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NEURAL FREQUENCY SWEEPER FOR ACCELERATING S-PARAMETERS CALCULATION OF PLANAR MICROWAVE STRUCTURES

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Abstract—This paper presents a new frequency-sweep approach for the efficient calculation of S-parameters of planar microwave structures. The approach is based on approximating the frequency dependence of the real and imaginary parts of the S-parameters using neural networks. Due to its superior performance, radial basis functions neural network (RBF-NN) is adopted. A limited number of frequency samples are used to train the RBF-NN. Then, the trained RBF-NN is capable of providing a smooth frequency response with very high accuracy in a fraction of a second. The proposed method is applied to a number of planar microwave structures such as: Patch antenna with an inset feed, band-rejection filter, and branch-line coupler. According to the presented results, a speed factor of at least 10 is measured, and a maximum percentage error of 3.29% is recorded.

1. INTRODUCTION

The neural network (NN) is similar to the human brain in three aspects: it consists of a large number of processing elements (the neurons or nodes), each node connects to a large number of other neurons, and the functionality of the network is determined by modifying the strengths of the connections during a learning phase [1]. Ability and adaptability to learn, generalisability, fast real-time operation, and ease of implementation have made NNs popular for a number of microwave design problems in recent years [2]. Citing just a number of examples: NNs have been used in the design of passive microwave circuits [3], analysis and synthesis of microstrip lines [4], calculation of the characteristic impedance of air-suspended trapezoidal and rectangular-shaped microshield lines [5], design of nonlinear microwave circuits based on active devices [6], design of microstrip patch antennas [7, 8], direction of arrival estimation with antenna arrays [9, 10], radar target recognition [11], aperture antenna shape prediction [12], inverse scattering of dielectric cylinders [13], near field to far filed transformation [14], and synthesis of antenna array [15, 16]. In addition to modeling the response, NNs can also be employed within the core of the full-wave solvers based on the method of moments [17, 18].

In this work neural networks are employed to accelerate the frequency sweep required by full-wave simulators for calculating the S-parameters of microwave devices. There are several techniques that can be used for this purpose. These techniques can be classified into three main categories. In the first category, the frequency response, such as an S-parameter, is approximated using Padé approximant. Several techniques can be used to achieve this task such as MBPE, AWE, CFH, and PVL [19]. The basic principle of these techniques is to extract the dominant poles and residues of the frequency response and represent it by a reduced-order model.

The second main category is the impedance matrix interpolation technique. This technique is based on the fact that most responses of interest, such as the current distribution and the S-parameters, exhibit rapid frequency variations. However, the impedance matrix elements are smoother in their variation with frequency. Consequently, it is better to frequency interpolate them rather than trying to interpolate the responses. The concept of the impedance matrix interpolation was proposed in [20]. The approach is further extended in [21]. These works are concerned with the analysis of structures in free space. A similar technique is presented in [22], which is suitable for planar structures in layered media.

The third category is based on the curve fitting of Green's functions at different frequency points [23]. This technique starts by calculating a number of basis integrals for each inner-product integral in the MoM impedance matrix. At each frequency point, a new set of weighting coefficients are calculated. This set together with the basis integrals are used to evaluate the corresponding inner-product at any frequency point.

The technique presented in this paper belongs to the first category. A neural network is trained to approximate the S-parameters at any frequency point. A limited number of frequency samples are used to train such neural network. Once trained, this neural network is capable of performing the frequency sweep in a fraction of a second. Section 2 presents the proposed frequency sweeper based on radial basis functions neural networks. This frequency sweeper has been used for rapidly calculating the S-parameters of a number of microwave structures in Section 3. The important conclusions are stated in Section 4.

2. NEURAL FREQUENCY SWEEPER

The remarkable ability of radial basis function neural networks (RBF-NN) to carry out general nonlinear function approximation tasks through learning from examples is exploited in this research. RBF-NN posses several advantages over the most commonly used back propagation neural network (BP-NN). RBF-NN trains faster than BP-NN. Moreover RBF-NN leads to better decision boundaries in a variety of applications.

