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Behavioral modeling of RF power amplifiers with time-delay feed-forward neural networks

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Abstract: A novel behavioral model using three-layer time-delay feed-forward neural networks (TDFFNN) is adopted to model radio frequency (RF) power amplifiers exhibiting memory nonlinearities. In order to extract the parameters, the back-propagation algorithm is applied to train the proposed neural networks. The proposed model is verified by the typical odd-order-only memory polynomial model in simulation, and the performance is compared with different numbers of taped delay lines (TDLs) and perceptrons of the hidden layer. For validating the TDFFNN model by experiments, a digital test bench is set up to collect input and output data of power amplifiers at a 60×10^6 sample/s sampling rate. The 3.75 MHz 16-QAM signal generated in the vector signal generator (VSG) is chosen as the input signal, when measuring the dynamic AM/AM and AM/PM characteristics of power amplifiers. By comparisons and analyses, the presented model provides a good performance in convergence, accuracy and efficiency, which is approved by simulation results and experimental results in the time domain and frequency domain.

Key words: behavioral model; power amplifier; time-delay feed-forward neural network (TDFFNN)

In modem wideband communication systems, high power amplifiers (HPAs) of the base station often produce severe memory effects and nonlinearities, which contribute to asymmetries between lower and upper intermodulation distortion (IMD) and spectral regrowth. Behavioral modeling of HPAs has attracted much interest in the past few years that has yielded various models such as the Saleh model, the Volterra series model, the Wiener model, the Hammerstein model, the polynomial model and the neural networks model, etc[1–12].

The simple static model is the Saleh model[1], which is used to model traveling-wave tube amplifiers, but it is often used to model solid state power amplifiers. The general nonlinear model with memory is the Volterra model[2]. However, high computational complexity makes the method impractical. So the Volterra model is usually reduced by some simplification methods[3]. The Wiener model[4–5] and the polynomial model[6–7], as in the special cases of the Volterra model, are widely adopted to model HPAs.

Recently, neural networks (NNs), which can approximate any continuous function arbitrarily well, have become an important method to model the nonlinear dynamic system, and they have been successfully used to model and design RF power amplifiers, microwave components and circuits. In this paper, a novel neural networks-based behavioral model of RF power amplifiers is employed and simulation and experimental results show that the model provides a good performance.

1 Behavioral Model of PAs

Behavioral RF PA models usually use the complex input and output sampled signals of PA, which can be represented as rectangular coordinates (in-phase I and quadrature-phase Q) or polar ones (magnitude and phase). And many topologies of NNs were reported in the literature for the modeling of PAs, such as two separate real-valued NNs[8], one real-valued NN with I and Q as inputs, and the complex-valued-based NNs[9], etc. Most of these neural networks are based on the multilayer perceptrons, recurrent NNs[10], or time-delay NNs[9].

The proposed RF PA model uses time-delay feed-forward neural networks, which consist of three layers: an input layer, a hidden layer and an output layer, as shown in Fig. 1. In contrast to the previous models mentioned, this method applies the envelope of the sampled input and output signals rather than in-phase I and quadrature Q components, and the phase information is not passed through the NNs but presented in the output layer, which is similar to the model in Ref. [11].

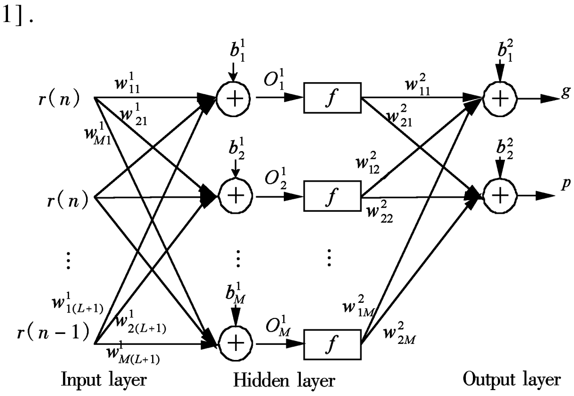

Fig. 1 Block diagram of the novel TDFFNN behavioral model

The following equation describes the relationships of the memory model of HPAs in this paper.

$$y(n)=g(r(n),r(n-1),\dots,r(n-L))\cdot \exp(\mathrm{j}(\phi(n)+p(r(n),r(n-1),\dots,r(n-L)))) \qquad (1)$$

where $g(\cdot)$ and $p(\cdot)$ represent the AM/AM and AM/PM distortions, respectively; $r(n)$ and $\phi(n)$ are the amplitude and phase of the input signal, respectively; and L is the memory depth of the model.

