Neurocomputational Analysis of a Multiband Reconfigurable Planar Antenna

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***Abstract*—Procedures using neural networks are developed for characterizing multiband reconfigurable antennas. A multilayer perceptron (MLP) is used to locate the operational frequency bands of the antenna at different reconfigured conditions. Another self-organizing map (SOM) neural network accomplishes the task of locating the switches to be turned ON for a desired frequency response. The developed formulation is tested on a laboratory prototype antenna.**

***Index Terms*—Multilayer perceptron (MLP), neural networks, reconfigurable antenna, self-organizing map (SOM).**

I. Introduction

IN RESPONSE to the ever-increasing needs of antenna bandwidth, considerable amount of effort is currently under way to develop multiband antennas. Much has also been achieved in implementing dual band antennas [1]–[3]. Mostly planar designs are preferred for these structures due to their added advantage of small size, low manufacturing cost and conformability. In recent years fractal antennas have been used as miniature multiband antennas [4]–[7] in which the self-similarity property is used to resonate the antenna at a number of frequency bands, equal to the number of fractal iterations in the antenna. Furthermore, the multiband property can also be achieved by making the structure reconfigurable, in which the different radiating elements of an array are connected together using switches to form groups of elements that resonate at different frequency bands [8]–[13]. Reconfigurable multiband antennas are attractive for many military and commercial applications where it is desirable to have a single antenna that can be dynamically reconfigured to transmit and/or receive on multiple frequency bands. Such antennas find applications in space-based radar, unmanned aerial vehicles, communication satellites, electronic intelligence aircraft and many other communications and sensing applications. The technology of design and fabrication of microelectromechanical systems (MEMS) for RF circuits has had a major positive impact on reconfigurable antennas [14]–[16].

For frequency reconfigurable antennas, the challenging tasks are twofold: 1) find an analytical procedure to locate the frequency bands of operation (analysis problem) and 2) how to connect the radiating elements together, such that the resulting module will have desired frequency bands (design problem), or in other words to determine which switches to turn ON, so that a specific set of elements will be active to make the structure to operate in the desired frequency bands.

Due to the multiscale nature of reconfigurable antennas, a single analytical method cannot characterize the whole structure. On the other hand, the use of different analytical methods for a single structure makes it a computationally intensive task, leading to the use of heavy computational resources. So there is a need to search for an analysis procedure for reconfigurable antennas that can characterize the antenna accurately.

In recent years neural networks and genetic algorithms are being used extensively for new antenna designs. In this paper, we have studied the use of neural networks (NNs) for analysis and design of a multiband reconfigurable planar antenna. NNs have emerged in recent years as a powerful technique for modeling general input-output relationships. The distinguished characteristics of NNs such as learning from data, to generalize patterns in data and to model nonlinear relationships, makes them a good candidate to apply for many different branches of engineering. In this work, we have used two different neural architectures for analysis and design of a reconfigurable antenna. In the analysis phase, NNs are used to locate the operational frequency bands for different combination of switches. This is treated as a mapping formation problem and is accomplished by an MLP trained in the backpropagation mode. In the design phase, the job of the NN is to determine the switches that are to be made ON for the structure to resonate at specific bands. This task is handled as a classification type of problem and is accomplished by a SOM neural network.

The following section describes the reconfigurable antenna structure under study. In Section III, the developed neurocomputational technique is described for analysis and design.

II. The Antenna Structure

The proposed neurocomputational technique is investigated for a laboratory prototype antenna. The structure under investigation is shown in Fig. 1. The basic antenna is a 130° balanced bowtie. A portion of the antenna corresponds to a two iteration fractal Sierpinski dipole. The remaining elements are added (three elements on each side) to make the antenna a more generalized reconfigurable structure. The reason for choosing this structure for modeling is two-fold. First is the multiband behavior of fractal Sierpinski antenna [4]–[6]. The second reason

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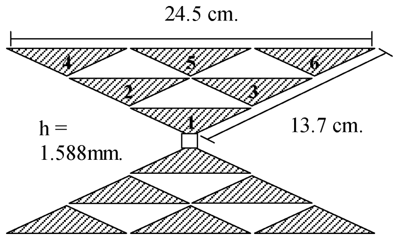


Fig. 1. Multiband antenna under investigation.

