A Method for Diagnosis of Current Faults in Antenna Arrays Using Neural Networks

D. Vakula, N. V. S. N. Sarma

Department of Electronics and Communication Engineering, National Institute of Technology, Warangal-506004, India

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ABSTRACT: A method for detection of faulty elements in antenna arrays from far-field radiation pattern is presented. The proposed technique finds variation of current from correct values in the faulty elements. A step wise approach is proposed to determine magnitude and phase of current excitation and location of faulty element using neural networks. The results with radial basis function neural network and probabilistic neural network are compared. © 2008 Wiley Periodicals, Inc. Int J RF and Microwave CAE 19: 270–276, 2009.

Keywords: far-field radiation pattern; current magnitude faults; current phase faults; artificial neural network and array factor

I. INTRODUCTION

In many real time applications it is required to have high-performance antenna array systems. To achieve this, the system must be monitored continuously. If any one or more of the elements in the array is not functioning properly due to failure of drive electronics, the antenna system will not function properly. The failure causes change in magnitude and phase of current fed to the antenna elements. Hence, a system is devised to detect the faults. The change in amplitude of the current in the antenna element is known as current magnitude faults. The change in phase of current is called current phase faults. Both these faults are defined as current faults. In the present article, a stepwise method is proposed to detect the location and change in current magnitude and phase of the faulty element.

The isolation of current magnitude fault is presented by Lee et al. [1] using built in transmission line signal injector embedded at radiating aperture. It is too expensive to use signal-injecting circuit at the design stage, in addition, size and weight are also increased. Bucci et al. have reported diagnosis of on-off faults in planar array from noisy far-field radiation pattern using global optimization technique [2]. Rodriguez et al. have used genetic algorithm to detect the faulty elements in small-size arrays [3]. But, the genetic algorithm has to be run several times to yield high accuracy for large size arrays. Bucci et al. diagnosed phase faults of planar arrays [4], but the current magnitude faults were not considered. Authors of the present article published a method to find error in current magnitude of faulty element if the location of the faulty element is known [5] and proposed a method to find error in current magnitude, phase, and location of single faulty element [6]. In the present article, an attempt is made to extend the concept to two faulty elements.

The presence of any aforementioned faults modify radiation pattern of the array which motivates to devise a method to diagnose faults. The proposed method detects the faults based on the change in the radiation pattern. Far-field radiation pattern can be measured without removing the array from its working site and without a serious interruption of its nor-

Correspondence to: D. Vakula; e-mail: dameravakula@yahoo.co.in

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mal operating conditions. For satellite-borne antennas and large earth-based antennas, it is convenient to detect faults by measurement of far-field radiation pattern. In this article artificial neural network (ANN) approach is adopted to identify the faults in the array due to ANN's built in flexibility, less computing time and robustness to noise. Initially, the ANN is trained with two thirds of all possible faulty patterns and is tested with remaining one third of the faulty patterns with predefined measurement errors. This method can be used for large earth-based antennas like atmospheric weather radar, astronomy radar, and satellite antenna arrays.

II. THEORY

In this section, equations for amplitude and phase of deviation pattern are derived for two cases.

a. Antenna array with single faulty element and
b. Array with two faulty elements

and in the next section, the description of ANNs adopted to detect the faults using the derived equations is given.

A. Array Factor for General Antenna Array Without Any Faults

A linear array of N number of isotropic elements uniformly distributed with spacing d along x-axis is considered as shown in Figure 1. The array factor $A(\theta)$ is given by [7]

$$A(\theta) = \sum_{n=1}^{N} a_n e^{j(n-\frac{N+1}{2})\phi} \tag{1}$$

where N, number of elements in the antenna array, $\phi = kd \sin\theta + \alpha$; $k = 2\pi/\lambda$ is propagation constant, α is phase shift introduced between successive elements, a_n is excitation coefficient, and θ is angle of observation from array normal.

