ANN for Fast and Accurate Determination of Resonant Frequency and Quality Factor for CSSRR

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Abstract:

Artificial Neural Network (ANN) has been employed for determination of resonant frequency and quality factor for complementary split ring resonator (CSSRR). It has been observed that as the number of training samples increases, the testing error decreases. The error in testing also decreases with the increase in the number of neurons in the hidden layer of the three layer multi-layer perceptron (MLP) network. The computational efficiency for this approach is very high in comparison to electromagnetic (EM) techniques, which takes more time. Usually it takes less than a second for training and testing the 60 samples using ANN whereas the EM simulator takes few hours to generate a single data, which is a huge gain in terms of computational efficiency. The accuracy of this approach is also very close to the EM simulation technique within 1%-2% errors.

Key Words: Artificial Neural Network (ANN), Computer-aided design (CAD), complementary single split ring resonator (CSSRR)

I INTRODUCTION:

The rapid development of commercial markets for wireless communication products over the past decade had led to an explosion of interest in improved circuit design approaches in the radio frequency (RF) and microwave areas. Electromagnetic (EM) simulation techniques for high frequency structures developed over the past decade have helped to bring the computer-aided design (CAD) for hybrid RF or microwave circuits to its current state of the art. But modeling still remains a major bottleneck for CAD of certain classes of RF/microwave circuits like coplanar waveguide (CPW) circuits, multi-layered circuits, integrated circuits (ICs), etc. Another factor in RF and microwave design is the increasing need for optimization–based design automation. There will be a trade-off between computation speed and accuracy in this approach. The recent development to overcome these issues is the use of artificial neural network (ANN) to the RF and microwave CAD problems. ANN, are information processing systems with their design inspired by the studies of the ability of the human brain to learn from observations and to generalize by abstraction [1]. Training ANN configurations using the data obtained from the EM simulations develops an ANN model for each of these components. Such ANN models have been shown to retain the accuracy obtainable from EM simulators and at the same time exhibit the efficiency in computation. ANN is also suited for modeling active devices and for circuit optimization and statistical design.

Neural-network modeling is an unconventional and modern approach for RF and microwave device design [2]. Neural networks can be trained to learn the behavior of passive/active components/circuits [3]. A trained neural network can be used for high-level design, providing fast and accurate answers to the task it has learned [4]. Neural networks are attractive alternatives to conventional methods such as numerical modeling methods, which could be computationally expensive, or analytical methods that could be difficult to obtain for new devices, or empirical modeling solutions whose range and accuracy may be limited. No prior knowledge about the input/output mapping is required for ANN model development. Unknown relationships are inferred from the data provided for training. ANN can generalize, i.e., they can respond correctly to the new data that has not been used for the model development. ANN has the ability to model highly nonlinear as well as linear input/output mappings. ANN provides a general methodology for the development of accurate and computationally efficient electromagnetic trained ANN models for use in CAD of RF/microwave circuits, antennas and systems. In this paper, neural network based software known as Neuromodeler [5], developed Prof. Q. J. Zhang's group at the Carleton Unievrsity, Canada is trained to model the resonant frequency and quality factor of a complementary square split ring resonator, which is a passive device. The length, width and gap width are taken as input parameters for the ANN model. A three layer Multi-layer Perceptron (MLP) is used for modeling of this device.

II. ANN MODELS FOR RF/MICROWAVE DESIGN

Neural network structures:

A typical neural-network structure has at least two physical components, namely, the processing elements and the interconnections between them [1]. The processing elements are called neurons and the connections between the neurons are known as links or synapses. Every link has a corresponding weight parameter associated with it. Each neuron receives stimulus from other neurons connected to it, processes the information, and produces an output. Neurons that receive stimuli from outside the network are called input neurons, while neurons whose outputs are used externally are called output neurons. Neurons that receive stimuli from other neurons and whose outputs are stimuli for other neurons in the network are known as hidden neurons. Different neural-network structures can be constructed by using different types of neurons and by connecting them differently.

Generic notation:
Let n and m represent the number of input and output neurons of a neural network. Let $\boldsymbol{x}$ be an n-vector containing the external inputs to the neural network, $\boldsymbol{y}$ be an m-vector containing the outputs from the output neurons, and $\boldsymbol{w}$ be a vector containing all the weight parameters representing various interconnections in the neural network. The definition of $\boldsymbol{w}$, and the manner in which $\boldsymbol{y}$ is computed from $\boldsymbol{x}$ and $\boldsymbol{w}$, determine the structure of the neural network.