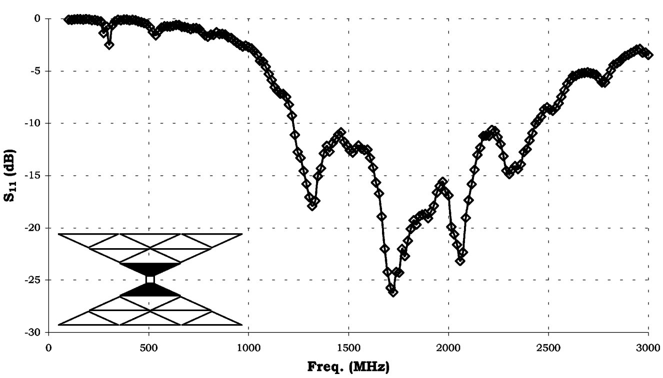


Fig. 2. Frequency response plot of the antenna with all the switches in OFF condition.

is that the broader angles move the operating bands to lower frequencies, which can be useful to reduce the antenna height. In addition, the input resistance and reactance variations become smoother when opening the flare angle [17], [18].

The antenna was fabricated on a Duroid substrate ($\varepsilon_r = 2.2$) with no radiating element touching to their adjacent elements. In the absence of actual MEMS switches, their electromagnetic performance is considered ideal and their placement is accomplished by small physical connections of the antenna's adjacent conducting parts. Our aim in this paper is to show the feasibility of use of NNs as an analysis tool for multiband reconfigurable antennas. With the use of actual MEMS switches, the same technique is equally applicable.

III. Applying Neurocomputational Technique for Analysis

A. Problem Formulation

By setting all the switches OFF the antenna is showing a resonance in the range 1.2–2.4 GHz (Fig. 2), and the radiation pattern is similar to that of the printed bow-tie dipole antennas. This is evident from the broadband nature of bowtie antennas [19]. But here it has to be noted that, even in the case of "all switches being OFF" the mutual coupling effects between the elements is still there in addition to the characteristics of a simple bowtie. Setting the switches to ON makes the antenna resonate at a number of different frequency bands. Through different combinations of switches it has been observed that the bands at which the antenna resonates depends on the switch positions that are at ON state. In order to implement this nonlinear mapping function between the ON switch positions and the resonance pattern of the reconfigurable antenna, we have used an MLP neural network trained in the backpropagation mode.

B. ANN Implementation

MLP neural networks are by far the most popular type of neural networks capable of approximating generic classes of functions [20]. These networks trained in the error backpropagation mode have already been used in many microwave engineering applications and specifically for antenna applications [21]–[23]. In these networks during training, the network adjusts its weights and thresholds in each iteration, using the update equations

$$v_{ho}^{k+1} = v_{hj}^{k} - \eta \frac{\partial E^k}{\partial v_{ho}} + \alpha\left(v_{ho}^{k} - v_{ho}^{k-1}\right) \tag{1}$$

$$w_{ih}^{k+1} = w_{ih}^{k} - \eta \frac{\partial E^k}{\partial w_{ih}} + \alpha\left(w_{ih}^{k} - w_{ih}^{k-1}\right) \tag{2}$$

$$\theta_{h}^{k+1} = \theta_{h}^{k} - \eta \frac{\partial E^k}{\partial \theta_{h}} + \alpha\left(\theta_{h}^{k} - \theta_{h}^{k-1}\right) \tag{3}$$

where v_{ho}: weighting factors between hidden and output layers; w_{ih}: weighting factors between input and hidden layers; $i = 1, 2, \ldots, n$: n is the number of input units; $h = 1, 2, \ldots, q$: q is the number of hidden units; $o = 1, 2, \ldots, p$: p is the number of output units; η and α being *the learning rate* and *momentum*, respectively.

