EM-ANN Models for Microstrip Vias and Interconnects in Dataset Circuits

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***Abstract*— A novel approach for accurate and efficient modeling of monolithic microwave/millimeter wave integrated circuit (MMIC) components by using electromagnetically trained artificial neural network (EM-ANN) software modules is presented. Full-wave EM analysis is employed to characterize MMIC components. Structures for simulation are chosen using design of experiments (DOE) methodology. EM-ANN models are then trained using physical parameters as inputs and S-parameters as outputs. Once trained, the EM-ANN models are inserted into a commercial microwave circuit simulator where they provide results approaching the accuracy of the EM simulation tool used for characterization of the MMIC components without increasing the analysis time significantly. The proposed technique is capable of providing simulation models for MMIC components where models do not exist or are not accurate over the desired region of operation. The approach has been verified by developing models for microstrip vias and interconnects in dataset circuits. A new hybrid (ΔS) modeling approach which makes use of existing approximate models for components is introduced and shown to be a more efficient method for developing EM-ANN models. An example of using EM-ANN models to optimize the component geometry is included.**

I. Introduction

EFFORTS TO lower the cost and reduce the weight/volume of monolithic microwave/millimeter wave integrated circuits (MMIC's) have resulted in high-density and dataset circuits where a large number of via interconnects are used. With this increased complexity and higher operating frequencies, accurate and efficient characterizations of via interconnect discontinuities and single-layer ground vias must be carried out in order to achieve accurate simulation results [1]. Several recent efforts have focused on the analytical and numerical evaluation of via discontinuities using quasi-static and full wave techniques [1]–[17]. Quasi-static models are valid only at low frequencies. Full-wave characterization can lead to accurate results, but at much higher computational expense which prevents their use in practical interactive CAD.

This paper presents a new methodology for accurate modeling of via interconnects using electromagnetically trained artificial neural networks (EM-ANN's). In the past, artificial neural networks (ANN's) have been used only to a very limited extent in the microwave engineering area. Applications reported in literature include: automatic impedance matching [18], microstrip circuit design [19], microwave circuit analysis and optimization [20], [21], modeling of GaAs MESFET process and device characteristics [22]–[24], and most recently, modeling of spiral inductors [25] and microstrip grounding vias [26]. We make use of the ANN approach for component modeling. The proposed technique uses the Design of Experiments (DOE) methodology to identify various component parameter values for which electromagnetic simulations need to be carried out in order to capture important input–output relationships. Use of the DOE approach allows for a minimum number of EM simulations that need to be performed. Simulation results are then used to train the ANN model, using physical parameters as inputs, to provide the correct S-parameter response over the desired frequency range. Since ANN's have been shown to have the ability to learn from data, to generalize patterns in data, and to model highly nonlinear relationships [27], [28], the trained model is valid for the entire ranges of the input variables. It may be noted that no circuit model (in terms of lumped inductor, etc.) is involved in the derivation of ANN models discussed here. Once the EM-ANN model has been trained, it is easily inserted into a commercial microwave circuit simulator. Optimization techniques can also be used with the trained EM-ANN model to find the optimal component structure for a given application. These models prove to be extremely useful in situations where an element is used many times with varying geometrical dimensions.

Applications of this methodology for modeling via elements in microstrip circuits and dataset via interconnects are presented. Two methods called complete and hybrid EM-ANN modeling are proposed. With the complete modeling, the EM simulator data is used to train the ANN model ab initio, without any additional information from existing approximate models. In the second method called hybrid EM-ANN modeling, existing approximate models are used to construct the input–output relationships of the component model. In this case, the EM simulator data is used to develop an ANN software module to correct for the difference between the approximate model and the EM simulation results. Integration of the EM-ANN models with a commercial microwave circuit simulator and structure optimization using these models are also demonstrated.

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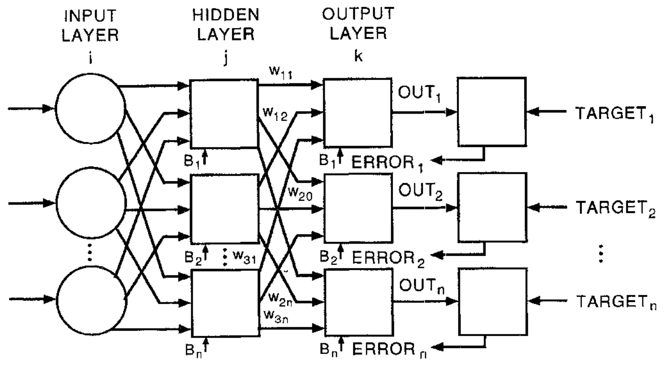


Fig. 1. Artificial neural network architecture.

II. ANN Modeling

A. ANN Model Structure and Learning

The ANN architecture used in this work is shown in Fig. 1 and consists of an input layer, an output layer, and one hidden layer. It is a dataset, feedforward ANN, utilizing the error backpropagation learning algorithm [28]. The hidden layer allows modeling of complex input–output relationships. Input vectors are presented to the input layer and fed through the network which then yields the output vector. Mapping of the input–output relationships can be represented by [29]

$$\boldsymbol{Y} = F(\boldsymbol{W}_2 \cdot F(\boldsymbol{W}_1 \cdot \boldsymbol{X} + \boldsymbol{B}_1) + \boldsymbol{B}_2) \tag{1}$$

where $\boldsymbol{X}$ is the input vector, $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$ are the weight matrices between the input and hidden layers and between the hidden and output layers, respectively; $\boldsymbol{B}_1$ and $\boldsymbol{B}_2$ are bias matrices, and $\boldsymbol{Y}$ is the output vector. $F(u)$ is the nonlinear activation function of each artificial neuron which for this work is taken to be

$$F(u) = \frac{1}{1 + \exp(-u)}. \tag{2}$$

The ANN learns relationships among sets of input–output data which are characteristic of the component under consideration. First, input vectors are presented to the input neurons and output vectors are computed. ANN outputs are then compared to desired outputs and errors are computed. Error derivatives are then calculated and summed up for each weight until all training sets have been presented to the network. These error derivatives are then used to update the weights for neurons in the model. Training proceeds until errors are lower than prescribed values. Details of the training algorithm are given in [30].

