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A Combined State Space Formulation/Equivalent Circuit and Neural Network Technique for Modeling of Embedded Passives in Multilayer Printed Circuits

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Abstract : In this paper, we present a new approach for modeling the high-frequency effects of embedded passives in multilayer printed circuits, utilizing state space equations or equivalent circuit together with neural network techniques. In this approach, the neural network based model structure is trained using full wave electromagnetic (EM) data. The resulting embedded passive models are accurate and fast, can be used in both frequency/time domain simulators. Examples of embedded resistor and capacitor models demonstrate that the combined model can accurately represent EM behavior in microwave/RF circuit design. In high-level circuit design, we applied our combined EM based neural models for signal integrity analysis and design of multilayer circuit to illustrate that the geometrical parameters can be continuously adjusted by using neural network techniques. Optimization and Monte-Carlo analysis are performed showing that the combined models can be efficiently used in place of computationally intensive EM models of embedded passives to speed up circuit design.

I. INTRODUCTION

The drive in the electronics industry for manufacturibility-driven design and time-to-market demands powerful and efficient computer-aided design (CAD) techniques. As the signal frequency increase, the dimensions of embedded passives in multilayer circuits become a significant fraction of signal wavelength. The conventional time/frequency domain electrical models for the components are not accurate anymore. As EM effects play an important role in microwave/RF circuit design, models with continuous physical/geometrical information must include EM effects [1]. Furthermore, the need of optimization and statistical analysis taking into account process variations and manufacturing tolerances in the components makes it extremely important that the component models should be accurate and fast so that the design solutions can be achieved feasibly and reliably.

Recently, artificial neural network (ANN) modeling approach has been studied for microwave modeling and design [2-4]. The neural models can be as fast as empirical models and as accurate as detailed physics models.

For high-level circuit design, the component models should be continuously varied both with frequency, geometrical and/or electrical parameters. Therefore, modeling techniques that can provide such continuous variations are essential and ANN models exactly meet for these requirements. They are continuous, multi-dimensional and can easily handle nonlinearities in problem behaviours. Neural network techniques have been widely used to model variety of microwave device/circuits such as transmission line components [5], bends [6], vias [7], spiral inductors [8], and FET devices [5, 9].

Embedded passives represent an emerging technology area that has the potential for increased reliability, improved electrical performance, size shrinkage, and reduced cost. The conventional approach for circuit and system design requires equivalent circuits to capture the response of embedded passives [10]. But the equivalent circuit method may not be accurate enough to reflect high frequency EM effects. Recently, neural network techniques have been introduced to model frequency behavior of embedded passives [1]. However, such ANN models, trained to learn S-parameters data, cannot be used directly into time-domain circuit simulation and optimization. Our target was to develop passive ANN based models from EM data that can be used directly in both time and frequency domain circuit design.

In this paper, we present a novel approach to model high-frequency effects of embedded passives in multilayer printed circuits based on combined equivalent circuit or state space theory together with neural networks. Our combined model is a hierarchical structure with two levels. In the lower level, a neural network maps the geometrical/physical parameters of the passive component into coefficient matrices of state equations or lumped component values of a given equivalent circuit. In the higher level, we export the coefficient matrices into the state space equation or component values into the equivalent circuit to compute the EM response in either frequency or time domain circuit design. The accurate and fast ANN based embedded passive models are trained from full wave EM data. Our method combines existing modeling techniques and recent neural network approaches to efficiently perform simulation and optimization. Based on neural network techniques, geometrical/physical parameters become design variables to improve circuit performance and reduce design/manufacture cost.

In Section II, the problem for neural modeling of embedded passives is summarized. In Section III, we present the combined equivalent circuit and neural network (EC-NN) modeling approach. The combined State space equation and neural network (SSE-NN) modeling approach is presented in section IV. The method is demonstrated by embedded resistor and capacitor examples in section V. Signal

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integrity of multilayer circuit, which includes SSE-NN models of embedded passives, is used to demonstrate the application of the model for circuit simulation. Optimization and Monte-Carlo analysis are performed showing that the geometry inputs can be continuously adjustable by using our combined models and the model evaluation is much faster than computationally intensive physical/EM model of passives in microwave design.

