Knowledge Based Neural Models for Microwave Design

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ABSTRACT

Neural networks have recently gained attention as a fast and flexible vehicle to microwave modeling, simulation and optimization. In this paper a new microwave-oriented knowledge based neural network (KBNN) is proposed, in which microwave knowledge in the form of empirical functions or analytical approximations are incorporated into neural networks. The proposed technique enhances neural model accuracy especially for unseen data and reduces the need of large set of training data. The advantages of the KBNN are demonstrated by MESFET and transmission line modeling examples.

1. Introduction

The drive for manufacturability-oriented design and reduced time-to-market in microwave industry requires design tools that are accurate and fast. In recent years a new CAD approach based on neural network models has been introduced for microwave impedance matching, modeling, simulation and optimization [1] [2] [3] [4]. Neural models can be much faster than original detailed EM/physics models, more accurate than polynomial and empirical models, allow more dimensions than table lookup models and are easier to develop when a new device/technology is introduced [5].

At present, most neural network models are extracted from training data. Large amount of training data is usually needed to ensure model accuracy. Generating large amount of training data could be very expensive for microwave problems because original detailed simulation/ measurement has to be performed for many combinations of different values of geometrical /material/process parameters in the EM or device physics problems. Adding prior knowledge into neural networks is an attractive way to improve model generalization capability [6]. The existing approaches to incorporate knowledge are largely using symbolic information in the form of rules to establish the structure and weights in a neural network, e.g., [7], and are often oriented to pattern recognition area. However in microwave modeling areas the most important knowledge are more functional than symbolic/structural [8] [9], making existing knowledge network methods unsuitable for microwave applications.

In this paper we propose a new microwave-oriented knowledge based neural network (KBNN) in which microwave knowledge in the form of empirical functions or analytical approximations are incorporated into neural networks. The proposed technique enhances neural model accuracy especially for unseen data and reduces the need of large set of training data. The advantages of the proposed network are demonstrated by MESFET and transmission line modeling examples.

2. Proposed Knowledge Based Neural Network (KBNN) and Its Training

The proposed KBNN structure is a nonfully connected structure shown in Figure 1. There are 7 layers in the structure, namely input layer $\mathbf{X}$, knowledge layer $\mathbf{Z}$, boundary layer $\mathbf{B}$, region layer $\mathbf{R}$, normalized region layer $\mathbf{R}'$, normalized knowledge layer $\mathbf{Z}'$ and output layer $\mathbf{Y}$. Knowledge layer $\mathbf{Z}$ is the place where microwave knowledge resides in the form of empirical functions $\Psi(.)$,

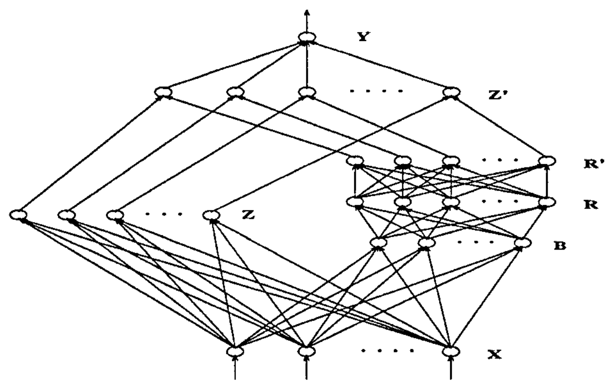

Fig. 1: The proposed Knowledge Based Neural Network (KBNN) structure.

