu H, Thakur VK, Zhang X. Non-cellulosic plant biopolymers: Structure, chemistry, and emerging applications. Prog Polym Sci. 2023;140:101638. https://doi.org/10.1016/j.

progpolymsci.2023.101638

25. Aditiya HB, Goralski CT, Goh CS. Advances and challenges in lignin-derived polymers for sustainable industrial applications. Renew Sustain Energy Rev. 2022;160:112268. https://doi.org/10.1016/j.rser.2022.112268

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AUTHORSHIP CONTRIBUTION

Conceptualization: S. Dhamotharan, M. Muthukrishnan, N. Bharanidharan, M. Prince, M. Sabareesh, P. Prabhu, Rashad Ismibayli.

Data curation: S. Dhamotharan, M. Muthukrishnan, N. Bharanidharan, M. Prince, M. Sabareesh, P. Prabhu, Rashad Ismibayli.

Formal analysis: S. Dhamotharan, M. Muthukrishnan, N. Bharanidharan, M. Prince, M. Sabareesh, P. Prabhu, Rashad Ismibayli.

Drafting - original draft: S. Dhamotharan, M. Muthukrishnan, N. Bharanidharan, M. Prince, M. Sabareesh, P. Prabhu, Rashad Ismibayli.

Writing - proofreading and editing: S. Dhamotharan, M. Muthukrishnan, N. Bharanidharan, M. Prince, M. Sabareesh, P. Prabhu, Rashad Ismibayli.

Chapter 12 / Capítulo 12

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ORIGINAL

A Unified Review of Thermal System Optimization and Automation Technologies Shaping Modern Marine and Oil-Gas Engineering

Una revisión unificada de las tecnologías de automatización y optimización de sistemas térmicos que configuran la ingeniería marina y de petróleo y gas moderna

Hariprasad Perumal[1] ✉, R. Premkumar[1] ✉, V. Chinnadurai[1] ✉, R.S. Avinand[1] ✉, K. Balakumar[1] ✉, P. Prabhu[1] ✉, V.H. Abdullayev[2] ✉

[1]Azerbaijan University of Architecture and Construction. Baku, Azerbaijan.

Corresponding Author: Hariprasad Perumal ✉

ABSTRACT

Thermal management and automation have become closely linked factors that drive innovation across marine propulsion systems and oil-gas engineering. This review indicates that the contemporary changes in heat-exchanger design, energy-efficient cooling strategies, and data-driven control architectures are redefining the performance levels that were expected in both sectors. For the marine sectors, the recent research shows that the focus is shifting towards the use of compact, high-flux thermal exchangers and hybrid cooling loops which have the capability to adjust to fluctuating onboard loads as well as meet stringent environmental regulations. Similarly, oil and gas works are going on to install more automated sensing, predictive diagnostics, and intelligent process control for stabilising thermal behaviour under harsh operating conditions. As a result of examining these innovations from a single perspective, the review points out the merging engineering principles - in particular, system-level optimisation, real-time monitoring and digitally supported decision-making - that are most likely to be the characteristics of the next-generation energy and fluid-handling infrastructures. The integration, therefore, volunteers that knowledge transfer from one sector to another may be the main factor that will lead the way to the engineering systems that are more resilient, efficient, and environmentally responsive at a faster rate. The latest marine heat exchangers primarily focus on a compact and efficient design that can be durable for a long time even in a harsh environment. This review paper explores the recent changes in design methods, performance enhancement techniques, material selection, and computer modeling strategies. It also highlights the problems of fouling, scaling, corrosion, and maintenance difficulties, which are major barriers to performance at a high level. In addition, this research identifies potential research themes such as the implementation of eco-friendly design principles, digital monitoring and predictive maintenance technologies, and additive manufacturing for the creation of custom and efficient heat exchanger parts. These innovations, in combination, provide the platform for the subsequent set of marine cooling solutions.

Keywords: Thermal System Optimisation; Marine Cooling Technologies; Oil–Gas Engineering; Real-Time Monitoring; Digital Engineering; Sustainable Industrial Operations.

RESUMEN

La gestión térmica y la automatización se han convertido en factores estrechamente vinculados que impulsan la innovación en los sistemas de propulsión marina y la ingeniería de petróleo y gas. Esta revisión indica que los cambios actuales en el diseño de intercambiadores de calor, las estrategias de refrigeración energéticamente eficientes y las arquitecturas de control basadas en datos están redefiniendo los niveles de rendimiento esperados en ambos sectores. En el sector marino, investigaciones recientes muestran que el enfoque se está desplazando hacia el uso de intercambiadores térmicos compactos de alto flujo y circuitos de refrigeración híbridos, capaces de adaptarse a las fluctuaciones de las cargas a bordo y de cumplir con las estrictas normativas ambientales. De igual manera, las plantas de petróleo y gas están implementando sistemas de detección más automatizados, diagnósticos predictivos y control inteligente de procesos para estabilizar el comportamiento térmico en condiciones operativas adversas. Al examinar estas innovaciones desde una perspectiva única, la revisión señala los principios de ingeniería integrados —en particular, la optimización a nivel de sistema, la monitorización en tiempo real y la toma de decisiones con soporte digital— que probablemente caracterizarán las infraestructuras de energía y manejo de fluidos de próxima generación. Por lo tanto, la integración, que permite que la transferencia de conocimiento de un sector a otro, sea el factor principal que impulse sistemas de ingeniería más resilientes, eficientes y respetuosos con el medio ambiente a un ritmo más acelerado. Los intercambiadores de calor marinos más recientes se centran principalmente en un diseño compacto y eficiente que ofrece una larga vida útil incluso en entornos hostiles. Este artículo de revisión explora los cambios recientes en métodos de diseño, técnicas de mejora del rendimiento, selección de materiales y estrategias de modelado informático. También destaca los problemas de incrustaciones, incrustaciones, corrosión y dificultades de mantenimiento, que constituyen importantes barreras para un rendimiento óptimo. Además, esta investigación identifica posibles temas de investigación como la implementación de principios de diseño ecológicos, tecnologías de monitorización digital y mantenimiento predictivo, y la fabricación aditiva para la creación de piezas de intercambiadores de calor personalizadas y eficientes. Estas innovaciones, en conjunto, sientan las bases para el futuro desarrollo de soluciones de refrigeración marina.

Palabras clave: Optimización de Sistemas Térmicos; Tecnologías de Enfriamiento Marino; Ingeniería de Petróleo y Gas; Monitoreo en Tiempo Real; Ingeniería Digital; Operaciones Industriales Sustentables.

INTRODUCTION

Marine cooling systems represent the thermal core of both seaborne and offshore engineering operations, thus they always keep the propulsion engines, the auxiliary machinery, and the onboard power-generation units in a stable working condition. Their main role is to control the temperatures in the engines and in the equipment that are used for different loads and under changing weather conditions all the while while making sure that the temperatures do not go beyond the allowed limits. These devices prevent the vessels from overheating, so they are still able to do the same under the prolonged exposure that is typical of ocean-going vessels, mechanical wear is kept at a minimum, combustion efficiency is improved, and the service time is extended. At the center of this setup is the heat exchanger that regulates the heat transfer from the sea, lubricating oils, and the specially engineered coolant mixtures. But the severe marine environment that includes the corrosive saltwater exposure, biological fouling, and unstable thermal loads is always a challenge for the design and operation of

the systems. As a result, the drop in efficiency has a chain effect on the engine power, fuel consumption, emission characteristics, and the maintenance planning in the long run.[1,2,3,4] The recent materials engineering and thermal efficiency improvements have substantially changed the marine heat exchanger design concept. The use of high-durability materials like titanium and Cu–Ni composites as well as quite new corrosion-resistant polymers have indicated not only the improvement of thermal conductivity but also the extension of the service life. Some issues of CFD and CAE methods have been solved at the same time they have been developed which means now they allow very precise studies of complex flow fields, finding the thermal hot spots, and the optimisation of the geometry taking place long before the manufacturing process. Additionally, additive manufacturing is speeding up the transition by making it possible to produce small exchangers with the complex internal channels that are impossible to be done traditionally. Notwithstanding these improvements, some problems still linger: foulings, scalings, and corroding, which are the main reasons for the decrease of the efficiency in heat-transfer and that are leading to the increasing maintenance costs. The implementation of economical marine operations has driven the requirements to be met for cooling systems to be even more environmentally friendly with the introduction of predictive monitoring systems and real-time data analytics for their support.[5,6,7,8] Similarly in the oil and gas industry, limited resources have led to an equally fast development of innovations in thermal management and emission control technologies. The industry is confronted with increasing regulatory pressures to lower emissions from the use of fossil energy and to optimize consumption patterns in accordance with carbon-neutral economic targets. Thermal systems are instrumental in stabilizing compressor trains, refining units, pumping networks, and vapor-handling operations in upstream, midstream and downstream facilities. Most importantly, it is the thermal characteristics of volatile organic compounds (VOCs) that need to be tightly controlled to avoid evaporative losses and reduce the release of harmful gases to the atmosphere. Research on gasoline terminals and tanker operations indicates that temperature has a major effect on VOC emission rates, thus local thermal and automated control strategies need to be implemented in tandem. Several sources elaborate on the use of modern vapor recovery devices including membrane-based capture systems and gas-dynamic cooling units, which are utilized to recover hydrocarbons in an efficient manner while at the same time allowing for the least amount of thermal energy losses to take place.[9,10,11,12,13] Automation and digitization have continually changed thermal optimisation through oil and gas operations. Advanced sensing platforms, real-time emission monitoring, and intelligent decision-support systems allow operators to predict thermal anomalies before they turn safety or efficiency failures.[14,15] The use of CFD to redesign shell-and-tube and plate heat exchangers has led to the substantial increase of thermal efficiency in the application of high-pressure syngas cooling, refinery heat recovery, and pipeline processing.[16,17] All of these alterations are leading towards one very clear trend: the integration of thermal-system optimisation, emissions control, and automation is becoming a fundamental engineering concept in both marine and oil–gas environments. By using predictive analytics, material innovation, and computational optimisation, the thermal infrastructures of the future will not only be more maritime but also hydrocarbon operations. They will be able to exhibit higher resilience, lower energy consumption, and less environmental impact. The thermal optimisation of oil–gas facilities is becoming increasingly tightly linked with emissions control, in particular, the management of volatile organic compounds (VOCs) that are generated during the storage, loading, and transport of hydrocarbons. The release of VOCs is very much dependent on temperature, and if there is inadequate thermal control, evaporation losses will accelerate thus increasing fire risks and amplifying environmental impacts as well. Recent surveys of gas stations and terminals reveal that monitoring demands have been gradually getting more stringent, while emission reductions have mainly been the consequence of improved thermal regulation and automation-assisted

detection systems.[18] The study on marine VOC recovery has come to the same conclusions about the challenges of shipboard environments, where tank temperatures change and the sea is inconstant, thus making vapor-handling processes difficult.[19] Technological methods like hollow-fibre membrane absorbers and advanced cooling-assisted vapor recovery units (VRUs) are effective in stabilising hydrocarbon temperatures while capturing evaporated fractions.[20,21] These devices, when coupled with predictive optimisation tools and digital sensors, can significantly diminish losses and be in line with the global low-carbon and sustainability directives.[22] A significant movement in both marine and oil–gas engineering is the merging of digital thermal-management technologies, in which the core system components are real-time data acquisition, machine-learning-enabled diagnostics, and automated control loops. On the offshore and subsea installations, the scope of automation has been broadened from simple process control to include thermal anomaly detection, equipment-level prognostics, and automated load balancing under challenging operational conditions.[23] Likewise, corresponding systems that employ onboard digital platforms to monitor heat-exchanger degradation, detect the fouling initiation, and suggest the adaptive operating strategies are now being implemented in marine cooling systems.[24] The integration of CFD-assisted design tools, smart monitoring, and closed-loop control results in an integrated thermal-performance ecosystem that can not only predict but also adapt. As oil–gas industries transition to energy-efficient, low-emission infrastructures, these common digital methods along with advanced materials and Additive Manufacturing are going to be the major drivers of cross-sector innovation. Eventually, this convergence implies that marine and hydrocarbon industries are moving to a single engineering paradigm that is thermal efficiency, operational reliability, and environmental compliance are co-engineered from the very beginning.

METHOD

Types of Marine Heat Exchangers

Marine heat exchangers are designed to locally cool the main engines, the auxiliary machinery and the onboard power system, and become generally several types depending on their material of construction and flow arrangement. Shell-and-tube exchangers are the most common, employing bundles of tubes housed in a cylindrical shell to absorb heat from seawater to the cooling liquids, thereby giving off long life and easy servicing. Plate heat exchangers intensify the heat exchange area by using a number of corrugated metal plates stacked together and thus achieving the most efficient heat transfer in the smallest spaces, which are the most suitable for vessels with strict weight and size limitations. Spiral and helical exchangers use a coiled portion to keep the flow turbulent and hence less fouling, thus they are the ones that can be used in the polluted water environments. Finned and compact exchangers further increase heat transfer efficiency by increasing the surface area and are most likely to be found in marine systems with great performances or limited space. More advanced configurations, such as microchannel and hybrid exchangers, provide better heat transfer and less coolant requirements, thus they are capable of meeting the modern energy efficiency, low emissions and marine environmental standards requirements.[6,7]

Table 1. Types of Marine Heat Exchangers vs Applications

Type of Marine Heat Exchanger	Description	Typical Applications on Ships
Shell and Tube Heat Exchanger	Consists of a series of tubes inside a shell; fluids flow through the tubes and shell side for heat exchange.	Main engine jacket cooling system Lube oil cooler Freshwater cooler

late Type Heat Exchanger (PHE)	Made of thin corrugated metal plates; compact, high heat transfer efficiency.	Central cooling system Auxiliary engine cooling Freshwater–seawater heat exchange
Air Cooled Heat Exchanger (Radiator Type)	Uses air as cooling medium instead of seawater; fans used for heat dissipation.	Generator engine cooling HVAC condensers on smaller vessels
Spiral Heat Exchanger	Spiral-shaped channels provide high heat transfer efficiency and easy cleaning.	Sludge oil heating Fuel oil heating
Double Pipe (Tube-in-Tube) Heat Exchanger	One fluid flow inside the inner tube, another between the inner and outer tubes.	Small auxiliary systems Lube oil cooling for small engines
Plate Fin Heat Exchanger	Uses fins between plates to increase surface area; compact and lightweight.	Refrigeration and air conditioning systems Gas–liquid heat recovery
Condenser (Marine Steam System)	Converts exhaust steam from turbines into water by seawater cooling.	Steam propulsion plants Auxiliary steam systems

Cooling Systems

Shell-and-tube heat exchangers

The factors that mainly contributed to the retention of shell-and-tube heat exchangers as the leaders in the market include their strength, versatility, and energy-efficient working mode. These characteristics are typical for processes where heat exchange is performed between two fluids accompanied by no direct mixing. The latter feature is especially important for cases, where the contamination of the liquid can not only significantly influence the chemical reactions, but also the quality of the final product and even its safety.[1] Their most common utilizations have been: the condensing and cooling of power plants, the cooling of marine engines, climate control through HVAC systems, and temperature regulation in the chemical and petrochemical industries, which is very helpful in many chemical reactions for stability and energy saving purposes. The reason of the shell-and-tube heat exchangers long-lasting and diverse applications rely on their ability to withstand a very broad range of operating conditions - from high-pressure and extreme temperatures (very high or very low) to large liquid flow rates - and still maintain a consistent thermal performance Shell-and-tube heat exchanger fundamentally consists of the cylindrical-shaped outer shell which encloses a bundle of tubes.[2] Normally, one liquid is allowed to flow through the tubes, while the other liquid is passed over the outside of the tubes but still within the shell. The tubes are the intermediaries in heat exchange between the two liquids and at the same time, they separate them, so no mixing of the fluids takes place. This is convenient for those operations in which the mixture may lead to contamination, corrosion, or the formation of some unwanted chemical reactions. The liquid in the tubes may be allowed to flow through the heat exchanger only once or may be made to have multiple passes.[3] The point that it can be built to have either single or multiple pass flow arrangements allows the engineer to come up with not only the best solution for heat transfer rate, pressure drop, and efficiency of a certain system but also the process requirements and space available. An essential element in the design of shell-and-tube heat exchangers is the decision to fit baffles. Baffles are the pieces that are fixed in the shell and their function is to change the direction of fluid, which is flowing through the shell, by pushing the fluid across the tubes instead of letting it go straight from the inlet to the outlet. Baffles, that cause crossflow and turbulence, are the main contributors to the heat transfer efficiency.

Besides that, they stop the happening of both hot spots and stagnation regions in the shell. There exist various baffle designs such as segmental, helical, and disk-and-doughnut and the choice of each depends on factors like the flow pattern, heat exchange goals, and allowable pressure drop. For instance, the segmental baffles, which are mostly used because of their simple structure and good turbulence production, provide efficient mixing. However, helical baffles have more powerful effects on the elimination of dead zones and less wear due to vibration.[4]

Due to their modular design, they can be taken apart, cleaned, and repaired much more easily than other heat exchangers.[6] In most cases, the removal of tube bundles is possible, after which they are cleaned by mechanical or chemical methods and reinstalled with a minimum of downtime which makes the shell-and-tube designs a cost-effective solution in the long run. In addition, modern maintenance programs that include the online monitoring of temperature differentials and pressure drops provide operators with the opportunity to recognize the first stages of fouling and take the action to solve the problem before that. As a result, shell-and-tube heat exchangers have ranked their position as one of the major components of the industrial thermal engineering systems alongside their robustness, versatility, and very good performance. Their strong build enables them to be combined with extreme temperature and pressure changes while their adaptability with tube arrangement, baffle arrangement, flow patterns, and material selection can be modified for practically any process.

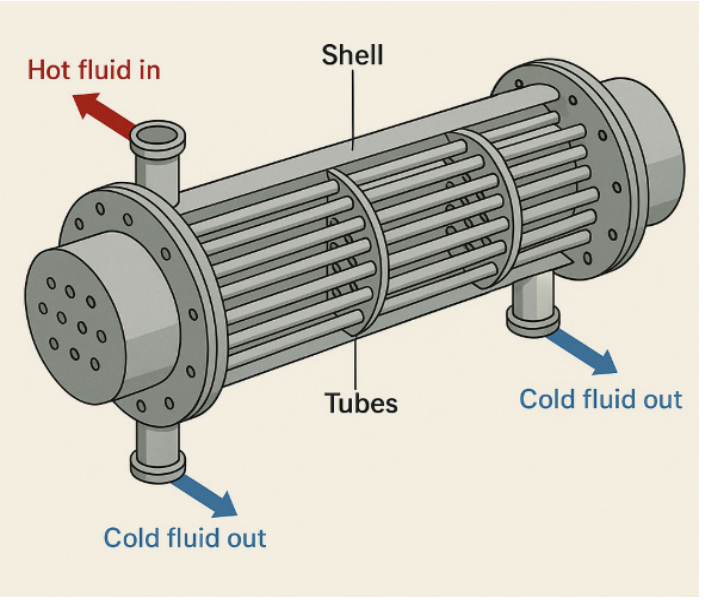

Figure 1. Shell-and-tube heat exchangers

In case these devices are regularly taken care of and materials are wisely chosen, they will deliver long-term reliability and trouble-free operation, which is energy efficiency, process safety, and decrease of operational costs.[7] In the case of fluid mixing, heat transfer is possible through these devices and their modularity makes inspection and cleaning simple, thus being a reason why, out of numerous different classes of exchangers, the shell-and-tube kind as shown in figure 1 is amongst the most used and reliable ones in modern industrial and marine applications.

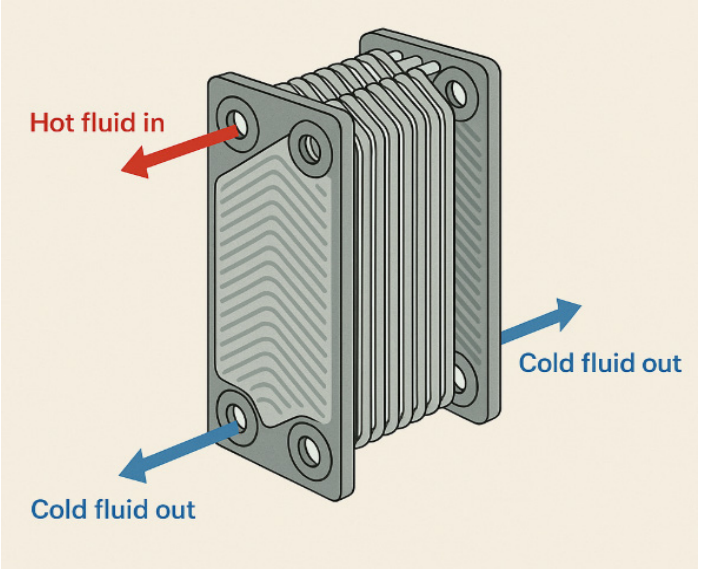

Figure 2. Plate heat exchangers

Spiral and compact designs

Spiral heat exchangers as shown in figure 3 are a type of heat exchangers that are very efficient.

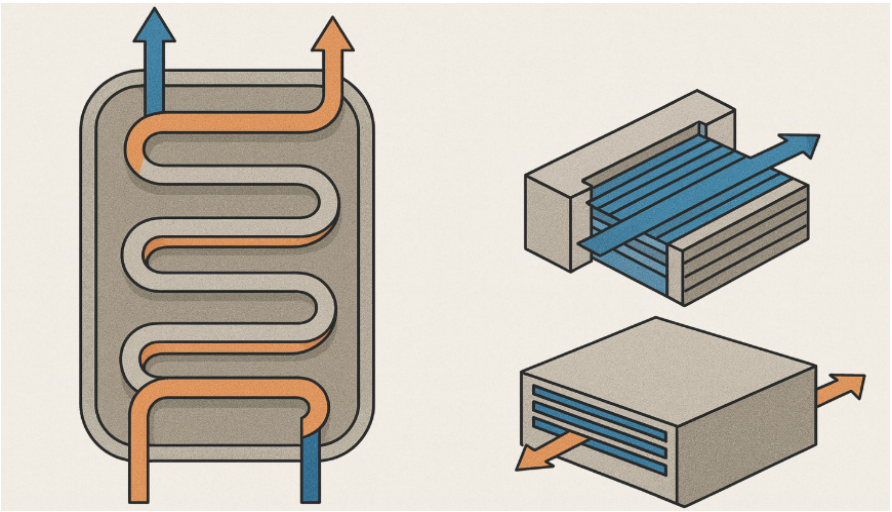

Figure 3. Spiral and compact designs

They are notable for their compactness, low fouling, and excellent thermal performance practically in any industry, over a wide range of temperatures and other operating conditions. The basic idea of the chamber structure is the turning of two flat metal sheets one above the other around a central core in such a way that two concentric spiral channels for the flow - one for the hot fluid and the other for the cold - will be formed. It is an extremely efficient way of heat transfer as each fluid will go through one continuous spiral path without any interruption from the inlet to the outlet. The spiral geometry provides several natural/practical advantages

over more traditional types like shell-and-tube or plate heat exchangers.[11] The most important advantage of the spiral heat exchanger at present is the large surface area-to-volume ratio produced by the spiral windings. Because the flow paths are long and tightly coiled, a significant part of the heat transfer surface area is exposed to the fluids in a small footprint. In fact, this device attains maximum heat transfer between fluid and surface, thereby increasing overall thermal efficiency and at the same time, the unit size is decreased and therefore less material is needed.

Hybrid and microchannel exchangers

Hybrid heat exchangers are a technological breakthrough that essentially represent the next level of thermal-exchange evolution. They can effectively combine the advantages of disparate heat exchanger designs into a single, integrated unit.

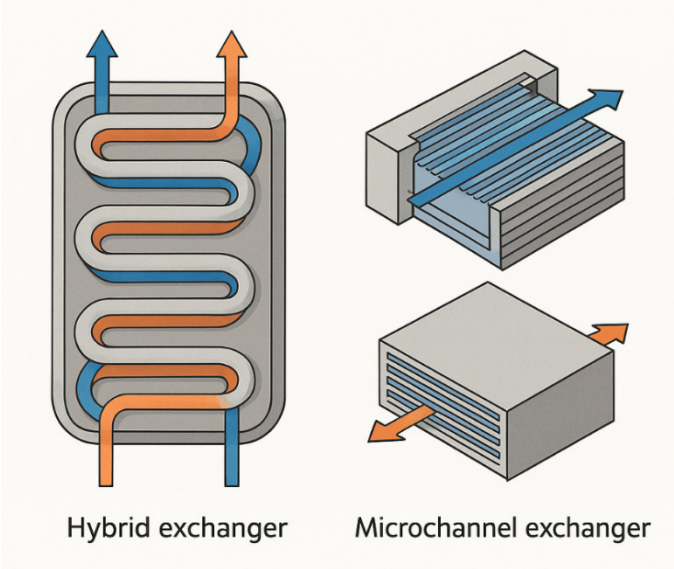

Figure 4. Hybrid and microchannel exchanger

By combining the features of different layouts in a very precise manner, hybrid exchangers can show the characteristics of a performance which a standard unit of a single type can hardly achieve.[15] Most illustrative in this regard is the example of a plate and shell hybrid which integrates thin, corrugated heat-transfer plates with a cylindrical pressure shell. The corrugated plates create very small flow channels which keep the flow turbulent and the surface-area-to-volume ratio high, therefore they achieve very high heat-transfer coefficients typical of plate-type exchangers as demonstrated in figure 4. Meanwhile, the outer cylindrical shell provides the mechanical strength necessary to withstand high pressures and temperature conditions, as those are normally encountered in industrial processes.

Enhancement methods vs. Reported Efficiency Gains

Enhancement strategies for marine and industrial heat exchangers are aimed at lifting the heat-transfer rates, lowering the pressure drops, and lessening the fouling, with reported efficiency improvements that go to different extents depending on the method and the conditions of operation. Usually, surface modification techniques like corrugated plates, finned tubes, or dimpled surfaces provide 10–30 % of the improvement by increasing the turbulence and the effective area. The thermal performance of the device could be increased by 20–50 %

with flow-induced enhancement methods which include helical baffles, spiral channels, and swirl generators, however, it could be a higher pumping power that is the cost sometimes. In some cases, such as compact or high-temperature systems, material-based enhancements including high-conductivity alloys or nanofluid coolants, have demonstrated 15–40 % efficiency gains. By reasons like optimized flow distribution and very high surface-area density, advanced methods like microchannel structures or additive-manufactured geometries normally result in 30–70 % improvements. In the end, hybrid combined enhancement methods—merging geometry, material, and flow strategies—can exceed efficiency gains of 70 % thus revealing the strong synergy between classical thermal engineering principles and novel high-performance technologies.

Table 2. Enhancement methods vs. Reported Efficiency Gains

Enhancement Method	Description	Reported Efficiency Gain / Performance Improvement
Finned Tubes	Addition of fins on tube surfaces to increase heat transfer area.	20–50 % increase in overall heat transfer coefficient.
Corrugated /Chevron Plates	Wavy plate design in plate heat exchangers creates turbulence and improves mixing.	30–70 % improvement in heat transfer rate compared to flat plates.
Twisted Tape Inserts	Helical tape inserted into tubes to induce swirl flow and turbulence.	25–60 % rise in convective heat transfer; pressure drop increases.
Nano fluids	Use of nanoparticles (Al_2O_3, CuO, TiO_2, etc.) in the working fluid to enhance thermal conductivity.	10–40 % higher heat transfer coefficient (depends on nanoparticle type/ concentration).
Surface Roughening / Dimpled Surfaces	Creating dimples or rough surfaces on heat transfer walls to promote turbulence.	15–35 % increase in Nusselt number; minor pressure losses.
Helical / Spiral Flow Passages	Curved flow paths increase secondary flow and mixing.	20–45 % better heat transfer effectiveness.
Use of Phase Change Materials (PCM)	Incorporating PCM for latent heat storage to smooth out temperature variations.	10–25 % improvement in thermal energy utilization efficiency.
Enhanced Flow Distribution (Baffles, Vortex Generators)	Improves mixing and prevents dead zones in shell or plate channels.	15–40 % rise in heat transfer coefficient.

Enhancement Methods vs. Reported Efficiency Gains in Oil & Gas Thermal Systems

The heat exchangers that are impacted by these severe situations in the oil and gas industry require the application of enhancement methods which do not only uphold their reliability but also increase their thermal efficiency in the whole refineries, offshore platforms, LNG units, and petrochemical plants. In these processes, surface-modification techniques like finned tubes, dimpled plates, and corrugated geometries are widely employed in crude preheaters, gas coolers, and stabilization units, that often achieve 10-30 % gains as a result of turbulence promotion and heat-transfer surface area extension as shown in figure 5 and table 3.

