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# Digital Predistortion Behavioral Modeling of Power Amplifiers: A Neural Network-Based Approach to Nonlinearity Compensation

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***Abstract*—This paper introduces a novel digital predistortion (DPD) algorithm created with a neural network (NN) framework to mitigate nonlinear distortions in GaN HEMT power amplifiers (PAs). The neural network-based method is based on a polynomial model, refined to accurately represent the dynamic AM-AM and AM-PM distortions that occur when the PA processes quadrature phase-shift keying (QPSK) modulated signals. A principal characteristic of the model is the integration of distinct subsystems for each memory node, allowing it to adjust the quantity of output nodes in accordance with the time-varying attributes of the input signal. The proposed method exhibits significant enhancements in adjacent channel power ratio (ACPR) and error vector magnitude (EVM) when compared to conventional and advanced neural network-based DPD techniques. It attains a reduction of over 7 dB in EVM and improves ACPR by 3 dB relative to the generalized memory polynomial (GMP) model, a commonly employed conventional method. Furthermore, the architecture achieves lower computational complexity than other deep learning-based DPD methods, while being approximately 1.5 times as sophisticated as the GMP approach.**

***Index Terms*—Digital prediditortion (DPD), generalized memory polynomial (GMP), neural network (NN), power amplifier (PA).**

## I. Introduction

In mobile communication, achieving high linearity and efficiency in power amplifiers (PAs) is essential to meet the stringent requirements imposed by modern modulation schemes and improve spectrum efficiency [1]–[4]. These systems require enhanced data transmission rates, expanded bandwidths, and greater spectral efficiency, driving the adoption of advanced modulation techniques like quadrature amplitude modulation (QAM) and orthogonal frequency-division multiplexing (OFDM). However, PAs, especially at higher power levels, tend to introduce significant nonlinearities that degrade system performance, especially regarding adjacent channel power ratio (ACPR), error vector magnitude (EVM), and spectrum regrowth [5]–[7].

Among the various PA technologies, Gallium Nitride (GaN) high electron mobility transistors (HEMT) have emerged as a leading solution for RF power amplification due to their high power density, wide bandwidth, high breakdown voltage, and superior efficiency compared to traditional silicon-based devices [8]–[10]. GaN HEMT technology enables PAs to deliver high output power while maintaining efficiency, making it ideal for 5G applications. However, GaN-based amplifiers exhibit significant nonlinearities, particularly at high output power levels, resulting in undesirable signal distortions such as amplitude modulation to phase modulation (AM-PM) and amplitude modulation to amplitude modulation (AM-AM) conversions [6], [11]. The nonlinear phenomena distort the signal, significantly elevating the adjacent channel leakage ratio (ACLR) and overall signal distortion. Therefore, these effects must be mitigated to preserve the quality of communication.

One of the most effective methods for compensating for these nonlinearities is DPD, which pre-distorts the input signal to cancel out the nonlinear effects of the PA. Conventional DPD methods, such as the generalized memory polynomial (GMP) model, offer a balance between modeling accuracy and computational complexity. The GMP model effectively captures static and dynamic nonlinearities but struggles with complex dynamic memory effects common in modern wide-band communication systems [12]–[14]. As communication systems operate with wider bandwidths and higher carrier frequencies, these memory effects become more pronounced, and simple polynomial-based models fail to provide sufficient accuracy.

In recent years, NN-based DPD techniques have gained traction due to their ability to model highly sophisticated, nonlinear, and dynamic behaviors in RF PAs. NNs have the advantage of being able to approximate any continuous function, making them highly flexible and adaptable for nonlinear systems like PAs. By leveraging NNs, it is possible to build models that capture both static and dynamic nonlinearities, accounting for memory effects in the system. NN-based DPDs can significantly improve the compensation of AM-AP and AM-AM distortions, reducing EVM and ACLR. Notwithstanding their potential, numerous current NN-based DPD models experience significant computational complexity owing to the extensive number of parameters and layers necessary for

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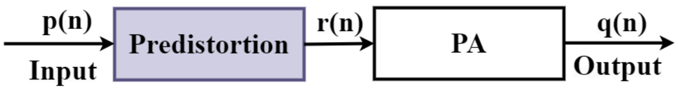


Fig. 1. Fundamental DPD.

precise modeling of nonlinearities [14], [15]. This complexity frequently constrains their practical application, especially in real-time scenarios with restricted computational resources, and low-latency signal processing is essential.

