Modeling Broad-band Power Amplifier Using Hybrid Time-Delay Neural Network

Hui Ming[1], Zhang Xingang[1], Zhang Meng[1]
[1] College of Physics & Electronic Engineering, and Intelligent control of petroleum equipment of Henan Province Engineering Laboratory, Nanyang Normal University, Nanyang 473061, China.

Abstract: A new hybrid time-delay neural network (TDNN) is proposed in this paper for modeling Broad-band power amplifier (BPA). This neural network includes the generalized memory effect of input signals, complex valued input signals and fractional order of complex valued input signal module, thus the modeling accuracy is improved significantly. To demonstrate the merits of this model, a 51-dBm BPA with a 25-MHz bandwidth mixed test signal is used for verification. Compared with real-valued TDNN, the hybrid TDNN is highly effective, leading to an improvement of 5 dB in the NMSE.

Key words: Power amplifier (PA); Neural network (NN); Linearization; modeling

Recently, the neural network (NN) models have attracted attention from researchers working on power amplifier (PA) modeling because of their successful implementation in pattern recognition, signal processing, system identification, and control[1-2]. Different neural topologies have been proposed, for example, complex valued single-input single-output feed-forward NN[3] and real-valued double-input double-output NN[4] are the most basic structures. These NNs have been found effective for forward modeling of static nonlinear PAs. However, these models do not consider the memory effects of PAs, especially when the PAs have strong memory effect, these models fall short of expectation.

Considering the memory effect, three dynamic neural structures have been proposed in the NN literature, namely, recurrent neural network[5], complex valued time-delay neural network (TDNN)[6] and real-valued focused time-delay neural network[7]. The recurrent neural network employs the feed-forward and feedback complex valued time-delay line, but the feedback time-delay line significantly affects model robustness. Present and past complex signals are used to train the time-delay neural network, but it cannot be used to describe the strongly nonlinearity of Doherty PA. The memory effect is considered in real-valued TDNN, and the present and past inputs of real-valued TDNN are real-valued. However, the real-valued TDNN has several hidden layers, and it is a back-propagation NN that demands a lengthy training time.

In this paper, a hybrid TDNN is proposed, simply called as hybrid TDNN. In this hybrid NN, the generalized memory effect [8] of input signals is considered. The inputs to the hybrid TDNN are complex valued signals and the fractional order of the complex valued signal module. The hybrid TDNN is based on the radial basis function (RBF), so it has only one hidden layer, which reduces computational complexity and training time greatly. Moreover, it has better modeling capability.

1 Topology of hybrid TDNN nonlinear model

The hybrid TDNN model is proposed in this paper, it includes the complex baseband signal and the fractional order of the complex baseband signal. Fig.1 shows the block diagram of the real- and complex valued hybrid TDNN model. The input and the output of the hybrid TDNN model are x(n+M) and y(n), respectively.

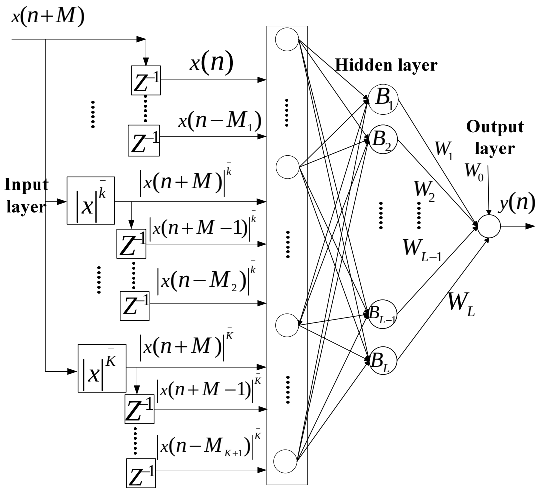

Fig.1 Block diagram of hybrid TDNN model

At any moment in the training sequence, the real- and complex valued hybrid TDNN model is presented with the input vectors of $M_1+1+KM+\sum_{k=1}^{K}(M_{k+1}+1)$ -by-1, including leading, aligned, and past inputs. The input vectors of the model are given below:

$$\begin{aligned}&\mathbf{X(n)}=\\&[x(n),x(n-1),......,x(n-M_1),......\\&\left|x(n+M)\right|^{\bar{k}},......,\left|x(n+1)\right|^{\bar{k}},\left|x(n)\right|^{\bar{k}},......,\left|x(n-M_{k+1})\right|^{\bar{k}},......\\&\left|x(n+M)\right|^{\bar{K}},......,\left|x(n+1)\right|^{\bar{K}},\left|x(n)\right|^{\bar{K}},......,\left|x(n-M_{K+1})\right|^{\bar{K}}]^T\end{aligned} \tag{1}$$

where $\left|x(n+M)\right|^{\bar{k}},......,\left|x(n+1)\right|^{\bar{k}}$ denote the fractional order of the amplitude of the leading input complex baseband data. $x(n)$ is the alignment time input value. $x(n-1),......,x(n-M_1)$ are the past time values.

