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A Novel Knowledge-Based Neural Network Approach to the Small-Signal Modeling of Packaged Diodes

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ABSTRACT: This paper proposes a novel knowledge-based neural network approach that, in the absence of specific device SPICE models, can utilize the measured data of actual diode devices to map the existing diode coarse model to a more accurate packaged model through neural network mapping techniques, thereby achieving precise and efficient modeling of the small-signal characteristics of diode devices. A knowledge-based neural network model for packaged diodes is proposed, which enhances modeling accuracy by learning the discrepancies between the diode coarse model and the actual device data. A training method for rapid parameter adjustment is suggested, where the neural networks within the input and output package modules automatically learn and adjust, continuously optimizing their internal parameters to enhance modeling efficiency. Modeling experiments conducted on the measurement data of the MA4AGFCP910 diode show that the proposed packaged diode model can effectively and accurately match the small-signal characteristic data of the diode device.

1. INTRODUCTION

In the field of semiconductor device modeling, the research on diode modeling has been continuously attracting attention [1–3]. Traditional modeling methods based on semiconductor physics are widely used due to their strong interpretability and adaptability. The equivalent circuit modeling method models the behavior of diodes by optimizing the values of circuit components, and its advantages lie in simplicity, low computational cost, and the ability to handle high-frequency issues [4–6] effectively. However, in the face of increasing design complexity and shorter design cycles, traditional methods may fall short in terms of efficiency and accuracy. Therefore, it has become necessary to develop new diode modeling methods to improve accuracy and efficiency.

Knowledge-based neural network modeling technology is an application of artificial intelligence in the field of microwave, utilizing neural networks to simulate the behavior of microwave components or systems [7–9]. Unlike traditional microwave modeling techniques that rely on mathematical formulas and physical laws, this method involves training neural networks to learn the input-output relationships of microwave devices. By using a large amount of experimental or simulated data to train the neural network, it can accurately predict the output of unknown data, drastically improving efficiency in device design and reducing the time required for modeling and testing processes, accelerate the design process, and reduce reliance on physical prototypes [10–12]. The knowledge-based neural network modeling technology [13, 14] offers a fast and flexible alternative to traditional microwave modeling methods, significantly improving design and analysis efficiency while maintaining a certain level of accuracy.

To improve the accuracy and efficiency of diode modeling, this paper proposes a novel knowledge-based neural network approach for the small-signal modeling of packaged diodes. This approach integrates the package module into a neural network model, thereby enabling the transformation of the existing coarse diode model into a more accurate packaged model.

2. THE PROPOSED KNOWLEDGE-BASED NEURAL NETWORK MODELING TECHNIQUE FOR PACKAGED DIODES

2.1. Proposed Diode Model Structure

To accurately fit the small-signal characteristics of devices, a diode neural network model structure is proposed in Figure 1. The proposed model consists of four main modules: input package module, diode coarse model module, output package module, and overall **S**-matrix analysis module. This design aims to simultaneously consider the combined impact of the diode coarse model module and the package modules on small-signal characteristics. By learning the differences between the diode coarse model and the actual device data, the neural network model can improve the accuracy of the modeling. The diode coarse model module is the core, representing the small-signal characteristics of the diode. In addition, two package modules are proposed to represent the behavior of the input and output package circuits, respectively. The constructed **S**-matrix analysis module is used to calculate the **S**-parameters of the overall packaged diode. **S**-parameter, also known as scattering pa-

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rameter, is an important parameter that describes the energy transmission characteristics between the ports of microwave devices. It can comprehensively reflect the device's insertion loss, return loss, and other characteristics.

In the proposed model shown in Figure 1, both the input and output package modules consist of an Artificial Neural Network (ANN) and an **S**-parameter calculation module. ANN is a multi-layer perceptron neural network that captures the behavior of the package circuit and represents the relationship between the frequency f and the five outputs. Specifically, when ANN1 receives the unique input signal frequency f, the natural variable B^I and phases θ_{11}^I, θ_{12}^I, θ_{21}^I, and θ_{22}^I of the **S**-parameters are obtained. Meanwhile, through ANN2, natural variables B^O and phases θ_{11}^O, θ_{12}^O, θ_{21}^O, and θ_{22}^O of the **S**-parameters are obtained. B^I and B^O are used to determine the amplitudes of the sub-S parameters, such as S_{11} and S_{12}, which describe the network's input reflection and gain characteristics. The amplitudes of the sub-S parameters reflect the intensity of these characteristics as they vary with frequency f. The subscripts denote the port numbers of the input/output package circuit, and superscripts I and O represent the input package and output package, respectively.

