Element Failure Diagnosis in a Planar Microstrip Antenna Array by the Use of Neural Networks

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Abstract

In this paper a neural network based approach, applicable in real time applications, is proposed for detecting the number and location of defective elements in a typical uniformly excited microstrip planar array antenna fed in a serial manner. Here the defective elements are those elements that are not excited by the feed lines but radiations due to the induced currents in the surface of these elements still remain. The neural network performs a nonlinear mapping between some samples of the degraded patterns of the simulated array antenna and the array elements which may have caused these degradations. After the training procedure the proposed fault diagnosis system is very fast and has a satisfactory success rate.

Introduction

Element failure in an array antenna may occur due to the disturbance in the driving equipments, feed lines or array elements themselves which may result in elements radiation complete or partial failures. Element failure in a symmetric array causes it to be an unsymmetrical array. It can distort the directivity of the antenna power pattern and it also leaves undesired effects on the side lobe level of the radiation pattern, voltage standing wave ratio and as a whole the good performance of the array antenna. Applying the built in monitoring and calibration systems including a network of sensors is a very effective method in detecting faulty elements of the arrays but it can enforce the probability of calibration system failures and an extended increase in volume, cost and design complexities on the system. Thus the importance of the smart solutions can be realized.

A genetic algorithm based method for detecting the number, location and the amount of failure in an 8×8 planar array was reported in [1]. In that report genetic algorithm was used to minimize a cost function that is the square of the difference between the power pattern of a predefined configuration of failed elements and the measured one. In [2], the element failure diagnosis of a planar array from its noisy far field power pattern was approached by the use of the genetic algorithm to reach an unambiguous solution of the problem. In [3], a reasonable method based on the array antenna simulation results was proposed for locating defective elements of a 16-element linear array from some samples of its simulated degraded patterns by the use of a MLP neural network. In that a defective element was considered as a non-radiating element but the mutual coupling effect between elements was considered. In [4], a support vector machine classifier was proposed to detect the defective elements in a linear array. In [5], the neural network was proposed for the diagnosis of phase and magnitude of the current faults and the location of the defective elements in a linear array from its degraded array factor. A case based

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reasoning algorithm was reported in [6] that resulted in an effective reduction in the search space of the genetic algorithm for the fault diagnosis in a linear array.
All of the aforementioned methods can be classified into two categories: In the first category are those methods that radiation patterns calculations in them are based on the array factor calculation. Evidently in these works mutual coupling effect has been neglected. In the second category are those methods that are based on the simulation results of antennas. However in these works mutual coupling effect is considered, the radiation of the defective elements in front of the normal elements has been neglected. But in practice a defective antenna element in the presence of other radiating elements could be a radiating element itself because of its surface induced currents due to the radiation fields of the normal elements. Thus the defective elements elimination is equal to the elimination of this radiation portion and may reduce reliability and success rate of the fault diagnosis system.

As in the former studies, in the present study element failure diagnosis is performed by the use of the far field characteristics of an array antenna. Here the defective element is not considered as a non-radiating element with no output and the radiation due to the induced currents is considered as well as the mutual coupling effect.

Description Of The Problem

Here the goal is to detect the number and location of the faulty elements in a 6×6 microstrip planar array antenna which is designed for working at the frequency of $16.46\ GHz$. Array elements are $5600\mu m \times 5600\mu m$ square patches excited uniformly by a serial feed line. The element spacing is 0.9λ in order to suppress grating lobes. This structure is placed on a substrate with ε_r= 2.2 and the whole structure simulation is performed by CST microwave studio as it is shown in figure.1. With all of the elements in good radiation condition the desired directivity pattern of the antenna has a gain of $21.4\ dBi$, a side lobe level of less than $-18.5\ dB$ and a voltage standing wave ratio equal to 1.2 at the design frequency.

Fault Generation And Pattern Deviations

In this work the maximum number of faulty elements is limited to two elements. In order to generate failure in one element, it supposed that the feed line of this element was distorted in a way that the element couldn't be fed by the directed serial feed lines. The corresponding E-plane patterns of the simulated antenna with two and one typically faulty elements are shown in figure.2. In the mentioned figure three cases are shown, one for the antenna with all elements in normal condition and the other ones for the antenna with 1 faulty element and 2 faulty elements. The corresponding VSWRs of the above cases are shown in figure.3. It can be seen evidently from the figures that element failure causes sharp variations in the side lobe level of the radiation pattern and the voltage standing wave ratio of the antenna. As it can be understood from the figures, effects of the elements failure can be more damaging with the increase in the number of faulty elements.

The Neural Network

MLP neural networks are generally multilayer feed forward neural networks. In this study a three layers MLP neural network is trained in the back propagation learning mode that uses the gradient decent optimization methods in the learning procedure, for readjusting the weights of the network from the below formula:

$$w_{ij}(t+1) = w_{ij}(t) - \eta \frac{\partial E}{\partial w_{ij}} \quad (1)$$

Where η is a constant called the learning rate, w is the connecting weight and E is the mean square error in the output layer. It is possible to use the *msereg* regularized performance function that is appropriate for the training procedure of the large training sets. This performance function could be defined by this formula:

$$msereg = \gamma \frac{1}{N} \sum_{i=1}^{N} (t_i - a_i)^2 + (1-\gamma) \frac{1}{n} \sum_{j=1}^{n} w_j^2 \quad (3)$$

Where γ, the performance ratio, is a user selected constant.