$$z_i = \Psi_i(\mathbf{x}, \mathbf{w}_i), \quad i = 1, 2, \ldots, K_z \tag{1}$$

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where $\mathbf{x}$ is a vector including neural network inputs $x_i, i = 1, 2, \ldots, K_x$ and $\mathbf{w}_i$ is a vector of parameters in the knowledge formula. Boundary layer $\mathbf{B}$ can incorporate knowledge in the form of problem dependent boundary functions $B(.)$ or in the absence of boundary knowledge just as linear boundaries,

$$b_i = B_i(\mathbf{x}, \mathbf{v}_i), \quad i = 1, 2, \ldots, K_b \tag{2}$$

where $\mathbf{v}_i$ is a vector of parameters in B_i defining an open or closed boundary in the input space $\mathbf{X}$. Let $\sigma(.)$ be a sigmoid function. Region layer ($\mathbf{R}$) contains neurons to construct regions,

$$r_i = \prod_{j=1}^{K_b} \sigma(\alpha_{ij} b_j + \theta_{ij}), \quad i = 1, 2, \ldots, K_r \tag{3}$$

where α_{ij} and θ_{ij} are the scaling and bias parameters, respectively. Normalized region layer $\mathbf{R}'$ contains rational function based neurons to normalize the outputs of region layer,

$$r'_i = \frac{r_i}{\sum_{j=1}^{K_r} r_j}, \quad i = 1, 2, \ldots, K_{r'}, \;\; K_{r'} = K_r \tag{4}$$

Normalized knowledge layer $\mathbf{Z}'$ contains second order neurons combining knowledge neurons and normalized region neurons,

$$z'_i = z_i r'_i, \quad i = 1, 2, \ldots, K_{z'}, \;\; K_{z'} = K_z = K_{r'} \tag{5}$$

Output layer $\mathbf{Y}$ collects all the information from normalized knowledge layer by a linear function.

$$y = \sum_{i=1}^{K_{z'}} \beta_i z'_i + \beta_0 \tag{6}$$

where β_i reflects the contribution of normalized knowledge neuron z'_i to output neuron y and β_0 is the bias parameter. The prior knowledge encoded in $\Psi(.)$ and/or $B(.)$ needs not to be very accurate and complete. The constant coefficients in the original empirical functions can be replaced by trainable parameters and more bias/scale parameters can be added to provide extra variability among different neurons. The proposed structure was inspired from the fact that practical empirical functions are usually valid only in a certain region of parameter space. To build a neural model for the whole space, several empirical formulas and the mechanism to switch among them are needed. The final switching boundary and final values of parameters in knowledge functions are determined by training.

Since our network does not follow a regularly layered Multilayer Perceptron structure and microwave empirical functions instead of standard activation functions are used in neurons, conventional backpropagation training is not applicable. A new backpropagation scheme is developed and combined with a quasi-Newton based l_2 optimization algorithm in the training of KBNN. The training errors first propagate from $\mathbf{Y}$ to $\mathbf{Z}'$ layers. Then the propagation is split into two parallel paths, one through the knowledge layer $\mathbf{Z}$, and the other through the region and boundary layers, i.e., $\mathbf{R}'$, $\mathbf{R}$ and $\mathbf{B}$, down to input layer $\mathbf{X}$.

3. MESFET Modeling Example

This example demonstrates a physics-based MESFET [1] model through the proposed KBNN. Device physical/process parameters(channel length, channel width, doping density, channel thickness) and terminal voltages, i.e., gate-source voltage and drain-source voltage, are neural network input parameters and drain current, i.e., i_d, is the neural network output. The original problem requires a slow numerical procedure to solve the physics-based equations [10]. The neural network models (KBNN or MLP) are much faster than original physics based FET model. Knowledge-based neural networks (KBNN) are developed incorporating empirical formulas of Ladbrooke [9]. To confirm the neural model, a new set of data, which is never seen during training, is used to test the neural network. The accuracy of the model is represented by the error and correlation coefficient between neural model output and testing data. The model accuracy of KBNN is much better than that of MLP as indicated in Table 1. With 300 training samples, KBNN can achieve similar accuracy as that from MLP trained by 500 training samples. Figure 2 and Figure 3 show the IV curves from MLP and KBNN. With insufficient training data of only 100 samples, KBNN is visibly more reliable than standard MLP.