II. Embedded Passives Neural Modeling: Problem Statement

Let $\boldsymbol{x}$ represent a N_x-vector containing parameters of a microwave device/circuit, e.g., length and width of an embedded resistor, or thickness and dielectric constant of an embedded capacitor. Let $\hat{\boldsymbol{y}}$ represent a $N_{\hat{y}}$-vector containing the responses of the component under consideration, e.g., Y- or S-parameters. The physics/EM relationship between $\hat{\boldsymbol{y}}$ and $\boldsymbol{x}$ can be highly nonlinear and multi-dimensional. The theoretical model for this relationship may not be available, or theory may be too complicated to implement, or the theoretical model may be computationally too intensive for online microwave design and repetitive optimization (e.g., 3D full-wave EM analysis inside a Monte-Carlo statistical design loop). We aim to develop a fast and accurate neural model by teaching/training a neural network to learn the embedded passive problem. Let the neural network model be defined as

$$\hat{\boldsymbol{y}}=\boldsymbol{f}_{ANN}(\boldsymbol{x},\boldsymbol{w}) \tag{1}$$

where $\boldsymbol{w}$ represents the parameters inside the neural network also called as the weight vector. The most widely used neural network structure is the feedforward multilayer perceptrons (MLP) [2, 5, 7] where neurons are grouped into layers, and each neuron in a layer acts as a smooth switch that produces a response between low and high state according the weighted responses of all neurons from the preceding layer. The neural network structure allows the ability to represent multidimensional nonlinear input/output mappings accurately, and to evaluate $\hat{\boldsymbol{y}}$ from $\boldsymbol{x}$ quickly. To enable a neural network to represent a specific microwave $\boldsymbol{x}$ - $\hat{\boldsymbol{y}}$ relationship, we first train the neural network to learn the microwave data pairs ($\boldsymbol{x}_i$, $\boldsymbol{d}_i$) where $\boldsymbol{x}_i$ is a sample of $\boldsymbol{x}$,$\boldsymbol{d}_i$ is a vector representing the $\hat{\boldsymbol{y}}$ data generated from microwave simulation or measurement under given sample $\boldsymbol{x}_i$, and i is the sample index. For training purpose, we define an error function $E(\boldsymbol{w})$ as

$$E(\boldsymbol{w})=\frac{1}{2}\sum_{i\in Tr}\sum_{k=1}^{N_{\hat{y}}}\left(f_{ANN\,k}(\boldsymbol{x}_i,\boldsymbol{w})-d_{ki}\right)^2 \tag{2}$$

where d_{ki} is the k^{th} element of $\boldsymbol{d}_i$, $f_{ANN\,k}$ ($\boldsymbol{x}_i$,$\boldsymbol{w}$) is the k^{th} output of the neural network for input sample $\boldsymbol{x}_i$ and Tr is an index set of all training samples. The objective of neural network training is to adjust neural network connection weights $\boldsymbol{w}$ such that $E(\boldsymbol{w})$ is minimized. A trained neural model can then be used online during microwave design stage providing fast model evaluation replacing original slow model from EM simulators. The benefit of the neural model is especially significant when the model is repetitively used in design processed such as optimization, Monte-Carlo analysis, and yield optimization [11]. However, MLP models, trained to learn S-parameters data, cannot be used directly into time-domain circuit simulation and optimization. We aim to develop a fast and accurate combined model, which uses equivalent circuit and neural network, through EM data to learn the embedded passive problem.

Let $\boldsymbol{g}_p$ = {$\boldsymbol{R}$, $\boldsymbol{L}$, $\boldsymbol{C}$} be a N_p-vector containing the values of lumped components of a given equivalent circuit topology T_p. We use a neural network to represent $\boldsymbol{g}_p$ as

$$\boldsymbol{g}_p=\boldsymbol{f}_{ANN}(\boldsymbol{x},\boldsymbol{w}) \tag{3}$$

and then the combined model can be defined as

$$\hat{\boldsymbol{y}}(\omega)=\boldsymbol{f}_f\left(T_p\left(\boldsymbol{f}_{ANN}(\boldsymbol{x},\boldsymbol{w})\right),\omega\right) \tag{4}$$

$$\boldsymbol{y}(t)=\boldsymbol{f}_t\left(T_p\left(\boldsymbol{f}_{ANN}(\boldsymbol{x},\boldsymbol{w})\right),t\right) \tag{5}$$

where ω is the angular frequency, $\hat{\boldsymbol{y}}(\omega)$ and $\boldsymbol{y}(t)$ are the combined model response in frequency and time domain respectively, e.g., $\hat{\boldsymbol{y}}(\omega)$ can be S- or Y-parameters and $\boldsymbol{y}(t)$ can be the currents $\boldsymbol{i}(t)$ and voltages $\boldsymbol{v}(t)$ of a two port embedded passive. Therefore, a combined model realizes the $\boldsymbol{x}$ - $\hat{\boldsymbol{y}}$/$\boldsymbol{y}$ relationship through a MLP and then equivalent circuit.

