Bacteria Foraging Optimization in Antenna Engineering: An Application to Array Fault Finding

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ABSTRACT: Finding fault elements in linear antenna arrays using bacteria foraging optimization (BFO) is presented. One of the better options of array diagnosis is to perform it by measuring the radiated field, because in this case, removal of the array from its working site is not required and thereby not interrupting its normal operation. This task of fault finding from far-field data is designed as an optimization problem where the difference between the far-field power pattern obtained for a given configuration of failed element(s) and the measured one is minimized w. r. t. the excitations of the array elements. This set of excitations on comparison with the excitations of the original array gives the idea of the fault position and their type, such as either complete fault or partial fault. BFO being relatively new to microwave community when compared with other soft-computing techniques, its performance was observed w. r. t. time of computation and convergence of the iterative process. Possibility of finding the faults from random sample points and use of minimum number of sample points for array fault finding are the novelties of the present work. Int J RF and Microwave CAE 23:141–148, 2013.

Keywords: antenna array; array fault finding; bacteria foraging optimization

I. INTRODUCTION

Diagnosis of faults in a large antenna array is one of the major problems in Antenna Engineering to tackle with. The reason for this is quite straightforward. First of all, in a large array, the possibility of having a fault may be due to fabrication defects or due to some other unforeseen reasons. Second, the fault in an array, that is, presence of antenna elements that are not contributing to radiation, either partly or fully, damages the radiation pattern, mostly in the form of increased side-lobe levels. The problem becomes more severe when the failed element(s) is/are close to the center of the array. Before placing the antenna array in its work place, it is normally tested for its performance. During this testing, the fault in the antenna array is usually located from its near-field measurements [1, 2]. But, the problem arises when the faults develop in the array after installation, and it is not possible to bring the antenna back to the laboratory for measurement. In an active antenna array, it is possible to control the excitations of the array elements remotely [3]. If the defects in the array can be accessed from the control station, then suitable compensation techniques can be applied to recover the pattern of the antenna by changing the excitations of the elements that are functioning properly [4–6]. This creates the need to locate the fault in an array based on its far-field measurement data.

Array fault finding methods using far-field data have been discussed in the literature [7–11]. Some of these methods are analytical approaches [7]. In addition to that, various soft-computing-based methods have also been used for this purpose because of the inherent advantages involved in applying these methods [8–11].

A critical look at soft-computing-based methods for array fault finding reveals that these methods are based on the fundamental principle that the array factor (AF) is related to the excitation coefficients by a discrete Fourier transform relationship. Accordingly, the diagnosis problem is equivalent to finding a function from the modules of its Fourier transform. This basically needs sampling of the

