Knowledge-Based Neural Networks for Modeling of Radio-Frequency/Microwave Components

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Abstract　An overview of advanced neural network methods for modeling radio-frequency (RF) and microwave electronic devices is presented. Knowledge-based engineering concept is utilized where the knowledge of RF/microwave electronics in the form of equivalent circuits and empirical formulas is combined with neural networks. Advantages of adding knowledge on the performance of the neural models in terms of generalization ability versus different sizes of training data through a knowledge based neural network (KBNN) technique are demonstrated and examples of comparisons with conventional MLP (without any knowledge-base) are given. Several methods of combining existing circuit models with neural networks, including the source difference method, the prior knowledge input method, and the space-mapped neural models, are also introduced. Application examples on modeling microwave transmission line and high electron mobility transistor (HEMT) device demonstrate that KBNN is an efficient approach for modeling various types of microwave devices.

Key words　knowledge-based engineering; modeling; neural networks; radio-frequency/microwave electronic devices

知识型神经网络的射频/微波器件建模方法

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【摘要】综述了用神经网络对射频与微波电子器件建模的方法，利用知识型的概念将射频或微波电子的等效电路和经验公式与神经网络有机的结合起来。将相关知识附加到神经网络模型的优势进行了论证.通过与无附加知识的传统多层感知器对比，证明了知识型神经网络的可行性。介绍了几种现有电路模型与神经网络结合的方法，如差分法、先于知识输入法及空间映射神经网络法。举例介绍了微波传输线和高电子迁移率晶体管的建模方法及过程，证明了基于知识的神经网络是各种微波器件建模的一种有效方法。

关　键　词　知识型;　建模;　神经网络;　射频/微波电子器件

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The application of artificial neural networks (ANN) to radio-frequency (RF) and microwave modeling has been recognized as a powerful alternative to conventional electromagnetic (EM)–based modeling techniques for computer-aided design of RF/microwave circuits in wireless electronics systems. Neural networks are trained to learn the highly complicated behavior of RF/microwave components, and the trained neural networks can provide quick solutions to the problem it learned. Such neural network based model is much faster for RF/microwave design compared to conventional electromagnetic based design[1-5].

With continuing developments in applications of

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neural networks to RF/microwave design, there is a growing need for reduction in the cost of model development and improvement in model reliability. The accuracy of the commonly used multilayer perceptron (MLP) model largely depends on adequacy of the training data, apart from the number of hidden neurons. Since MLP belongs to the type of black-box models structurally embedding no problem-dependent information/knowledge, it derives the entire information about the RF/microwave behavior from the training data. Consequently, a large amount of training data is usually needed to ensure model accuracy. In microwave applications, training data is obtained either by simulation of original EM/device-physics problem, or by measurements. Generating large amount of training data could be very expensive, because simulation/measurement may have to be performed at many points in the model input parameter space (e.g., for various combinations of geometrical/process/bias parameters). Without sufficient training data, the resulting neural models may not be reliable. Moreover, even with sufficient training data, the reliability of MLP when used for extrapolation purpose is not guaranteed and in many cases is very poor.

This paper describes advanced methods in the microwave neural network modeling area where existing RF/microwave knowledge is combined with neural networks. Such knowledge provides additional information of the original problem that may not be adequately represented by limited training data. Instead of using a pure neural network to represent a microwave behavior, existing empirical models are used to improve generalization capability of neural models. At the same time, neural networks can help to bridge the gap between empirical models and EM solutions.

1 Engineering Knowledges for RF/Microwave Modeling

In RF/microwave modeling area, the knowledge about the RF and microwave problems is often in the form of empirical or equivalent circuit models. In addition, the fundamental laws govern the RF/microwave device behaviour, such as Maxwell's equations, Kirchoff's equations, and so forth can also be used to describe the component behavior. Detailed models based on EM/physics equations are accurate. However, they can be computationally intensive. Simple empirical and equivalent models often exist for passive and active RF/microwave components, but such models may not be as accurate as desired. Furthermore, a single model may not be adequate enough to represent the component behavior in the entire input space. Exploiting the learning ability of neural networks, we use neural networks to overcome the accuracy deficiencies in existing empirical/equivalent models. By adding the empirical/equivalent circuit into neural network structures, we can reduce need for large amount of training data and improve model reliability. The resulting knowledge based models would have the speed of empirical or neural models, and the accuracy of EM/physics models.

