

Deep neural nets based power amplifier non-linear pre-distortion

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Abstract. This paper proposed a novel method based on deep neural networks (auto-encoder) model, to construct the pre-distortion model for non-linear feature of power amplifier. As auto-encoder nets are high non-linear function, with the optimization of object function to tune the weights, the nets can reach any non-linear model. For widely used power amplifier, this method can help setting the pre-distortion model. In this paper, deep (more layers) network structure have been adopted in the auto-encoder model. The experimental results show the effectiveness and efficiency of deep neural network based power amplifier non-linear pre-distortion technique.

1. Introduction

Wireless communication technology is attracting much research attention in recent years and is of importance to further information development. However, it has strict linearization requirements on power amplifier (PA) for suppressing adjacent channel interference and reducing bit-error rate. Digital pre-distortion is one of the most effective linearization techniques and widely used to compensate for the nonlinearity in the PA. The most commonly used pre-distortion methods [1] involve polynomial model, memory polynomial pre-distortion model [2-3], BP neural network pre-distorter [9], and so on. The deep neural network has also received a lot of attention in the literature and has been applied in various research fields successfully. This paper proposes a deep neural network [5-6] based power amplifier non-linear pre-distortion technique to construct the pre-distortion model and the results of this study show that the proposed method is effective.

2. Pre-distortion Technique

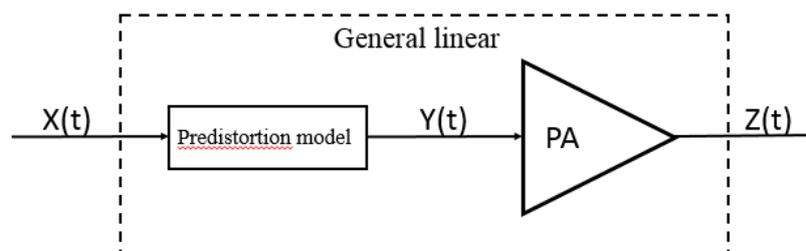


Figure 1. Pre-distortion technique



Pre-distortion is one of the main linearization techniques that have the inverse characteristic of the PA to nonlinearity.

2.1. Pre-Distortion Technology

Pre-distortion is based on the indirect learning architecture, as shown in Fig. 2. The benefit of the indirect learning architecture is that we should not assume a PA model and estimate the PA parameters, therefore pre-distortion is a common choice due to its effectiveness and ease of implementation.

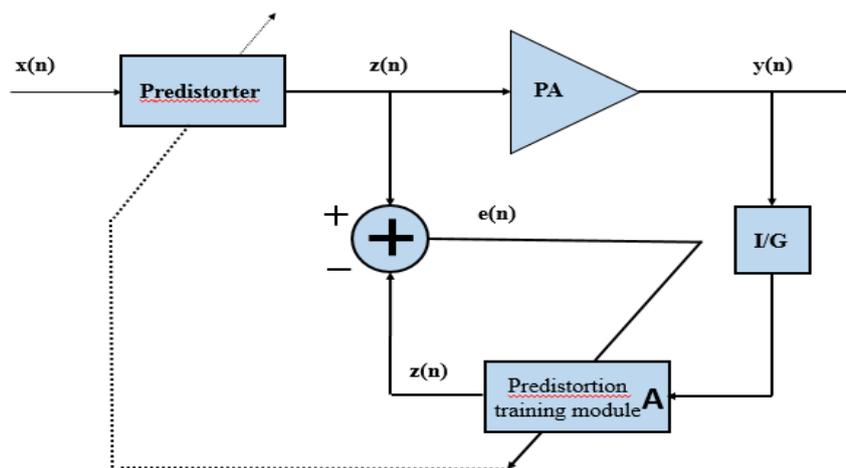


Figure 2. Indirect learning structure

2.2. Traditional Neural Network Pre-distortion Model

Among the various pre-distortion techniques, this paper focuses on black propagation (BP) neural network pre-distortion model [9].

