Advanced Simulation of Microstrip Patch Antenna
Using Artificial Neural Networks

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Abstract

In this contribution we address a new task in the area of Artificial Neural Networks ANN, namely, the development of libraries of neural models for passive and active components. This is a task with a potential significance to many microwave simulators. A new technique addressing microwave neural model accuracy and efficient model development will be proposed. As a numerical example, the generalization capability, i.e. the model attitude at reproducing input data sets not used in the training process will be reported for the case of the scattering parameters of a microstrip patch antenna.

Introduction

Given their inherent ability to approximate any non-linear continuous function without requiring any prior knowledge, ANN, in the last few years, have increasingly obtaining the attention of the scientific community, leading to the implementation of several neural based control strategies. One such approach incorporates ANN into the predictive control scheme. This approach has the appealing advantage of handling one of the main limitations exhibited by standard model based on predictive control (MPC), that is, the requirement of a suitable mathematical model and/or of long computational time.

Recently, a new computer-aided design (CAD) approach based on neural networks has been introduced for modeling of passive and active microwave components [1] and microwave circuit design [2]. A neural network can be developed by learning and abstracting from microwave data, a process called training. Once trained, the neural network can then be used during microwave design to provide instant answers to the task it learned. The recent work by microwave researchers demonstrated the ability of neural networks to learn and to model a variety of microwave components, such as microstrip patch antennas [3], spiral inductors, FET devices, coplanar waveguide (CPW) circuit components, and packaging and interconnects [4]. Neural models can be much faster than original detailed EM (Electromagnetics)/physics models, more accurate than 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.

This contribution addresses a new task in this area, namely, the development of libraries of neural models for passive and active components, a task with a potential significance to many microwave simulators. A new technique addressing microwave neural model accuracy and efficient model development will be proposed.

Developing libraries of neural models is very costly due to massive data generation and repeated neural network training. A new kind of neural network approach is presented in this contribution, allowing both microwave functional knowledge and library inherent structural knowledge to be incorporated into neural models. The library models are developed through a set of base neural models, which capture the basic characteristics common to the entire library, and high-level neural modules which map the information from base models to the library model outputs. The proposed method substantially reduces the cost of library development through reduced need for data collection and shortened time of training.

As a numerical example, the generalization capability, i.e. the model attitude at reproducing input data sets not used in the training process will be reported for the case of the scattering parameters of a microstrip patch antenna loaded with different kinds of dielectric materials.
**Artificial Neural Networks**

One popular type of ANN architecture, that was used in our work, is a feed-forward, three-layer perceptron structure (MLP3) consisting of an input layer, a hidden layer, and an output layer, as shown in Figure 1.

In this research Radial Basis Function Neural Networks (RBF-NN) are adopted. RBF-NN possess several advantages over the most commonly used back propagation neural network (BP-NN). RBF-NN trains faster than BPNN. Moreover RBF-NN leads to better decision boundaries in a variety of applications. The main features of the RBF-NN are the utilization of Gaussian distribution transfer functions in the hidden layer, pure linear transfer functions in the output layer, dynamic capacity allocation algorithm for training in the hidden layer, and the least mean squares algorithm for training in the output layer.

The hidden layer allows complex models of input–output relationships. ANNs learn relationships among sets of input–output data that are characteristic of the device or system under consideration. After the input vectors are presented to the input neurons and output vectors are computed, the ANN outputs are compared to the desired outputs and errors are calculated. Error derivatives are then calculated and summed for each weight, until all of the training sets have been presented to the network. The error derivatives are used to update the weights for the neurons, and training continues until the errors become no greater than prescribed values.

![Figure 1. Artificial neural network architecture.](image)

The objective is to develop libraries of passive and active microwave component models. Suppose a library consists microwave component models. For each model, say, the n-th model in the library, the input and output parameters are represented by vectors $X_n$ and $Y_n$, respectively. The library development is to create models to represent the multidimensional nonlinear relationship of

$$Y_n = Y_n(X_n)$$

for each value of $n$.

We call the spaces spanned by $X_n$ and $Y_n$ as the input space and the output space, respectively. For example, to model a microstrip patch antenna, $Y_n$ could represent the input impedance $Z_{in}$ and the radiation pattern. $X_n$ could represent the physical/geometrical parameters of the patch antenna such as conductor width, separation between coupled conductors, substrate height, and dielectric constants. In the proposed approach, we first develop a set base models to capture the basic electrical or microwave characteristics common to the entire set of models in the library. For example, in a library of various microstrip patch antennas, the Green's function for planar stratified media is one of the common characteristics needed for all the models in the library.

Each base model is trained by sufficient number of samples to a high accuracy. This task is done only once in the beginning of library development. The benefit of creating these base models is realized when we subsequently reuse them and combine them in developing many component models for the library. For each model in the library a multilayer neural network structure is defined. The purpose of
this structure is to construct an overall model from several modules so that the library base relationship can be maximally reused for every model throughout the library. This structure consists of a high-level neural module denoted as $H_n$ and several low-level neural modules denoted as $L^i_n$ with $i = 1, K, N_L^n$ being $N_L$ the total number of low level neural modules in the n-th library. The low-level modules are realized by directly using the base models. The high-level module is realized by a neural network

$$Y_n = H_n(X_n, V_n)$$

where $V_n$ includes all neural network weights for the module $H_n$.

**Applications**

In this section the scattering parameters of the scattering parameters of a microstrip patch antenna is studied. The working frequency is 7 GHz. Figure 2 shows the geometry of the microstrip patch antenna. The patch is square in shape and fed with a microstrip line. The feed point is inset to enhance the degree of matching at resonance. The patch is meshed using 12×12 square segments, each with dimensions 1.2 mm × 1.2 mm. The width of the microstrip line is modeled using 2 such square segments. The length of the feeding microstrip line is selected such that it is long enough to perform the deembedding correctly and to be an integer multiple from the segment dimension (1.2 mm). These mesh specifications for both the patch and the microstrip line have been used in all the numerical evaluations made.

![Figure 2. Geometry of a microstrip patch antenna with an inset (all dimensions are in mm).](image)

The magnitude of the reflection coefficient $S_{11}$ of the patch as obtained using our software written with MATLAB 6.5 is plotted versus frequency in Figure 3. The figure shows also a reasonable match between the patch and the microstrip line around 7 GHz. Figure 4 shows the error in percent between the measured data (obtained with a commercial numerical code) and the ANN models for $S_{11}$. Very good agreement between the two solvers is observed. From this plot, we see that the ANN model agrees with measurement data to within 1.5% using as few as five training points. We have also seen that the ANN model agrees with measurement data to within 1% for most frequencies using as few as nine training points. These results show that it is possible to cut down on design times by measuring only a few frequency points and developing an ANN model rather than measuring numerous points and dealing with large data files. The ANN model, trained on only a few measurement points, can be much more accurate than linearly interpolating, as is commonly done in practice. For example, if one were to measure the $S_{11}$ parameter at five points and perform linear interpolation between frequencies then the maximum error would be 4.5%, as opposed to only 1.5% for the ANN model, trained using the same five points.

**Conclusions**

We have successfully applied ANNs for the development of libraries of neural models for passive and active components and have shown that the numerical examples about the reflection coefficient of microstrip patch antenna that make use of an ANN-based numerical code compare favorably to the
ones obtained with a commercial solver. We finally quantified the training errors as a function of the number of training points.

![Figure 3](image1)

**Figure 3.** Reflection coefficient vs. frequency.

![Figure 4](image2)

**Figure 4.** Magnitude of the ANN-modeled reflection coefficient error vs. frequency.

**REFERENCES**