To tackle these challenges, our research presents a neural network-based DPD model characterized by optimized complexity and enhanced performance. The model employs a streamlined architecture while preserving the capacity to capture sophisticated nonlinearities and memory effects. Utilizing an innovative neural network architecture with optimized parameters, we diminish the computational burden while preserving high accuracy in linearization. This method is appropriate for wideband PA's functioning at elevated frequencies, specifically those utilizing GaN HEMT technology. Furthermore, our model employs DPD techniques to alleviate nonlinearities without augmenting hardware complexity, rendering it scalable for next-generation wireless systems, including 5G and beyond.

This paper introduces an innovative neural network-based DPD architecture designed to enhance linearization performance while reducing computational complexity, as illustrated in Fig. 1. The architecture employs an analytical polynomial model, utilizing distinct sub-systems for each memory node, thereby permitting adaptable configurations for different memory lengths. The model is designed to precisely represent the dynamic AM-PM and AM-AM characteristics of GaN HEMT PAs utilizing quadrature phase-shift keying (QPSK) modulated signals. The document is organized as follows: Section II addresses the formulation of the problem and traditional DPD methodologies. Section III delineates the proposed neural network-based DPD architecture. Section IV delineates the data generation and training methodology. Section V delineates the modeling outcomes, while Section VI concludes with prospective directions.

## II. Experimental setup and system model

The models utilized in this work are developed for a GaN HEMT PA operating within the frequency range of 2.4 GHz. For this, we used baseband in-phase (I) and quadrature (Q) waveforms at the input and output of the device under test (DUT), which were obtained using a comprehensive experimental setup involving the generation and measurement of signals through vector network analyzers and signal generators. The DUT was characterized using two test signals: a 40 MHz OFDM signal and a 20 MHz QPSK-modulated signal as shown in Fig. 2. The carrier configuration for the OFDM signal involved selectively activating outer carriers while inner carriers remained off to induce strong memory effects within the PA due to the non-uniform power distribution across the bandwidth.

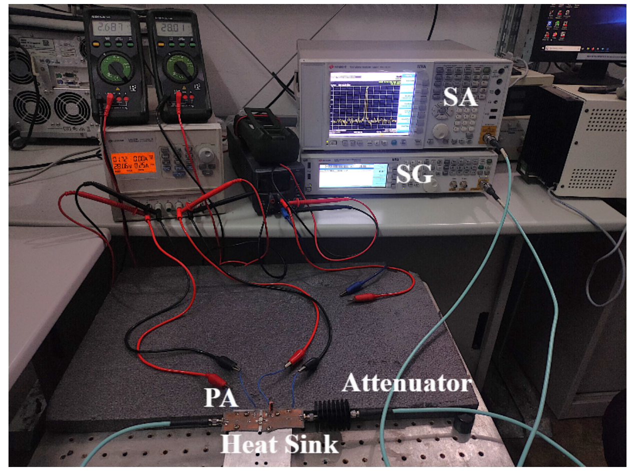


Fig. 2. Measurement setup for PA.

These test signals exhibited peak-to-average power ratios (PAPR) of 9.5 dB for the QPSK signal and 10.2 dB for the OFDM signal. The PA was characterized at an input power back-off equivalent to the PAPR of each test signal, ensuring that the input power reached but did not surpass the PA's saturation point. This setup enabled a comprehensive assessment of the nonlinear characteristics and memory effects of the PA under real-world communication signal conditions, validating the proposed DPD model [16].

Mathematical representation of the nonlinear behavior of a PA:

$$q(n) = f_{\text{PA}}(p(n)), \tag{1}$$

The function $f_{\text{PA}}$ signifies the nonlinear gain of the PA, whereas $p(n)$ indicates the input signal at a specific time $n$. In modern wireless communication systems, this nonlinearity results in undesirable signal distortions, encompassing fluctuations in both amplitude and phase, which adversely affect the transmitted signal and neighboring channels. A DPD function, $f_{\text{DPD}}(\cdot)$, is employed to rectify the nonlinear characteristics of the PA. The objective is to guarantee that the DPD and PA joint operation closely approximates a linear response. This relationship can be expressed mathematically as follows:

$$q_{\text{c}}(n) = f_{\text{PA}}(p(n);\theta)(f_{\text{DPD}}), \tag{2}$$

To optimize the parameters $\theta$ of the DPD model, we aim to minimize the discrepancy between the output $q_c(n)$ from the cascaded DPD and PA system and the target linear output $q_d(n) = Gp(n)$, where $G$ represents the PA's linear gain. This optimization reduces the nonlinear distortions inherent to the PA by closely aligning $q_c(n)$ with $q_d(n)$.