Radial basis function neural network is composed of three layers called input, hidden, and output layers as shown in Fig. 1. The input layer is made up of L nodes, where L is the dimension of the input vector. The task of the input layer is to pass the inputs of the network to the hidden layer. The hidden layer in turn performs a nonlinear mapping from the input space to a new space. It is made up of M nodes, each with a radial activation function. The most common choice for this function is the Gaussian function which has a peak at the center and decreases monotonically as the distance from the center increases. The region of the input space over which the node has an appreciable response, is known as the "*spread*". It is important that the spread should be large enough to enable the hidden nodes to respond to overlapping regions of the input space, but not so large that all the hidden nodes respond in the same manner. The output layer is made up of N linear nodes which are fully connected to the hidden nodes. Therefore the output nodes form a linear combination of the outputs of the hidden nodes.

In this research, the Neural Networks Toolbox of MATLAB [24], is used. The main features of the RBF-NN of this toolbox 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 [25], and the least mean squares algorithm for training in the output layer.

Figure 2 shows the topology of the proposed frequency-sweeper which is based on radial basis functions neural network. The proposed RBF-NN takes the frequency as an input and predicts the real and imaginary parts of all S-parameters of interest. A number of frequency samples are selected within the frequency band of interest. S-parameters of the microwave structure under investigation are calculated *a prior* at the selected frequency samples. The combination of frequency points (inputs) and the corresponding S-parameters (outputs) are known as patterns. These patterns are divided into two interlaced parts. The first part is used to train the frequency-sweeper, while the second part is used to test it.

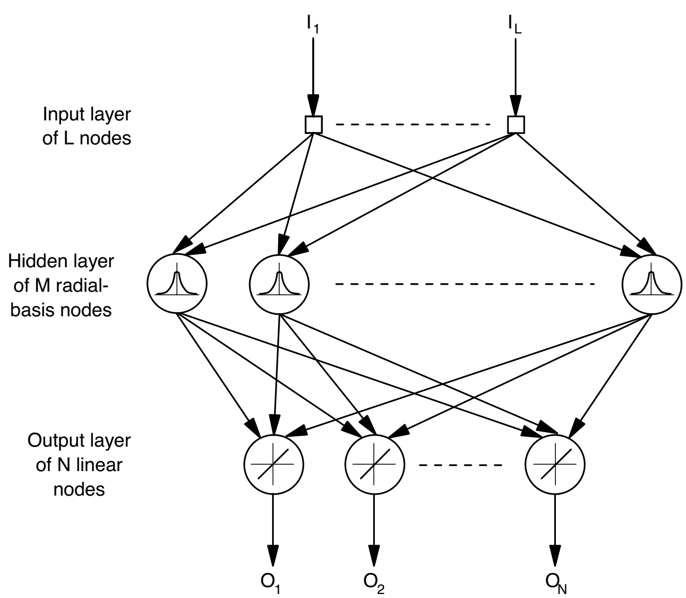

Figure 1. Radial basis functions neural network (RBF-NN).

Although the magnitude of an S-parameter on the dB scale, is usually of more interest than its real and imaginary parts, the latter show smoother behavior. The former always possesses sharp variations around resonance frequency [17, 23]. For this reason, it is much more efficient to model the real and imaginary parts rather than the magnitude on the dB scale. Then, the dB value can be very easy calculated in terms of the real and imaginary parts: $S(\mathrm{dB}) = 20\log_{10}\left(\sqrt{\mathrm{Re}^2(S) + \mathrm{Im}^2(S)}\right)$.

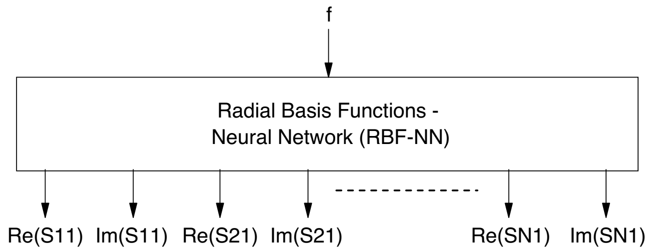

Figure 2. Topology of the proposed frequency sweeper based on RBF-NN.