III. Combined Equivalent Circuit and Neural Network (EC-NN) Modeling Approach

A. Introduction of EC-NN Model

A number of fast equivalent circuit models of embedded passive components are available. In [12, 13], two methods are presented for developing equivalent circuit using optimization methods. Synthesize lumped element equivalent circuit from rational function is presented in [10]. Although we can get equivalent circuit in many ways from measured or simulated EM data, an equivalent circuit only represents a fixed embedded passive structure. If the embedded passive's geometrical/physical parameters need to be changed, we have to re-generate a new equivalent circuit to match it.

In this paper, EC-NN model exploits neural network features to accurately predict element values of equivalent circuit based on geometrical/physical parameters. EC-NN model, motivated by [14], is a hierarchical model with two levels. At the lower level, a neural model maps the geometrical/physical parameters of the passive component into lumped component values of a given equivalent circuit. At the higher level, we supply these values into the equivalent circuit to compute the EM response in frequency or time domain circuit design.

B. EC-NN Model development

We utilize an existing equivalent circuit and combine it with a MLP together to make the model automatically as function of geometrical/physical parameters. The EM data of embedded passives, which consists of geometrical/physical parameters as inputs and real/imaginary parts of S-parameters as outputs, are generated by simulation or measurement.

To create data for neural network training, we extract the lumped component values based on the existing equivalent circuit through a set of measured/simulated sample pairs of EM data. Considering some measurement noise in the EM data, the parameter extraction criterion for each set of input geometry is defined as an optimization objective function as

$$\underset{g_p}{Min}\sum_{i\in T_r}\sum_{k=1}^{N_g}\left\|f_f\left(T_p\left(g_p\right),\omega\right)-d_{ki}\right\| \tag{6}$$

This objective function shows that adjusting the lumped component values g_p to map the S-parameters of high-frequency response of the equivalent circuit best match the EM data in the interested frequency bandwidth. Due to the complexity of the error function, iterative algorithms are used to explore the lumped component values. The optimization algorithms we used are gradient and quasi-Newton methods. We collected the lumped component values versus geometrical/physical parameters as neural network training data. We teach/train a MLP to learn the relationships between equivalent circuit component values and geometry. Let g_{pi} be a vector representing g_p data under given sample x_i. The error function is defined as

$$E(w)=\sum_{i\in Tr}\sum_{k=1}^{N_p}\left\|f_{ANNk}(x_i,w)-g_{pki}\right\| \tag{7}$$

where g_{pki} is the k^{th} element of g_{pi}. After training, the MLP can accuratly calculate the component values varied with continous geometry for the given equivalent circuit. The last step is to export the EC-NN model into a user defined simulation format, e.g., SPICE sub-circuit netlist format. The EC-NN model includes two sections. The first section is a set of mathematical equations to represent the internal structure of neural network that calculate the lumped component values based on different geometry/physical inputs. The second section is the updated equivalent circuit, which receives the element values from MLP outputs. In a circuit simulator, the EC-NN model will be feed by geometrical/physical parameters as inputs. The MLP automatically calculates the element values in a user defined equivalent circuit and supply the values into the equivalent circuit to represent EM behavior in frequency and time domain.

IV. Combined State Space Equation and Neural Network (SSE-NN) Modeling Approach

A. Formulation in Frequency-Domain

Topology of equivalent circuit is a sensitive factor of the combined model accuracy and a given topology may not be suitable for different geometry and frequency range. In order to develop an accurate model, which can be represented more efficiently in both time and frequency domain simulation, we proposed the combined SSE-NN modeling approach.

EM data of an embedded passive can be collected depending on different geometrical/physical parameters from full wave EM simulation/measurement. For a given frequency range, we can use transfer functions (polynomial rational functions) to represent the electrical behavior (e.g., admittance **Y** matrix) of the embedded passives. For any two-port embedded passives, the following three transfer functions are adequate to represent Y_{11}, Y_{21}, and Y_{22}, respectively.

$$H_1(s)=\frac{b_0+b_1s+\cdots+b_{n-1}s^{n-1}+b_ns^n}{a_0+a_1s+\cdots+a_{n-1}s^{n-1}+s^n} \tag{8.a}$$

$$H_2(s)=\frac{d_0+d_1s+\cdots+d_{n-1}s^{n-1}+d_ns^n}{a_0+a_1s+\cdots+a_{n-1}s^{n-1}+s^n} \tag{8.b}$$

$$H_3(s)=\frac{c_0+c_1s+\cdots+c_{n-1}s^{n-1}+c_ns^n}{a_0+a_1s+\cdots+a_{n-1}s^{n-1}+s^n} \tag{8.c}$$

where $s=j\omega$, and n is the number of effective order of the passive. Let us define a real coefficient vector, as $g_v = \{a_0, a_1, \ldots a_{n-1}; b_0, b_1, \ldots b_n; c_0, c_1, \ldots c_n; d_0, d_1, \ldots d_n\}$. Using space-mapping concept [6], a relationship exists between the coefficients and geometrical/physical parameters. However, the relationship would be highly nonlinear and too complicated. Therefore, we utilize neural network features to learn the highly nonlinear relationship between the coefficients and geometrical/physical parameters.

