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Saleh Assisted Deep Neural Network Behavioral Model of Radio Frequency Power Amplifiers

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Abstract

In modern broadband communication systems, radio frequency power amplifiers suffer from severe nonlinear distortion and memory effects. To accurately analyze the impact of their characteristics on communication systems, it is necessary to establish precise amplifier models. In recent years, deep neural networks have been widely applied to power amplifier modeling. In order to describe the complex dynamic characteristics of power amplifiers, the deep neural network often requires a large number of hidden layers, which leads to large model scale and difficulties in training. To address this issue, a novel behavioral model is proposed in this paper. It combines the classical Saleh model with a deep feedforward neural network. Since the Saleh model can be identified using the least squares method without requiring iterative gradient algorithms, the computational load of model training is significantly reduced. Simulation results demonstrate that, compared to deep neural network models with equivalent parameter quantities, the proposed model exhibits higher accuracy and faster convergence.

Keywords

Behavioral Model, Radio Frequency Power Amplifier, Deep Neural Network, Saleh Model

1. Introduction

Radio frequency power amplifiers (RF PAs) are key components in wireless communication systems, used to amplify modulated band-pass signals to the required power level and then transmit them via antennas. When the input power is low, the power amplifier (PA) generally exhibits good linearity. However, in practical applications, to improve power efficiency, it is always desirable for the amplifier to operate near its saturation point, at which time, the amplifier demonstrates significant nonlinear characteristics, leading to severe distortion in the output signal [1] [2].

In 5G communication systems, ultra-wideband transmission leads to a significant increase in the power density of radio frequency links. This requires PAs to possess the capability of more efficient signal transmission and achieve high-linearity signal transmission at higher frequency bands. When analyzing a PA system, it is first necessary to establish an effective nonlinear model of the amplifier to quantitatively describe its characteristics, and only then can a reasonable linearization scheme be formulated.

Modeling is the use of mathematical methods to describe the characteristics of power amplifiers. Based on different modeling approaches, the models of power amplifiers can be divided into two major categories: physical models and behavioral models. The physical model starts with the internal specific structure of the amplifier and uses circuit laws to establish the parameter relationships between components. The behavioral model, however, regards the amplifier as a "black box" with unknown internal structure and builds a model of the object using input-output responses.

Neural networks inherently possess the ability to represent complex nonlinearities, and thus have gained favor among researchers in the study of PA modeling techniques [3]. Chang *et al.* discovered that as the number of power amplifier states increases, it is necessary to increase the depth of the neural network. However, having too many hidden layers in deep neural networks may lead to problems such as vanishing gradients and overfitting, which can result in a decline in model performance. To overcome this drawback, the authors proposed a modeling method based on a residual deep neural network [4]. Reference [5] proposed a multi-channel convolutional long short-term deep neural network approach, which improves the performance of power amplifier nonlinear models while reducing model complexity. Reference [6] proposed a phase-normalized recurrent neural network to characterize RF PAs in broadband communication systems with significant memory effects.

With the application of intelligent communication in 5G, the input signal states of the PA, such as power and bandwidth states, can dynamically change in real time according to service requirements. This dynamic variation leads to changes in the PA's state and causes the PA to exhibit complex nonlinear effects [7]. To describe these complex nonlinear characteristics, it is necessary to increase the number of layers in neural networks. However, an excessive number of layers can result in a large network scale, a surge in training computational load, and may lead to issues such as overfitting and gradient vanishing.

To address this issue, a Saleh-assisted deep neural network (SA-DNN) model is proposed in this paper. It combines the classic Saleh model with a deep neural network (DNN) to establish a modeling method for power amplifiers. Since the parameters of the Saleh model can be identified using the least squares method, there is no need to employ gradient algorithms for iteration. Compared to a DNN model of the same scale, the SA-DNN model significantly reduces computational complexity, achieving higher convergence speed and accuracy.

2. Nonlinearity and Memory Effects of RF PAs

The phenomenon that amplitude modulation at the input side leads to amplitude modulation at the output side when a signal passes through a nonlinear power amplifier is referred to as AM-AM conversion, as shown in **Figure 1**. The nonlinearity of the amplifier not only causes AM-AM conversion but also induces a phase shift in the output signal, meaning that the phase magnitude changes with variations in the input signal's amplitude. This phenomenon is called AM-PM conversion [8]. It is generally considered that the amplitude and phase of the amplifier's output signal are primarily determined by the amplitude of the input signal and are almost independent of the phase of the input signal.