3. APPLICATIONS

In this section, the proposed frequency sweeper is applied to three planar microwave structures: Patch antenna with an inset feed, band-rejection filter, and branch-line coupler. All these structures are assumed made of perfect conductor on top of a Duroid substrate with dielectric constant of 2.2 and thickness of 0.794 mm, backed with a perfect conductor ground plane. The preparation of the training and testing patterns is carried out using ADS/Momentum [26]. Momentum is a 2.5D full-wave solver based on the integral equation formulation solved using the method of moments. For meshing the microwave structures under investigation, mixed rectangular and triangular segments are used. Twenty cells per wavelength combined with a narrow edge mesh are adopted.

3.1. Patch Antenna with an Inset

Figure 3 shows a patch antenna fed with microstrip line with an inset. This structure has only one port and characterized by a single S-parameter, S_{11}. The real and imaginary parts of this parameter are plotted versus frequency in Fig. 4. This figure shows two sets of results for $\mathrm{Re}\,(S_{11})$ and $\mathrm{Im}\,(S_{11})$. The first set represents the exact results as obtained using ADS/Momentum. The second set represents the RBF-NN prediction of the test patterns. Very good agreement between the two sets can be observed. For training this RBF-NN, 13 equally spaced frequency points are used, which need 46.57 seconds to be prepared using the full-wave simulator. The time required for training this RBF-NN is 46.7 msec. It has 10 neurons in its hidden layer. Another 26 equally spaced points are used to test the RBF-NN, these points are marked in Fig. 4. The maximum percentage errors in the prediction of $\mathrm{Re}\,(S_{11})$ and $\mathrm{Im}\,(S_{11})$ are -2.94% and 2.09%, respectively.

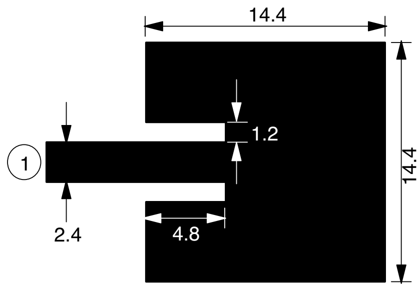

Figure 3. Patch antenna with an inset feed (all dimensions are in mm).

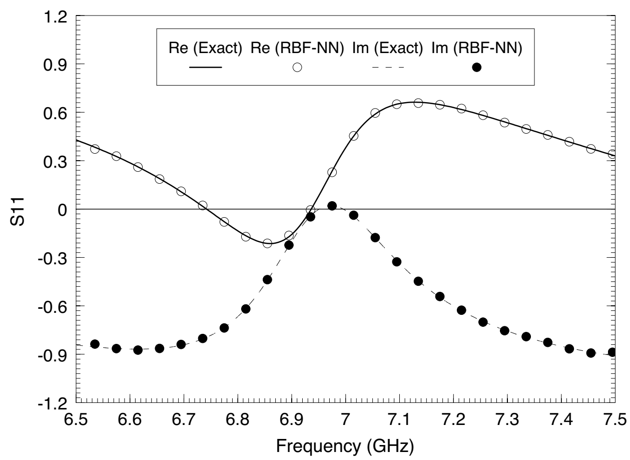

Figure 4. $\mathrm{Re}(S_{11})$ and $\mathrm{Im}(S_{11})$ of the patch antenna versus frequency as obtained using the exact simulator and the RBF-NN model.

The time required by the trained RBF-NN to calculate 201 points is 41.9 msec. Hence the total time required to obtain these 201 points using RBF-NN is: Time required to prepare 13 training points (46.57 sec) + time required for training (46.7 msec) + time required for sweeping (41.9 msec) = 46.66 sec. To calculate the same 201 points using ADS/Momentum, 12 minutes are required. This means that the proposed frequency sweeper is about 15.43 times faster.