In the coefficient parameter extraction procedure, we used gradient and quasi-Newton optimization algorithms to enforce $H(s)$ to best match EM data. The objective function was defined as

$$\underset{g_v}{Min}\sum_{i\in Tr}\sum_{k=1}^{3}\left\|H_k(g_v,\omega)-d_{ki}\right\| \tag{9}$$

and we use a neural network to learn the relationship between coefficient vector g_v and EM input parameters x,

$$g_v = f_{ANN}(x\ ,w)\,. \tag{10}$$

We used the center point of input space as the initial point to optimize the coefficient vector values.

B. State Space Equation for Time-Domain Simulation

Using coefficients $\boldsymbol{g}_v$ in (8), we can define

$$
A=\begin{bmatrix}
0 & 1 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0\\
0 & 0 & 1 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0\\
\vdots & \vdots & \vdots & \ddots & 0 & \vdots & \vdots & \ddots & \vdots & \vdots\\
-a_0 & -a_1 & -a_2 & \cdots & -a_{n-1} & 0 & 0 & \cdots & 0 & 0\\
0 & 0 & \cdots & 0 & 0 & 0 & 1 & 0 & \cdots & 0\\
0 & 0 & \cdots & 0 & 0 & 0 & 0 & 1 & \cdots & 0\\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots\\
0 & 0 & \cdots & 0 & 0 & -a_0 & -a_1 & -a_2 & \cdots & -a_{n-1}
\end{bmatrix}_{2n\times 2n}
$$

$$
B=\begin{bmatrix}0 & 0 & \cdots & 1 & 0 & 0 & \cdots & 0\\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 1\end{bmatrix}^T_{2n\times 2} \quad D=\begin{bmatrix}b_n & d_n\\ d_n & c_n\end{bmatrix}_{2\times 2} \qquad (11)
$$

$$
C=\begin{bmatrix}b_0-a_0b_n & \cdots & b_{n-1}-a_{n-1}b_n & d_0-a_0d_n & \cdots & d_{n-1}-a_{n-1}d_n\\ d_0-a_0d_n & \cdots & d_{n-1}-a_{n-1}d_n & c_0-a_0c_n & \cdots & c_{n-1}-a_{n-1}c_n\end{bmatrix}_{2\times 2n}
$$

to form the state space equation,

$$
\begin{cases}\dot{x}(t)=Ax(t)+Bu(t)\\ y(t)=Cx(t)+Du(t)\end{cases} \qquad (12)
$$

where $x(t)$ is a vector of internal states, u and y are vectors of the input and output signals, e.g., input voltages and output currents of the embedded passive respectively. Our combined model can be then implemented into a time domain circuit simulator using the state space equation (12) or into a frequency domain circuit simulator using (8).

C. Stability and passivity

To assure stability requirement in time domain simulation, the poles of the combined SSE-NN model need to be on left half plane (LHP) [15]. To enforce all the poles of the transfer functions of embedded passives to be into LHP, we added a set of constraints in the parameter extraction as

$P_{even\text{-}order}=\prod_{i=1}^{T} P_{2i}$; where $P_{2i}=(s^2+k_{2i}s+k_{3i})$ and $T = n/2$, if $k_{2i}>0$ & $k_{3i}>0$; all of real and complex roots in LHP.

$P_{odd\text{-}order}=P_1\cdot\prod_{i=1}^{T} P_{2i}$; where $P_1=(s+k_1)$ and $T=(n-1)/2$, if $k_1>0$, $k_{2i}>0$ & $k_{3i}>0$; all of real and complex roots in LHP.

where $\boldsymbol{k}=\{k_1, k_{21}, k_{31}, \ldots k_{2T}, k_{3T}\}$ is a vector of components that lead to elements in the matrix A. For example, in a 3rd order combined model, the denominator coefficients are defined as $a_0=k_1\cdot k_3$; $a_1=k_1\cdot k_2+k_3$; and $a_2=k_1+k_2$, respectively.