Vectors $\mathbf{w}_1$ and $\mathbf{w}_2$ contain all the synaptic weights in neural networks f_{ANN1} and f_{ANN2}, respectively. These weights represent the connections between neurons and are key parameters for processing input information. During the training process, the PALSO algorithm is used to continuously adjust and update vectors $\mathbf{w}_1$ and $\mathbf{w}_2$ to optimize network performance. The key part of the sensitivity analysis of the proposed ANN model is to analyze the first-order partial derivatives of the output functions f_{ANN1} and f_{ANN2} with respect to the weights $\mathbf{w}_1$ and $\mathbf{w}_2$ [15]. The functioning of these two neural networks can be described as

$$(B^I, \theta_{11}^I, \theta_{12}^I, \theta_{21}^I, \theta_{22}^I) = f_{ANN1}(f, \mathbf{w}_1) \tag{1}$$

$$(B^o, \theta_{11}^o, \theta_{12}^o, \theta_{21}^o, \theta_{22}^o) = f_{ANN2}(f, \mathbf{w}_2) \tag{2}$$

where f_{ANN1} and f_{ANN2} represent multi-layer feedforward neural networks, and $\mathbf{w}_1$ and $\mathbf{w}_2$ are vectors containing all internal synaptic weights within the neural networks f_{ANN1} and f_{ANN2}, respectively.

The **S**-parameter calculation module converts the obtained natural variables and **S**-parameter phases into specific **S**-parameter values, including the real and imaginary parts of S_{11}, S_{12}, and S_{22}. S_{21} is not chosen as an output because the dual network has the relationship $S_{21} = S_{12}$, which reduces the output dimensionality of the input/output modules and simplifies the model structure. The output of the input package module is represented as $Re(S_{ij}^I)$ and $Im(S_{ij}^I)$, and the output of the output package module is similarly represented as $Re(S_{ij}^O)$ and $Im(S_{ij}^O)$. The real and imaginary parts of the **S**-parameters are denoted by the prefixes *Re* and *Im*, respectively, with subscripts ij (where $ij = 11$, 12, 22) indicating the port numbers of the input/output package circuit, and superscripts I and O representing the input and output package, respectively. According to [13], this paper derives the relationship between the amplitude and phase, and the real/imaginary parts of the **S**-parameters obtained from the **S**-parameter calculation module can be described by Formulas (3) and (4).

For the diode coarse model module, the input signals consist of the bias current I_{dc} and frequency f, and the output signals are represented as $Re(S_{ij}^C)$ and $Im(S_{ij}^C)$. In subscripts ij (where $ij = 11, 12, 21, 22$), i represents the incident port of the signal, while j indicates the port for signal reflection or transmission. Superscripts I and O represent the input package and output package, respectively.

The overall **S**-matrix (Scattering Matrix) analysis module is essential for calculating the **S**-parameter matrices corresponding to the input package module, diode coarse model module, and output package module. The module's output signals, expressed as $Re(S_{ij}^F)$ and $Im(S_{ij}^F)$, form the **S**-parameters of the modeled object. In subscripts ij (where $ij = 11$, 12, 21, 22), i represents the incident port of the signal, while j indicates the port for signal reflection or transmission. Therefore, the model can perform packaged modeling of diodes solely through terminal signals, without the need for an in-depth understanding of their internal and physical structures.

$$\begin{cases} Re(S_{ij}^I) = \frac{1}{1+e^{-B^I}} \times \cos(\theta_{ij}^I), \quad Im(S_{ij}^I) = \frac{1}{1+e^{-B^I}} \times \sin(\theta_{ij}^I) \quad i = j \\ Re(S_{ij}^I) = \sqrt{1 - \left(\frac{1}{1+e^{-B^I}}\right)^2} \times \cos(\theta_{ij}^I), \quad Im(S_{ij}^I) = \sqrt{1 - \left(\frac{1}{1+e^{-B^I}}\right)^2} \times \sin(\theta_{ij}^I) \quad i \neq j \end{cases} \tag{3}$$

and

$$\begin{cases} Re(S_{ij}^O) = \frac{1}{1+e^{-B^O}} \times \cos(\theta_{ij}^O), \quad Im(S_{ij}^O) = \frac{1}{1+e^{-B^O}} \times \sin(\theta_{ij}^O) \quad i = j \\ Re(S_{ij}^O) = \sqrt{1 - \left(\frac{1}{1+e^{-B^O}}\right)^2} \times \cos(\theta_{ij}^O), \quad Im(S_{ij}^O) = \sqrt{1 - \left(\frac{1}{1+e^{-B^O}}\right)^2} \times \sin(\theta_{ij}^O) \quad i \neq j \end{cases} \tag{4}$$