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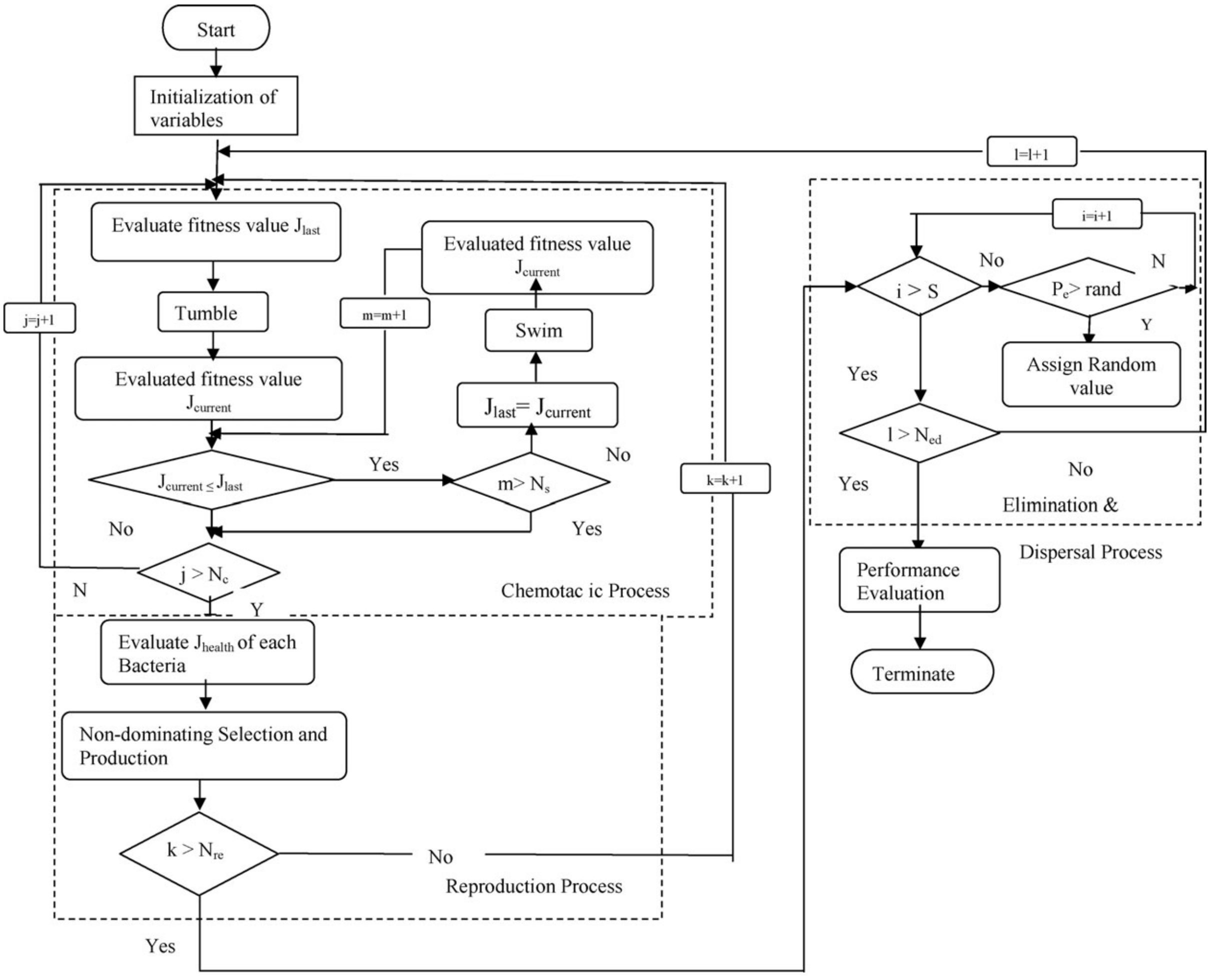

Figure 1 Flowchart for BFO.

function (far-field radiation pattern) at equidistant points. When the same problem is looked from a practical antenna scenario angle and more specifically from a faulty array point of view, it is not always possible to get a point with sufficient radiated power at equal distance intervals. In this article, we have shown the possibility of finding the fault from the far-field radiation pattern information at random points in addition to the implementation of the same problem with equidistant points. Instead of analytical approaches, bacteria foraging optimization (BFO) was used for the solution. BFO is a robust evolutionary computational technique and is relatively new to microwave community. In some cases, it outperforms other soft-computing techniques such as genetic algorithm (GA) [12–14] and particle swarm optimization (PSO) [15].

The rest of the article is organized in the following ways: Section II describes the formulation of the problem, followed by a brief description of the BFO algorithm in Section III. Implementation of the developed methodology for a typical case of fault finding is described in Section IV. A performance analysis of the BFO for different types of faults has been done in Section V, and finally, a conclusion has been drawn from the whole work.

II. PROBLEM FORMULATION

The AF of an N-element linear array, equally spaced, nonuniform amplitude, and progressive phase excitation is given by Ref. [16]

$$\mathrm{AF}(\theta) = \sum_{n=1}^{N} a_n e^{j(n-1)(kd\ \cos\theta+\beta)}, \tag{1}$$

where a_ns are the nonuniform amplitude excitation of elements. The spacing between the elements is d, and β is the progressive phase shift.

