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Applications of Neural Networks in Wireless Communications

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Abstract

In recent years, the art of using neural networks (NNs) for wireless-communication engineering has been gaining momentum. Although it has been used for a variety of purposes and in different ways, the basic purpose of applying neural networks is to change from the lengthy analysis and design cycles required to develop high-performance systems to very short product-development times. This article overviews the current state of research in this area. Different applications of neural-network techniques for wireless communication front ends are briefly reviewed, stressing the purpose and the way neural networks have been implemented, followed by a description of future avenues of research in this field.

Keywords: Neural networks; neural network applications; land mobile radio cellular systems; antennas; microstrip antennas; antenna arrays; multi-band antennas; wideband antennas

1. Introduction

A neural network is a simplified mathematical model of a biological neural network. It consists of a collection of interconnected neurons. From an engineering prospective, it can be regarded as an extension of the conventional data-processing technique. The following definition of neural networks may be offered [1]: "A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: (1) knowledge is acquired by the network through a learning process, and (2) interneuron connection strengths known as synaptic weights are used to store the experiential knowledge." The rapidly evolving field of neural-network applications in wireless communication has witnessed several excellent contributions [3, 4]: different problems have been successfully attacked; new methodologies have been introduced and significant progress has been made in this dynamic area [5-7]. Leaving aside the details of neural networks, for which several extensive books are available [1, 2], here we emphasize the applications made so far. Table 1 summarizes the different applications of neural networks to wireless-communications engineering. The following are some of the reasons for which the art of applying the neural-network technique is gradually becoming popular among researchers in the communications area:

Table 1. A list of some of the applications of neural networks for wireless communications.

Applications	Purpose/Advantage	Type of Network Used	References
Microstrip antenna analysis	To develop fast ANN models for microstrip antennas, to avoid lengthy full-wave EM analysis with a faster method	Multilayer feed-forward network	10-15, 17-20, 24
Design of microstrip antenna/CPW patch antenna	To bypass the repeated use of complex iterative processes, to avoid CPU intensive simulation procedures	Multilayer feed-forward network, Hopfield network, radial-basis-function network	16, 21-23, 25-26
Direction-of-arrival (DOA) estimation	To reduce the computational complexities of the previously available methods of DOA estimation	Radial-basis-function network	27-33
Adaptive beamforming	Real-time implementation of beamformer to respond to the time-varying environment	Hopfield network, radial-basis-function network	34, 35
Wideband mobile antenna design	To avoid lengthy full-wave EM analysis with a faster method	Multilayer feed-forward, knowledge-based neural network	38

1.1 Nonlinearity

On keen observation of any wireless engineering phenomenon – viz., the design or analysis of antennas, estimation of direction of arrival, adaptive beamforming techniques, etc. – it is noted that these always have a quite nonlinear relationship with their corresponding input variables. The inherent nonlinearities associated with these phenomena makes them ideally suited for neural networks. Multilayer neural networks are employed to model such nonlinear relationships. Neural networks are also robust in function approximation. In fact, in theory, a feed-forward neural network with at lest one hidden layer can approximate any nonlinear function. Substantially, a feed-forward multilayered network can be considered to be a "universal approximator" [8].

1.2 CAD Applications

Computer-aided design (CAD) typically requires the development of suitable codes for modeling. Models based on closed-form formulas are simple but, at the same time, they are less accurate. Commercial software uses computer-intensive numerical methods such as the FEM, the full-wave MoM, and FDTD, etc. But the resulting codes are often too slow for design purposes, since they take a lot of computation time. On the other hand, neural networks can perform computations at a very high rate because of their massive parallelism and highly connected structure. They can learn the characteristics of input signals and adapt to changes in the data because of their adaptive nature; they can perform functional approximations because of their nonlinear nature. Besides this, a distinct advantage of neurocomputing is that after proper training, a neural network completely bypasses the repeated use of complex iterative processes for new cases presented to it. All these facts are suitable for the development of CAD models. These CAD models, capable of accurately predicting the parameters, are also very useful to wireless communication engineers. Although a neural network takes time during its training, it supplies instant results in its implementation phase.