B. ANN Model Training

A simultaneous training and testing methodology is used while training the EM-ANN models [31]. To begin with, simulated data is separated into three datasets: 1) one for training; 2) one for simultaneous testing and additional training; and 3) the third for independent model verification. In this way, testing set errors can be monitored as training progresses. When testing errors begin to increase, the training is stopped, preventing overfitting of the training data. If overfitting occurs, the ANN model will not have good predictive capabilities.

Another important issue with ANN modeling is model complexity. Complexity is increased by adding additional neurons to the hidden layer. A network with too few neurons will not be able to map complex input–output relationships, while a network with too many neurons adds complexity, increases training time, and tends to overfit the training data instead of generalizing. A simple to complex procedure is used to determine network architecture. First, a simple network architecture is chosen, usually containing one hidden layer with a small number of neurons. If learning is slow or desired accuracy is not achieved, additional neurons are added to the hidden layer. The best network architecture is retained, identifying the optimal network.

III. DOE Methodology

In order to train the EM-ANN models, a number of EM simulations need to be performed. These simulation points need to be chosen so that important input–output relationships are presented to and learned by the EM-ANN model. Simple models require less simulation points, while highly nonlinear models require an increased number of simulations.

For some components, analytical models are possible and input–output relationships may be expressed in closed form. When the input–output relationships are too complex, experimental data may need to be obtained to characterize the component. For many complex relationships, design of experiments (DOE) methodology is used to systematically study the input–output relationships of a component or process.

A designed experiment is a test or a series of tests in which purposeful changes are made to the input variables of a process or system so that the causes of changes in the output response can be observed and identified [32]. Experimental data is then used to build the model of the input–output relationship using response surface methodology (RSM).

In RSM problems, the input–output relationships are unknown. The first step is to approximate the input–output relationships. This is usually done using low-order polynomials or another fitting technique over a small portion of the input variables ranges. However, when the process is influenced by a large number of input variables, is highly nonlinear, has more than one output variable, or when a global fit to the response surface is needed, conventional fitting methods are limited [3], [21].

An alternative approach for modeling of the response surface is the use of ANN's [33]. ANN's are able to deal with highly nonlinear and multiple input/output variables effectively, providing excellent interpolative capabilities [27]–[30]. This allows development of a global model representing a component.

Although response surface methods were developed for regression analysis, they can be used to determine simulation points which effectively cover the region of interest. When building a model, one would like to perform as few EM simulations as possible, for achieving the desired accuracy. This implies starting with a low-order experimental design and sequentially building up to higher-order designs by adding additional simulation points.

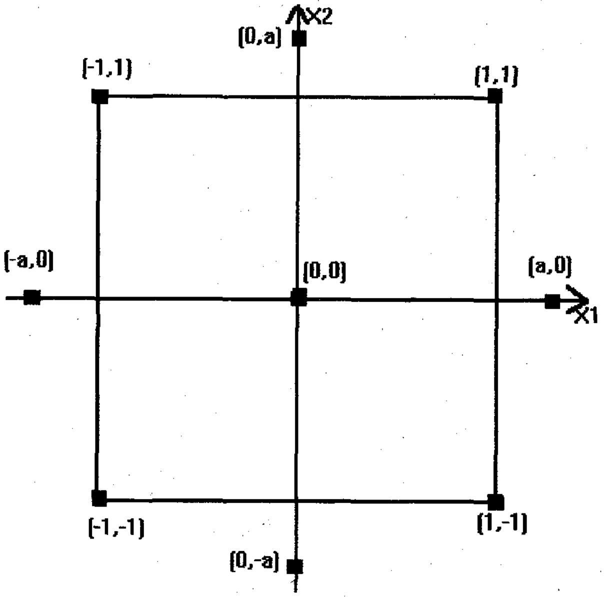


Fig. 2. Distribution of simulation points for a central composite experimental design when the number of design variables is only two (x1 and x2).

Central composite design approach [32], shown in Fig. 2 for a case with two design parameters, is used in this work to obtain the initial structures to be simulated for EM-ANN modeling. Central composite designs require 2^k corner points, one center point, and $2(k)$ axial points, where k is the number of variable parameters. When it is found that the input–output relationships of the component have not been sufficiently captured, additional simulation points are added to fit the higher order nonlinearities.

IV. Complete EM-ANN Modeling

Complete EM-ANN modeling refers to the case when the EM simulation results are used to train the ANN model ab initio without making use of any other approximate model for the component. Inputs for the EM-ANN models are frequency and physical parameters, while outputs are the desired S-parameters. Results of complete EM-ANN modeling are presented for one and two port microstrip vias, stripline-to-stripline dataset interconnects, and microstrip-to-microstrip dataset interconnects.