For uniform excitation ($a_n = 1$) the normalized array factor $A_N(\theta)$ is given by

$$A_N(\theta) = \frac{1}{N}\sum_{n=1}^{N} e^{j(n-\frac{N+1}{2})\phi} \tag{2}$$

1. Derivation for Amplitude and Phase of Deviation Pattern of an Array with Single Faulty Element.

The array factor $A_r(\theta)$ for N element array

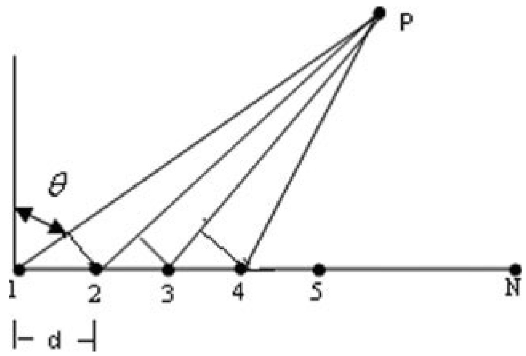

Figure 1. Linear antenna array.

with current magnitude in rth element as a_r and phase error as $\delta\phi_r$ can be obtained from eq. (2) as

$$A_r(\theta) = \frac{1}{N}\sum_{\substack{n=1\\ n\neq r}}^{N} e^{j\left(n-\frac{N+1}{2}\right)\phi} + \frac{a_r}{N} e^{j\left(r-\frac{N+1}{2}\right)\phi+\delta\phi_r} \tag{3}$$

The deviation pattern $A_d(\theta)$ of the array is defined as the difference between fault-free pattern and pattern with faulty element.

$$\begin{aligned} A_d(\theta) &= A_N(\theta) - A_r(\theta) \\ &= \frac{1}{N}\sum_{n=1}^{N} e^{j\left(n-\frac{N+1}{2}\right)\phi} - \frac{1}{N}\sum_{\substack{n=1\\ n\neq r}}^{N} e^{j\left(n-\frac{N+1}{2}\right)\phi} \\ &\quad - \frac{a_r}{N} e^{j\left(r-\frac{N+1}{2}\right)\phi+\delta\phi_r} \\ &= \frac{1}{N} e^{j\left(r-\frac{N+1}{2}\right)\phi} - \frac{a_r}{N} e^{j\left(r-\frac{N+1}{2}\right)\phi+\delta\phi_r} \\ &= \frac{1}{N}[\cos\phi_r + j\sin\phi_r - a_r\cos(\phi_r+\delta\phi_r) \\ &\quad - ja_r\sin(\phi_r+\delta\phi_r)] \\ &= \frac{1}{N}[\cos\phi_r - a_r\cos(\phi_r+\delta\phi_r) \\ &\quad + j(\sin\phi_r - a_r\sin(\phi_r+\delta\phi_r))] \end{aligned} \tag{4}$$

where

$$\phi_r = \left(r - \frac{N+1}{2}\right)\phi$$

$$A_d(\theta) = B_r(\theta)\angle\xi_r(\theta)$$

where amplitude of deviation pattern is

$$B_r(\theta) = \frac{1}{N}\left[1 + a_r{}^2 - 2a_r\cos\delta\phi_r\right]^{1/2} \tag{5}$$

Phase of deviation pattern is

$$\xi_r(\theta) = \sin^{-1}\left[\frac{\sin\phi_r - a_r\sin(\phi_r+\delta\phi_r)}{NB_r(\theta)}\right] \tag{6}$$

The phase of the deviation pattern along the normal to the array can be obtained by substituting $\theta = 0$ in (6) and is given by

$$\xi_r(0) = \sin^{-1}\left[\frac{-a_r \sin \delta\phi_r}{NB_r(0)}\right] \tag{7}$$

From the eq. (5) it is evident that amplitude of deviation pattern is independent of angle of observation and location of faulty element. Further, it is clearly understood from eq. (7) that the phase of deviation pattern at zero angle of observation is independent of location of faulty element. The derived eqs. (5) and (7) are used in calculating the magnitude and phase errors of current in faulty element.