1.3 Reduction of Mathematical Complexity

In general, physics/EM-based analysis procedures are computationally complex. The use of neural networks can considerably reduce the complexity. A straightforward application of a neural network uses the data derived from these complex mathematical procedures to train a neural network. After proper training, these neural models can be used in place of the computationally intensive physics/EM-based models to speed up the analysis. Another approach is to apply a neural network in conjunction with the mathematically complex physics/EM-based analysis methods [9].

2. Some Issues in Using Neural Networks

In using neural networks, the identified problem at hand first has to be checked for its suitability for neural-network implementation. This means that it is advisable not to resort to neural-network techniques for simple linear functions, or for problems that can be implemented through a direct, closed-form formula.

After specifying the problem, it can either be implemented in total using neural network, or the whole problem can be divided into parts, and neural networks can be used to implement a part. By implementing the problem in its totality, the neural network acts as a black box, and does not disclose the physics behind it to the end user. On the other hand, partial implementation with a neural network preserves the background phenomena of the problem, to some extent. The knowledge-based neural network also preserves the background physics of the problem, to some extent. In some cases, existing prior knowledge is used to train the network [40].

The accuracy of a properly trained network depends on the accuracy of the data used to train the network. Therefore, care should be taken while generating training data, whether the data are generated by simulation or experimentally. Preprocessing of input and output data sometimes reduces the training time of the network to a large extent. Effective data representation is another step in this direction [41].

With the increase in network size, the number of training patterns required for proper generalization also increases. Because the generation of data in RF/microwave problems is very expensive, it is therefore often desirable to develop the network with the minimum number of neurons in the hidden layer(s) as possible (the number of input- and output-layer neurons is problem dependent and fixed), while at the same time avoiding over-training and

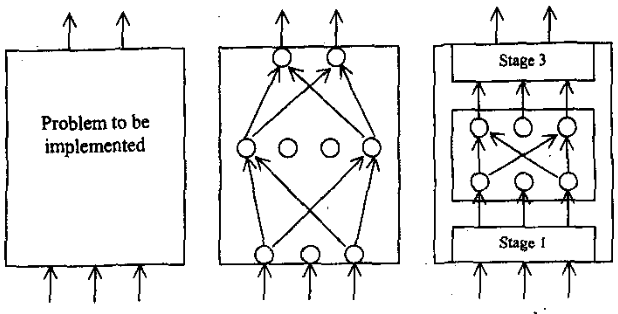

Figure 1. The problem at hand can be modeled using a neural networks as a whole, where it works as a black box, or a neural network can be used to model a part of the whole problem.

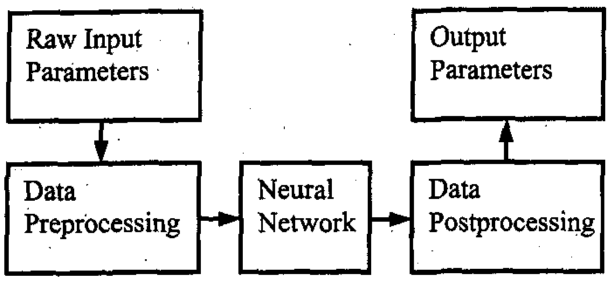

Figure 2. The paradigm of a neural-network application.

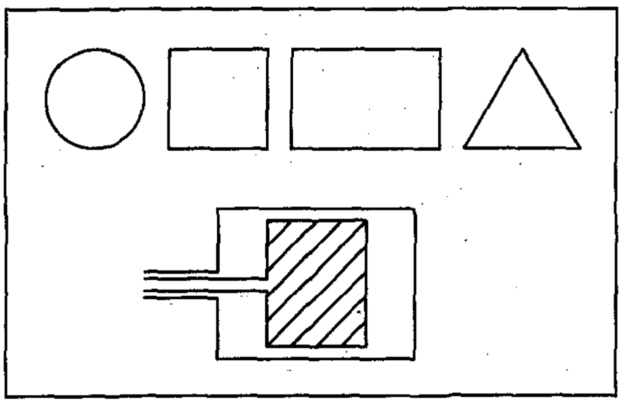

Figure 3. Low-profile antennas considered to date for neural-network applications. Microstrip structures include circular, square, rectangular, and triangular; coplanar waveguide patch/slot antennas.

under-training. For this, generated data may be divided into training and test sets, for observing the error behavior with the progress of training. As a rule of thumb, the minimum number of hidden-layer neurons required to avoid over-training and to obtain good accuracy for testing data is $\sqrt{N_i N_o}$, where N_i is the number of input-layer neurons and N_o is the number of output-layer neurons.