2 Knowledge-Based Neural Networks for RF/Microwave Modeling

To improve neural network accuracy/ generalization capability, several attractive ways have been proposed, where neural networks can be combined with empirical/equivalent models, such as the difference method (DM), the prior knowledge input method (PKI), the knowledge based neural network method (KBNN), and space mapping neural modeling (SM). These and other advanced structures are described here.

2.1 Knowledge Based Neural Network (KBNN)

An advanced structure combining microwave knowledge and neural network is the KBNN method, first proposed in Ref. [6] and further described in Ref. [4]. In this method, microwave knowledge in the form of empirical functions or analytical approximations is embedded into the neural network internal structure. Such knowledge complements the capability of learning and generalization of neural networks by providing additional information which may not be adequately represented in a limited set of training data. The combined model can learn and predict component behaviors originally seen in detailed physics/EM models, and predict such behaviors much faster than original models.

Switching boundary and region neurons are introduced in the model structure to reflect RF/microwave designs, where different equations or formulas with different parameters can be interchangeably used in different regions of the input parameter space. By inserting the microwave empirical formulas into the neural network structure (neuron activation functions), the empirical formulas can be refined/adjusted as part of the overall neural network training process. This technique enhances neural model accuracy especially for the data not seen during training (generalization capability), and reduces the need for a large amount of training data over conventional neural models for RF/microwave design. During the training process, shift and scale parameters of the empirical functions, other parameters in the empirical functions, boundary locations (defined by boundary neurons), and shape of regions for the empirical functions (defined by region neurons), are all automatically adjusted such that the training error between KBNN model output and that of the training data is minimized.

The final model provides the overall input-output relationship through knowledge formulas and other layers in the network. This model can be used together with the existing models in a circuit simulator. An example of such implementation is NeuroADS[7], which plugs neural network models, such as KBNN, into the ADS[8] simulator.

The motivation for developing the KBNN structure was from the fact that practical empirical functions are usually valid only in a certain region of the parameter space. To build a neural model for the entire space, several empirical formulas and a mechanism to switch among them are needed. The KBNN model retains the essence of neural networks in the sense that the exact location of each switching boundary, and the scale and position of each knowledge function, are initialized randomly and then refined automatically by the training process. The KBNN structure does not follow the rigorous layer-by-layer structure in MLP. Due to the use of such an advanced structure, the conventional backpropagation training is not applicable, thus a training algorithm specifically developed for this structure was introduced in Ref. [6]. Besides, this KBNN technique enhances neural model accuracy especially for unseen data and reduces the need of large set of training data. It has a significant impact on statistical analysis and design of RF/microwave circuits.

2.2 The Difference Method

One of the earlier methods in the direction of knowledge based neural network is the source difference method[4,9]. The idea is to exploit the existing information in the form of empirical or equivalent circuit models together with the neural models to develop fast and accurate hybrid EM-ANN models. In other words, one can use the known information of the component to simplify the input-output relationship to be modeled by a neural network. The microwave behaviors of the component (e.g., S-parameters) are generated using EM simulation in the region of interest (i.e., model utilization range in input space). The behaviors of the component are also computed from the existing approximate model. A fast neural model is then developed to learn the difference between the EM simulation results and the approximate model. Because both the empirical and the neural models are fast, the final combined model is also fast. The overall structure consists of an empirical or equivalent circuit model (approximate model) to represent the available knowledge, and a neural network that represents the difference between EM simulation data and approximate model[10], is shown in Fig. 1.