Training minimizes the error E between the neural network predicted y_o and the desired outputs d_{ko}

$$E = \sum_{k=1}^{N} E^k = \sum_{k=1}^{N} \left[\frac{1}{2} \sum_{o=1}^{p} \left(y_o - d_{ko}\right)^2 \right] \tag{4}$$

where $k = 1, 2, \ldots, N$; where N is the total number of training samples used for training. The transfer functions usually used for the hidden units are *sigmoidal* whereas for the output units, it is *linear*.

Selection of training parameters for neural networks and the entire training process mostly depends on experience besides the type of problem at hand. The accuracy of a properly trained NN depends on the accuracy and the effective representation of the data used for its training. Numerical data has to be generated for those parameters the user wants to use in neural network training. The numerical data generation process for the present problem is described below. The parameters to be mapped, for which data generation is required, are the reconfigurable antenna structures and their corresponding frequency response.

Data Generation and Preprocessing: For generating data, we measured the frequency domain response ($| S_{11} |$) of the antenna for various combinations of ON switch positions, using an HP8714ES network analyzer. The operational frequency range of the antenna is 0.1–3.0 GHz. The frequency response plot is then sampled at equidistant frequency points so that the sampled plot adequately represents the original plot, emphasizing the -10 dB mark points. This was done in order to use as few neurons as possible in the output layer of the network, because our aim here is to develop the network that can represent the frequency response ($| S_{11} |$) of the antenna for various switch combinations. It was found that at least 40 sample points adequately represent the original frequency response of the reconfigurable structure. These sampled points are then scaled to remain within the range [−1, 1] and then used as the output training data of

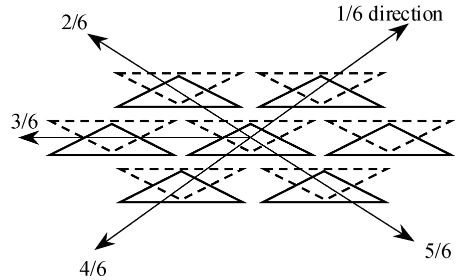
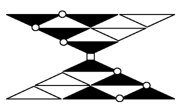


Fig. 3. Strategy used to choose the bit sequence representing the switch position and condition for creating input training data.



= **010100010010000101**

Fig. 4. Bit string equivalent of a typical reconfigurable structure. The small circles represent the ON switch positions and the corresponding active elements are marked dark.

the network. Scaling of data is desirable for efficient training of neural networks [25].

The corresponding input training data of the network for the frequency response output consists of bit strings (1s and 0s) representing the switch position and condition (either ON or OFF). A "1" represents an ON switch whereas a "0" represents an OFF switch. Although there is no restriction in choosing the order sequence, in this work we have used the following strategy. The order of switch position and condition for both half of the dipole starts from the tip element directly connected to the source and looking at each angular direction as shown in Fig. 3. This continues for each element on both halves (upper and lower). A total of 18 bits covers the entire 12 elements of the antenna array and its surrounding switches. The bit string for a typical reconfigurable structure is shown in Fig. 4. These bit strings are used as the input training data for the network. Scaling of the input data is not required as they are already in the range [0, 1].

C. Observations

A set of 78 input-output pairs was used for training of the network. For proper training, the number of units in the single hidden layer was determined to be 22. The trained network was then tested for the frequency response of the reconfigurable structure for different combinations of switches. The response of some of the typical combinations is shown in Fig. 5(a)–(c). The responses are also compared with the measured values. Now the developed network can be used to find out the operational frequency bands of the multiband antenna. The advantage of using NNs is that it avoids the computational complexity involved in the numerical modeling of the antenna. Furthermore, the response time is very fast for NNs.

IV. Applying Neurocomputational Technique for Design

A. Problem Formulation

Formulating the problem for design is more challenging than analysis, because of the large number of combinations of switches and the corresponding different frequency responses.