A. Broadband GaAs Microstrip Vias

Fig. 3 shows the structure and some parameters of the one-port via under consideration. The height of the substrate, the dielectric constant, and all loss parameters are considered constant for this example. The width of the incoming microstrip line, W_l, the side of the square shaped via pad, W_p, and the diameter of the via hole, D_{via}, are the three variable design parameters. Input variables for the EM-ANN and their ranges are given in Table I.

EM simulations were performed from 5–55 GHz in 10-GHz steps using a commercially available full-wave electromagnetic simulator (HP-Momentum) [34]. Via structures for 15 DOE central composite points, as well as for 14 additional training/testing points spaced midway between the previous points, were simulated. In addition, 16 structures were simulated for independent verification of the model after completion of the training.

Best results were obtained by using ten neurons in the hidden layer and the 15 central composite points, as well as the 14 interior points for training the network. This training required a total of 50 min time on a 486 computer (66 MHz). Figs. 4 and 5 show the results for the training and verification sets, respectively. Shown are the variations of the EM-ANN results versus the HP-Momentum results, which should be linear for a perfect fit.

TABLE I
VARIABLE INPUT PARAMETERS FOR GaAs MICROSTRIP GROUND VIA MODELING

Input Parameter	Minimum Value	Maximum Value
Frequency	5 GHz	55 GHz
W_l/W_p	0.3	1.0
D_{via}/W_p	0.2	0.8
W_l/H_{sub}	0.1	2.0

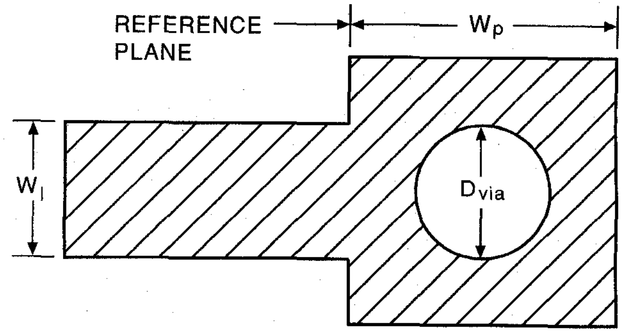


Fig. 3. GaAs microstrip ground via geometry. Substrate thickness =4 mil, $\varepsilon_r = 12.9, \tan\delta = 0.002, \sigma_{\text{metal}} = 4.1 \times 10^7$, and $t_{\text{metal}} = 0.1$ mil.

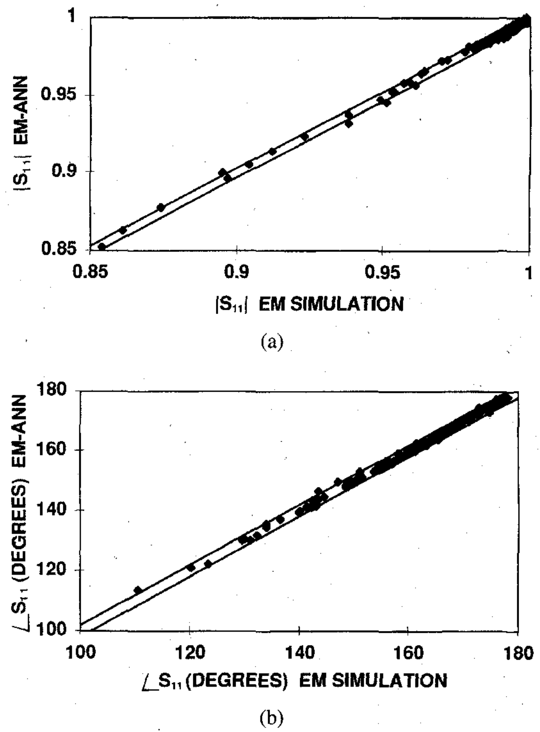


Fig. 4. Comparison of EM-ANN model results with full-wave analysis of a microstrip 1-port via (training dataset). (a) Magnitude response with ± 0.003 error bounds and (b) phase response with ± 2 degree error bounds.

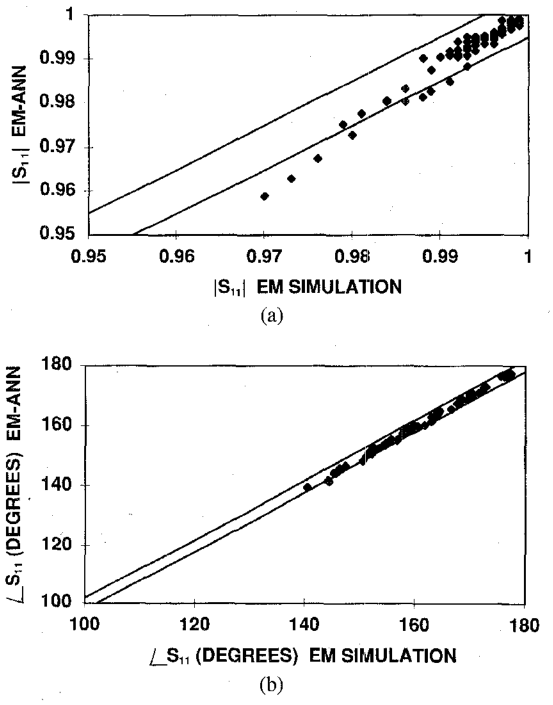


Fig. 5. Comparison of EM-ANN model and full-wave results for GaAs microstrip via verification dataset. [Note the expanded scale compared to that in Fig. 4(a)]. (a) Magnitude response with ± 0.005 error bound and (b) phase response with ± 2 degree error bounds.