The training data for the ANN portion of the overall model is obtained by calculating the difference between the EM data and the corresponding solutions from the approximate model. The finished model for the user has two components, that is, the empirical model and the trained neural model. This hybrid EM-ANN model will be used during online microwave design. The empirical model computes the approximate outputs, and the trained neural model predicts the difference. In this way, the neural model can help to correct for the differences in the outputs. The EM-ANN model offers the accuracy of EM simulation but at a speed much faster than EM simulation. Using the source difference method, fast and accurate microwave component models can be developed with less training data. The time required for model development is also shorter. The difference method is also the simplest knowledge based neural network methods.

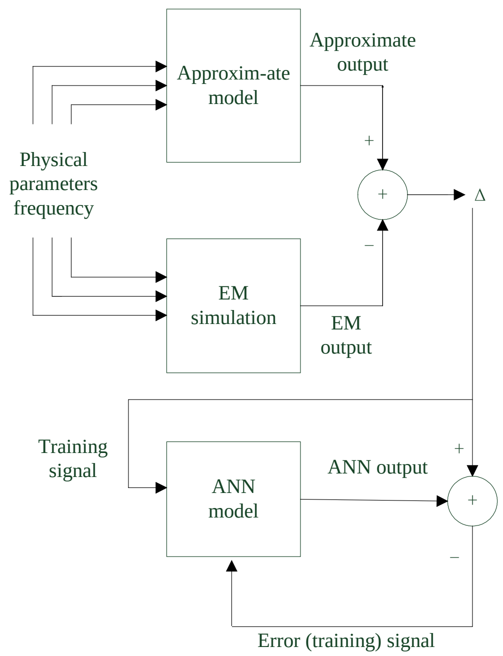


Fig. 1 Scheme of the difference method

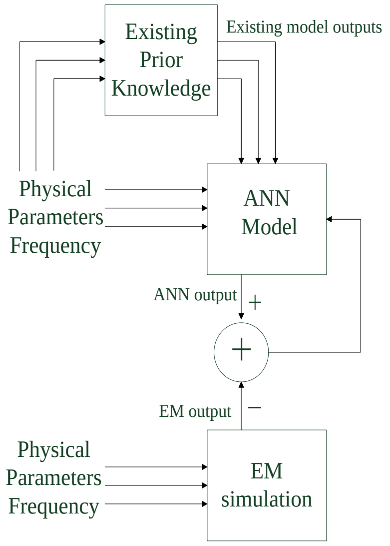


Fig. 2 Scheme of the PKI method

2.3 Prior Knowledge Input Method (PKI)

An interesting knowledge based approach is the prior knowledge input method proposed in Ref. [10]. Prior knowledge, for example, can be in the form of analytical equations, empirical models, or already trained ANN models. Normally, the existing empirical models or analytical equations do not give the required accuracy over the desired range of operation. In the PKI method, the empirical model outputs are used as inputs to the neural network model, in addition to the original problem inputs. In this case, the input-output mapping to be learned by the neural network is that between the outputs of the existing approximate model and the original problem. For the case where the target outputs are the same as the approximate model outputs, the learning problem is reduced to a one-to-one mapping. The overall structure consists of an empirical or equivalent circuit model (approximate model) to represent the available knowledge. It also has a neural network that represents the mapping between the outputs of the approximate model and the original problem[10], as shown in Fig. 2. The quality of this mapping is enhanced by including the original problem inputs as additional inputs to the neural network. The PKI is also called the additional input method.

The model development process includes a data preprocessing phase and a neural network training phase. In the data preprocessing phase, the EM training data is fed to the approximate model, whose output will be used as input data for ANN training. The other part of the inputs to the ANN is the original input of the overall hybrid model. The output of the ANN is in the original EM data. In the second phase, the ANN model can be trained with the preprocessed data.

By combining the trained neural model with the empirical model during the online microwave design, we obtain the overall PKI model. The evaluation of the neural network starts from the outputs of the approximate model and results of the evaluation will be the overall model responses, matching the accuracy of EM simulation. The PKI model is faster than direct EM simulation models, and is more accurate than the original empirical model.