Neural network modeling approach:
The neural network can represent the behavior of any microwave device only after learning the original $\boldsymbol{x} - \boldsymbol{y}$ relationship through a process called *training.* Samples of ($\boldsymbol{x}$- $\boldsymbol{y}$) data, called the training data, should first be generated from original device EM simulators or from the device measurements. Training is done to determine neural network weights $\boldsymbol{w}$ such that the neural model output best matches the training data. A trained neural network model can then be used during microwave design providing answers to the task it learned. The original EM based microwave device modeling problem cab be expressed as $\boldsymbol{y}=\boldsymbol{f}(\boldsymbol{x})$ where $\boldsymbol{f}$ is the detailed EM based input–output relationship [2]. The neural network model for same device is defined as $\boldsymbol{y}= \boldsymbol{f}\ (\boldsymbol{x},\ \boldsymbol{w})$. The neural-network approach can be compared with conventional approaches for a better understanding. The first type is the detailed modeling approach such as EM-based models for passive components and physics-based models for active components. The overall model, ideally, is defined by a well-established theory and no experimental data is needed for model determination. However, such detailed models are usually computationally expensive. The second type is an approximate modeling approach, which uses either empirical or equivalent-circuit-based models for passive and active components. The evaluation of approximate models is much faster than that of the detailed models. However, the models are limited in terms of accuracy and input parameter range over which they can be accurate. The neural-network approach is a new type of modeling approach where the model can be developed by learning from accurate data of the RF/microwave component. After training, the neural network becomes a fast and accurate model representing the original component behaviors.

MLP Neural Network:
In the MLP neural network, the neurons are grouped into layers [1]. The first and the last layers are called input and output layers, respectively, and the remaining layers are called hidden layers. For example, an MLP neural network with an input layer, one hidden layer, and an output layer, is referred to as three-layer MLP (or MLP3). In the MLP network, each neuron processes the stimuli (inputs) received from other neurons. The process is done through a function called the activation function in the neuron, and the processed information becomes the output of the neuron. The universal approximation theorem states that there always exists a three-layer MLP neural network that can approximate any arbitrary nonlinear continuous multidimensional function to any desired accuracy. This forms a theoretical basis for employing neural networks to approximate RF/microwave behaviors, which can be functions of physical/geometrical/bias parameters. MLP neural networks are distributed models, i.e., no single neuron can produce the overall $\boldsymbol{x} - \boldsymbol{y}$ relationship. For a given $\boldsymbol{x}$, some neurons are switched on, some are off, and others are in transition. It is this combination of neuron switching states that enables the MLP to represent a given nonlinear input–output mapping. During training process, the MLPs weight parameters are adjusted and, at the end of training, they encode the component information from the corresponding $\boldsymbol{x} - \boldsymbol{y}$ training data.

Network size and layers:
For the neural network to be an accurate model of the problem to be learned, a suitable number of hidden neurons are needed. The number of hidden neurons depends upon the degree of non-linearity of $\boldsymbol{f}$ and the dimensionality of $\boldsymbol{x}$ and $\boldsymbol{y}$ (i.e., values of $\boldsymbol{n}$ and $\boldsymbol{m}$). Highly nonlinear components need more neurons and smoother items need fewer neurons [3]-[4]. However, the universal approximation theorem does not specify as to what should be the size of the MLP network. The precise number of hidden neurons required for a given modeling task remains an open question. So, either by experience or a trial-and-error process is used to judge the number of hidden neurons. The appropriate number of neurons can also be determined through adaptive processes, which add/delete neurons during training. The number of layers in the MLP can reflect the degree of hierarchical information in the original modeling problem. In general, the MLPs with one or two hidden layers (i.e., three- or four-layer MLPs) are commonly used for RF/microwave applications.

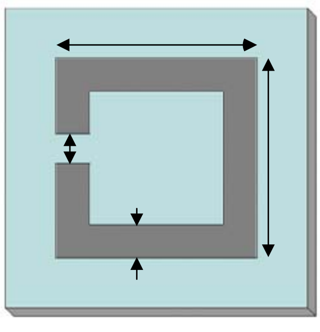

Fig.1

Figure 1 Structure of single Split Ring Resonator showing its dimensions

III. RESULTS

In this investigation on Complementary Single Split Ring Resonator (CSSRR), the input parameters for the ANN model are the physical dimensions L, W, G, where L-length, W-width and G-gap dimensions of the resonator depicted in Figure 1. The outputs of the ANN model are resonant frequency f_r and quality factor Q. Data generation is performed using a Finite Element Method (FEM) based EM simulator for 60 physical configurations using eigenmode analysis. Note that the complementary square split ring resonators are etched in the ground plane of FR4 substrate of relative permittivity 4.4 and thickness 1.6mm. And a microstrip line of suitable width is printed on the top surface of the substrate. All the structure are enclosed in a box of $\lambda/4$ size to do the simulation in eignemode analysis and the first or dominant mode resonance frequency and Q factor are recorded as sample data for the ANN. Various input parameters are varied and the corresponding output parameters are recorded. Usually it takes few hours to run a single simulation to generate a sample data using the EM simulator. The generated data is then divided into training and test data. A three-layer MLP neural-network structure with 7 hidden neurons is trained using quasi- Newton method. The accuracy of the developed neural models is shown in terms of training error and average test error.