3. Applications

Table 1 summarizes the applications of neural networks in wireless communications. More specifically, neural-network applications were found in the antenna literature as far as wireless communication engineering was concerned. So, we feel it is appropriate to review the progress made so far in this area of research, particularly that of using neural networks for wireless communication front ends. We categorized this under three different headings – (1) low-profile antennas, (2) arrays and smart antennas, and (3) wideband and multi-band antennas – in order to discuss the progress made in each of these areas. Although a variety of applications was found in the literature, the general paradigm of using neural network is as shown in Figure 2. In most cases it is found that the preprocessing of raw input/output data followed by an obvious post processing is helpful from a network-training point of view, but this is not always mandatory. The user can choose his or her own data-processing strategy, depending on convenience.

3.1 Applications to Low-Profile Antennas

The emerging applications of wireless-communications systems require high-performance, low-profile antennas to operate in fixed, mobile, handheld, and airborne environments. As communication devices become smaller due to the integration of electronics, the antenna becomes a significantly larger part of the overall package volume. This results in a demand for a similar reduction in antenna size. When the antenna occupies an appreciable volume of the compact wireless device, and as transceivers are integrated into other devices, the accurate characterization of the antenna becomes necessary for the device's high performance. Several of the low-profile antenna categories, such as microstrip antennas and coplanar waveguide patch antennas (Figure 3) have been analyzed and designed using neural networks [10-26]. All of these applications exploited the ability of a neural network to model nonlinear relationships. Some applications used previously reported experimentally measured data for training, whereas others used data derived from simulations. In some cases, a neural network was used in conjunction with computationally intensive analysis methods, such as the spectral-domain method [19, 20, 23, 24].

Neural network models have been developed for analysis parameters such as the input resistance, bandwidth, and resonant frequency of different regularly shaped microstrip antennas [10-15, 17, 18]. A block-diagram representation of a typical example of calculating the resonant frequency of a triangular microstrip antenna [10] is shown in Figure 4. The inputs to the network are the side length, the height of the substrate, the dielectric constant, and the mode numbers.

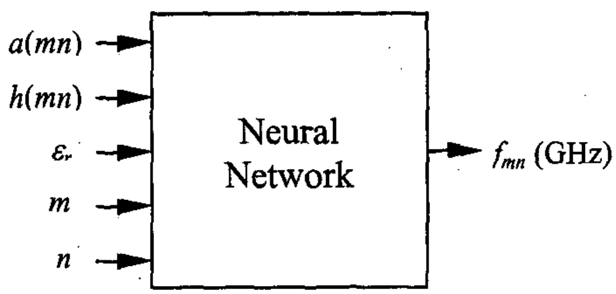

Figure 4. The resonant-frequency calculation of a triangular microstrip antenna using neural networks. A 5 × 5 × 3 × 1 multilayer perceptron, trained using a back-propagation algorithm, was used.

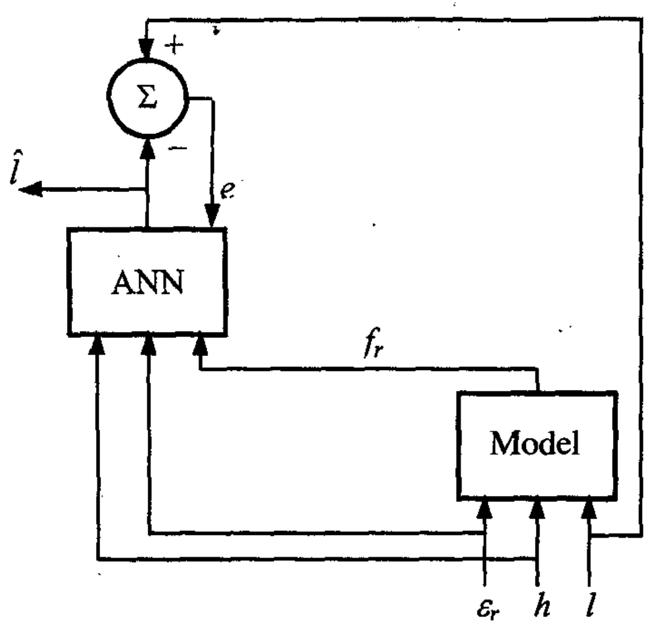

Figure 5. The calculation paradigm for the design of a square patch antenna. ε_r is the dielectric constant, l is the side length of the patch, $\hat{l}$ is the output of the ANN, and Wolf and Knoppik's model for a square patch was used.