The patterns of the defected array were formed from Eq. (1) by making amplitude excitation equal to zero to represent a completely fault element and half of the original excitation to represent a partially fault element. Then, the following cost function was minimized using BFO w. r. t. the amplitude excitations of the array:

$$I = \sum_{k=1}^{M} [|\mathrm{AF}_d(\theta_k) - \mathrm{AF}_o(\theta_k)|]^2, \tag{2}$$

where M is the number of sample points on the pattern used for approximating the pattern of the array, AF_d is the

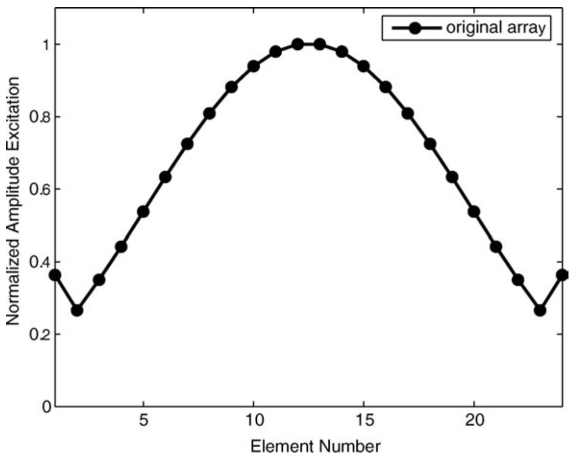

Figure 2 Amplitude distribution of the Chebyshev array without faults.

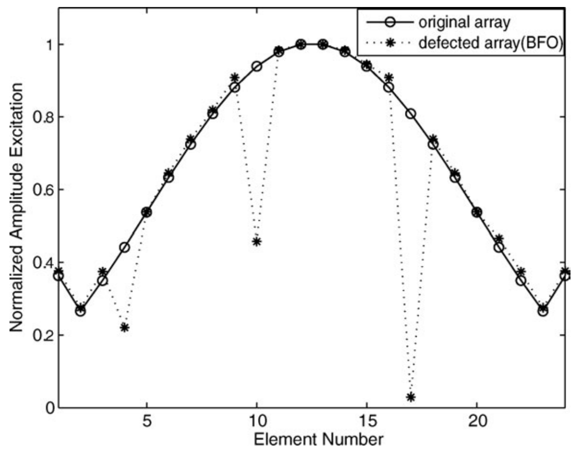

Figure 4 Performance of BFO with 35 sample points.

measured AF, $AF_o(\theta_k)$ is the instantaneous AF at kth sample point obtained from BFO during computation. Comparison of the excitation outputs from the optimizers with the excitations of the original array gives the idea of the position and nature of fault in the defected array.

III. BFO TECHNIQUE

Over the years, various soft-computing approaches have been gaining popularity among scientists in every branch of engineering [17]. Engineers are trying techniques such as neural networks, GA, PSO, BFO, and its variants for finding an easy solution of their problem. The robustness of these techniques has been tested in problems encompassing every engineering field. In this article, we have used BFO to find a solution for the problem of finding faults in antenna array from its far field. Although this optimizer has already been used in other fields, but, so far, its application is limited in Antenna Engineering [18–22]. For completeness of the article, here we have briefly described the BFO algorithm.

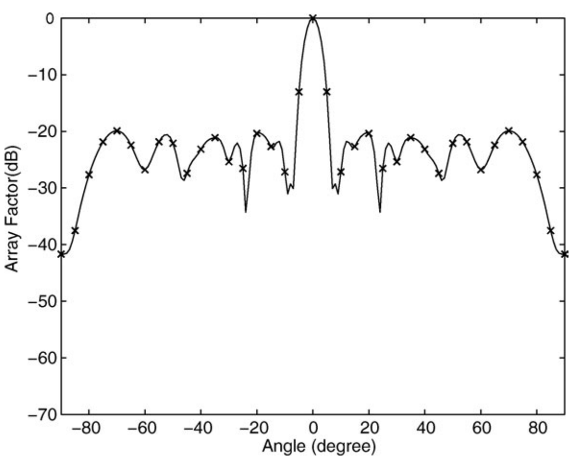

Figure 3 Defected array pattern with fault at fourth, 10th (50%), and 17th (100%) element with 35 sample points.

BFO technique was introduced by Passino [23] in 2002. It is a nongradient optimization problem that is inspired from the imitation of the food-ingesting (foraging) behavior of *Escherichia coli* bacteria, which are present in our intestines. In this method, a group of bacteria move in search of rich nutrient concentration and away from noxious elements such that they maximize their energy intake per unit time spend in foraging. The BFO proceeds by selecting or eliminating bacteria based on their foraging strategies. The natural selection tends to eliminate animals with poor foraging strategies and favor those having successful foraging strategies. After many generations, the poor foraging strategies are either eliminated or reshaped into the good ones. The foraging strategy is governed by four different steps that include chemotaxis, swarming, reproduction, and elimination–dispersion.

