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# A Power Amplifier Modeling Method Based on the Time Delay Deep Neural Network

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**Abstract:** ***A power amplifier (PA) modeling method based on the time delay deep neural network (TDDNN) is proposed in this paper. By integrating time-delay units with a multi-layer hidden neural network structure, the TDDNN enhances the modeling capability for dynamic nonlinear systems. Time-delay information and a multi-layer network architecture are incorporated into the TDDNN to improve its ability to capture the memory effects and nonlinear characteristics of input signals, thereby increasing modeling accuracy. Meanwhile, the number of hidden layer neurons in TDDNN is reduced, which optimizes the structural complexity of the model. The feasibility of this innovative structure is demonstrated through a case study of a Motorola PA. Experimental validation indicates that the proposed TDDNN method not only improves modeling accuracy but also effectively reduces computational complexity, offering an efficient solution for modeling complex dynamic nonlinear systems.***

**Keywords:** Time delay deep neural network, Power amplifier modeling, Multi-layer network**.**

## 1. Introduction

With the advent of the 5G era, modern wireless communication systems are expanding into millimeter-wave and terahertz frequency bands [1]. Concurrently, base stations are becoming increasingly miniaturized, energy-efficient, and highly integrated, posing greater demands on system design [2]. As a critical nonlinear component in wireless communication systems, the performance of power amplifiers (PAs) significantly influences system metrics such as power, efficiency, and linearity [3]. To enhance spectral efficiency, PAs often operate under high-power conditions, leading to nonlinear distortion that severely degrades communication performance [4]. Consequently, the high-precision PA modeling is essential for predicting nonlinear effects, optimizing circuit design, and reducing development costs.

Traditional PA modeling methods are relatively mature. Physical models, based on device structures and physical equations, offer high accuracy but are computationally intensive [5]. Equivalent circuit models, which utilize computer-aided design (CAD) techniques to simplify complex circuits, enable rapid modeling but require extensive tuning [6-7]. Lookup table models, which rely on extensive empirical data, provide high accuracy but are limited by reduced simulation speed [8]. With continuous advancements in semiconductor technology, traditional modeling approaches face challenges in efficiently adapting to complex new devices, underscoring the need for fast and efficient modeling techniques.

Artificial neural networks (ANNs) can learn the nonlinear mapping between input and output signals without requiring knowledge of circuit structures, thereby establishing behavioral models with strong generalization capabilities [9]. Time delay neural networks (TDNNs) have been widely applied in PA modeling due to their superior temporal modeling capabilities [10]. However, traditional single-hidden-layer TDNNs often require an increased number of neurons to achieve high modeling accuracy when addressing complex nonlinear effects, which escalates computational complexity [11]. To overcome this limitation, TDDNNs have garnered increasing attention [12]. By employing a multilayer architecture to hierarchically extract features, TDDNNs enhance modeling accuracy while reducing the number of neurons per layer, thus enabling more efficient designs.

In this paper, a PA modeling method based on the TDDNN is proposed. Through theoretical analysis and experimental validation, the study explores the advantages of TDDNN in terms of accuracy and complexity, providing new insights into efficient PA modeling. This work lays a foundation for the development of next-generation wireless communication systems and the application of neural networks in the radio frequency and microwave domains.

## 2. Description of the Model

### 2.1 The Structure Description of Traditional TDNN

The TDNN is a type of feedforward neural network designed to incorporate dynamic information by using past system input values along the time dimension as part of the current network input [13]. The structure of TDNN is similar to the traditional artificial neural network (ANN), which consists of the input layer, the hidden layer and the output layer.

Compared to conventional ANNs, TDNNs offer enhanced capabilities for modeling nonlinear systems with dynamic characteristics by leveraging temporal data [13]. When applied to PA modeling, TDNNs are particularly effective in capturing the nonlinear characteristics and memory effects of PAs by integrating time-delay information [14]. This approach combines historical and current input signals to accurately represent dynamic behavior. Figure 1 illustrates the topology of a three-layer TDNN model with time-delay units.