3.2. Band-rejection Filter

The proposed neural network frequency sweeper is applied on another example, which is a band-rejection filter, as shown in Fig. 5. Due to

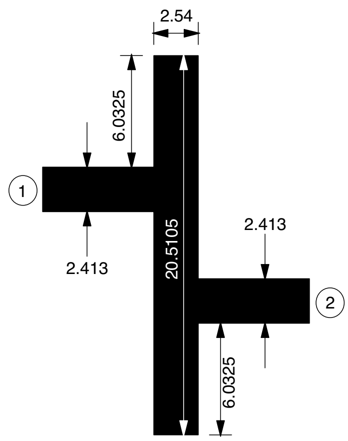

Figure 5. Band-rejection filter (all dimensions are in mm).

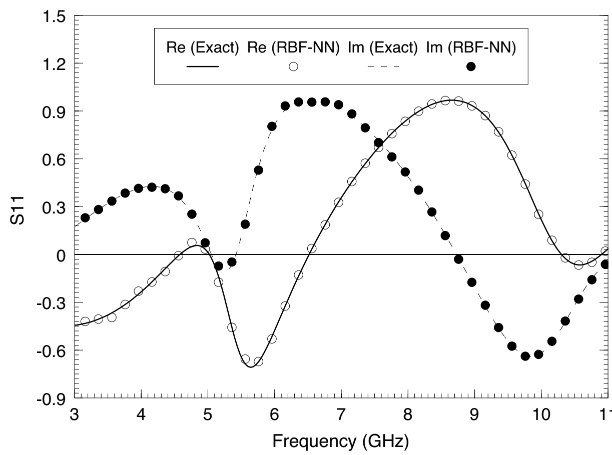

Figure 6. $\text{Re}(S_{11})$ and $\text{Im}(S_{11})$ of the band-rejection filter versus frequency as obtained using the exact simulator and the RBF-NN model.

symmetry of the two ports of this filter, $S_{11} = S_{22}$. From reciprocity, $S_{21} = S_{12}$. Hence, this filter is characterized by only two independent S-parameters: S_{11} and S_{21}. The real and imaginary parts of these parameters are the outputs of the RBF-NN of this filter. Figs. 6 and 7 show S_{11} and S_{21}, respectively, as obtained using RBF-NN and the exact simulator. It is clear that both results agree very well. Quantitatively, the maximum percentage errors in the prediction of

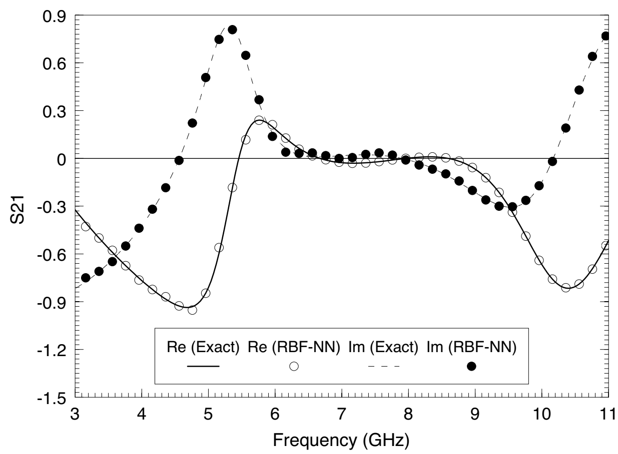

Figure 7. Re(S_{21}) and Im(S_{21}) of the band-rejection filter versus frequency as obtained using the exact simulator and the RBF-NN model.

Re (S_{11}), Im (S_{11}), Re (S_{21}), and Im (S_{21}) are 2.78%, 2.51%, −2.35%, and −2.23%, respectively. For training the RBF-NN of this filter, 20 frequency samples are used. It has 16 neurons in the hidden layer.

The proposed RBF-NN model requires a total time of 124.53 sec to produce 201 frequency points. This time can be distributed as follows: Time required to prepare 20 training points using ADS/Momentum (124.48 sec) + time required for training (49.1 msec) + time required for sweeping (4.91 msec) = 124.53 sec. To calculate the same 201 points using the full-wave simulator, 20.85 minutes are required. Hence the proposed frequency sweeper offers a speed factor of about 10.