A. Chemotaxis

The movement of *E. coli* bacteria toward the nutrient-rich area is simulated by an activity called chemotaxis. This process is achieved by swimming and tumbling. In swimming, bacteria move in a predefined direction with fixed

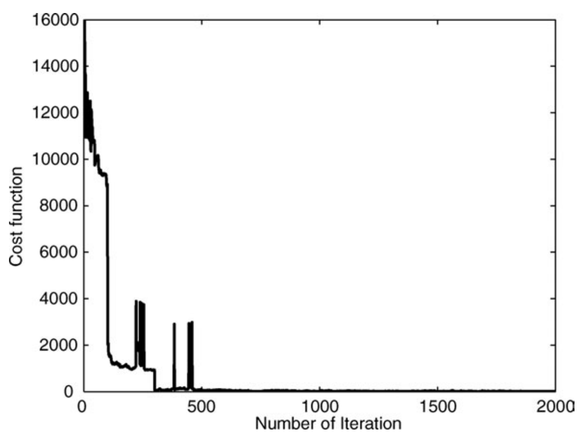

Figure 5 Error performance of BFO.

TABLE I BFO Parameters

Parameters	Values
Number of Bacteria (S)	30
Swimming length (N_s)	50
Number of chemotactic steps N_c ($N_c > N_s$)	100
Number of reproduction (N_{re})	10
Number of elimination−dispersal events (N_{ed})	2
Probability of elimination and dispersal (P_{ed})	0.25

swim length. In tumbling, the bacteria position themselves in some random direction in which swimming is performed. Hence, the modes of operation that a bacterium performs in its entire lifetime are that of running (swimming for a period of time), tumbling, or switching between running and tumbling. Suppose $\theta^i(j,k,l)$ represents the position of ith bacterium at jth chemotactic, kth reproductive, and lth elimination–dispersal step, the process of chemotaxis can be represented as:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\Phi(j), \tag{3}$$

where $\Phi(j)$ is the random unit vector that is used to define the direction of movement after a tumble. C is termed as ''run length unit.'' $C(i)$ is the size of the step in the direction specified by $\Phi(j)$. If at $\theta^i(j+1,k,l)$, the cost function is lower than that at $\theta^i(j,k,l)$, another step size $C(i)$ is taken in the same direction.

B. Swarming

It is group behavior or cell-to-cell signaling exhibited by bacteria while moving toward rich nutrient area. It is always desired that the bacterium that has searched the optimum path of food should try to attract other bacteria. This helps them propagate collectively as concentric patterns of swarms with high bacterial density while moving up in the nutrient gradient. Mathematically, swarming is modeled as:

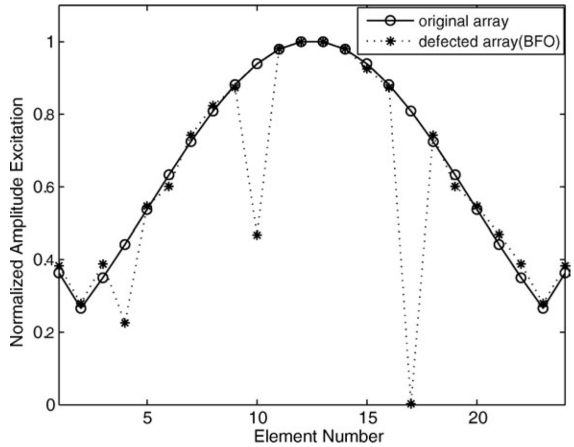

Figure 7 Performance of BFO with 18 sample points.

