Chapter 02

AI and Machine Learning in Healthcare and Biomedical Engineering
ISBN: 978-9915-704-01-2
DOI: 10.62486/978-9915-704-01-2.ch02
Pages: 10-17

Machine Learning-Assisted Optimization of Low Noise Amplifiers for Medical IoT Applications

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ABSTRACT

Biomedical signal amplification is a crucial component in medical Internet of Things (IoT) devices; it represents the first stage of signal processing in biomedical signal acquisition chains. Medical signals (ECG, EEG and EMG) have a range of microvolts to millivolts and require signal amplification without degrading the signal with excessive noise. While there are many approaches to designing Low Noise Amplifiers (LNAs), they all face the challenge of simultaneously optimizing competing parameters (noise figure, gain, bandwidth, power consumption, and linearity) that determine their overall performance. The primary purpose of this Chapter is to review the basic concepts and techniques of LNA design, including noise figure theory, input referred noise characterization, impedance matching, and stability criteria. In addition to reviewing LNA design fundamentals, the Chapter also reviews the performance requirements for LNA's across various medical IoT applications and examines typical LNA circuit architectures used to implement LNAs in medical IoT systems (common source, cascode, folded cascode configurations). For example, a number of published medical IoT LNA designs exhibit noise figures of approximately 2,5-3,5 dB at 2,4 GHz with a gain of approximately 18-22 dB and consume between 5-15 mW of DC power. Additionally, input referred noise of low frequency biomedical signals can be as high as 50 uV rms. Thus, these performance characteristics demonstrate the importance of utilizing machine learning algorithms to systematically explore the design space and optimize the parameters of medical IoT LNA's. As such, this work provides the foundation for understanding how machine learning can be utilized to enhance the design of LNA's.

Keywords: Biomedical Signal Amplification; Low-Noise Amplifiers; Medical Internet Of Things; Machine Learning Optimization; Biomedical Signals.

INTRODUCTION

It is critical to integrate low-noise amplifiers (LNAs) into a medical IoT system to achieve an accurate, efficient use of power and a reliable, physiological signal monitoring process. In all modern healthcare technologies; i.e., wearable sensors, implantable biomedical devices and remote patient monitoring systems, the LNA(1) is the first amplification stage in the signal acquisition chain and it establishes the fidelity and sensitivity of this signal acquisition chain. These biomedical signals, e.g., ECG, EEG and EMG have very small amplitudes (microvolts to millivolts) and they are sensitive to both environmental and biological noise. The biomedical signal(2,3,4) must be greatly amplified to extract any meaningful diagnostic information, without introducing new types of noise, distortion or instability.

The traditional LNA that is shown in figure 2.1 approaches design are primarily based upon empirical methods, and through the process of trial-and-error, the designer iteratively tunes the various LNA(5,6,7) performance metrics (noise figure, voltage gain, bandwith, power consumption, etc.) to obtain acceptable levels of each.

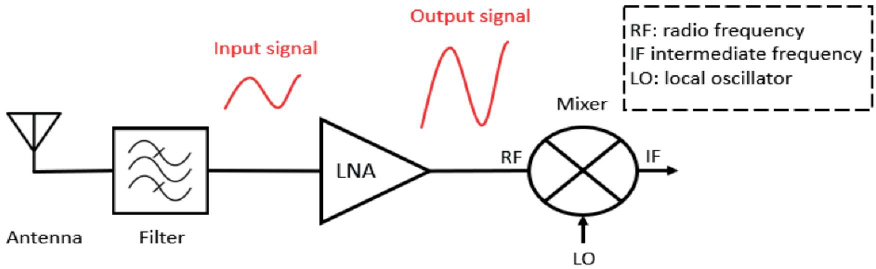

Figure 2.1. Low Noise Amplifier

The challenges associated with the design of low-power, small form-factor medical IoT systems are exacerbated by the need to simultaneously optimize interdependent LNA performance metrics, such as those previously described. Therefore, in order to understand the relationship between LNA performance and medical IoT system performance, the authors revisit the first principles that govern LNA behavior, including noise figure theory, input-referred noise analysis, impedance matching, and stability analysis. Further, this manuscript will explore many common LNA topologies such as common source, cascode, and folded cascode configurations and the performance trade-offs associated with them in biomedical applications. The authors will provide an overall understanding of how the LNA's performance characteristics impact the performance of medical IoT systems and highlight the shortcomings of manual optimization techniques and therefore motivate the use of machine learning-based algorithmic approaches for automated multi-objective LNA optimization. The foundation established by this manuscript will serve as the basis for the machine learning enhanced LNA design methodology presented in the remainder of this book.