Enhancement Method	Reported Efficiency Gains
Surface Modification	10–30%
Flow-Induced	20–50%
Material-Based	15–40%
Advanced Design	30–70%

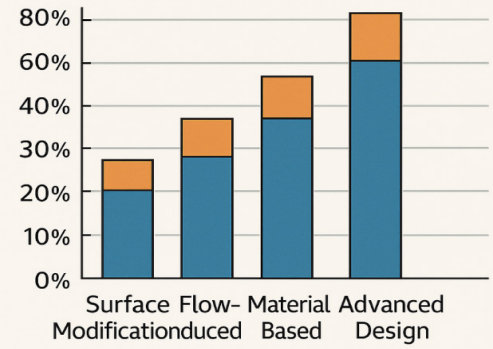

Figure 5. Enhancement Methods vs. Efficiency Gains

Flow-induced enhancements such as helical baffles, twisted-tube bundles, and swirl generators are particularly potent in viscoelastic fluids like crude oil or glycol mixtures where they yield 20-50 % improvements while also removing the stagnant zones that lead to fouling. Besides that, material-based methods like copper-nickel alloys, titanium composites, and nanofluid-enhanced coolants open up the room for additional efficiency increases of 15-40 % in high-pressure sour-gas streams, LNG vaporisers, and offshore produced-water coolers.[20,21,22]

Table 3. Enhancement Methods Used in Oil & Gas Thermal Systems

Enhancement Method	Oil & Gas Application	Typical Efficiency Gain
Surface Modification	Crude preheaters, gas coolers	10–30 %
Flow-Induced	Offshore glycol coolers, crude exchangers	20–50 %
Material-Based	Sour-gas coolers, LNG vaporizers	15–40 %
Advanced Design	Subsea compression, refinery compact exchangers	30–70 %

Oil Industry Performance & Optimization Insight

Advanced enhancement techniques, such as microchannel architectures and additive-manufactured exchanger blocks, are gaining traction subsea compression systems, high-density refinery exchangers, and compact gas-treatment skids. These innovations achieve 30–70 % greater efficiency, lower coolant needs, and improve thermal uniformity—very important for the prevention of coke formation in heavy-oil processing or thermal shock in LNG operations as shown in figure 6 y table 4. Hybrid solutions combining surface geometry, advanced materials, and optimized flow paths usually deliver the highest performance, with the potential of over 70 % improvements, most notably in catalytic reformers, amine regeneration units, and regenerative crude preheaters. Together, these upgrades enable oil and gas facilities to cut fuel consumption, stabilise process temperatures, and comply with increasingly tight emissions and energy-efficiency regulations.[24]

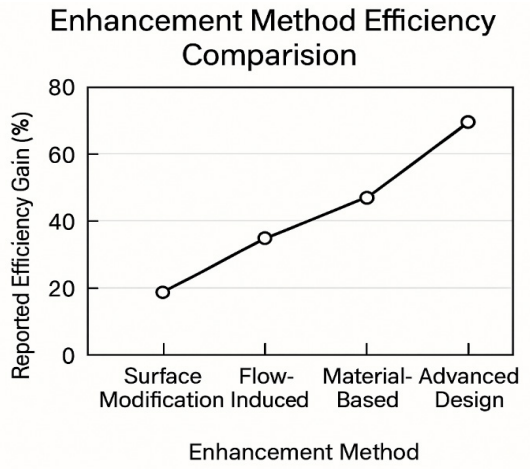

Figure 6. Enhancement Method Efficiency Comparison

Table 4. Performance Gains Observed in Oil-Related Case Studies

System Type	Enhancement Technique	Reported Improvement
Crude Distillation Unit	Helical baffles	+42 % heat-transfer rate
LNG Process Cooler	Microchannel block	+65 % thermal efficiency
Offshore Heat Recovery	Finned tubes	+28 % energy recovery
Petrochemical Reactor Cooling	Nanofluid coolant	+37 % heat-transfer coefficient

RESULT AND DISCUSSION

Performance Challenges in Marine Environment for Fixed Tube Sheet (Streight) Heat Exchanger

The standard society marine industry shell-and-tube heat exchangers with fixed tube-sheet, straight-tube is the most common design as shown in figure 7. The main reasons for their selection are their simple construction, small volume, and strength. When all these factors are combined, they become the most suitable systems for vessels, floating production/storage/offloading units, and other sea-going installations where high reliability, long service life, and easy-to-integrate limited space are the most logical criteria.[13] However, if the performance and lifetime of heat exchangers are indifferent, the marine environment will still be able to harm them.

Unlike most industrial systems onshore, marine heat exchangers need to withstand the dynamic motions, fluctuating operating conditions, and harsh environmental factors simultaneously - this combination of factors makes the equipment significantly more stressed. Under such circumstances, it is quite necessary to put the facility in its best condition both in terms of design and operation if the criteria of safety, efficiency, and long-term reliability are to be fulfilled. Problems caused by marine vibration and dynamic loading are rarely at the top of the list that most of the problems resulting in the chain of events below are. The situation is such that vessels as well as floating production/storage/offloading units undergo several types of movements (e.g. heaving, pitching, and rolling) to which changes in flow rates and transient operational conditions are added. The forces generated by these movements reach the heat exchanger through the structural supports and piping, thus they cause flow-induced vibration, resonance, and fatigue of the tubes.[15] In fixed-tube-sheet arrangements where the tubes on both ends are tightly attached to both tube sheets, the tube bundles actually become more rigid

as the bundle cannot move separately to absorb the displacement caused by the movement. Incorrect baffle spacing, absence of anti-vibration supports, or too long span of the tubes between the baffles may cause wear which may, in turn, lead to the wear-related occurrence of fretting, fatigue, or loosening of the tube-to-tube-sheet joint areas as a result of the wear that has been caused by the factors mentioned above.

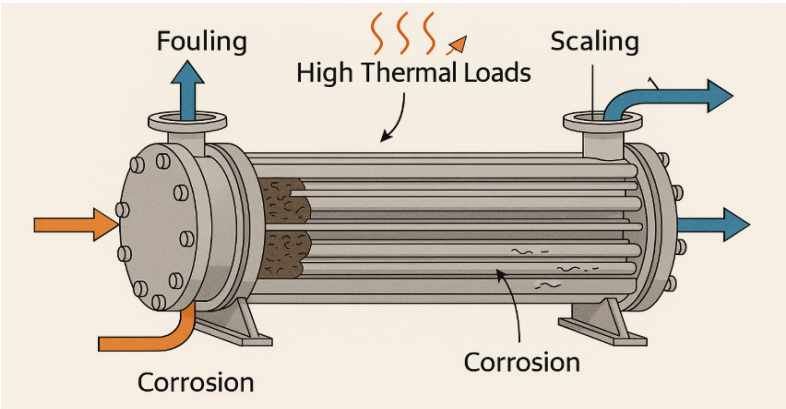

Figure 7. Fixed Tube Sheet Heat Exchanger

Comparative Studies and Benchmarking for Fixed Tube Sheet Heat Exchanger

In essence, fixed tube-sheet (straight-tube) heat exchangers in oil and gas operations remain the focal point of comparative studies that emphasize their reliability, minimal space requirement, and ability to handle a broad spectrum of crude, condensate, and process-cooling tasks as shown in figure 8. Performance-mapping studies reveal that the straight-tube layout ensures stable heat exchange even under moderate fouling and thermal load conditions. Such devices, therefore, find their uses as refinery pre-heaters, desalters, gas-oil coolers, and produced-water exchangers. Yet, in a head-to-head comparison with floating-head, U-tube, or spiral-wound designs, straight-tube heat exchangers are more likely to exhibit a lesser degree of tolerance to differential thermal expansion and a higher propensity for the tube-side to be coated with the deposition of, e.g., heavy crude fractions or high-salinity brines. Benchmarking schemes take various measures to quantify efficiency such as the overall heat-transfer coefficient (U), pressure drop, fouling factor progression, and open-to-closed-cycle maintenance. In crude stabilization and offshore process trains, straight-tube heat exchangers are usually able to perform 10–20 % less of their thermal efficiency as compared to advanced spiral or helical ones but are still the first choice of solution in situations where mechanical simplicity, high-pressure containment, and cost-effective deployment are needed.[21] Fixed tube sheet exchangers also reveal in detail operational limitations directly from their harsh chemistries of hydrocarbons, dissolved gases, and corrosive seawater that is usually used in cooling circuits in oil-sector benchmarking studies. Heavy oils, waxy crudes, and asphaltene-rich streams are leading the tube-side fouling process, while high-chloride water is intensifying the corrosion risks at the tube sheet interface, thus most of the times the service life of the exchangers is the one that is going to be compared to the alloy-based or plate-type configurations. Modern comparative analyses focus heavily on choosing materials—like duplex stainless steel, Cu–Ni alloys, or titanium—as the major factor that can result in almost double the lifetime of offshore and downstream units. Besides, the benchmarking done at refineries and petrochemical complexes indicates that the performance difference of advanced exchanger types can be reduced by the use of flow-distribution baffles, tube inserts, and cleaning schedules optimization. In those operations which are highly dependent on thermal processes like catalytic reforming and LNG

precooling, straight-tube exchangers are still able to hold a competitive position when they are upgraded through CFD-based redesign and predictive fouling monitoring. Thus, they become a cost-efficient, strong benchmark choice for oil and gas facilities that have to strike a balance between the performance demands and maintenance and economic constraints.[22]

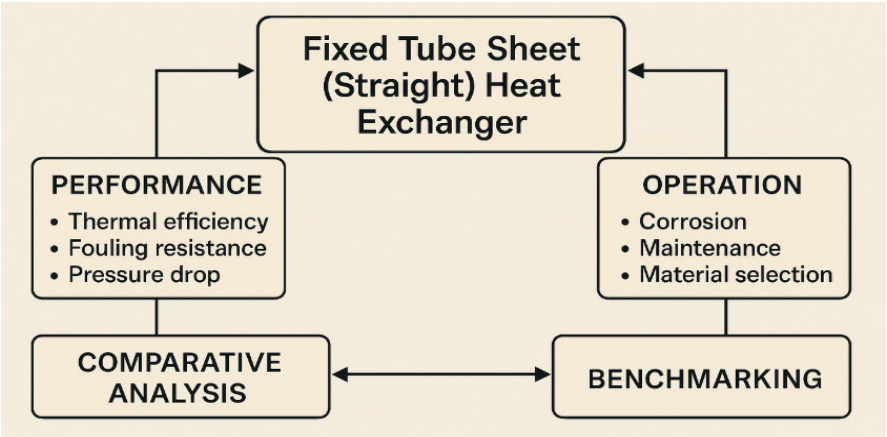

Figure 8. Comparative Studies and Benchmarking for Fixed Tube Sheet

Future Research Directions for Fixed Tube Sheet (Straight) Heat Exchanger

It is possible to anticipate that most of the changes or improvements in fixed tube sheet (straight) heat exchangers will result from innovations in material technology, the addition of digital monitoring systems, and the use of eco-friendly design strategies. In order to satisfy the requirement of a service life in the marine and offshore environments under aggressive chloride exposure, it is expected that more corrosion-resistant and thermally conductive alloys such as duplex stainless steels, titanium grades, and advanced Cu–Ni blends will be typical. By way of example, the additive manufacturing and precision-engineered geometries may open up the more effective flow distribution and lessened fouling by which the maintenance challenge caused by heavy oils, seawater cooling, and high-particulate streams has been solved for a long time.

At the same time, the deployment of smart sensors, real-time fouling prediction models, and machine-learning-based performance dashboards will drastically change the methods used for monitoring and maintaining these exchangers. The implementation of digital twins, condition-based cleaning, and remote operation frameworks will not only reduce the times of shutdown but also increase the thermal stability of refinery, LNG, and offshore platforms. In addition, global sustainability requirements will be a factor that pushes the industry to implement low-energy cooling methods, to embrace hybrid exchanger configurations, and to take up modular designs that reduce emissions and increase the overall plant efficiency. Taken together, these imminent changes illustrate a shift towards heat exchanger systems for the marine and oil-gas industries that are highly resilient, digitally optimized, and environmentally compliant.

CONCLUSIONS

The fixed tube sheet heat exchanger with straight tubes continues to be the most popular choice in the industrial and marine sectors, especially in oil and gas processing, because of its simple construction, long service life, and relatively cheap fabrication. The tubes are fixed in the tube sheets that are welded to the shell, thus the joints are strong and leak-tight which also makes tube-side cleaning easy—a feature that is very helpful when dealing with stabilized

crude, produced water, or clean condensate streams. The design with its small size and easy fabrication is also well suited for the execution of steady-state duties involving relatively clean fluids and moderate thermal gradients, like those met in utility cooling, lube-oil systems, and refinery heat-recovery loops. On the other hand, this design that features a fully restrained tube arrangement also has some significant risks. In oil-sector operations where temperature swings are considerable—such as during crude preheating, amine regeneration, or gas-oil cooling—the lack of tube expansion capability can lead to high thermal stresses at the tube-to-tube-sheet interface, which is a main cause of failure in many offshore and refinery case studies. Furthermore, limited access to the shell side makes mechanical cleaning difficult; therefore, this design is not suitable for services where the shell side is likely to foul with heavy crude, waxy fractions, brine contaminants, or solids-bearing produced fluids. Hence, fixed tube sheet exchangers should only be used when the shell-side media are clean and the operating conditions are within moderate limits. The engineers are increasingly using the optimized baffle configurations, better surface treatments, and advanced tube geometries in order to overcome the drawbacks of the oil applications and thus achieving higher performance. These measures help to alleviate thermal stress and fouling problems while at the same time maintaining the inherent advantages of the heat exchanger.

BIBLIOGRAPHIC REFERENCES

1. Li Y, Dai G. Energy Saving and Emission Reduction of Fossil Energy Based on Low Carbon Economy and Its Consumption Structure Optimization. Int J Low-Carbon Technol. 2019;14:381–5.

2. Hua LY, Cui T, Li JX, Zou BD, Yang YY, Cheng G. VOCs Removal and Emission Monitoring of Beijing Bulk Gasoline Terminals in 2012–2019. Huan Jing Ke Xue. 2021;42:1328–32.

3. Guo T, Jiao Y, Tang Y, Lu D, Kong X, Shen J, et al. Marking the Status and Development of Marine VOCs Recovery Technology. E3S Web Conf. 2021;248:01010.

4. Zhou JY, Wang BF, Nie LH, Lu JX, Hao YJ, Xu RR. Experimental Study on Emission of VOCs from Tanker Using Hollow Fiber Membrane Absorption Method with Different Absorbents. IOP Conf Ser Mater Sci Eng. 2018;292:012113.

5. Vlasenko VS, Karakozov AA, Perveev AA. Vapor Recovery Unit of Gasoline from the Tanks of Filling Stations with GasDynamic Cooling. IOP Conf Ser Earth Environ Sci. 2020;459:032043.

6. Fetisov V, Mohammadi AH, Pshenin V, Kupavykh K, Artyukh D. Improving the Economic Efficiency of Vapor Recovery Units at Hydrocarbon Loading Terminals. Oil Gas Sci Technol–Rev IFP Energ Nouv. 2021;76:38.

7. Wang J, Nan J, Wang Y. CFD-Based Optimization of a Shell-and-Tube Heat Exchanger. Fluid Dyn Mater Process. 2023;19:2761–75.

8. Dvorˇák V, Vít T. CAE Methods for Plate Heat Exchanger Design. Energy Procedia. 2017;134:234–43.

9. Khail AA, Erisen A. A Review: CFD Approaches of Plate Heat Exchangers. Arch Comput Method Eng. 2023;30:1157–65.

10. Afgan I, Kahil Y, Benhamadouche S, Ali M, Alkaabi A, Berrouk AS, et al. Cross Flow over Two Heated Cylinders in Tandem Arrangements at Subcritical Reynolds Number Using Large Eddy

Simulations. Int J Heat Fluid Flow. 2023;100:109115.

11. Mellal M, Benzeguir R, Sahel D, Ameur H. Hydro-Thermal Shell-Side Performance Evaluation of a Shell and Tube Heat Exchanger under Different Baffle Arrangement and Orientation. Int J Therm Sci. 2017;121:138–49.

12. Li Y, Jiang X, Huang X, Jia J, Tong J. Optimization of High-Pressure Shell-andTube Heat Exchanger for Syngas Cooling in an IGCC. Int J Heat Mass Transf. 2010;53:4543–51.

13. Bashtani I, Esfahani JA, Kim KC. Hybrid CFD-ANN Approach for Evaluation of Bio-Inspired Dolphins Dorsal Fin Turbulators of Heat Exchanger in Turbulent Flow. Appl Therm Eng. 2023;219:119422.

14. AL-Khaffajy M, Mossad R. Optimization of the Heat Exchanger in a Flat Plate Indirect Heating Integrated Collector Storage Solar Water Heating System. Renew Energy. 2013;57:413–21.

15. Han L, Yang K, Yang J, Li R, Li Y, Deng L, et al. A Thermal Calculation Model for Tubular Condensing Heat Exchanger. Appl Therm Eng. 2024;244:122701.

16. Aydin A, Yas¸sar H, Engin T, Buyukkaya E. Optimization and CFD Analysis of a Shell-and-Tube Heat Exchanger with a Multi Segmental Baffle. Therm Sci. 2022;26:1–12.

17. Abushammala O, Hreiz R, Lemaître C, Favre É. Optimal Design of Helical Heat/Mass Exchangers under Laminar Flow: CFD Investigation and Correlations for Maximal Transfer Efficiency and Process Intensification Performances. Int J Heat Mass Transf. 2020;153:119610.

18. Cavazzuti M, Agnani E, Corticelli MA. Optimization of a Finned Concentric Pipes Heat Exchanger for Industrial Recuperative Burners. Appl Therm Eng. 2015;84:110–7.

19. Bhandurge S, Wankhade AM, Jadhao PK. Analysis and experimentation of shell and tube heat exchanger with different orientation of baffles. Int J Res Sci Eng Technol. 2016;3:7–14.

20. Zhang H, Li Y, Xu T. Advances in high-efficiency heat exchanger configurations for marine propulsion and auxiliary systems. Appl Therm Eng. 2023;224:120098.

21. Rahman MM, Al-Sarkhi A, Azzi A. Thermal and flow optimisation strategies for energy-intensive oil and gas operations: A comprehensive review. Energy. 2022;261:125220.

22. Park J, Kim S, Lee D. Automation-driven performance enhancement in offshore and subsea process plants: Sensors, controls, and intelligent decision platforms. J Pet Sci Eng. 2024;236:111434.

23. Gao X, Wang F, Chen L. Integrated thermal management and digital control frameworks in marine engineering systems. Ocean Eng. 2021;238:109742.

24. Elshaer M, Mahmoud M, Habib MA. Smart monitoring and predictive diagnostics for thermal anomalies in oil and gas facilities: Trends and future prospects. Energy Rep. 2023;9:618–31.

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AUTHORSHIP CONTRIBUTION

Conceptualization: Hariprasad Perumal, R. Premkumar, V. Chinnadurai, R.S. Avinand, K. Balakumar, P. Prabhu, V.H. Abdullayev.

Data curation: Hariprasad Perumal, R. Premkumar, V. Chinnadurai, R.S. Avinand, K. Balakumar, P. Prabhu, V.H. Abdullayev.

Formal analysis: Hariprasad Perumal, R. Premkumar, V. Chinnadurai, R.S. Avinand, K. Balakumar, P. Prabhu, V.H. Abdullayev.

Drafting - original draft: Hariprasad Perumal, R. Premkumar, V. Chinnadurai, R.S. Avinand, K. Balakumar, P. Prabhu, V.H. Abdullayev.

Writing - proofreading and editing: Hariprasad Perumal, R. Premkumar, V. Chinnadurai, R.S. Avinand, K. Balakumar, P. Prabhu, V.H. Abdullayev.

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ORIGINAL

Modeling Concentration Dynamics under Michaelis-Menten Kinetics

Modelado de la dinámica de concentración según la cinética de Michaelis-Menten

P. Jeyabarathi[1], L. Rajendran[1] ✉

[1]Department of Mathematics, AMET (Deemed to be university). Chennai-603112, Tamilnadu, India.

Corresponding Author: L. Rajendran ✉

ABSTRACT

A theoretical model simulates substrate-to-fructose conversion by enzymatic reactions, described using a nonlinear reaction-diffusion equation based on Michaelis-Menten kinetics. The model's one-dimensional boundary value problem mimics processes in catalytic membranes or bioreactors, solved both analytically and numerically. Key methods include the Akbari-Ganji and hyperbolic function approaches, providing robust expressions for substrate concentration and flux dependent on pore-level Thiele modulus and kinetic parameters. Analytical and numerical results show satisfactory agreement, supporting the methods' reliability. Sensitivity analysis reveals how kinetic parameters impact substrate utilization—information valuable for optimizing industrial enzymatic processes in chemical and biochemical engineering.

Keywords: Enzymatic Reactions; Mathematical Modeling; Non-Linear Differential Equations; Akbari Ganji's Method, Hyperbolic Function Method.

RESUMEN

Un modelo teórico simula la conversión de sustrato a fructosa mediante reacciones enzimáticas, descrita mediante una ecuación de reacción-difusión no lineal basada en la cinética de Michaelis-Menten. El problema de valor límite unidimensional del modelo imita los procesos en membranas catalíticas o biorreactores, resueltos tanto analítica como numéricamente. Los métodos clave incluyen los enfoques de Akbari-Ganji y de la función hiperbólica, que proporcionan expresiones robustas para la concentración y el flujo de sustrato en función del módulo de Thiele a nivel de poro y los parámetros cinéticos. Los resultados analíticos y numéricos muestran una concordancia satisfactoria, lo que respalda la fiabilidad de los métodos. El análisis de sensibilidad revela cómo los parámetros cinéticos influyen en la utilización del sustrato, información valiosa para optimizar los procesos enzimáticos industriales en ingeniería química y bioquímica.

Palabras clave: Reacciones Enzimáticas; Modelado Matemático; Ecuaciones Diferenciales no Lineales; Método de Akbari-Ganji; Método de la Función Hiperbólica.

INTRODUCTION

Enzymatic conversion of glucose to fructose using immobilized glucose isomerase (IGI) has become a cornerstone in food processing, most efficiently conducted in packed-bed reactors

composed of microporous particles that provide substantial surface area for reaction due to their varied pore size distribution.[1,2] This process takes advantage of enzyme entrapment within reactor particle pores, allowing for continuous operation modes—such as fixed-bed and fluidized-bed reactors—with industrial-scale productivity and robust performance.[3,4,5] Modeling glucose-to-fructose conversion in packed-bed reactors requires consideration of the complex interplay between mass transport and nonlinear reaction kinetics, often approached through percolation theory and pore network model. Analytical techniques—including homotopy analysis, wavelet-based algorithms, and recent Akbari-Ganji and hyperbolic function methods—have produced reliable steady-state concentration and flux estimates, although a truly general solution applicable to all operational conditions remains elusive.[6,7,8] This work seeks to address that gap by deriving general analytical solutions for substrate concentration and current in packed-bed reactors.

Mathematical Formulation of the Problem

The reaction scheme for converting substrate to fructose by enzymatic reaction is described as follows:[3]

$$G + E \underset{k_{-1}}{\overset{k_1}{\leftrightharpoons}} X \underset{k_{-2}}{\overset{k_2}{\leftrightharpoons}} F + E \qquad (1)$$

Where G, E and F represent for substrate, enzyme, and fructose, respectively, and X stands for the intermediate complex generated, and k_1,k_2 and k_{-1},k_{-2} are the forward and backward kinetic constants, respectively.

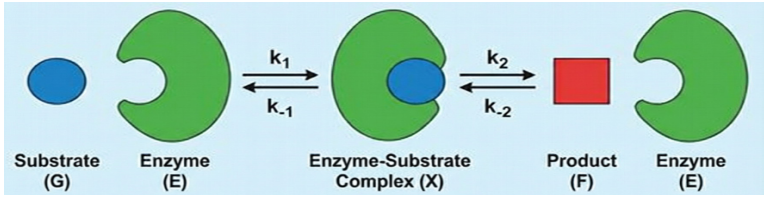


Figure 1. Schematics diagram of converting substrate to fructose by enzymatic reaction

This scheme illustrates that the enzyme is a catalyst; it participates in the reaction by forming an intermediate complex but is ultimately regenerated in its original form, ready to catalyze another reaction cycle. The reversibility indicates that under certain conditions (e.g., high product concentration), the reaction can proceed in the reverse direction, converting the product back into the substrate. The mass balance equation for the enzymatic reaction process in packed bed-reactors, as discussed by Dadvar et al.[3], can be expressed in a dimensionless form that captures the key mass transport and reaction phenomena. In general, the equation takes the form of a diffusion-reaction equation where diffusion is the primary mass transport mechanism inside the porous particles of the packed bed, and enzymatic reaction acts as a sink term. A representative form of such an equation is:

$$C(z)'' - \Phi_p^2 C(z)[1 + \beta C(z)]^{-1} = 0 \qquad (2)$$

$$C = \frac{\bar{G}}{(G_0 - G_e)}, z = \frac{x}{l}, \beta = \frac{\overline{C_0}}{K_m}, \Phi_p^2 = \frac{2\, l^2 V_m'}{r\, D_p K_m}, V_m' = \frac{v_m}{a} \qquad (3)$$

Here is the pore-level Thiele modulus and l is the pore length. The dimensionless boundary conditions are:[17]

$$C(z=0) = C_{z0} \quad (4)$$

$$C(z=1) = C_{z1} \quad (5)$$

The set of relations (2)-(5) contains four dimensionless parameters: C_{z0}, C_{z1}, β and Φp . To diminish this number up to three, we define the dimensionless concentration c(z) = $C(z)/C_{z0}$, thus leaving only three parameters $c(1) = C_{z1}/C_{z0}$, $\beta' = \beta\ C_{z0}$ and Φp. Now the equations (2)- 5) becomes.

$$\frac{d^2c(z)}{d\,z^2} - \Phi_p^2 \frac{c(z)}{1+\beta' c(z)} = 0 \quad (6)$$

The dimensionless boundary conditions are:

$$c(z=0) = 1 \quad (7)$$

$$c(z=1) = \frac{c_{z1}}{c_{z0}} = c(1) \quad (8)$$

The current becomes:

$$J_{ij} = \left(\frac{dc(z)}{dz}\right)_{z=1} \quad (9)$$

Approximate analytical expression of the concentration using Akbari-Ganji's method

A wide spectrum of asymptotic and semi-analytical techniques has been developed to tackle nonlinear differential equations. Among these, the homotopy perturbation method,[9,10,11] Akbari-Ganji's method (AGM),[12,13] the Adomian decomposition method,[14] the Taylor series method,[15] the variational iteration method. The solution obtained by AGM is close to the exact solution and has enough precision and accuracy compared to the other methods**.** The trail solution consists unknown constant coefficients. Then the unknown coefficients are computed using initial/boundary conditions and the differential equation. In contrast, other methods utilize a complicated process to achieve the solution. Using this method, we obtain the analytical expression of substrate concentration, as follows:

$$c(z) = 1 + (c(1)-1)z + \frac{c(1)\Phi_p^2}{2(1+\beta' c(1))}(z^2 - z) \quad (10)$$

It is the simplest and novel analytical expression of a substrate concentration c(z) for all dimensionless parameters c(1),β' and Φ_p. Now, from equation (10), the normalized current can be obtained as follows:-

$$J_{ij} = (c(1)-1) + \frac{c(1)\Phi_p^2}{2(1+\beta' c(1))} \quad (11)$$

Numerical Simulation

Numerically, the non-linear equation (7) in immobilised glucose in the packed-bed reactor are solved for the given boundary conditions.

