ARTIFICIAL NEURAL NETWORKS FOR ACCURATE MICROWAVE CAD APPLICATIONS

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ABSTRACT

A unique approach for applying neurocomputing technology for accurate CAD of microwave circuits is described. In our proposed method, a multilayer perceptron neural network (MLPNN) is trained to predict the scattering parameters of MMIC passive elements based on the element's physical dimensions. The s-parameters were obtained by performing a full-wave electromagnetic (EM) analysis of these elements. An X-band MLPNN spiral inductor model is developed. The MLPNN computed s-parameter values are in excellent agreement with those obtained from EM simulations with correlations greater than 0.99 for all modeled parameters.

INTRODUCTION

For MMIC design the effectiveness of modern CAD methods relies on accurate models of active and passive circuit elements. As circuit densities and operating frequencies increase, the accuracy of conventional modeling techniques become questionable. Typical circuit simulator supplied passive element models do not accurately account for the parasitic and coupling effects which occur at microwave/millimeter wave frequencies [1]. To remedy this situation, libraries of passive components have been developed by actually fabricating, testing, and storing the results of hundreds of elements [2]. This approach is problematic since the libraries are process dependent, costly to create, and limits the designer to a discrete set of components.

More recently, electromagnetic (EM) analysis tools have become commercially available which accurately model passive structures into the millimeter wave frequency range [3]. EM simulation effectively models passive element dispersion and mutual coupling effects ignored by traditional circuit simulation tools. However, EM simulation methods, such as those in [4], take tremendous computational efforts and are not practical for interactive CAD.

In this paper a methodology is described in which a MLPNN is implemented to model monolithic IC passive elements to nearly the same degree of accuracy as that afforded by EM simulation. An example is provided in which the s-parameters of microstrip square spiral inductors are modeled. Inputs to the neural network model are the physical dimensions of the inductor and the desired frequency. The outputs are the s-parameters for that inductor at the respective frequency points. Once trained, the computation time of the modeled parameters is negligible, which makes the MLPNN models suitable for interactive CAD applications. Furthermore, the MLPNNs ability to generalize may eliminate the need to always perform such time consuming EM simulations.

To demonstrate the application of this technique, a MLPNN is trained to model the s-parameters of 32 distinct square spiral inductors at X-band, 7-11 GHZ in 1 GHz steps. The s-parameters were obtained from full wave electromagnetic simulations. Also, the MLPNNs ability to generalize the s-parameters of inductors outside the training set is demonstrated.

EM SIMULATIONS

Electromagnetic simulation of square spiral inductors were performed using *em* from

Sonnet Software [5]. Scattering parameters for 32 inductors were obtained over a frequency range of 1 to 15 GHz at 1 GHz intervals. The physical dimensions of the inductors varied in width (10, 15, 20, 25 μm), length (200, 225, 275, 300 μm), spacing (10, 15, 20 μm), and number of turns (1.5, 2.5). The dielectric and metalization were consistent for all inductors.

Since the spiral inductor is a passive component the magnitude and phase of the forward transmission coefficient (S21) is equivalent to the magnitude and phase of the reverse transmission coefficient (S12). In this work, it was observed that the magnitude of the input reflection coefficient (S11) and the magnitude of the output reflection coefficient (S22) were also nearly equal. Therefore, only a set of five s-parameters (MAG S11, ANG S11, MAG S21, ANG S21, and ANG S22) were used for MLPNN modeling and the subsequent comparisons between the EM simulated and MLPNN computed s-parameters.

MLPNN MODELS

The neural network architecture used in this modeling effort is the multilayer perceptron neural network. The governing equations of the MLPNN and the algorithm used to implement it is given in [6]. The MLPNN is trained in the supervised mode using the generalized delta learning rule. It has one hidden layer and uses continuous perceptrons. The size of the hidden layer was determined experimentally by selecting the number of hidden nodes which resulted in the lowest training error while maintaining adequate generalization. Each model took less than 15 minutes to train on a 100 MHz computer.

A block diagram of the MLPNN model is shown in Figure 1. The input parameters for the model are the frequency and the inductor's physical dimensions. The resulting outputs represent the simulated s-parameter values. Training and test data vectors are created by forming an input-output parameter pair for each inductor.