The calculation of the resonant frequencies of various regularly shaped microstrip antennas, using a single network, was demonstrated in [17]. In this reference, the areas of other shapes (e.g., triangular and circular) were equated to an equivalent rectangular microstrip antenna. The inputs to the generalized neural-network model were thus the length, the width, the height, and the dielectric constant of the substrate, and the mode numbers. It thus needed preprocessing of the raw data in order to calculate the resonant frequency. Accuracy and simplicity were the key features of these networks so developed. Therefore, they could be useful for the development of fast CAD algorithms.

Neural networks have also been used in conjunction with a spectral-domain technique termed the Neurospectral Method for the analysis of microstrip antennas [19, 20, 24]. The complex resonant frequency of microstrip resonators and the input impedance of rectangular microstrip antennas have been calculated using this method. The aim was to reduce the computational complexities involved in the spectral-domain approach (SDA). In this work, the singularities arising in the spectra-domain approach were suitably handled by neural networks, thereby considerably decreasing the computation time of the spectra-domain approach. The results also compared well to those from the spectral-domain approach.

On the design side of low-profile antennas, neural networks have been used for the design of square, rectangular, and circular microstrip antennas, and for coplanar-waveguide patch antennas [16, 21-23, 25-26]. The calculation paradigm of the design of a square patch antenna is illustrated in Figure 5.

The neurospectral method, used to design rectangular patch antennas [23], uses the following proposition, which handles the singularities occurring in the spectral-domain approach:

Proposition: If $f(x,y)$ is a function with singularities at (x_i, y_i) in the ranges of x and y, and if $g(x,y)$ is a continuous function such that $g(x,y) = f(x,y)$ at all nonsingular points of $f(x,y)$, then $f(x,y)$ can be expressed in terms of $g(x,y)$ as

$$f(x,y) = g(x,y) + \sum_{i,j} g(x,y)\delta(x - x_i)\delta(y - y_i).$$

Using an artificial neural network, it is easy to implement the function $g(x,y)$. After that, instead of integrating the function $f(x,y)$, one can use its alternate (the right-hand side of the equation) as the integrand. Application of this proposition drastically decreases the computation time of the spectral-domain approach. Although the neurospectral technique development stage is a time-consuming step, compared to the development stages of other commercial CAD models, the technique takes much less time during its implementation stage.

Another generalized physical design procedure for patch antennas using neural networks was discussed in [26]. This dealt with the physical design of patch antennas, given the desired parameters such as the resonant frequency, the feed-point position, the substrate thickness, the relative permittivity, the input impedance, and the efficiency. Electromagnetically trained artificial neural network (EM-ANN) models have also been developed for the design of coplanar-waveguide patch antennas as a part of the design of low-profile antennas using a neural network [25]. The modeling using electromagnetically trained artificial neural network models compared well with electromagnetic simulation and measurement, validating the approach.

3.2 Applications in Arrays and Smart Antennas

The future of wireless systems will certainly include wider deployment of arrays. Arrays use multiple antennas, or elements, to achieve enhanced performance, including high gain. They can also support electrical beam steering to improve transmission and reception, and null steering to reject interfering signals. The trend toward the increased use of antenna arrays and the development of new approaches for using arrays to improve system performance is going on in wireless communication. In this respect, neural networks have been successfully applied to direction-of-arrival estimation and beam forming for antenna arrays [27-35]. The key point of using neural networks is that the mapping between the received signal and the antenna's behavior is a continuous function, and therefore it is possible to model it with an neural network trained at discrete samples along the function.

Radial-basis-function neural networks were developed to reduce the computational complexities of monopulse and MUSIC algorithms [27, 28]. Radial-basis-function networks have the ability to interpolate data in higher dimensions. The main advantage of radial-basis-function neural networks is the substantial reduction in the CPU time needed to estimate the direction of arrival. The robustness of neural-network-based direction-finding systems in noise and under conditions of external interference was observed in [29].