In Fig. 1, the TDFFNN structure models two nonlinear functions ($g(\cdot)$ and $p(\cdot)$), whose inputs are composed of the

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amplitude $r(n)$ and taped delay lines(TDLs). The relationships are described as

$$g(\cdot) = \sum_{k=1}^{M} w_{1k}^{2} O_{k}^{1}(n) + b_{1}^{2} \tag{2}$$

$$p(\cdot) = \sum_{k=1}^{M} w_{2k}^{2} O_{k}^{1}(n) + b_{2}^{2} \tag{3}$$

where $O_k^1(n) = f(\mathrm{net}_k^1(n))$,

$$\mathrm{net}_k^1(n) = \sum_{i=0}^{L} w_{k(i+1)}^{1} r(n-i) + b_k^1 \tag{4}$$

and the active function is

$$f(x) = \tanh(x) = \frac{1-\mathrm{e}^{-2x}}{1+\mathrm{e}^{-2x}} \tag{5}$$

w and b represent the scale weights and biases, respectively. All the parameters can be adjusted, so that the proposed network exhibits the desired behavior.

In the input layer, L represents the number of previous samples included in the mode and TDLs are used for considering the history envelope of the input signal, which is needed for the memory effects modeling of dynamic AM/AM and AM/PM characteristics. If $L=0$, the model will become the memory-less model with static AM/AM and AM/PM characteristics.

2 Training and Simulation

In the training procedure of the time-delay feed-forward neural networks, the standard back-propagation or Levenberg-Marquardt back-propagation algorithm[13] can be employed to adjust the parameters and minimize the cost function. Here, the cost function is described by the mean squared error(MSE) performance function, that is

$$E = 10\log_{10}\left(\frac{\sum_{n} |y_{\mathrm{pa}}(n) - y_{\mathrm{model}}(n)|^2}{N}\right) \tag{6}$$

where $y_{\mathrm{pa}}(n)$ is the measured output signal of the PA, and $y_{\mathrm{model}}(n)$ is the output signal of the TDFFNN model, and N is the number of samples. In order to evaluate the TDFFNN model, the odd-order-only memory polynomial model[7] extracted from the actual class AB PA is used for simulation and comparison.

$$y(n) = \sum_{\substack{k=1\\ \text{odd}}}^{K} \sum_{q=0}^{Q} c_{kq} x(n-q) |x(n-q)|^{k-1} \tag{7}$$

where $K=5$ and $Q=2$. The efficient modulation scheme (16-QAM symbols of 8 times oversampling with a raised cosine shaping filter) is used to generate the input baseband signal in Matlab, and the output signal can be easily calculated by the odd-order-only memory polynomial model. With the input and output samples collected from the memory polynomial model, the TDFFNN model can be simulated and the parameters in the model can be optimized after training.

Typical convergence curves of the training process are shown in Fig. 2 with $L=0, 1, 2, 3$ and $M=10$. In Fig. 3, while the number of perceptrons in the hidden layer M increases from 2 to 10, the MSE curves($L=2$) of different M are compared with each other. From Fig. 2 and Fig. 3, we can see that the MSE drops when L or M increases, while the lowest value of the convergence curves of the MSE is about 10^{-4} when L and M are large enough, because the achieved MSE relates to the structure of the model and training algorithms, etc. The structure of fewer perceptrons also has better convergence curves. It means more complex structure maybe is not the best choice when considering the compromise between efficiency and accuracy. Fig. 4 shows the power spectral density(PSD) comparison between the TDFFNN model and the odd-order-only memory polynomial model.