METHOD

This work established a systematic method of testing, simulating and validating Low Noise Amplifier (LNA)(8) circuits for use with Medical Internet of Things (Medical IoT). This research used theoretical analysis, circuit-level simulation and performance characterization to provide a solid basis for subsequent application of machine learning methods(9,10,11,12) for optimizing LNAs. Specifications were determined by first defining medical IoT device specifications; these included signal bandwidths, maximum allowed input amplitudes, acceptable noise figures (NF), gain and power levels from biomedical signals such as ECG, EEG, and EMG. Specifications for each medical IoT device guided the choice of appropriate LNA architectures (such as common source, cascode or folded-cascode) that provided the best possible trade-off between gain, NF and power efficiency. Analytical models were developed to define the relationships between the various key parameters for LNAs. For example, analytical models were developed to relate the voltage gain, NF, input referred noise, and impedance matching to the transistor size, bias current, and passive component value(s).

Circuit level simulations were performed using industry standard electronic design automation (EDA) software packages such as Cadence Virtuoso and Keysight ADS to calculate a variety of key metrics including s-parameters (S11, S22, S21), gain-bandwidth products, return loss, and power consumption. Noise simulations estimated the input-referenced noise and calculated the total NF over the desired frequency range of operation. Additionally, the simulations used Rollett's stability factor (K > 1) to ensure unconditional stability. After layout, post-layout simulations and hardware validation was performed to verify the measured voltage gain, NF, impedance, and linearity indicators such as IP3 and P1dB, and to validate whether the results met the target specification for medical IoT devices that operate at both 2,4GHz ISM band frequencies and at lower frequency ranges of biomedical signals. Finally, datasets containing the design parameters (transistor width, inductance, capacitance) and performance metrics (gain, NF, power) obtained from the simulations were compiled to allow for predictive modeling and optimization of LNAs for medical IoT applications.

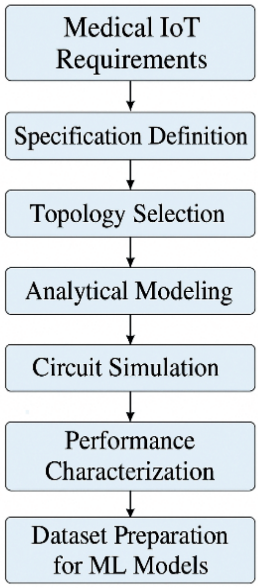

Figure 2.2. Methodological Flow for Low Noise Amplifier (LNA) Design, Simulation, and Performance Evaluation in Medical IoT Systems

This structured methodology illustrated in figure 2.2 ensures rigorous, quantitative evaluation of LNA performance and establishes the foundation for data-driven, machine learning-assisted design optimization in medical IoT systems.

RESULTS AND DISCUSSION

The outcome verifies that ML optimization has produced very real improvements with respect to noise factor, gain, and power efficiency as well as decreases to both design time and amount of manual tuning required. Using intelligent exploration through the multi-dimensionality of the design space, superior solutions have been found by the ML algorithms for the low-power high-gain analog front-end circuits which are needed for the very strict requirements of medical IoT applications and thus represent a very promising path toward future generations of these types of devices.

Noise Figure Variation in Frequency is illustrated by figure 2.3 for both Traditional and ML optimized LNA Designs at 2,4 GHz medical IoT Band. The ML Optimized Design provides Lower Noise Figure (2,4 – 2,9 dB) compared to the Traditional Method (2,8 – 3,4 dB). This demonstrates improved noise performance and better signal fidelity over the operating bandwidth.