Table 1. Comparison beteween numerical and analytical results for dimensionless concentration of substrate c(z) for various values of parameter Φ_p^2 when ß'=5,c(1)=0,7

z	Φ_p^2=0,01					Φ_p^2=4					Φ_p^2=9				
	Concentration			Error (%)		Concentration			Error (%)		Concentration			Error (%)	
	Num.	AGM Eq. ()	HFM Eq. ()	AGM Eq. ()	HFM Eq. ()	Num.	AGM Eq. ()	HFM Eq. ()	AGM Eq. ()	HFM Eq. ()	Num.	AGM Eq. ()	HFM Eq. ()	AGM Eq. ()	HFM Eq. ()
0	1,0000	1,0000	1,0000	0,0000	0,0000	1,0000	1,0000	1,0000	0,0000	0,0000	1,0000	1,0000	1,0000	0,0000	0,0000
0,2	0,9393	0,9393	0,9393	0,0000	0,0000	0,8876	0,8892	0,8812	0,1803	0,7210	0,8253	0,8265	0,8199	0,1454	0,6543
0,4	0,8786	0,8786	0,8786	0,0000	0,0000	0,8019	0,8039	0,7945	0,2494	0,9228	0,7097	0,7102	0,7071	0,0704	0,3663
0,6	0,8180	0,8180	0,8180	0,0000	0,0000	0,7424	0,7439	0,7367	0,2020	0,7677	0,6516	0,6511	0,6525	0,0767	0,1381
0,8	0,7575	0,7575	0,7574	0,0000	0,0132	0,7085	0,7093	0,7057	0,1129	0,3952	0,6497	0,6490	0,6514	0,1077	0,2617
1	0,7000	0,7000	0,7000	0,0000	0,0000	0,7000	0,7000	0,7000	0,0000	0,0000	0,7000	0,7000	0,7000	0,0000	0,0000
	Average error (%)			0,0000	0,0022	Average error (%)			0,1241	0,4678	Average error (%)			0,0667	0,2367

Table 2. Comparison beteween numerical and analytical results for dimensionless concentration of substrate c(z) for various values of parameter ß' when ,Φ_p^2=4,c(1)=0,7

z	ß'=1					ß'=5					ß'=10				
	Concentration			Error (%)		Concentration			Error (%)		Concentration			Error (%)	
	Num.	AGM Eq. ()	HFM Eq. ()	AGM Eq. ()	HFM Eq. ()	Num.	AGM Eq. ()	HFM Eq. ()	AGM Eq. ()	HFM Eq. ()	Num.	AGM Eq. ()	HFM Eq. ()	AGM Eq. ()	HFM Eq. ()
0	1,0000	1,0000	1,0000	0,0000	0,0000	1,0000	1,0000	1,0000	0,0000	0,0000	1,0000	1,0000	1,0000	0,0000	0,0000
0,2	0,8047	0,8066	0,8025	0,2361	0,2733	0,8876	0,8892	0,8812	0,1803	0,7210	0,9106	0,9112	0,9055	0,0659	0,5600
0,4	0,6824	0,6805	0,6827	0,2784	0,0440	0,8019	0,8039	0,7945	0,2494	0,9228	0,8359	0,8366	0,8296	0,0837	0,7537
0,6	0,6266	0,6216	0,6290	0,7980	0,3830	0,7424	0,7439	0,7367	0,2020	0,7678	0,7757	0,7764	0,7706	0,0902	0,6575
0,8	0,6340	0,6299	0,6362	0,6467	0,3470	0,7085	0,7093	0,7057	0,1129	0,3952	0,7301	0,7304	0,7273	0,0411	0,3835
1	0,7000	0,7000	0,7000	0,0000	0,0000	0,7000	0,7000	0,7000	0,0000	0,0000	0,7000	0,7000	0,7000	0,0000	0,0000
	Average error (%)			0,3265	0,1745	Average error (%)			0,1241	0,4678	Average error (%)			0,0468	0,3924

We have used the function pdex1 in Scilab/ Matlab software to solve the initial-boundary value problems numerically. This numerical solution is compared with the present AGM and HFM. Tables 1-2 show the comparison of analytical and simulation results for the concentration. Upon comparison, it gives a satisfactory agreement when all values of the other parameters. The maximum average error between numerical and our AGM and HFM are 0,33 % and 0,47 %.

Approximate analytical expression of the concentration using hyperbolic function method

The hyperbolic function method is also a special case of Akbari-Ganji's method. Analytical expressions for the substrate concentration and normalized current are obtained using the hyperbolic function method as follows:

$$c(z) = \frac{\sinh\left(A(1-z)\right)+c(1)\sinh(Az)}{\sinh(A)} \qquad (12)$$

$$A = \frac{\Phi_p}{\sqrt{1+\beta' c(1)}}$$

$$J_{ij} = A[\, c(1)\coth(A) - \mathrm{cosech}(A)] \qquad (13)$$

When ß›=0, the concentration of substrate from the equation (12) reduces to:

$$c(z) = \frac{\sinh\left(\Phi_p(1-z)\right)}{\sinh(\Phi_p)} + \frac{c(1)\sinh(\Phi_p z)}{\sinh(\Phi_p)} \qquad (14)$$

This is the exact solution of the equation (6) when ß'=0.

RESULTS AND DISCUSSION

Equations (10) and (12) represents the closed and simple approximate analytical expression of substrate concentration for all values of the parameters. Equations (11) and (13) is a new simple analytical flux expression. The values of the parameters c(1),ß' and Φp determine the substrate concentration. Also, from the equation (A1), the concentration of substrate is minimum when:

$$z = \frac{-C_1}{2C_2} \qquad (15)$$

Where:

$$c_1 = c(1) - 1 - \frac{\Phi_p^2\, c(1)}{2\left(1+\beta' c(1)\right)}, c_2 = \frac{\Phi_p^2 c(1)}{2(1+\beta' c(1))} \qquad (16)$$

The minimum value is:

$$c(z)_{min} = 1 - \frac{C_1^2}{4C_2} \qquad (17)$$

When:

$$c(1) = 0.7, \beta' = 5, \Phi_p^2 = 9,$$

Using the equation (15) to (17), we get the minimum $c(z)_{min}$=0,64 when z=0,7. This result is confirmed in figure 1 (b).

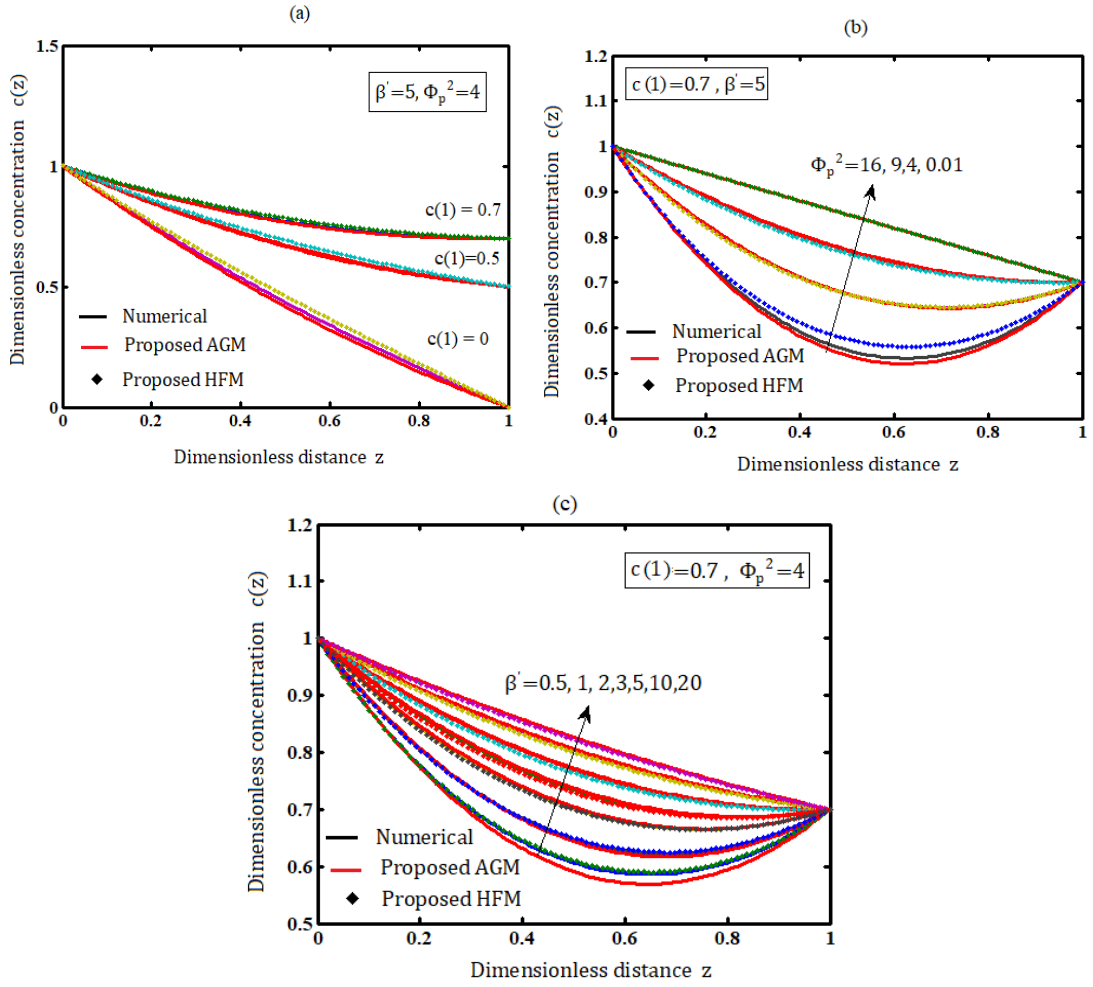
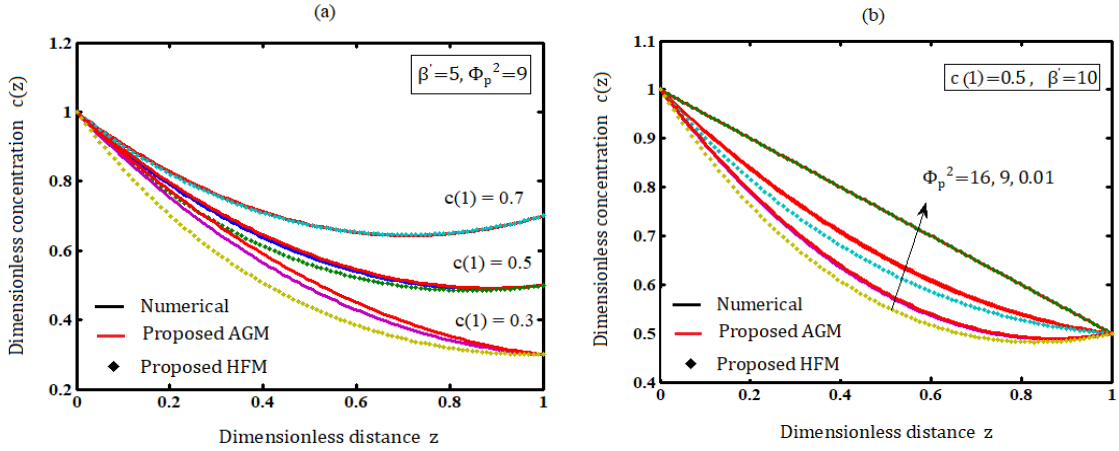


Figure 1 Comparison of analytical expressions (equations (10) and (12)) of concentration of substrate c(z) with simulation result for various value parameters c(1),β' and Φp



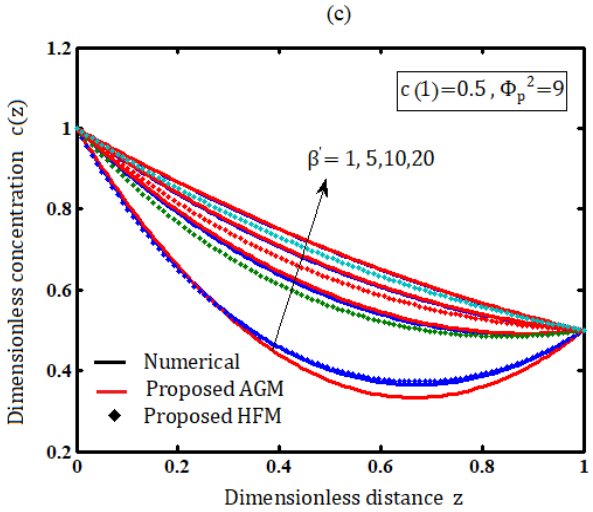
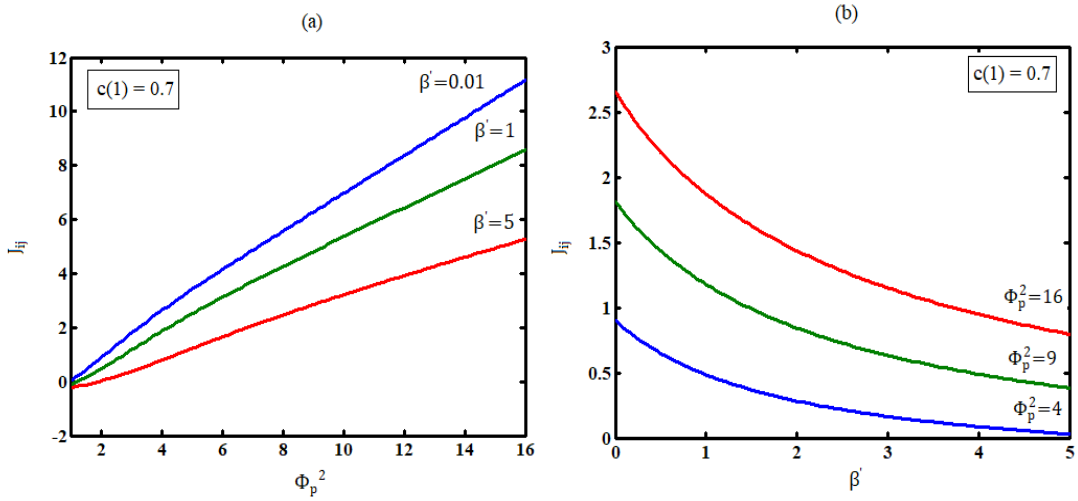


Figure 2. Comparison of analytical expressions (Equations. (10) and (12)) of concentration of substrate c(z) with simulation result for various value parameters c(1), Φp and ß'

The parameter Thiele modulus Φ_p can be varied by changing either the pore length or the amount of glucose immobilized in the matrix. This parameter describes the relative importance of diffusion and reaction in the pore. Figures 1(a-e) represent the dimensionless steady- state concentration of glucose C for different values of the Thiele modulus Φp. From the figure it is inferred that the concentration of glucose C(z) is decreased when Thiele modulus Φp increases. Also, the concentration is uniform when $\Phi_p \ll 0{,}01$ for all values of other parameters. $\Phi_p=0$ implies no chemical reaction, and hence $C(z)= C_{z0}$ for all z when $C_{z1}= C_z0$. But the maximum or minimum value of the concentration of glucose depends upon the value of C_{z1} and C_{z0}.

Figures 2 represent the dimensionless steady- state concentration for different values of the dimensionless kinetic parameter ß. From figure (2), it is observed that, when dimensionless kinetic parameter ß increases, the corresponding substrate concentration also increases for some fixed values of the other dimensionless parameters. When $ß \gg 100$ and $C_{z1}= C_{z0}$ the concentration of glucose $C(z)= C_{z0}$ for all z.



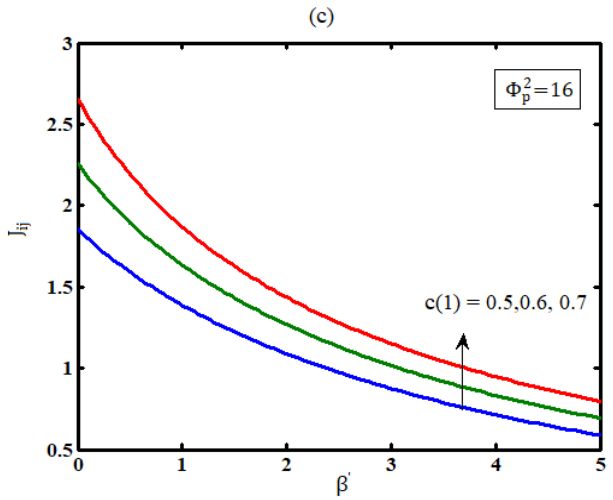


Figure 3. Effect of the parameters Φ_p^2,ß',and c(1) on the flux J_{ij} using equation ()

Figure 3 (a-d) represent the dimensionless flux J_{ij} versus dimensionless kinetic parameter ß for various values of Thiele modulus Φ_p. From this figure, it is evident that the flux value increases as the kinetic parameter ß and Thiele modulus Φ_p increases.

Sensitivity analysis of the parameters

The sensitivity analysis yields the influence of each parameter on the current. By evaluating the slope of the current with respect to the desired parameters, their influence on current can be ascertained. Figure 4 depicts the sensitivity analysis of the steady-state current. The percentage of change in current with respect to the parameters C_{z0}, C_{z1}, Φ_p and ß are 42, 47, 10 and 1 respectively. It is inferred that the concentration at the boundaries, C_{z0} and C_{z1} has a significant influence in dictating the current density, followed by the Thiele modulus Φ_p and rate constant ß.

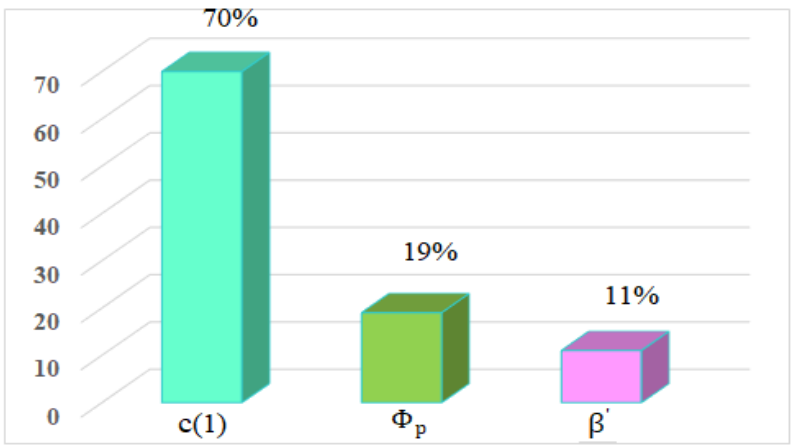


Figure 4. Sensitivity analysis of the parameters: Percentage change in dimensionless current density when c(1)=0,5,Φ_p^2=9 and ß'=0,5

CONCLUSIONS

The steady-state concentration and flux of immobilized glucose isomerase in packed-bed reactors governed by Michaelis–Menten kinetics are analyzed. Approximate closed-form analytical solutions for both concentration and flux are derived using the Akbari–Ganji method and the hyperbolic function method. These expressions provide a straightforward way to estimate glucose concentration and flux over a broad range of parameter values. A sensitivity analysis is also performed to illustrate how key parameters influence the flux. The approach presented here is flexible and can be extended to solve other nonlinear reaction–diffusion equations in immobilized enzyme reactors with complex boundary conditions.

BIBLIOGRAPHIC REFERENCES

1. Marshall RO, Kooi ER. Enzymatic conversion of D-glucose to D-fructose. Science. 1957;125(3248):648-9.

2. Dadvar M, Sohrabi M, Sahimi M. Pore network model of deactivation of immobilized glucose isomerase in packed-bed reactors. I. Two-dimensional simulation at the particle level. Chem Eng Sci. 2001;56(8):2803-16.

3. Dadvar M, Sahimi M. Pore network model of deactivation of immobilized glucose isomerase in packed-bed reactors. II. Three-dimensional simulation at the particle level. Chem Eng Sci. 2002;57(6):939-52.

4. Dadvar M, Sahimi M. Pore network model of deactivation of immobilized glucose isomerase in packed-bed reactors. Part III: Multiscale modelling. Chem Eng Sci. 2003;58(22):4935-51.

5. Ponrani VM, Rajendran L. Mathematical modelling of steady-state concentration in immobilized glucose isomerase of packed-bed reactors. J Math Chem. 2012;50(5):1333-46.

6. Ananthaswamy V, Padmavathi P, Rajendran L. Simple Analytical Expressions of the Steady State Concentration and Flux in Immobilized Glucose Isomerase of Packed-Bed Reactors. Rev Bioinforma Biom. 2014;3(1):29-37.

7. Selvi MSM, Hariharan G. Wavelet-Based Analytical Algorithm for Solving Steady-State Concentration in Immobilized Glucose Isomerase of Packed-Bed Reactor Model. J Membrane Biol. 2016;249(4):559-68.

8. Abukhaled M. Variational Iteration Method for Nonlinear Singular Two-Point Boundary Value Problems Arising in Human Physiology. J Math. 2013;2013:720134.

9. Akbari N, Gholinia M, Gholinia S, Dabbaghian S, Ganji DD. Analytical and numerical study of hydrodynamic nano fluid flow in a two–dimensional semi-porous channel with transverse magnetic field. Sigma J Eng Nat Sci. 2018;36(3):587-608.

10. Akbari MR, Akbari S, Kalantari E, Ganji DD. Akbari-Ganjis method AGM to chemical reactor design for non-isothermal and non-adiabatic of mixed flow reactors. J Chem Eng Mater Sci. 2020;11(1):1-9.

11. He JH. Taylor series solution for a third order boundary value problem arising in Architectural Engineering. Ain Shams Eng J. 2020;11(4):1411-4.

12. Wazwaz AM. Optical bright and dark soliton solutions for coupled nonlinear Schrödinger (CNLS) equations by the variational iteration method. Optik. 2020;207:164457.

13. He JH, El-Dib YO, Mady AA. Homotopy Perturbation Method for the Fractal Toda Oscillator. Fractal Fract. 2021;5(3):93.

14. He JH, El Dib YO. Homotopy perturbation method with three expansions. J Math Chem. 2021;59(4):1139-50.

15. Devi MC, Pirabaharan P, Rajendran L, Abukhaled M. Amperometric biosensors in an uncompetitive inhibition process: a complete theoretical and numerical analysis. React Kinet Mech Cat. 2021;133(2):655-68.

16. Jeyabarathi P, Rajendran L, Abukhaled M. Semi-analytical expressions for the concentrations and effectiveness factor for the three general catalyst shapes. Reac Kinet Mech Cat. 2022;135(4):1739–54.

17. Chemistry LibreTexts. Michaelis-Menten kinetics: Principles, equation & uses. 2024. https://chem.libretexts.org/Bookshelves/Biological_Chemistry/Supplemental_Modules_(Biological_Chemistry)/Enzymes/Enzymatic_Kinetics/Michaelis_Menten_Kinetics

FINANCING

None.

CONFLICT OF INTEREST

None.

AUTHORSHIP CONTRIBUTION

Conceptualization: P. Jeyabarathi, L. Rajendran.
Data curation: P. Jeyabarathi, L. Rajendran.
Formal analysis: P. Jeyabarathi, L. Rajendran.
Drafting - original draft: P. Jeyabarathi, L. Rajendran.
Writing - proofreading and editing: P. Jeyabarathi, L. Rajendran.

ANNEXES

Appendix-A. Models of transport and reaction

The rate equation of enzyme for a pseudo-steady state condition can be written as follows:

$$\frac{d\,X}{d\,t} = k_1 E\,G - (k_{-1} + k_2)X + k_{-2}\,EF \simeq 0, \qquad \text{(A1)}$$

Where E,G, and F is the concentration of enzyme, glucose and fructose, respectively. The reaction rate is given by:

$$R = \frac{v_m\,\bar{G}}{K_m + \bar{G}} \qquad \text{(a1)}$$

Where:

$$v_m = \frac{K_{mr} v_{mf}(1+K^{-1})}{K_{mr} - K_{mf}}, K_m = \frac{K_{mf}\,K_{mr}\left[1+(K_{mf}^{-1}+KK_{mr}^{-1})G_0(1+K)^{-1}\right]}{K_{mr-}K_{mf}},$$
$$K = \frac{F_e}{G_e} = \frac{v_{mf}}{v_{mr}}\frac{K_{mr}}{K_{mf}} \qquad \text{(A2)}$$

The non-linear mass balance reaction- diffusion equation is written as follows:(17)

$$D_p(\lambda)\frac{d^2G}{d\,z^2} - \frac{2}{ra}R = 0 \qquad \text{(A3)}$$

Where $\lambda=R_{M/r}$, R_M is the molecular radius and r is the pore radius, and a is the surface area per unit weight of the particle. D_p is the pore diffusivity. Equation (A3) can be rewritten in the following way.

$$D_p\frac{d^2\bar{G}}{d\,z^2} - \frac{2}{ra}\frac{V_m\bar{G}}{(K_m+\bar{G})} = 0 \qquad \text{(A4)}$$

This equation is transformed in the dimensionless form of equation (2), which is given in the text.

Appendix B: Approximate analytical expression of the concentration using Akbari-Ganji's method

We can assume that the trail solution of the equation (6) is:

$$c(z) = \sum_{i=0}^{2} c_i\,z^i = c_0 + c_1 z + c_2 z^2 \qquad \text{(B1)}$$

Where c_0, c_1 and c_2 are constants. Using the boundary conditions (7) and (8) we get

$$c_0 = 1, c_1 + c_2 = c(1) - 1 \qquad \text{(B2)}$$

Now define the function H by

$$H(z) = \frac{d^2c(z)}{d\,z^2} - \Phi_p^2 \frac{c(z)}{1+\beta' c(z)} = 0 \qquad \text{(B3)}$$

Using the equation (B1), equation (B3) at z=0 becomes

$$H(z=1) = 2\,c_2 - \frac{\Phi_p^2\, c(1)}{1+\beta' c(1)} = 0 \qquad \text{(B4)}$$

Using equation (B2) in equation (B4), gives:

$$c_2 = \frac{\Phi_p^2 c(1)}{2(1+\beta' c(1))}\,,\; c_1 = c(1) - 1 - \frac{\Phi_p^2\, c(1)}{2(1+\beta' c(1))} \qquad \text{(B5)}$$

Equation (B5) and (B2) into Eq. (B1) gives the closed form of analytical expression of a substrate concentration c(z) for all dimensionless parameters c(1),Φ_p and ß'.

$$c(z) = 1 + (c(1)-1)z + \frac{\Phi_p^2\, c(1)}{2(1+\beta' c(1))}(z^2 - z) \qquad \text{(B6)}$$

The current becomes:

$$J_{ij} = (c(1)-1) + \frac{\Phi_p^2\, c(1)}{2(1+\beta' c(1))} \qquad \text{(B7)}$$

Appendix C: Approximate analytical expression of the concentration using Hyperbolic function method:

Assume that the solution to equation (6) is of the following hyperbolic form:

$$c(z) = A_0 \cosh(m\,z) + B_0 \sinh(m\,z) \qquad \text{(C1)}$$

where A_0, B_0 and m are constant. From boundary conditions (7) and (8), the values of A_0 and B_0 are readily obtained, that is:

$$A_0 = 1,\; B_0 = \frac{c(1) - \cosh(m)}{\sinh(m)} \qquad \text{(C2)}$$

Now the equation (C1) becomes:

$$c(z) = \frac{\sinh\big(m(1-z)\big)}{\sinh(m)} + \frac{c(1)\sinh(mz)}{\sinh(m)} \qquad \text{(C3)}$$

To determine the constant m in equation (C3), we consider the functional form of equation (6)

$$F(z) = \big(1+\beta' c(z)\big)\frac{d^2\,C(z)}{d\,z^2} - \Phi_p^2 c(z) = 0 \qquad \text{(C4)}$$

By substituting Eq. (C4) into Eq. (C3), we obtain:

$$F(z)|_{z=0} = (1+\beta' c(1))\, m^2 = \Phi_p^2 \qquad \text{(C5)}$$

From the above equation we get:

$$m = \frac{\Phi_p}{\sqrt{1+\beta' c(1)}} \qquad \text{(C6)}$$

Substitute equation (C6) into Eq. (C3) gives the following closed form of analytical expression of a substrate concentration c(z) for all dimensionless parameters c_{z1}/c_{z0} ,Φ_p and βc_{z0}.

$$c(z) = \frac{\sinh\left(\frac{\Phi_p}{\sqrt{1+\beta' c(1)}}(1-z)\right)}{\sinh\left(\frac{\Phi_p}{\sqrt{1+\beta' c(1)}}\right)} + \frac{c(1)\sinh\left(\frac{\Phi_p}{\sqrt{1+\beta' c(1)}}z\right)}{\sinh\left(\frac{\Phi_p}{\sqrt{1+\beta' c(1)}}\right)} \qquad \text{(C7)}$$

The current becomes:

$$J_{ij} = \frac{\Phi_p}{\sqrt{1+\beta' c(1)}}\left[c(1)\coth\left(\frac{\Phi_p}{\sqrt{1+\beta' c(1)}}\right) - \operatorname{cosech}\left(\frac{\Phi_p}{\sqrt{1+\beta' c(1)}}\right)\right] \qquad \text{(C8)}$$

Appendix D

MATLAB code for numerical solution of the non-linear Eq. (6)

```
function pdex4
m = 0;
x = linspace(0,1);
t = linspace(0,1000);
sol = pdepe(m,@pdex4pde,@pdex4ic,@pdex4bc,x,t);
u1 = sol(:,:,1);
figure
plot(x,u1(end,:))
title('u1(x,t)')
xlabel('Distance x')
ylabel('u1(x,2)')
%------------------------------------------------------------
function [c,f,s] = pdex4pde(x,t,u,DuDx)
c = [1];
f = [1] .* DuDx;
alpha=1;
beta=0,01;
F=-((alpha^2)*u(1))/(1+beta*u(1));
s=[F];
% ------------------------------------------------------------
function u0 = pdex4ic(x)
```

```
%create a initial conditions
u0 = [1];
% ------------------------------------------------------------
function [pl,ql,pr,qr] = pdex4bc(xl,ul,xr,ur,t)
%create a boundary conditions
a=1;b=1;
pl = [ul(1)-a];
ql = [0];
pr = [ur(1)-b];
qr = [0];
```

Chapter 14 / Capítulo 14

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ORIGINAL

Solution of the non-isothermal reaction-diffusion equation in a spherical biocatalyst

Solución de la ecuación de reacción-difusión no isotérmica en un biocatalizador esférico

R. Rajalakshmi[1] ✉, S. Naganathan[2], L. Rajendran[3]

[1]Department of Mathematics, Government Arts College for Women. Ramanathapuram-623501, Tamilnadu, India
[2]Department of Mathematics, Sethupathy Government Arts College. Ramanthapuram-623502, Tamilnadu, India.
[3]Department of Mathematics, AMET Deemed to be University. Kanathur, Chennai 603112, Tamilnadu, India.