Multiple-source tracking with neural-network-based smart antennas is another novel application of neural networks for wireless communication front ends [30]. A family of radial-basis-function neural networks was used in this work, to perform both detection and direction-of-arrival estimation. The field of view of the antenna array was divided into spatial angular sectors, which were, in turn, assigned to a different pair of radial-basis-function neural networks. This work revealed the fact that neural-network-based direction-finding algorithms possess the ability to locate sources that are greater than the number of array elements.

An application of a neural fuzzy network for direction-of-arrival estimation was reported [31]. Direction-of-arrival estimation as an application of neural networks can also be found in [32, 33]. The procedures used differed in their approach, in the types of network used, in the amount of problem complexity involved, and in the number of directions that could be simultaneously detected.

Beamforming is one of the main functions of a phased-array processing system. It involves forming multiple beams through applying appropriate delays and element weightings to the signals received by the sensors. The purpose of this is to suppress unwanted jamming interference, and to produce the optimal beamformer response, which contains minimum contributions due to noise. An analog circuit was implemented for computing the minimum-variance distortionless response (MVDR) to the beamforming problem based on neural networks [34]. The minimum-variance distortionless-response-based neural circuit worked satisfactorily under a stringent environment of strong jammers, as well as closely spaced jammers.

A new approach to the problem of neural-network-based beamforming was introduced in [35]. In this work, the computation of the optimum weights was accomplished using three-layer radial-basis-function neural networks. The results obtained from this network were in excellent agreement with the Wiener solution. The network was successful in tracking multiple users, while simultaneously nulling interference caused by co-channel users. Neural-network applications to antenna arrays were also used in [36] to avoid interference.

3.3 Applications in Wideband and Multi-Band Antennas

As integration increases, a single antenna is often required to support two or more of the many wireless services across a broad frequency range. Multi-band and wideband antennas are being developed to meet this need. The trend towards multi-band capability will continue and accelerate as more services at different frequencies become available. As services and frequency requirements proliferate, wideband antennas may be a more economical solution. Wideband antennas perform consistently across a continuous block of spectrum, providing capabilities for current and future applications that are not limited to specific, narrow bands.

A literature survey revealed that a few examples of work have been done in neural-network modeling for wideband antennas [37, 38]. In [37], a broad-impedance-bandwidth rectangular planar monopole antenna design was made with neural-network models. The operating band of this planar monopole antenna was 1700-2500 MHz, suitable for DCS (1710-1880 MHz), PCS (1850-1990 MHz), DECT (1880-1990 MHz), PHS (1895-1920 MHz), IMT-2000 (1885-2025 MHz), UMTS (1920-2170 MHz), and WLAN (2400-2485 MHz) operations in mobile communication. The optimum structure found with a neural-network optimizer for this antenna was $L = 36$ mm, $W = 16$ mm, h (the height of the radiating structure above the ground plane) $= 0.8$ mm, with a foam substrate ($\varepsilon_r = 1$) having 0.005 mm thickness. As future mobile communications needs mobile terminal antennas with wideband and multimode operation capabilities, this compact wideband planar monopole antenna, designed using neural-network models, can provide the solution, to some extent. Besides the fact that the neural-network models developed were reliable and accurate, as was evident from the simulation results, the neural-network models dramatically saved the time spent on antenna design.

Knowledge-based neural-network modeling techniques have been utilized for the design of wide-bandwidth coplanar waveguide patch/slot antennas [38]. The coplanar waveguide patch/slot antenna, designed using the developed model, exhibited a 32% impedance bandwidth near 5.4 GHz in a 50 Ω system. The modeling approach developed was general, and can be used for modeling other antenna structures, as well.

4. Future Trends

There is a push to develop low-profile and embedded antennas throughout the wireless communications industry, for a variety of applications. In addition to the obvious requirement for small antennas on handheld terminals, low-profile antenna designs are important for fixed wireless applications. Two major challenges arise in the design of small antennas. First, there is a fundamental relationship among the size, bandwidth, and efficiency of an antenna. Second, the gain is related to the size of the antenna: that is, small antennas typically provide lower gain. A review of the literature revealed that neural networks have been applied for the analysis/design of microstrip antennas and coplanar waveguide patch antennas. Many other types of low-profile compact antennas with high efficiency are available for use in compact terminals. These include the inverted-L, inverted-F, dual inverted-F, and planar inverted-F antennas. Neural networks can be used to find an optimized, compact structure for these antennas, and to find ways to extend their bandwidths. Knowledge-based neural networks may be helpful in this, using existing ideas about these antennas.