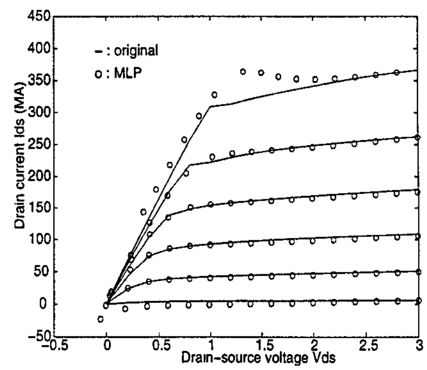

Fig. 2: IV curves from MLP for MESFET modeling example. The model was trained with insufficient training data of only 100 samples.

4. Transmission Line Modeling Example

This example demonstrates the proposed KBNN in modeling transmission lines for analysis of high speed VLSI interconnects [5]. Electromagnetic (EM) simulation of transmission lines is slow especially if it needs to be repeatedly evaluated. Neural networks learned from EM data are much faster than original EM simulation. In this example, MLP and KBNN were used to model the mutual inductance, l_{12}, between two conductors of a transmission line. The inputs of the model are width of conductor, thickness of conductor, separation between two conductors, height of substrate, relative dielectric constant and frequency. KBNN was built with the existing empirical

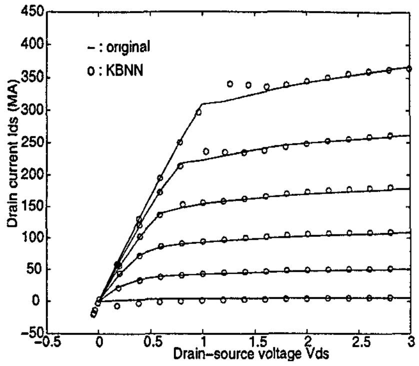

Fig. 3: IV curves from KBNN for MESFET modeling example. The model was trained with insufficient training data of only 100 samples.

inductance formula of Walker [8]. The ability to extrapolate beyond the boundary of training data is a challenge but an important aspect of a model. The testing data in this example was deliberately selected around/beyond the boundary of the model effective region in input parameter space to compare KBNN and MLP as shown in Table 2. With enough training data, both KBNN and MLP show good accuracy. But with small training data, KBNN shows much better accuracy than MLP due to the built-in knowledge as illustrated in Figure 4 and Figure 5.

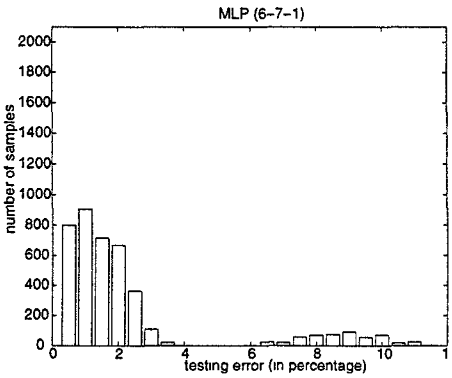

Fig. 4: Histogram of testing error of MLP for transmission line modeling example for 4096 testing samples around/beyond training data boundary. The model was trained by only 100 training samples.

For both examples the model testing errors from KBNN are less than those from MLP as shown in Figure 6 and Figure 7, and advantage of KBNN is even more significant when training data is insufficient.

The neural models learn component behaviors originally seen in physics/EM models, and predict such behavior much faster than original models. It will have a significant impact on statistical design of microwave circuits.

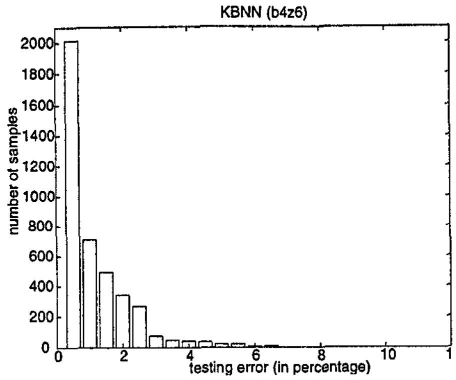

Fig. 5: Histogram of testing error of KBNN for transmission line modeling example for 4096 testing samples around/beyond training data boundary. The model was trained by only 100 training samples.