$$\begin{aligned} J_{cc}(\theta, P(j,k,l)) &= \sum_{i=1}^{S} J^i_{cc}\left(\theta, \theta^i(j,k,l)\right) \\ &= \sum_{i=1}^{S}\left[-d_{\text{attract}}\exp\left(-w_{\text{attract}}\sum_{m=1}^{p}\left(\theta_m-\theta^i_m\right)^2\right)\right] \\ &\quad + \sum_{i=1}^{S}\left[h_{\text{repellant}}\exp\left(-w_{\text{repellant}}\sum_{m=1}^{p}\left(\theta_m-\theta^i_m\right)^2\right)\right] \end{aligned} \tag{4}$$

where $J_{cc}(\theta,P(j,k,l))$ is the objective function value to be added to the actual cost function to make a time varying objective function. S is the total number of bacteria; p indicates number of design parameters to be optimized. $\theta = [\theta_1, \theta_2, \ldots, \theta_p]^T$ is a point in the p-dimensional search space. $\theta^i{}_m$ is the mth component of ith bacterium at position θ^i. d_{attract}, w_{attract}, $h_{\text{repellant}}$, and $w_{\text{repellant}}$ are the measure of quantity and diffusion rate of the attractant and repellant effect magnitude, respectively, and should be chosen carefully. $P(j,k,l) = \{\theta^i(j,k,l)|i = 1, 2, \ldots, S\}$ is the position of each bacterium in the population of S.

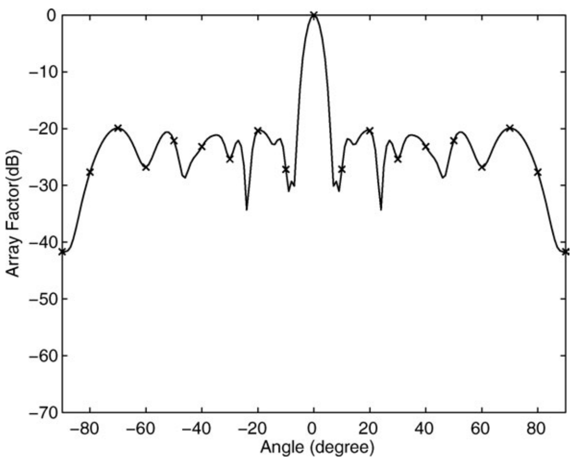

Figure 6 Defected array pattern with fault at fourth, 10th (50%), and 17th (100%) element with 18 sample points.

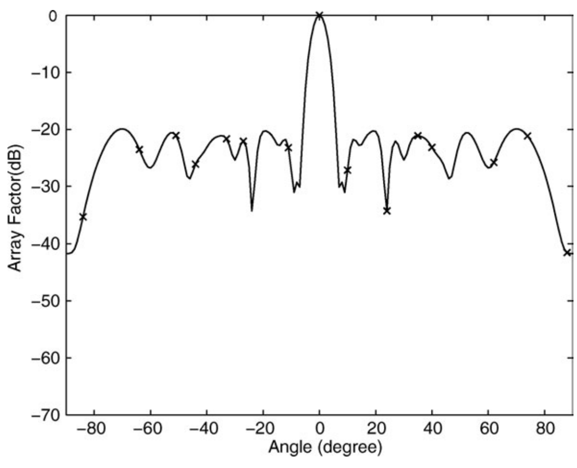

Figure 8 Defected array pattern with fault at fourth, 10th (50%), and 17th (100%) element with random sample points.

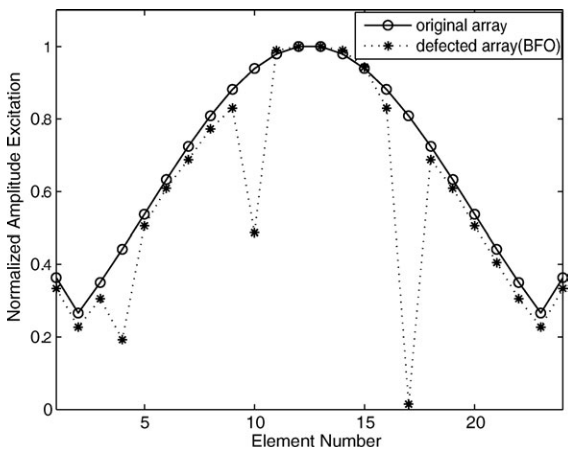

Figure 9 Performance of BFO with random sample points.

C. Reproduction

The fitness value for ith bacterium after traveling N_c chemotactic steps can be evaluated by

$$J^i_{\text{health}} = \sum_{j=1}^{N_c+1} J^i(j,k,l), \tag{5}$$

where J^i_{health} represents the health of the ith bacterium. The least healthy bacteria constituting half of the bacterial population are eliminated. The other healthy bacteria each split into two bacteria that are placed at the same location. As a result, the population size remains unchanged.