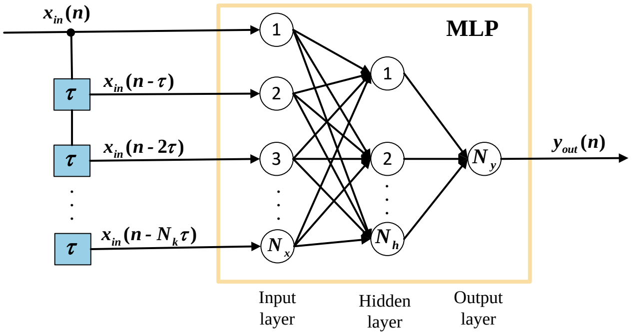


**Figure 1:** The model structure of TDNN.

In this model, $x_{in}(n)$ represents the input signal of the time delay neural network, where $n$ =1, 2, … indicates the number of input signals. $v_{in}(n-N_k\tau)$ denotes the input signals after passing through the time-delay units and entering the network. $N_k$ denotes the number of time delays. $\tau$ denotes the time-delay value. $N_x$ represents the number of neurons in the input layer. The number of hidden layer neurons is $N_h$, which is adjustable based on the nonlinearity required by the model. $N_y$ represents the number of output layer neurons, while $y_{out}(n)$ denotes the output signal, where $n$ =1, 2, … indicates the number of output signals.

### 2.2 The Proposed TDDNN Model of PA

The TDDNN is an advanced model developed on the basis of the TDNN, which further enhance the ability to model dynamic nonlinear systems through the use of multiple hidden layers [15]. The TDDNN inherits the characteristics of the TDNN that introduces dynamic information through delay units, and achieves more complex feature extraction and hierarchical modeling of nonlinear relationships by increasing the number of hidden layers.

In the TDDNN, each hidden layer is responsible for extracting features at different levels. For instance, the first hidden layer primarily captures the basic dynamic characteristics of the input signal, while the subsequent hidden layers progressively extract higher-order nonlinear features and memory effects [16]. This multi-level feature extraction capability makes the TDDNN more efficient than the single-hidden-layer TDNN in capturing complex dynamic nonlinear relationships, while also reducing the number of neurons in the each hidden layer, thereby decreasing the model's overall complexity.

As shown in Figure 2, the three-hidden-layer TDDNN structure can be utilized to model nonlinear PAs with memory effects. In this model, the input layer receives the current input signal $v_{in}(n)$ and its past time-delayed values $v_{in}(n-N_k\tau)$, introducing dynamic information through time-delay units, where $N_k$ represents the number of delays. $n$ =1, 2, … indicates the number of input signals. The number of neurons in the input layer is $N_x$. The hidden layers gradually extract the nonlinear and dynamic features of the input signal through a hierarchical network structure. The model employs a three-hidden-layer structure, with the number of neurons in each layer $N_h$ adjustable according to modeling requirements. The number of output layer neurons is $N_y$, and the output layer generates the PA output signal $z_{out}(n)$, completing the nonlinear mapping between input and output relationships. $n$ =1, 2, … indicates the number of output signals.

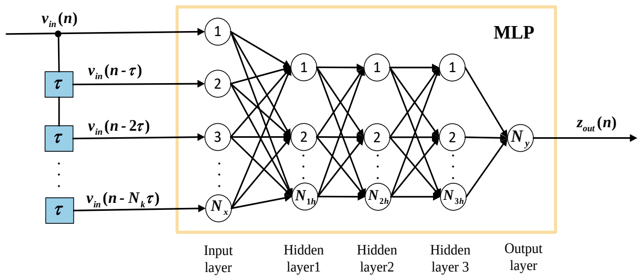


**Figure 2:** TDDNN (3-hidden layer) model structure of power amplifier.

The TDDNN model formula of the PA is (1), where $f_{ANN}$ denotes the neural network of PA from input to output.

