A Hierarchical Neural Network Approach to the Development of Library of Neural Models for Microwave Design

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Abstract

Neural networks recently gained attention as a fast and flexible vehicle to microwave modeling, simulation and optimization. This paper addresses a new challenge in this area, i.e., development of libraries of microwave neural models. A hierarchical neural network framework is presented utilizing the knowledge of basic relationships common to all library components. The proposed method improves the reliability of neural models, while significantly reducing the cost of library development through reduced need for data collection and shortened time of training.

Introduction

Recently a new CAD approach based on neural networks has been introduced for microwave modeling, simulation, optimization, and impedance matching [1]-[5]. A neural network can be developed by learning and abstracting from data, a process called training. Once trained, it can then be used during microwave design to provide instant solutions to the task it learnt [2]. 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. The costs for developing neural models are mainly data collection and neural network training. Techniques addressing microwave neural model accuracy and efficient model development have been proposed, e.g., [1], [4], [5].

The success of these work opened the door for an even more exciting possibility, i.e., developing massive neural network models for libraries of microwave components. This is of practical significance, since the realistic power of many CAD tools depends upon the richness and the accuracy of their library models. For neural models, while the cost for individual model development has been made manageable, e.g., [1]-[5], massively developing neural models for libraries requires massive data generation, and repeated model training. This task is highly expensive and not adequately treated in the existing literature.

In this paper a hierarchical neural network framework is proposed for the development of library models. The basic characteristics common to all library components are extracted and incorporated into base neural models. A high level neural module is then trained to map from the base model solution to the ultimate model solution for each component in the library. Examples of transmission line neural model libraries, useful for design of high-speed VLSI interconnects, are developed.

Proposed Hierarchical Neural Network Model for Library Development

Suppose the total number of microwave models in a library is N_c. Using the standard neural model approach, e.g., multilayer perceptron structure (MLP), costly data collection and extensive model training have to be done for each model in the library. The total cost for library development will be very high.

The proposed technique is motivated by the modular neural networks and the networks embedding structural knowledge, introduced in the neural network community, e.g., [6][7]. However these existing types of network structures are mostly oriented towards signal processing and pattern recognition tasks and not directly suitable for microwave modeling problems.

In the proposed approach, we first develop a set of base models to capture the basic characteristics common to various components of the library. For example, the self inductance of a conductor is a common characteristic in a library of various transmission line models. Let $B_j(\boldsymbol{u}, \boldsymbol{W}_j)$ represent the

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jth base model, W_j being the parameter vector of B_j, $j \in 1,\ldots,N_b$. For each model in the library, a hierarchical neural network structure is defined as shown in Figure 1. The purpose of this structure is to decompose the overall model problem into small parts so that library base relationship can be maximally reused for every model throughout the library. This structure consists of a high level neural module denoted as $H^n(z, V^n)$, V^n being the parameter vector of H^n, and several low level neural modules denoted as L_i^n, $i=1, \ldots, N_l$. The low level modules are realized by knowledgeable selection of base models. There is a

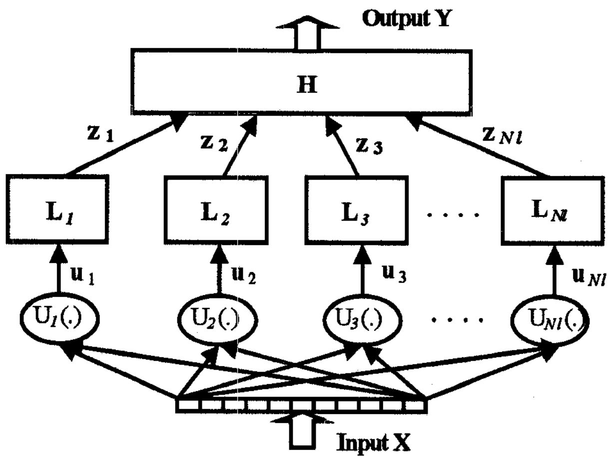

Figure 1: The proposed hierarchical neural network structure.

knowledge hub $U_i(.)$ associated with each low level module, extracting inputs only relevant to this module out of X. The overall library development is summarized in the following steps:

Step1: Extract basic characteristics from library, using microwave empirical knowledge.