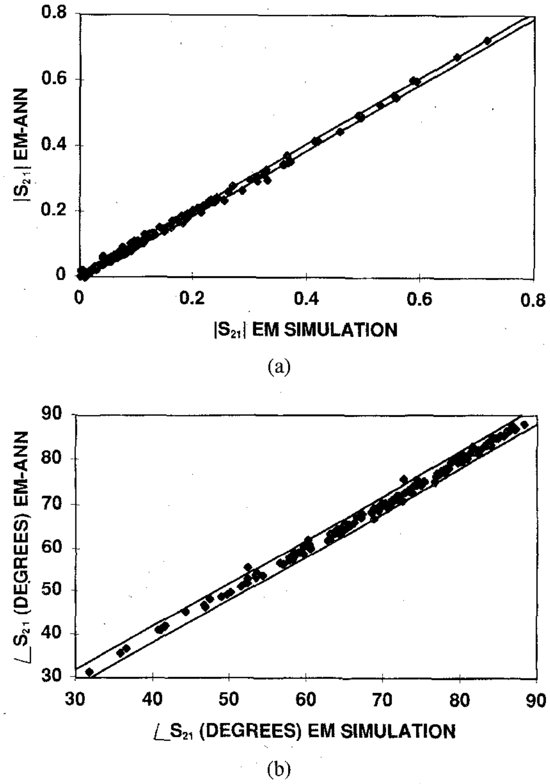


Fig. 6. Comparison of EM-ANN model results with full-wave analysis of a 2-port microstrip via (training dataset). (a) Magnitude response with ± 0.01 error bounds and (b) phase response with ± 2 degree error bounds.

B. Two-Port Microstrip Vias

In addition to the one-port vias described above, two-port vias were also modeled using this approach. The structure and input variables are the same as shown in Fig. 3 and in Table I, except for an added port, making the structure symmetrical. As with the one-port vias, best results were obtained by using the 15 central composite points and the 14 interior points for training. Ten neurons were required for the hidden layer. The training required 90 min time on a 486 computer (66 MHz). Figs. 6 and 7 show S_{21} variations for the training and verification results, respectively.

It may be noted that the EM-ANN via models are able to achieve accuracy comparable to EM simulation over the entire 5–55 GHz range. Since a full-wave analysis is used, all the dielectric, conductor, and radiation losses, as well as all parasitic effects, are included. The developed models may now be used in linear analysis and in nonlinear analysis where harmonic frequency components are generated.

C. Stripline-to-Stripline Dataset Interconnect

Fig. 8 shows the structure of a 50-Ω stripline-to-stripline dataset interconnect for which an EM-ANN model has been developed. Reference planes are set at $W_{\text{line}}/2$ from the center of the via. The variable design parameters are the diameter of the via, D_{via}, and the diameter of the ground access opening, D_{gnd}. All other parameters are fixed. Model input variables and their ranges are given in Table II.

EM simulations were performed from 1–26 GHz in 5-GHz steps. Interconnect structures for nine central composite points and eight additional training/testing points were simulated. In addition, 12 structures were simulated for model verification purposes.

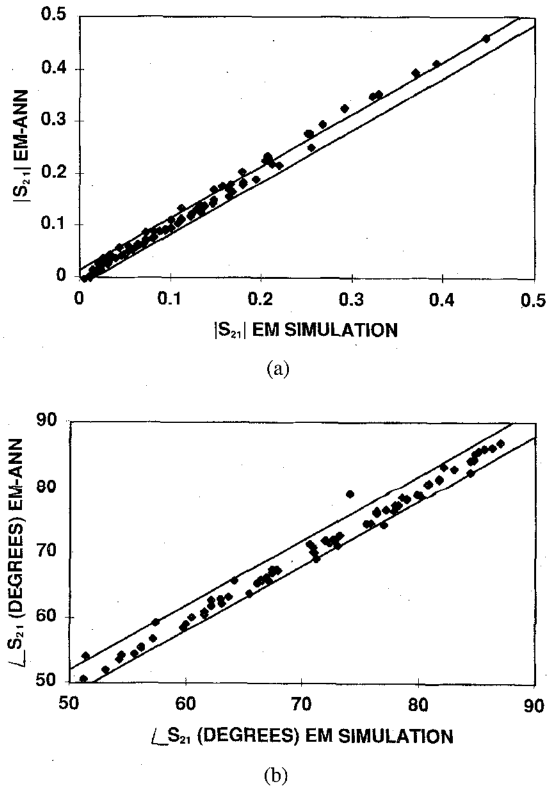


Fig. 7. Comparison of EM-ANN model results with full-wave analysis of 2-port microstrip via (verification dataset). (a) Magnitude response with ± 0.015 error bounds and (b) phase response with ± 2 degree error bounds.

TABLE II
VARIABLE PARAMETERS FOR STRIPLINE-TO-STRIPLINE INTERCONNECT MODEL

Input Parameter	Minimum Value	Maximum Value
Frequency	1 GHz	26 GHz
D_{via}/W_{line}	0.365	0.8
D_{gnd}/D_{via}	1.25	6

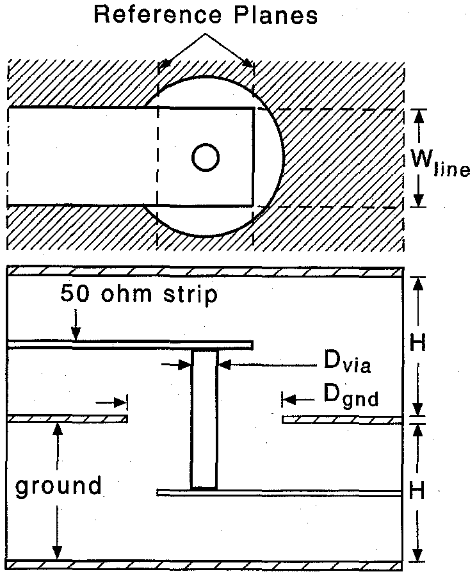


Fig. 8. Stripline-to-stripline interconnect structure with $W_{\text{line}} = 13.675$ mil, $Z_o = 50$ ohms, $\varepsilon_r = 2.94$, $\tan\delta = 0.0012$, $t_{\text{metal}} = 1.4$ mil, $\sigma_{\text{metal}} = 5.7 \times 10^7$, and $H = 20$ mil.