BP neural network is a multi-layer feed-forward neural network, which has the function of non-linear reflection showing complex rule of cause and effect. BP neural network commonly having a single hidden layer consists of N input nodes, M hidden nodes and Q output nodes. The hidden layer function is defined as:

$$Y = f(W_1 X) \quad (1)$$

Where, f says activation function and usually uses purelin transfer function. Considering the nonlinear characteristics of pre-distortion model, it usually adopts the sigmoid function as the activation function in the pre-distortion model. W_1 says the weights between the input layer nodes and the hidden layer nodes. Output layer function is as follows:

$$Z = g(W_2 Y) \quad (2)$$

Where, g adopts the sigmoid function as the activation function. W_2 represents the weights between the hidden layer nodes and the output layer nodes. The error function of BP neural network is as follows:

$$E = \sum_{i=1}^N (Z_i - X_i) \quad (3)$$

Where, X_i says the i th input samples and Z_i says the i th output samples. The BP neural network model is of low computation complexity and easy hardware implementation and has certain practical value. But because of its low network layers with three layers and small network depth caused by the little nodes, the model can't learn into the exact model in a relatively short time. Aiming at the problem, this paper puts forward the pre-distortion model of deep neural network.

3. The Pre-distortion Model Based on Deep Neural Network

This section introduces the role of the deep neural network in the pre-distortion model and concrete implementation methods. In this paper, the Auto-encoder is adopted as the deep neural network.

3.1. The Deep Neural Network

The deep neural network is the result of artificial neural network and its motive is to establish and simulate human brain neural network for learning and analyzing. It imitates the human brain mechanism to explain the data and it is a kind of multilayer perceptron containing many hidden layers. The concept of depths [6] first put forward by Hinton et al in 2006. He proposed deep belief networks (DBN) and unsupervised greedy layer-by-layer training algorithm to solve the deep structure optimization problem. Then he put forward multi-layer automatic encoder (Auto-encoder) deep network. This paper uses the multi-layer Auto-encoder network structure. At present, deep learning has been widely applied to the image and text classification [10-12], clustering [13], object segmentation [14] and other fields.

3.2. Auto-encoder Network

Auto-encoder network composes of multiple single restrained Boltzmann machine network stack, and the network is divided into encoder and decoder network. It is as shown in figure 3. Single RBM network uses minimizing the energy function between the visible layer and hidden layer to optimize the weights W , but Auto-encoder network usually obtain initialized weights from multilayer RBM with the process called pre-training as shown in figure 3(a). Auto-encoder is got by do fine-tuning to the network based on the process. In fact it is also a kind of deep neural network called DNN, as shown in figure 3 (b).