In wireless communication systems, the requirements for adjacent channel interference are very stringent. The spectrum of the modulated signal should be confined within its own channel and is not allowed to leak into adjacent channels. The nonlinear characteristics of the amplifier not only cause AM-AM and AM-PM conversions but also widen the spectrum of the input signal, resulting in the regrowth of the signal spectrum that was originally confined within a certain channel [9]. The impact of amplifier nonlinearity on the power spectrum of the transmitted signal is shown in **Figure 2**.

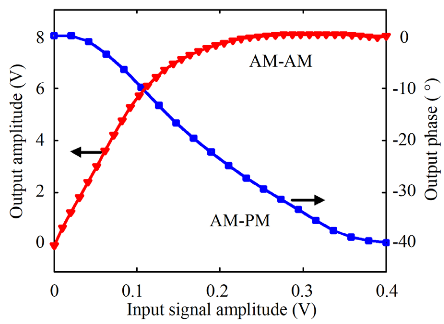

Figure 1. AM-AM and AM-PM conversions.

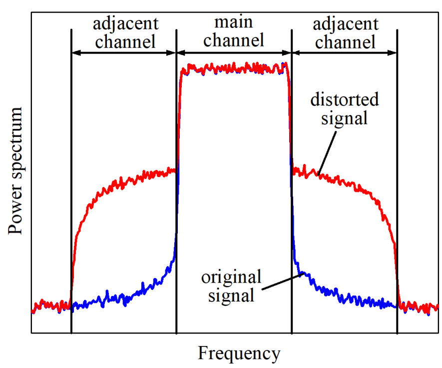

Figure 2. Spectral regrowth caused by PA nonlinearity.

Based on whether the memory effects of the amplifier are considered, the behavioral models can be divided into two types: memoryless models and models with memory. The memory effects refer to the phenomenon that the current output signal of an amplifier depends not only on the current input signal but also on historical input signals. In the study of RF PAs, the existence of the memory effects was noticed early on [10]. However, in narrowband applications, since the signal bandwidth is much smaller than the device bandwidth, the memory effects of the amplifier are very weak. Therefore, memoryless models were generally adopted in early research. The most commonly used memoryless model is the power series model, which represents the amplifier's output signal using a power series of the input signal, with its mathematical expression as

$$y(n) = \sum_{k=1}^{K} c_k x^k(n), \tag{1}$$

where $x(n)$ represents the envelope of the input signal at time n, $y(n)$ represents the envelope of the output signal, K is the model order, and c_k denotes the model coefficients, which can be complex numbers. The complex-coefficient power series model simultaneously describes the amplifier's AM-AM and AM-PM conversions. The advantage of the power series model lies in its simple form and ease of parameter identification.

However, modern communication systems are developing towards the direction of wide bandwidth and multi-carrier. In broadband communication systems such as 4G and 5G, the memory effects of amplifiers are significant, and memoryless models cannot accurately describe PA characteristics. Therefore, in recent years, the research focus of power amplifier modeling techniques has shifted to memory-based models. Among memory-based models, the Volterra series model is highly representative [11], and its mathematical expression is

$$\begin{aligned} y(n) = h_0 &+ \sum_{i_1=0}^{M-1} h_1(i_1) x(n-i_1) + \sum_{i_1=0}^{M-1}\sum_{i_2=0}^{M-1} h_2(i_1,i_2) x(n-i_1) x(n-i_2) + \cdots \\ &+ \sum_{i_1=0}^{M-1} \cdots \sum_{i_k=0}^{M-1} h_k(i_1,i_2,\cdots,i_k) x(n-i_1) x(n-i_2) \cdots x(n-i_k) + \cdots \end{aligned}, \tag{2}$$

where $h_k(i_1,i_2,\cdots,i_k)$ represents the k-th order complex Volterra kernel, and M is the memory depth. The main issue with the Volterra series is that as the nonlinear order and memory depth of the model increase, the number of kernel functions explodes exponentially, resulting in an excessively large computational workload for parameter estimation. To address this, researchers have made improvements and proposed various simplified models, such as the memory polynomial model, generalized polynomial model, and the dynamic deviation reduction model [12] [13].

Actual measurements indicate that when the frequency of the input signal varies within a relatively narrow range, the nonlinear characteristics of the amplifier remain essentially constant. As the bandwidth of the input signal increases, the memory effects of the RF PA become more pronounced, and the input-output relationship curve exhibits dynamic characteristics. When the input signal bandwidth increases to a certain extent, both the AM-AM and AM-PM curves of the amplifier cease to be clear and instead exhibit a "dispersion" state, as shown in Figure 3 and Figure 4. Some literature refers to this phenomenon as "hysteresis".