RESULTS

Two examples are given below. In the first example, an MLPNN was trained and tested

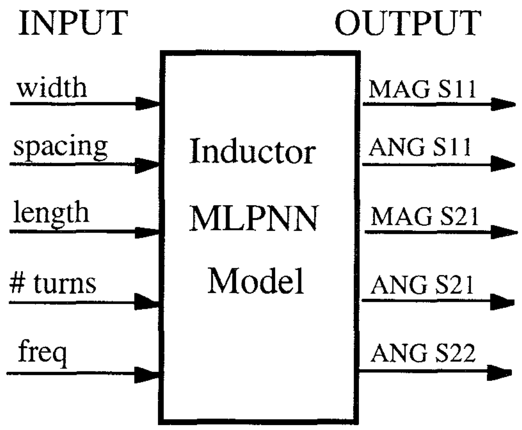


Figure 1. Block diagram of MLPNN model.

using all 32 data vectors. This example determines the network's ability to accurately learn the complex input-output mappings present in the data. The correlations between the EM simulated s-parameters and the MLPNN computed s-parameters were computed as given in [7] as

$$r = \frac{\sum (x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum (x_i-\bar{x})^2 \sum (y_i-\bar{y})^2}} \quad (1)$$

where x_i is the measured value, y_i is the MLPNN computed value, $\bar{x}$ is the measured sample mean, and $\bar{y}$ is the MLPNN computed sample mean. The correlation coefficient, r, for each output parameter is given in Table 1. The MLPNN modeled parameters are extremely accurate with correlations approaching one.

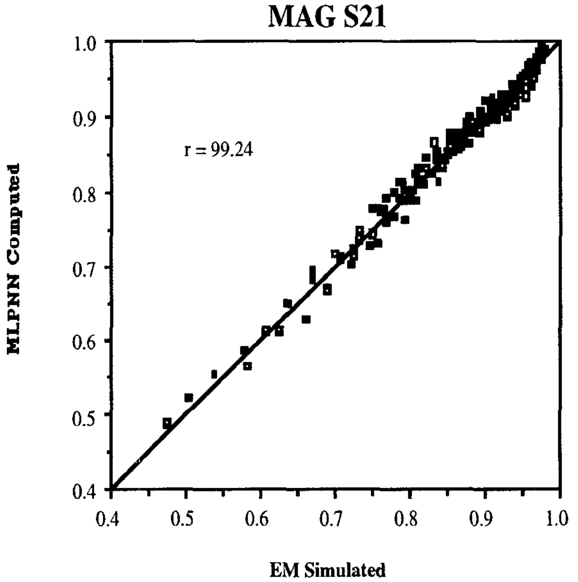
Figures 2a and b show scatter plots of EM simulated and MLPNN modeled values for the magnitude and angle of the forward transmission coefficient, MAG S21 and ANG S21, respectively. These results exhibit minimum error and provide an excellent indication of the MLPNN's ability to capture the input-output relationships present in the data.

In the second example, the same 32 data vectors from the first example were used to examine the MLPNN's ability to generalize. The data set was examined, and 25 vectors were selected for MLPNN training. The remaining 7 vectors were used to test network generalization. Table 2 lists the correlation coefficient between

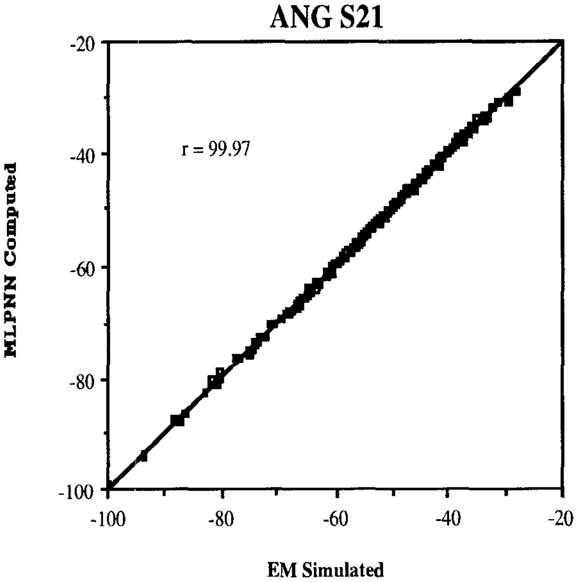
TABLE 1

Correlation coefficient between the EM simulated and MLPNN computed s-parameter values from example one.

