

# End-to-End Deep Learning Linearization for RF Power Amplifier Modules

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**Abstract**—Power Amplifiers (PAs) in modern wideband wireless systems inherently exhibit severe nonlinear distortion and dynamic memory effects, which degrade signal integrity and induce spectral regrowth. While Digital Predistortion (DPD) is the standard linearization technique, conventional Memory Polynomial (MP) models often face accuracy limitations when addressing highly nonlinear systems. To address these challenges, this paper proposes a high-performance DPD model based on Deep Learning (DL). Distinct from traditional segmented extraction methods, this study adopts a holistic, end-to-end modeling strategy that treats the entire cascaded amplification network—including power distribution and parallel PA arrays—as a unified nonlinear system. A Deep Neural Network (DNN) architecture is employed to accurately learn the inverse nonlinear characteristics of the system. Experimental results demonstrate that the proposed method significantly suppresses adjacent channel interference and linearizes AM-AM and AM-PM responses. Quantitatively, the proposed model achieves a Normalized Mean Squared Error (NMSE) of  $-32.04$  dB, substantially outperforming the  $-19.59$  dB benchmark of the traditional MP model.

## I. INTRODUCTION

HIGH-EFFICIENCY Power Amplifiers (PAs) in modern wireless systems inevitably suffer from severe nonlinear distortion and memory effects, which degrade signal integrity and induce spectral regrowth. While Digital Predistortion (DPD) is the standard solution, conventional behavioral models, such as the Memory Polynomial (MP) model, often struggle to balance modeling accuracy with computational complexity in highly nonlinear regimes due to the exponential growth of coefficients [1]. To address these limitations, this paper proposes a high-performance DPD scheme based on Deep Neural Networks (DNN). We introduce a holistic "whole module" modeling strategy that treats the entire cascaded RF amplification chain as a unified system for end-to-end training. Experimental results demonstrate that this approach achieves a Normalized Mean Squared Error (NMSE) of  $-32.04$  dB, significantly outperforming traditional polynomial-based methods.

## II. SYSTEM MODELING AND METHODOLOGY

### A. Validation System Architecture

A forward DPD validation system was constructed to emulate a high-power RF transmission chain, as shown in Fig. 1. The system comprises a signal source, DPD module, power distribution network, parallel PA array, and a power combiner. A critical innovation of this study is the adoption of a holistic "end-to-end" modeling strategy. Instead of extracting coefficients from individual components—which risks error

propagation—we treat the entire analog link (from divider input to combiner output) as a unified nonlinear system. This approach captures the aggregate nonlinear behavior of the complete chain, ensuring superior modeling fidelity compared to segmented extraction methods.

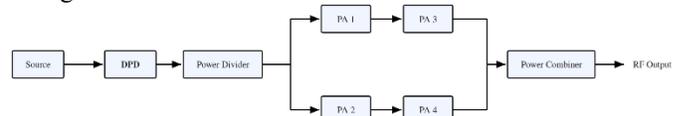


Fig. 1. Block diagram of the forward DPD validation system employing a holistic modeling strategy.

### B. DPD Principle and Memory Polynomial Model

To establish a performance baseline, the Generalized Memory Polynomial (MP) model is employed. This standard behavioral model approximates the PA output using a superposition of polynomial terms and delay taps to capture both instantaneous nonlinearity and memory effects. It serves as the benchmark for evaluating the linearization efficiency of the proposed method.

### C. Deep Learning-Based DPD Model

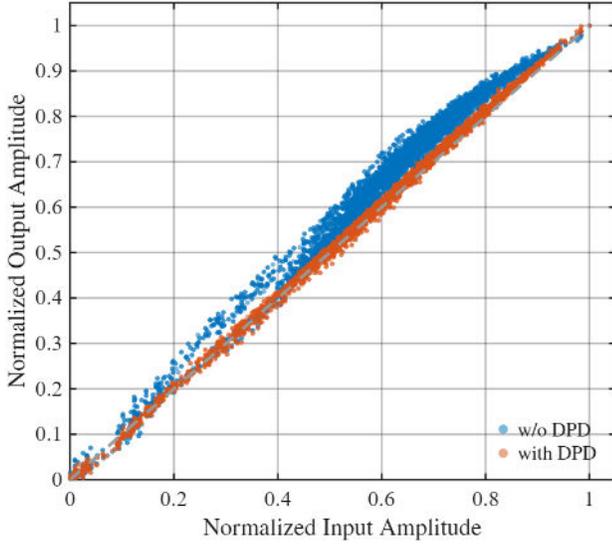
To overcome the accuracy limitations of polynomial-based models in highly nonlinear regimes, this paper proposes a DPD model based on a Deep Neural Network (DNN). The DNN architecture is designed to accurately map the nonlinear inverse response of the PA system. In this framework, the complex baseband signals extracted from the holistic system are decomposed into their In-phase (I) and Quadrature (Q) components to serve as input features. The network architecture comprises an input layer, multiple hidden layers equipped with nonlinear activation functions to capture complex distortion characteristics, and an output layer. The model is trained using a supervised learning approach, employing an optimization algorithm to minimize the loss function, which is defined as the Normalized Mean Squared Error (NMSE) between the predicted pre-distorted output and the ideal linear reference. Through this iterative process, the network weights are optimized to effectively minimize spectral regrowth and linearize both AM-AM and AM-PM responses [2].