The criterion for passivity can be defined if the eigenvalues of $\boldsymbol{G}$ = Re{Y} are positive [15, 16]. This condition can be assured if $y_{12}y_{21}\le y_{11}y_{22}$, where the y_{jk} $(j,k = 1,2)$ are real parts of the Y matrix elements. It has been used as an optimization constraint in the $\boldsymbol{g}_v$ parameter extraction procedure.

The above criterions are added in the parameter extraction to ensure that the rational functions not only accurately represent EM behavior but also enforce the time domain model to be stable and passive.

D. Structure of the Combined SSE-NN Model

Our combined SSE-NN model is a hierarchical structure with two levels. At the lower level, a neural network maps the geometrical/physical parameters into $\boldsymbol{g}_v$ vectors. At the higher level, we insert the coefficient vectors into the state equations to compute the EM response in frequency or time domain simulation. Fig. 1 shows the structure of the combined model for both EC-NN and SSE-NN.

For circuit CAD tools in time domain, we export our SSE-NN into SPICE sub-circuit format. The lower neural network will be described by a set of mathematical equations, which calculate the coefficient values based on different geometrical/physical parameters and pass them into higher level. The equivalent circuit can be generated from (11) and (12).

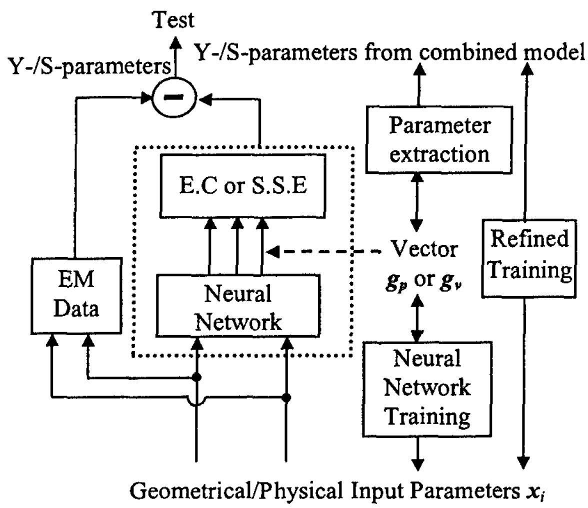


Figure 1. Structure of the combined EC-NN and SSE-NN models illustrating the model development process and the testing phase. E.C. and S.S.E. represent equivalent circuit and state space equation respectively.

E. Combined SSE-NN Model Development

EM data has component's geometrical/physical parameters and frequency as inputs and S-parameters as outputs. The next phase is parameter extraction, which is carried out for each geometry over the entire frequency range. The objective here is to determine the coefficient values that best fit the original EM data. Different geometrical parameter values and their corresponding coefficient values are then re-arranged into neural network training data. A 3-

layer MLP neural network is trained using quasi-Newton algorithm in *NeuroModeler* [17]. For any given geometrical dimensions of the component within the range of the training data, the trained MLP can predict the elements of vector g_v. We combine the state equation with the neural model using our hierarchical setup to obtain the overall combined model. The inputs to the combined model are the geometrical dimensions of the embedded component. The intermediate outputs of the model are the corresponding coefficient vector values. The final outputs of the combined model are component's EM behavior, e.g., S-parameters. In the test phase, an independent set of test data containing S-parameters versus new geometrical parameter values (i.e., never seen during training) is generated using the EM simulator. This data is used to test the accuracy of the combined model. In the final phase, we formulate the combined model into a set of mathematical expressions to be directly used to carry out high-level circuit design in time-domain simulators.

V. Examples

In order to demonstrate the proposed modeling approach, we developed embedded resistors and capacitors in EC-NN and SSE-NN models. We applied the SSE-NN models in signal integrity of multilayer circuit design to efficiently perform optimization and statistic analysis.

A. Embedded Resistor

Accurate modeling of EM behaviors of embedded passive used in high-speed multilayer printed circuit board is important for efficient high-speed circuit design. In this example, a combined EC-NN model of an embedded resistor shown in Fig. 2 is developed. The EM data of the embedded resistor is automatically generated from EM simulation of Sonnet [18]. Length (L) and width (W) are used as inputs. The outputs are real and imaginary parts of S_{11} and S_{21} in the EM data. Fig. 3 shows the structure of the EC-NN model for the embedded resistor, which includes an equivalent circuit and a 3-layer MLP neural network.

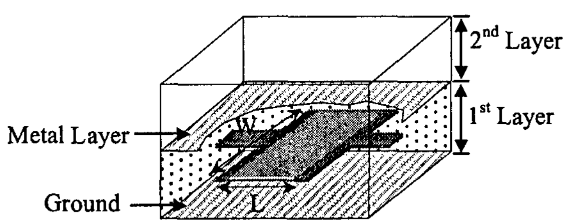


Figure 2. 3-D physical structure of embedded resistor.