$\left|x(n)\right|^{\bar{k}}$ and $\left|x(n-M_{k+1})\right|^{\bar{k}}$ are the fractional of the input training baseband data module values for the present and the past times, respectively.

$\bar{k}=k-0.5$, $k=[0,1......K]$, $\bar{K}=K-0.5$.

M is the leading memory depth of the proposed model, and M_1, M_2,…. M_{k+1} are the aligned memory depths of the proposed model. The output of the model is complex baseband data of the output training signal. At any moment in the training sequence, the output vector is a 1-by-1 vector.

$$\mathbf{Y(n)}=y(n) \tag{2}$$

The dynamic input-output relationship of the real- and complex valued hybrid TDNN shown in Fig.1 is described as follows:

$$y(n) = f(\mathbf{X}(n)) \quad (3)$$

where f is the RBF. Therefore, equation (3) can be rewritten as follows:

$$y(n) = w_0 + \sum_{i=1}^{L} w_i B_i \quad (4)$$

L is the length of hidden nodes. B_i is given as follows:

$$B_i = \exp\left(- \frac{\sum_{a=1}^{A} \left(X(a,n) - C_i(a) \right)^2}{\beta^2} \right) \quad (5)$$

Here, $X(a,n)$ is the a-th element of $\mathbf{X(n)}$, and $C_i(a)$ is the center of the RBF. $A = M_1 + 1 + KM + \sum_{k=1}^{K}(M_{k+1}+1)$. β is a constant given as $sp/\sqrt{-\ln 0.5}$. sp is a spread constant in the interval [0.8-2.5]. This can be referenced from the help file of the newrb function in Mathworks' Matlab.

2 Training and performance assessment of hybrid TDNN -based nonlinear model

The test platform utilized is similar to that in [9].Training of the real- and complex valued hybrid TDNN model involves two stages: hidden layer training and output layer training. In the first stage, the orthogonal least square (OLS) training scheme is employed as a forward regression procedure to determine the centers of the model ($C_i(m)$). The number of regression steps is equal to the number of hidden nodes. Then, the weight (w_i) of the model can be obtained through singular value decomposition. After the centers and the weight of the hybrid TDNN are determined, the model is thus obtained.

Three thousand (3K) sample data from the mixed signal measurements were used to train the real- and complex valued hybrid TDNN. Another ten thousand (10K) sample data were used to test the trained model.

In order to determine the optimal number of hidden nodes L in the proposed model and demonstrate its merits based on the above parameters, the above four models, namely, real- and complex valued hybrid TDNN, real-valued TDNN, real-valued NN and complex valued TDNN, were compared in terms of NMSE by varying the number of nodes from 80 to 320 in steps of 60. The NMSE performance of these four models is shown in Fig.2, where Fig.2 correspond to input powers of -7.5dBm. In the experiment, for the real valued TDNN and the complex valued TDNN models, the memory depth is 3.

Meanwhile, the hybrid TDNN model shows significant improvement compared with the real-valued TDNN, real-valued NN, and complex valued TDNN models in terms of modeling accuracy for BPA nonlinearity with average input powers of -7.5dBm. Especially, for the strong nonlinearity of the BPA, the NMSE of the real- and complex valued hybrid TDNN model improves up to 5 dB compared to the real-valued TDNN model for 200 nodes. Therefore, the number of nodes is set to 200 to ensure that the hybrid TDNN and the real valued TDNN models have optimal modeling accuracy and computational complexity. In conclusion, the hybrid TDNN model has a greater advantage over the other NN models in modeling the memory effect and the static nonlinearity of the PA.

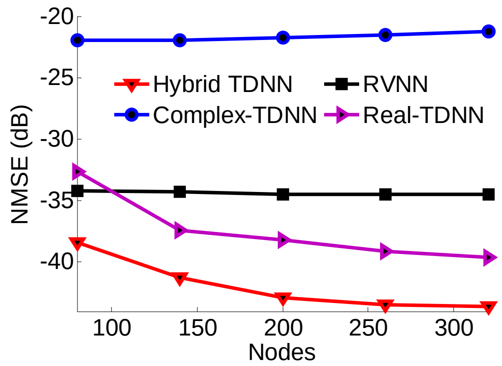

Fig.2 Performances of different models in terms of NMSE

3 Conclusion

In this paper, a hybrid TDNN model is proposed, which can predict the strongly dynamic nonlinearity of a BPA. Three other neural network topologies were selected for comparison with the hybrid TDNN model, namely, real-valued TDNN, real-valued NN, complex valued TDNN. To avoid cumbersome calculations and reduce the training time considerably, the RBF is used in these NNs. The hybrid TDNN model led to a nearly 5 dB improvement in the NMSE compared with the optimal real valued TDNN model for input of -7.5 dBm mixed signal.

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