Corresponding Author: R. Rajalakshmi ✉

ABSTRACT

This study develops a comprehensive mathematical model for substrate concentration in a spherical biocatalyst pellet under non-isothermal conditions, capturing the combined effects of heat and mass transfer along with reaction kinetics. Analytical solutions for the concentration profile and effectiveness factor are derived using the Taylor Series Method and validated against numerical simulations, revealing high accuracy and excellent agreement. The research further analyzes how dimensionless parameters, such as the Thiele modulus and Biot number, influence the effectiveness factor, emphasizing the effectiveness of the Taylor Series Method for modeling complex nonlinear bioreaction systems

Keywords: Non-Isothermal Reaction-Diffusion; Biocatalyst Pellet; Taylor Series Method; Effectiveness Factor; Thiele Modulus.

RESUMEN

Este estudio desarrolla un modelo matemático integral para la concentración de sustrato en un pellet esférico de biocatalizador en condiciones no isotérmicas, capturando los efectos combinados de la transferencia de calor y masa, junto con la cinética de la reacción. Las soluciones analíticas para el perfil de concentración y el factor de efectividad se derivan mediante el método de las series de Taylor y se validan con simulaciones numéricas, revelando una alta precisión y una excelente concordancia. La investigación analiza en profundidad cómo parámetros adimensionales, como el módulo de Thiele y el número de Biot, influyen en el factor de efectividad, destacando la eficacia del método de las series de Taylor para modelar sistemas complejos de biorreacción no lineales.

Palabras clave: Reacción-Difusión no Isotérmica; Pellet de Biocatalizador; Método de las Series de Taylor; Factor de Efectividad; Módulo de Thiele.

INTRODUCTION

Biocatalytic processes within porous spherical supports are widespread in chemical and biochemical industries. The design and optimization of these systems require a deep

understanding of the interplay between reaction kinetics, heat transfer, and mass transport. In particular, non-isothermal reaction-diffusion systems pose a significant challenge due to the non-linearity introduced by the temperature dependence of reaction rates.

The paper by Jamal and Khuri presented an analytical treatment of such systems using Green's Function and the Fixed-Point Iteration Method.[1] Complementing that, this thesis develops an alternative[2,3] analytical approach based on the Taylor Series Method (TSM) for the steady-state concentration profile.[4,5,6]

This method offers a direct and recursive means to evaluate concentration distributions. We derive expressions for concentration y(x), determine unknown constants using experimental data, and calculate the effectiveness factor η. The solutions are validated against numerical results, and the effects of key parameters on system behavior are discussed.[7,8]

Mathematical Model

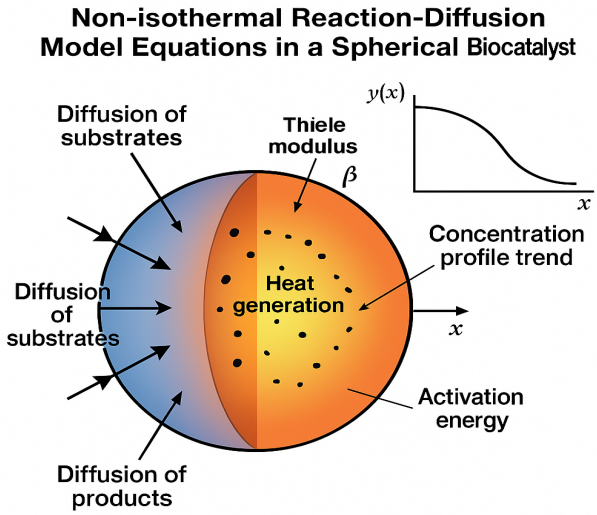


Figure 1. Substrate transport, heat diffusion, and reaction zone representation inside a spherical biocatalyst

Many chemical reactions take place inside a catalyst pellet, which is a porous material. Consider an inert permeable spherical solid particle. It is assumed that the biochemical reaction follows Michaelis–Menten kinetics. The application of mass balance for the substrate (A) over a thin spherical shell inside the biocatalyst yields the following model equation (2,3).

$$D_e\left(\frac{d^2C_A}{dr^2}+\frac{2}{r}\frac{dC_A}{dr}\right)=\frac{r_m C_A}{(K_m+C_A)} \qquad (1)$$

Where; C_A is the concentration of substrate, D_e is the effective diffusivity, r is the radial distance, r_m is the maximum reaction rate, K_m is the Michaelis–Menten constant. The boundary conditions are:

$$\text{At } r=0,\ \frac{dC_A}{dr}=0 \text{ (center of catalyst)} \qquad (2)$$

At $r = R$, $C_A = C_{As}$(catalyst surface) (3)

Normalizing equation (1) using the following dimensionless variables.

$$y = \frac{C_A}{C_{AS}},\ x = \frac{r}{R},\ \phi = \sqrt{\frac{-r_{AS}R^2}{D_e D_{AS}}} = \sqrt{\frac{r_m R^2}{D_e K_m(1+\beta)}}\ ;\ \beta = \frac{C_{AS}}{K_m} \qquad (4)$$

Equation (4) gives the following dimensionless equation. We consider a steady-state, non-isothermal, nonlinear reaction–diffusion model in a spherical biocatalyst pellet. The dimensionless form of the governing equation for the normalized substrate concentration y(x) is given by:

$$y''(x) + \frac{2}{x}y'(x) - r(y) = 0,\ 0 \le x \le 1,\ \ r(y) = \phi^2 \frac{(1+\beta)y(x)}{1+\beta y(x)} \qquad (5)$$

Where *x* is the dimensionless radial coordinate, y(*x*) is the dimensionless concentration ϕ is the Thiele modulus, ß is a dimensionless activation energy parameter. The boundary conditions are given below:

$y'(0) = 0$ (6)
$y(1) = 1$ (7)

The effectiveness factor η for a spherical pellet is defined as:

$$\eta = \frac{3}{\phi^2}\frac{dy}{dx}|_{x=1}$$

Solution Methodology: Taylor Series Expansion

The nonlinear equation is analytically solved by expanding y(x):

$$y(x) = y(0) + \frac{y'(0)x}{1!} + \frac{y''(0)x^2}{2!} + \frac{y'''(0)x^3}{3!} + \frac{y'^v(0)x^4}{4!} + \frac{y^v(0)x^5}{5!} \qquad (8)$$

We obtain the solution of the normalized concentration y(*x*) as:

$$y(x) = k + \left(\phi^2 \frac{(1+\beta)k}{1+\beta k}\right)\left(\frac{1}{6}\right)x^2 \qquad (9)$$

To find k

By applying the boundary condition from Equation (5b) in (8) it becomes:

$$k + \left(\phi^2 \frac{(1+\beta)k}{1+\beta k}\right)\left(\frac{1}{6}\right) - 1 = 0 \qquad (10)$$

By using MAPLE, we can find the value of k by giving the experimental values for the unknown parameters ϕ, ß.

Effectiveness factor η for a spherical pellet

By applying the equation (9) in equation (6) the analytical expressions for the Effectiveness factor (η):

$$k + \left(\phi^2 \frac{(1+\beta)k}{1+\beta k}\right)\left(\frac{1}{6}\right) - 1 = 0 \qquad (10)$$

$$\eta = \left(\frac{3}{\phi^2}\right)\left(\left(\phi^2 \frac{(1+\beta)k}{1+\beta k}\right)\left(\frac{1}{3}\right)x\right)_{x=1} \qquad (11)$$

$$\eta = \left(\frac{(1+\beta)k}{1+\beta k}\right) \qquad (12)$$

By using MAPLE for equation. (9) We can find the value of '*k*'. Also, applying experimental values for β, in (11), we can find the Effectiveness factor η for a spherical pellet.

RESULTS AND DISCUSSION

The analytical expression for y(x) derived via the Taylor Series Method (TSM) has been evaluated and validated against numerical results across various values of the Thiele modulus ϕ and activation energy parameter ß. The following results and visual comparisons demonstrate the accuracy and applicability of the method.

Table 1. Comparison between the numerical and analytical results for y(x) for various values of ϕ for ß=1

	Numerical			TSM			Deviation		
x	ϕ=0,5	ϕ=1	ϕ=1,5	ϕ=0,5 k=0,9592	ϕ=1 k=0,8471	ϕ=1,5 k=0,6930	ϕ=0,5	ϕ=1	ϕ=1,5
0,1	0,9601	0,8474	0,6830	0,9596	0,8487	0,6961	0,0000	0,0000	0,0001
0,2	0,9609	0,8504	0,6891	0,9609	0,8534	0,7055	0,0000	0,0000	0,0001
0,3	0,9628	0,8576	0,7034	0,9630	0,8612	0,7212	0,0000	0,0000	0,0001
0,4	0,9656	0,8681	0,7245	0,9659	0,8721	0,7431	0,0000	0,0000	0,0001
0,5	0,9692	0,8818	0,7523	0,9696	0,8861	0,7713	0,0000	0,0000	0,0001
0,6	0,9737	0,8988	0,7869	0,9742	0,9033	0,8058	0,0000	0,0000	0,0001
0,7	0,9790	0,9190	0,8287	0,9796	0,9236	0,8465	0,0000	0,0000	0,0001
0,8	0,9852	0,9426	0,8779	0,9858	0,9470	0,8935	0,0000	0,0000	0,0001
0,9	0,9922	0,9696	0,9348	0,9929	0,9735	0,9467	0,0000	0,0000	0,0001
1,0	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,0000	0,0000	0,0000
Average Deviation							0,0000	0,0000	0,0001

Table 2. Comparison between the numerical and analytical results for y(x) for various values of ϕ for ß=2

	Numerical			TSM			Deviation		
x	ϕ=0,5	ϕ=1	ϕ=1,5	ϕ=0,5 k=0,9589	ϕ=1 k=0,8431	ϕ=1,5 k=0,6765	ϕ=0,5	ϕ=1	ϕ=1,5
0,1	0,9599	0,8445	0,6703	0,9593	0,8447	0,6798	0,0000	0,0000	0,0001
0,2	0,9607	0,8476	0,6767	0,9606	0,8495	0,6897	0,0000	0,0000	0,0001

0,3	0,9626	0,8550	0,6918	0,9627	0,8575	0,7062	0,0000	0,0000	0,0001
0,4	0,9654	0,8658	0,7141	0,9656	0,8687	0,7294	0,0000	0,0000	0,0001
0,5	0,9691	0,8798	0,7433	0,9694	0,8831	0,7591	0,0000	0,0000	0,0001
0,6	0,9736	0,8972	0,7797	0,9740	0,9007	0,7954	0,0000	0,0000	0,0001
0,7	0,9790	0,9178	0,8233	0,9795	0,9215	0,8383	0,0000	0,0000	0,0001
0,8	0,9851	0,9418	0,8743	0,9858	0,9455	0,8878	0,0000	0,0000	0,0001
0,9	0,9921	0,9692	0,9332	0,9929	0,9728	0,9439	0,0000	0,0000	0,0001
1,0	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,0000	0,0000	0,0000
Average Deviation							0,0000	0,0000	0,0001

Table 3. Comparison between the numerical and analytical results for y(x) for various values of ϕ for ß=3

	Numerical			TSM			Deviation		
x	ϕ=0,5	ϕ=1	ϕ=1,5	ϕ=0,5 k=0,9587	ϕ=1 k=0,8409	ϕ=1,5 k=0,6667	ϕ=0,5	ϕ=1	ϕ=1,5
0,1	0,9598	0,8430	0,6630	0,9592	0,8425	0,6701	0,0000	0,0000	0,0000
0,2	0,9606	0,8462	0,6696	0,9605	0,8474	0,6803	0,0000	0,0000	0,0001
0,3	0,9626	0,8536	0,6852	0,9626	0,8555	0,6973	0,0000	0,0000	0,0001
0,4	0,9654	0,8645	0,7082	0,9655	0,8668	0,7211	0,0000	0,0000	0,0001
0,5	0,9690	0,8788	0,7383	0,9693	0,8815	0,7517	0,0000	0,0000	0,0001
0,6	0,9736	0,8963	0,7756	0,9739	0,8993	0,7891	0,0000	0,0000	0,0001
0,7	0,9789	0,9172	0,8202	0,9794	0,9204	0,8333	0,0000	0,0000	0,0001
0,8	0,9851	0,9414	0,8724	0,9857	0,9448	0,8843	0,0000	0,0000	0,0001
0,9	0,9921	0,9690	0,9322	0,9929	0,9724	0,9421	0,0000	0,0000	0,0001
1,0	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,0000	0,0000	0,0000
Average Deviation							0,0000	0,0000	0,0001

Table 4. Comparison between the numerical results and Taylor series solution for y(x) for various values of ß for ϕ =0,5

	Numerical			TSM			Deviation		
x	ß=1	ß=2	ß=3	ß=1 k=0,9592	ß=2 k=0,9589	ß=3 k=0,9587	ß=1	ß=2	ß=3
0,1	0,9601	0,9599	0,9598	0,9596	0,9593	0,9592	0,0000	0,0000	0,0000
0,2	0,9609	0,9607	0,9606	0,9609	0,9606	0,9605	0,0000	0,0000	0,0000
0,3	0,9628	0,9626	0,9626	0,9630	0,9627	0,9626	0,0000	0,0000	0,0000
0,4	0,9656	0,9654	0,9654	0,9659	0,9656	0,9655	0,0000	0,0000	0,0000
0,5	0,9692	0,9691	0,9690	0,9696	0,9694	0,9693	0,0000	0,0000	0,0000
0,6	0,9737	0,9736	0,9736	0,9742	0,9740	0,9739	0,0000	0,0000	0,0000
0,7	0,9790	0,9790	0,9789	0,9796	0,9795	0,9794	0,0000	0,0000	0,0000
0,8	0,9852	0,9851	0,9851	0,9858	0,9858	0,9857	0,0000	0,0000	0,0000
0,9	0,9922	0,9921	0,9921	0,9929	0,9929	0,9929	0,0000	0,0000	0,0000
1,0	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,0000	0,0000	0,0000
Average Deviation							0,0000	0,0000	0,0000

Table 5. Comparison between the numerical results and Taylor series solution for y(*x*) for various values of ß for ϕ =1

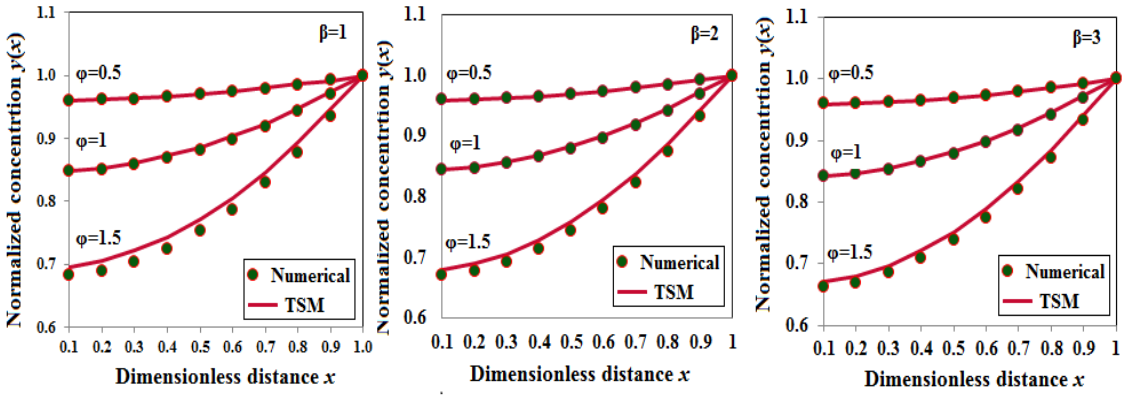
x	Numerical			TSM			Deviation		
	ß=0,5	ß=1	ß=10	ß=0,5 k=0,8508	ß=1 k=0,8471	ß=10 k=0,8362	ß=0,5	ß=1	ß=10
0,1	0,8500	0,8474	0,8399	0,8523	0,8487	0,8379	0,0000	0,0000	0,0000
0,2	0,8530	0,8504	0,8432	0,8569	0,8534	0,8429	0,0000	0,0000	0,0000
0,3	0,8600	0,8576	0,8508	0,8645	0,8612	0,8513	0,0000	0,0000	0,0000
0,4	0,8703	0,8681	0,8620	0,8751	0,8721	0,8630	0,0000	0,0000	0,0000
0,5	0,8837	0,8818	0,8766	0,8888	0,8861	0,8780	0,0000	0,0000	0,0000
0,6	0,9003	0,8988	0,8946	0,9056	0,9033	0,8964	0,0000	0,0000	0,0000
0,7	0,9202	0,9190	0,9159	0,9254	0,9236	0,9181	0,0000	0,0000	0,0000
0,8	0,9433	0,9426	0,9406	0,9482	0,9470	0,9432	0,0000	0,0000	0,0000
0,9	0,9699	0,9696	0,9686	0,9741	0,9735	0,9716	0,0000	0,0000	0,0000
1,0	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,0000	0,0000	0,0000
Average Deviation							0,0000	0,0000	0,0000

Table 6. Comparison between the numerical results and Taylor series solution for y(*x*) for various values of ß for ϕ =1,5

X	Numerical			TSM			Deviation		
	ß=0,5	ß=1	ß=10	ß=0,5 k=0,7064	ß=1 k=0,6930	ß=10 k=0,6430	ß=0,5	ß=1	ß=10
0,1	0,6939	0,6830	0,6467	0,7094	0,6961	0,6467	0,0001	0,0001	0,0000
0,2	0,6997	0,6891	0,6538	0,7184	0,7055	0,6576	0,0001	0,0001	0,0000
0,3	0,7133	0,7034	0,6706	0,7333	0,7212	0,6758	0,0001	0,0001	0,0000
0,4	0,7334	0,7245	0,6951	0,7543	0,7431	0,7013	0,0002	0,0001	0,0000
0,5	0,7600	0,7523	0,7271	0,7813	0,7713	0,7341	0,0002	0,0001	0,0001
0,6	0,7932	0,7869	0,7666	0,8142	0,8058	0,7741	0,0002	0,0001	0,0001
0,7	0,8334	0,8287	0,8135	0,8532	0,8465	0,8215	0,0002	0,0001	0,0001
0,8	0,8810	0,8779	0,8681	0,8981	0,8935	0,8761	0,0002	0,0001	0,0001
0,9	0,9363	0,9348	0,9302	0,9490	0,9467	0,9380	0,0001	0,0001	0,0001
1,0	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	0,0000	0,0000	0,0000
Average Deviation							0,0001	0,0001	0,0000

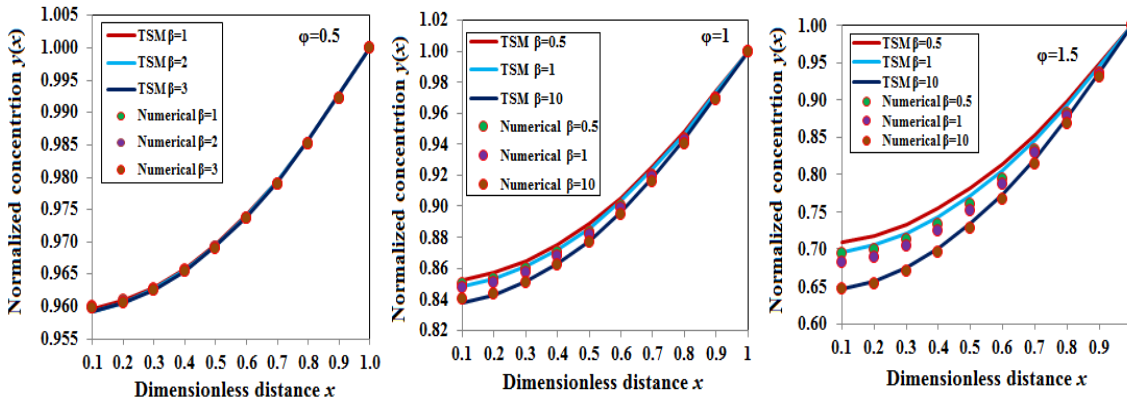
Comparison of Analytical and Numerical Solutions for Various ϕ

Tables (1,2,3) and figures 2(a-c) show the concentration profiles for three values of ß = 1, 2, 3 as ϕ varies over 0,5, 1,0, 1,5, and 2. The observation that as ϕ increases, the substrate concentration at the center decreases due to stronger diffusion limitations. The Taylor Series results are in near-perfect agreement with numerical results, showing deviations of 0,0001 or less. This validates the efficiency of the TSM, especially for moderate nonlinearity.



(a) (b) (c)

Figure 2 (a-c). Comparison between the numerical and analytical results for y(*x*) for various values of ϕ for ß=1, 2, & 3



(a) (b) (c)

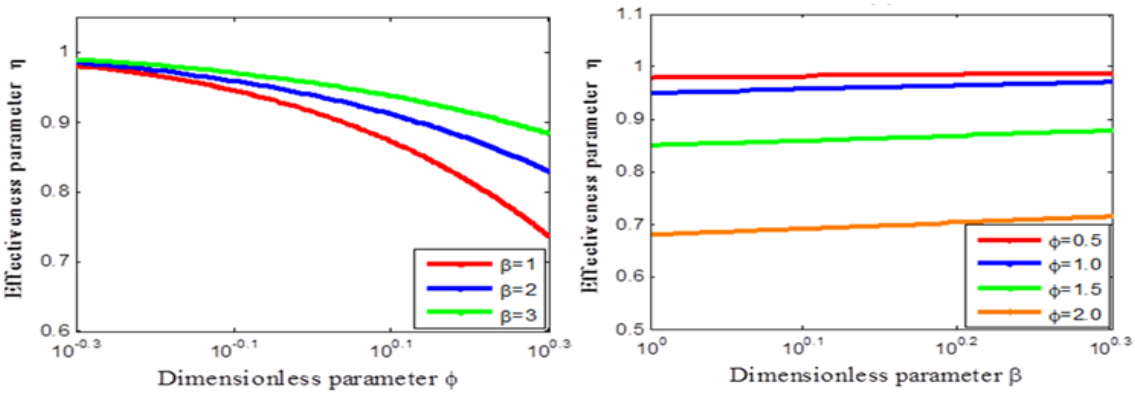
Figure 3 (a-c). Comparison between the numerical and analytical results for y(*x*) for various values of ß for ϕ =0,5, 1, & 1,5.

Effectiveness factor for a spherical pellet (η)

Table 7. Effectiveness factor (η) effectiveness factor (η) for various values of ß for ϕ=0,5, 1,1,5, 2, various values of ϕ for β=1, 2, 3

ß	ϕ	*k*	η	ϕ	ß	*k*	H
1	0,5	0,9592	0,9792		1	0,9592	0,9792
	1,0	0,8471	0,9172	0,5	2	0,9589	0,9859
	1,5	0,6930	0,8187		3	0,9587	0,9893
	2,0	0,5352	0,6972		1	0,8471	0,9172
2	0,5	0,9589	0,9859	1,0	2	0,8431	0,9416
	1,0	0,8431	0,9416		3	0,8409	0,9548
	1,5	0,6765	0,8625	1,5	1	0,6930	0,8187
	2,0	0,5000	0,7500		2	0,6765	0,8625

3	0,5	0,9587	0,9893		3	0,6667	0,8889
	1,0	0,8409	0,9548	2	1	0,5352	0,6972
	1,5	0,6667	0,8889		2	0,5000	0,7500
	2,0	0,4768	0,7847		3	0,4768	0,7847



(a) (b)

Figure 4 (a-b). Comparison between the numerical results and the analytical results for y(*x*) for ß = 1, 2, 3 as ϕ varies over 0,5, 1,0, 1,5, and 2

Comparison for Various ß at Fixed ϕ

Tables (4,5,6) and figures 3(a-c) analyze the effect of the thermal sensitivity ß at fixed ϕ = 0,5, 1,0, 1,5, and 2. The Observations that as ß increases, the exponential term becomes more sensitive, steepening the gradient near the surface. Even under strong non-linearity (e.g., ß = 10), the analytical solution shows excellent agreement with the numerical one. This demonstrates the robustness of the Taylor series approach for a wide parameter range.

Effectiveness Factor Analysis

Table (7) and figure 4(a-b) present the effectiveness factor η for various combinations of ϕ and ß. For a fixed ß, increasing ϕ decreases η due to higher internal diffusion resistance, and for a fixed ϕ, increasing ß increases η, reflecting enhanced reaction rates from thermal sensitivity. These findings highlight the importance of optimizing transport and reaction parameters.

Accuracy and Practical Implications

The average deviations between numerical and analytical solutions are minimal (mostly 0,0001 or less), confirming the high fidelity of TSM. Low-order Taylor expansions can reliably model the system for engineering applications. This provides a fast, accurate alternative to computationally intensive simulations in catalyst design.

CONCLUSIONS

This analytical investigation addresses a non-isothermal, nonlinear reaction–diffusion system within a spherical biocatalyst pellet. The Taylor Series Method provides an accurate, recursive solution for the dimensionless concentration profile, $y(x)$, and the effectiveness factor, η, a vital metric for catalytic performance. Analytical results align closely with numerical solutions across various Thiele modulus (ϕ) and Biot number (β) values, underscoring the precision and reliability

of TSM for these problems. Insights into the effects of these parameters offer valuable guidance for optimizing reactor design, demonstrating that the Taylor Series Method offers a practical and computationally efficient approach to analyzing complex nonlinear systems.

Nomenclature

ϕ Thiele Modulus None.
η Effectiveness factor None.
ß Dimensionless heat of reaction None.
x=r/R, y=$C_{A/}C_{AS}$.
C_A Concentration of reactant A inside the pellet.
C_{AS} Concentration of reactant A at the pellet surface.
R Radius of spherical catalytic pellet.
r Distance along the radial direction of the catalytic pellet.
r_A Arrhenius reaction rate.
D_e Effective diffusivity inside the catalytic pellet.
D_{AS} Effective diffusivity at the surface of the catalytic pellet.
K_m Michaelis–Menten constant.

BIBLIOGRAPHIC REFERENCES

1. Jamal B, Khuri SA. Non-isothermal Reaction–Diffusion Model Equations in a Spherical Biocatalyst: Green's Function and Fixed Point Iteration Approach. International Journal of Applied and Computational Mathematics. 2019 Jul;5(4):120.

2. Danish M, Kumar S, Kumar S. OHAM solution of a singular BVP of reaction cum diffusion in a biocatalyst. International Journal of Applied Mathematics. 2011;41(3):223-7.

3. Holmes MH. Introduction to Perturbation Methods. Springer; 2013.

4. Hristov I, Kovac J, Kovacova A. Solving Linear and Nonlinear Problems Using Taylor Series Method. Computational and Applied Mathematics. 2024;43:5. https://www.degruyter.com/document/doi/10.1515/comp-2024-0005/html.

5. Piecewise Analytical Approximation Methods for Initial-Value Problems of Nonlinear Ordinary Differential Equations. Mathematics. 2025;13(3):333. https://doi.org/10.3390/math13030333.

6. Sylvia SV, Salomi RJ, Rajendran L, Abukhaled M. Poisson–Boltzmann equation and electrostatic potential around macroions in colloidal plasmas: Taylor series approach. Solid State Technology. 2020;63(6):10090-10106.

7. Nirmala K, Devi MC, Rajendran L. Analysis of Steady-State Behavior of EC′ Catalytic Mechanism at Rotating Disk Electrode: Taylor Series Approach. European Journal of Molecular & Clinical Medicine. 2020;7(11):440-7.

8. Rani RU, Rajendran L, Lyons MEG. Steady-state current in product inhibition kinetics in an amperometric biosensor: Adomian decomposition and Taylor series method. Journal of Electroanalytical Chemistry. 2021;886:115103.