The neural network is trained to learn the relationship about the input geometry and the four lumped component values (R1, R2, C1, C2). After the MLP is well trained, it can accurately calculate the component values based on any within geometrical/physical parameters for the given equivalent circuit even the parameters was never used in training. Testing is performed by comparing the outputs of the overall EC-NN model and EM data, shown in Fig. 4(a).

Because the neural network can provide the accurate component values continuously varied with geometry for the equivalent circuit, the combined EC-NN model can be in place of the computationally intensive physical/EM model to efficiently provide EM effects in optimization and statistic design.

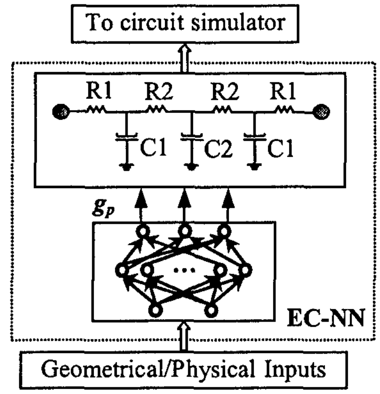
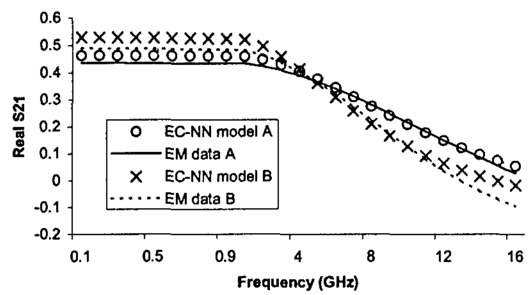
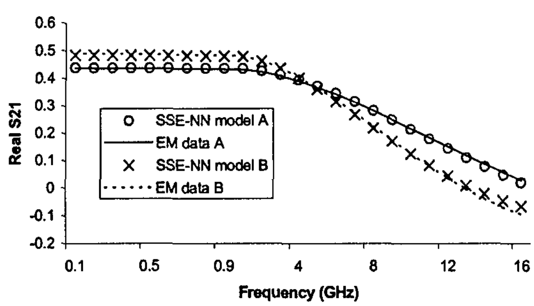


Figure 3. The structure of the combined EC-NN model for embedded resistors. The equivalent circuit is user defined.



(a)



(b)

Figure 4. Comparison of real part of S_{21} of embedded resistor EC-NN model outputs (a) or SSE-NN model outputs (b) and independent EM data which was never used in training. Curves A are generated based on W = 1.346 and L = 0.279 mm. Curves B are generated based on W = 0.99 and L = 0.254 mm.

The test error of combined EC-NN model is 5.8%. Further improvement of accuracy requires new topology of equivalent circuit. Instead of using human based trial and error process, we use the proposed SSE-NN modeling method. As the equivalent circuit for the embedded resistor uses three capacitors, a 3rd order transfer function can express the behavior of the embedded resistor in the SSE-NN model.

Table I shows the model test error, which we achieved, based on various orders of state equations in SSE-NN modeling development. The test error demonstrated that the optimal number of internal states is three. In 4th order model, the additional internal state could not play an important role in the EM behavior representation. However, more coefficients are needed in transfer function, more freedom in parameter extraction and neural network training.

The best results are obtained with the 3rd order SSE-NN model. The agreement between 3rd order SSE-NN model and EM data is achieved even though the independent testing data was never seen in training, shown in Fig. 4(b). To verify stability and passivity, the three LHP poles of the embedded resistor model are -1.4411 and -0.0144 ± j0.0539, and the passivity condition is satisfied as shown in Fig. 5.

Table I. Comparison of resistor SSE-NN model with different order formulations.

Order	Test Error
2nd	1.59%
3rd	1.12%
4th	2.38%

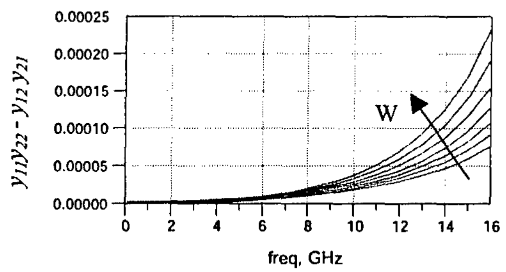


Figure 5. The 3rd order SSE-NN model in frequency-domain simulation and y_{jk} (j,k = 1,2) are real part of the **Y** matrix elements. The W is swept from 0.952mm to 1.397mm.