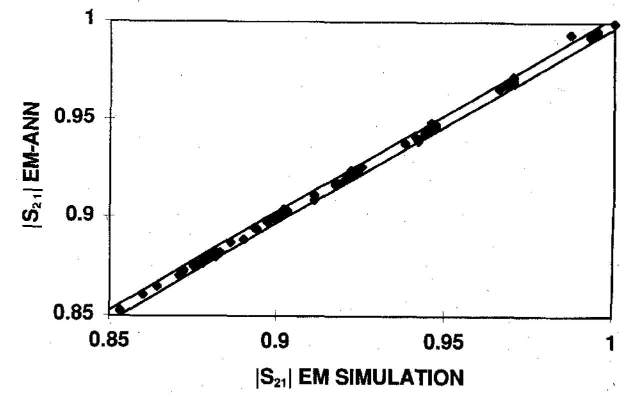
Using the nine central composite points plus the eight additional interior points for training the model yielded the best results. Nine neurons were used in the hidden layer. Training time was 115 min on a 486 computer (66 MHz). Figs. 9 and 10 show the S_{21} results for the training and verification sets, respectively. As with the GaAs ground vias, excellent results were obtained.

D. Microstrip-to-Microstrip dataset Interconnect

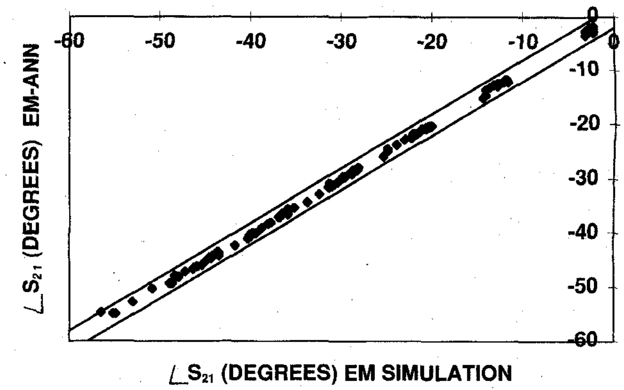
Fig. 11 shows the structure of a 50-Ω microstrip-to-microstrip dataset interconnect for which an EM-ANN model has been developed. Reference planes are set at $W_{\text{bot}}/2$ and $W_{\text{top}}/2$ from the center of the via for the bottom and top microstrip lines, respectively. The variable design parameters are the diameter of the via, D_{via}, and the length of the overhang for the top microstrip line, L_{OH}. All other parameters are fixed. Model input variables and their ranges are given in Table III.

EM simulations were performed from 2–12 GHz in 2-GHz steps. Interconnect structures for nine central composite points and eight additional training/testing points were simulated. In addition, 16 structures were simulated for model verification purposes.

Using the nine central composite points plus the eight additional interior points for training the model yielded the best results. Eight neurons were used in the hidden layer. Training time was 90 min on a 486 computer (66 MHz). Figs. 12 and 13 show the S_{21} results for the training and verification sets, respectively. As with the previously developed models, excellent results were obtained.



(a)



(b)

Fig. 9. Comparison of EM-ANN model results with full-wave analysis of a stripline-to-stripline interconnect (training dataset). (a) $|S_{21}|$ response with ± 0.003 error bounds and (b) $\angle S_{21}$ response with ± 2 degree error bounds.

V. HYBRID (ΔS) EM-ANN MODELING

Many times an approximate model may already exist for a component. In cases where the existing model is not as accurate as desired, this approximate model can be used to create a hybrid EM-ANN model. That is, one can use something already known about the component to simplify the input–output relationships for training the EM-ANN model.

The hybrid EM-ANN model is formed by generating the difference in S-parameters between the existing approximate model and the EM simulation results (ΔS). The ΔS data is then used to train the EM-ANN model. Physical parameters are still used as the inputs of the EM-ANN model, but the output has been replaced by ΔS. This results in a smaller range of the output variables, ΔS compared to complete S-parameters, and a simpler input–output relationship. This simpler input–output relationship requires less EM simulation points to capture important data trends. This simplification is very desirable since EM simulations consume a major portion of the time spent on developing an EM-ANN model.

