Advanced Microwave Modeling Framework Exploiting Automatic Model Generation, Knowledge Neural Networks and Space Mapping

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Abstract **— In this paper, we propose an efficient Knowledge based Automatic Model Generation (KAMG) technique, aimed at generating microwave neural models of highest possible accuracy using fewest accurate data. The technique is comprehensively derived to integrate three distinct powerful concepts, namely, automatic model generation, knowledge neural networks and space mapping. We utilize two types of data generators - fine data generators that are accurate and slow (e.g., CPU-intensive 3D-EM simulators); coarse data generators that are approximate and fast (e.g., inexpensive 2D-EM). Motivated by the space-mapping concept, the KAMG utilizes extensive approximate data but fewest accurate data to generate neural models that accurately match fine data. Our formulation exploits a variety of knowledge network architectures to facilitate reinforced neural network learning from both coarse and fine data. During neural model generation by KAMG, both coarse and fine data generators are automatically driven using adaptive sampling. The proposed technique is demonstrated through examples of MOSFET, and embedded passives used in multi-layer PCBs.**

I. Introduction

Recently, a neural network based CAD approach has been introduced for microwave modeling and design [1]-[5]. Neural models are developed from microwave data through a process called training. These models are used during design to provide fast estimation of device/circuit behaviors [2]. Neural network techniques have been applied to a wide variety of microwave problems, e.g., transistors [2], embedded passives [3], CPW bends [4] and filters [5]. Reliable CAD solutions need accurate neural models, which in turn, require lots of accurate training data. For example, an embedded capacitor neural model with 3D accuracy requires lots of expensive training data from a detailed 3D-EM simulator.

Several techniques have been developed to reduce the need for expensive data. The Automatic Model Generation (AMG) algorithm [3] uses fewer data by avoiding unnecessary samples in smooth sub-regions of the input space. Knowledge networks such as Knowledge Based Neural Networks (KBNN) [1] and Prior Knowledge Input (PKI) method [4] utilize existing knowledge (e.g., empirical models), thereby reducing the need for expensive training data.

For the first time, we propose a robust KAMG technique that takes advantage of multiple data generators. We define the approximate and accurate data generators as coarse and fine data generators respectively. Motivated by space-mapping optimization concept [6], the proposed technique achieves efficient neural model generation through extensive use of coarse data together with fewest fine data. Knowledge networks are exploited to enable coarse and fine data to best contribute toward reinforced neural network learning. The KAMG framework allows the use of a variety of knowledge neural network architectures such as Difference Method (DM), KBNN, PKI and Space Mapped Neural Networks (SMNN) [5]. Stage-wise training and adaptive data sampling of AMG are used to automate neural model generation by KAMG.

II. Proposed KAMG Technique

Let x and y represent input and output vectors of a microwave modeling problem. Let $y = g(x)$ and $\tilde{y} = h(x,w)$ represent detailed EM/physics and neural model relationships between x and y, where g is a data generator, h is a neural network model, and w is the neural model weight vector. During neural network training, w is adjusted such that the error between y and $\tilde{y}$ is minimized. Let coarse and fine data generators be denoted by g_c and g_f respectively. For example, x could represent length of an embedded capacitor; $g_c(x)$ and $g_f(x)$ could represent S_{11} computed from 2D and 3D-EM respectively. We define h_c, h_s, and h_f as coarse, sub, and overall (fine) neural models. The objective of KAMG technique is to generate an accurate overall neural model h_f by extensive utilization of g_c and minimal use of g_f. The proposed KAMG technique includes three major phases.

In the first phase, the KAMG technique generates a coarse neural model $\tilde{y}_c = h_c(x,w_c)$, where w_c denotes weight parameters of the coarse model. The training objective here is to minimize the difference between coarse data generator outputs and coarse neural model outputs, i.e.,

$$\min_{w_c} \sum_{x \in L_c} \left\| g_c(x) - h_c(x,w_c) \right\| \tag{1}$$

by adjusting w_c, where L_c represents the set of coarse training data. Set L_c is empty initially, and is periodically updated during training by adaptive sampling and automatic driving of g_c (e.g., 2D-EM simulator). Worst sub-regions of the model input space are identified, and incremental training data are generated using a dynamic composite grid following our original AMG [3]. Coarse neural model h_c is trained using g_c extensively, because it is inexpensive. Neural model h_c captures primary or dominant portions of the original x-y relationship.