D. Elimination and Dispersal

In this event, bacteria in a region are eliminated or a group is dispersed into a random location due to the local environmental effect. This event changes the life of the bacteria either gradually by consumption of nutrients or suddenly due to some other effect. This event possibly destroys chemotactic progress but in contrast they also assist it, as dispersal may place bacteria near good food source. Elimination and dispersal help in reducing the behavior of stagnation (i.e., being trapped in a premature solution point or local optima). A flowchart for the BFO is shown in Figure 1.

IV. IMPLEMENTATION

A 24-element linear broadside Chebyshev array with $\lambda/2$ interelement spacing was taken as the candidate antenna to implement the developed procedure of fault finding using BFO. Standard analytical procedure [16] was applied to find the nonuniform amplitude excitations for a -30 dB side-lobe level in the Chebyshev array as shown in Figure 2. Random complete and partial faults were created by making their excitations either equal to zero or half of the original value, respectively. The cost function in Eq. (2) was then minimized using BFO w.r.t. the excitations of the elements. Different combinations of faults such as (i) single complete fault, (ii) more than one complete fault, and (iii) combination of partial and complete faults were investigated. Results for a typical case, viz., partial faults in fourth, 10th elements, and complete fault in 17th element, are illustrated in Figures 3 and 4. Figure

TABLE II Element Excitations Obtained with Different Sample Points

		18 Samples		35 Samples		Random Sample Points	
Element No.	Chebyshev Excitations	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
1	0.3636	0.3665	0.0302	0.3657	0.0154	0.3700	0.0153
2	0.2660	0.2698	0.0257	0.2602	0.0096	0.2621	0.0137
3	0.3507	0.3661	0.0185	0.3586	0.0115	0.3469	0.0168
4	**0.4422**	**0.2340**	**0.0134**	**0.2235**	**0.0105**	**0.2297**	**0.0138**
5	0.5357	0.5347	0.0213	0.5416	0.0121	0.5245	0.0136
6	0.6330	0.6347	0.0254	0.6321	0.0096	0.6375	0.0176
7	0.7248	0.7258	0.0149	0.7264	0.0126	0.7336	0.0116
8	0.8089	0.8085	0.0129	0.8063	0.0102	0.7960	0.0150
9	0.8815	0.8736	0.0168	0.8781	0.0070	0.8755	0.0115
10	**0.9393**	**0.4601**	**0.0164**	**0.4740**	**0.0132**	**0.4794**	**0.0097**
11	0.9794	0.9733	0.0172	0.9751	0.0058	0.9710	0.0126
12	1.0000	0.9983	0.0052	1.0000	0	1.0000	0
13	1.0000	0.9983	0.0052	1.0000	0	1.0000	0
14	0.9794	0.9733	0.0172	0.9751	0.0058	0.9710	0.0126
15	0.9393	0.9272	0.0186	0.9314	0.0098	0.9432	0.0134
16	0.8815	0.8736	0.0168	0.8781	0.0070	0.8755	0.0115
17	**0.8089**	**0.0149**	**0.0138**	**0.0165**	**0.0084**	**0.0221**	**0.0133**
18	0.7248	0.7258	0.0149	0.7264	0.0126	0.7336	0.0116
19	0.6330	0.6347	0.0254	0.6321	0.0096	0.6375	0.0176
20	0.5357	0.5347	0.0213	0.5416	0.0121	0.5245	0.0136
21	0.4422	0.4524	0.0299	0.4457	0.0166	0.4382	0.0207
22	0.3507	0.3561	0.0185	0.3586	0.0115	0.3469	0.0168
23	0.2660	0.2698	0.0257	0.2602	0.0096	0.2621	0.0137
24	0.3636	0.3665	0.0302	0.3657	0.0154	0.3700	0.0153

The bold values correspond to the excitation of failed elements.