2. Derivation for Amplitude and Phase of the Deviation Pattern of an Array with Two Faulty Elements. The array factor $A_{rs}(\theta)$ with two faulty elements is obtained from eq. (2) as given by

$$A_{rs}(\theta) = \frac{1}{N}\sum_{\substack{n=1\\ n\neq r\\ n\neq s}}^{N} e^{j\left(n-\frac{N+1}{2}\right)\phi} + \frac{a_r}{N}e^{j\left(r-\frac{N+1}{2}\right)\phi+\delta\phi_r} + \frac{a_s}{N}e^{j\left(s-\frac{N+1}{2}\right)\phi+\delta\phi_s} \tag{8}$$

where a_r and $\delta\phi_r$ are magnitude and phase error of current in rth element and a_s and $\delta\phi_s$ are the magnitude and phase error of current in sth element

The deviation pattern $A_d(\theta)$ for this array is given by

$$\begin{aligned}A_d(\theta) &= A_N(\theta) - A_{rs}(\theta)\\ &= \frac{1}{N}\sum_{n=1}^{N} e^{j\left(n-\frac{N+1}{2}\right)\phi} - \frac{1}{N}\sum_{\substack{n=1\\ n\neq r,s}}^{N} e^{j\left(n-\frac{N+1}{2}\right)\phi}\\ &\quad - \frac{a_r}{N}e^{j\left(r-\frac{N+1}{2}\right)\phi+\delta\phi_r} - \frac{a_s}{N}e^{j\left(s-\frac{N+1}{2}\right)\phi+\delta\phi_s}\\ &= \frac{1}{N}e^{j\left(r-\frac{N+1}{2}\right)\phi} + \frac{1}{N}e^{j\left(s-\frac{N+1}{2}\right)\phi}\\ &\quad - \frac{a_r}{N}e^{j\left(r-\frac{N+1}{2}\right)\phi+\delta\phi_r} - \frac{a_s}{N}e^{j\left(s-\frac{N+1}{2}\right)\phi+\delta\phi_s}\\ &= \frac{1}{N}\begin{bmatrix}\cos\ \phi_r + j\sin\ \phi_r + \cos\ \phi_s + j\sin\ \phi_s\\ -a_r\cos(\phi_r+\delta\phi_r) - ja_r\ \sin(\phi_r+\delta\phi_r)\\ -a_s\cos(\phi_s+\delta\phi_s) - ja_s\ \sin(\phi_s+\delta\phi_s)\end{bmatrix}\end{aligned} \tag{9}$$

where

$$\phi_r = \left(r - \frac{N+1}{2}\right)\phi, \quad \phi_s = \left(s - \frac{N+1}{2}\right)\phi,$$
$$A_d(\theta) = B_{rs}(\theta)\angle\xi_{rs}(\theta) \tag{10}$$

where

$$B_{rs}(\theta) = \frac{1}{N}\begin{bmatrix}2 + a_r^2 + a_s^2 - 2a_r\ \cos\ \delta\phi_r\\ -2a_s\ \cos\ \delta\phi_s + 2\cos(\phi_r - \phi_s)\\ -2a_s\ \cos(\phi_r - \phi_s - \delta\phi_s)\\ -2a_r\ \cos(\phi_s - \phi_r - \delta\phi_r)\\ +2a_r a_s\ \cos(\delta\phi_r - \delta\phi_s)\end{bmatrix}^{1/2} \tag{11}$$

is the amplitude of deviation pattern for the two faulty elements case and

$$\xi_{rs}(\theta) = \sin^{-1}\left[\frac{\sin\phi_r + \sin\phi_s - a_r\sin(\phi_r+\delta\phi_r) - a_s\sin(\phi_s+\delta\phi_s)}{N\times B_{rs}(\theta)}\right] \tag{12}$$

is the phase of the deviation pattern.

From eq. (11) it is understood that amplitude of the deviation pattern is same if distance between two faulty elements is same.