2.2. Proposed Training Method

To accurately simulate the packaged diode, the proposed knowledge-based neural network model needs to learn the device data. Therefore, in the model development, the training of the neural network is crucial. During the training process, the system automatically adjusts the weights in the neural network to achieve precise correspondence between the model output and actual device data. The training error is the standard for measuring the learning effect of the model, revealing the discrepancy between the model output and actual data. The training process will continue until the errors calculated from both training and testing data meet the preset accuracy standards. The error function for the **S**-parameters of the

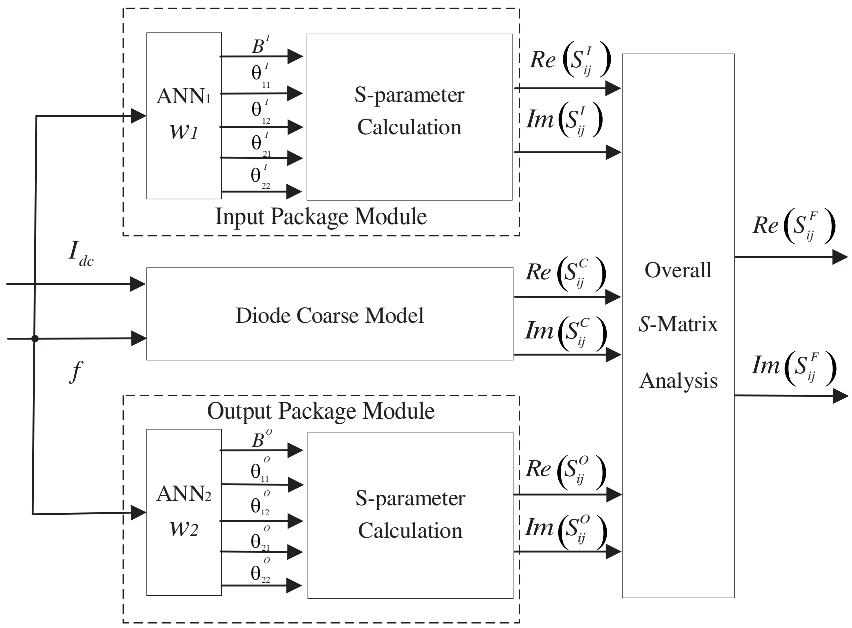

FIGURE 1. The structure of the proposed packaged diode model.

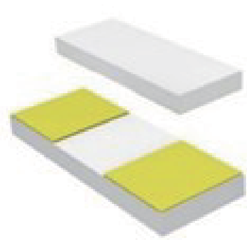

FIGURE 2. MA4AGFCP910 diode physical appearance.

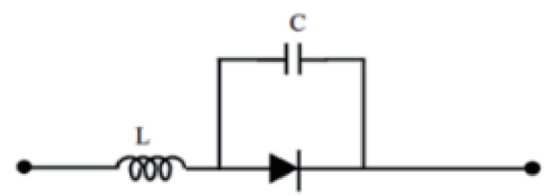

FIGURE 3. NSR201 diode internal model structure.

packaged diode is given in Equation (5).

$$E(\mathbf{w}) = \frac{1}{2}\sum_{n=1}^{N} ||S(I_{dc}^{n}, freq^{n}, \mathbf{w}_1, \mathbf{w}_2) - S_{Df}^{n}||^2 \tag{5}$$

where $\mathbf{S}_{Df}$ represents the **S**-parameters of the fine model, and $\mathbf{S}(\cdot)$ refers to the **S**-parameters of the packaged diode model. Superscript "n" is used to denote the nth set of training or testing data, while superscript "N" is used to indicate the total number of training or testing data sets. $\mathbf{w}_1$ and $\mathbf{w}_2$ represent the weight parameters of the input package circuit module and output package circuit module, respectively, and are the key parameters that need to be adjusted when using the neural network to optimize the model.