ANNEXES

Appendix A: Taylor Series Method Summary

The solution of the normalized concentration y(x) using the Taylor series method is as follows. The non-linear differential equation is given as follows:

$$y''(x) + \frac{2}{x}y'(x) - r(y) = 0,\ 0 \le x \le 1, \qquad (13)$$

$$r(y) = \phi^2 \frac{(1+\beta)y(x)}{1+\beta y(x)}$$

The boundary conditions are given below:

$$y'(0) = 0 \qquad (14)$$
$$y(1) = 1 \qquad (15)$$

The effectiveness factor η for a spherical pellet is defined as:

$$\eta = \frac{3}{\phi^2}\frac{dy}{dx}|_{x=1} \qquad (16)$$

We assume that the solution of equation (13). y(*x*), can be expanded in a Maclaurin series:

$$y(x) = y(0) + \frac{y'(0)x}{1!} + \frac{y''(0)x^2}{2!} + \frac{y'''(0)x^3}{3!} + \frac{y'^v(0)x^4}{4!} + \frac{y^v(0)x^5}{5!} \qquad (17)$$

To determine the value of the derivatives at *x*=0 we rewrite equation (13), as:

$$y"(x) = -\frac{2}{x}y'(x) + r(y) \qquad (18)$$

Assuming r(y) is sufficiently differentiable we may then evaluate derivatives of y(*x*) recursively giving:

$$y'''(x) = \frac{-2}{x}y''(x) + \frac{2}{x^2}y'(x) + r'(y)y'(x) \qquad (19)$$
$$y'^v(x) = \frac{-2}{x}y'''(x) + \frac{4}{x^2}y''(x) - \frac{4}{x^3}y'(x) + r'(y)y''(x) + r''(y)y'(x)^2 \qquad (20)$$
$$y^v(x) = \frac{-2}{x}y'^v(x) + \frac{6}{x^2}y'''(x) - \frac{12}{x^3}y''(x) + \frac{12}{x^4}y'(x) + r'(y)y'''(x) + 3r''(y)y'(x)y''(x) + r'''(y)y'(x)^3 \qquad (21)$$

Where:

$$r(y) = \phi^2 \frac{(1+\beta)y(x)}{1+\beta y(x)}, r'(y) = \frac{dr(y)}{dx}, r''(y) = \frac{d^2r(y)}{dx^2}, r'''(y) = \frac{d^3r(y)}{dx^3} \qquad (22)$$

We now evaluate:

$$y''(0)\,, y'''(0), y'^{v}(0), y^{v}(0) \qquad (23)$$

by substituting *x*=0 into. Furthermore, we can impose the boundary condition y' (0)=0 to give:

$$y'(0) = 0, \qquad (24)$$

$$y"(0) = r(y_0), \qquad (25)$$

$$y'''(0) = \frac{-2}{x}y"(0) = \frac{-2}{x}r(y_0), \qquad (26)$$

$$y'^{v}(0) = \frac{-2}{x}y'''(0) + \frac{4}{x^2}y''(0) + r'(y_0)y''(0) = \frac{8}{x^2}r(y_0) + [r'(y_0)]r(y_0), \qquad (27)$$

$$y^{v}(0) = \frac{-2}{x}y'^{v}(0) + \frac{6}{x^2}y'''(0) - \frac{12}{x^3}y''(0) + r'^{(y_0)}y'''(0) = \frac{-40}{x^3}r(y_0) \qquad (28)$$

By using equation. (10)-(14), we obtain the solution of the normalized concentration y(*x*) as:

$$y(x) = y_0 + \frac{r(y_0)x^2}{2!} + \frac{\frac{-2}{x}r(y_0)x^3}{3!} + \frac{\left(\frac{8}{x^2}r(y_0)+[r'(y_0)]r(y_0)\right)x^4}{4!} + \frac{\left(\frac{-40}{x^3}r(y_0)\right)x^5}{5!} + \cdots \qquad (29)$$

Where y_0 is the unknown value y(0).
Let:

$$y_0 = k$$

$$r(y) = \phi^2\frac{(1+\beta)y(x)}{1+\beta y(x)} \qquad (30)$$

$$r'(y) = \frac{dr(y)}{dx} = (1+\beta)\phi^2\left[\frac{(1+\beta y(x))y'(x)-y(x)\beta y'(x)}{(1+\beta y(x))^2}\right] = \phi^2\frac{(1+\beta)y'(x)}{(1+\beta y(x))^2} \qquad (31)$$

$$r(y_0) = \phi^2\frac{(1+\beta)k}{1+\beta k} \text{ and } r'(y_0) = \phi^2\frac{(1+\beta)y'(0)}{(1+\beta k)^2} = 0 \qquad (32)$$

By using equation (30) We obtain the solution of the normalized concentration y(*x*) as:

$$y(x) = k + \left(\phi^2\frac{(1+\beta)k}{1+\beta k}\right)\left(\frac{1}{6}\right)x^2 \qquad (33)$$

To find k:
By applying the boundary condition from (31) it becomes

$$k + \left(\phi^2\frac{(1+\beta)k}{1+\beta k}\right)\left(\frac{1}{6}\right) - 1 = 0 \qquad (34)$$

By using MAPLE We can find the value of *k* by giving the experimental values for the unknown parameters ϕ, β.

Effectiveness factor η for a spherical pellet

By applying the equation (30) the analytical expressions for the Effectiveness factor (η):

$$\eta = \left(\frac{3}{\phi^2}\right)\left(\left(\phi^2 \frac{(1+\beta)k}{1+\beta k}\right)\left(\frac{1}{3}\right)x\right)_{x=1} \qquad (35)$$

$$\eta = \left(\frac{(1+\beta)k}{1+\beta k}\right) \quad (36)$$

By using MAPLE We can find the value of '*k*'. Also, applying experimental values for β, in (16), we can find the Effectiveness factor η for a spherical pellet.

Chapter 15 / Capítulo 15

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ORIGINAL

AI Applications for Environmental Monitoring and Pollution Control

Aplicaciones de IA para la monitorización ambiental y el control de la contaminación

Sahar Yousif Mohammed[1] ✉, Hadeel M saleh[2] ✉, Maad Mijwil[3,4] ✉, Mostafa Abotaleb[5] ✉

[1]Department of Translation , College of Arts, Anbar University. Iraq.

[2]Center for Continuing Education Anbar University. Iraq.

[3]College of Administration and Economics, Al-Iraqia University. Baghdad, Iraq.

[4]Computer Techniques Engineering Department, College of Engineering Technologies, Al-Iraqia Science University. Baghdad, Iraq.

[5]Engineering School of Digital Technologies, Yugra State University. Khanty-Mansiysk, 628012, Russia.

Corresponding Author: Sahar Yousif Mohammed ✉

ABSTRACT

The chapter discusses the growing role of Artificial Intelligence (AI) in environmental monitoring and pollution control, and specifically how it can be used in the gas, oil, and chemical industries. As the ecological threats in the world are becoming more complicated, i.e. climate change, dangerous emissions, the degradation of resources, etc., the manual sampling and the use of periodic inspection as conventional methods of monitoring is becoming less efficient. Artificial intelligence offers a radical innovation in environmental management by offering real-time and data-driven predictive decision-making by means of the fusion of satellite images data, IoT sensor data, drones, and industrial devices data. The machine learning and deep learning techniques enhance the detection of pollutants, prediction of emission trends, optimization of industrial processes, and regulatory compliance. Additional aspects of AI and IoT, edge computing, use of AI in policy and decision making, and moral, societal and technical concerns of environmental AI devices are also explored in the chapter. Finally, it points out to new trends, such as digital twins, federated learning, autonomous robots, and climate-conscious AI models. All this demonstrates that AI is becoming one of the facilitators of sustainable, smart, and resilient environmental management.

Keywords: Artificial Intelligence (AI); Environmental Monitoring; Pollution Control; Machine Learning; Sustainability Systems.

RESUMEN

Este capítulo analiza el creciente papel de la Inteligencia Artificial (IA) en la monitorización ambiental y el control de la contaminación, y en particular su aplicación en las industrias del gas, el petróleo y la química. A medida que las amenazas ecológicas mundiales se complican, como el cambio climático, las emisiones peligrosas y la degradación de los recursos, el muestreo manual y la inspección periódica como métodos convencionales de monitorización se vuelven menos eficientes. La IA ofrece una innovación radical en la gestión ambiental al ofrecer una toma de decisiones predictiva en tiempo real basada en datos mediante la fusión de datos de imágenes satelitales, datos de sensores del IoT, drones y dispositivos industriales. Las técnicas

de aprendizaje automático y aprendizaje profundo mejoran la detección de contaminantes, la predicción de tendencias de emisiones, la optimización de procesos industriales y el cumplimiento normativo. El capítulo también explora otros aspectos de la IA y el IoT, la computación de borde, el uso de la IA en la formulación de políticas y la toma de decisiones, y las preocupaciones morales, sociales y técnicas de los dispositivos de IA ambiental. Finalmente, se señalan nuevas tendencias, como los gemelos digitales, el aprendizaje federado, los robots autónomos y los modelos de IA con conciencia climática. Todo esto demuestra que la IA se está convirtiendo en uno de los facilitadores de una gestión ambiental sostenible, inteligente y resiliente.

Palabras clave: Inteligencia Artificial (IA); Monitoreo Ambiental; Control de la Contaminación; Aprendizaje Automático; Sistemas de Sostenibilidad.

INTRODUCTION

Overview of Global Environmental Challenges

The increased global concern on climate change, depletion of resources and polluting industries has exerted pressure on the oil, gas and chemicals industry which are energy consuming sectors forcing them to update their environmental management policies like never before. These technologies are at the core of the ongoing Triple Planetary Crisis: climate change, pollution of the environment, and the destruction of biodiversity.[1] Despite the international agreements on reducing emissions, the chemical pollution of the world, the destruction of water resources, and greenhouse gas emissions, the processes of industrial development continue to play a significant role in the world. One of the most pressing problems is the emission of methane (CH 4), and it remains very high.

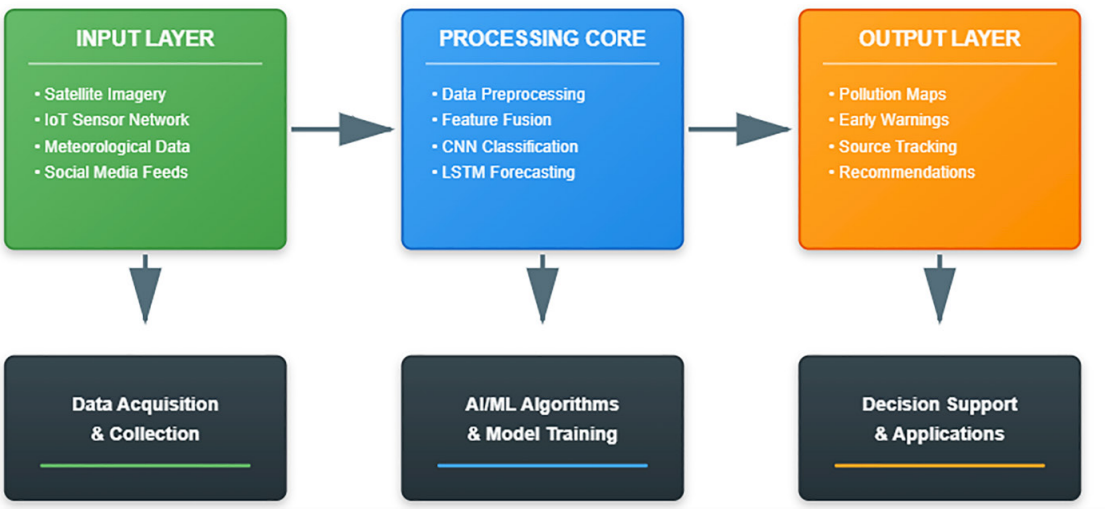

Figure 1. Three -Tier Archticture Integreting Multi-Source Data ,AI Processing And Actionable Outputs

According to an International Energy Agency (IEA) assertion, the activities of the fossil fuels continue to generate over 120 million tonnes of methane annually which is one of the greatest short-term climate pollutants. Due to its Global Warming Potential (GWP) of more than 80 times that of CO2 over a 20-year time period,[2] Methane mitigation has now become a global priority.

Table 1. Summary of Key Environmental Challenges and the Enabling Role of AI in Energy-Intensive Industries

Theme	Problem / Context (from the text)	AI / EMS Implication
Triple Planetary Crisis	Oil, gas, and chemical industries are at the center of climate change, environmental pollution, and biodiversity loss.	These sectors are priority targets for transforming environmental management and decarbonization strategies.
Industrial contribution to environmental impacts	Global industrial activities continue to drive GHG emissions, chemical contamination, and water resource degradation despite international commitments to reduce emissions.	Strong need for more effective, data-driven monitoring and control tools that can capture the complete industrial footprint.
Methane (CH_4) emissions	Methane from fossil fuel operations exceeds 120 million tonnes annually; with a GWP > 80× CO_2 on a 20-year timescale, it is one of the most impactful short-lived climate pollutants.	Methane mitigation has become a top global priority, requiring precise detection and quantification, and rapid response across assets and facilities.
Other pollutants and water issues	Industries must manage produced water, hazardous chemicals, and persistent organic pollutants (POPs) while maintaining safe and efficient operations.	Integrated monitoring systems are needed to track water quality, toxic releases, and complex pollutant mixtures in real time.
Regulatory and policy pressure	International frameworks (e.g., UNEP's Global Framework on Chemicals and the Emissions Gap Report) call for transformative, data-driven solutions that support sustainable development targets.	Compliance is no longer just reporting; it requires robust, transparent, and auditable environmental intelligence platforms.
Limitations of traditional EMS	Traditional EMS relies on manual sampling, periodic inspections, and reactive responses, leading to delayed and incomplete visibility into emissions, water quality, and ecosystem disturbances.	Conventional methods cannot keep pace with the scale, complexity, and speed of modern industrial activities, creating a gap between operations and sustainability objectives.
Role of Artificial Intelligence (AI)	AI integrates data from sensors, satellites, drones, and industrial equipment to deliver real-time environmental insights. ML models can detect anomalies, predict equipment failures, optimize processes, and support compliance.	AI acts as a transformative enabler for environmental monitoring and pollution control, augmenting or replacing traditional EMS with intelligent, automated decision-support systems.
Shift to predictive environmental intelligence.	There is a transition from reactive monitoring to predictive, automated environmental intelligence as industries move toward net-zero and sustainability goals.	Predictive, AI-driven systems allow early intervention, emission mitigation, and continuous optimization, aligning industrial performance with climate and sustainability targets.
Aim of the chapter	The chapter examines how AI can enhance environmental monitoring and pollution control, highlighting key technologies, methods, and applications.	Provides a conceptual and practical foundation for using AI to bridge the gap between industrial operations and global sustainability objectives in the coming decades.

In the meantime, industries also face an increased pressure to treat generated water, toxic chemicals, and intractable organic pollutants (POPs) and remain safe and efficient at the same time. The international regulations such as the UNEP Global Framework on Chemicals and

the Emissions Gap Report note that transformative, data-driven measures are important to minimize the effects and need to be taken in order to meet the Sustainable Development Goals.[3] Traditional Environmental Management Systems (EMS) that are currently operated manually through sampling, systems that are periodically inspected and the reactive-based systems are simply not responsive enough to keep pace with the magnitude and rapidity of the modern industrial operations. These methods are generally used to provide access to emissions, water quality, and ecosystem disruption late or incompletely. Artificial Intelligence (AI) is emerging as a facilitator in this respect at a great speed. The AI systems use sensor, satellite and drone data, as well as industrial data to transmit real-time, informative environmental data. Machine learning models are significantly superior to the conventional tools in detecting pollutants, anticipating equipment malfunctions, optimizing industrial processes, and facilitating compliance. This is the shift towards reactive monitoring and predictive and automated environmental intelligence as the industries keep aiming at achieving the net-zero targets and sustainability goals. In this chapter, the author explains how AI may be applied in enhancing environmental surveillance and reducing pollution. It brings out the best technologies that are most critical, practices, and uses that change the way industries measure, analyze, and reduce their ecological footprint. The opening part provides a foundation on the ways AI can be used to bridge the gap between industrial operations and global sustainability ambitions in the next centuries.[4,5]

Why AI is Becoming Essential in Modern Environmental Systems

Traditional Environmental Management Systems (EMS) have been extensively founded on reactive, that is, manual sampling, routine checks and merely responding to alarm triggers when environmental thresholds have been hit.[6] In the context of Industry 4.0, such approaches have become even more inadequate as the amount of environmental data is increasing exponentially, industrial operations get more complicated and the processes of regulation are quickening down. As the trend is to shift towards real-time monitoring and data-driven decision-making in industries, Artificial Intelligence (AI) and Machine Learning (ML) are emerging as the intelligence layer of the modern environmental engineering because of the following three factors:[7]

Transition from Reactive to Predictive Management

The fundamental concept is that AI transforms the detection-and-fix paradigm to a prediction and prevention paradigm. Recent studies have shown that ML algorithms have the ability to use past data on the processes to foretell equipment failures, which may be valve fatigue, cases of corrosion, or seal leakage, several weeks before resulting in fugitive emissions or operational disruptions.[8] This predictive capability lowers the amount of releases of pollutants to the environment, enhances reliability and safety, as well as limiting unexpected downtime.[9]

Managing the Complexity of Big Environmental Data

Modern industrial plants receive vast quantities of environmental data every day with the help of the Industrial Internet of Things (IIoT) sensors, satellite surveillance, drone inspections, and weather networks. These data streams are too large, fast and of a kind that are not analyzable by humans. Multimodal data may include visual, infrared, thermal, and chemical data, and if analyzed by AI, powerful learning may occur. These models can be utilized to determine so-called super-emitters by determining the small fraction of the components that generate the majority of the leaks.[10] That would enable specific intervention and a more effective distribution of resources.

Ensuring Real-Time Compliance and Regulatory Transparency

Global environmental regulations are currently moving towards emissions reporting based on measurements. The frameworks such as the Oil and Gas Methane Partnership 2.0 (OGMP 2.0)

demand that all information must be verified, accurate and verifiable and not a forecast derived out of the engineering computations. Even in the absence of physical analyzers or limited conditions, AI-driven soft sensors can be used to make real-time estimates of the concentrations of pollutants, including NOx, SOx, and methane. Such smart monitoring systems are beneficial in terms of increasing 24/7 auditability, improving the quality of compliance reporting and traceable records to regulatory agencies.[11]

Scope and Purpose

The chapter gives an overview of how the field of Artificial Intelligence (AI) can be used to improve environmental monitoring and pollution control in oil, gas, and chemical industries. It explains the way AI can help to collect environmental data, manage the industry effectively, and make sure that it complies with the regulations. The chapter presents the contribution of the modern AI tools by describing how it could be applied to the environmental science and data engineering to reduce emissions, create a sustainable environment, and enhance real-time ecological management. The aim of this chapter is to:

1. How do AI-based surveillance systems, such as computer vision, satellite imaging, and smart sensors, work in gathering the right data of the environment?
2. Show how AI can be used to run processes in a way that makes them sustainable, including less flaring, improved wastewater treatment, and energy consumption.
3. Provide new methods of digital governance, such as Digital Twins and automated reporting systems in improving their accountability and environmental regulations.

Data Sources for Environmental Monitoring

The idea of the environmental monitoring is based on the wide variety of the data resources that provide real time data about the air, waters, soil and industrial emissions. The present-day surveillance systems operate on chains of IoT devices which are used to measure the concentrations of gasses, temperature/humidity and water quality indicators, and the concentration of any particulate matter in real time.[12] One such satellite and remote-sensing platform is the NASA and Copernicus missions that provide high-resolution images to identify changes in land-use, vegetation stress, thermal change, and macro-scale pollution patterns. In addition, the visual, thermal, and gas-sensing payloads mounted on drones provide scalability and rapid data collection of areas that are inaccessible, e.g. pipelines, flare stacks, and water bodies. Environmental data can also be found in the government and international open data like EPA Air Quality Data, NASA Earth Observations and global climate databases. Although these sources are often abundant, noises, values missing, sensor drift, etc. may most likely be found, and thus pre-processing and AI-based data cleaning are the key to getting plausible and valid measurements of the environment.[13,14]

Machine Learning Techniques in Environmental Analysis

Machine learning will also play a significant role in the analysis of environmental data since it results in accurate prediction, classification, and identification of trends related to pollution. The popular examples of such models include the random Forest (RF), Support Vector, and Artificial Neural Networks (ANN) and are used to predict and evaluate the environmental risks of pollutants based on the labeled data. Unsupervised learning is useful in identifying anomalies, as well as new pollution hotspots, and any latent patterns in large datasets, even in the absence of labels. The time-series forecasting deep learning techniques (Long Short-term Memory) networks, Gated Recurrent Unit (GRUs), and hybrid deep learning are required to forecast the future rates of pollution, as well as to analyze long-term trends. The main environmental analysis is also based on feature engineering where important environmental variables, including weather condition, chemical indicators, and other features will be chosen

or developed to help improve accuracy and performance of the model.[15]

Deep Learning for Environmental Monitoring

The capability of deep learning to perform the tasks with the large, dense, and multidimensional data has helped to adopt it as an effective tool of environmental monitoring. CNNs have been widely used in satellite, drone, and thermal imagery to see the locations of oil spills, identify the changes in land usage, track the behavior of a wildfire, and map areas vulnerable to floods with a very impressive degree of accuracy.[16] Time-series data can be successfully employed to predict the long-term behavior of the environment, forecast the trends of pollutants, and recurrent neural network models such as LSTM and GRU can be successfully utilized in air quality forecasting. Unsupervised deep learning systems, such as Deep Autoencoders, may be employed to identify an abnormal emission or sensor failure or environmental anomaly that might be related to leakage or malfunction. Such neural learning algorithms can be applied in quicker, more precise, and automated scanning of the environment and are indispensable to the modern monitoring systems.[17]

AI-Enabled Pollution Control Systems

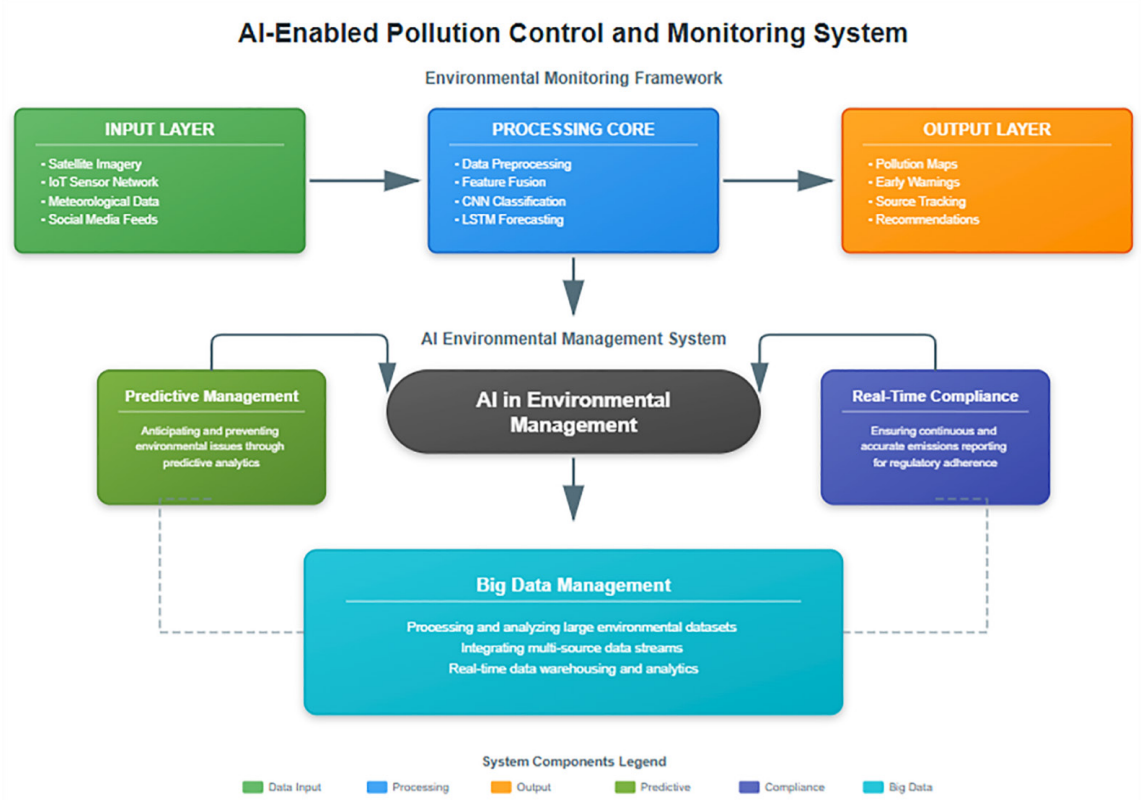

Figure 2. Integrated AI-Enabled Pollution Control and Environmental Monitoring System

Intelligent, AI-controlled pollution control systems enable real-time monitoring and minimization of emissions, enhancing environmental performance and system operation. These systems can automatically monitor air and water pollutants, detect abnormal emission events, and issue early alerts to operational systems before they reach critical levels. In factories, AI algorithms can detect leaks and optimize combustion cycles, as well as flare using predictive control based on sensor data. In cities, AI-based traffic management systems can be used to

reduce vehicle emissions by adjusting signal timing based on congestion levels.[18] There is also the increased use of AI in wastewater treatment plants to streamline chemical dosage, aeration, and energy use, leading to cleaner effluents and lower operating expenses. On the whole, AI-based pollution management is more accurate and responsive than many other environmental management methods, making it more sustainable.[19]

AI in Environmental Policy and Decision Making

Artificial intelligence (AI) has become an issue in the context of environmental policy and decision-making, which can provide strong tools in the collection, monitoring, prediction, and analysis of data.[20] AI can track real-time environmental dynamics, such as the deforestation process, air and water pollutants, wildlife tracking, and climate changes with the implementation of satellite cameras, sensors, and robots. Its predictive models help governments and organizations to forecast results of climate change, determine the risk of disasters, and compare policy choices to find out which strategies are most effective in reducing and adapting to its impacts. The intelligent decision support systems assist the policymakers in cost benefit analysis, environmental impact analysis and optimum resource distribution in areas like energy planning, agriculture and urban development.[21] The benefits of such applications are high accuracy of results, faster insights and reduced costs as well as improved long term planning. Nevertheless, there are also obstacles associated with data quality, transparency, equity, privacy and overreliance on technology, they introduce. Nevertheless, AI is a continuous field of work that will result in the evidence-based environmental governance and assist in making more sustainable and informed decisions in climate policy, conservation, pollution management, and resource management.[22]

Integration of AI with IoT and Edge Computing

Integrating the AI and the Internet of Things (IoT) with the edge computing can establish an effective ecosystem where interconnected devices can acquire, process, and respond to information in real time, and centralized systems are minimally or not relied on. In this hybrid architecture, the IoT devices scan large amounts of data on the physical world and edge processing reduces response time, bandwidth usage and dependency on the cloud computing. This system will be enhanced by AI, which will allow the gadgets to comprehend the information, establish trends, predictions, and make decisions independently without sending information to remote servers.[23] When such components are combined with each other, the entire mechanism becomes quicker. There are faster reactions, operations proceed more efficiently, and information belonging to users remains more secure as much less data is to be passed through the network. Precisely, it is useful in tasks like smart cities, self-driving cars, automation in industries, environmental systems and health care, when the milliseconds count. This capability of the system to identify anomalies in real time, to provision predictive maintenance, maximize energy consumption and to propel the context aware automation is made possible by making AI more resilient and adaptive with an embedded predictive ability at the system edge. That contributes to considering AI, IoT, and edge computing as a fundamental technology stack of next-generation intelligent systems, which are scalable, efficient, and responsive.[24]

Ethical, Social, and Technical Challenges

Implementing the environmental AI systems is related to a number of ethical, social, and technical issues, which must be addressed to guarantee the responsible usage of the data privacy. One of the main concerns is also the privacy of information, since environmental sensors (such as drones, satellite imaging and distributed sensors) may mutually capture sensitive personal or geolocation data by accident, and the question of surveillance and data protection appears.[25] Uneven coverage of data, sensor noise, old data, and sampling bias also play their role in biased

and uncertain predictions of AI that results in inaccurate or unfair predictions. Additionally, AI models are mostly applied as black boxes, which limits their reliability, interpretability, and transparency, which is imperative when these systems are applied to provide directions to the policies of the population, environmental risk analysis, or city layout. Finally, ecological justice aspects outline the fact that less-privileged or underserved communities may not be tracked or may be disproportionately affected by flawed AI-based decisions which can only widen presented disparities. To establish credible, equitable, and effective environmental AI systems, the concerns are all interrelated, which is crucial to address.[26]

Future Trends

In future simulation, prediction and scenario testing, the environmental AI is moving towards more intelligent, robust and integrated systems with digital twins of ecological systems. Simulation, prediction and testing Virtual replicas of ecosystems, watersheds, cities or climate processes will permit real-time simulation, prediction and testing and this will enhance improved decision-making and adaptive management.[27] The concept of federated learning is currently very popular in the analysis of distributed environmental data and achieving privacy, allowing models to be trained on sensors, institutions, regions without direct sharing of raw data. The autonomous environmental robots such as drones, underwater vehicles, and ground platforms will be more autonomous and competent, and will be able to monitor the environment in large scales, sample and respond to the environmental hazards more quickly. At the same time, climate-conscious AI will involve climate physics, long-term trends, and extreme events patterns into the algorithmic processes to make the predictions more precise and applicable to the rapidly evolving world. All these trends are heading towards the future as AI-controlled tools are becoming more interdependent, adaptable, and environmentally aware.[28]

CONCLUSIONS

AI-based environmental monitoring and pollution control is the future of the environmental monitoring and pollution management as it gives more precise, speedy insights than ever. The transformation of raw environmental data into useful intelligence to empower the identification of emissions, industrial optimization, and regulatory compliance, as well as a powerful policy and decision-making tool in ecological sustainability have been discussed in this chapter as AI is changing. Together with machine learning, deep learning, IoT-driven sensing, and edge computing, they have created a single ecosystem that has the potential to analyze, predict and autonomously act in the environment in real time. At the same time, ethical and social aspects including privacy, prejudice, transparency, and environmental equity show that the AI technology should be developed and implemented responsibly. Digital twins, federated learning, climate-conscious, and even autonomous environmental robots will all be part of AI in the future and will push the boundaries of AI. Lastly, the place of AI within the ecological systems will also change: it will become an unavoidable factor of cleaner operations, sustainable environment, and a more eco-friendly industrial future.