The amplitude and phase for this case at zero angle of observation are given by

$$B_{rs}(0) = \frac{1}{N}[4 + a_r^2 + a_s^2 - 4a_r\ \cos\ \delta\phi_r - 4a_s\ \cos\ \delta\phi_s + 2a_r a_s\ \cos(\delta\phi_r - \delta\phi_s)]^{1/2} \tag{13}$$

$$\xi_{rs}(0) = \sin^{-1}\left[\frac{-a_r\sin\ \delta\phi_r - a_s\sin\ \delta\phi_s}{N\times B_{rs}(0)}\right] \tag{14}$$

From eqs. (13) and (14) it is apparent that both the quantities are independent of location of faulty elements. The eqs. (13) and (14) are used to find magnitude and error in phase of current in faulty elements for the array with two faults. Further eq. (11) is used to determine the distance between faulty element locations. Finally, to account for the noise and measurement errors a random variable is introduced.

III. ARTIFICIAL NEURAL NETWORKS

Artificial neural network (ANN), a set of inter linked nodes, is mainly used for classification and approximation of unknown function. Different architectures like feed forward back propagation neural networks, radial basis function neural networks (RBF), and probabilistic neural networks (PNN) are used for classification and implemented with different algorithms. Among these three architectures RBF and

TABLE I. Parameters of the Array

Serial No	Parameter	Value	Value
1	No. of isotropic elements	51	101
2	Distance between successive elements	$\lambda/2$	$\lambda/2$
3	Excitation	1 Amp	1 Amp
4	No. of samples of radiation pattern between angles 0 and 90 degrees	16	16
5	Error in current magnitude considered	60%, 70%, 80%, 90%, 110%, 120%, 130%, 140% of 1 Amp	60%,70%,80%,90%,110%, 120%,130%,140% of 1 Amp
6	Error in phase	−20, −15, −10, −5, 5, 10, 15, 20 degrees	−20, −15, −10, −5, 5, 10, 15, 20 degrees
7	No. of possible faulty patterns for one faulty element	51 × 8 × 8	101 × 8 × 8 combinations
8	No. of possible faulty patterns for two faulty elements	1275 × 64 × 64	5050 × 64 × 64 combinations
9	% Measurement error considered (±)	0,3,6	0,3,6

PNN are faster, do not suffer from problems such as local minima, require less number of examples to train, more accurate, and can tolerate measurement errors.

The problem of detecting faults in the two cases mentioned earlier is dealt with ANNs. Two types of ANNs are used to for this purpose and comparison is made on their performance.

A. Radial Basis Function

Radial basis function (RBF) network is a nonlinear, layered, and feed forward network. It consists of three layers, namely, input layer, hidden layer and output layer. The input layer consists of source nodes. The second layer, called a hidden layer, is of high enough dimension. The output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input space to the hidden space is nonlinear and that from hidden space to the output space is linear. Each hidden node evaluates a kernel function of the incoming input. The classifier output is a weighted linear summation of the kernel functions. The error function of the classifier is given by [8] and is to be minimized during learning.

$$E = \sum_{x \in X} \sum_{i=1}^{M} (d_i(x) - y_i(x))^2 \qquad (15)$$

where X is the set of all training samples, M is the number of classes of the training samples, d_i is the desired response, and y_i is the actual response.

This RBF is utilized in this article to determine the location of faulty element or elements.

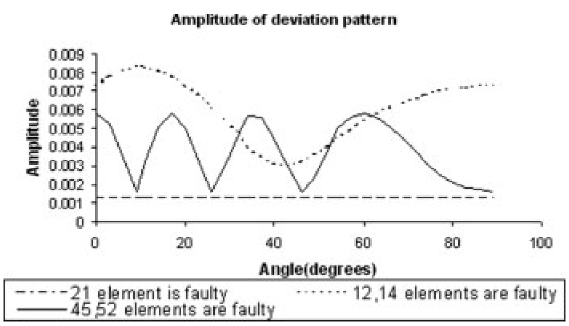

Figure 2. Amplitude of deviation pattern for the array with 101 elements.