To improve the efficiency of model optimization, we propose a novel construction and training method for the packaged diode model. This method is characterized by modular modeling, which allows different parameters to control different characteristics. In the first stage of training, we adjust the weights $\mathbf{w}_1$ and $\mathbf{w}_2$ of the neural network within the package module, to align the small-signal model with the device data in **S**-parameter simulations. In the second stage, we further train the packaged diode module and package module using **S**-parameter data, to improve the overall accuracy of the modeling. Once training is complete, the proposed model surpasses existing models in terms of accuracy and is capable of replacing actual devices for the design and simulation of original circuits.

3. EXAMPLES

In this experiment, to verify the accuracy and effectiveness of the proposed model, we selected the gallium arsenide (AlGaAs) inverted chip diode MA4AGFCP910 as the research object, which is a P-type-Intrinsic-N-type (PIN) diode, and the selection range of training and testing data is detailed in Table 1. The frequency range is from 2 to 50 GHz with a step size of 1 GHz. The current range is from 5 to 15 mA with a step size of 1 mA. Figure 2 shows the physical appearance of the diode device. The Schottky barrier diode NSR201 model is selected as the first coarse model. The internal model structure of the NSR201 Diode is shown in Figure 3. Tests revealed that the error between the NSR coarse model and actual device data was 270.58%. Subsequently, a PIN diode model identical to the MA4AGFCP910 diode type in Advanced Design System (ADS) was selected as the second coarse model, and the error of the PIN coarse model was 164.09%. The mismatch between the above two coarse models and the device data is not negli-