$$z_{out}(n) = f_{ANN}\begin{pmatrix} v_{in}(n), v_{in}(n-\tau), v_{in}(n- \\ 2\tau), \ldots v_{in}(n-N_k\tau) \end{pmatrix} \quad (1)$$

In general, the neural network in the middle layer uses algorithms such as backpropagation (BP) or quasi-Newton methods to approximate the nonlinear relationship between the input and output signals of a PA [11], optimizing the neural network weights to minimize the error between the input and output signals. The TDDNN offers a more efficient solution for modeling nonlinear systems with complex dynamic characteristics by combining time-delay units and multi-layer structures. By reducing the number of neurons in each hidden layer while maintaining high modeling accuracy, the TDDNN effectively optimizes computational complexity.

## 3. Results and Discussion

To validate the TDDNN modeling method, the modeling is performed on the MOSFET PA from the software ADS template library under large-signal conditions. The input voltage, the input current, and the output voltage generated under varying input power levels and fundamental frequencies are used as training and testing data. This data included DC current, the real and imaginary parts of the fundamental frequency components, as well as the second and third harmonics. The load of the Motorola PA circuit is fixed at 50 ohms, with an input bias of 2 V and an output bias of 5.8 V. The training range for the Motorola PA is as follows: Input power: 0 to 18 dBm, step 1 dBm; Fundamental frequency: 900 to 950 MHz, step 5 MHz. The testing range was: Input power: 0.5 to 17.5 dBm, step 1 dBm; Fundamental frequency: 902.5 to 947.5 MHz, step 5 MHz.

In this example, two TDDNNs are used to model Motorola PA. One TDDNN describes the relationship between the input voltage and the output voltage of the Motorola PA circuit, and the other TDDNN describes the relationship between the input voltage and the input current as a supplement, making the overall model of Motorola PA more accurate. And both TDNNs use two time delay units. The specific model structure is shown in Formula (2) and Formula (3):

$$v_{out}(n) = f_{ANN1}(v_{in}(n), v_{in}(n-\tau), v_{in}(n-2\tau)) \quad (2)$$

$$i_{in}(n) = f_{ANN2}(v_{in}(n), v_{in}(n-\tau), v_{in}(n-2\tau)) \quad (3)$$

For comparison, we used the multilayer perceptron (MLP) model [26] as an existing neural network modeling method to model Motorola's PA. Additionally, a TDNN model was trained as a machine learning approach for establishing the PA model. The number of neurons in the hidden layers of the proposed TDDNN model, the MLP model, and the TDNN model, under the condition of minimizing modeling error, is compared in Table 1.

**Table 1:** Comparison of the number of hidden layer neurons of the three modeling methods under the minimum modeling error

| Modeling Method | Model Structure | Training error | Test error | Number of hidden layer neurons |
|---|---|---|---|---|
| MLP | $V_{in} - I_{in}$ | 4.8386% | 4.8899% | 45 |
| | $V_{in} - V_{out}$ | 5.5693% | 5.5712% | |
| TDNN | $V_{in} - I_{in}$ | 0.3238% | 0.3271% | 31 |
| | $V_{in} - V_{out}$ | 0.4703% | 0.4711% | |
| Proposed TDDNN | $V_{in} - I_{in}$ | 0.3385% | 0.3407% | 16 |
| | $V_{in} - V_{out}$ | 0.4663% | 0.4698% | |

As observed from the Table I, the MLP model, which does not account for time-delay information, fails to accurately characterize the memory effect of the PA, resulting in relatively large training and testing errors. Moreover, the MLP model employs the highest number of neurons in its hidden layers. While the accuracy of the TDNN model is comparable to that of the proposed TDDNN model, the TDNN requires a greater number of hidden layer neurons. The proposed TDDNN model not only meets the required accuracy for PA modeling but also utilizes the fewest hidden layer neurons, significantly reducing the number of model parameters.