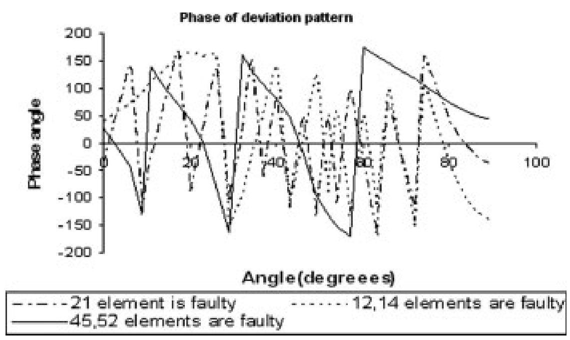

Figure 3. Phase of deviation pattern for the array with 101 elements.

TABLE II. Comparison of Deviation Pattern with Derived Equations for 101-Elements Array

Location of Faulty Elements	Magnitude of Current (Amp)	Phase of Current (degrees)	Magnitude of Deviation Pattern at $\theta = 0$ (Amp) From Figure 1	Magnitude of Deviation Pattern at $\theta = 0$ (Amp) From eq. (5) or (13)	Phase of Deviation Pattern at $\theta = 0$ (degrees) From Figure 2	Phase of Deviation Pattern at $\theta = 0$ (degrees) From eq. (7) or (14)
21	0.9	−5	0.0013	0.0013	−37.2	−36.68
12, 14	0.6, 0.9	−15, −20	0.0073	0.0073	38.87	38.91
45, 52	0.7, 0.8	−15, −5	0.0058	0.0058	25.5	25.36

B. Probabilistic Neural Network

The probabilistic neural network (PNN) is basically a classifier. The general classification problem is to determine the class membership of a multivariate random vector ***X*** into one of N possible groups where $N = n1, n2 \ldots n_m$. With the knowledge of probability density functions (PDF), hn(X), for all groups, X can be classified according to the Bayes optimal decision rule. X is classified into population i if the following inequality holds,

$$p_i c_i h_i(X) > p_j c_j h_j(X) \qquad (16)$$

where, p, is prior probability of membership in a group n; and c, is cost of misclassification into group n.

The common density estimator to estimate a univariate PDF from a random sample is given by

$$d(x) = \frac{1}{(2\pi)^{r/2}\sigma^r n} \sum_{i=1}^{n} e^{-\frac{|x-x_i|^2}{2\sigma^2}} \qquad (17)$$

The scaling parameter, σ, defines the width of the area of influence and should decrease as the sample size increases. Equation (17) is the foundation of the original PNN proposed by Specht [9].

PNN architecture consists of four layers, namely, input layer, pattern layer, summation layer, and output layer. The neurons in the input layer distribute the inputs to the pattern units. Each pattern neuron computes a distance measure between the input and the training case represented by that neuron. The summation layer has one neuron for each class. Each summation neuron that is dedicated to a single class sums the pattern layer neurons corresponding to numbers of that summation neuron's class [9]. The number of nodes in pattern layer is equal to number of input nodes and number of nodes in summation layer is equal to number of classes.

This PNN-based ANN is also used to find the location of faulty elements.

TABLE III. Parameters of RBF Artificial Neural Network

Parameter	ANN1	ANN2	ANN3
Number of input nodes	16	16	16
Number of hidden nodes	16	16	16
Number of output nodes	1	1	1
Number of training patterns	101	Equal to difference between faulty locations	Equal to difference between faulty locations

C. Method Adopted for Detection of Faults Using ANNs

To solve the problem of detecting the faults, three ANNs are used.

One is (ANN1): To locate the faulty element in single faulty element array.

Second one (ANN2): To find the distance between the faulty elements in two faulty elements array, and Third one (ANN3): To identify the location of two faulty elements.

The fault diagnosis of antenna array is done by following a step-wise approach as the combinations of faults that can occur in an antenna array are many. The steps are listed below.

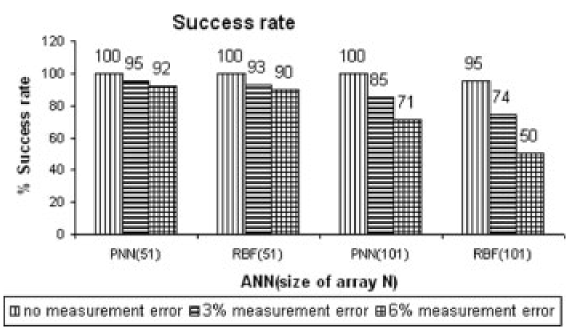

Figure 4. Success rate of fault diagnosis for 51, 101 element array using PNN and RBF networks.