2.4 Space-Mapped Neural Modeling

While the PKI method uses ANN to modify the outputs of the empirical model, there is another method where ANN is used to modify the input of the empirical model. The method, called the space-mapped neural network approach, was proposed in Ref. [11-12]. The space-mapping (SM) technique [13] combines the computational efficiency of coarse models with the accuracy of fine models. The coarse models are typically empirical functions or equivalent circuit models, which are computationally very efficient. However, such models are often valid only in a limited range of input-space, beyond which the model predictions become inaccurate. On the other hand, detailed or "fine" models can be provided by an electromagnetic (EM) simulator, or even by direct measurements. The detailed models are very accurate but can be expensive (e.g., CPU-intensive simulations). The SM technique establishes a mathematical link between the coarse and the fine models, and directs the bulk of the CPU-intensive computations to the coarse model, while preserving the accuracy offered by the fine model. The neural network module maps the original problem input-space $\boldsymbol{x}_f$ (i.e., fine model input-space) into a coarse model input-space $\boldsymbol{x}_c$. The coarse model then produces the overall output $\boldsymbol{y}$, which should match the EM data (i.e., fine model output).

The specific process is as follows: First, let the vectors $\boldsymbol{x}_c$ and $\boldsymbol{x}_f$ represent the design parameters of the input-space in coarse and fine models, respectively, and $\boldsymbol{R}_c(\boldsymbol{x}_c)$ and $\boldsymbol{R}_f(\boldsymbol{x}_f)$ are the corresponding model responses. The aim of SM is to find an appropriate mapping P from the fine model parameter input-space $\boldsymbol{x}_f$ to the coarse model parameter input-space $\boldsymbol{x}_c$.

$$\boldsymbol{x}_c = P(\boldsymbol{x}_f) \tag{1}$$

such that:

$$\boldsymbol{R}_c(P(\boldsymbol{x}_f)) \approx \boldsymbol{R}_f(\boldsymbol{x}_f) \tag{2}$$

Once the mapping is found, the coarse model can be used for fast and accurate simulations.

The illustration of the space-mapping neural modeling concept is shown in Fig. 3.

For EM modelling, there are many available empirical models based on quasistatic analysis: they usually yield good accuracy over a limited low range of frequencies. This limitation is overcome through a frequency-sensitive mapping from the fine to the coarse parameter space. This is realized by considering frequency as an extra input variable of the ANN that implements the mapping.

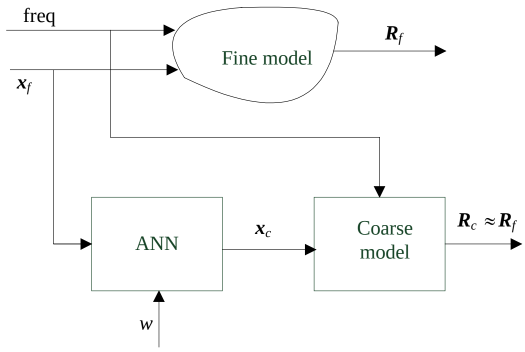


Fig. 3　Scheme of the space-mapped neural modeling

Frequency dependent space-mapped neural modeling (FDSMN) and frequency space-mapped neural modeling (FSMN) are two common forms of SM neural modeling.

In the FDSMN approach, both coarse and fine models are simulated at the same frequency, but the mapping from the coarse to the fine parameter input-space is dependent on the frequency[11], as illustrated in Fig. 4.

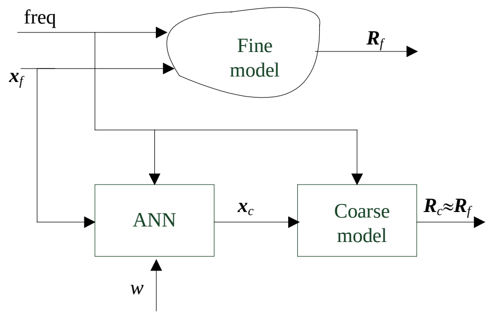


Fig. 4　Scheme of the frequency dependent space-mapped neural modeling

With a more comprehensive domain, the FSMN technique establishes a mapping not only for the design parameters but also for the frequency variable, such that the coarse model is simulated at a mapped frequency $\boldsymbol{f}$, to match the fine model response [11]. This is realized by adding an extra output to the ANN that implements the mapping, as shown in Fig. 5.