## III. RESULTS

### A. Linearization Performance Analysis

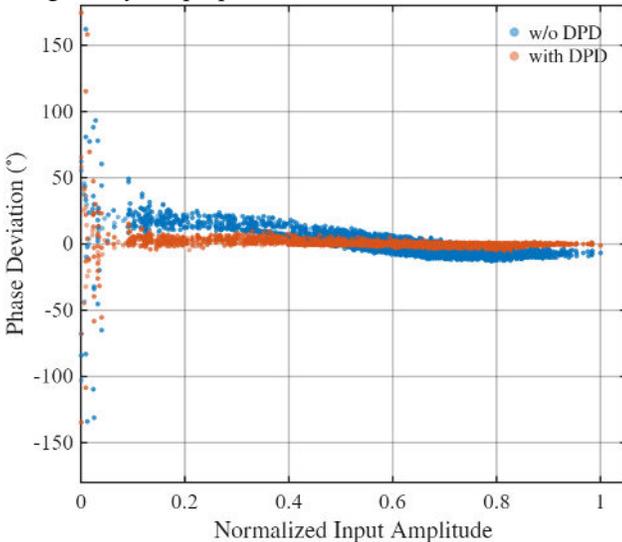
To comprehensively assess the linearization efficacy of the proposed Deep Learning-based model, we first conducted a rigorous time-domain analysis focusing on the Power Amplifier's static nonlinear characteristics. Specifically, the Amplitude-to-Amplitude (AM-AM) and Amplitude-to-Phase

(AM-PM) conversion responses were examined to evaluate the model's ability to compensate for gain compression and phase distortion across the full dynamic range.



**Fig. 2.** Comparison of AM-AM response before and after DPD application.

As illustrated in Fig. 2, the AM-AM conversion characteristics highlight the system's amplitude linearity. The uncompensated response exhibits severe gain compression and nonlinear scattering, particularly as the input drive level approaches the saturation region. In contrast, applying the proposed Deep Learning-based DPD results in a linearized trajectory that converges closely to the ideal linear reference. This alignment confirms that the inherent nonlinearity has been effectively mitigated by the proposed model.



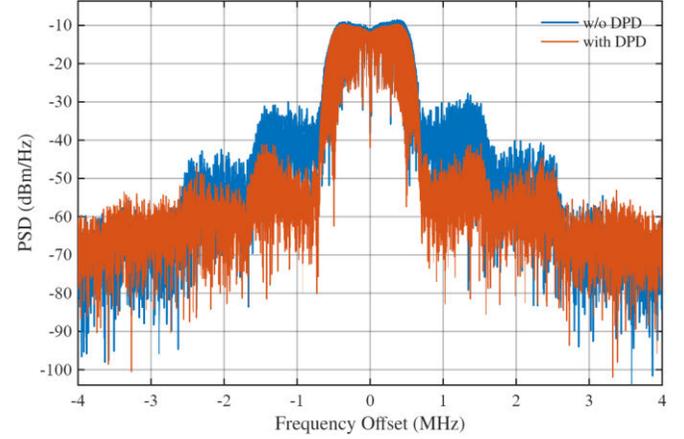
**Fig. 3.** Comparison of AM-PM response before and after DPD application.

As depicted in Fig. 3, the AM-PM response characterizes the phase distortion induced by the PA. The uncompensated system exhibits a diverging phase deviation across varying power levels. Conversely, the output processed by the proposed DPD

model demonstrates successful correction of this distortion, with the phase error compressed towards zero degrees throughout the entire dynamic range.

### B. Frequency Domain Analysis

To evaluate the suppression of out-of-band interference, the Power Spectral Density (PSD) of the output signal was analyzed. Fig. 4 compares the output spectra with and without linearization.



**Fig. 4.** Power Spectral Density (PSD) of the output signal with and without DPD.

The spectrum without DPD displays severe spectral regrowth, characterized by high side-lobes that would cause adjacent channel interference. Upon applying the proposed DPD, the spectral regrowth is significantly suppressed. The linearized spectrum exhibits a sharp, vertical roll-off, closely resembling the ideal linear amplification requirements and demonstrating a substantial reduction in intermodulation distortion.

## IV. CONCLUSION

This work validates a robust Digital Predistortion (DPD) scheme based on Deep Neural Networks (DNN) employing a novel holistic modeling strategy. By treating the entire cascaded RF link as a unified system for data extraction, the proposed method significantly outperforms conventional approaches. Experimental results confirm effective linearization of AM-AM and AM-PM responses and suppression of spectral regrowth. Quantitatively, the model achieves a Normalized Mean Squared Error (NMSE) of -32.04 dB, a substantial improvement over the -19.60 dB baseline of the Memory Polynomial model. These findings underscore the superior efficacy of integrating deep learning algorithms with end-to-end circuit modeling for modern RF front-end linearization.

## REFERENCES

- [1] T. Liu et al., "Digital Predistortion Linearization with Deep Neural Networks for 5G Power Amplifiers," in 2019 European Microwave Conference in Central Europe (EuMCE), Prague, Czech Republic, 2019, pp. 216-219.
- [2] B. Gong et al., "Dual-Block Learning: A Frequency-Based Method for Accuracy Optimization in Wideband PA Linearization," in 2024 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB), Toronto, ON, Canada, 2024, pp. 1-6.