3.3. Branch-line Coupler

The last example is a branch-line coupler, as shown in Fig. 8. This coupler has 4 ports and characterized by 16 S-parameters. Due to symmetry and reciprocity, only four S-parameters are independent, namely S_{11}, S_{21}, S_{31}, and S_{41}. The RBF-NN frequency sweeper of Fig. 2 is applied to this coupler. For training the associated RBF-NN, 15 frequency samples are used. The trained RBF-NN has 11 neurons in its hidden layers. For testing this RBF-NN, another 30 points, uniformly distributed along the frequency band of interest, are used. Figs. 9, 10, 11, and 12 show the exact and the RBF-NN results of S_{11}, S_{21}, S_{31}, and S_{41}, respectively. Again, both methods lead to very close results. The maximum percentage errors in the prediction of Re (S_{11}),

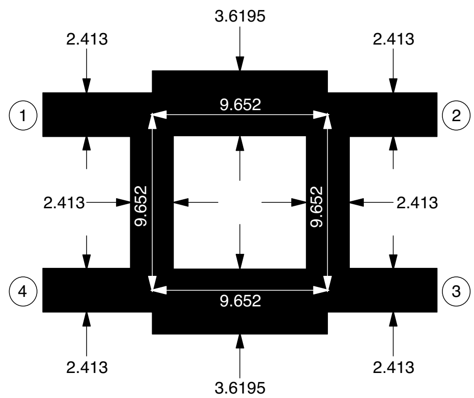

Figure 8. Branch-line coupler (all dimensions are in mm).

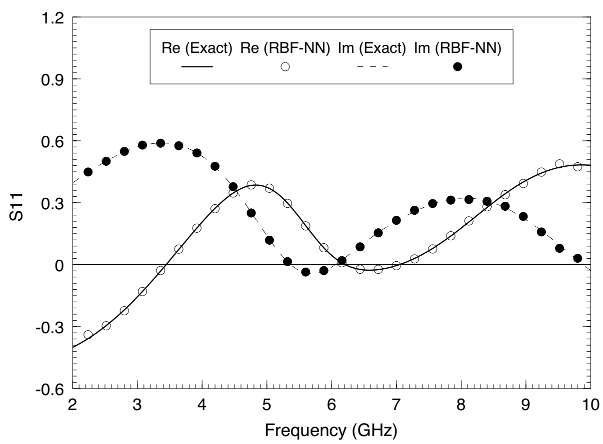

Figure 9. $\mathrm{Re}(S_{11})$ and $\mathrm{Im}(S_{11})$ of the branch-line coupler versus frequency as obtained using the exact simulator and the RBF-NN model.

$\mathrm{Im}\,(S_{11})$, $\mathrm{Re}\,(S_{21})$, $\mathrm{Im}\,(S_{21})$, $\mathrm{Re}\,(S_{31})$, $\mathrm{Im}\,(S_{31})$, $\mathrm{Re}\,(S_{41})$, and $\mathrm{Im}\,(S_{41})$ are 3.05%, −2.10%, 2.61%, 3.29%, 3.09%, 1.78%, 1.03%, and 2.84%, respectively.

The computation time budget of the RBF-NN to predict 201 frequency points is: Time of simulating 15 frequency points (247.7 sec) + time required for training (46.9 msec) + time required for frequency sweeping of 201 points (6.45 msec) = 247.75 sec. The same 201 points are simulated using ADS/Momentum within 55.32 minutes. The RBF-NN of this coupler is about 13.4 times faster than the full-wave simulator.