As far as antenna arrays are concerned, a lot of work has been done in direction-of-arrival estimation and beamforming using neural networks. However, more avenues can still be identified for the analysis, design, and application of antenna arrays. Aircraft and military ships have limited space for onboard antennas. They require arrays that support communications, radar, signal intelligence, and navigation across a wide range of frequencies. The same is the case for civilian vehicles that carry radios for

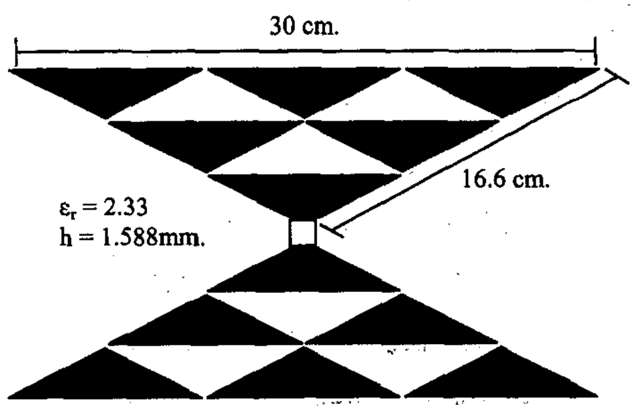

Figure 6. A reconfigurable antenna structure.

communication, navigation, and entertainment. Designing these wideband, multifunctional arrays is always challenging. The challenges can be met, to some extent, with the use of neural-network techniques. Wideband elements, such as log-periodic elements, spiral, and sinuous elements, can be used as the basis of the array. Neural-network analysis models can be developed by using experimental data for different analysis parameters of these antennas. Furthermore, these wideband elements must be arranged carefully, to allow the main beam of the array to be scanned over a wide angular range at all frequencies within the array's bandwidth. Because the beam pattern is a function of the placement of the elements and is nonlinear, a solution for the placement of the elements can be found with the help of neural networks. A frequency-dependent effect, mutual coupling, is an important consideration for antenna arrays. The effects of mutual coupling on different parameters of the array can be estimated as a function of frequency using neural networks, as well.

When a single array configuration does not meet the demands of an application, a reconfigurable array can be used. These reconfigurable antennas are becoming popular among antenna engineers [39, 40]. Newer approaches use PIN diode or micro-electromechanical-system (MEMS) switches to reconfigure arrays, or elements within the array, for specific frequency bands or operational scenarios. But to accomplish the analysis of these types of antennas, the switch and the antenna elements need different analysis techniques, which result in a cumbersome procedure

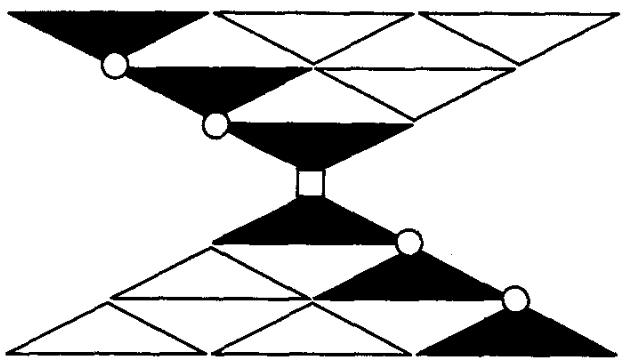

Figure 7a. The reconfigurable antenna structure: The ON switch positions are marked with small circles, and the corresponding activated array elements are shaded black.

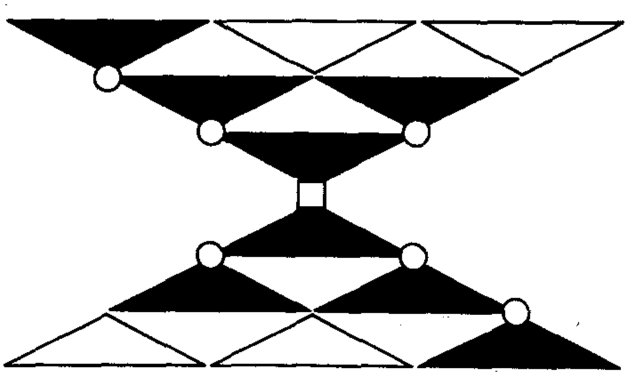

Figure 7b. The reconfigurable antenna structure: The ON switch positions are marked with small circles, and the corresponding activated array elements are shaded black.