To train the space mapped neural model, we either initialize the ANN part as an unit mapping, or use parameter extraction of the coarse model to provide the intermediate training data for ANN. The final training can be a combined optimization of the hybrid ANN and the coarse model to match original EM training data. After training is finished, the model available for users is the hybrid of ANN and coarse model where coarse model inputs are the ANN outputs. The space mapped neural model retains the speed of coarse and ANN models, and the model accuracy is near that of the fine EM model.

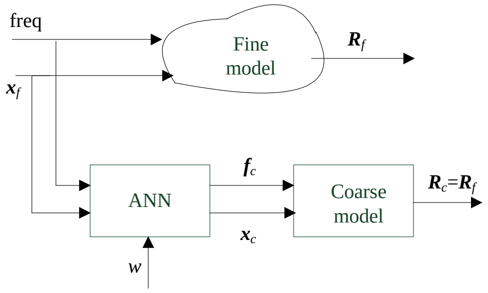


Fig. 5 Scheme of the frequency space-mapped neural modeling

The combined neural network and space mapping approach has been further extended into nonlinear active device modeling area. An interesting approach is the Neuro-space mapping (Neuro-SM) technique, which is a systematic computational method to address the situation where an existing device model cannot fit new device data well. In other words, it uses neural networks to map the coarse model to hte fine model. By modifying the current and voltage relationships in the model, Neuro-SM produces a new model exceeding the accuracy limit of the existing model. The method has been applied to large signal transistor device modeling. The use of such developed Neuro-SM models in harmonic balance based circuit simulations have demonstrated that the Neuro-SM is an efficient approach for modelling various types of microwave devices. It is useful for systematic and automated update of nonlinear device model library for existing circuit simulators.

2.5 Other Advances of Knowledge-Based Neural Network Methods for RF/Microwave Modeling

Over the recent years, there have been many advances in the application of neural networks combined with RF/microwave knowledge for modeling and design of RF microwave circuits and systems. One of the important advance is the neuro-space mapping method applied to active device modeling[14-15] and to statistical modeling of large-signal devices[16], which helps to predict statistical behavior of devices subject to manufacturing tolerances and process variations. Another interesting development is the combination of neural network methods and computational electromagnetics for fast simulation and design of electromagnetic structures[17-18]. An interesting use of neural network is inverse modeling[19], where neural network is used to reversely find the physical geometrical parameters of a device from given electrical specifications. Combination of ANN and efficient global optimization techniques [20] and recurrent neural network methods [21] have been applied to microwave passive and active device and circuit modeling. The utilization of transfer function as knowledge to represent frequency domain circuit behavior is combined with neural networks for passive microwave component modeling [22]. High-dimensional neural network method combining microwave filter decomposition with modular neural networks enabled the neural network method to model microwave filters with 11 design variables[23].

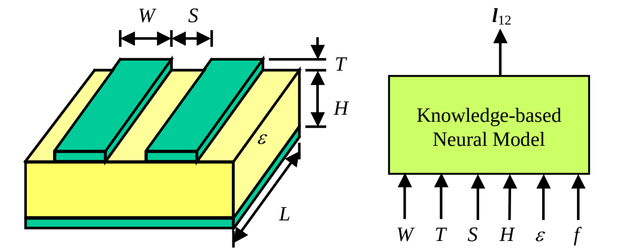
3 Example of Knowledge-Based Neural Networks