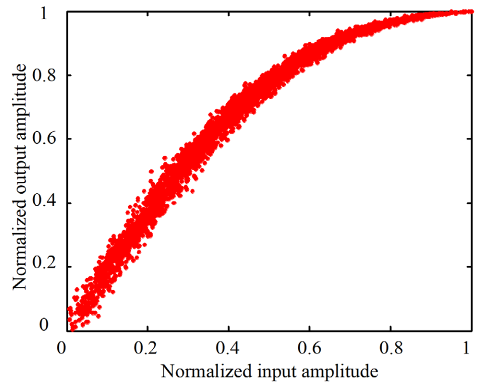

Figure 3. AM-AM conversion with memory effects.

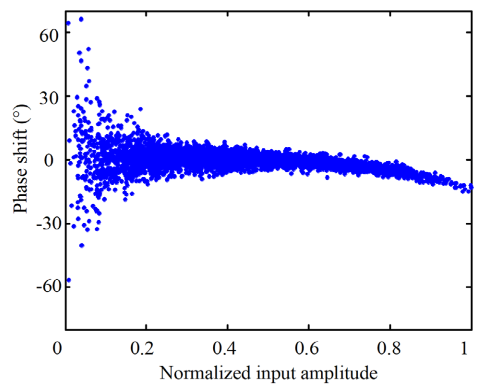

Figure 4. AM-PM conversion with memory effects.

3. Saleh Model

Saleh proposed a nonlinear model for traveling wave tube amplifiers in 1981, which uses the following two expressions to describe the AM-AM and AM-PM conversions of the amplifier respectively [14].

$$A(r)=\frac{\alpha_{\mathrm{A}} r}{1+\beta_{\mathrm{A}} r^2} \tag{3}$$

$$\Phi(r)=\frac{\alpha_{\Phi} r^2}{1+\beta_{\Phi} r^2} \tag{4}$$

where r is the envelope amplitude of the input signal and α_{A}, β_{A}, α_{Φ}, and β_{Φ} are parameters to be determined. The parameter identification process of the Saleh model is as follows. Firstly, Equation (3) and Equation (4) are uniformly expressed as

$$B(r)=\frac{\alpha_{\mathrm{B}} r^n}{1+\beta_{\mathrm{B}} r^2}, \tag{5}$$

where $n = 1$ or 2 and α_B and β_B are model parameters to be identified. The least mean square error technique is employed to fit the measured data, thereby determining the parameters α_B and β_B. Suppose N sets of measured data $\left(r_i, B_i\left(r\right)\right)$ are obtained, where $i = 1, 2, \cdots, N$. Let

$$w_i = \left[\frac{B_i\left(r\right)}{r_i^n}\right]^{-\frac{1}{k}}. \tag{6}$$

The parameters α_B and β_B in the model are determined by

$$\alpha_B = \frac{\left(\sum_{i=1}^{N} r_i^2\right)^2 - N\sum_{i=1}^{N} r_i^4}{\left(\sum_{i=1}^{N} r_i^2\right)\left(\sum_{i=1}^{N} w_i r_i^2\right) - \left(\sum_{i=1}^{N} r_i^4\right)\left(\sum_{i=1}^{N} w_i\right)} \tag{7}$$

and

$$\beta_B = \frac{\left(\sum_{i=1}^{N} r_i^2\right)\left(\sum_{i=1}^{N} w_i\right) - N\sum_{i=1}^{N} w_i r_i^2}{\left(\sum_{i=1}^{N} r_i^2\right)\left(\sum_{i=1}^{N} w_i r_i^2\right) - \left(\sum_{i=1}^{N} r_i^4\right)\left(\sum_{i=1}^{N} w_i\right)}. \tag{8}$$

The Saleh model is a classic model for PAs. Its advantages lie in its extremely simple mathematical expression, with only four parameters in the model. Moreover, it can be solved using the least squares method, resulting in a small computational load. However, the Saleh model is a memoryless model and cannot be directly applied to broadband power amplifier modeling in modern communication systems. In the next section, we will combine the classic Saleh model with a deep neural network to model power amplifiers.

4. Saleh Assisted Deep Neural Network Model

As a universal nonlinear function approximation tool, artificial neural networks display significant advantages in nonlinear system modeling due to their characteristics, such as excellent nonlinear qualities, flexible and effective self-organizing learning methods, and fully distributed storage structures, thereby winning the favor of many researchers. Among the modeling techniques for RF PAs, the feedforward neural network is the most widely applied. A feedforward neural network typically consists of an input layer, one or more hidden layers, and an output layer. The input layer receives external input signals, while neurons in each subsequent layer only receive outputs from neurons in the preceding layer. Since there are no feedback pathways in the network, it is referred to as a feedforward network.