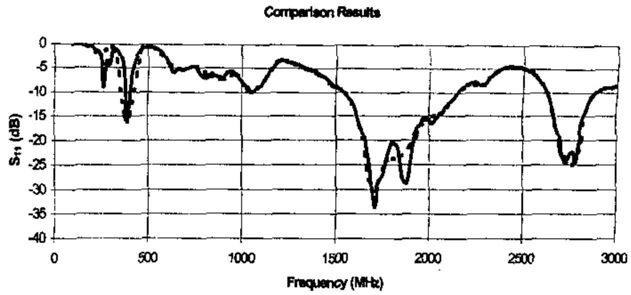

Figure 8a. The S_{11} values from measurements (solid line) and the output of the neural network (dashed line) for the antenna configuration shown in Figure 7a.

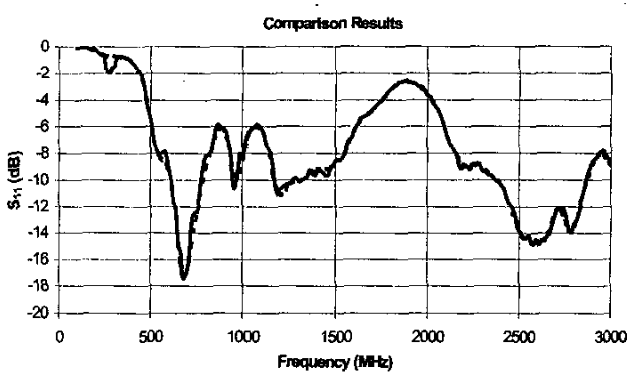

Figure 8b. The S_{11} values from measurements (solid line) and the output of the neural network (dashed line) for the antenna configuration shown in Figure 7b.

for the characterization of these antennas. Neural networks can play a major role at this point, either to reduce the computational complexity involved in the analysis, or to find the switch positions in the array structure in order to get the required characteristics of the antenna.

As an example, we have analyzed a MEMS-based frequency-reconfigurable antenna using neural networks. The MEMS switch-based antenna used for modeling is shown in Figure 6. The basic antenna was a 130° balanced bowtie, chosen due to its inherently high bandwidth. The electromagnetic performance of the RF MEMS switches was considered to be ideal, and their placement was accomplished by small physical connections of the antenna's adjacent conducting parts. Making all the switches OFF, the antenna had a bandwidth from 1.5 GHz to 2.5 GHz, and the radiation pattern was similar to that of a printed dipole antenna. However, setting the switches to ON made the antenna resonate at a number of different frequencies. The frequencies at which it resonated were completely a function of the switch positions that were in the ON state. In order to implement this nonlinear function, we used a multilayer perceptron network, trained in the backpropagation mode. The network took 0s (for an OFF switch) and 1s (for an ON switch) in a specific sequence, and presented the S_{11} as its output at the prespecified sampled frequency points. After proper training of the network, the antenna was tested for results with a specific combination of switches. The graphical results for two different combinations of switches (Figures 7a and 7b) are shown in Figures 8a and 8b, respectively. The network that was developed not only reduced the computational complexities involved in the numerical modeling of reconfigurable antennas, but also gave excellent results.

5. Conclusion

The recent surge of interest among communication engineers in applying neural-network techniques as a tool of analysis/design has opened many avenues for tackling the needs in wireless communications. High-performance antennas are being developed to satisfy the competing demands of emerging wireless applications. This article reviewed the current applications of neural networks in these high-priority areas, and traced the further avenues in which neural networks could play a major role. Recently, the possibility of developing antenna designs that in some way exploit the properties of fractals to achieve the goals of compact size, low profile, conformal, and multi-band antennas, at least in part, has attracted a lot of attention [42-44]. Neural networks can also find suitable places for analysis of these antennas.

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