3.1 Microwave Transmission Line Modeling

This example, based on Ref. [6], demonstrates the knowledge based neural networks in modeling microwave transmission lines for analysis of high speed VLSI interconnects. Electromagnetic (EM) simulation of transmission lines is extremely slow especially when it needs to be repeatedly evaluated. The speed of neural networks learning from EM data has been found much faster than the original EM simulation. The transmission line and its model inputs/outputs are shown in Fig. 6. In this example, MLP and KBNN were used to model the cross sectional per unit length mutual inductance, $\boldsymbol{l}_{12}$, between two conductors of a transmission line. The inputs to the model are width of conductor (W, or $\boldsymbol{x}_1$), thickness of conductor (T, or $\boldsymbol{x}_2$), separation between two conductors (S, or $\boldsymbol{x}_3$), height of substrate (H, or $\boldsymbol{x}_4$), relative dielectric constant (ε, or $\boldsymbol{x}_5$), and frequency (f, or $\boldsymbol{x}_6$). There are empirical formulas for mutual inductance, for example:

$$I_{12} = \frac{\mu_r \mu_0}{4\pi} \ln\left[1 + \frac{(2x_4)^2}{(x_1 + x_3)^2}\right] \qquad (3)$$

This equation becomes the knowledge to be incorporated into the knowledge layer neurons.



a. The microwave transmission line　　b. its model inputs and outputs

Fig. 6　The microwave transmission line and its model

The structure of the knowledge based neural network is shown in Fig. 7. There are six layers in the structure [6], namely input layer X , knowledge layer Z , boundary layer B , region layer R , normalized region layer R' , and output layer Y . The input layer X accepts parameters x from the outside model. The final output layer provides the solutions of the circuit or device responses. Here we describes an KBNN example based on Ref. [6].

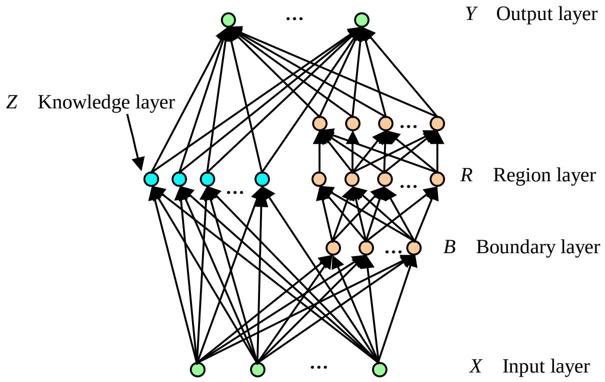


Fig. 7　Structure of knowledge based neural networks for RF microwave modeling

Two KBNNs of size ($b2z3$ and $b4z6$) were trained and compared with three MLPs (6-7-1, 6-15-1 and 6-20-1). The size of KBNN is described by the number of boundary and knowledge neurons (e.g., b2z3 means 2 boundary and 3 knowledge neurons[6]). The size of MLP is described by the number of input, hidden and output neurons, e.g., 6-7-1 means 6 inputs, 7 hidden and 1 output neurons, respectively.

Five sets of data were generated by EM simulation. The first three sets with 100, 300 and 500 samples were generated and used for training. A set 500 samples never used in training are used as test data.

Fig. 8 compares the accuracy of the KBNN versus that of the MLP. The curves in Fig.8 are from models of various sizes and trainings with different initial weights. The advantage of KBNN over MLP is more significant when less training data is available. A significantly superior performance of KBNN showed up in the case of a smaller training data set, e.g., 100 samples. Furthermore, the overall tendency suggests that KBNN trained by a small training data set is comparable to MLP trained by a larger training data set.

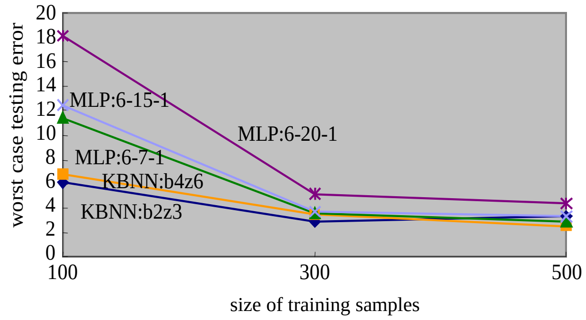


Fig. 8　Model accuracy comparison of KBNN and MLP in terms of worst case testing error for the transmission line example