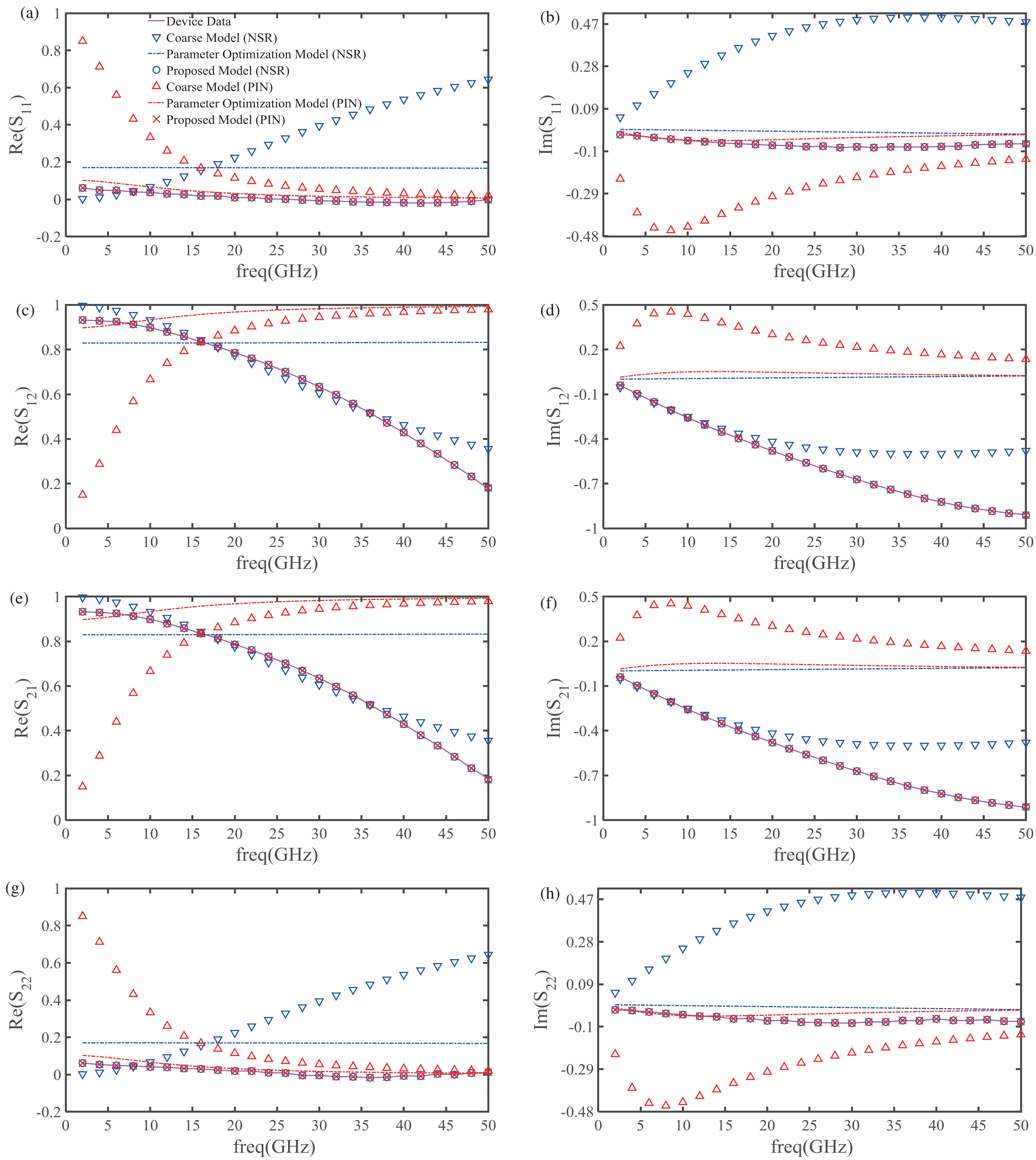

FIGURE 4. Comparison of **S**-parameter measurement data and model at the operating bias point of the MA4AGFCP910 diode ($I_{dc} = 5\,\text{mA}$).

TABLE 1. Training data and test data for **S**-parameters modeling.

	Data type	Frequency (GHz)	Current (mA)
S-parameter simulation	Training data	2:1:50	5:5:15
	Test data	2.5:1:49.5	

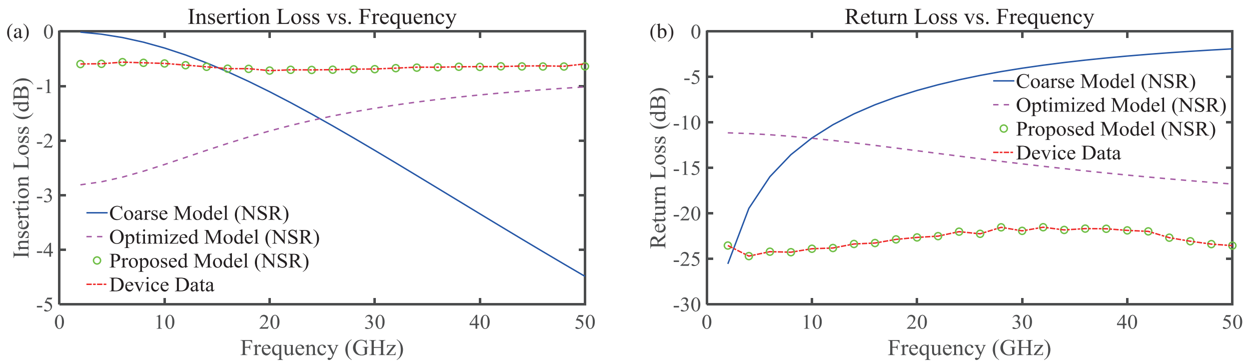

FIGURE 5. Comparison of insertion loss and return loss values of various diode models based on NSR at the operating bias point of the MA4AGFCP910 diode ($I_{dc} = 5\,\text{mA}$).

TABLE 2. The parameters for NSR coarse model and PIN coarse model.

Parameter	NSR_Value	PIN_Value	Parameter	NSR_Value	PIN_Value
IS	123 nA	10 mA	**Ibv**	7.65 µA	10 µA
N	1.28	1	**EG**	0.69 eV	1.11 eV
BV	5.338 V	50 V	**XTI**	2	3
RS	12.2 Ohm	0.75 Ohm	**VJ**	0.5 V	0.85 V
CJO	0.1 pF	0.23 pF	**FC**	0.5	0.5

TABLE 3. Training and test errors between diode model and device data.

	Model type	Coarse Model	Parameter Optimization Model	Proposed Model
NSR	**Training error (%)**	270.58	79.31	0.93
	Test error (%)	270.60	79.31	1.03
PIN	**Training error (%)**	164.09	44.35	0.90
	Test error (%)	164.12	44.36	1.03

gible. The main parameters of the two diode coarse models are detailed in Table 2.