TABLE IV. Test Results for 101-Element Array When a Single Faulty Element Exists for PNN Network with 6% Measurement Error

Actual Failures			Results from the Method		
Location of Faulty Elements	Magnitude of Current (Amp)	Phase of Current (degrees)	Location of Faulty Elements	Magnitude of Current (Amp)	Phase of Current (degrees)
r	a_r	$\delta\phi_r$	r	a_r	$\delta\phi_r$
10	0.6	−10	10	0.6	−10
41	0.8	−15	41	0.8	−15
55	1.2	5	55	1.2	5
66	0.9	10	66	0.9	10
75	1.2	20	75	1.2	20

Step I: Classifying the number of faulty elements (single faulty element array or two faulty elements array).

Single faulty or two faulty elements array is classified based on the amplitude of deviation pattern. If amplitude of deviation pattern is invariant with angle of observation, the array is classified as array with single faulty element otherwise it is classified as array with two faulty elements.

Step II (a): To find the magnitude, phase of current and location of single fault element. The error in excitation is determined with the help of eq. (5) and (7). Based on eq. (6), ANN1 is trained with phase of deviation pattern to identify the location of faulty element.

Step II (b): The error in excitation is determined using eqs. (13) and (14).

The distance between the faulty locations is determined by training ANN2 with amplitude of deviation pattern. ANN3 is trained with phase of deviation pattern to find location of faulty elements.

IV. RESULTS AND DISCUSSIONS

The method described in the earlier sections is implemented for two cases: one is array with 51 elements and other one is with 101 elements assuming that there exists either single or two faulty elements. The spacing between elements is taken as $\lambda/2$ and all the elements are isotropic, excited with current of magnitude 1 Amp.

As the deviation pattern plays an important role in diagnosing the faults in antenna arrays, it requires large numbers of samples to describe the deviation pattern correctly. This dictates a large number of input nodes for the neural network. As large neural network is hard to implement and needs a lot of time for training, the number of input nodes to ANN is to be minimized. An appropriate method is used to minimize the numbers of input nodes in a given ANN to improve the efficiency.

All possible faulty patterns for single and two faulty elements in the array are divided into two sets: training set and test set. The selection of an adequate set of patterns to train a neural network is very important. The neural network has to be trained with a set of input output data pairs. The training will be stopped if any one of the following conditions is satisfied: maximum number of epochs, maximum time, and minimum performance error. The test set is chosen randomly to test the ANN by introducing three possible errors: no measurement error, ±3%

TABLE V. Test Results for 101-Element Array When Two Faulty Elements Exists For PNN Network with 6% Measurement Error

Actual Failures						Results from the Method					
Location of Faulty Elements		Magnitude of Current (Amp)		Phase of Current (degrees)		Location of Faulty Elements		Magnitude of Current (Amp)		Phase of Current (degrees)	
r	s	a_r	a_s	$\delta\phi_r$	$\delta\phi_s$	r	s	a_r	a_s	$\delta\phi_r$	$\delta\phi_s$
31	27	1.1	0.9	−10	10	31	27	1.1	0.9	−10	10
31	56	0.8	0.7	15	5	31	56	0.8	0.7	15	5
28	86	0.7	1.2	−20	−10	28	86	0.7	1.2	−20	−10
75	96	0.8	0.9	10	5	75	96	0.8	0.9	10	5
45	55	1.2	1.4	−15	20	45	55	1.2	1.4	−15	20

and ±6% measurement errors. Table I lists the various parameters considered as inputs for the ANN.

Using the parameters listed in Table I, the deviation pattern is determined. Figures 2 and 3 show the amplitude and phase of deviation pattern of an array with 101 elements for specific faults.