We analyze the nonlinearities by examining the PA's performance via AM-AM and AM-PM distortions. The AM-AM distortion defines the correlation between variations in output amplitude and input amplitude.

$$|q(n)| = f_{\text{AM-AM}}(|p(n)|), \tag{3}$$

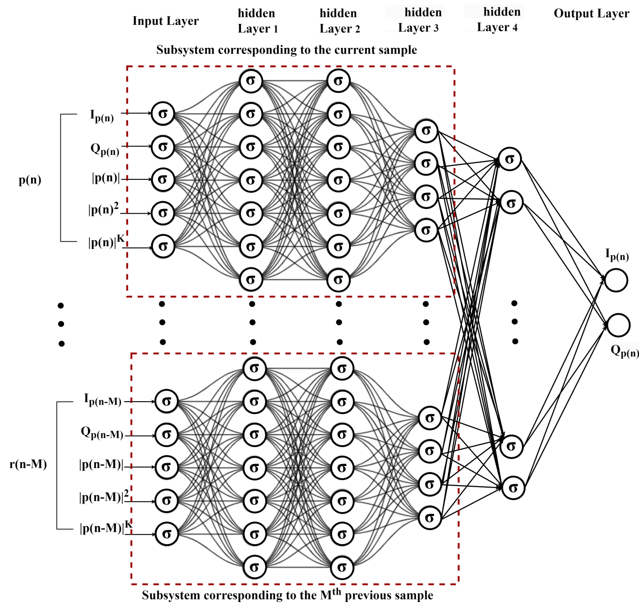


Fig. 3. Proposed DPD.

Where $|p(n)|$ and $|q(n)|$ are the amplitudes of the input and output signals, respectively. Similarly, the AM-PM distortion, which describes the phase shift induced by the PA, is expressed as:

$$\arg(q(n)) = \arg(p(n)) + f_{\text{AM-PM}}(|q(n)|), \tag{4}$$

where $\arg(p(n))$ and $\arg(q(n))$ represent the phases of the input and output signals, and $f_{\text{AM-PM}}(|q(n)|)$ represents the phase distortion function.

The interplay between AM-AM and AM-PM distortions underscores the intricate relationship between PA input and output signals. These distortions illustrate the influence of nonlinearities on the signal's amplitude and phase. A DPD model must effectively address both amplitude distortions and phase shifts induced by the power amplifier. By managing these distortions, the DPD can mitigate spectral regrowth and enhance signal integrity, ensuring compliance with regulatory emission standards while maintaining superior signal quality.

Additionally, the complexity of a NN-based DPD model is influenced by variables such as the number of layers ($L$), memory depth ($M$), and the order of nonlinearity ($P$). This dependency can be described as follows:

$$\text{Complexity}_{\text{NN}} \approx \mathcal{O}(L \cdot M \cdot P). \tag{5}$$

This equation illustrates the trade-off between model complexity and performance, indicating that although neural network-based dynamic programming decisions can attain reduced errors relative to polynomial-based models, their computational requirements are contingent upon the network's architecture and memory depth. As such, optimal configurations should be chosen to balance performance improvements with computation overhead, particularly when scaling to more sophisticated modulated signals or higher frequency ranges.

## III. Proposed DPD Model

Polynomial functions are widely employed in modeling PAs because they can analytically ascertain regenerated spectral components via polynomial coefficients. These functions enable the depiction of nonlinearities in power amplifiers by approximating the correlation between input and output signals. The baseband MP model is extensively utilized to address nonlinear behavior and memory effects in PAs. This model adeptly captures the dynamic response of PAs by integrating historical input values, rendering it highly suitable for analyzing devices with intricate memory effects and ensuring precise prediction of their spectral behavior.

$$r(n) = \sum_{k=0}^{K} \theta_k p(n)|p(n)|^k \tag{6}$$

Here, $K$ represents the highest order of non-linearity. From Equation (1), $r(n)$ is modeled as a nonlinear function of $p(n)$, expressed as a linear combination of $p(n)$ and $|p(n)|^k$. Although NNs can approximate this mapping, this approach typically requires sophisticated architectures with many parameters and layers. By simplifying the mapping to learn the relationship from $[p(n), |p(n)|, \ldots, |p(n)|^k]$ to $r(n)$, we can reduce the network's complexity. In practical PA scenarios, memory effects are common due to time delays, where the output depends on past input samples $p(n-m)$. To account for this, the DPD model must integrate these past samples.