OUT PUT	MAG S11	ANG S11	MAG S21	ANG S21	ANG S22
r	.9903	.9995	.9924	.9997	.9999



a)



b)

Figure 2. Scatter plot of EM simulated and MLPNN computed parameters from the first example a) MAG S21 b) ANG S21

the EM simulated s-parameters and the MLPNN modeled s-parameters for the test data set. As indicated by the values of the resulting correlation coefficients listed in Table 2, there is excellent agreement between the EM simulated and MLPNN computed values over the desired frequency. There exist a minimal decrease in r value between the training set of example 1 and test set of example 2.

Figures 3a and b show scatter plots of EM simulated and MLPNN modeled values for the magnitude and angle of the forward transmission coefficient, MAG S21 and ANG S21, respectively. These results exhibit minimum error and provide an excellent indication of the MLPNN's ability to provide accurate generalizations.

TABLE 2

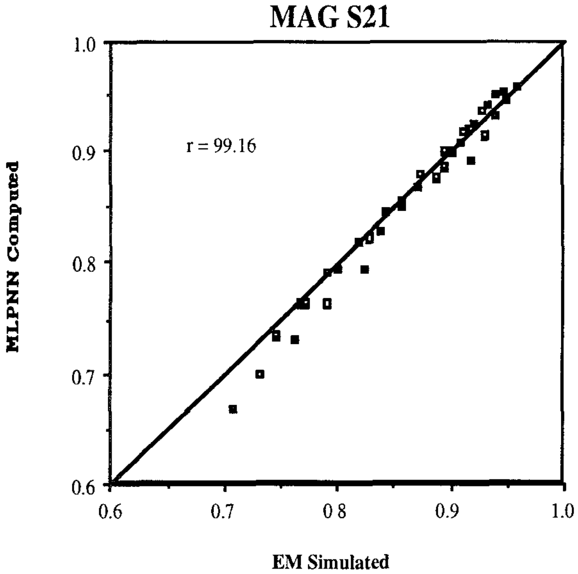
Correlation coefficients from the second example between the EM simulated and MLPNN computed s-parameter values for the test set.

OUT PUT	MAG S11	ANG S11	MAG S21	ANG S21	ANG S22
r	.9925	.9927	.9916	.993	.994

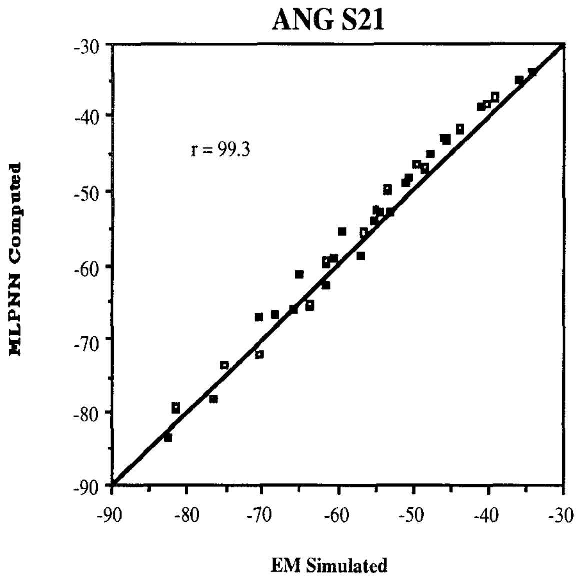
The purpose of the second example was simply to obtain some measure of the MLPNN's ability to generalize the data. The results indicate that the network is capable of providing accurate generalizations. The authors are currently conducting a detailed design of experiments to establish the extent to which the MLPNN can generalize the inductor data.

CONCLUSIONS

This paper presents an approach in which a neural network is employed to accurately model microwave monolithic IC passive element characteristics. The MLPNN demonstrates the ability to compute s-parameters nearly as accurate as those obtained from full wave electromagnetic simulations. Once trained, the computation time is negligible as compared to other techniques such as full wave EM. This computational speed makes the network suitable for interactive CAD



a)



b)

Figure 3. Scatter plot of EM simulated and MLPNN computed parameters from the example 2 test set a) MAG S21 b) ANG S21.

applications. This approach demonstrates that the performance of passive elements at microwave and/or millimeter wave frequencies can be accurately predicted without the need to develop costly model libraries.

The MLPNN also exhibits the capability to generalize and predict quite accurate model parameters for data outside the training set. However, a detailed design of experiments approach needs to be taken before this can be fully established. Although the two examples illustrated only inductor passive element modeling, the methodology may be applied to other passive elements.

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