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AI/ML applications in RF design: PA linearization, spectrum sensing, and component modeling

Abstract

Recent advances in artificial intelligence (AI) and machine learning (ML) are transforming radio frequency (RF) design and system optimization. This paper reviews key applications of AI/ML techniques in three critical RF domains: power amplifier (PA) linearization, spectrum sensing, and passive component modeling. These applications demonstrate the ability of data-driven models to enhance performance, reduce design complexity, and enable adaptive behavior in real-time RF systems.

Keywords: data-driven models, system optimization, AI, ML, memory polynomial, neural networks

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Abbreviations: AI, artificial intelligence; ML, machine learning; RF, radio frequency; PA, power amplifier; DPD, digital predistortion; LSTM, long short-term memory; CNNs, convolutional neural networks; ACPR, adjacent channel power ratio; EVM, error vector magnitude; SNR, signal-tonoise ratios; SVR, support vector regression; EM, electromagnetic

Introduction

Power amplifier linearization with AI

Modern wireless transmitters require highly linear PAs to reduce spectral regrowth and comply with emission standards. Digital predistortion (DPD) is widely used to correct the PA's nonlinearity, but traditional polynomial-based models such as memory polynomial or Volterra models are limited in handling long memory effects and dynamic nonlinearities. Machine learning models, especially long short-term memory (LSTM) and convolutional neural networks (CNNs), have shown significant promise in learning the inverse behavior of PAs from measured input-output data.[1] These models are capable of capturing complex dynamic distortions with high accuracy, improving adjacent channel power ratio (ACPR) and error vector magnitude (EVM) compared to conventional DPD methods.[2–4]

Figure 1 shows a DPD architecture where an LSTM-based neural network is trained to minimize distortion across a wide frequency band. Such methods are particularly useful in 5G NR transmitters operating under varying signal bandwidths. Recent studies have expanded on this using CatBoost optimization,[2] phase-normalized neural networks,[3] and complex-valued modeling techniques.[4]

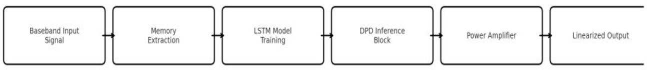

Figure 1 LSTM-based DPD for PA Linearization.

Spectrum sensing using deep learning

Spectrum sensing is essential for dynamic spectrum access in cognitive radios. Traditional methods such as energy detection or matched filtering are ineffective under low signal-tonoise ratios (SNR) or channel fading. Deep learning models, particularly CNNs, have been successfully applied to classify modulated signals and detect spectrum occupancy from raw I/Q data or spectrograms.[10] These models learn spectral patterns from training data and generalize to unseen wireless environments. In addition, recurrent neural networks (RNNs) such as LSTMs have been used to capture temporal dependencies in signal structures.

Figure 2 illustrates a CNN-based spectrum sensing block, which outperforms traditional detectors in terms of detection probability and false alarm rate under challenging channel conditions. Such approaches are critical in applications like 6G spectrum sharing, radar coexistence, and interference avoidance. Recent CNN-based methods,[5] hybrid waveletdeep learning models,[6] and spectrum prediction reviews[7] have further advanced this domain.

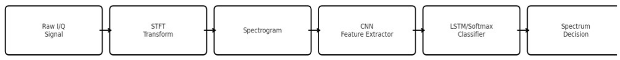

Figure 2 Deep Learning-Based Spectrum Sensing.

Component modeling using regression & ML

Accurate modeling of passive and active RF components is crucial for system-level simulation and co-design. Traditional equivalent circuit modeling requires expert intervention and may not scale across process or temperature variations. Data-driven regression models offer an automated alternative to predict performance metrics such as Sparameters, impedance, and Q-factor under varying conditions. Support vector regression (SVR), gradient boosting, and Gaussian process regression have been used to replace slow electromagnetic (EM) simulations in tasks like capacitor array tuning, spiral inductor modeling, or via stub impedance estimation.

Figure 3 shows a regression-based modeling pipeline that takes EM-simulated data and trains a compact surrogate model for capacitor networks. This dramatically reduces simulation time while maintaining high accuracy, enabling rapid design iterations. Recent benchmarks using transformers and surrogate modeling[8,9] demonstrate sub-1% error and rapid optimization capabilities.

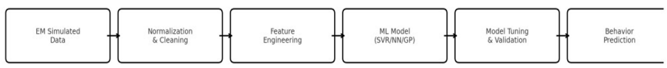

Figure 3 ML Pipeline for RF Component Modeling.

Conclusion

AI/ML models are emerging as vital tools in the RF design toolbox. Applications in PA linearization, spectrum sensing, and component modeling show that these approaches provide not only performance benefits but also accelerate design cycles. As data availability increases and computing power scales, more RF functions will shift toward AI-assisted or AI-native implementations. Integrating ML models into design flows, chipsets, and test setups is a key step toward intelligent RF systems.

Acknowledgments

None.

Conflicts of interest

The author declares there is no conflict of interest.

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