TABLE III Time Analysis for Five Random Configuration of One Defective Element

Fault Positions	Time (s)			
	18 Samples		35 Samples	
1	107.54	Average time 107.09	199.73	Average time 204.56
2	111.21		204.84	
5	108.97		212.90	
10	103.22		202.50	
20	104.54		202.85	

TABLE V Time Analysis for Five Random Configuration of Three Defective Elements

Fault Positions	Time (s)			
	18 Samples		35 Samples	
5, 7, 12	142.72	Average time 152.92	226.89	Average time 248.06
1, 7, 13	155.22		270.45	
1, 9, 20	145.65		225.30	
12, 17, 24	152.30		219.65	
4, 21, 24	165.57		297.74	

3 shows the defected pattern with the position of 35 equidistant sample points. Figure 4 shows the comparison of amplitude excitations of the original array with the defected array obtained with BFO. From this comparison, the position and the nature of the faults can be clearly marked. Figure 5 shows the error minimization plots for the BFO optimizer. The optimizer was subjected to sufficient number of iterations, because kinks were observed in the error minimization plot for initial few iterations.

V. PERFORMANCE ANALYSIS OF BFO

In the process of optimization to locate the defective element position in a failed antenna array, the current amplitude of each antenna element was considered as the optimizing parameter for BFO algorithm. The parameters taken in the optimization process is shown in Table I. The optimizer converges to the correct solution, in the analysis done in the previous section with 35 sample points (samples taken in $-90° \leq \theta \leq 90°$ range in every 5°).

The process was then tested for the same typical fault situation by taking 50% of the sample points that were taken in the previous analysis. Figure 6 shows the position of the sample points. In this case, the optimizer was also able to provide successful results (Fig. 7). In the next attempt, we tried to locate the defects with an even smaller number of sample points, and in this process, it was observed that when the sample points were less than 12 in the range $-90° \leq \theta \leq 90°$, we were unable to find the location of the defective element in a single attempt. So, there was a reduction in the success rate when a sufficient number of sample points are not available.

In a bid to further explore the fault finding procedure, instead of taking equidistant points, we tried it with random selection of points. The sample points were taken ($\theta = -84°, -64°, -51°, -44°, -33°, -27°, -11°, 10°, 24°, 29°, 35°, 40°, 62°, 74°$, and 88°) as shown in Figure 8 for the same fault situation and the optimizer was put to work to locate the faults. In this case, the optimizer was also able to exactly locate the faults along with their type (Fig. 9). Table II shows the excitations obtained using the BFO for each of the above-described cases. Because different runs of BFO produce different outcomes, therefore, the mean and standard deviation of the excitation values obtained over a 30 separate runs are given in Table II. Comparison of the obtained excitations with that of the original array shows the level and position of the fault in the defected array. Then, a rigorous time of computation was made. The BFO was run to locate the faults for five random cases of different categories of fault situations and an average time was found out (Tables III–VI). It was further observed that the computation time increases with the number of failed elements. If the number of faults increases, then the problem becomes more difficult to handle and a large number of samples may provide a better result. In such case, the time required will be longer.

TABLE IV Time Analysis for Five Random Configuration of Two Defective Elements

Fault Positions	Time (s)			
	18 Samples		35 Samples	
5, 7	121.8	Average time 132.12	252.52	Average time 236.72
20, 23	120.25		235.17	
18, 20	137.65		236.24	
4, 21	138.00		226.74	
8, 12	142.94		232.96	

VI. CONCLUSIONS

The task of fault finding in antenna arrays was approached as an optimization problem and was solved using the BFO technique. This evolutionary computing method was used to find the amplitude excitations from the far-field pattern of the defected array that was then compared with the excitations of the original array to find the location and level of fault in the defected array. Partial as well as complete fault cases were considered and located successfully.

TABLE VI Time Analysis for Five Random Configuration of Combination of Complete and Partial Defective Elements

Fault Positions	Time (s)			
	18 Samples		35 Samples	
8, 12 (100%), 20 (50%)	133.15	Average time 150.27	229.14	Average time 260.16
13, 18 (50%), 24 (100%)	204.31		327.38	
11, 20 (100%), 15 (50%)	132.52		246.05	
1, 18 (100%), 2 (50%)	138.17		249.55	
4, 10 (50%), 17 (100%)	143.23		248.70	

Equidistant sample points as well as random sample points were tested for fault finding. BFO being a relatively new optimizer to microwave community, its performance was examined from convergence and time of computation point of view. Although a linear Chebyshev array was taken as the test antenna in this work, the same methodology can be extended for any type of array. Convergence of the optimizer for different types of fault situations confirms that this optimizer can be used on other antenna problems with many variables.

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BIOGRAPHIES

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