Step2: Construct and train base neural models incorporating the knowledge from step 1 into a functional Knowledge Based Neural Network (KBNN) structure [1]. Specifically, find W_j such that $B_j(u, W_j)$ matches training data, for $j=1, \ldots, N_b$. Let $n=1$.

Step3: For the *nth* model in the library, construct the hierarchical neural network shown in Figure 1. Select base models for low level modules and define structural knowledge hubs $u_i^n = U_i^n(X)$, which maps the model input space into base model input space, for $i=1, \ldots, N_l$. This is done using structural knowledge of how base models affect the *nth* library model.

Step4: Train the high level neural module H^n, i.e., find V^n such that the overall model outputs match training data.

Step 5: If $n=N_c$, then stop, otherwise proceed to train the next library component by setting $n=n+1$ and go to Step 3.

Example 1: Library of Stripline Models.

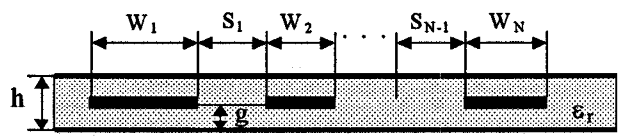

Figure 2: N-conductor stripline component. For the *nth* component in stripline library, $N = n$.

Multiconductor transmission line models are essential for delay and crosstalk analysis in high-speed VLSI interconnect design [8]. EM simulation of transmission line responses is slow especially if it needs to be repetitively evaluated. Neural models, trained off-line from EM data, can be used online during VLSI interconnect design providing instant solutions of the original EM problem. For practical VLSI interconnect design, libraries of 1-conductor, 2-conductor, ..., N-conductor transmission line models are needed. A brute force approach is to train each neural model separately, requiring massive data generation and training. Here we apply the proposed hierarchical approach to develop a library of neural models for N-conductor striplines shown in Figure 2 for different values of N. In the example there are five models in the library, n=1, 2, 3, 4, 5. And for each *nth* model, $N=n$. Table 1 defines the inputs and outputs of each model.

Base Model Selections: Two base models, B_1 for self inductance and B_2 for mutual inductance are defined. The inputs to the base models include physical/geometrical parameters such as conductor width (w), conductor height (g), substrate height (h), separation between conductors (s), and relative dielectric constant(ε_r). The outputs of B_1 and B_2 are self and mutual inductances, respectively. The stripline empirical formulas in [9] are adopted as functional knowledge incorporated into the KBNNs [1], which are the realizations of the base models B_1 and B_2. The base models B_1 and B_2 are trained to an average testing accuracy of *0.39%* and *0.16%* respectively.

Library component	Component name	Neural model inputs	Neural model outputs	Reuse of base models (B_1 & B_2)
$n=1$	1 condcutor model	$w\ g\ h\ \varepsilon_r$	L_{11}	B_1
$n=2$	2 conductor model	$w_1\ w_2\ s\ g\ h\ \varepsilon_r$	L_{11}, L_{12}, L_{22}	2 x B_1, 1 x B_2
$n=3$	3 conductor model	$w_1\ w_2\ w_3\ s_1\ s_2\ g\ h\ \varepsilon_r$	$L_{11}, L_{12}, L_{13}, L_{22}, L_{23}, L_{33}$	3 x B_1, 3 x B_2
$n=4$	4 conductor model	$w_1\ w_2\ w_3\ w_4\ s_1\ s_2\ s_3\ g\ h\ \varepsilon_r$	$L_{11}, L_{12}, L_{13}, L_{14}, L_{22}, L_{23}, L_{24}, L_{33}, L_{34}, L_{44}$	4 x B_1, 6 x B_2
$n=5$	5 conductor model	$w_1\ w_2\ w_3\ w_4\ w_5\ s_1\ s_2\ s_3\ s_4\ g\ h\ \varepsilon_r$	$L_{11}, L_{12}, L_{13}, L_{14}, L_{15}, L_{22}, L_{23}, L_{24}, L_{25}, L_{33}, L_{34}, L_{35}, L_{44}, L_{45}, L_{55}$	5 x B_1, 10 x B_2

Table 1: Stripline Library Components.

Example of Library Model: n=1: For n=1, the library model is directly the base model B_1.

