Modeling for Nonlinear High-speed Links Based on Deep Learning Method

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***Abstract*— With the nonlinearity degree increasing in high-speed links, the traditional fast time-domain system simulation techniques based on linear time-invariant hypothesis cannot accurately predict the system response. In this paper, a modeling method based on deep learning method is proposed to develop a time-domain model to accurately deal with the nonlinear factor in the high-speed links. Compared with the SBR-based fast time-domain simulation method, the simulated results show that the proposed modeling method based on deep learning can facilitate accurate and fast transient simulation.**

Keywords—deep learning method; nonlinear; signal integrity

I. INTRODUCTION

With the advancement of technology, people's demand for high-speed systems is getting higher and higher. Especially the arrival of the 5G era has led to a sharp increase in the amount of transmitting data. As a result, the transfer rate also increases dramatically. It is the high frequency characteristics of transmission lines, such as dielectric loss, skin effect, crosstalk, and reflection that affect the signal quality at the receiving end and even cause bit errors [1]. As a result, accurate characterization of high-speed links becomes more and more important.

The transient approach and statistical approach are two fundamental methods to characterize the system's response to high speed links. Transient simulation can deal with non-linear features, but the simulation time is proportional to the input sequence length [2]. Therefore, it is impossible to achieve the estimation of the worst-case performance and predict the eye opening for an arbitrary low system bit error rate (BER) value such as 10^{-16}. In order to accurately predict and optimize the performance of the passive interconnects in the early design phase, several fast time-domain techniques have been developed, such as the single bit response (SBR), double edge response (DER), and multi-edge response (MER) [2-4]. Compared to the conventional SPICE-like transient approach, the statistical channel simulator provides an efficient way to predict the performance of high-speed links with serious non-ideal electrical behaviors. It is widely used to predict the worst-case eye diagrams and system BER of high-speed links [5-6]. However, for the fast time-domain techniques, it is assumed that the high-speed links are linear and time invariant. With the nonlinear features of the high-speed links becoming more and more serious, the fast time-domain techniques may become inefficient to predict the performance of the high-speed link.

In analog and radio-frequency circuit design, there are two groups of nonlinear circuits. The first category is composed of

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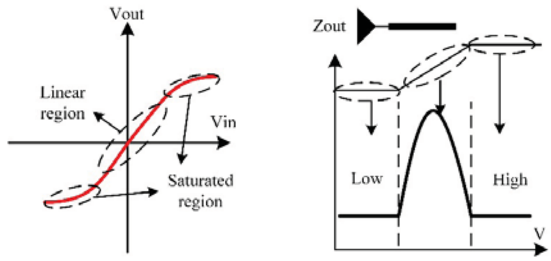


Fig. 1. Nonlinear factors in high speed links.

circuits that are inherently nonlinear, such as the saturation properties of the amplifier in transmitters and receivers, and the variance of the output impedance of the transmitters [7-9], as shown in the Fig. 1. The second group are circuits that are linear in theory, but end up operating in non-linear regions such as the continuous-time linear equalizer (CTLE) and decision feedback equalizer (DFE).

In order to deal with the nonlinear factor in high-speed links, deep learning method is a promising candidate which has been successfully applied to complex problems of different engineering areas [7, 10-12]. In this paper, a modeling method based on deep learning is proposed to build a system-level model of the high-speed links, which can deal with the nonlinear factors and accurately compute the received signal at the receiver (RX).

II. BACKGROUND OF DEEP LEARNING METHOD

The Neural network is an important algorithm of machine learning. In the neural network, there are input layers, hidden layers, and output layers. And each layer contains a lot of neural unit, shown in Fig. 2. In order to deal with complex information, the internal structure of the system and the interconnection between the internal nodes can be changed and adjusted through perceiving the changes of external information. The basic neural unit in the neural network is shown in Fig. 3. Parameters $x1$, $x2$, and $x3$ represent different characteristics of the input data. The neural units in different layers have different weight coefficient w. The neural unit of hidden layers and output layers also have a bias factor b, which reflect the difficulty level to create a positive or negative excitation. The deep learning network can be trained by adjusting the weight coefficient w and the bias factor b to obtain the best prediction effect. Suppose the neural unit in Fig. 3 is the jth hidden layer; its input layer has three input neural unit $x1$, $x2$ and $x3$; the weight coefficients between the input layer and the jth hidden layer are $w1$, $w2$, $w3$, respectively, the bias factor of the jth hidden layer is b_j. The output of the