3.2　Neuro-SM Models of a HEMT Trained with Physics-Based Device Data

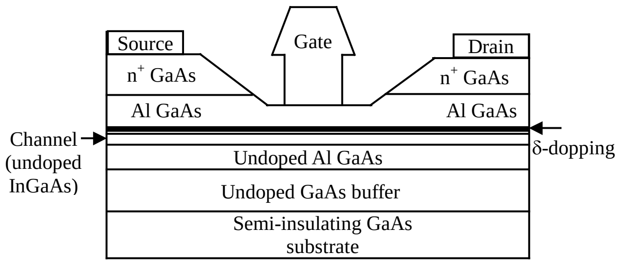
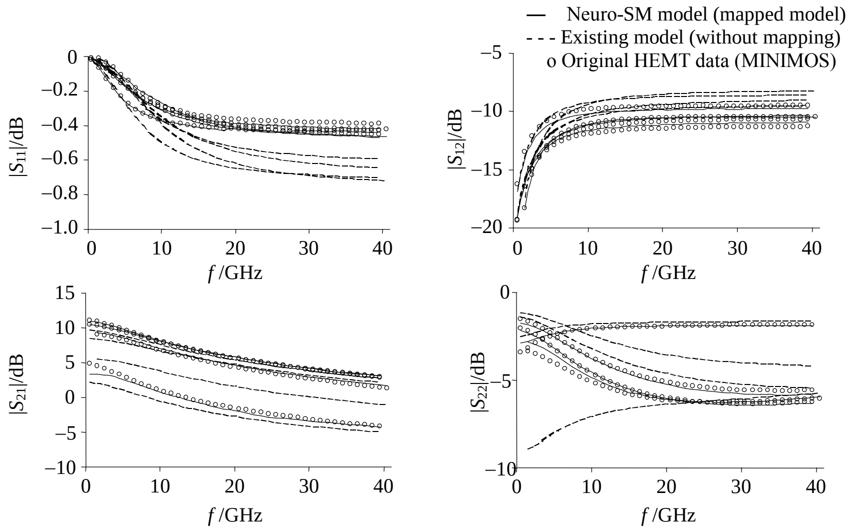
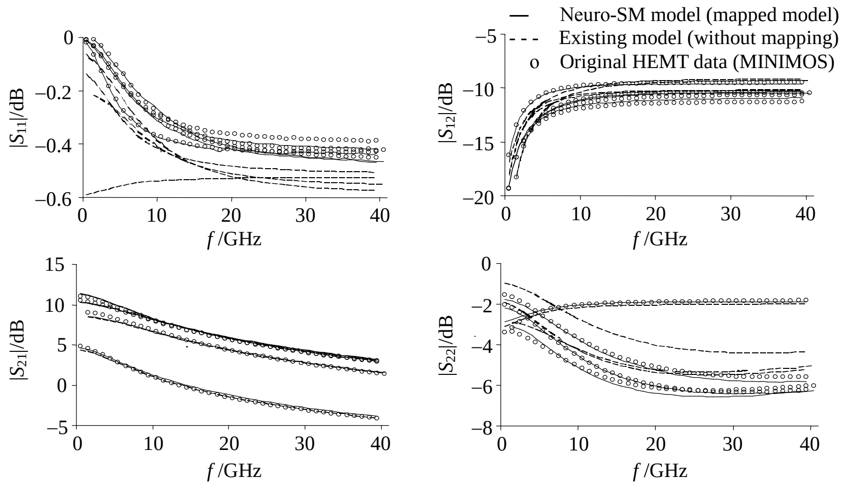


Fig. 9　Physical structure of a HEMT device

The high-electron mobility transistor device (HEMT)[24] is important in high-frequency circuit design. Physics-based numerical simulators and equivalent circuit models[25], Ref. [29] have been used for HEMT modeling. In this example, based on Ref. [14], Neuro-SM is used to learn physics-based data of the HEMT device. Training data (dc and bias-dependent S-parameter data) were generated from a physics-based device simulator, MINIMOS[25], by solving the device Poison equations. The HEMT structure used in setting up the physics-based simulator is shown in Fig. 9. It was modeled by three Neuro-SM implementations (circuit-based Neuro-SM with perturbation, circuit-based Neuro-SM with adjoint neural network sensitivity of Ref. [26], and the Neuro-SM) with three different coarse models, i.e., Curtice[27], Statz[28], and Chalmers (Angelov)[29] models, resulting in nine cases for extensive studies of the Neuro-SM technique.