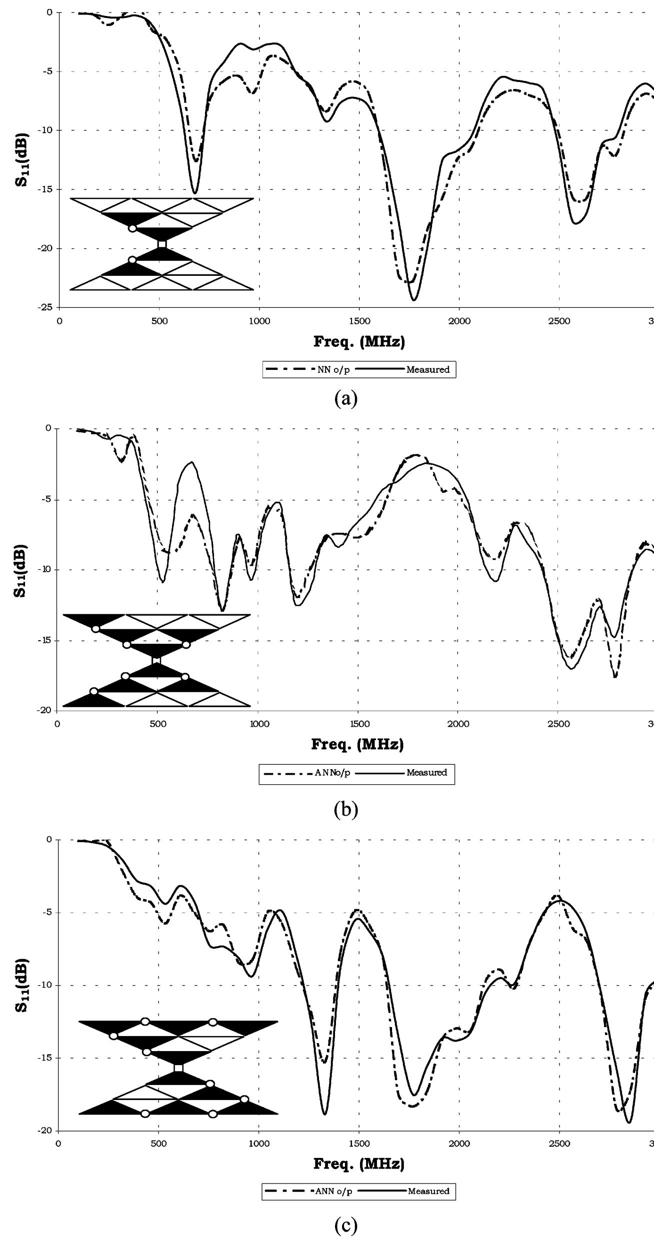
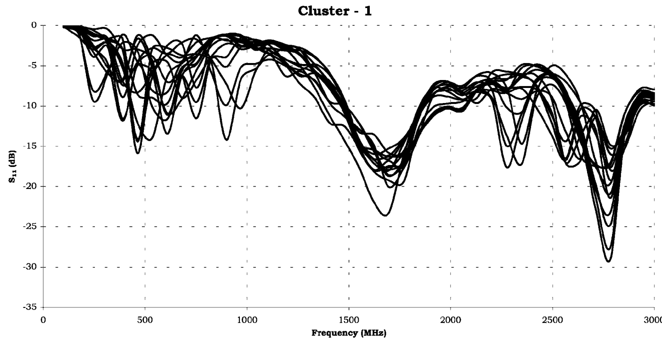
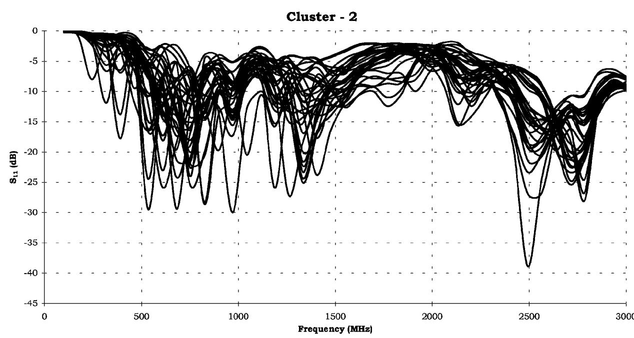


Fig. 5. (a-c): Comparison of NN output of some typical reconfigurable structures with the measured value.