It is observed from Figure 2 that amplitude of deviation pattern is constant with angle of observation for single element faulty array. Comparison of amplitude and phase of deviation pattern depicted in Figures 2 and 3 with values obtained from derived equations at zero angle of observation are given in Table II. Deviation pattern is sampled uniformly at 16 points between angles 0° and 90° which are used as inputs to the neural network for training.

Table III lists the parameters of neural network based on RBF. Two different ANNs are used for fault diagnosis one is RBF and the other one is PNN. The performance of these two networks in the form of success rate for 51 and 101 elements array is compared in Figure 4. One hundred and one-elements array using PNN network with 6% measurement error are tabulated in Tables IV and V.

V. CONCLUSIONS

RBF- and PNN-based neural network models are applied to diagnose current faults of an antenna array. The neural network can be trained off line for any number of elements, spacing, and excitation. Once the network is trained, it can detect location and current magnitude and phase of faulty element in the antenna array. A high success rate demonstrates the validity of the proposed technique.

REFERENCES

1. K.M. Lee, R.S. Chu, and S.C. Liu, A built-in performance monitoring/fault isolation and correction (PM/FIC) system for active phased array antennas, IEEE AP-International Symposium 1993, AP-Digest, MI, USA, Jun 28–Jul 2, 1993, pp. 206–209.
2. O.M. Bucci, A. Capozzoli, and G. D'Elia, Diagnosis of array faults from far field amplitude—Only data, IEEE Trans Antennas Propag 48 (2000), 647–652.
3. J.A. Rodriguez, F. Ares, H. Palacios, and J. Vassal'lo, Finding defective elements in planar arrays using genetic algorithms, Progress in Electromagnetic Research, PIER29, 29, 2000, pp. 25–37.
4. O.M. Bucci, A. Capozzoli, and G. D'Elia, A method for the diagnosis of phase faults in array antennas from amplitude only field data, IEEE International Conference-2000, 4, USA, pp. 2238–2241.
5. N.V.S.N. Sarma and D. Vakula, Single fault detection of an array using neural networks, Antenna Measurement Techniques Association Meeting & Symposium (AMTA-2004) held at Stone Mountain, GA, USA, October 17–22, 2004, pp. 337–339.
6. D. Vakula and N.V.S.N. Sarma, A generalized method to diagnose faults in antenna arrays using neural networks, Antenna Measurement Techniques Association Meeting & Symposium (AMTA-2006) held at Austin, TX, USA, October 22–27, 2006, pp. 290–292.
7. J. Ronen and R.H. Clarke, Monitoring techniques for phased array antennas, IEEE Trans Antennas Propagation AP-44 (1985), 1313–1327.
8. A. Patnaik and R.K. Mishra, ANN techniques in microwave engineering, IEEE Microwave Magazine, 1 March 2000, pp. 55–60.
9. D.F Specht, Probabilistic Neural Networks, Neural Networks 3 (1990), 109–118.

BIOGRAPHIES

Damera Vakula obtained her Bachelors degree in Electronics and Communications Engineering from Nagarjuna University, AP, India, and Masters degree from BIT Mesra, India, with Microwave Engineering as specialization in 1992 and 1994, respectively. She has more than 10 years of experience in teaching at various organizations. Currently, she is with the Department of Electronics and Communication Engineering as Lecturer at National Institute of Technology, Warangal, India. Her areas of interest include microwave engineering, phased array antennas, and neural networks. Presently, she is working on fault diagnosis of antenna arrays toward obtaining her doctoral degree.

N. V. S. N. Sarma obtained his Bachelors degree in Engineering with specialization Electronics and Communications Engineering from College of Engineering, Kakinada, Jawahar Lal Nehru Technological University in the year 1984. His Masters and Doctoral degrees are from Indian Institute of Technology, Karagapur, India, in the years 1985 and 1992, respectively. He has been with the Department of Electronics and Communications Engineering at National Institute of Technology, Warangal, India, at various positions since 1990. Currently, he is heading the Department of ECE, NIT, Warangal. About 30 papers are at his credit in international and national journals and conferences. His areas of interest include numerical electromagnetics, fractal shaped microstrip antennas, adaptive antenna arrays, and fault diagnosis of phased antenna arrays.