The MP model [12] is a standard approach for designing DPD for nonlinear PAs with memory effects. The DPD output $r(n)$ can be represented as:

$$r(n) = \sum_{k=0}^{K} \sum_{m=0}^{M} \theta_{km} p(n-m)|p(n-m)|^k \tag{7}$$

In this equation, $M$ denotes the memory length. Eq.5 expands on the earlier model (Eq.7) by including multiple memory nodes. Inspired by the MP structure, we designed the NN with distinct sub-systems for each memory node $(p(n), p(n-1), \ldots, p(n-m))$. Each sub-system processes the input for a specific memory node, and the results are combined later, as shown in Fig. 3. This design helps the NN to model nonlinear memory effects effectively.

The MP model, incorporating a unity delay element denoted by $r^{-1}$, is frequently utilized to fit complex measurements of PAs. This model is expressed as:

$$V_{out}(n) = \sum_{q=0}^{Q} \sum_{k=1}^{K} \tilde{a}_{kq} \cdot V_{in}(n-q)^{2k-1} \tag{8}$$

Here, $\tilde{a}_{kq}$ represents the sophisticated MP coefficients, estimated through a simple least-squares method. The variables $q$, $Q$, and $K$ denote the memory interval and indicate the maximum memory and polynomial orders, respectively. $V_{\text{in}}(n)$ and $V_{\text{out}}(n)$ are the sophisticated input and output samples at the $n$-th time step.

**Algorithm 1** Neural Network-Based Digital Predistortion (NN-DPD)

**Inputs:** Training dataset $\{x_{\text{train}}(n), y_{\text{linear}}(n)\}$, Number of epochs $E$, Learning rate $\eta$, Regularization parameter $\lambda$
**Outputs:** Trained NN model
**Initialize:** NN weights and biases
**for** each epoch $e$ from 1 to $E$ **do**
  **for** each training sample $n$ **do**
    Perform forward pass:
$$\hat{x}_{\text{pred}}(n) = \text{NN}(x_{\text{train}}(n), x_{\text{train}}(n-1), \ldots, x_{\text{train}}(n-M))$$
    Compute prediction error:
$$\text{Error}(n) = y_{\text{linear}}(n) - \hat{x}_{\text{pred}}(n)$$
    Compute loss function:
$$\mathcal{L} = \frac{1}{N}\sum_{n=1}^{N}\left(|\text{Error}(n)|^2 + \lambda\|\theta\|^2\right)$$
  **end for**
  Perform backward pass and compute gradients
  Update network parameters:
$$\theta \leftarrow \theta - \eta \cdot \nabla_\theta \mathcal{L}$$
**end for**
Save the trained model
**for** each testing sample $n$ **do**
  Perform forward pass:
$$\hat{x}_{\text{pred}}(n) = \text{NN}(x_{\text{test}}(n), x_{\text{test}}(n-1), \ldots, x_{\text{test}}(n-M))$$
  Compute prediction error:
$$\text{Error}(n) = y_{\text{linear}}(n) - \hat{x}_{\text{pred}}(n)$$
**end for**
Compute Error EVM, ACPR
Report results: EVM, ACPR

$$F_q(n-q) = \sum_{k=1}^{K} \tilde{a}_{kq} \cdot V_{in}(n-q)^{2k-1} \tag{9}$$

$$V_{out}(n) = \sum_{q=0}^{Q} F_q(n-q) \tag{10}$$

Output is $V_{out}(n)$, this model accounts for both the instantaneous and past input signals, allowing it to capture the PA's nonlinear and memory effects accurately.

## IV. Data Generation and Training Mechanism

The proposed NN-based DPD system is designed to compensate for the nonlinearities of the PA. The data generation and training mechanism are critical in accurately modeling these nonlinear behaviors.

### A. Data Generation Process

A QPSK-modulated signal serves as the input for the PA, as it encompasses both AM-PM and AM-AM distortions. The input signal $x(n)$, supplied to the PA, generates the distorted output $y_{\text{PA}}(n)$. To address memory effects, the data is sampled at an elevated rate, producing input-output pairs $\{x(n), y_{\text{PA}}(n)\}$, which constitute the training set for the NN-DPD.