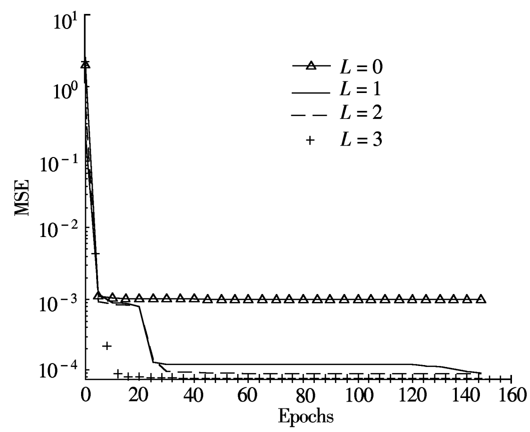

Fig. 2 Convergence curves of the training process($M=10$)

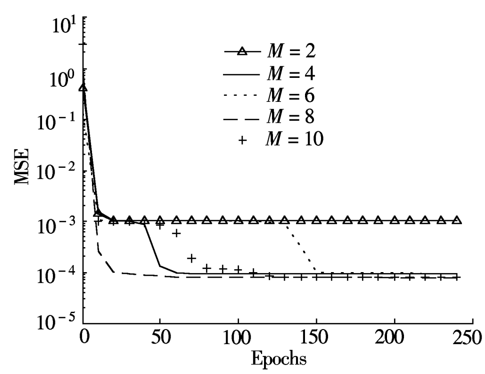

Fig. 3 Convergence curves of different M of the hidden layer ($L=2$)

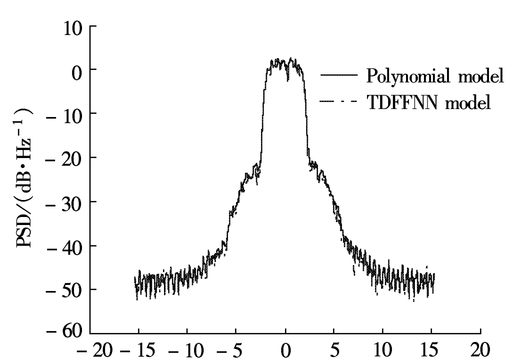

Fig. 4 PSD comparison of the TDFFNN model and the memory polynomial model($L=2$)

3 Experimental Results

In order to characterize the PA, I/Q data are collected by 60×10^6 sample/s sampling using the test bench shown in Fig. 5 and Fig. 6, which includes one DAC(AD9777), two ADCs(AD9862), an FPGA, a modulator, a demodulator, an up converter, a down converter, and a PA[14-16].

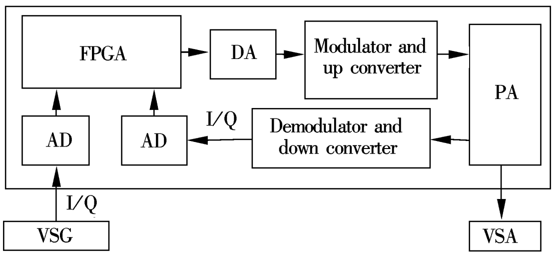

Fig. 5 Block diagram of the test bench

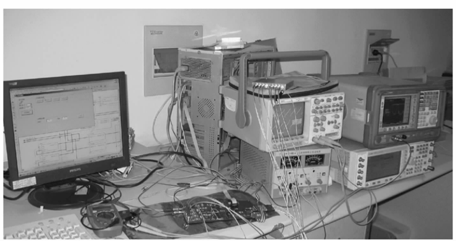

Fig. 6 Photograph of the test bench[16]

Here, the wideband 16-QAM signal generated in the vector signal generator(VSG) is chosen to measure the dynamic AM/AM and AM/PM characteristics of the PA and the output of the PA whose center frequency is 2. 14 GHz can be measured by a vector signal analyzer(VSA).

With 4 096 input and output I/Q samples of the PA, the typical convergence curve of the training process is shown in Fig. 7. About 24×10^3 input and output samples, which have never been used in training are used for validation data of our proposed model. Fig. 8 depicts the time-domain validation results of I and Q components of the TDFFNN model for a 16-QAM signal. The behavioral model matches the measurement data very well.