Example—Two-Port Broadband GaAs Microstrip Via: To demonstrate hybrid EM-ANN modeling, the two-port broadband GaAs microstrip via is used. Complete EM-ANN modeling results have been shown in Section IV. Here, a hybrid

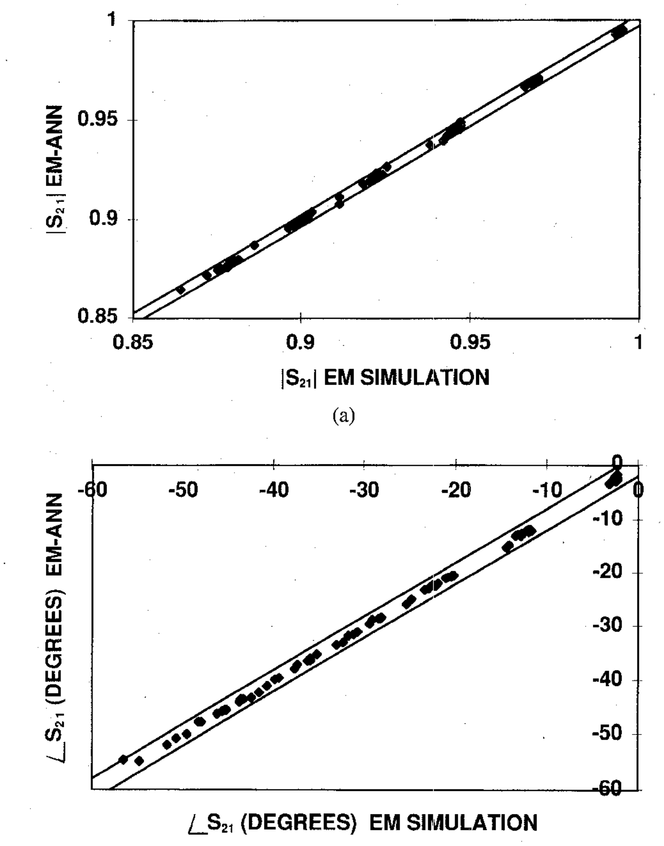


Fig. 10. Comparison of EM-ANN model results with full-wave analysis of a stripline-to-stripline interconnect (verification dataset). (a) $|S_{21}|$ response with ± 0.003 error bounds and (b) $\angle S_{21}$ response with ± 2 degree error bounds.

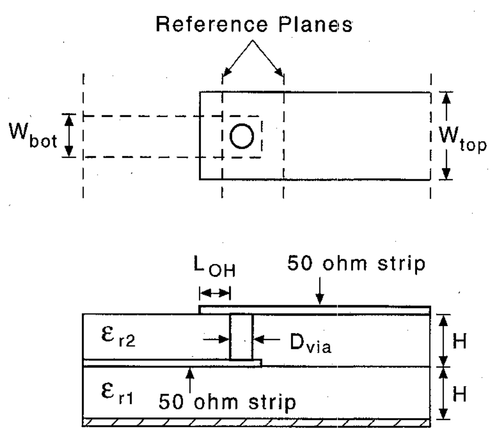


Fig. 11. Microstrip-to-Microstrip interconnect with $Z_o = 50$ ohms, $W_{\text{bot}} = 23$ mil, $W_{\text{top}} = 125$ mil, $\varepsilon_{r1} = 10.2$, $\varepsilon_{r2} = 2.2$, $\tan\delta = 0.0012$, $t_{\text{metal}} = 1.4$ mil, $\sigma_{\text{metal}} = 5.7 \times 10^7$, and $H = 25$ mil.

EM-ANN model is developed and compared to the complete EM-ANN modeling results.

An existing approximate model for the inductance of a microstrip via element is given in [3]. The existing model was found to give reasonable results at lower frequencies (<15 GHz), but as frequency increased, errors between the model and EM simulation increased also. Inaccuracies of the model, especially at higher frequencies, may be due to pad inductance, pad capacitance, discontinuity effects, and radiation from the via-hole [1], [35].

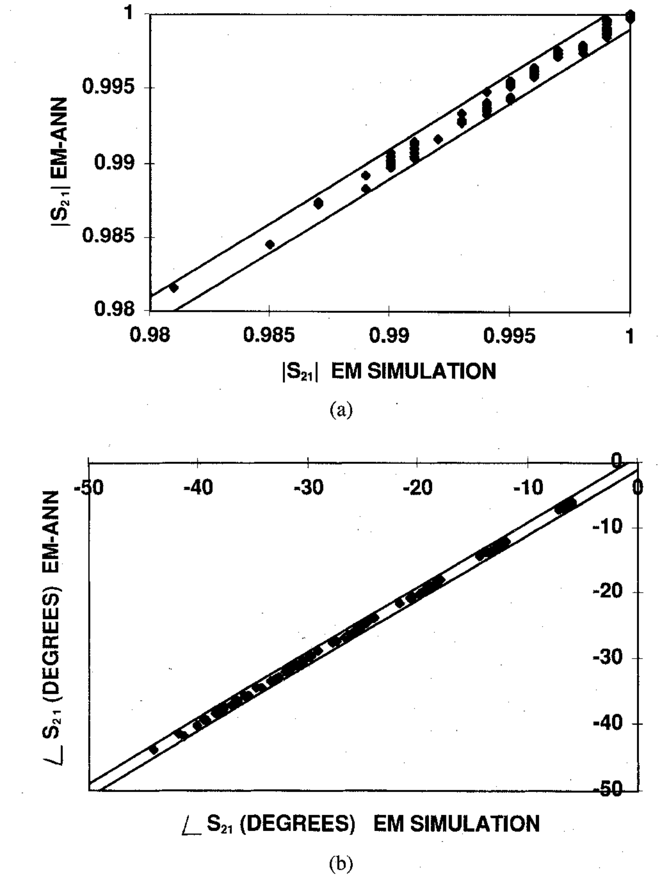


Fig. 12. Comparison of EM-ANN model results with full-wave analysis of a microstrip-to-microstrip interconnect (training dataset). (a) $|S_{21}|$ response with ± 0.001 error bounds and (b) $\angle S_{21}$ response with ± 1 degree error bounds.