The PA model integrates MP effects, utilizing delayed nodes to signify the dynamic response of the PA. This configuration enables the training model to learn and rectify distortions more efficiently.

$$y(n) = \sum_{m=0}^{M} \sum_{p=1,3,5,\ldots}^{P} h_{m,p} \cdot x(n-m)|x(n-m)|^{p-1} \tag{11}$$

Where $y(n)$ is the PA output signal, $x(n-m)$ is the delayed input signal, $h_{m,p}$ are the coefficients, $M$ is the memory depth, and $P$ is the nonlinearity order.

The NN-based DPD modifies the input signal to ensure the output from the PA is linear. The predistorted input signal is given by:

$$\hat{x}(n) = \text{NN}\left(x(n), x(n-1), \ldots, x(n-M)\right) \tag{12}$$

Where $\hat{x}(n)$ is the predistorted input, $\text{NN}(\cdot)$ is the NN function, and $M$ is the memory depth.

### B. Training Mechanism

The proposed NN-DPD architecture consists of sub-systems that process memory nods independently, offering flexibility in handling varying memory lengths. The network is trained using a supervised learning approach. The loss function minimizes the difference between the desired linear output $y_{\text{linear}}(n)$ and the predistorted signal $\hat{x}_{\text{pred}}(n)$ as:

$$\mathcal{L} = \frac{1}{N}\sum_{n=1}^{N}\left(|\text{Error}(n)|^2 + \lambda\|\theta\|^2\right) \tag{13}$$

Where $\text{Error}(n) = y_{\text{linear}}(n) - \hat{x}_{\text{pred}}(n)$, and $\theta$ are the network parameters, with regularization to prevent overfitting. The network weights are optimized using gradient-based methods like Adam, adjusting the parameters $\theta$ for efficient convergence.

### C. Testing and Validation

The model's performance is assessed using a test dataset, with evaluation metrics comprising EVM and ACPR. The EVM measures the divergence of the actual signal from the ideal signal and is computed as:

$$\text{EVM} = \sqrt{\frac{\sum_{n=1}^{N}|\text{Error}(n)|^2}{\sum_{n=1}^{N}|y_{\text{linear}}(n)|^2}} \tag{14}$$

$$\text{ACPR} = 10\log_{10}\left(\frac{P_{\text{adjacent}}}{P_{\text{main}}}\right) \tag{15}$$

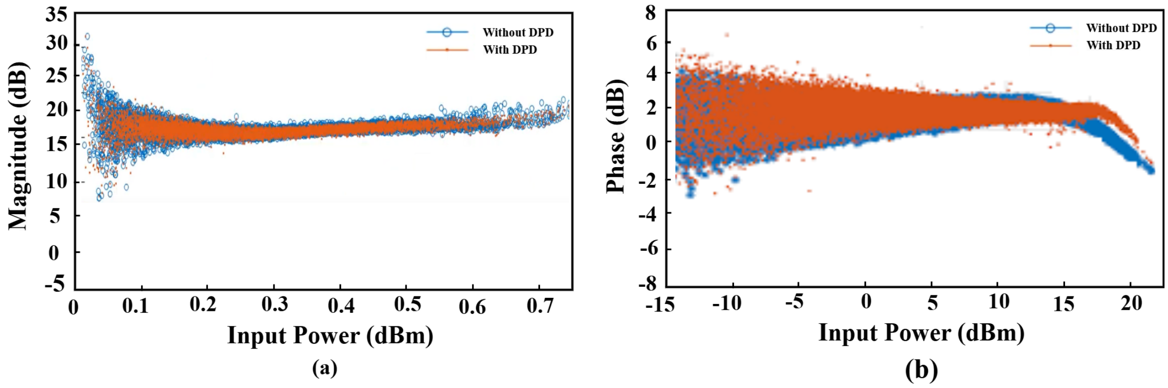


Fig. 4. (a) AM-AM Characteristics, (b) AM-PM Characteristics.