The purpose here is to correlate any frequency response, within the operational range of the antenna, with a reconfigurable structure as closely as possible. We approached the design procedure as a clustering problem and used a SOM neural network [24] for classification of the frequency response plots. The task of the SOM is to map a continuous input space of activation patterns onto a discrete output space of neurons by a process of competition among the neurons in the network. Based on the shape of the frequency response plots, the SOM NN classifies the responses into different clusters. Each Cluster has some similarity among the frequency responses in the operational range and their depth. The Clusters so formed are then related with their corresponding antenna structure. Therefore, for each Cluster a set of typical reconfigurable structures was formed. Given a frequency response plot, the corresponding approximate reconfigurable structure can be traced out from

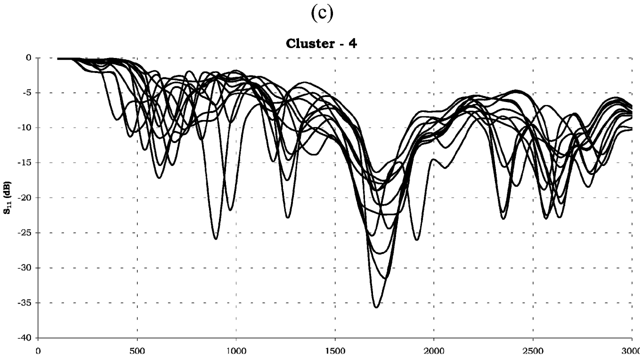


(a)



(b)

(c)



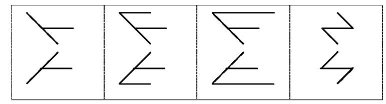
(d)

Fig. 6. (a-d). Clusters of the frequency responses of the reconfigurable structures as made by the SOM network.

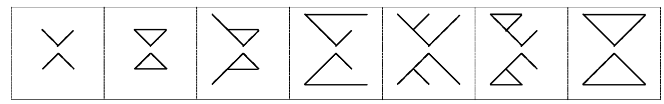
these sets of typical structures, depending on, to which Cluster the frequency response is adapting, as determined by the SOM.

B. ANN Implementation

The SOM NN consists of an input layer of nodes, where the inputs to the NN are applied, and an output layer of nodes, where the categorization (grouping/clustering) of the inputs are formed. The nodes in the output layer, most often are organized in a two-dimensional (2-D) array. Training is performed in an unsupervised way using Kohonen learning algorithm [24]. The training can be viewed as a procedure that learns to group input patterns in Clusters in a way inherent to the data. To train the SOM NN, continuous valued input vectors are presented in random sequence to the network. The mapping from the external input patterns to the network's activity patterns is realized by correlating the input patterns with the connection weights. After enough input patterns have been presented, weights converging to output nodes of the SOM NN specify Cluster centres that represent the input patterns.



(a)



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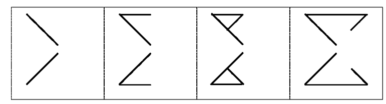

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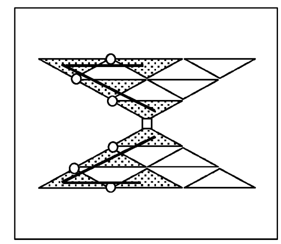

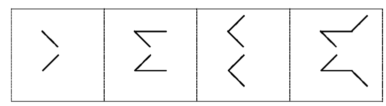

(d)

Fig. 7. (a-d) Reconfigurable structures corresponding to the Clusters 1 – 4 as shown in Fig. 6(a)–(d) respectively. The inset picture shows the formation of paths for a typical configuration. Structures corresponding to these or their variants can be used to get the desired frequency response of the reconfigurable antenna.

In the present problem, the inputs to the SOM NN is the frequency responses ($| S_{11} |$) fed through 40 nodes (sampled frequency points). So, the output training data for analysis problem was used in the design problem as the input to the network. In the output layer, we took four neurons, because it was observed that classifying the response plots into four groups marks each Cluster with distinguished features. The adaptive process for SOM used in this work is as described in [25]. In this the weights of a 2-D SOM network are updated according to

$$\mathbf{w}_j(t+1) = \mathbf{w}_j(t) + \eta(t) h_{j,i(x)}(t)(\mathbf{x} - \mathbf{w}_j(t)) \qquad (5)$$