Example of Library Model: n=3: For library model n=3, we reuse the base models as the low level neural modules shown in Figure 1. The high-level neural module H^3 is realized by a 2-layer perceptron with 6 inputs and 6 outputs. Only a small amount of training data (15 samples) is needed to train this 3-conductor stripline model since the raw/fundamental relationships of the model have already been captured in the base models. However, with the conventional MLP neural model, even 500 samples are not enough to achieve a model of similar accuracy, shown in Figure 3.

All Library Models: All library models, n = 2, 3, 4, ... in the library, can be developed systematically in a similar way as model #3. It should be noted that efforts in developing those additional models are small and incremental, since only few training data is needed, and only the high-level neural module H^n needs to be trained for each n.

Overall Library Accuracy and Development Cost: A Comparison Using standard MLP for each model, the total training time for all library models is 6 hours and 30 minutes on SparcStation 5. Using the proposed approach, the total training time is 36 minutes. The total amount of training data needed by standard MLP is 2664 samples and by the proposed approach is only 649 (including 564 samples for base model, and 85 samples for subsequent library models) as shown in Table 2. The proposed technique yields reliable neural models even with very small amount of training data.

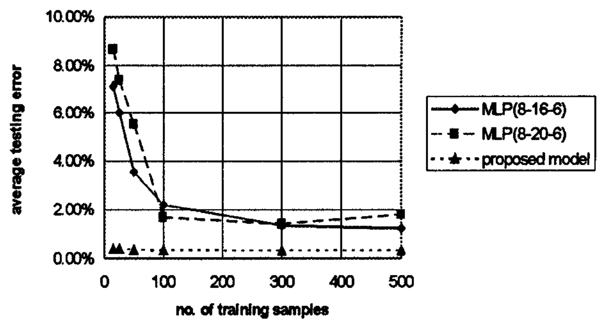

Figure 3: Model accuracy comparison (average error on test data) between standard MLP and the proposed model for 3-conductor stripline component.

Stripline Component Name	No. of training samples needed		Model accuracy (Average error on test data)	
	Standard MLP	Proposed model	Standard MLP	Proposed model
Over head	0	$264^1 + 300^2$	-	-
1 conductor model	264	0	0.42%	0.39%
2 conductor model	300	10	1.01%	0.56%
3 conductor model	500	15	1.25%	0.40%
4 conductor model	700	25	1.30%	0.79%
5 conductor model	900	35	0.99%	0.63%
Library	Total = 2664	Total = 649	Average = 0.99%	Average = 0.55%

Table 2: Comparison of Number of Training Samples Needed and Model Accuracy for Stripline Library When Developed by Standard MLP and the Proposed Neural Network Structure, respectively. [1] for base model B_1 training and [2] for base model B_2 training.

Example 2: Library of Microstrip Models.

In this example, we develop neural models for N-conductor microstrip lines for each value of N, N=1, 2, 3, ..., 5, i.e., a library of 5 models. Two base models incorporating the microstrip empirical formulas in [9] are developed first. Using standard MLP for each library model, the total training time for all library models is 4 hours on SparcStation 5 and using the proposed approach, the total training time is 20 minutes. The total amount of training data required by standard MLP is 1700 samples collected through electromagnetic simulations. The total amount of training data required by the proposed approach is only 550 (including 400 samples for base model, and 150 samples for all subsequent library models) as shown in Table 3.

Microstrip Component Name	No. of training samples needed		Model accuracy (Average error on test data)	
	Standard MLP	Proposed model	Standard MLP	Proposed model
Over head	0	$100^1 + 300^2$	-	-
1 condcutor model	100	0	0.16%	0.16%
2 conductor model	300	10	0.47%	0.50%
3 conductor model	300	15	0.70%	0.77%
4 conductor model	500	50	0.75%	0.93%
5 conductor model	500	75	0.88%	1.07%
Library	Total = 1700	Total =550	Average = 0.59%	Average = 0.69%

Table 3: Comparison of Number of Training Samples Needed and Model Accuracy for Microstrip Library When Developed by Standard MLP and the Proposed Neural Network Structure, respectively. [1] for base model B_1 training and [2] for base model B_2 training.

Conclusions

A new problem, i.e., library of microwave neural model development is addressed. A hierarchical neural model approach is developed exploiting the inherent relations between library components. Compared to the presently used MLP neural model structure, the proposed approach yields accurate models even with very limited amount of training data. Improved model reliability and cost reduction of library development have been achieved, due to faster training and less need for data generation.

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