After completing the training of the MLP, TDNN, and TDDNN models for the Motorola PA in NeuroModelerPlus software, the three models were validated in ADS by comparing their time-domain responses against the original simulation data of the Motorola PA. To clearly demonstrate the modeling results, four representative fundamental frequency points within the test range were selected. These included two power levels, 10.5 dBm and 17.5 dBm, and two frequencies, 907.5 MHz and 942.5 MHz, resulting in four intersecting curves. Fig. 3 presents the detailed experimental results. It can be observed that the TDNN and TDDNN models closely match the simulation data across all four time-domain curves, whereas the MLP model exhibits relatively larger errors.

To further validate the fitting performance of the proposed model for the Motorola PA, detailed comparisons between the three models and the original simulation data of the Motorola PA were conducted in Figure 4 to 7. These comparisons include curves at all test power levels for the frequencies of 917.5 MHz, 927.5 MHz, 937.5 MHz, and 947.5 MHz.

Figure 4 compares the input current curves of the proposed TDDNN model, the MLP model, and the TDNN model at the selected frequency points. The output voltage curves at the selected frequency points are compared in Figure 5. These figures demonstrate that both the TDNN and TDDNN models accurately fit the original simulation data of the Motorola PA across the entire range of input power levels, from low to high. In contrast, the MLP model exhibits relatively poorer fitting performance.

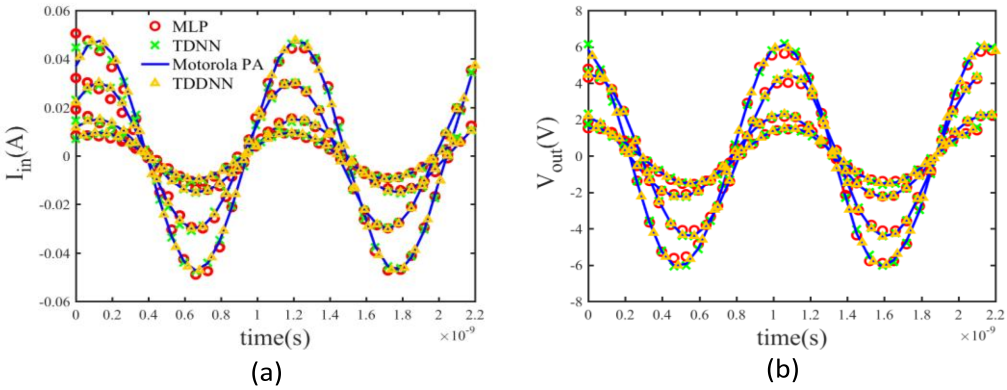


**Figure 3:** Comparison of the time-domain curves of the proposed TDDNN model, the MLP model, the TDNN model and the original Motorola PA circuit (ADS). (a) Result of the input current. (b) Results of the output voltage.