B. Embedded Square Capacitor

The physical structure of an embedded square capacitor is shown in Fig. 6. The input parameters include length (L), capacitor dielectric constant (ε_{rcap}), and frequency. Real and imaginary parts of S-parameters are generated from 3D full wave EM simulator, Ansoft-HFSS [19]. Fig. 7 shows the equivalent circuit used in our combined EC-NN model for the embedded capacitor.

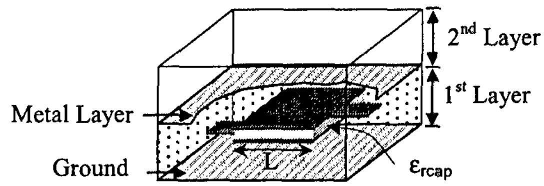


Figure 6. 3-D physical layout of embedded capacitor.

The neural network is trained to learn the embedded capacitor inputs and lumped component values. For example, L1=0.035nH, C1= 1.135pF, C2=0.537pF when L=0.736mm and ε_{rcap}=17.5. The S-parameter comparison between the EC-NN model and original EM data is shown in Fig. 8(a). Table II illustrates the different test error, which we achieved, based on varied order formulas in SSE-NN modeling development.

The optimal transfer function is 3rd order to represent the EM based capacitor. Testing is performed by comparing the outputs of combined SSE-NN models and EM data. The agreement between our 3rd order SSE-NN model and EM data is obtained even though the independent testing data was never seen in training, shown in Fig. 8(b).

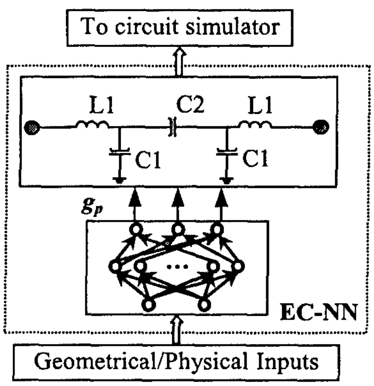
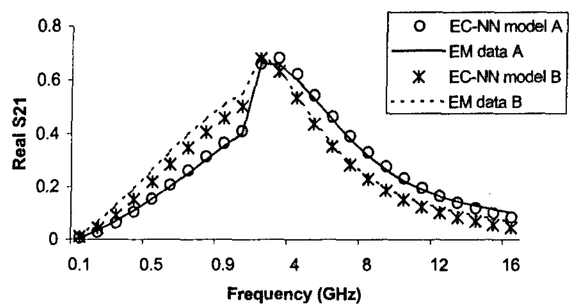
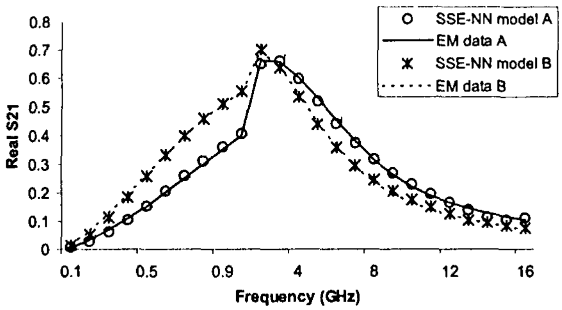


Figure 7. The combined EC-NN model structure for embedded capacitor. The equ ivalent circuit is user defined.



(a)



(b)

Figure 8. Comparison of real part of S_{21} of embedded capacitor EC-NN model outputs (a) or SSE-NN model outputs (b) and independent EM data. Curves A and B are generated based on inputs L = 0.736mm and L = 0.787mm respectively.

Table II. Comparison of capacitor SSE-NN model with different order formulations.

Order	Test Error
2nd	2.20%
3rd	1.67%
4th	2.57%

3. Signal Integrity Example

To further confirm the validity of the proposed combined model in time-domain, we plugged the above resistor and square capacitor SSE-NN models into a time-domain simulator, i.e., *Hspice* [20] to perform circuit simulation and optimization including geometrical and physical parameters of the embedded passives. The models help to achieve a convenient link between EM behaviors and high-level circuit design, improving design accuracy and efficiency. In this paper, we use signal integrity of multilayer circuit as shown in Fig. 9, where the length and width of embedded resistor and length and dielectric constant of embedded capacitor are adj ustable.

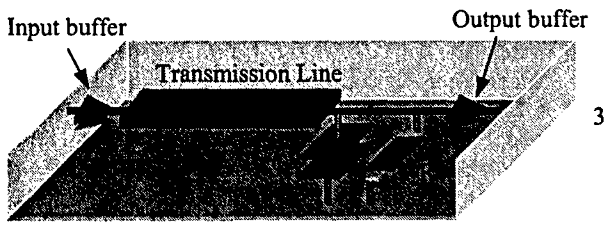


Figure 9. Three dimensional illustration of signal integrity of multilayer circuit with embedded resistor and capacitor.