The principle idea of KAMG is to systematically construct a knowledge neural network that could enable coarse information from h_c and fine data from g_f to harmonize neural network learning. Several existing knowledge architectures including DM, KBNN, PKI and SMNN have all been incorporated into our formulation.

In the second phase, a sub neural model h_s is initialized through a simple training process re-using L_c from the first phase. Training objective for initialization is:

$$\min_{w_s} \sum_{x \in L_c} \| 0 - h_s(x, w_s) \| \tag{2}$$

for Difference Method,

$$\min_{w_s} \sum_{x \in L_c} \| \tilde{y}_c - h_s(x, w_s) \| \tag{3}$$

for KBNN,

$$\min_{w_s} \sum_{x \in L_c} \| \tilde{y}_c - h_s(x, \tilde{y}_c, w_s) \| \tag{4}$$

for PKI, and

$$\min_{w_s} \sum_{x \in L_c} \| x - h_s(x, w_s) \| \tag{5}$$

for SMNN, by adjusting w_s. KAMG then utilizes h_c and h_s to construct an initial overall neural model as

$$\tilde{y}_f = h_f(x, w_f) = h_f(x, w_c, w_s). \tag{6}$$

For example, initial neural model is given by,

$$h_f(x, w_c, w_s) = h_c(x, w_c) + h_s(x, w_s) \tag{7}$$

for Difference Method and

$$h_f(x, w_c, w_s) = h_s(h_c(x, w_c), w_s) \otimes h_r(x, w_s) \tag{8}$$

for KBNN. Here, $h_r(x, w_s)$ is region network that defines boundaries in x-space and $\otimes$ is a gating operator [1]. Initial neural models for PKI and SMNN are given by,

$$h_f(x, w_c, w_s) = h_s(x, h_c(x, w_c), w_s) \tag{9}$$

and

$$h_f(x, w_c, w_s) = h_c(h_s(x, w_s), w_c). \tag{10}$$

Through trainings in second phase, KAMG ensures that the initial overall neural model nearly equals coarse neural model, i.e.,

$$h_f(x, w_c, w_s) \cong h_c(x, w_c). \tag{11}$$

As such, initial overall neural model h_f can be at least as accurate as the existing coarse model, before using any fine data.

In the third phase, initial overall neural model h_f is further trained (refined) using fine data from g_f. The KAMG emphasizes on capturing the problem behaviors missed in the first phase (i.e., those missing in coarse data generator or coarse neural model). The training objective is to minimize the difference between fine data generator outputs and overall neural model outputs, while keeping the coarse portion of h_f fixed, i.e.,

$$\min_{w_s} \sum_{x \in L_f} \| g_f(x) - h_f(x, w_c, w_s) \| \tag{12}$$

where L_f represents the set of fine training data. Set L_f is also empty initially, and is updated by adaptive sampling and automatic driving of g_f (e.g., 3D-EM simulator). By exploiting knowledge architectures, the KAMG technique performs training using fewest fine data, i.e., Size(L_f) << Size(L_c). In the third phase training, w_s is adjusted while w_c remains fixed. The proposed KAMG technique is illustrated in Figure 1.

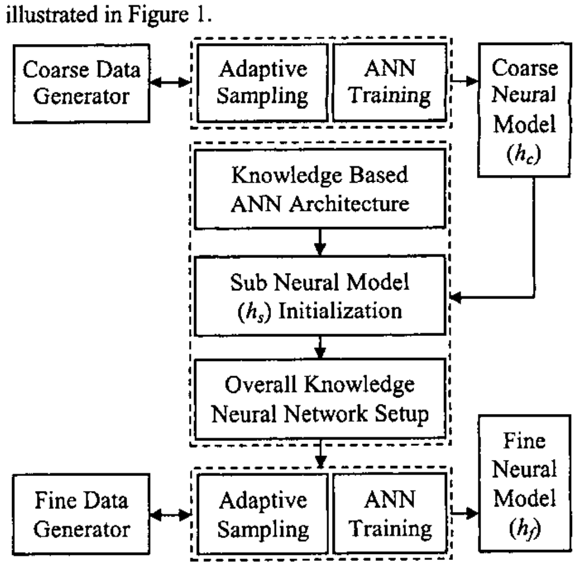

Fig. 1. Flow-chart of the proposed KAMG technique.