TABLE III
VARIABLE PARAMETERS FOR MICROSTRIP-TO-MICROSTRIP INTERCONNECT MODEL

Input Parameter	Minimum Value	Maximum Value
Frequency	2 GHz	12 GHz
D_{via}/W_{bot}	0.2	0.9
L_{OH}	1 mil	15 mil

The ΔS parameters were evaluated for the structures given in Section IV and then used for training the hybrid EM-ANN model. Results for the hybrid and complete modeling using only 15 central composite training points are shown in Table IV. Ten neurons were used in the hidden layer for both models. The hybrid model required 20 min training time while the "complete" model began overfitting after just 2 min of training time on a 486 computer (66 MHz). Errors are significantly lower for the hybrid EM-ANN model.

To further show the advantages of the hybrid model over the complete model, models were developed using 15 central composite points and 14 additional interior points for training. Results are shown in Table V. Ten neurons were used in the hidden layer. Training times were 80 min and 90 min for the hybrid and complete EM-ANN models, respectively.

TABLE IV
COMPARISON OF HYBRID AND COMPLETE EM-ANN MODELS (15 TRAINING POINTS)

	Training Dataset				Verification Dataset			
	$\|S_{11}\|$	$\angle S_{11}$	$\|S_{21}\|$	$\angle S_{21}$	$\|S_{11}\|$	$\angle S_{11}$	$\|S_{21}\|$	$\angle S_{21}$
Hybrid Model:								
avg. absolute error	0.0033	0.80°	0.0045	0.74°	0.0060	0.74°	0.0049	0.86°
standard deviation	0.0031	0.63°	0.0041	0.62°	0.0066	0.53°	0.0039	0.87°
Complete Model:								
avg. absolute error	0.0124	1.25°	0.0246	1.63°	0.0182	1.34°	0.0284	2.34°
standard deviation	0.0114	1.15°	0.0209	1.55°	0.0213	1.11°	0.0282	2.06°

TABLE V
COMPARISON OF HYBRID AND COMPLETE EM-ANN MODELS (29 TRAINING POINTS)

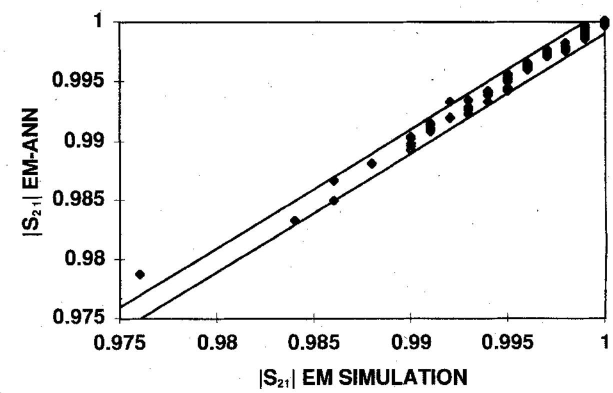
	Training Dataset				Verification Dataset			
	$\|S_{11}\|$	$\angle S_{11}$	$\|S_{21}\|$	$\angle S_{21}$	$\|S_{11}\|$	$\angle S_{11}$	$\|S_{21}\|$	$\angle S_{21}$
Hybrid Model:								
avg. absolute error	0.0016	0.41°	0.0026	0.46°	0.0024	0.58°	0.0031	0.64°
standard deviation	0.0015	0.36°	0.0029	0.41°	0.0028	0.57°	0.0033	0.78°
Complete Model:								
avg. absolute error	0.0036	0.41°	0.0068	0.44°	0.0042	0.43°	0.0088	0.77°
standard deviation	0.0033	0.40°	0.0049	0.47°	0.0038	0.35°	0.0092	0.77°

The hybrid model with 29 training points shows improvement in most error categories over the hybrid model with 15 training points. Significant improvement is seen in the complete EM-ANN model error results. Note that most hybrid EM-ANN errors are significantly lower than complete model errors.

A significant advantage of the hybrid modeling technique is apparent by comparing the error results of the hybrid model with 15 training points to the complete model with 29 training points. Errors in both cases are of the same order. The advantage is seen by noting that the number of EM simulations needed to train the hybrid model for the given accuracy is almost half that needed for the complete model. This results in a time saving of 5 h and 51 min (11 h 35 min: 5 h 44 min) on an HP 700 workstation for this example. Thus we can conclude that the hybrid (ΔS) modeling approach is much more efficient for developing EM-ANN models.

VI. INTEGRATION OF EM-ANN MODEL WITH A CIRCUIT SIMULATOR

After training, the EM-ANN models were integrated into a microwave network simulator (HP-MDS) [36]. Fig. 14 compares the new EM-ANN one-port via model (NET1) with HP-Momentum results and the current *MSVIA* element available in HP-MDS. Note that the *MSVIA* reference plane is at the center of the hole, while our reference plane is at the edge of the pad. Therefore, a more accurate model, also shown in Fig. 14, may be constructed by adding additional HP-MDS elements such as *MSSTEP, MSTL,* and *MSOC* to account for the pad length