3.3. The Pre-distortion Model Based on Deep Neural Network

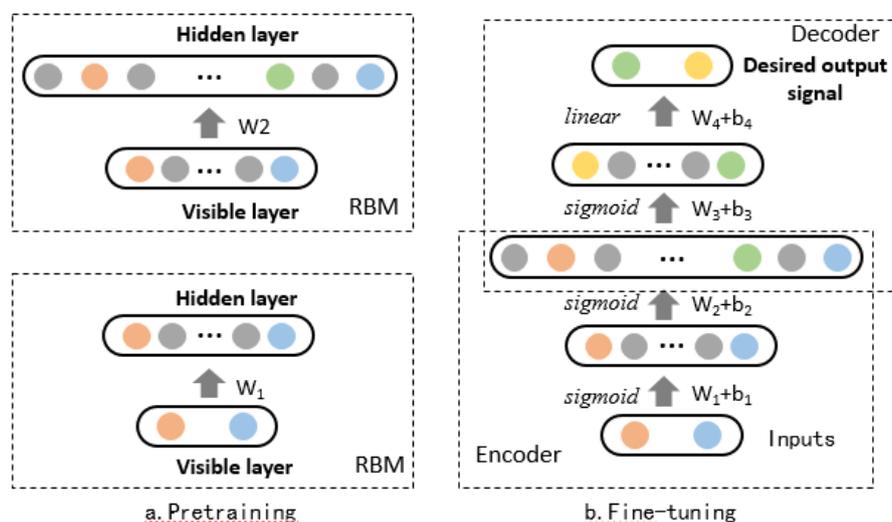


Figure 3. Auto-encoder nets pre-distortion structure

In view of the pre-distortion model, this paper adopts Auto-encoder network structure based on five-layer nonlinear mapping network. Among them the bottom layer uses the sigmoid function as the activation function. Considering the range of output is beyond the scope of (0, 1), on the top layer (output layer) the paper uses the linear function (linear) as the activation function. The specific network structure is 2-10-30-10-2. The structure of the neural network diagram is as shown in figure 3. Unlike typical Auto-encoder network, the input here is not the same as the output.

The objective function of the neural network is:

$$\min E = \frac{1}{N} \sum_{i=1}^N (Z_i - X_i) \quad (4)$$

Where, N says the number of signal sample, X_i says the i th input signal and Z_i says the i th desired output signal. In this article, the stochastic gradient descent method is used to optimize the objective function.

4. Experiments

In view of the algorithm of this paper, simulations are made through the matlab simulation platform and the power spectral density and ACPR got by calculating are used to evaluate the pre-distortion model of deep neural network.

4.1. Power Spectral Density

Using the pre-distortion model of deep neural network to train and iterate to 100 times, it can get ideal pre-distortion model. By the power spectral density diagram shown in figure 4 it can be observed visually the model has a better pre-distortion effect. In figure 4 there are as follows from left to right in turn: input signal, pre-distortion output signal, output signal after the pre-distortion processing based on the deep neural network.

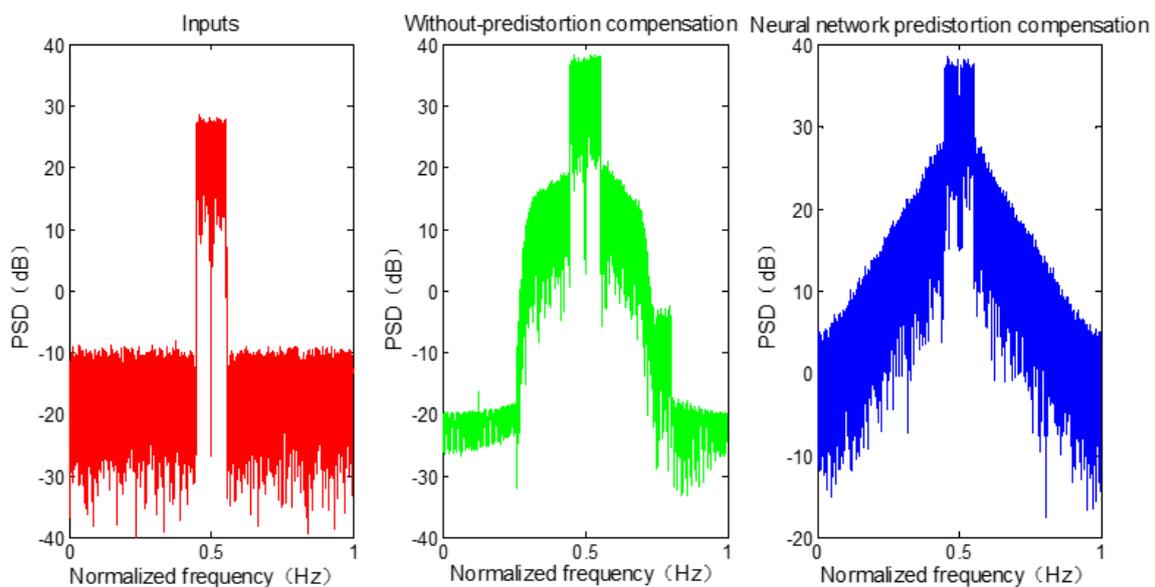


Figure 4. Curve of PSD

4.2. Quantitative Index Evaluation

The pre distortion model for power amplifier, usually use the adjacent channel power ratio ACPR (Adjacent Channel Power Ratio), Normalized mean square error NMSE (Normalized Mean Square Error) and Error vector magnitude EVM (Error Vector Magnitude) to evaluate. Among them, adjacent channel power ratio ACPR is defined as:

$$ACPR = 10 \log_{10} \frac{\int_{f_2}^{f_3} s(f) df}{\int_{f_1}^{f_2} s(f) df} \quad (5)$$