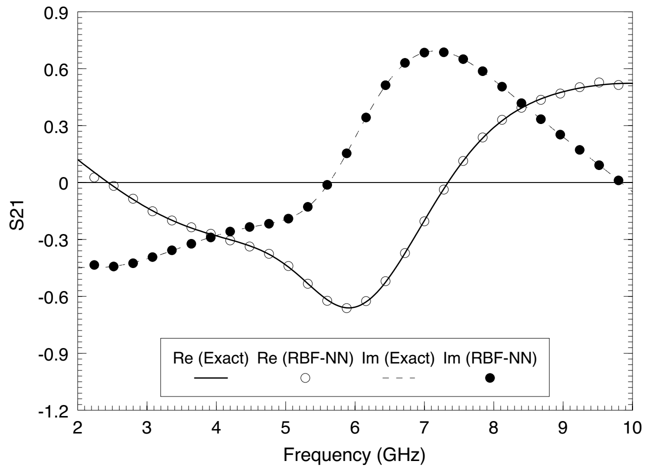

Figure 10. $\mathrm{Re}(S_{21})$ and $\mathrm{Im}(S_{21})$ of the branch-line coupler versus frequency as obtained using the exact simulator and the RBF-NN model.

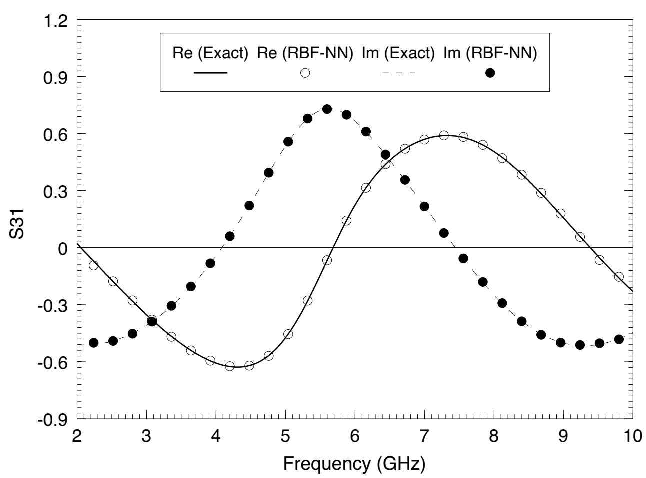

Figure 11. $\mathrm{Re}(S_{31})$ and $\mathrm{Im}(S_{31})$ of the branch-line coupler versus frequency as obtained using the exact simulator and the RBF-NN model.

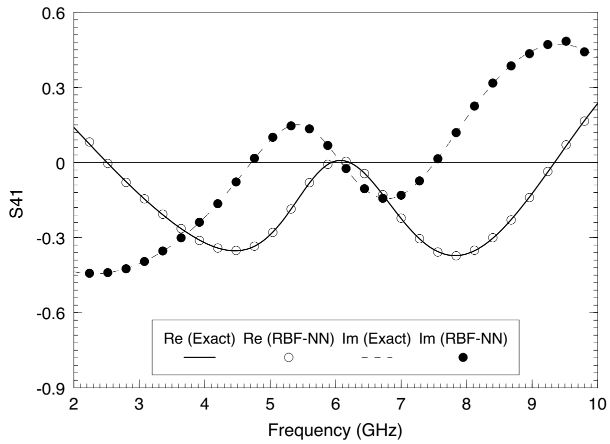

Figure 12. Re(S_{41}) and Im(S_{41}) of the branch-line coupler versus frequency as obtained using the exact simulator and the RBF-NN model.

4. CONCLUSION

A new RBF-NN model is presented in this paper. The model takes the frequency as an input and provides the real and imaginary parts of the S-parameters as outputs. Such model can be used to perform the frequency sweep required for characterizing a planar microwave structure. A limited number of frequency points uniformly distributed along the frequency band of interest, are used to train the RBF-NN frequency sweeper. The presented results demonstrate that the trained RBF-NN performs the frequency sweep very fast and with very high accuracy. For the examples studied in this paper, the maximum recorded percentage error in the prediction of the real and imaginary parts of S-parameters is 3.29%. For these examples, the RBF-NN sweeper is at least 10 times faster than the full-wave simulator. The proposed method is quite general and can be applied to any planar microwave structure.

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