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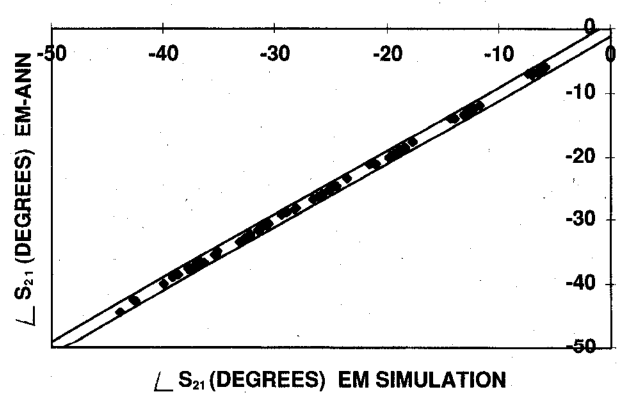
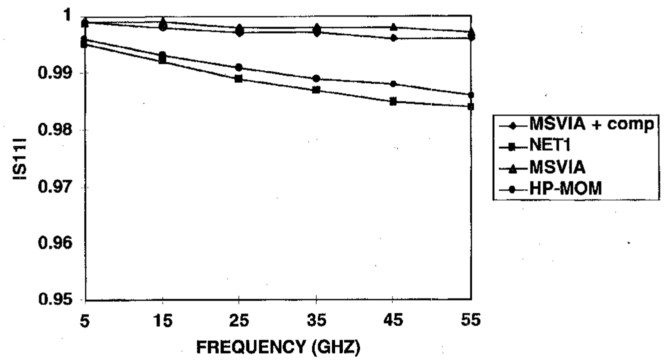
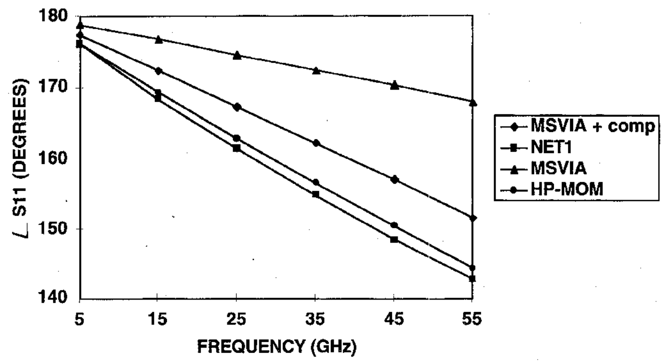


(b)

Fig. 13. Comparison of EM-ANN model results with full-wave analysis of a microstrip-to-microstrip interconnect (verification dataset). (a) $|S_{21}|$ response with ± 0.001 error bounds and (b) $\angle S_{21}$ response with ± 1 degree error bounds.



(a)



(b)

Fig. 14. Comparison of Net1 model, HP-Momentum, HP-MDS via element *MSVIA*, and *MSVIA* with added components. GaAs via with $\varepsilon_r = 12.9, H_{\text{sub}} = 4$ mil, $t_{\text{metal}} = 0.1$ mil, $\sigma_{\text{metal}} = 4.1 \times 10^7, \tan\delta = 0.002, W_l/W_p = 0.3875, D_{\text{via}}/W_p = 0.4$, and $W_l/H_{\text{sub}} = 0.3375$.

TABLE VI
COMPARISON OF SIMULATION TIMES FOR THE GaAs VIA DESCRIBED IN FIG. 14

Model	Simulation Time
HP-MDS, *MSVIA*	0.30 sec
HP-Momentum	12.48 min
Net1 (EM-ANN Model)	0.33 sec

and the step in width. However, even this constructed HP-MDS model cannot accurately characterize the via hole over the entire range of the input variables, whereas the EM-ANN via model can. Excellent results are achieved by the EM-ANN models when compared to HP-Momentum simulations. Simulation times for NET1, MSVIA, and HP-Momentum on an HP 700 workstation are shown in Table VI. Note that the new EM-ANN model does not require a significant increase in simulation time over the current HP-MDS model.

VII. Optimization of Component Structure

Once an EM-ANN model has been developed, it can be used to find the optimal physical structure of a component for a given application. This can be accomplished by using standard techniques such as random and gradient optimization [36]. To demonstrate the usefulness of optimization, an example is considered.

A. Stripline-to-Stripline Dataset Interconnect

For this EM-ANN model, two variable physical parameters are the diameters of the via and ground access opening. This structure has been considered in [12] and it was found that good performance was obtained as long as the diameter of the via was large and the ratio of the diameter of the ground access to that of the via was near 4.2 : 1. In fact, this ratio is the same as that of the inner and outer conductors of a 50-Ω coaxial line with $\varepsilon_r = 2.94$. However, only a limited number of structures were simulated. One would expect that the ratio for the stripline-to-stripline interconnect might be less than for a coaxial line, increasing the capacitance of the structure in order to compensate for only having a partial outer conductor.

Initial values for the physical parameters were set at 0.3 for D_{via}/W_1 and 6.0 for $D_{\text{gnd}}/D_{\text{via}}$. These are clearly not optimal values. Optimization was completed by maximizing the transmission coefficient yielding $D_{\text{via}}/W_1 = 0.77$ and $D_{\text{gnd}}/D_{\text{via}} = 3.4$. These results agree well with our expectations as mentioned earlier.

VIII. Conclusion

We have presented a novel approach for accurate and efficient modeling of MMIC components by using electromagnetically-trained ANN software modules. The approach has been verified by developing models for microstrip via and interconnects in dataset circuits and integrating these models in a commercially available microwave circuit simulator. Two methods, complete EM-ANN modeling and hybrid (ΔS) EM-ANN modeling, have been developed. The hybrid (ΔS) EM-ANN modeling that makes use of existing approximate models for components is shown to be a more efficient approach. It has been demonstrated that EM-ANN models can be used for optimizing the component structure efficiently. The proposed technique is capable of providing CAD models for components for which available models are not accurate over the desired range of operation.

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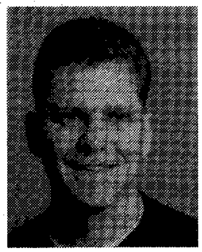

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