BIBLIOGRAPHIC REFERENCES

1. Constantino SM, Sparkman G, Kraft-Todd GT, Bicchieri C, Centola D, Shell-Duncan B, et al. Scaling up change: a critical review and practical guide to harnessing social norms for climate action. Psychol Sci Public Interest. 2022;23(2):50-97.

2. Voulvoulis N, Giakoumis T, Hunt C, Kioupi V, Petrou N, Souliotis I, et al. Systems thinking as a paradigm shift for sustainability transformation. Glob Environ Change. 2022;75:102544.

3. Awewomom J, Dzeble F, Takyi YD, Ashie WB, Ettey ENYO, Afua PE, et al. Addressing global

environmental pollution using environmental control techniques: a focus on environmental policy and preventive environmental management. Discov Environ. 2024;2(1):8.

4. Middleton N. The global casino: an introduction to environmental issues. Routledge; 2024.

5. Litvinenko V, Bowbrick I, Naumov I, Zaitseva Z. Global guidelines and requirements for professional competencies of natural resource extraction engineers: implications for ESG principles and sustainable development goals. J Clean Prod. 2022;338:130530.

6. Ansari SPM, Odongo JO, Nomani MZM, Salahuddin G, Hasan MF, Pallathadka LK. Evaluating the role of the environment management system based on artificial intelligence. Mater Today Proc. 2022;56:2240-4.

7. Martínez-García AN. Artificial Intelligence for Sustainable Complex Socio-Technical-Economic Ecosystems. Computation. 2022;10(6):95.

8. Shehadeh HK. Evaluating the Impact of Transitioning Maintenance Strategy from Reactive to Proactive in Power Generation Companies: An Empirical Analysis. WSEAS Trans Bus Econ. 2024;21:820-38.

9. Xing S, Wang Y. Proactive data placement in heterogeneous storage systems via predictive multi-objective reinforcement learning. IEEE Access. 2025.

10. Li C, Huang M. Environmental sustainability in the age of big data: opportunities and challenges for business and industry. Environ Sci Pollut Res. 2023;30(56):119001-15.

11. Thanasas GL, Kampiotis G, Karkantzou A. Enhancing transparency and efficiency in auditing and regulatory compliance with disruptive technologies. Theor Econ Lett. 2025;15(1):214-33.

12. Himeur Y, Rimal B, Tiwary A, Amira A. Using artificial intelligence and data fusion for environmental monitoring: a review and future perspectives. Inf Fusion. 2022;86:44-75.

13. Butt MA, Voronkov GS, Grakhova EP, Kutluyarov RV, Kazanskiy NL, Khonina SN. Environmental monitoring: a comprehensive review on optical waveguide and fiber-based sensors. Biosensors. 2022;12(11):1038.

14. Sharma R, Arya R. UAV based long range environment monitoring system with Industry 5.0 perspectives for smart city infrastructure. Comput Ind Eng. 2022;168:108066.

15. Mohammed SY, Jumaah NS, Abbas E, Ali HM, Aljanabi M. Healthcare Intelligence and Decision Making: Big Data's Role in Predictive Analytics for Clinical Decision-Making. Mesopotamian J Big Data. 2024;2024:223-9. https://doi.org/10.58496/MJBD/2024/016

16. Mohammed NSY. Enhancing COVID-19 Patients Detection using Deep Transfer Learning Technique Through X Ray Chest Images. J Adv Res Appl Sci Eng Technol. 2023;32(1):290–302. https://doi.org/10.37934/araset.32.1.290302

17. Popescu SM, Mansoor S, Wani OA, Kumar SS, Sharma V, Sharma A, et al. Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management. Front Environ Sci. 2024;12:1336088.

18. Santos MR, Carvalho LC. AI-driven participatory environmental management: Innovations, applications, and future prospects. J Environ Manage. 2025;373:123864.

19. Kelly BO, Chen S, Zhou EP, Elshakankiri M. AI-Enabled Plastic Pollution Monitoring System for Toronto Waterways. In: 2023 10th International Conference on Internet of Things: Systems, Management and Security (IOTSMS). IEEE; 2023. p. 53-8.

20. Singh S, Singh M. Role of Artificial Intelligence for Environment Protection: An Analysis. Artif Intell Law. 2025:165-75.

21. Khalid J, Chuanmin M, Altaf F, Shafqat MM, Khan SK, Ashraf MU. AI-driven risk management and sustainable decision-making: role of perceived environmental responsibility. Sustainability. 2024;16(16):6799.

22. Chavhan S, Gupta D, Gochhayat SP, N CB, Khanna A, Shankar K, et al. Edge computing AI-IoT integrated energy-efficient intelligent transportation system for smart cities. ACM Trans Internet Technol. 2022;22(4):1-18.

23. Rupanetti D, Kaabouch N. Combining edge computing-assisted internet of things security with artificial intelligence: applications, challenges, and opportunities. Appl Sci. 2024;14(16):7104.

24. Soundariya A, Behera NK, Selvakumar P, Chandel PS, Gupta S, Manjunath TC. AI and Environmental Ethics: The Role of AI in Addressing Climate Change Ethical Considerations in AI-Driven Environmental Solutions. In: Human Values, Ethics, and Dignity in the Age of Artificial Intelligence. IGI Global Scientific Publishing; 2025. p. 321-46.

25. Santos MR, Carvalho LC. AI-driven participatory environmental management: Innovations, applications, and future prospects. J Environ Manage. 2025;373:123864.

26. Hoang TD, Ky NM, Thuong NTN, Nhan HQ, Ngan NVC. Artificial intelligence in pollution control and management: status and future prospects. In: Artificial Intelligence and Environmental Sustainability: Challenges and Solutions in the Era of Industry 4.0. 2022. p. 23-43.

27. Leena Sri R, Vetriveeran D, Sambandam RK, Jenefa J, Thangavel K. Transformative Trends in AI for Environmental Monitoring: Challenges, Applications. Environ Monit Using Artif Intell. 2025:1-28.

28. Alotaibi E, Nassif N. Artificial intelligence in environmental monitoring: in-depth analysis. Discov Artif Intell. 2024;4(1):84.

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AUTHORSHIP CONTRIBUTION

Conceptualization: Sahar Yousif Mohammed, Hadeel M Saleh, Maad Mijwil, Mostafa Abotaleb.
Data curation: Sahar Yousif Mohammed, Hadeel M Saleh, Maad Mijwil, Mostafa Abotaleb.

Formal analysis: Sahar Yousif Mohammed, Hadeel M Saleh, Maad Mijwil, Mostafa Abotaleb.

Drafting - original draft: Sahar Yousif Mohammed, Hadeel M Saleh, Maad Mijwil, Mostafa Abotaleb.

Writing - proofreading and editing: Sahar Yousif Mohammed, Hadeel M Saleh, Maad Mijwil, Mostafa Abotaleb.

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ORIGINAL

Employees' Well-Being in Accreditation Environments: A Comparative Analysis of Higher Education Accreditation and Chemical Industry Certification Processes

Bienestar de los empleados en entornos de acreditación: un análisis comparativo de los procesos de acreditación de la educación superior y de certificación de la industria química

B. Neeraja[1], B.V. Jayanthi[1], Suchitra[2], A. Devendran[3], K. Arun Kumar[4], Christo Ananth[5]

[1]School of Management Studies, Chaitanya Bharathi Institute of Technology. Hyderabad.

[2]FoMS, Dr.MGRERI. Chennai, Tamilnadu.

[3]Associate Professor, Department of Data Science, Sri Ramachandra Institute of Higher Education and Research (SRIHER) (Deemed to be University). Chennai Tamilnadu.

[4]Director, Tech Jedi. USA.

[5]Faculty of Artificial Intelligence and Digital Technologies, Samarkand State University. Uzbekistan.

Corresponding Author: Christo Ananth

ABSTRACT

The increasing focus on institutional accreditation has raised a lot of concern among employee and employees particularly because of the stress accompanied by extended working hours, constant assessments, and intermittent inspections of the institution. With the pursuit of recognition and quality assurance among higher education institutions/ chemical industries , employees — in particular, female workforce — face greater stress and vulnerability to burnout. This paper offers an in-depth analysis on how accreditation processes create unique psychological and professional challenges for employees. Specifically, women professionals—whether employee or industry employees—experience disproportionate challenges due to dual responsibilities and systemic gendered expectations. In addition to this, the research also provides strategic interventions that institutions need to take up to balance the sustainability of work-life and contribute to workplace satisfaction at a greater level through an efficient knowledge management system. Through an integrated and comparative analysis, the paper examines stressors, emotional responses, and burnout risks among employee and chemical-industry employees. It also proposes institutional support mechanisms, gender-sensitive policies, and sustainable well-being strategies designed to mitigate accreditation-related stress.

Keywords: Employee Well-being; Accreditation Process; Mental Health of Employees; Work-Life Balance; Employee Stress Management; Certifications.

RESUMEN

El creciente enfoque en la acreditación institucional ha generado gran preocupación entre los empleados, en particular debido al estrés que conllevan las jornadas laborales prolongadas, las evaluaciones constantes y las inspecciones intermitentes de la institución. Con la búsqueda de reconocimiento y garantía de calidad en las instituciones de educación superior y las industrias químicas, los empleados, en particular las mujeres, se enfrentan a un mayor estrés

y vulnerabilidad al agotamiento profesional. Este documento ofrece un análisis profundo sobre cómo los procesos de acreditación generan desafíos psicológicos y profesionales únicos para los empleados. Específicamente, las mujeres profesionales, ya sean empleadas o empleadas de la industria, experimentan desafíos desproporcionados debido a la doble responsabilidad y las expectativas sistémicas de género. Además, la investigación también proporciona intervenciones estratégicas que las instituciones deben adoptar para equilibrar la sostenibilidad de la vida laboral y personal y contribuir a una mayor satisfacción en el lugar de trabajo mediante un sistema eficiente de gestión del conocimiento. A través de un análisis integrado y comparativo, el documento examina los factores estresantes, las respuestas emocionales y los riesgos de agotamiento profesional entre los empleados y los empleados de la industria química. También propone mecanismos de apoyo institucional, políticas con perspectiva de género y estrategias de bienestar sostenible diseñadas para mitigar el estrés relacionado con la acreditación.

Palabras clave: Bienestar del Empleado; Proceso de Acreditación; Salud Mental de los Empleados; Equilibrio entre vida Laboral y Personal; Gestión del Estrés Laboral; Certificaciones.

INTRODUCTION

Accreditation in the contemporary sphere of higher education has evolved into this form of a guiding mechanism for institutions in search of prestige and validated standards of quality. Accrediting bodies assess institutions against these criteria, focusing on the effectiveness of education delivery and governance, and continuous institutional improvement. Accreditation is a crucial part of an institution's development; however it is also very taxing on the employee. Whether in universities seeking NAAC grades or chemical industries targeting ISO or NABL certification, accreditation serves as an external validation of quality, safety, and performance. High-stakes accreditation has well-known negative impacts on the mental health of faculty and staff, with the burdens of long working hours, high administrative burden, and ongoing assessment likely contributing to poor overall well-being.[1,2,3]

In fact, female employee face unprecedented challenges in juggling both professional and personal responsibilities. This study problematizes these issues reflectively and forges structured ways to ensure that employee do not suffer significantly adverse mental health and professional sustainability behaviours arising from accreditation.[4,5,6]

Higher Education Accreditation: An Overview

Accreditation in higher education (HE) centres around evaluating:

- Curriculum Quality: documentation includes BoS and Academic Council minutes, curriculum revision reports, course outcome (CO) statements, program outcome (PO) mappings, syllabus copies, and industry-aligned content updates. Records of stakeholder feedback from employers, alumni, students, and experts, along with evidence of regular curriculum review cycles, ensure relevance, rigor, and continuous improvement.[7]
- Teaching–Learning Processes: records to be maintained include detailed course files containing syllabus, lesson plan and CO–PO mapping, attendance records, laboratory manuals, assessment sheets, samples of evaluated answer scripts and evidence of ICT-enabled and innovative teaching practices. Records of continuous assessments, tutorials, assignments and blended learning activities are to be systematically maintained for audit verification.[8]
- Research Output: the institution should maintain their records of faculty publications along with proof of indexing, citations, and impact factor; sponsored research project proposals, sanction letters, and utilisation certificates; consultancy and MoUs; patent

documentation, IPR filings, and technology transfer; and evidence of research at an institutional level, conferences, workshops, and student research.[9]

- Student Support Services: records to be maintained include mentoring and counselling reports, internship and placement records, scholarship details, grievance redressal reports, and evidence of remedial classes and bridge courses. Records regarding the various achievements of students in co-curricular and extracurricular activities, training programmes undertaken by them, and support services extended like career guidance and skill-development activities, should be duly preserved for evaluation.[10]
- Governance: institutions should maintain documents about governing body structure, statutory committee minutes, strategic plans, academic calendars, and institutional development plans. IQAC reports, audit statements, policy approvals, and annual reports should be archived. There are necessary records for demonstrating compliance with regulatory bodies, vision–mission statements, and quality assurance processes.[11]
- Infrastructure: it requires documents such as campus blueprint, Stock registers, laboratory facilities, maintenance logs, service and maintenance records and safety compliance certificates. Documentation regarding library records, ICT infrastructure details, internet bandwidth proofs, and AMC agreements has to be maintained. The documentation should outline the availability, adequacy, and upkeep of academic, administrative, and technological infrastructure.[12]
- Faculty Development: documentary proof of FDP and MDPS attended by the employees. Wion includes records of faculty participation in FDPs, refresher courses, and training programs, performance appraisals, professional development plans, and membership to academic or professional bodies. Evidence of organised training programs, orientation sessions, and pedagogical workshops is also to be maintained to justify continuous upskilling and faculty development.[13]
- Stakeholder Engagement: the institutions have to document various interactions conducted with stakeholders in terms of MoUs, minutes of the industry advisory board, reports on feedback from alumni and employers, and records of parent-teacher meetings. Outreach programs, community service, and stakeholder involvement in curriculum development should be documented with evidence to underscore meaningful engagement and collaboration that support institutional growth.[14]

Bodies such as NAAC, NBA, and international accrediting organisations assess institutions on various parameters, which are pre-defined and need a lot of coordination within the team / institution. Accreditation timelines involve preparatory phases, documentation collation, mock inspections, and external members' visits—which demand intense involvement of faculty teams.[15]

Accreditation and Certification in the Chemical Industry

The chemical industry, due to its inherent environmental and safety risks, operates under even more stringent accreditation and certification frameworks. Common accreditation systems include:

ISO Certifications

- ISO 9001 – Quality Management Systems
- ISO 14001 – Environmental Management Systems
- ISO 45001 – Occupational Health and Safety
- ISO 17025 – Testing and Calibration Laboratories (NABL accreditation)

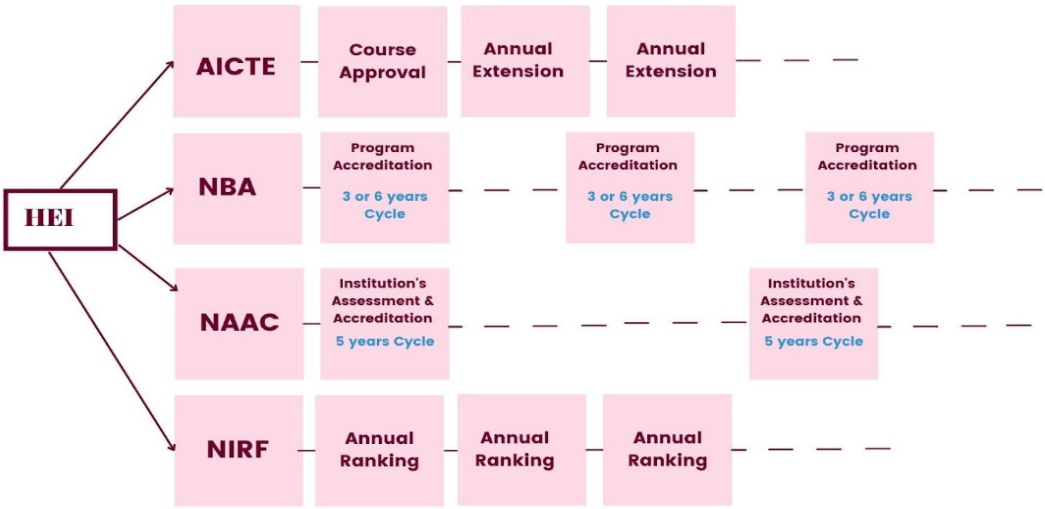

Figure 1. List of Accreditation bodies for Higher Education Institutions

National and International Accreditations

- NABL accreditation for chemical testing labs.
- Responsible Care Accreditation by the Indian Chemical Council.
- Good Manufacturing Practices (GMP) for chemical and pharmaceutical units.
- REACH Compliance (EU) for chemical exports.
- Environment Impact Assessment (EIA) for hazardous chemical operations.

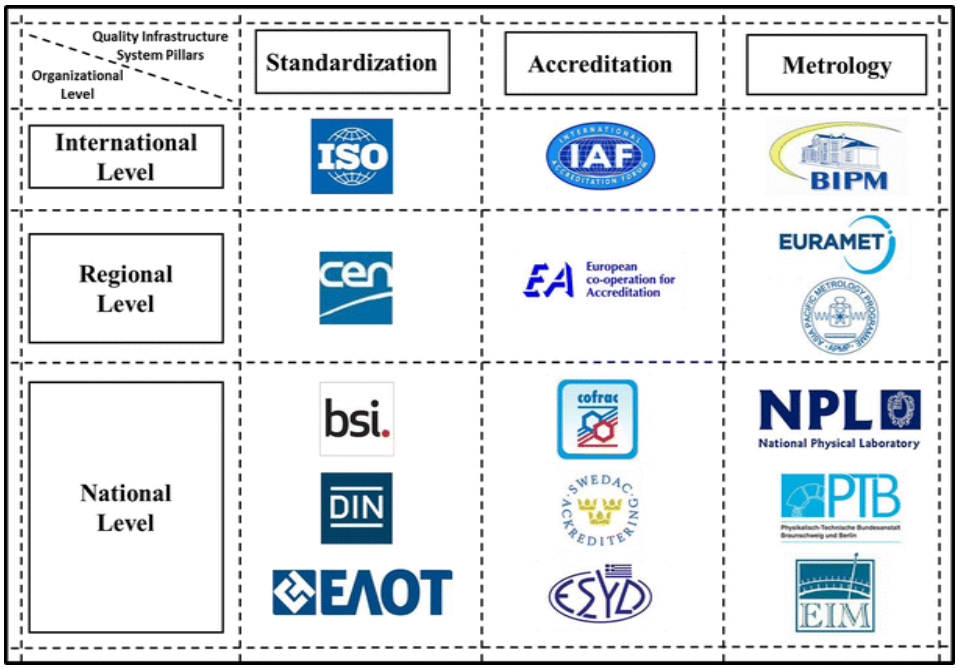

Figure 2. List of Accreditations for chemical industries

Routine and Surprise Audits

Chemical factories undergo

1. Safety inspections.
2. Equipment integrity checks.
3. Waste-management audits.
4. Hazardous material handling assessments.
5. Emission monitoring.
6. Risk analysis inspections.

Like educators in HEIs, industry employees must maintain continuous audit readiness, follow Standard Operating Procedures (SOPs), and ensure documentation accuracy.

Issues Faced by Employee Due to the Accreditation Process

The accreditation process is one of the factors causing these areas of concern for employee.

Time management: with a high demand for enormous time to be dedicated in documentation and backup proof related to teaching, and lesson planning, in addition to time needed to engage with students, the educator's time table would be extended with both academic and administrative work . It will be very difficult to accommodate such demands within regular working hours (8:00/9:00 AM – 4:00/6:00 PM).[16,17]

Handling Complex Standards: the nature of the predefined standards for accreditation is complicated, which demand a clear understanding of the pedagogical strategies that are in line with various teaching learning practices in a particular institution. Much of the effort entails painstaking documentation of classroom practice as well as student feedback.[18]

Documentation is everything - the burden on employees is in gathering proofs of preparation /organised/ participated /coordinated various events and filed them with all back up as demanded by the institution. Employee face a heavy documentation burden because compliance with many of the accreditation criteria is repetitive. When the preparing lessons plan may vary during the delivery of the same. For which the deviation ned to be recorded and filed properly else explanation would be demanded with proof. So instead of effective delivery, the core profession might accidentally be eroded.[19]

Continuous Professional Development: the pre request of accreditation bodies insists that teachers undergo continuous professional development. This, in turn, calls for FDPs, Capacity building programs (CBP) workshops, and seminars. But if these sessions are planned outside of standard working hours, or in other institutions altering the classes or work load for other employees would be difficult. It may create a havoc on the shift system maintained by the institution . So this participation is reduced to just a formality, a box to check, rather than a chance to learn something new.[20]

Qualifying the Internal Sector: encouraging the stakeholders' participation includes students, parents, and institutional affiliates feedback and review about the institution practices and performance, which is a very critical aspect of the accreditation process, although relatively much more challenging. The comments from various stake holders are required back by institutional norms that reflect the requirement on employees to approach feedback about themselves through various lenses, which include whistles blown from professional bodies regarding their portfolios. It therefore created an unnecessary problem in data collection, compiling analysis and action plan for the same.[21]

More work, longer hours: the request to collect a lot of proofs and documents with large datasets and multiple reviews is extremely time-consuming. The faculty would be frustrated and irritated to iterate, edit, and re-edit the same documents with inputs and feedback from selection committees, core teams, and criterion heads, thus consuming huge amounts of time. It can be particularly gruelling for teachers to have to do documentation records after a whole

day of teaching before they are allowed to leave school.[22]

Beyond their instructional duties, academic staff carries other administrative duties that include coordination with the accreditation teams along with attending meetings as scheduled. Accredit comes with extended hours of work.[23]

Performance Anxiety and the Fear of Failure: institutional success is implicitly tied to the results of assessment in accreditation which reflects positive recognition and citations. Evaluative process for accreditation purpose piles immense pressure among employee who face tough performance-related demands. Similarly, the inspections put employees under a microscope, which negatively adheres to their mental and emotional health. Performance pressures on women employee are even more daunting, as this is a world where women are expected to prove excellence at a much higher level. A lot of people fall victim to something called "imposter syndrome, "which is doubting one mind despite objectively ample evidence of its competence.[24]

Women employees suffer with more stress and strain when compared to their male colleagues since they are conditioned to feel that they have to work harder in order to prove that their quality of professionalism is at par with male colleagues. The continued pressure adds to stress levels and emotional exhaustion, which in turn contributes to adverse job satisfaction and wellbeing.[25]

Chemical Industry

Employees must maintain

- Logbooks: these are used to record daily operational activities, equipment usage, maintenance activities, and observations to understand the activities in the industry or department. Therefore, to track the movement of each material.
- Calibration Records: records prove that the instruments cleared all testing procedures , adjusted, and are in working condition as per guarantee the reliability of measurement, consistency of process, and quality standards.
- Safety Documentation: the checklists, for safety documentation is filled as per the guidelines for safety documentation, assistance in safe operations, prevention of hazards, training of employees, and organizational or regulatory compliances.
- Process Control Charts: the process control charts monitor performance trends, discover variation, support quality monitoring, and allow timely corrective action to maintain processes in a stable and efficient manner.
- Waste Tracking Sheets: which document the type of waste generated, amount, method of disposal, and time of disposal are maintained properly . This helps in effectively managing wastes, maintaining compliance with regulations, and ensuring environmental responsibility.
- Incident Reports: incident reports capture the details of the unexpected event along with causes, impacts, and corrective action to support risk reduction, safety improvement, and prevent occurrences in the future.

Unique Challenges Faced by a Female Employee Due to Gender: the burden of accreditation normally falls disproportionately on female employee. Family responsibilities, which many women hold at home and many organizations relict at their shoulders, cannot be ignored in nurturing a child with empathetic parenting. With both responsibilities, the entrepreneurs face additional stress and cannot devote much time to focus on professional development and the process of accreditation.[26,27]

Also, the institutional leadership in academia remains largely male, providing few networks for female academics facing challenges in their careers. The absence of gender-sensitive

schemes creates an unfair division of work, thus aggravating work-related stress and discontent.

Women in the chemical industry face

Figure 3. Women at work place- multitasking

There are safety issues related to night shifts: inadequate security, isolation, limited transport access, and insufficient workplace monitoring in hazardous environments make women particularly vulnerable during night shifts:

- Limited access to leadership in technical audits: Women are often given fewer opportunities to lead technical audits based on gender bias, stereotypes, and assumptions regarding their technical authority or competence.
- Male-dominated audit panels intimidate them: These teams, dominated by men, can intimidate women by making them feel belittled, scrutinized, or hesitant to raise concern and display their expertise.
- Assumptions about their physical capability concerning chemical handling: Prejudices regarding women's physical strength result in unjustified restrictions to roles, which in turn limit hands-on experiences, growth opportunities, and equal participation in chemical operations.
- Emotional Burden to Stay "Error-Free" in Hazardous Environments: Women have to face pressure to be impeccable on account of gendered scrutiny, which raises emotional stress, self-doubt, and a fear of mistakes impacting one's credibility.

People working in the chemical industry often refer to an audit as: "the most stressful week of the year." "a period when everyone is on high alert. anxiety-filled days where even small mistakes feel dangerous.[28]

Inadequate health support and Resources: while awareness for mental health challenges has increased due to recent headlines, systems to support staff in schools continue to leave many wanting. This has become an issue of concern, contributing to burnout and anxiety, is a lack of access by many faculty to mental health counselling, stress management and well-being resources. The leaders in the roles of accreditation, however, may have higher levels of stress, and rarely are their pressure relief valves at the institutional level. This pushes the employee to adopt the short-term survival mechanisms like overwork, or failing to take good care of themselves, all of which cause the build-up of long-term mental health issues.[29]

Figure 4. Common causes of stress at Workplace

Methods to Reduce Stress About Accreditation

Addressing the Priorities: the responsibility to prioritise and address administrative work versus classroom responsibility in a balanced way will become overwhelming but a sound strategy on how to tackle this task is vital in mitigating the stress and time management problems.

Intentional Assignment: programs need to be properly channelled both academic / administrative activities for accreditation compliance, without placing undue demands on faculty for other professional development activities.[30]

Figure 5. Stress Management Techniques at workplace

Management of Stress and Burnout: tough it is a known fact that the Accreditation is stressful in the short run, and institutions need to be doing things in the long run to avoid faculty burnout, such as providing mental health support and workload distribution is a must.

Keeping Up with Changing Standards: by way of accreditation, faculty itself can learn and leverage on training to know the changes taking place with respect to newer standards being implemented and follow the same from day one of the schedule or work allocation.[31]

Collaboration-Friendly: when faculty collaborate and coordinate in their work related to accreditation, this helps distribute the workload and makes it easier to prepare documentation and meet standards for compliance.