The proposed SA-DNN model structure is shown in **Figure 5**. It consists of an input layer, a Saleh layer, several hidden layers, and an output layer. A time-delayed structure is adopted to simulate the memory effects of the amplifier. $x(n)$ represents the input signal of the amplifier at time instant n, z^{-1} is a delay unit used to simulate the memory effects of the amplifier, and y is the output signal of the amplifier. The input signal is expressed as

$$\boldsymbol{X}=\left[x(n)\quad x(n-1)\quad \cdots \quad x(n-M+1)\right]^{\mathrm{T}}, \tag{9}$$

where the superscript T denotes the transpose of a matrix, and M represents the memory depth of the model. After the input signal passes through the Saleh model, the resulting signal is

$$\boldsymbol{Y_S}=\left[y_{s0}\quad y_{s1}\quad \cdots \quad y_{s(M-1)}\right]^{\mathrm{T}}. \tag{10}$$

The first hidden layer contains q neurons. $\boldsymbol{W}_1$ is the connection weight matrix from the Saleh layer to the first hidden layer. The bias of the first hidden layer is

$$\boldsymbol{B}_1=\left[b_{11}\ \ b_{12}\ \ \cdots\ \ b_{1q}\right]^{\mathrm{T}}. \tag{11}$$

F(·) is the activation function of the hidden layer, and here we choose the hyperbolic tangent function. Thus, the output of the first hidden layer is

$$\boldsymbol{H}_1=\tanh\left(\boldsymbol{W}_1\times\boldsymbol{Y_S}+\boldsymbol{B}_1\right). \tag{12}$$

By analogy, we can obtain the outputs of each hidden layer and the final output of the model.

In model training, the least squares method is employed to identify the parameters of the Saleh module. For the feedforward neural network module, the gradient descent algorithm is used to continuously reduce the mean squared error (MSE) of the model output during the iterative process [15].

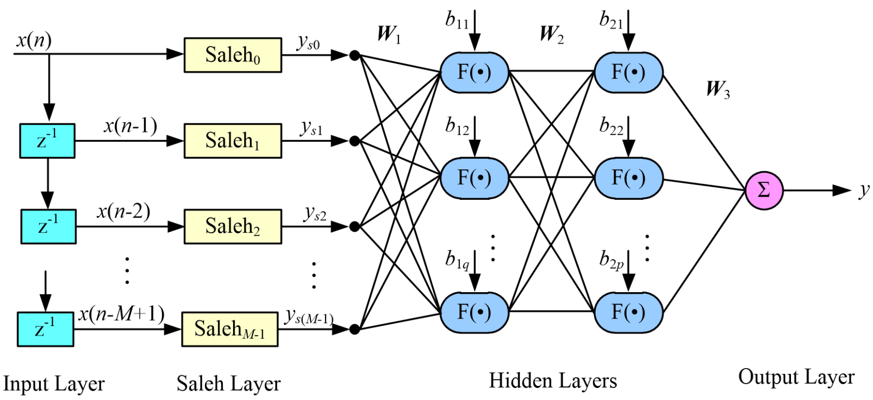

Figure 5. Structure of SA-DNN model.

In Figure 5, only two hidden layers are depicted, while the actual number of hidden layers can be set according to needs. Theoretically, the more hidden layers there are, the more precise the model will be. However, in practice, an excessive number of hidden layers may lead to the following issues.

- Vanishing gradient

As the number of layers in a neural network increases, problems arise in gradient calculation during the backpropagation process. Vanishing gradient refers to the phenomenon that, as the number of the layers increases, the gradient gradually diminishes during backpropagation, resulting in neurons near the input layer receiving almost no effective training and experiencing slow weight updates.

- Overfitting

An excessive number of layers can cause the neural network to overfit the training data, leading to poor performance on test data, a phenomenon known as overfitting. This occurs because an excessive number of parameters can precisely fit the noise in the training data rather than capturing the true underlying patterns.

- Significant increase in computational resource requirements

Increasing the number of layers in a neural network significantly boosts computational load and storage demands. There are a large number of connections between neurons in each layer, and as the number of layers increases, the quantity of these connections grows rapidly. This implies that more computation time and memory space are required during both training and inference processes. In the established model structure, the Saleh layer with time-delay structure can partially fit the nonlinear characteristics and memory effects of the amplifier, effectively reducing the required scale of the deep neural network.

This design attempts to reduce the number of hidden layers and parameters by introducing Saleh layers into a feedforward neural network, without compromising model accuracy. Alternatively, equivalently stated, it aims to enhance model accuracy when the number of model parameters remains roughly the same.