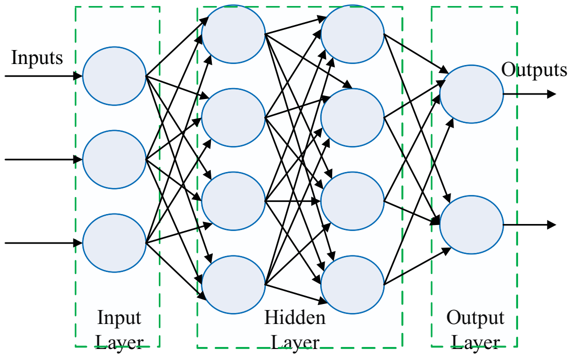


Fig. 2. A typical model of deep learning method.

neural unit is shown as follows:

$$y_j = f_{active}(Z_j) \tag{1}$$

$$Z_j = w_1x_1 + w_2x_2 + w_3x_3 = \sum_{i=1}^{3} w_{ij}x_i + b_j \tag{2}$$

The activation function is also called nonlinear function which is used to increase the ability to solve the complex problems that the linear model can't handle. There are three kinds of activation function: Sigmoid function, Tanh function, and ReLU function. The expressions are shown as follows:

$$f_{\text{Sigmoid}}(x) = \frac{1}{1+e^{-x}} \tag{3}$$

$$f_{\text{Tanh}}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4}$$

$$f_{\text{ReLU}}(x) = \max(0, x) \tag{5}$$

Another important function is the loss function which is mainly used to guide the convergence direction of the model by using the difference between the training value and the predicted value. When the neural network is trained, the loss function will be continuously reduced to receive a higher accuracy by constantly changing all the parameters in the neural network. Back Propagation (BP) algorithm based on the gradient descent method can be used to compute the minimum value of the loss function. For the neural network with n inputs and m outputs, the function of the BP algorithm is a continuous mapping from the n-dimensional Euclidean space to the m-dimensional Euclidean space, which is a highly nonlinear mapping relationship. Because the strong learning ability of neural network and the powerful nonlinear mapping ability of BP algorithm, deep learning method is used to model the nonlinearity of this high-speed link in this paper.

III. Modeling Method Based on SIMULINK and Deep Learning Method

In order to flexibly deal with the nonlinear factors in high-speed links, a model based on SIMULINK is proposed first. Then the modeling method based on deep learning method is proposed.

A. Model for High-speed Links Based on SIMULINK

A high-speed channel model is built in SIMULINK, as

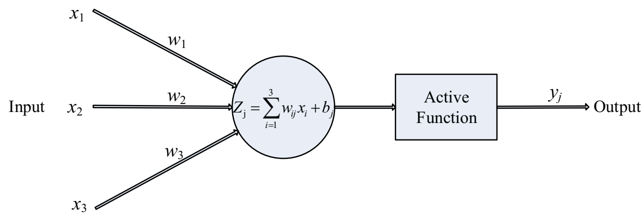


Fig. 3. Basic neural unit in the neural network.

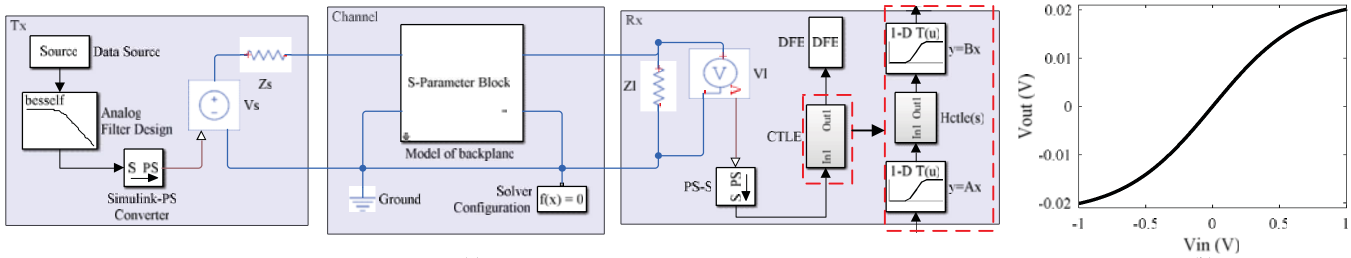
shown in Fig. 4(a). It mainly includes three parts: transmitter (Tx), passive channel, and receiver (RX). In the Tx, a “data source” module is added as excitation source. An analog filter is used to model the high-frequency loss. The output impedance of TX is modeled as a voltage-controlled resistor which is a kind of nonlinear factor in the TX. The S-parameter is used to represent the passive channel. In the RX model, it includes CTLE and DFE equalizers. The “Y=Ax” and “Y=Bx” modules are added to model the amplifier in the CTLE module. When the received signal transmitted into the CTLE equalizer. The saturation properties of the “Y=Bx” module is presented shown in Fig. 4(b).

In order to verify the accuracy of the Simulink-based High-speed link module, the simulated results by Simulink and HSPICE are compared for a link without nonlinear factor. The exciting source with 10Gbps data rate and 10ps rising time and following time is used as input signal. The simulated result is shown in Fig.6, which shows the Simulink-based channel model with great accuracy.