Investing in Technology by Chemical Industries

ERP systems: institutions have to integrate procurement, production, and inventory with finance in real time, minimizing errors, for improving efficiency, and enabling quicker readiness for audits.

LIMS: would stream line the workflows by managing samples, maintaining test records, ensuring traceability, and increasing accuracy in quality control, research, and regulatory compliance processes.

QR-based documentation: in the present tech world almost all the documentations are having QR code so this would help in instant access to SOPs, safety guidelines, equipment data, and records; reduces paperwork; ensures transparency and traceability for faster audit verification.

Automated audit trackers: automated audit trackers monitor would support the team by giving alerts and sending reminders, document non-conformities, to help the teams close gaps efficiently, boosting preparedness for internal and external audits.

These drastically reduce the burden on educators and employees.

Institutional Support Options

Strategic Timing: institutions should clearly chart out time for academic and administrative work therefore the employees would get clarity on time for accreditation work in order to avoid the all-cramming-all-knighting and instead make continuous progress.

Network of professional support partners and academic networks would help them in guiding the team on the proper direction without any repetitive work.

Utilize Technology to report, document, assemble evidence, and communicate with stakeholders can also reduce the burden on employees and workload for accreditation.

Promotion of Self-Care: institutions should establish environments that would be adoptive for the well-being of employees, allowing them to practice self-care, have flexible workstyles and schedules, and be involved in stress-relieving programs.[32]

The Road to Accreditation - Strategy towards Sustainable Practices

Accreditation demands need to be aligned with goals of teaching: accreditation stipulations need to be incorporated into curriculum designing so that the curriculum synchronizes institutional goals with the requirements of accreditation.

Ongoing Self-Assessment: faculty are called to reflect on their teaching practices in relation to the standards for accreditation, for purposes of improvement and innovation.

An Opportunity for Growth: rather than linking accreditation requirements to educator burden, professional development activities should be positioned by institutions as high-return growth opportunities.

Building a culture of collaboration: institutions need to create an inclusive academic climate within which they can see the light at the end of the tunnel and be able to work together toward meeting targets on accreditation and quality improvement.

Clear Communication: communication with all stakeholders of the organization that is,

students, parents, and administrators helps to clarify the process of accreditation and the importance in maintaining educational standards.

Workload Management Strategies to implement

Once excessive workload issues are identified, institutions could manage such issues by implementing structured approaches creating administrative roles for non-teaching personnel to take over administrative responsibilities, use of task forces with specific accreditation-related tasks (mostly handling documentation), and introducing policies to simplify documentation to minimize faculty burden.

Finally, institutions might want to offer flexible work hours or post-accreditation leave for faculty so they have time to recover from the equivalent of taking an academic SAT. Balanced workloads enable employee to meet accreditation standards without negatively affecting their own teaching and well-being.

Offering Mental Health Guidance and Counselling Services

Schools need to invest in robust mental health support systems for faculty that are specific to faculty needs. Employee need to be engaged through workshops on stress management and mindfulness activities (yoga) as integrated components of the educational ecosystem. Moreover, female faculty may benefit from greater access to supportive environments and mentorship to address their unique experiences. 9 Foster a workplace culture of well-being Stress takes away the joy of work.

Figure 6. Stress by employees during the Accreditation process

A Mentality of Work-Life Balance

Those institutions that hope to maintain a growing and moving forward academic environment or industrial environment must ensure that there is an even distribution of work-life balance. Including more flexible work schedules, the ability to work remotely, childcare support, and a balance between professional duties and personal life. Avoiding burnout can only happen if employee have enough time for themselves and if systems enact policies that are visible in reducing work volume. The first and most fundamental step to supporting the mental and physical well-being of employee is to create clear boundaries and promote the use of vacation and self-care opportunities.

Focusing on the barriers women face and how to support them

- Gender sensitivity: institutions should have policies that particularly address the challenges women teachers face during the accreditation process. These should include, but are not limited to, limiting burdensome administrative tasks, mentorship opportunities for women faculty in leadership, and work-life balance programs. Then at the management levels they can ensure a sensitive and respectful atmosphere where the females are valued and supported for professional growth. The more women participate in decision-making roles, share workload equitably, and receive leadership training, the more balanced academia will be.
- Collaboration and Teamwork Play a Vital Role in Accreditation Preparation: accreditation is not an individual but an institutional task. Moreover, making collective teams for documentation, assessment, and meeting the compliance demands can reduce the burden on an individual educator. Group Work Lowers Stress, Prevents Burnout, and Improves Efficiency of the Accreditation Process When responsibilities are shared and institutional structures support communication, employee can navigate the accreditation demands more easily.

CONCLUSIONS

Accreditation forms the bedrock of institutional recognition and quality but also takes a high toll on employees' mental health and well-being. Educational institutions and industries must champion employee well-being-through the strategic design of workloads, mental health measures, work-life balance policies, gender-sensitive initiatives, and institutional frameworks that promote collective achievements-to help mitigate some of these challenges. These strategies not only will help mitigate the need for accreditation compliance but also will create an academic environment that moves institutions to a stronger foundation of educator satisfaction, retention, and productivity in the long run. The sharing of information and sharing of tasks will improve efficiency, eliminate duplication of effort, and allow teachers to concentrate on their primary duties and not worry without undue stress. Good time management, resource management, and responsibility management together help in creating a healthy work culture which, ultimately, leads to the functioning of any institution with ease. After all, valuing the health of employees will ensure better health of institutions, communities, and the more accountable public. As the saying goes, 'Health is ensuring that employees are healthy and serves as the base for a healthier, wealthier nation.

BIBLIOGRAPHIC REFERENCES

1. Barratt T, Yong J, Afroz T. Teacher wellbeing and teaching excellence in higher education: Exploring the PERMA framework. High Educ Q. 2024;78(3):456-78. https://doi.org/10.1111/hequ.12563

2. Day C, Qing G. Teacher emotions: Wellbeing and effectiveness. In: Advances in Teacher Emotion Research. 2009. p. 15-31. https://doi.org/10.1007/978-1-4419-0564-2_2

3. Greenberg MT, Brown JL, Abenavoli RM. Teacher stress and health: Effects on teachers, students, and schools. University Park: Edna Bennett Pierce Prevention Research Center, Pennsylvania State University; 2016. https://www.prevention.psu.edu/uploads/files/rwjf430428.pdf

4. Jennings PA, Greenberg MT. The prosocial classroom: Teacher social and emotional competence in relation to student and classroom outcomes. Rev Educ Res. 2009;79(1):491-525. https://doi.org/10.3102/0034654308325693

5. Kinman G, Wray S. Work-related wellbeing in UK higher education: A scoping study. London: Universities and Colleges Employers Association; 2018. https://www.ucea.ac.uk/library/publications/wellbeing2018/

6. Klassen RM, Chiu MM. Effects on teachers' self-efficacy and job satisfaction: Teacher gender, years of experience, and job stress. J Educ Psychol. 2010;102(3):741-56. https://doi.org/10.1037/a0019237

7. Kyriacou C. Teacher stress: Directions for future research. Educ Rev. 2001;53(1):27-35. https://doi.org/10.1080/00131910120033628

8. McCallum F, Price D. Teacher wellbeing: A review of the literature. Sydney: Association of Independent Schools of NSW; 2016. https://www.aisnsw.edu.au/Resources/WAL%204%20%20SP/Teacher%20Wellbeing%20Literature%20Review.pdf

9. Montgomery C, Rupp AA. A meta-analysis for exploring the diverse causes and effects of stress in teachers. Can J Educ Adm Policy. 2005;(43):1-29. https://journalhosting.ucalgary.ca/index.php/cjeap/article/view/42745

10. Skaalvik EM, Skaalvik S. Motivated for teaching? Associations with school goal structure, teacher self-efficacy, job satisfaction and emotional exhaustion. Teach Teach Educ. 2017;67:152-60. https://doi.org/10.1016/j.tate.2017.06.006

11. Taris TW, Schreurs PJG, van Iersel-van Silfhout IJ. Job stress, job strain, and psychological withdrawal among Dutch teachers: Testing a model. J Educ Psychol. 2001;93(4):817-25. https://doi.org/10.1037/0022-0663.93.4.817

12. Van Droogenbroeck F, Spruyt B, Vanroelen C. Burnout among senior teachers: Investigating the role of workload and interpersonal relationships at work. Teach Teach Educ. 2014;43:99-109. https://doi.org/10.1016/j.tate.2014.07.005

13. Ashford NA, Hall RP. Technology, policy, and the chemical industry: Regulatory impacts. Cambridge: MIT Press; 2011.

14. Bakker AB, Demerouti E. The job demands–resources model: State of the art. J Manag Psychol. 2007;22(3):309–28.

15. Berridge EJ, Maniam B. Accreditation and faculty workload: The hidden costs of quality assurance. J Educ Learn. 2018;7(2):21–30.

16. Brittingham B. Accreditation in the United States: How did we get to where we are? New Dir High Educ. 2009;145:7–27.

17. Clarke S. Safety leadership: A meta-analytic review of transformational and transactional leadership. J Occup Organ Psychol. 2013;86:22–49.

18. Cooper MD. Towards a model of safety culture. Saf Sci. 2000;36(2):111–36.

19. Eaton JS. The role of accreditation in the changing higher education landscape.

Washington: Council for Higher Education Accreditation; 2012.

20. Gunningham N. Regulation, compliance, and the chemical industry: Worker stress and organisational impact. J Environ Law. 2012;24(2):235–64.

21. Hale AR, Borys D. Working to rule or working safely? Part 1: Safety regulation and chemical plant employees. Saf Sci. 2013;57:223–35.

22. Harvey L. The power of accreditation: Views of academics. J High Educ Policy Manag. 2004;26(2):207–23.

23. Huisman J, Wester Heijden D. Quality assurance in higher education: Trends, debates, and practices. Qual High Educ. 2010;16(6):1–13.

24. Kasperson RE, Pijawka D. Societal response to hazards: Chemical accidents. Risk Anal. 1985;5(3):275–86.

25. Kinman G, Wray S, Strange C. Emotional labour, burnout and job satisfaction in UK academics. J High Educ Policy Manag. 2011;33(3):229–41.

26. Mearns K, Whitaker SM, Flin R. Safety climate, communication, and compliance in petrochemical and chemical industries. Saf Sci. 2001;39(3):157–72.

27. Parker SK, Axtell CM, Turner N. Designing a safer workplace: Importance of employee involvement. J Occup Health Psychol. 2001;6(2):211–28.

28. Sabharwal M, Corley E. Faculty job satisfaction across gender and discipline. Res High Educ. 2009;50(8):831–59.

29. Santiago P, Tremblay K, Basri E, Arnal E. OECD reviews of tertiary education: Global report. Paris: OECD Publishing; 2008.

30. Shin J, Harman G. New challenges for higher education: Accreditation, quality assurance and institutional research. Berlin: Springer; 2009.

31. U.S. Chemical Safety Board. Investigation reports: Chemical accident case studies and safety recommendations. Washington: U.S. Chemical Safety and Hazard Investigation Board. https://www.csb.gov/

32. Vincent R, Amalberti R. Safer healthcare: Strategies for the real world. Berlin: Springer; 2016.

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AUTHORSHIP CONTRIBUTION

Conceptualization: B. Neeraja, B.V. Jayanthi, Suchitra, Devendran, Arun Kumar, Christo Ananth.

Data curation: B. Neeraja, B.V. Jayanthi, Suchitra, Devendran, Arun Kumar, Christo Ananth.

Formal analysis: B. Neeraja, B.V. Jayanthi, Suchitra, Devendran, Arun Kumar, Christo Ananth.

Drafting - original draft: B. Neeraja, B.V. Jayanthi, Suchitra, Devendran, Arun Kumar, Christo Ananth.

Writing - proofreading and editing: B. Neeraja, B.V. Jayanthi, Suchitra, Devendran, Arun Kumar, Christo Ananth.

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ORIGINAL

Machine Learning for Fuel Consumption Prediction and Driving Profile Classification Based on ECU Data Next-Generation Engineering

Aprendizaje automático para la predicción del consumo de combustible y la clasificación del perfil de conducción según datos de la ECU Ingeniería de última generación

P Deepthi[1], M.Nithya[1], P.Mounika[1], K.Mourya[1], P.Mano Vardhan Reddy[1], Christo Ananth[1], Yusupov Ozod Rabbimovich[1]

[1]Department of Computer Science & Engineering, Madanapalle Institute of Technology & cience. Madanapalle, India.
[2]Faculty of Artificial Intelligence and Digital Technologies, Samarkand State University. Uzbekistan.
[3]Head of Department, Software Engineering, Artificial Intelligence and Digital Technologies, Samarkand State University. Uzbekistan.

Corresponding Author: P Deepthi

ABSTRACT

The classification of driving profiles and predicting real-time fuel consumption have gained significant interest over the recent years since it determines environmental sustainability besides efficiency of the vehicle. The project objectives are to use machine learning techniques to classify different driving behaviour and calculate fuel consumption with the help of the information received by the engine control unit (ECU). Currently, the use of such techniques as XGBoost, SVR (Support Vector Regression), or Ridge Regression are used. The proposed system will enhance the effectiveness in prediction and profile classification since it will involve additional algorithms like the Random Forest, Logistic Regression and Adaboost. The fuel consumption patterns are categorized into five patterns Sporty, Eco, Calm, Normal, and Aggressive which form the driving habits of the car. This does not only help in the better understanding of driving habits but also helps in the creation of adaptive fuel efficiency strategies. The project will not only enhance the performance of the vehicles but also improve the environment with the use of more advanced machine learning procedures in Eco-Engineering Approaches to Reduce Carbon and Methane Emissions.

Keywords: Machine Learning; Fuel Consumption; Driving Profile Classification; ECU Data; XGBoost; SVR; Ridge Regression; Random Forest; Logistic Regression; Adaboost; Nanomaterials; Robotics.

RESUMEN

La clasificación de perfiles de conducción y la predicción del consumo de combustible en tiempo real han cobrado gran interés en los últimos años, ya que determinan la sostenibilidad ambiental, además de la eficiencia del vehículo. Los objetivos del proyecto son utilizar técnicas de aprendizaje automático para clasificar diferentes comportamientos de conducción y calcular el consumo de combustible con la ayuda de la información recibida por la unidad de control del motor (ECU). Actualmente, se emplean técnicas como XGBoost, SVR (Regresión de Vectores

de Soporte) o Regresión de Ridge. El sistema propuesto mejorará la eficacia de la predicción y la clasificación de perfiles, ya que incorporará algoritmos adicionales como Random Forest, Regresión Logística y Adaboost. Los patrones de consumo de combustible se clasifican en cinco patrones: Deportivo, Eco, Tranquilo, Normal y Agresivo, que conforman los hábitos de conducción del vehículo. Esto no solo contribuye a una mejor comprensión de los hábitos de conducción, sino que también facilita la creación de estrategias adaptativas de eficiencia de combustible. El proyecto no solo mejorará el rendimiento de los vehículos, sino que también contribuirá a mejorar el medio ambiente mediante el uso de procedimientos de aprendizaje automático más avanzados en enfoques de ecoingeniería para reducir las emisiones de carbono y metano.

Palabras clave: Aprendizaje Automático; Consumo de Combustible; Clasificación de Perfiles de Conducción; Datos de la Ecu; Xgboost; Svr; Regresión de Cresta; Bosque Aleatorio; Regresión Logística; Adaboost; Nanomateriales; Robótica.

INTRODUCTION

Besides the advancement in machine learning, the incorporation of nanomaterials in robotics and automotive engineering are also emerging possibilities of enhancing energy efficiency and accuracy of sensors. The sensors based on nanomaterials, graphene-based sensors or carbon nanotube sensors allow detecting pressure, temperature, and fuel flow parameters in a more accurate way and give a more detailed and reliable information to the Engine Control Unit (ECU). Such improved data when introduced into machine learning models may further improve the accuracy of fuel consumption prediction and the classification of driving behaviors. Therefore, some of the future possibilities of integrating nanomaterial-enabled sensors with data-driven analytics in developing innovative vehicles that are sustainable are also considered in this study.

The world is transforming the automotive industry due to its adoption of intelligent technologies and solutions based on data. Vehicle performance data analysis is more than ever with the increasing use of the fuel efficiency, sustainability and smarter driving. The heart of this is the Engine Control Unit (ECU) that collects immense data of sensor information that are capable of describing not only the functioning of the vehicle but also the driver.

The project is planned to apply machine learning in two significant directions: fuel consumption data are used, and the distinction between driving styles can be experimented with. The system will be capable of estimating the fuel consumption and classifying the driver habits into the profile such as Sporty, Eco, Calm, Normal, and Aggressive and recognizing the tendencies of the real-time driving information. The lessons can be applicable to encourage the fuel saving behaviors among individuals as well as help the manufacturers and fleet operators to alter the behavior of their drivers towards the necessity to drive in an environmentally friendly manner.

Similar to the traditional rule-based frameworks, the approach makes use of the state-of-the-art machine learning frameworks, including Random Forest, Logistic Regression, and Adaboost with the help of the already existing algorithms, including XGBoost, Support Vector Regression (SVR), and Ridge Regression. The combination of the techniques leads to more accurate predictions and classification results.

The application of this project can be used in a number of fields, including intelligent transportation, fleet management, and individual driver navigation. On a bigger scale, it assists in reducing carbon emissions and sustainable mobility through data-driven decision-making.[1,2,3,4]

Literature survey

Traditional Approaches to Fuel Consumption Prediction

The initial models of fuel consumption prediction were based on physics-based and statistical

analysis, mostly applying to linear, polynomial regression and the table of look-up models that were constructed on the basis of empirical data. These procedures worked well in a simple case but failed in non-linearity, dynamic driving habits and environmental changes. In their research, A study examined the issue of real-time predicting fuel consumption by applying machine learning. The authors showed that contemporary ML algorithms are much more accurate and flexible than traditional statistical models.[1] In the same way, A study have applied Support Vector Regression (SVR) in the process of driving behavior analysis in order to optimize fuel consumption.While SVR provided improved performance over classical methods, it still required feature engineering and had high computational complexity.[2]

Machine Learning-Based Fuel Consumption Prediction

Supervised learning methods have been used recently to estimate fuel consumption using ECU (Engine Control Unit) data. Parameters of interest that are analyzed in these models include engine RPM, throttle position, vehicle speed, and fuel injection rate in order to provide accurate predictions.

A study analyzed ECU data using XGBoost, demonstrating its ability to handle non-linear relationships and feature importance ranking. However, their study found that XGBoost requires fine-tuning to avoid overfitting.[4] A study enhanced prediction accuracy by integrating the Adaboost algorithm, which iteratively improves weak learners to create a strong predictive model. Their study highlighted that ensemble learning techniques outperform individual regression models in fuel consumption prediction.[5]

Driving Profile Classification for Fuel Efficiency

The driving behavior is a major factor in fuel consumption and so driving profile classification is a significant element of intelligent fuel management systems.[6]

A study implemented machine learning techniques to classify drivers into categories based on fuel consumption patterns. Their research used K-Means clustering and Decision Trees but noted that classification accuracy depends on feature selection and dataset quality.[7] A study introduced an Adaptive Driving Profile Classification system using Random Forest, which improved the precision of driving behavior segmentation. Their approach categorized drivers into Eco, Sporty, Aggressive, and Normal profiles based on ECU parameters.[8]

Enhancing Prediction with Deep Learning and Big Data

With increasing availability of vehicle sensor data and cloud-based telemetry systems, deep learning models have shown promise in improving fuel consumption predictions and driver behavior classification.[9]

A study investigated Ridge Regression using deep neural networks as a method of vehicle fuel efficiency analysis, and they found that neural network-based Ridge Regression models were more accurate than conventional ML models, although large labeled datasets were necessary to train them.[10]

The authors noted that big data analytics would aid in predicting fuel consumption by highlighting that by integrating cloud-based ML models, it will be more viable to predict fuel consumption in a large-scale fleet.[11,12]

Sensor-Based and ECU Data-Driven Fuel Estimation

Sensor-based fuel estimation models have increased in use as the technology of the automobile industry has advanced. Telemetry systems based on the ECU can deliver live information about the fuel injection, engine load, throttle position and acceleration, which can be utilized to create more accurate ML models. CAN Bus data integration allows consideration of vehicle

holistically. operations, to enhance predictive accuracy. H. The authors examined fuel efficiency analysis with XGBoost on ECU sensor data, however the book did not use any feature selection to build their model.[13] Proposed by a study, the system based on IoT will combine ML algorithms with real-time vehicle monitoring and enhance the accuracy of prediction.[14]

MultimodalApproaches for Fuel Consumption Prediction

To advance more in fuel consumption forecasting, scholars have considered multimodal ones, combining:Sensors (ECU + GPS + accelerator) Hybrid ML-DL models Edge AI used to predict vehicle diagnostics a study investigated the topic of multimodal sensor integration, which enhances the accuracy of prediction by 15 % over single ML models.[15,16,17,18]

The study is the testing of hybrid ML-DL systems, according to which CNNs and LSTMs jointly improve the time-series prediction of fuel consumption.[20,21,22,23]

Summary of Literature Review

The literature review shows that there are key trends and challenges: Traditional statistical models (linear regression, polynomial regression) cannot handle the complex and real-time fuel consumption data, Machine learning models (SVR, XGBoost, Adaboost, Random Forest) will improve prediction accuracy but must select features efficiently and utilize an ensemble learning strategy, Driving behavior classification can be used to improve fuel economy, but must use adaptive and real-time classification methods, and Deep learning approaches can achieve better predictive accuracy at the cost of limited ability to operate in real time due to computational constraints.[24,25,26,27,28]

METHOD

The system architecture is a systematic process and starts with the data received by the Engine Control Unit (ECU) of the vehicle. The ECU measures several parameters in real time including injection of fuel, engine load, throttle position, speed of the vehicle, acceleration and revolution per minute (RPM). These parameters play a crucial role in the estimation of the fuel consumption and categorizing the driving behavior. Besides that, the external sources of data, such as detailed vehicle performance indicators, may be collected under the name of Controller Area Network (CAN) buses and On-Board Diagnostics (OBD-II).

Data Collection from ECU

The system is backed by the data collection stage. In the present work, the information was obtained by reading the ECU of modern cars through the “On-Board Diagnostics (OBD-II)” interface that offers a broad set of telemetry parameters. These are some of the main metrics, engine RPM, throttle position, vehicle speed, intake air temperature, manifold absolute pressure (MAP), mass air flow (MAF), and engine load percentage. The sensor data was captured on-time during real-life driving and saved in a CSV format that is structured. The data produced is in form of a few thousand rows where each row represents a particular time-based snapshot of the operating condition of the vehicle. Regular logging interval and adequate synchronization of the sensor values allowed capturing time-varying driving patterns with sufficient accuracy to be used both on regression and classification tasks.

Data Preprocessing and Normalization

Once the data was acquired, the most important task was to preprocess it properly in order to preserve the quality and reliability of the dataset. Due to the high dynamics in the vehicular environment, the raw data of the ECU may be noisy, incomplete, or inconsistent due to sensor faults or delays in recording. In order to tackle these problems, preprocessing started with missing value management by applying both forward fill and mean substitution approaches to

different types of features. To illustrate, features exhibiting smooth temporal behavior were processed using forward filling whereas missing values were filled by means of column-wise averages. The outliers which might adversely impact the model performance were identified through Z-score analysis and interquartile range and either rectified or eliminated. After this, the Min-Max scaling will normalize all numerical features to adjust the values between 0 and 1. This made the feature contributions balanced and enhanced the efficiency of machine learning algorithms in training. In case of the presence of categorical data, data encoding techniques, like Label Encoding, or One-Hot Encoding, would have been used; nevertheless, the data in this dataset consisted primarily of continuous numerical variables.

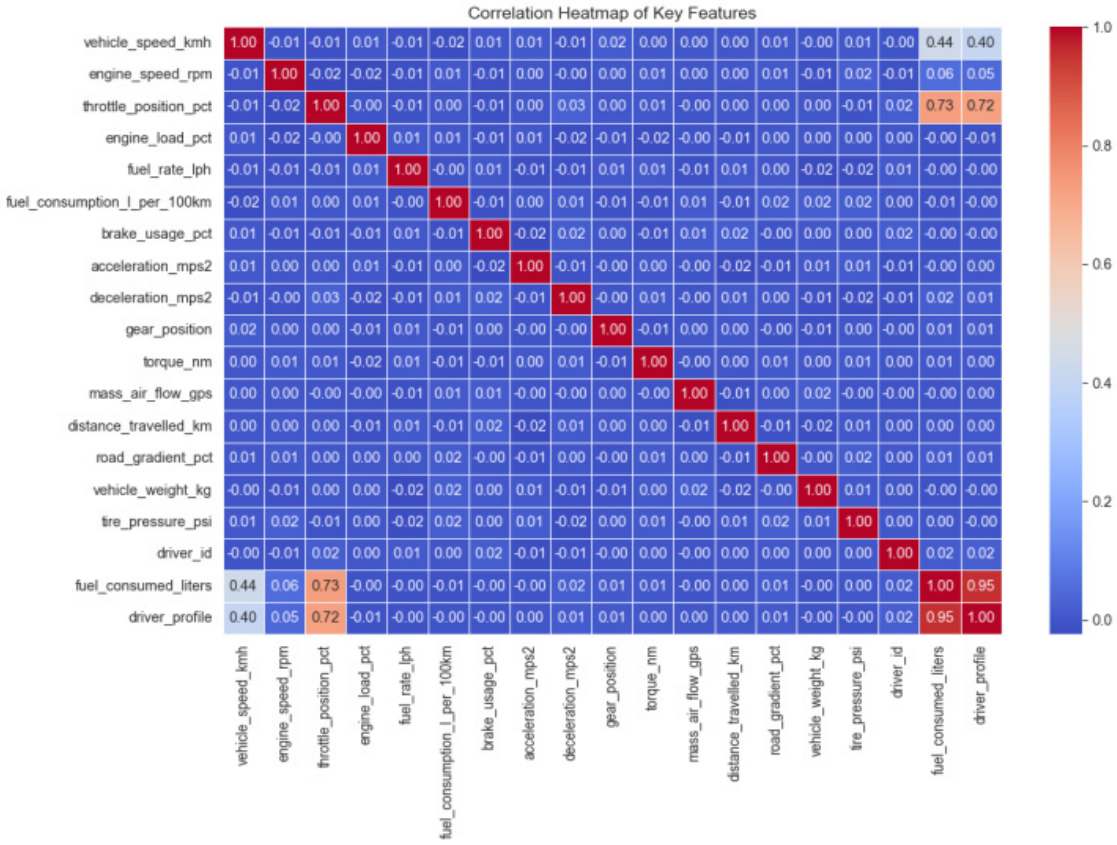

Figure 1. Correlation Heatmap of Key Features

Feature Selection and Engineering

Once the data was thoroughly cleaned and normalized, feature selection and engineering constituted the next major part of the machine learning pipeline. This step is very crucial since it determines the accuracy, performance and interpretability of the model. It is typical in high-dimensional data sets, which are common in automotive ECU (Engine Control Unit) telemetry data, to have features which are irrelevant, redundant and even counterproductive to effective learning.

To address this, a correlation analysis was first performed to study the linear relationships between independent features and the target variable, fuel consumption. A “correlation heatmap” was then generated to visually highlight these relationships and to identify features

that were highly correlated. Features with a very low or near-zero correlation to the target variable were marked as less informative and considered for removal. Moreover, high inter-feature correlation (multicollinearity) was also thoroughly investigated with the help of Variance Inflation Factor (VIF) scores to make sure the rest of the features were not redundant. Some models such as linear regression and ridge regressions may overfit and give unstable coefficient estimates, especially when the features to be modeled become highly collinear.

After this statistical analysis Recursive Feature Elimination (RFE) was used as extra refinement of feature sets through a wrapper approach. RFE is used to train a machine learning model (Random Forest Regressor) recursively and rank features based on their importance scores. The process of feature removal is repeated in every iteration, with the model being re-trained. This is done until the most appropriate collection of features is found which provides the best predictive performance at the least complexity.

Besides RFE, domain knowledge and expert judgment were also introduced in order to keep the features that are known to have physical or mechanical importance to fuel consumption. Indicatively, such characteristics as engine RPM (revolutions per minute) and vehicle speed have a direct influence on engine workload and fuel consumption. Equally, throttle position and engine load can be used to gain an understanding of driver input and real-time power requirement, whereas intake air temperature and MAF (Mass Air Flow) can be used to understand environmental and combustion conditions.

The final set of selected features used for model training included:

- Engine RPM – Indicates how hard the engine is working.
- Throttle Position – Reflects driver acceleration behavior.
- Vehicle Speed – Influences aerodynamic resistance and fuel efficiency.
- Engine Load – Measures the percentage of total power demand.
- Intake Air Temperature – Affects fuel combustion efficiency.
- Mass Air Flow (MAF) – Represents the volume of air entering the engine, important for fuel-air mixture calculations.