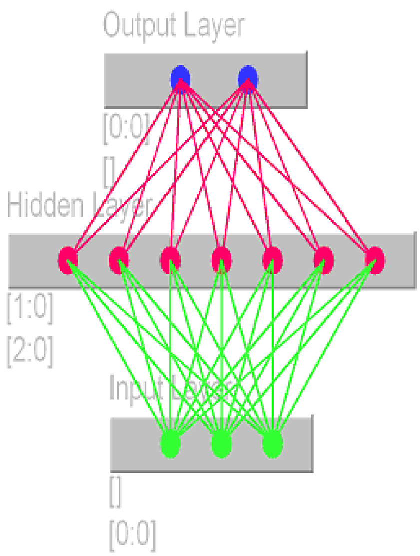

Fig. 2 (a)

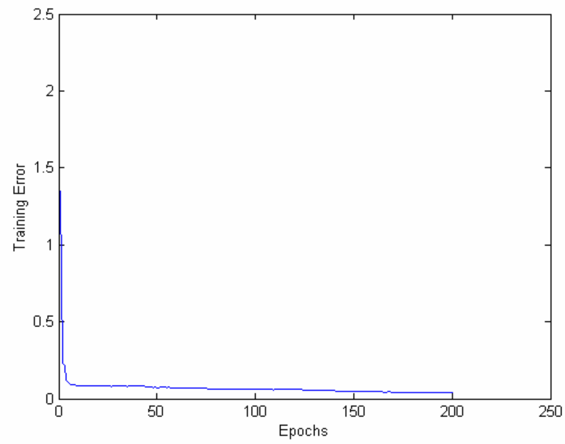

Fig. 2 (b)

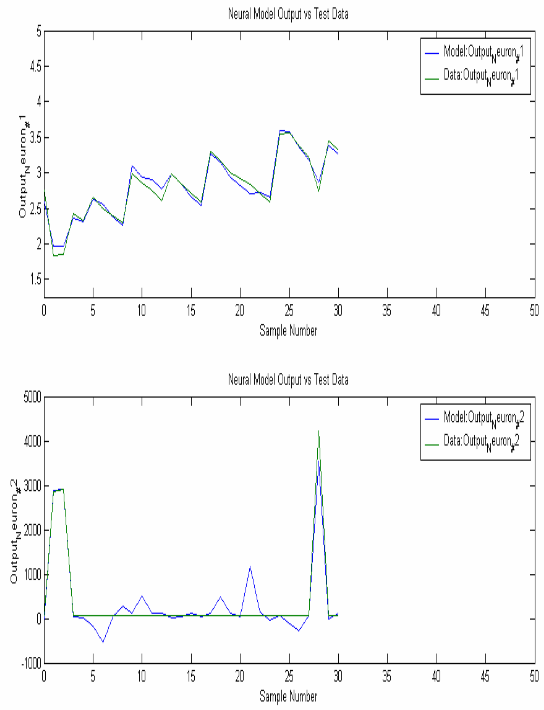

Fig. 2 (c)

Figure 2 (a) A three-layer perceptron neural network with 3 input neurons, 7 hidden neurons and 2 output neurons b) Graph of training error versus epochs (c) Graph of testing error versus sample number

Training:
No. of epochs: 200
No. of samples: 60.
Training method: Quasi-Newton method (MLP)
Training error: 0.01821967.

Testing:
No. of epochs: 200
No. of samples: 45
Average test error: 0.0264347.

CONCLUSION

ANN has been employed for fast and accurate determination of the resonant frequency and quality factor of CSSRRs. It has been observed that as the number of training samples increases, the testing error decreases, the error also decreases with the increase in the number of neurons in the hidden layer. The computational efficiency for this approach is very high when compared to EM technique, which takes more amount of time. Usually it takes less than a second for training and testing the 60 samples using ANN. In comparison to the EM simulator, which takes few hours to generate a single data, ANN based approach takes less a second to generate 60 data, which is a huge gain in terms of computational efficiency. The accuracy of this approach is also very close to the EM simulation technique within 1%-2% errors, which is quite accurate.

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REFERENCES

[1] S. Haykin, "*Neural Networks: A comprehensive Foundation*," Prentice Hall of India, July 1998

[2] Q. J. Zhang and K. C. Gupta, "*Neural Networks for RF and Microwave Design*," Artech House, July 2000

[3] Q. J. Zhang, K. C. Gupta, and V. K Devabhaktuni, "Artificial Neural Networks for RF and Microwave Design," *IEEE Trans. Microw. Theory Tech.*, pp. 1339-1350, Apr. 2003

[4] X. Ding, V. K. Devabhaktuni, B. Chattaraj, M. C. E. Yagoub, M. Deo, J. Xu, and Q.-J. Zhang, "Neural-Network Approaches to Electromagnetic-Based Modeling of Passive Components and their Applications to High-Frequency and High-Speed Nonlinear Circuit Optimization," *IEEE Trans. Microw. Theory Tech.*, pp. 436-449, Jan. 2004

[5] *Neuromodeler 1.5*, Carleton University, Canada

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