where $\eta(t)$ is the time varying learning parameter given by $\eta(t) = \eta_0 \exp(-t/\tau_2), t = 0, 1, 2, \ldots; \eta_0\ (\approx 0.1), \tau_2\ (\approx 1000)$ are constants. $h_{j,i(x)}(t)$ is the neighborhood function given by

$$h_{j,i(x)}(t) = \exp\left(\frac{-d_{j,i}^2}{2\sigma^2(t)}\right),\ t = 0, 1, 2, \ldots \qquad (6)$$

where σ is the "effective width" of the topological neighborhood given by $\sigma(t) = \sigma_0 \exp(-t/\tau_1),\ t = 0, 1, 2, \ldots;\ \tau_1 = (1000/\log \sigma_0)$, $\sigma_0\ (\approx 1)$ a constant. $d_{j,i}$ is the lateral distance between winning neuron i and excited neuron j.

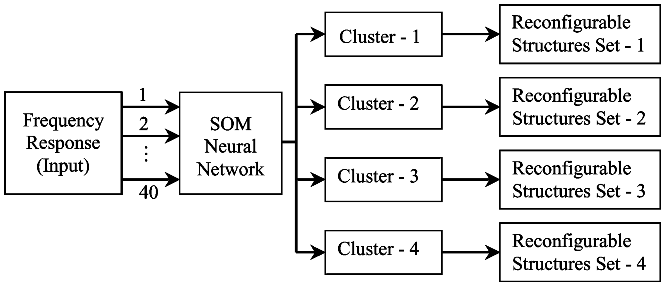

Fig. 8. Paradigm of reconfigurable structure design.

The four Clusters of frequency responses as formed by the properly trained SOM NN are shown in Fig. 6(a)–(d).

C. Observations

The class of curves in Cluster-1 [Fig. 6(a)] represents a broadband in the range 1500–2000 MHz and a deep band around the mid-frequency of 2750 MHz. The typical structures corresponding to Cluster-1 are shown in Fig. 7(a). Fig. 7 shows only the paths of the active elements in the reconfigurable antenna structure and the inset picture shows the formation of paths for a typical configuration) and these combinations normally do not excite the lower frequencies. The configurations corresponding to Cluster-2 [Fig. 6(b)] shows operational bands in the lower frequency ranges (500–1000, 1000–1500 MHz) and prominent band in the highest frequency range (2500–2780 MHz) with a large isolation between these lower and higher bands. The class of curves in Cluster-3 differs from that of Cluster-1 in the point that the mid-frequency band (1600–2000 MHz) in Cluster-3 is more prominent and mostly they show small bands in the lower frequency ranges also, in addition to the deep high-frequency band. The structures corresponding to Cluster-4 [Fig. 7(d)] shows a broad prominent band around the frequency 1750 MHz but they don't show prominent lower or higher frequency bands.

The developed SOM network now can be used for design purposes. The paradigm of the design process is shown in Fig. 8, and described below.

Step 1: Give the network the desired frequency response (input);

Step 2: SOM NN matches the frequency response to the closest Cluster;

Step 3: The antenna configuration can be chosen from the set of structures corresponding to that Cluster, starting with a simple structure with minimum number of switches;

Step 4: Depending on requirement, more elements can be excited over the original structure.

As the response of the SOM NN is almost instantaneous, the approximate configuration of the antenna for any frequency response (in the operational frequency range of the antenna) can be traced out within no time. This is the advantage of using neurocomputational technique, reducing drastically the time for reconfiguring the structure.

V. Conclusion

Two different neural network structures are used for analysis and design of a laboratory prototype frequency reconfigurable antenna. In analysis, an MLP trained in the backpropagation mode is developed to identify the operational frequency bands of the reconfigurable structure. It drastically reduces the mathematical complexity involved in the different numerical methods used to model the entire reconfigurable antenna due to its multiscale structure. The design phase is approached as a clustering problem and a SOM network is used to categorize the frequency responses of the reconfigurable structure. Corresponding to a new frequency response, the position of the switches to be made ON can be identified from a group of typical structures approximately. The developed neurocomputational methodology can be extended for characterizing any reconfigurable electromagnetic structure.

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