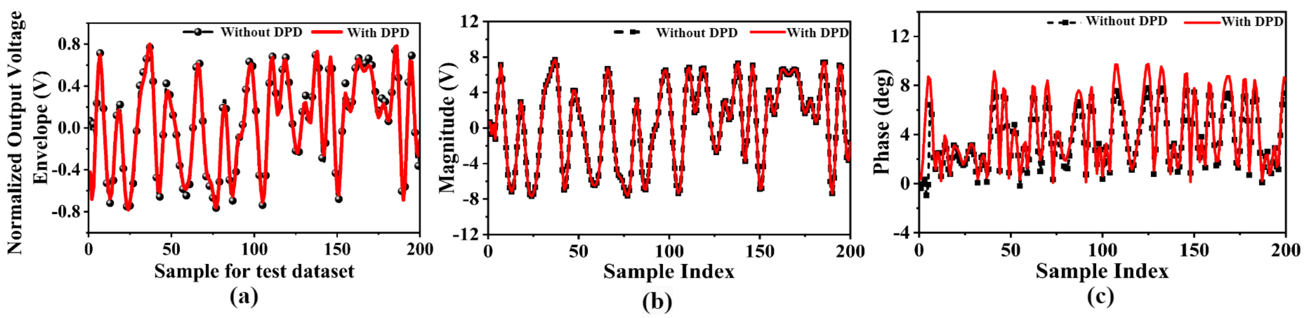


Fig. 5. Result of Without and With DPD (a) Normalized output voltage, (b) Magnitude Compared, (c) Phase Compared.

The model shows significant performance improvements with low complexity, making it ideal for real-time applications in wireless communications.

## V. Modeling Results of DPD

This section provides the modeling results for two PA models implemented using Advanced Design System (ADS) software: the Generalized GMP model and a NN-based model. The GMP model is characterized by a polynomial order of seven and a memory depth of five, designed to account for both the nonlinear behavior and memory effects present in the PA. On the other hand, the NN model is composed of five input neurons, seven hidden layer neurons, and two output neurons. This configuration aims to offer a more flexible and efficient representation of the PA's sophisticated behavior. The activation functions utilized include a linear transfer function for the input-output layers, while the hidden layers employ a hyperbolic tangent sigmoid function, which enhances the model's ability to handle nonlinearity more effectively.

For accurate representation of PAs with significant memory effects, using realistic stimulus signals is essential. Digitally modulated signals with non-constant envelopes, particularly those exhibiting higher PAPR, are highly effective in revealing the PA's nonlinear and memory effects. In this study, a QPSK signal with 19 dBm of power, a center frequency of 2.4 GHz, and a 50 MHz bandwidth was selected as the input signal. Roughly 6000 input-output data samples were gathered, providing a comprehensive dataset for training both the GMP and NN models. This dataset facilitated the accurate capture of the PA's dynamic AM-AM and AM-PM characteristics, as illustrated in Fig. 4. Table I compares various DPD techniques and shows that the NN achieves the best performance in terms of EVM, outperforming the others by a margin of 3.5 dB, with the proposed method ranking second. However, when evaluating ACPR, the proposed method demonstrates superior performance, surpassing all other techniques

TABLE I
ACPR and EVM of the Proposed DPD

| Ref. | ACPR (Without DPD) | ACPR (With DPD) | EVM (Without DPD) | EVM (With DPD) |
|---|---|---|---|---|
| [7] | -36.52 | -38.75 | -35.47 | -36.1 |
| [11] | -55.74 | -56 | - | - |
| **Our Work** | **-67.89** | **-69.9** | **-65.41** | **-66.23** |

The results indicate that both models demonstrate strong agreement with the measured data. The maximum modeling error between the measured and predicted data was $10^{-2}$ for the GMP model and significantly lower at $10^{-5}$ for the NN model, which was trained for 100 iterations. The minimal differences observed between the measured and modeled data in Fig. 5 further validate the efficacy of both models. Although increasing the polynomial order or training iterations can further reduce the error, very high polynomial orders can introduce computational instability due to matrix inversion. To address this, conventional polynomials may be replaced with orthogonal polynomials, enhancing model robustness.

## VI. Conclusion

This study presents the NN-DPD framework developed to alleviate the intrinsic nonlinearities in GaN HEMT PAs. The proposed DPD solution utilizes an architecture based on polynomial models, employing sub-systems for each memory node, thereby offering adaptability in managing diverse memory depths and dynamics in AM-AM and AM-PM conversions. Comprehensive simulations utilizing a QPSK-modulated signal exhibited enhanced performance, achieving over 7 dB improvement in EVM and a 3 dB increase in ACPR relative to the GMP model. The complexity of the proposed model is approximately 1.5 times greater than that of GMP, establishing it as an efficient alternative among deep learning-based DPD techniques. The findings highlight the NN-DPD architecture's potential to enhance linearization efficiency while preserving minimal computational overhead, rendering it exceptionally appropriate for advanced wireless communication systems of the next generation. Subsequent efforts will refine this methodology for more extensive modulation schemes and real-time applications.

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