III. EXAMPLES

A. MOSFET Neural Model Development Using Circuit Based and Physics Based Data Generators

This example illustrates development of MOSFET neural models with physics-level accuracy, but without using too much physics-based expensive training data. Input x contains drain and gate voltages. Drain current is the only neural model output y. Equivalent circuit model [7] is used as coarse data generator and physics-based simulator [8] is used as fine data generator.

The KAMG technique is applied to various knowledge architectures. As can be seen in Figure 2, all the neural models from KAMG achieved better accuracies with fewer expensive data, as compared to neural model from AMG. For a given model accuracy, the KAMG requires fewer fine data than AMG and conventional grid-based manual neural modeling approach, as shown in Table I. Table II shows that the proposed KAMG models outperform corresponding conventional knowledge models, when only a few accurate data are available.

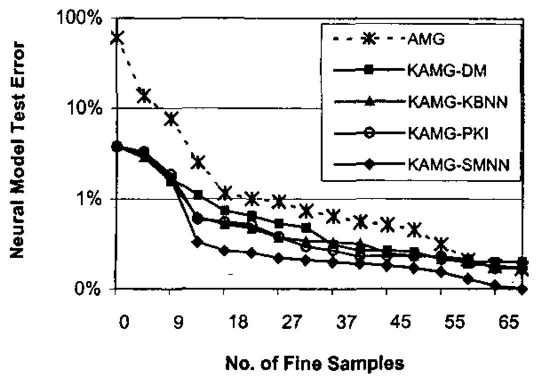

Fig. 2. Accuracy comparison of MOSFET neural models generated by proposed KAMG and existing AMG techniques. KAMG achieved better accuracies with fewer fine data.

TABLE I. COMPARISON OF FINE DATA NEEDED BY VARIOUS NEURAL MODELING TECHNIQUES TO ACHIEVE MOSFET MODELS WITH 0.50% TEST ERROR.

Neural Modeling Technique	No. of Fine Data Used
Conventional training	66
AMG (without knowledge)	49
Proposed KAMG-DM	32
Proposed KAMG-KBNN	23
Proposed KAMG-PKI	25
Proposed KAMG-SMNN	14

TABLE II. ACCURACY COMPARISON BETWEEN MOSFET NEURAL MODELS DEVELOPED BY VARIOUS MODELING TECHNIQUES USING 23 FINE DATA.

Neural Modeling Technique	Test Error
Conventional training	3.82%
AMG (without knowledge)	1.00%
Conventional DM	1.53%
Proposed KAMG-DM	0.65%
Conventional KBNN	0.59%
Proposed KAMG-KBNN	0.48%
Conventional PKI	0.92%
Proposed KAMG-PKI	0.52%
Conventional SMNN	0.45%
Proposed KAMG-SMNN	0.25%

B. Embedded Resistor Neural Model Development Using Planar-EM and 3D-EM Data Generators

Fast and accurate modeling of 3D-EM behaviors of embedded passives is important for multi-layer PCB design. Resistor length and signal frequency are input parameters, and S-parameters are neural model outputs. Planar EM simulator [9] is used as coarse data generator and 3D-EM simulator [10] is used as fine data generator. Figure 3 and Table III demonstrate that the proposed KAMG technique uses fewer fine (expensive) data to achieve a given neural model accuracy, as compared to both AMG without knowledge and conventional training.

In a worst situation, i.e., when fine data is unavailable to the user, neural models from KAMG are at least as accurate as coarse neural model. For the embedded resistor, all the KAMG neural models exhibit 7.02% average test error, before training with any fine data.