Another way of enhancing model learning was to feature scale all the selected features, in which the Min-Max normalization was used that scaled each value to a range between 0 and 1. This was particularly crucial to models such as Support Vector Regression (SVR) that are feature sensitive.

In future iterations, additional feature engineering techniquessuch as the creation of derived features (e.g., acceleration = Δspeed/Δtime) or the inclusion of interaction terms (e.g., throttle position × RPM)could be employed to extract even more meaningful patterns from the raw ECU data. This would further enhance the model's ability to capture complex driving behaviors and fuel consumption dynamics.

Machine Learning Model Development for Fuel Consumption Prediction

The core of the system is founded on the development and experiment of predictive machine learning models to forecast the fuel consumption using real-time ECU information. To obtain accurate and valid results, several regression approaches were experimented, such as linear simple regression models and other more sophisticated ensemble-based regression. To begin with, we started with the Linear Regression model as the basic model due to the simplicity of its design and interpretation. Nevertheless, it was not very effective since it failed to capture the non-linearities that tended to characterize vehicle dynamics and patterns of fuel consumption. Ridge Regression was developed in order to address issues like multicollinearity, and to increase generalization. L2 regularization also penalized large values of coefficients and contributed to reducing variance, which increased the results over the baseline. Even so, neither of the linear methods was sufficient to fully describe the complicated relationships

between such features as engine RPM, throttle position, and vehicle speed. Consequently, Support Vector Regression (SVR) and Radial Basis Function (RBF) kernel were applied in order to fit non-linear relationships better. SVR offered better predictive performance due to its input feature mapping into higher-dimensional space, but it was costly computationally and needed to be carefully tweaked with hyperparameters, and therefore not suitable to be used on large-scale data sets. To further enhance prediction capability, ensemble learning techniques were introduced. Random Forest, through its aggregation of decision trees, helped reduce overfitting and variance, while XGBoost, an advanced gradient boosting algorithm, outperformed all other models. XGBoost demonstrated high efficiency, strong regularization, and the ability to handle missing values, sparse data, and feature interactions effectively. It also provided built-in feature importance analysis and better generalization. After training and validation, XGBoost delivered the strongest performance, explaining 93 % of the variation in fuel consumption. The model achieved a "Mean Absolute Error (MAE)" of 0,14 L/100 km, a "Root Mean Squared Error (RMSE)" of 0,21 L/100 km, and an "R^2 score" of 0,93. These outcomes highlight that ensemble methods—particularly XGBoost—are highly effective for achieving accurate fuel consumption predictions, making them a vital part of the proposed intelligent vehicle analytics system.

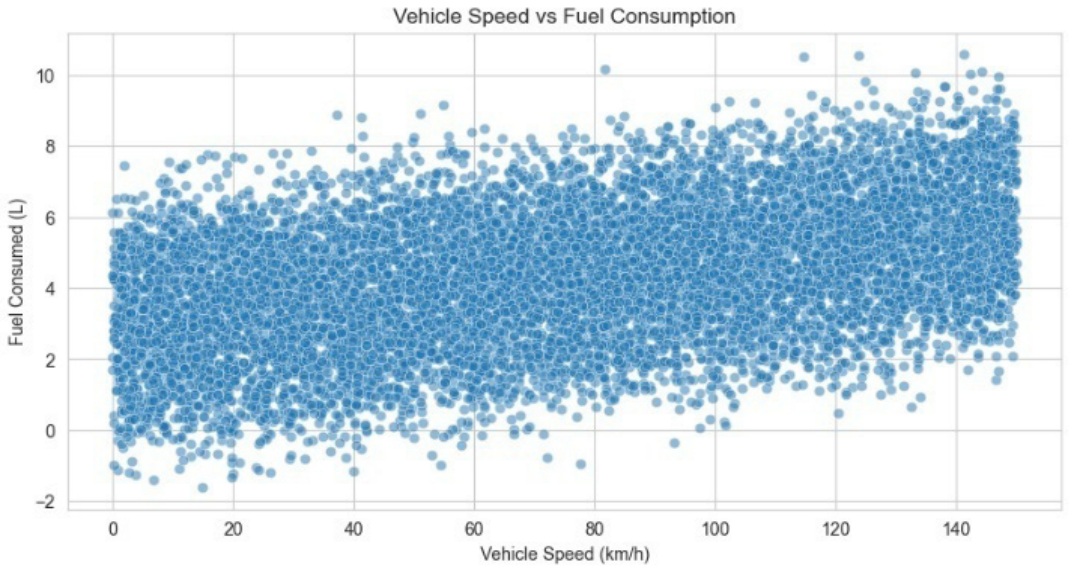

Figure 2. Vehicle Speed vs Fuel Consumption

Ensemble models (especially Random Forest and Gradient Boosting (XGBoost)) have turned out to be more precise by averaging the results of a great number of decision trees and by reducing both variance and bias at the same time. By the parameters of the assessment such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R-squared (R 2) score, XGBoost has been discovered to be the most efficient model, primarily owing to the stable regularization features and the proven success with structured data. In order to have a good generalization to the unseen cases, the model was trained on 80 percent of the data and tested on the remaining 20 percent.

Driving Profile Classification

In addition to fuel consumption prediction, classification module was also used in the project to determine driving profiles based on real-time vehicle behavior. As driving style has a direct

effect on fuel consumption, the system separates drivers into five classes, namely Eco, Calm, Normal, Sporty and Aggressive. This scanning is based on logical principles on the forecasted fuel rate and sensor data like RPM, throttle position, trends in acceleration and frequency of braking. As an illustration, aggressive driving was associated with constant high RPM levels and frequent throttle spikes, and environmentally friendly behavior with stable RPM levels and little throttle activity. These empirical thresholds were implemented as rules determined through the analysis of the training data and visualization of the most important trends. Based on the availability of labeled behavioral data in future, this modular framework may be upgraded with supervised learning methods, like Decision Trees or Logistic Regression.

System Implementation and Integration

These features are made available in easy to use form by designing a full stack application. The server was done in Python and popular libraries like Scikit-learn, Pandas and XGBoost were used to train and execute the models. The application was developed on top of a lightweight Flask web server that allowed the user to submit ECU datasets using a basic graphical interface. After uploading the data, the server is used to run it through the trained model pipeline to make predictions of both the fuel consumption and the driving profile classification. The results are then presented in a form of a visual display along with actionable insights and recommendations on how to be a better fuel consumer. The system is also linked to a MySQL database that has the sessions of the users, prediction results, and performance summaries over time so as to support persistence and historical analysis.

Future Scalability and Deployment Considerations

The approach establishes a seamless data analysis workflow that converts crude ECU data into useful information to empower individuals as well as fleet managers to make well-informed choices. The modular structure of the system also enables its future upgrades, including the real-time data streaming, mobile apps implementation, and external APIs integration to provide the traffic or weather data. The system has a significantly greater prediction accuracy and adaptability than the traditional rule-based methods because of the data-driven, machine learning-based approach. The combination of the regression and classification methods makes it a full solution to the analysis and improvement of the fuel consumption behavior in a modern car.

RESULTS

The development of the fuel consumption prediction and driving behavior classification system was tested on the real-world data, which was provided by a car through the interface called the “OBD-II” to its Engine Control Unit (ECU). The measurement of the performance of the machine learning models was provided with the help of a mixture of the statistical measures and the graphical analysis. Strong evidence has been found in the findings that show reliability, accuracy and practical applicability of the system in the automotive fuel analytics.

Regression Model Evaluation

Fuel consumption prediction This machine learning pipeline was trained and evaluated with an 80-20 split of data. XGBoost Regressor model was much more effective than other algorithms, including Linear Regression, Ridge Regression, and Support Vector Regression (SVR). The end performance of the XGBoost model was as follows:

- Mean Absolute Error (MAE): 0,14 L/100km
- Root Mean Squared Error (RMSE): 0,21 L/100km
- R-squared (R^2) Score: 0,93

The findings indicate that the accuracy of prediction is high with small error. The R 2 of

0,93 indicates that the model has managed to account 93 percent of the variation in fuel consumption, which clearly shows that the chosen features are relevant and learning algorithm is effective at the same time. To further confirm its performance, the line graph was drawn between the actual and predicted fuel consumption values as 10 representative samples of test were taken. The visualization showed that there was near-perfect overlap between the two with slight variations. This uniformity of the results of various samples speaks volumes to the strength and validity of the model.

Residual Error Analysis

The analysis of residual generated a residual plot that showed the variance between the real and the predicted fuel consumption of each test case. This was done to discover any systematic error in the model predictions as also to understand more about the distribution of errors. The residuals are not so excessive and move around the zero line evenly. The fact that the distribution is centered and symmetrical also proves that the model does not always overestimate or underestimate fuel consumption and, therefore, has an unbiased behaviour. Moreover, the fact that there is no visible trend in the residuals confirms that the model was able to capture both linear and nonlinear trends. This is good indication that the model has generalized well and it is not overfitted to the training dataset.

Classification of Driving Profiles

To classify driving behavior, a rule-based engine was created, which relies on thresholds obtained by analyzing such important features as RPM, throttle position, and acceleration rate. It was determined based on these values that the drivers will be divided into five categories: Eco, Calm, Normal, Sporty, and Aggressive. In order to test this component, the system was compared to manually labeled driving sessions in which the behavior of the drivers was annotated according to the observed patterns.

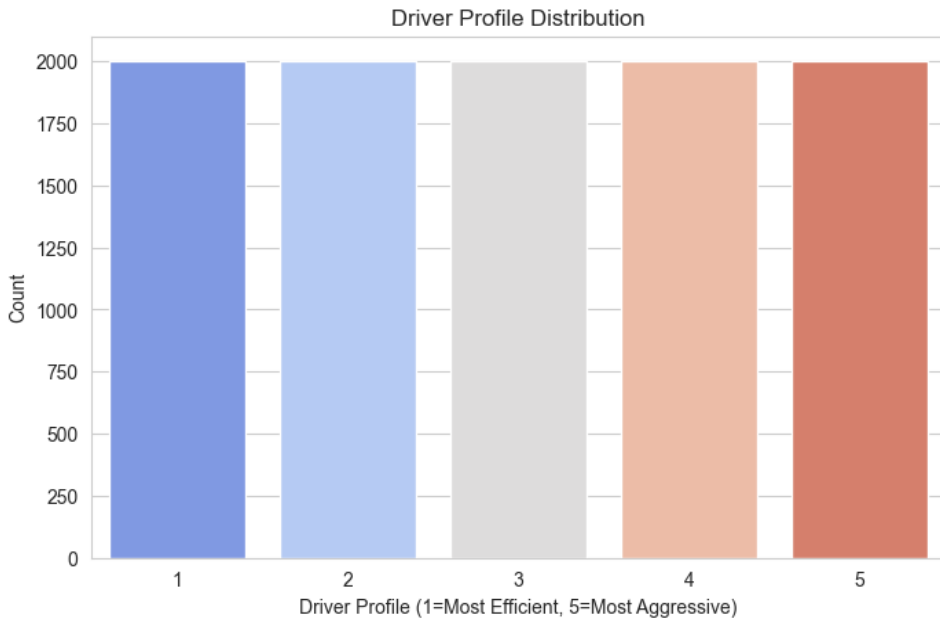

Figure 3. Bar chart representing the distribution of classified driving behavior

The classification module had a precision of about 91 which is a good outcome bearing in mind that the rule-based logic is not supervised. The confusion matrix showed that the system was especially useful in determining the behavior of Eco and Aggressive, which have clear patterns of the parameters (low vs high, throttle use). There were minor misclassifications of between the term normal and calm since the behavioral patterns overlapped but did not essentially influence the usefulness of the system.A bar graph was drawn to represent the distribution of driving styles among the various test cases. Such an understanding is not only useful to individual drivers to learn to behave in a certain way, but also to the manager of a fleet that wants to minimize the fuel consumption by promoting efficient driving.

Comparative Model Analysis

The multiple regression models were compared to ensure that the most performing model was selected. The comparison of four models, the Linear Regression, Ridge Regression, SVR, and XGBoost, are compared based on the MAE, RMSE, and R2 scores as shown in table 1.

Table 1. Performance Comparison of Regression Models for Fuel Consumption Prediction

Model	MAE (L/100km)	RMSE (L/100km)	R^2 Score
Linear Regression	0,24	0,33	0,81
Ridge Regression	0,21	0,29	0,85
SVR (RBF Kernel)	0,18	0,26	0,88
XGBoost	0,14	0,21	0,93

As it can be seen, XGBoost is always the best among the others, so it is the model that can be deployed. The ensemble property of XGBoost, regularization, and ability to assume interaction between features all add to its high accuracy.

Scalability and Real-World Implications

The possible practical use of this system is one of the worthiest results of this system. The system can be installed in cars to provide real-time feedback with only minor hardware costs (OBD-II scanner and minimum computer). Bigger fleet management applications would be possible with the implementation of this system combined with cloud-based information storage and dashboard to monitor driver behavior and fuel trends of hundreds of vehicles.

The usability of the web interface is increased through the deployment-ready web interface, which enables users to upload ECU log files and get the predicted fuel consumption values and driving behavior evaluation at the same time. The precision of the system along with its modularity has rendered it a great candidate to be integrated into intelligent transport systems (ITS), telematics systems, and driver coaching systems.

The most efficient characteristics of the developed system are that it can potentially be scaled practically and implemented in different vehicles environments. The system was designed in a user-friendly manner and thus, it requires little hardware to run the system, since it only entails an average OBD-II scanner, a simple computing machine or smart phone hence, rendering the system very inexpensive and affordable to the small-scale users and individual drivers. Such a low barrier of entry, means that it will easily fit in the existing vehicles without costly retrofitting or proprietary sensors. Besides personal application, the system is of immense potential when it comes to larger capacity operations such as fleet management and commercial logistics. The positive aspects of cloud computing technologies and centralized data storage can be used to scale the system up to hundreds or even thousands of vehicles at the same time.

In such instances, the information of the various vehicles can be pooled, checked, and shown in one dashboard offering the fleet managers a detailed insight into driving behavior patterns, fuel consumption rates, and vehicle diagnosing. The web interface that is ready to be deployed enhances the ease of use and accessibility of the product as it makes the users able to upload the ECU log files and receive an immediate analytic response.

The interface is easy to use and enables visualization of the data in graphs and behavioral summaries and thus it can be easily used by the inexperienced user. Moreover, the system modularity will also ensure the flexibility of the future expansions, such as the incorporation of the real-time information of the GPS, weather, or traffic jam. It also has a good position to merge with Intelligent Transport Systems (ITS), telematics systems and eco-driving guidance systems. These integrations can help in driver coaching, fuel efficiency policy enforcement and predictive maintenance schedule. Ultimately, this system is not merely a technical prototype anymore- it is a scalable and smart system with the ability to address the problem of economic and environmental concerns of modern transportation and therefore is a component of sustainability initiatives of enabling scalable and fuel-efficient data-driven driving behaviors, as well as eco-friendly driving behaviors.

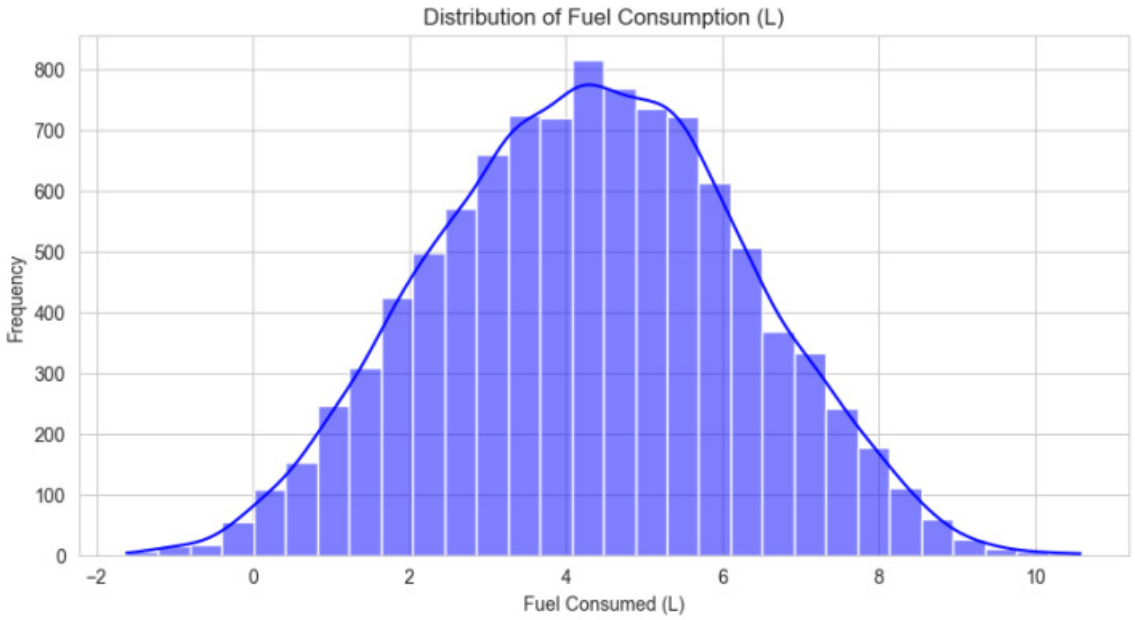

Figure 4. Line graph comparing actual and predicted fuel consumption values across 10 test samples

These findings affirm the efficiency of the system, both in regression and classification. The joint effect of accurate fuel consumption forecasting and smart behavior classification is highly promising to be used in driver coaching systems, vehicle telematics and fleet efficiency monitoring solutions. Furthermore, the modular design of the system makes addition of new capabilities, e.g., weather effect, traffic jam intensity, and even the road slope, very simple to increase the accuracy of the predictions.

CONCLUSIONS

The paper provides a comprehensive and innovative approach to grouping driving styles and predicting fuel consumption of the vehicle based on the data retrieved via Engine Control

Unit (ECU). The integration of machine learning in vehicles is one of the greatest milestones considering the growing need of fuel-efficient and eco-friendly transport means.

The proposed system fills the gap between raw ECU data and meaningful insights by using the power of supervised regression along with the logic of rule-based classification. The experimental results point to the fact that the XGBoost Regressor is effective to predict the fuel consumption based on the key parameters: speed, RPM, throttle position, and air intake. The model has been identified as very predictive and the R 2 is 0,93, MAE is 0,14 L/100km and RMSE is 0,21 L/100km. Such results warrant the ensemble learning of automotive analytics, especially when the data is nonlinear and might be subject to multiple interdependent variables.

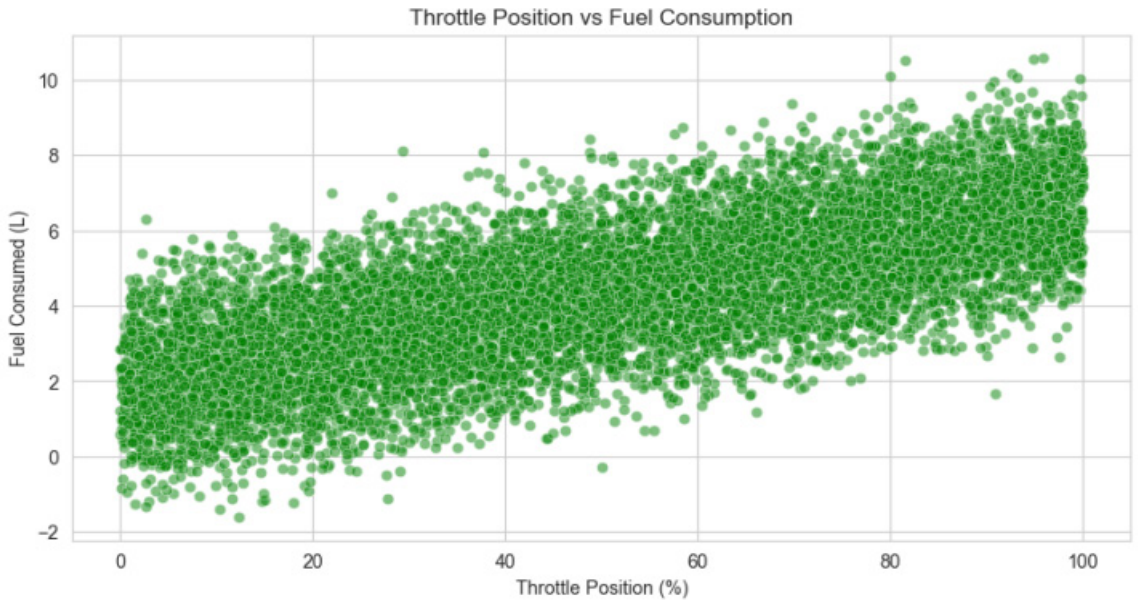

Figure 5. Throttle Position vs Fuel Consumption

At the same time, the classification module of the system does a great job in classifying the behaviour of the driver into concise profiles. It is not only a source of information about certain driving behaviors but also an effective tool of improving fuel consumption, as well as reducing the strain on the components of the car. The system has a classification accuracy of 91, and this indicates that it is effective in the real environment. This is one of the greatest contributions of this work which is practically applicable. In contrast to the conventional methods which involve a costly instrumentation or special sensors, this system uses the readily available ECU data by the OBD-II port. This renders the system affordable and simply implementable even on old vehicles. Furthermore, the web-based user interface guarantees the access to a broad spectrum of user, including individual drivers and vehicle owners, as well as large-scale fleet managers.

In a wider sense, the project is relevant to the intelligent transportation systems (ITS), telematics and eco-driving technologies. It is in line with the global aspirations of environmental sustainability and smarter urban mobility because it provides a scalable, modular and data-driven solution. With fuel prices that tend to fluctuate and environment regulations becoming stricter, devices such as the one created in this project allow users to have the knowledge at their disposal to drive smarter and emit less.

In future, there are a number of improvements that can be made. Future integration of other data feeds like GPS, real-time traffic and weather conditions can also be used to increase the accuracy of predictions and situational awareness. This can be optimized with the deep learning

architecture such as LSTM or GRU architecture which could support time-series modeling of driving behaviour such that patterns are learned based on sequential behaviour. Additionally, this project may turn into an on-the-go assistant with real time implementation with edge devices such as Raspberry Pi or car infotainment system based on Android.

To conclude, the suggested system is an excellent prototype of the smart fuel analytics and classification of driving behavior. It gives fresh prospects of research, innovation and commercialization of the automotive business, which is beneficial both economically and environmentally. This project does present a strong base to the future of intelligent mobility solutions through the implementation of machine learning, and the use of current vehicle infrastructure, which can help acquire data more precisely and enhance the accuracy of its learning. Future studies might also focus on the implementation of nanomaterial-based sensors in vehicle systems to make future intelligent mobility solutions more accurate. The interface between nanomaterials, robotics and machine learning has great potential in the intelligent transport systems of the upcoming age.

BIBLIOGRAPHIC REFERENCES

1. Wadud P, MacKenzie D, Leiby P. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp Res Part A Policy Pract. 2016;86:1–18.

2. Kamble A, Gupta H, Trivedi A. A review on energy-efficient driving pattern classification and analysis using vehicle telematics data. IEEE Trans Intell Transp Syst. 2021;22(5):2563–74.

3. Iman A, Asadollah A, Bhatti MI. Fuel consumption estimation based on driving behavior using machine learning techniques. Sensors. 2021;21(5):1589–1601.

4. Araujo R, Portugal D, Nunes U. Data mining for driving styles: a computational approach. In: Proc IEEE Intell Veh Symp; 2010. p. 322–7.

5. Wang Y, Chen L, Ran B. A machine learning approach to detect aggressive driving behaviors using smartphone sensors. Transp Res Rec. 2019;2673(10):217–28.

6. Zheng H, Qin Y, Wang J, Wang C. Fuel consumption prediction model based on XGBoost algorithm and big data. J Adv Transp. 2020;2020:8873074.

7. Kuderer M, Gulati S, Burgard W. Learning driving styles for autonomous vehicles from demonstration. In: Proc IEEE Int Conf Robot Autom (ICRA); 2015. p. 2641–6.

8. Adnan R, Usman M, Arshad A. Driving style classification using machine learning techniques. Procedia Comput Sci. 2018;130:927–32.

9. Jeong J, Hwang J, Lee Y. Driving pattern analysis and classification using OBD-II data. In: Proc Int Conf Big Data Smart Comput (BigComp); 2016. p. 250–3.

10. Tanaka K, Tanabe M, Watanabe S. Fuel efficiency estimation using deep neural networks for eco-driving. IEEE Trans Intell Transp Syst. 2022;23(2):915–27.

11. Di Domenico D, De Nunzio G, Micheli SC. A data-driven approach to fuel consumption forecasting using multimodal information. Appl Energy. 2021;291:116790.

12. Kerner BS. Experimental features of traffic breakdown at highway bottlenecks. Phys Rev Lett. 1997;79(20):4030–3.

13. Lee SJ, Kim J, Ko YB. OBD-II data-based vehicle fuel consumption and CO_2 emission estimation using machine learning algorithms. IEEE Access. 2021;9:16188–98.

14. Naik S, Tiwari A. Deep learning approach for driving behavior classification and prediction. In: Proc IEEE Int Conf Artif Intell Comput Appl (ICAICA); 2020. p. 244–9.

15. Perrotta F, Parry T, Neves LC, Mesgarpour M. A machine learning approach for the estimation of fuel consumption related to road pavement rolling resistance. In: Proc IALCCE; 2018.

16. Wang Q, Zhang R, Wang Y, Lv S. Machine learning-based driving style identification of truck drivers in open-pit mines. Electronics. 2020;9(1).

17. Yao J, Moawad A. Estimating vehicle energy consumption through large-scale simulations and machine learning techniques. Transp Res Part C Emerg Technol. 2019;101:276–96.

18. Abukhalil T, et al. Fuel consumption using OBD-II and support vector machine model. J Robot. 2020;2020:1–9.

19. Perrotta F, Parry T, Neves LC. Machines for truck fuel consumption modeling. In: Proc IEEE Int Conf Big Data; 2017. p. 3810–5.

20. Bhat A, Yadav V, Dargan V, Yash. Sign language to text conversion using deep learning. In: Proc 3rd Int Conf Emerg Technol (INCET); 2022. p. 1–7. https://doi.org/10.1109/INCET54531.2022.9824885.

21. Duraisamy P, et al. Transforming sign language into text and speech through deep learning technologies. Indian J Sci Technol. 2023;16(45):4177–85. https://doi.org/10.17485/IJST/v16i45.2583.

22. Thakar S, et al. Sign language to text conversion in real time using transfer learning. arXiv. 2022:2211.14446. https://doi.org/10.48550/arXiv.2211.14446.

23. Seviappan A, et al. Sign language to text conversion using RNN-LSTM. In: Proc ICDSAAI; 2023. p. 1–6. https://doi.org/10.1109/ICDSAAI59313.2023.10452617.

24. Shekhar S. Real-time conversion of sign language to text using deep learning models. In: Proc ICONAT; 2024. p. 1–7. https://doi.org/10.1109/ICONAT61936.2024.10774717.

25. Wang Z, et al. Hear sign language: a real-time end-to-end sign language recognition system. IEEE Trans Mob Comput. 2022;21(7):2398–410. https://doi.org/10.1109/TMC.2020.3038303.

26. Kulkarni M, Naglot D. Real-time sign language recognition using the Leap Motion controller. In: Proc ICICT; 2016. p. 1–5. https://doi.org/10.1109/INVENTIVE.2016.7830097.

27. J P, et al. Real-time hand sign language translation: text and speech conversion. In: Proc ICCPCT; 2024. p. 488–93. https://doi.org/10.1109/ICCPCT61902.2024.10673038.

28. Sudhakaran P, et al. Converting voice signal to visual Indian sign language. In: Proc ICONSTEM; 2024. p. 1–6. https://doi.org/10.1109/ICONSTEM60960.2024.10568884.

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None.

AUTHORSHIP CONTRIBUTION

Conceptualization: Deepthi P, M.Nithya, P.Mounika, K.Mourya, P.Mano Vardhan Reddy, Christo Ananth.

Data curation: Deepthi P, M.Nithya, P.Mounika, K.Mourya, P.ManoVardhanReddy, Christo Ananth.

Formal analysis: Deepthi P, M.Nithya, P.Mounika, K.Mourya, P.ManoVardhanReddy, Christo Ananth.

Drafting - original draft: Deepthi P, M.Nithya, P.Mounika, K.Mourya, P.ManoVardhanReddy, Christo Ananth.

Writing - proofreading and editing: Deepthi P, M.Nithya, P.Mounika, K.Mourya, P.ManoVardhanReddy, Christo Ananth.

Additional Information

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