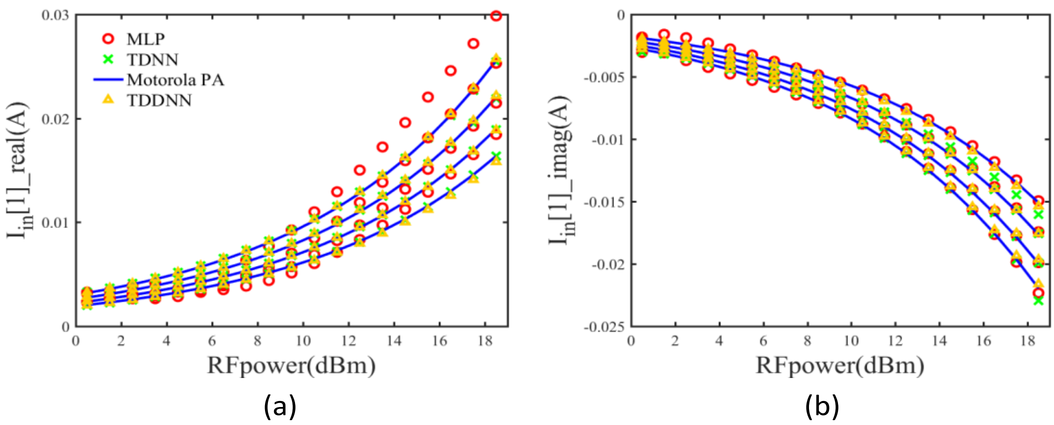


**Figure 4:** Comparison of the input current of the proposed TDDNN model, the MLP model, the TDNN model and the original Motorola PA circuit (ADS). (a) Real part curves. (b) Imaginary part curves.

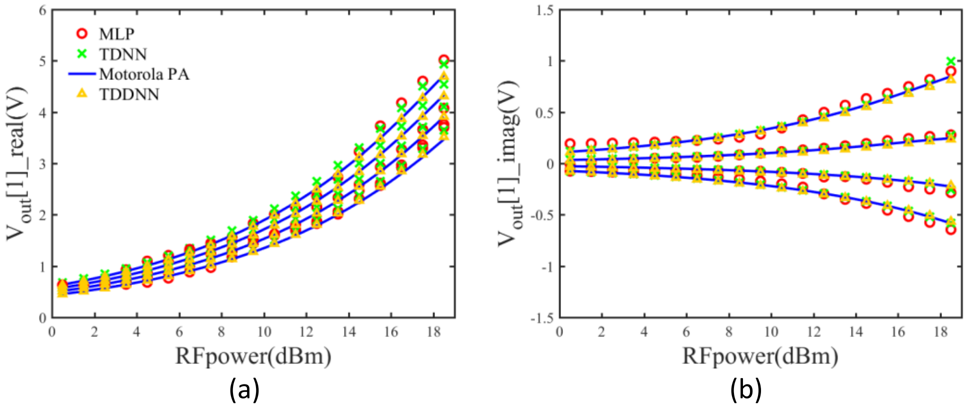


**Figure 5:** Comparison of the output voltage of the proposed TDDNN model, the MLP model, the TDNN model and the original Motorola PA circuit (ADS) in the frequency domain. (a) Real part curves. (b) Imaginary part curves.

The comparison of the fundamental frequency signal, second harmonic signal, and third harmonic signal of the output power between the original simulation data of the Motorola PA, the MLP model, the TDNN model, and the proposed TDDNN model is shown in Figure 6. Figure 7 compares the output gain among the original simulation data of the Motorola PA, the MLP model, the TDNN model, and the TDDNN model.