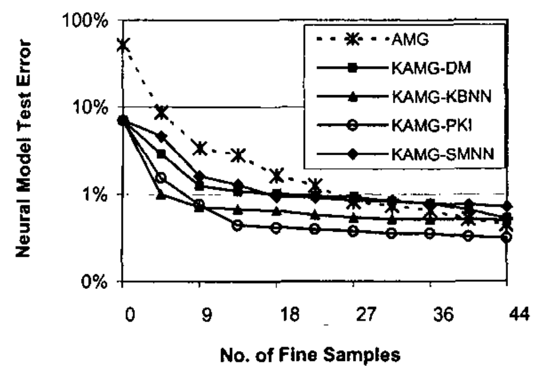

Fig. 3 Accuracy comparison of embedded resistor neural models generated by proposed KAMG and existing AMG.

TABLE III. ACCURACY COMPARISON BETWEEN RESISTOR NEURAL MODELS DEVELOPED BY VARIOUS MODELING TECHNIQUES USING 18 FINE DATA.

Neural Modeling Technique	Test Error
Conventional training	2.85%
AMG (without knowledge)	1.65%
Proposed KAMG-DM	1.02%
Proposed KAMG-KBNN	0.65%
Proposed KAMG-PKI	0.42%
Proposed KAMG-SMNN	0.95%

C. Embedded Capacitor Neural Model Development Using Planar-EM and 3D-EM Data Generators

Embedded capacitor used in multi-layer PCBs is considered. The input x includes capacitor length and signal frequency. Real and imaginary parts of S-parameters are the model outputs y. Planar EM simulator [9] is used as coarse data generator and 3D-EM simulator [10] is used as fine data generator. Figure 4 shows that the proposed KAMG technique yields neural models with better accuracies as compared to AMG, when same amounts of fine data are used. As a result, data generation time (CPU) is significantly reduced as can be seen in Table IV.

TABLE IV. COMPARISON OF FINE DATA NEEDED BY VARIOUS NEURAL MODELING TECHNIQUES TO ACHIEVE CAPACITOR MODELS WITH 1% TEST ERROR.

Neural Modeling Technique	No. of Fine Data	CPU for Data Generation
Conventional training	125	625 min
AMG (without knowledge)	96	480 min
Proposed KAMG-DM	48	240 min
Proposed KAMG-KBNN	14	70 min
Proposed KAMG-PKI	24	120 min
Proposed KAMG-SMNN	23	115 min

IV. CONCLUSIONS

We proposed an advanced KAMG technique for automatic generation of knowledge based neural models. The technique integrates powerful concepts such as AMG, knowledge neural networks, and space mapping, into an even more powerful framework. Motivated by the space-mapping concept, the KAMG exploits both coarse and fine data generators for efficient neural model development. A variety of knowledge architectures have been utilized to accomplish reinforced neural network training from coarse and fine data. The KAMG is further strengthened by automation through adaptive sampling. For a given model accuracy, the proposed technique uses fewest fine data as compared to all other existing techniques including AMG and conventional knowledge methodologies. Fewer fine training data translates into significantly reduced CPU time for data generation, thus resulting in faster model development.

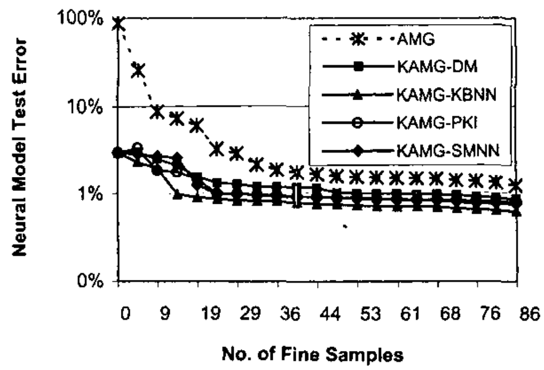

Fig. 4. Accuracy comparison of capacitor neural models generated by proposed KAMG and existing AMG techniques. KAMG achieved better accuracies with fewer fine data.

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