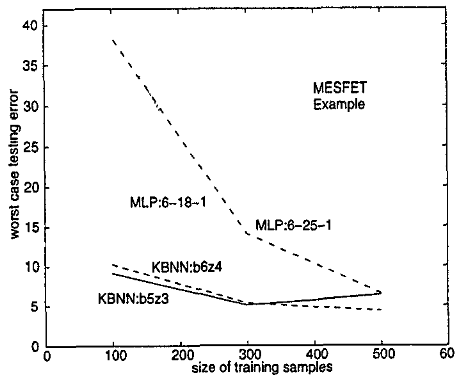

Fig. 6: Model accuracy of KBNN and MLP for MESFET modeling. Testing error from KBNN is in general less than that from MLP. The data shown are obtained from training sample sets of sizes 100, 300 and 500.

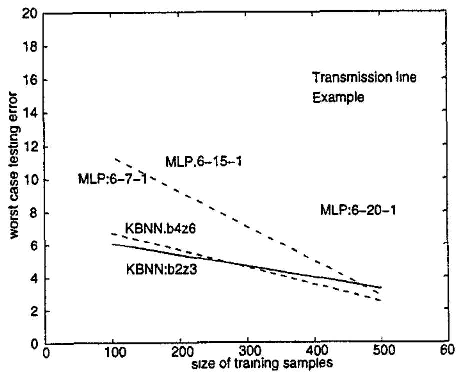

Fig. 7: Model accuracy of KBNN and MLP for transmission line modeling. Testing error from KBNN is in general less than that from MLP. The data shown are obtained from training sample sets of sizes 100 and 500.

training sample size	neural net type	model size	no. of weights	average test error	largest test error	correlation coefficient
100	Standard (MLP)	6-18-1	145	3.06%	40.16%	0.9417
	Standard (MLP)	6-25-1	201	3.69%	38.55%	0.9626
	Knowledge based (KBNN)	b5z3	147	1.17%	9.11%	0.9972
	Knowledge based (KBNN)	b6z4	207	1.00%	10.21%	0.9979
300	Standard (MLP)	6-18-1	145	0.95%	9.85%	0.9976
	Standard (MLP)	6-25-1	201	0.97%	14.05%	0.9967
	Knowledge based (KBNN)	b5z3	147	0.72%	5.05%	0.9991
	Knowledge based (KBNN)	b6z4	207	0.73%	5.32%	0.9990
500	Standard (MLP)	6-18-1	145	0.73%	6.48%	0.9989
	Standard (MLP)	6-25-1	201	0.81%	6.54%	0.9985
	Knowledge based (KBNN)	b5z3	147	0.63%	6.35%	0.9993
	Knowledge based (KBNN)	b6z4	207	0.61%	4.33%	0.9993

Table: 1: Model Accuracy Comparison Between Standard MLP and Knowledge Based Neural Network (KBNN) for MESFET Modeling Example with Testing Data.

training sample size	neural net type	model size	no. of weights	average test error	largest test error	correlation coefficient
100	Standard (MLP)	6-7-1	57	2.30%	11.35%	0.9981
	Standard (MLP)	6-15-1	121	2.78%	12.42%	0.9962
	Standard (MLP)	6-20-1	161	3.44%	18.17%	0.9919
	Knowledge based (KBNN)	b2z3	51	1.16%	6.06%	0.9993
	Knowledge based (KBNN)	b4z6	128	1.12%	6.72%	0.9993
500	Standard (MLP)	6-7-1	57	0.90%	2.88%	0.9996
	Standard (MLP)	6-15-1	121	0.89%	3.35%	0.9997
	Standard (MLP)	6-20-1	161	0.82%	4.42%	0.9996
	Knowledge based (KBNN)	b2z3	51	0.81%	3.30%	0.9996
	Knowledge based (KBNN)	b4z6	128	0.90%	2.51%	0.9995

Table: 2: Model Accuracy Comparison Between MLP and KBNN for Transmission Line Modeling Example with Testing Data.

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