$S(f)$ is the function of power spectral density, $[f_1, \text{ and } f_2]$ is transmission channel, $[f_2, f_3]$ is adjacent channel. The expression of NMSE is:

$$NMSE = 10 \log_{10} \frac{\sum_{n=1}^N |z(n) - \hat{z}(n)|^2}{\sum_{n=1}^N |z(n)|^2} \quad (6)$$

Among them, where Z denotes actual signal value, \hat{z} indicates the Model calculation signal value, NMSE reflects approaching degree between model and Physical actual module. The Expression of EVM is:

$$EVM = \sqrt{\frac{E[|e^2|]}{E[|X^2|]}} \times 100\% \quad (7)$$

In the formula, where X denotes the ideal signal output value, e indicates the errors between ideal signal output value and whole model output, the degree of distortion of global model to the extent of signal can be measured by EVM.

Evaluation parameters of the model are shown in table 1. the table shows that the degree of accuracy based on deep neural networks pre-distortion model is higher than the traditional pre-distortion model, linear input and output has been basically achieved after joining the pre-distortion, which Confirms the feasibility of the model. Figure 5 shows the training iterative NMSE graph of the deep neural networks pre-distortion model, it can be seen in the figure that its convergence speed is faster and achieves the ideal result in the 50th iteration.

Table 1. Deep neural network based non-linear pre-distortion

Model \ evaluation index	ACPR(DB)	NMSE(DB)	EVM (%)
polynomial model	-36.02	-48.91	0.36
And memory polynomial model	-24.88	-43.71	0.70
Pre-distortion model based on DNN	-38.27	-50.12	0.33

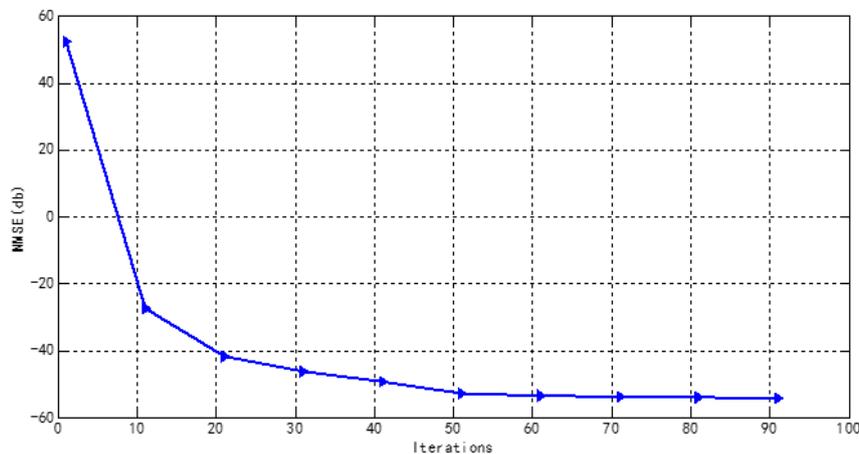


Figure 5. Iteration curve of NMSE

5. Conclusion

This paper presents a new pre-distortion model based on deep neural networks (auto-encoder), it can effectively realize the linearization of power amplifier (PA). Experimental results confirm the effectiveness of the proposed method. Deep neural network used in the pre-distortion model has two advantages, 1). The accuracy is higher, it can fit nonlinear model of the power amplifier effectively; 2). The iteration speed is faster, because of the deep neural network has deeper network structure than ordinary (monolayer) neural network, thus it has the stronger ability to learn, it can achieve faster speed of convergence in the practical application.

In future, we will focus on the number of nodes and layers of the deep neural networks to the further experiment. In addition, we will also consider joining the drop-out [7, 8] technology to improve the neural network training speed.

6. Acknowledgment

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7. References

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