In the process of model construction, we trained the data for the two coarse models based on the neural network structure proposed in Subsection 2.1 and the training method described in Subsection 2.2. We automatically optimized the neural network parameter weights within each model's package module to ensure that the model's outputs closely approximate the device data. The construction and training of the proposed model are carried out in the NeuroModelerplus software, and the validation of the proposed model is implemented in the ADS software. Following the training phase, we exported the outputs of the package modules from the neural network structure to ADS, where we constructed the NSR packaged model and PIN packaged model separately for model validation. To assess the accuracy of the models, we utilized test data that was distinct from the training set, a step that ensured the model to maintain a strong generalization capability on unseen data.

By comparing the trained proposed model with the actual device data, we evaluated the training and testing errors of the proposed model, with the results presented in Table 2. The study found that our proposed knowledge-based neural network method, by considering the impact of encapsulation on device performance and integrating the encapsulation effect into the neural network model, effectively reduced the error between the coarse model and actual device data, achieving precise fitting of the target device's small-signal behavior in actual circuits.

In another study, we compared various modeling methods. Within the ADS software, we utilized a parametric modeling approach to optimize the two previously mentioned coarse models, namely the NSR Parameter Optimization Model and the PIN Parameter Optimization Model. The error rate of the NSR coarse model was reduced to 77.31%, and the error rate of the PIN coarse model was reduced to 44.35%, as detailed in Table 3. Although parametric optimization reduced the model error, the error was still relatively high. In contrast, our proposed packaged diode modeling method has achieved more significant results in terms of diode device modeling accuracy.

As shown in Figure 4, under a 5-mA bias current, we compared the device data with several different diode models, and it can be seen that our proposed model is highly consistent with the device data. Figure 5 illustrates a comparison of insertion loss and return loss values for various models based on the NSR diode at a working bias point of 5-mA. Similarly, Figure 6 presents a comparison of these values for different models based on the PIN diode under the same bias current condition.

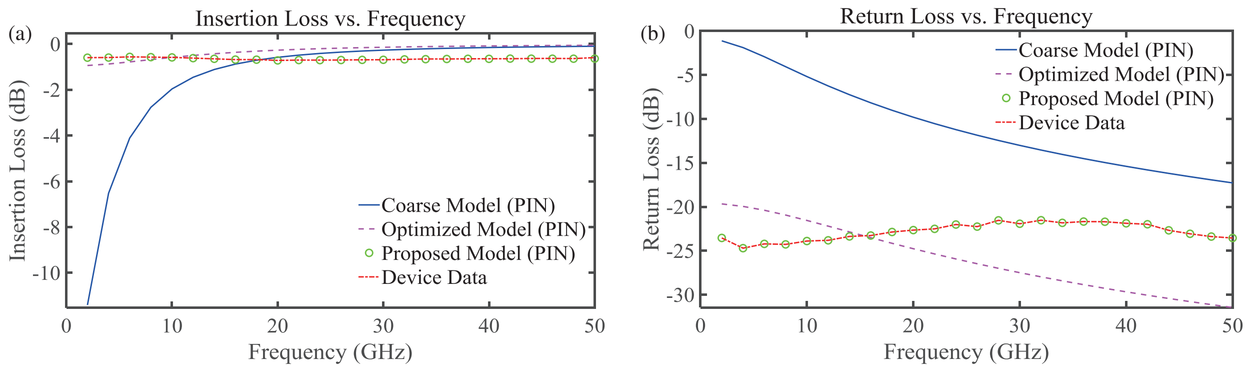

FIGURE 6. Comparison of insertion loss and return loss values of various diode models based on PIN at the operating bias point of the MA4AGFCP910 diode ($I_{dc} = 5\,\text{mA}$).

4. CONCLUSIONS

This paper has proposed a knowledge-based neural network approach for small-signal modeling of packaged diodes, offering a new perspective in the field of diode modeling. Compared to traditional parameter optimization methods, the proposed model has significantly reduced the error between coarse diode models and actual device data, enhancing the modeling accuracy. Furthermore, the proposed model has integrated the package module in the neural network to assess its impact on device performance, which is crucial for precise modeling of packaged diodes and is often overlooked by traditional methods. Lastly, the proposed model relies solely on terminal signals without needing internal structural and physical information of the packaged diode. In future work, we intend to refine the proposed model by integrating the characteristics of diodes such as transient behavior and noise properties. Meanwhile, we will also explore the development of modeling methods for other types of diodes.

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