5. Model Validation

To verify the proposed modeling method, a simulation model of a Doherty radio frequency power amplifier was established in Advanced Design System (ADS) to obtain the input-output dataset required for training and testing. The PA was operated at 2.4 GHz with the output power of 33 dBm. A signal with a bandwidth of 40 MHz was fed to the RF PA. The sampling frequency was 160 MHz.

The model construction and training were completed on the PyTorch platform. PyTorch is an open-source deep learning framework released by Facebook in 2016, which facilitates the establishment of the SA-DNN model and the completion of its training.

To evaluate the effectiveness of the model, we compared the SA-DNN model with the DNN model. For the sake of fairness, both models should contain approximately the same number of parameters. In the SA-DNN model, there are about 3150 parameters, while the DNN model contains about 3200 parameters.

The training curves are shown in **Figure 6**. Here, we define one epoch as the process of using all samples in the training dataset once. During each epoch, the training algorithm inputs all samples into the model in a preset order for forward propagation, loss calculation, backward propagation, and parameter updates. The DNN model almost stabilized after approximately 150 epochs, achieving a final MSE of −48.5 dB. The SA-DNN model reached stability after around 75 epochs, with a final MSE of −55.0 dB. It can be seen that, under the premise of roughly comparable model sizes, the proposed SA-DNN model exhibits faster convergence speed and higher accuracy compared to the DNN model.

Power spectrum analysis was performed in MATLAB. **Figure 7** presents a comparison of the power spectral density (PSD) between the output signals of two models and the original output signal. From Figure 7, it is observed that the PSD of the output signal from the SA-DNN model is closer to that of the original signal. Figure 8 illustrates this point more clearly. Relative to the original output signal, the PSD error of the DNN model's output signal ranges approximately from −2 to +6 dB/Hz, whereas the error range of the SA-DNN model is approximately from −4 to 0 dB/Hz. It is thus evident that, regardless of whether in the time domain or frequency domain, when the model scales are comparable, the SA-DNN model demonstrates higher accuracy than the DNN model.

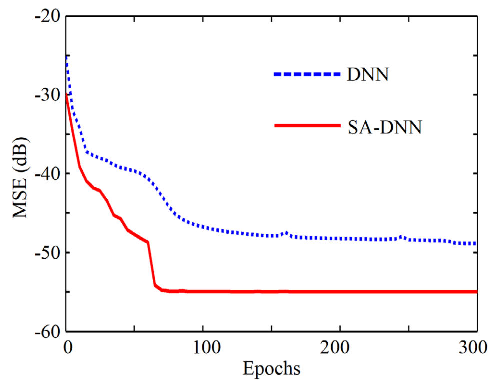

Figure 6. Training curves.

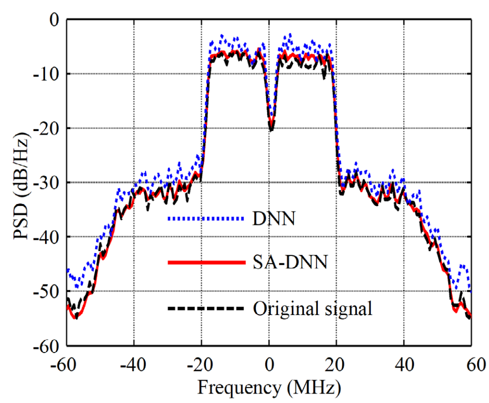

Figure 7. Comparison of PSD.

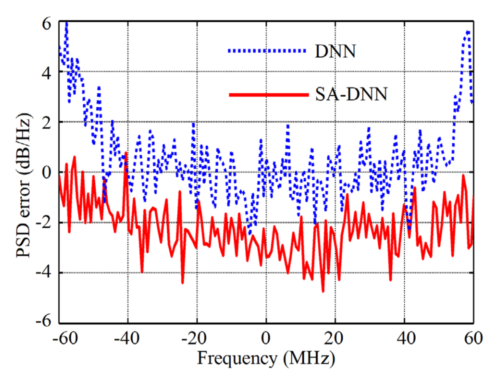

Figure 8. Comparison of PSD error.

6. Conclusion

In this paper, a Saleh-assisted deep neural network behavioral model is proposed to describe the complex memory-containing nonlinear characteristics of radio frequency power amplifiers in modern communication systems. Simulation results demonstrate that, compared to deep neural network models of the same scale, the SA-DNN model exhibits faster convergence speed and higher accuracy. Alternatively, when the accuracy is comparable, the SA-DNN model can reduce the number of model parameters, thereby saving the computational effort required for training.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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