B. Deep learning Model

For the neural network model, the deep learning model based on BP algorithm is adopted. The activation function is set as Tanh function and Sigmoid function, and the optimization algorithm is set as Adam algorithm. The input of TX and the output of RX in the SIMULINK model is used as the training data to train the deep learning model. The input data is a 20,000-bits PRBS sequence and there are 100 sampling points in each UI. The input layer and output layer have 100 neurons, respectively. After many training experiments, it can achieve the best result when the number of the hidden layer and the node of each hidden layer are set to 3 and 30, respectively.

In order to verify the accuracy of the model, three kinds of nonlinear behaviors are added to this high-speed link: the mismatch between the rising and falling edge, voltage controlled output impedance of TX, and the saturation properties of transmitters and receivers as shown in Fig. 4(b). The excitation source with 10Gbps data rate, 10ps rising time, and 20ps following time is used as the input signal of Tx. Fig. 6 shows the output waveforms simulated by SIMULINK, deep learning model, and SBR-based method. It can be seen that deep learning method has a good accuracy and can deal with the nonlinear link and that the SBR-based method cannot predict the system response of the nonlinear links. The inner contours of the eye diagrams for 10,000-bit output signal is shown in Fig. 7. The eye-heights and eye width computed by different methods are listed in Table I. Since the SBR-based method is based on the linear and time invariant hypothesis, it shows a great limitation for the nonlinear links.



(a) (b)

Fig. 4. (a) Structure diagram of nonlinear high-speed link. (b) Saturation properties of y=Ax

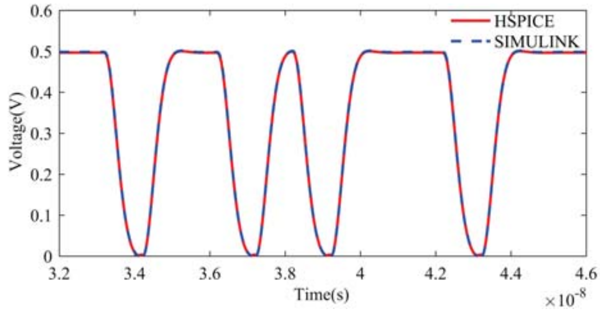


Fig. 5. Comparison of the simulated result by HSPICE and SIMULINK model.

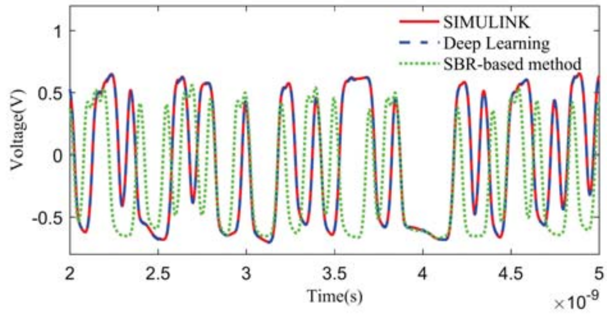


Fig. 6. Three ways to solve the waveform of the output response.

IV. Conclusion

With the nonlinearity degree increasing in high-speed links, the traditional fast time-domain system simulation techniques based on linear time-invariant hypothesis cannot accurately construct the system response. In this paper, the modeling method based on deep learning method is proposed to develop a time-domain model to accurately deal with the nonlinear factor in the high-speed links. Comparing the simulated results by SIMULINK and SBR-based fast time-domain methods shows that the SBR-based method has great limitation for the nonlinear links, and that the deep learning modeling method has a great accuracy and can facilitate accurate and fast transient simulation.

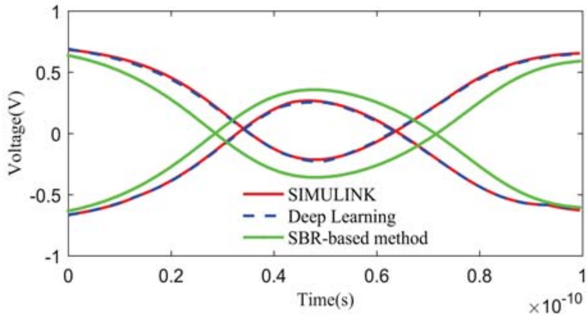


Fig. 7. Inner contours of the eye diagrams

TABLE I. Comparison of Eye-height and Eye-width Obtained by Three Ways

	SIMULINK-based model	**Deep learning-based model**	**Error (%)**	**SBR-based method**	**Error (%)**
Eye height (v)	0.4808	0.4846	0.7%	0.7162	48.9%
Eye width (ps)	29.5	29.5	0%	43	45.7%

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