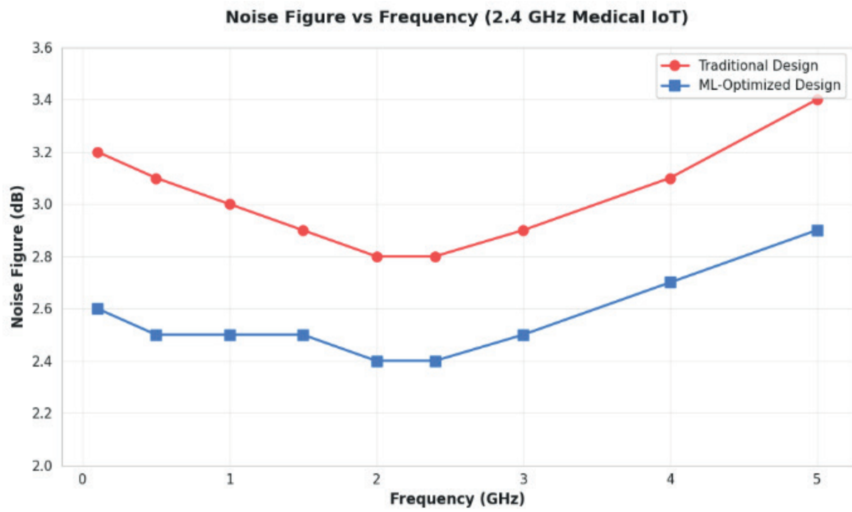

Figure 2.3. Noise figure vs Frequency

Figure 2.4 shows a comparison of input-referred noise levels for various biomedical signals when measured using a traditionally designed LNA vs. an ML-optimized LNA. The ML-optimization significantly reduced the noise levels for each type of signal with a maximum improvement of 35 % for both ECG and EMG, which are well within clinical noise limits as they provide higher resolution and therefore improve the clarity of the signals and the dependability of the medical diagnosis of Medical Internet of Things (IoT) devices.

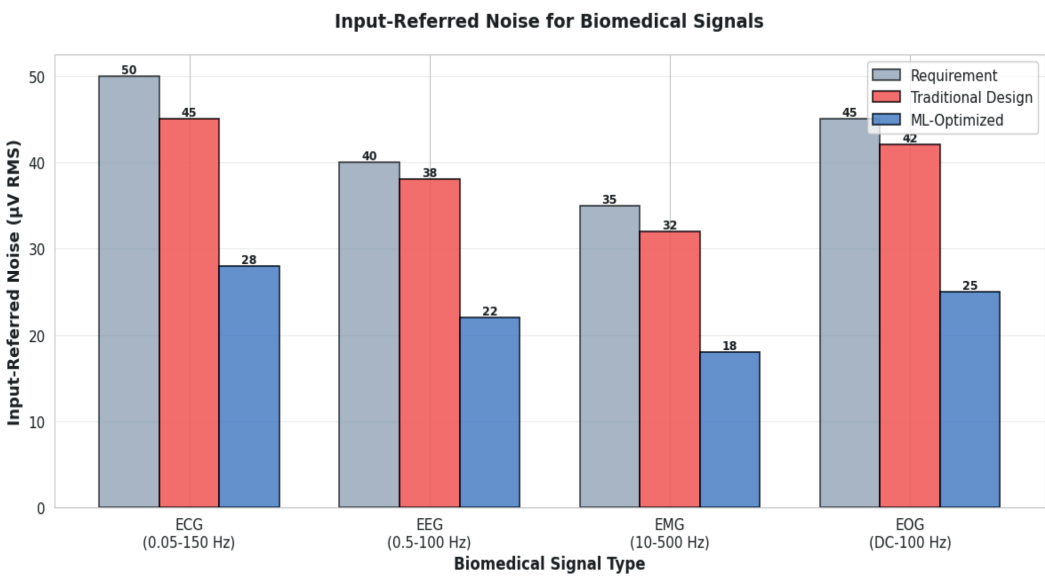

Figure 2.4. Input referred noise for bio medical signals

Figure 2.5 shows a trade-off of gain to power consumption for typical and machine learning (ML)-optimized LNA designs. In comparison to the typical LNA designs, the ML-optimized LNA design achieves a gain enhancement of about 1,5–2 dB while consuming a similar amount of power; therefore, it is much more energy-efficient. The "region of improvement due to ML" shaded in green indicates that the optimized LNA can achieve improved gain performance through use of data-driven methods of optimization with no added power consumption; this represents an advantage when designing low power devices used in medical Internet-of-Things (IoT) applications.