In optimization process, whenever optimization changes the geometry, the corresponding combined models are called with the new geometrical dimensions as inputs. From output comparison, as shown in Fig. 10, the output curves have been improved in terms of distortion and time delay.

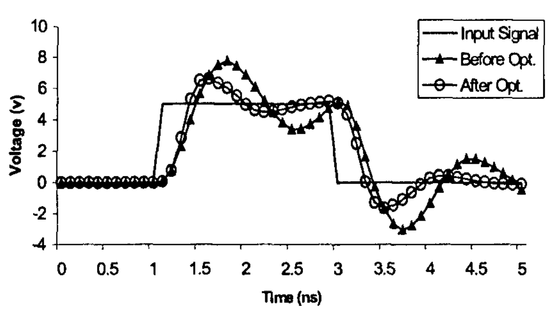


Figure 10. Comparison of signal from input buffer, and output signals before and after combined SSE-NN models optimization.

The optimization used 136 iterations including repetitive evaluation of combined SSE-NN models to reach the criteria of the optimization goal and the total computation time based on our combined SSE-NN models is 3.75minutes. The results show that the combined models provide possibility to adjust the geometry of embedded passives in high-frequency circuit design. Because we used neural models to learn the nonlinear relationship between geometry and coefficient vectors, the geometry becomes variable in circuit design.

We also performed statistical analysis of the signal integrity circuit with our SSE-NN models in a three-coupled transmission line circuit as shown in Fig. 11. Monte-Carlo analysis of signal integrity curves with geometrical parameters as statistical design variables are shown in Fig. 12. The total simulation time for 500 output curves based on the geometry tolerance around the nominal design center is 8.24 minutes using proposed neural models by *Hspice*. However, the required time of Ansoft-HFSS for 500 different geometry is more than 8 hours. The proposed combined models retain the advantages of neural network learning, speed, and accuracy, and provide EM effects in high-level circuit design.

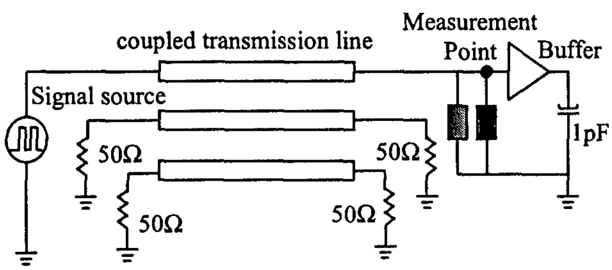


Figure 11. The three coupled transmision line circuit.
■ : EM capacitor SSE-NN model;
■ : EM resistor SSE-NN model

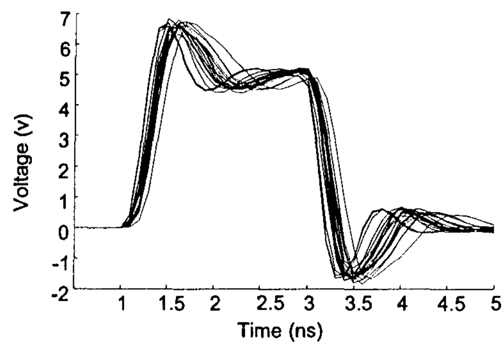


Figure 12. Output of Monte-Carlo analysis of the 3-coupled transmission line example using SSE-NN models of embedded passives. Here 20 randomly chosen curves are shown out of 500 simulations of the circuit of Fig. 11.

VI. Conclusions

In this paper, we presented a new method for modeling embedded passives suitable for both frequency and time domain simulation. The combined models, which utilize neural network and equivalent circuit or state space equation techniques, are developed from EM data.

The accuracy of the combined EC-NN model will depend on the equivalent circuit in the combined model for the entire frequency range. If the accurate and reliable equivalent circuit is available, EC-NN will be generated efficiently, because the number of lumped elements in equivalent circuit is less than the number of coefficient values in state space equations.

In combined SSE-NN model development, we automatically generate an accurate solution for modeling embedded passives, avoiding human based trial and error process in conventional approach. The combined SSE-NN modeling technique acts as a bridge to combine slow physical EM model and fast equivalent circuit model to together. In high-speed circuit design, the combined neural models allow geometrical/physical parameters to become design variables in circuit simulation. Therefore, manufacture geometrical tolerance can be taken into account in circuit design efficiently and accurately.

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