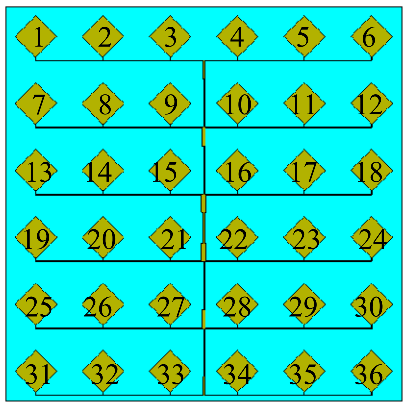

Figure 1. Layout of $\mathbf{6} \times \mathbf{6}$ element patch array for 16.46 GHz

Method Implementation And ANN Training

The neural network inputs are some samples of the $\phi = 90°$ cuts of the simulated radiation patterns of the antenna with failure in some randomly chosen elements. 667 different combinations of element failure, resulted from interrupting in the feed lines of the faulty elements, have been simulated by the CST microwave studio that contain cases with 2 faulty elements and 1 faulty element and the case in which the antenna has no faulty elements. All of the patterns are sampled in the [-90° , +90°] elevation angles using 5-degree steps and then are normalized along a preprocessing approach to construct the ANN input vectors. The neural network output has 2 elements. Analyzing the output of the neural network is as follows: If both elements have a value of zero it will be inferred that the array antenna has no faulty elements but if the output vector contains one nonzero element it can be concluded that the array antenna has one faulty element, finally when both of the output vector elements are nonzero it can be understood that the array antenna has two faulty elements. Also the amount of the nonzero elements of the output vector returns the location of the faulty elements in the array starting from the left top of the array antenna in figure.1.

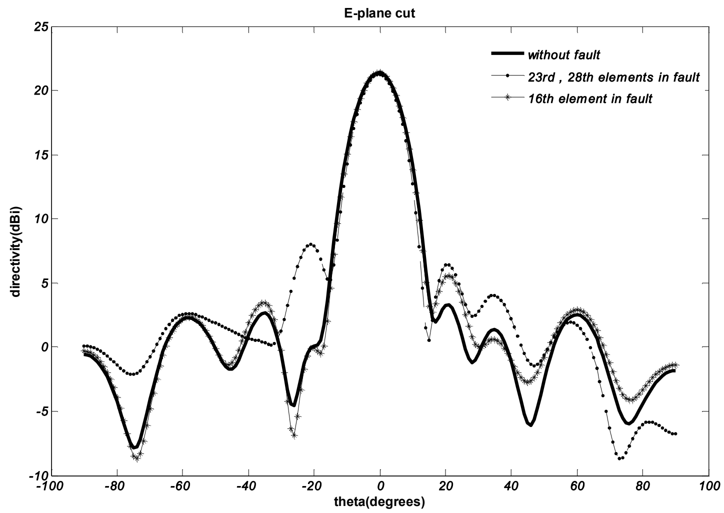

Figure 2. E-plane patterns of the array with 1 faulty element, 2 faulty elements and without any faulty elements

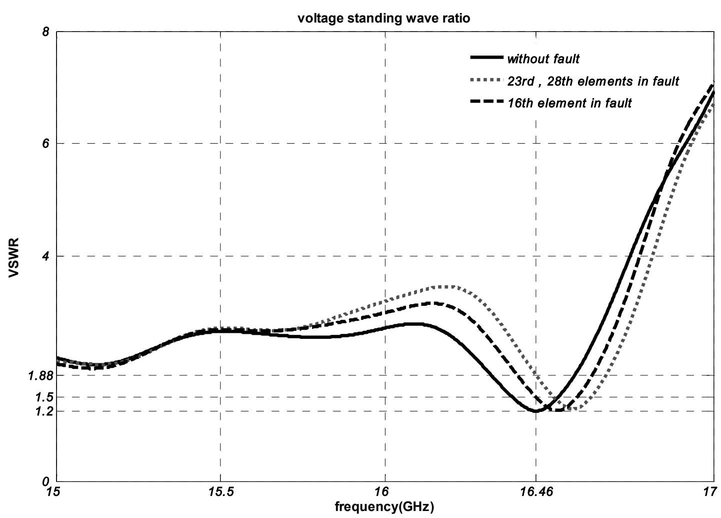

Figure 3. VSWRs of the array with 1 faulty element, 2 faulty elements and without any faulty elements

Fault Detection Using The Trained MLP

The trained neural network was tested for some randomly chosen fault cases. The training parameters and the success rate of the MLP neural network are shown in table1. In all of the tested cases the network has correctly detected the element failures. The results of the fault detection for some of the tested cases are shown in table2.

Conclusion

Locating the faulty elements of a microstrip planar array antenna with uniform excitation, using some samples of its degraded patterns is performed by the use of a three layer MLP neural network trained in the back propagation learning mode. In this work the results are based on the radiation patterns of a simulated 6 × 6 microstrip array antenna rather than a physically implemented antenna. The major difference between this work and the preceding works is in the consideration of mutual coupling effect as well as the radiated power of the so called faulty element due to the radiation fields of the normal elements.

Table1. Training parameters and the success rate of the MLP neural network

# input layer neurons	# hidden layer neurons	# output layer neurons	Performance function	Performance function goal	Learning rate	Success rate (%)
37	100	2	Msereg	1×10^{-6}	0.05	100

Table2. Results of the element failure detection by the MLP neural network for some of the randomly tested patterns

Faulty elements numbers		MLP neural network results		Faulty elements numbers after preprocessing	
12	18	0.3333	0.5001	12	18.003
21	22	0.5834	0.6111	21.001	22
23	28	0.6389	0.7777	22.9	27.9
16	__	0.4448	0.0003	16.011	0.01
30	__	0.8374	0.0043	30.147	0.155

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