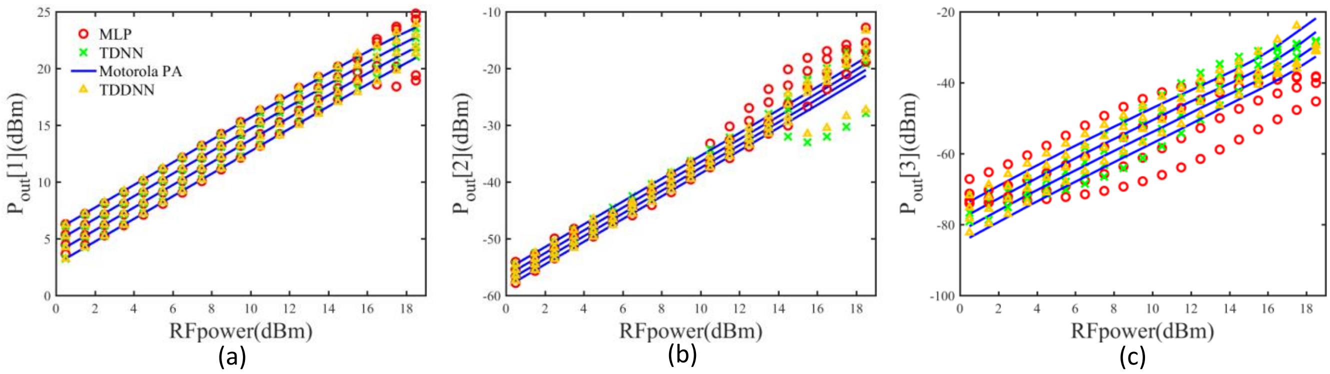


**Figure 6:** Comparison of the output power of the proposed TDDNN model, the MLP model, the TDNN model and the original Motorola PA circuit (ADS). (a) The fundamental frequency signal. (b)The second-order harmonic signal. (c) The third-order harmonic signal.

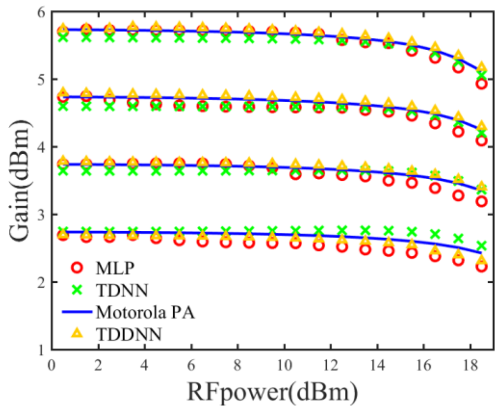


**Figure 7:** Comparison of the gains of the proposed TDDNN model, the MLP model, the TDNN model and the original Motorola PA circuit (ADS).

The comparison of modeling results using the MLP, TDNN, and TDDNN models for the Motorola PA demonstrates that the TDDNN-based modeling method achieves high accuracy under large-signal conditions. To further investigate the impact of the number of hidden layer neurons on model accuracy, we compared the accuracy of the three models by setting the same number of hidden layer neurons for the Motorola PA. Here, we set the number of hidden layer neurons to 16 for all models. Table 2 presents a comparison of the modeling errors of the three models under the same hidden layer neuron configuration.

**Table 2:** Comparison of accuracy between the three modeling methods under the same number of hidden layer neurons

| Modeling Method | Number of hidden layer neurons | Model Structure | Training error | Test error |
|---|---|---|---|---|
| MLP | 16 | $V_{in} - I_{in}$ | 7.5651% | 7.5492% |
| | | $V_{in} - V_{out}$ | 6.9874% | 7.0871% |
| TDNN | | $V_{in} - I_{in}$ | 0.9721% | 0.9752% |
| | | $V_{in} - V_{out}$ | 1.1190% | 1.1031% |
| Proposed TDDNN | | $V_{in} - I_{in}$ | 0.3385% | 0.3407% |
| | | $V_{in} - V_{out}$ | 0.4663% | 0.4698% |

As shown in Table 2, the TDDNN model achieves the lowest training and testing errors under identical hidden layer neuron configurations. This result highlights the effectiveness of the TDDNN-based modeling approach for the Motorola PA, demonstrating superior convergence and accuracy, particularly in highly nonlinear regions at elevated input power levels.

## 4. Conclusion

A novel TDDNN model for PA modeling is introduced in this study. By incorporating a multi-layer hidden structure, the ability to capture dynamic nonlinear relationships is significantly enhanced. The model's performance has been validated through experiments on the Motorola PA, where high accuracy was achieved with reduced computational complexity and fewer neurons compared to the traditional MLP and the TDNN models. The TDDNN model is confirmed to be an efficient solution for complex nonlinear dynamic system modeling, offering strong support for next-generation wireless communication systems. The application of neural networks in the RF and microwave fields is expanded through this approach. As communication frequencies continue to extend toward the terahertz range, the optimization of TDDNN is expected to become a key research focus.

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