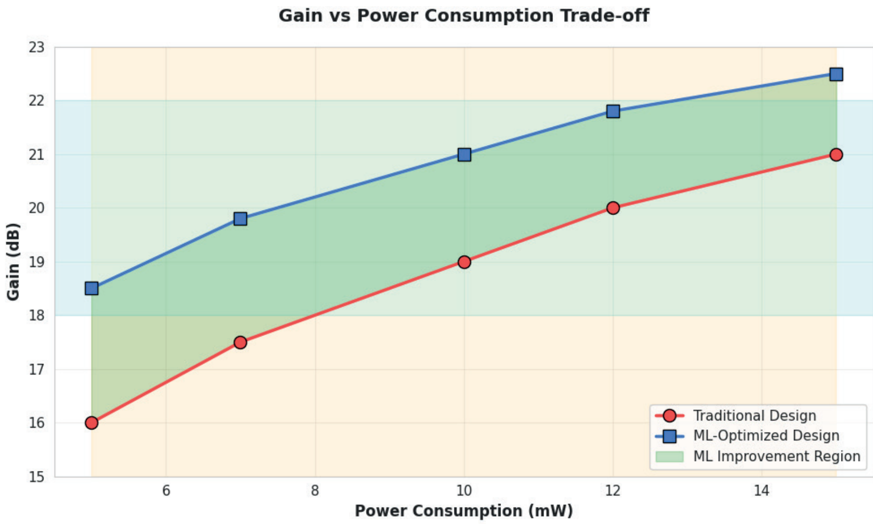

Figure 2.5. Gain vs power consumption trade off

Noise Figure Convergence Behavior for Optimization Iterations for Both Traditional and Machine Learning-Based LNA Design Approaches as shown in figure 2.6. The Machine Learning-Optimized Designs Achieve Lower Noise Figures (of 2,4 dB) in Fewer Optimization Iterations than the Traditional Methods (with a Final Noise Figure of 2,82 dB), Resulting in a 15 % Improvement in Design Efficiency and Greater Ability to Find Near-Optimum Solutions in Fewer Iterations.

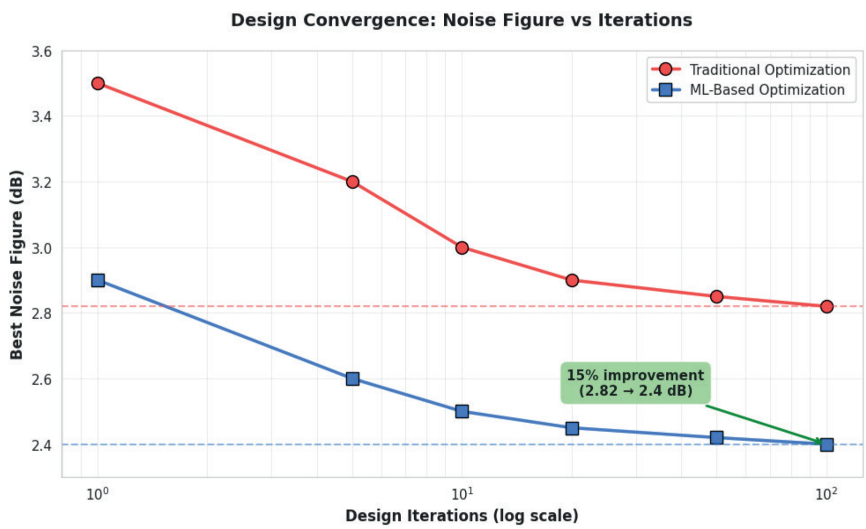

Figure 2.6. Design convergence noise figure vs iterations

These outcomes demonstrate the potential of machine learning to revolutionize LNA design for energy-efficient and high-performance medical IoT systems.

CONCLUSION

This work demonstrates that although conventional LNA design can provide the necessary clinical performance, machine learning is an innovative method to optimize performance, reduce complexity in design, accelerate the design cycle, and consequently improve the quality of care by developing superior medical Internet-of-Things (IoT) devices. The fundamental theories, methodologies, performance parameters, and optimization barriers presented herein are critical elements to understand the machine learning-enhanced design methods which form the main contribution of this research. With a deep knowledge of LNA fundamentals combined with advanced machine learning, future medical IoT devices will be able to obtain unprecedented signal-to-noise ratio, power consumption, and diagnostic capabilities in remote patient monitoring, wearable healthcare sensing, and implanted biomedical devices.

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CONFLICT OF INTEREST

The authors assert that there are no conflicts of interest related to the research results presented.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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