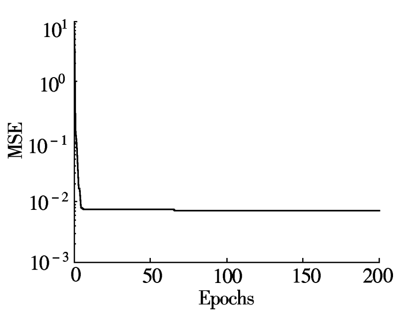

Fig. 7 Convergence curves of the training process($M = 10, L = 1$)

Fig. 9 shows PSD comparison between the TDFFN behavioral model and the measurement data of the 16-QAM signal with a 3. 75 MHz bandwidth and at a 2. 14 GHz center frequency. In Fig. 8 and Fig. 9, the validation results in the time domain and frequency domain give satisfactory results. The error between the TDFFNN model and the measurement is determined by the modeling and measuring accuracy, which cannot be eliminated.

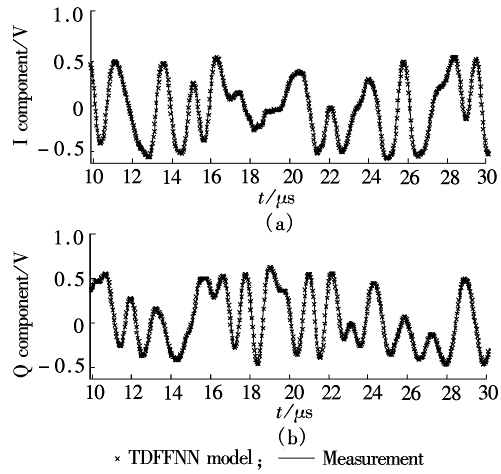

Fig. 8 Validation results of the I and Q components in the time domain(divided by linear gain of PA). (a) I component; (b) Q component

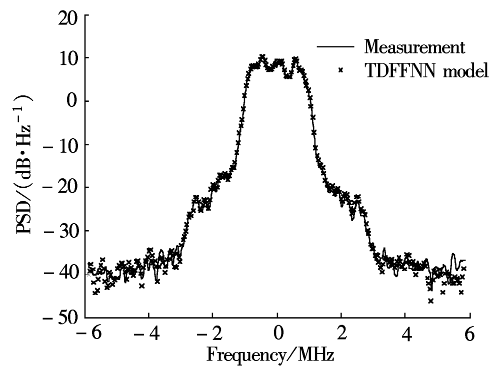

Fig. 9 PSD comparison between the TDFFN model and the measurement data of the 16-QAM signal

4 Conclusion

In this paper, a novel behavioral model using time-delay feed-forward neural networks(TDFFNN) is adopted to model RF power amplifiers exhibiting memory effects and nonlinearities. The dynamic nonlinear behavior of the PA can be reproduced by the proposed TDFFNN model very well. The back-propagation algorithm is used to train the TDFFNN model so as to extract the model parameters. Validation and accuracy assessment of the developed TDFFNN model in the time domain and frequency domain show an agreement between the TDFFNN behavioral model output data and measurement data for a baseband signal of a 3. 75 MHz bandwidth.

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射频功率放大器前馈输入延迟神经网络模型

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摘要：提出一种三层前馈输入延迟神经网络模型用于建立射频功率放大器有记忆的非线性行为模型. 反向传播算法用来训练神经网络以提取神经网络模型参数. 在仿真中，提出的模型可以通过典型的偶次多项式有记忆功率放大器模型来证明，并且比较了不同数目的延迟单元和隐层神经感知器的模型结构下的性能. 为了用实验验证模型的有效性，建立了能达到 60×10^6 sample/s 采样率数字测试平台用于采集功率放大器的输入和输出数据. 选用矢量信号源产生的 3.75 MHz 16-QAM 信号作为功放输入信号来测试功放的动态 AM/AM 和 AM/PM 特性. 通过分析比较时域和频域仿真结果和实验测试结果，模型在收敛性、精度和执行效率方面都达到很好的效果.

关键词：行为模型；功率放大器；前馈输入延迟神经网络

中图分类号：TN830.6