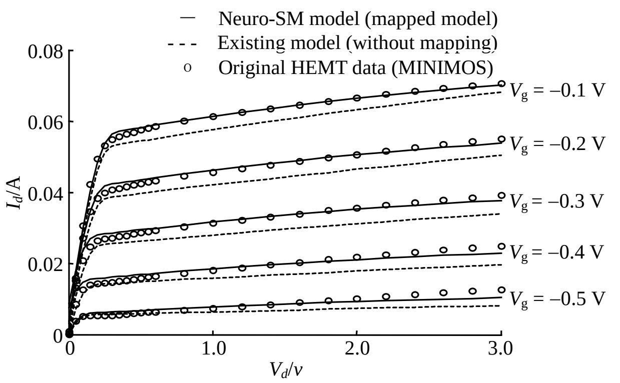


a. Statz model

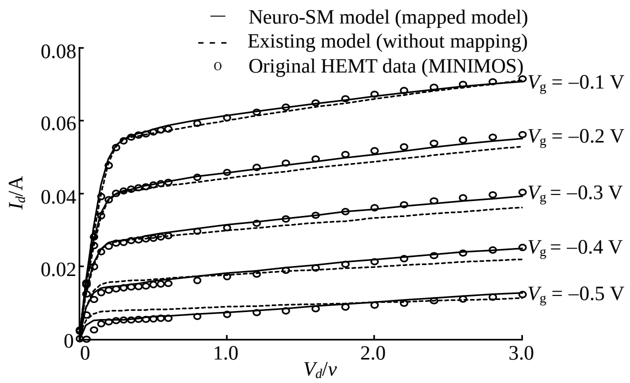


b. Chalmers model

Fig. 10 *S*-parameter comparison between the original HEMT data from MINIMOS, existing models (without mapping), and Neuro-SM models in the HEMT example [14]



a. Statz model



b. Chalmers model

Fig.11 dc comparison between the original HEMT data from MINIMOS, existing models (without mapping), and Neuro-SM models in the HEMT example [14].

The comparison of Neuro-SM models and original physics data is shown in Fig. 10 and Fig. 11 for different coarse models (Statz, and Chalmers). Fig. 10 demonstrates S-parameter comparison between the original HEMT data from MINIMOS, existing models (without mapping), and Neuro-SM models in the HEMT example[14]. All plots show S-parameters in decibels versus frequency in gigahertz. Comparison was done at four different dc biases at gate voltage (–0.4 V, –0.2 V) and drain voltage (0.2 V, 2.4 V). Fig. 11 demonstrates dc comparison between the original HEMT data from MINIMOS, existing models (without mapping), and Neuro-SM models in the HEMT example[14]. The gate voltage Vg for both models is from –0.5 V～–0.1 V. Training of Neuro-SM models was done using such dc data and the bias-dependent S-parameter data in Fig. 10 simultaneously.

Mapping neural networks with 10 to 15 hidden neurons are found suitable for this example. Training time was recorded for 100 iterations on a Pentium IV 2.8-GHz computer. Neuro-SM enables fast and accurate modeling of device physics. To further demonstrate the efficiency of the Neuro-SM, the trained models were incorporated into ADS to compare the evaluation time with MINIMOS. S-parameter simulation of 20 frequencies at 150 biases was preformed. MINIMOS took approximately 75 min, while ADS with the Neuro-SM model used only 10 s.

4 Conclusions

This paper describes knowledge based neural networks and their recent developments for microwave modeling. Four major types of knowledge based approaches are overviewed, including the difference method, the prior knowledge input method, the space mapped neural network method, and the knowledge based neural network methods. By incorporating knowledge into neural networks, we can obtain better model accuracy using limited training data. This approach also provides a platform to combine the simplicity of existing empirical and equivalent models with the learning capability of neural networks, leading to systematic enhancement of existing models through computer-based learning.

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