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Research Article

Evolutionary Algorithm-Inspired Binary Sequence-Based Hybrid Fault Detection Method for Nonuniformly Excited Linear Antenna Array

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In this article, a novel method of fault detection in nonuniformly excited linear antenna array has been reported. This method uses an evolutionary algorithm-based technique to generate approximate radiation pattern in tune with reference faulty pattern for a nonuniformly excited linear antenna array. Based on the approximation, a binary sequence-based method of exact fault detection has been developed. In order to illustrate the effectiveness of the method, 12- and 20-element Dolph Tschebyscheff linear antenna array with amplitude fault has been considered. Superiority of the proposed method has been demonstrated through comparative study.

1. Introduction

Faults in antenna arrays occur when one or more elements of the array partially or totally fail; i.e., it starts malfunctioning or just stops working. As a result, degradation of radiation characteristics of the antenna array takes place. Consequently, it is necessary to detect the number of faults and their exact locations in order to take corrective measures, so that the degraded radiation characteristics can be improved. In this regard, many researchers have proposed various methods to achieve fault detection in linear antenna array [1–32].

Lee et al. in [1] have demonstrated near-field probing data for 8×8 dipole array fault detection but found moderate accuracy in the method. In [2], Rahnamai et al. proposed a neural network-based array failure detection and isolation method. Later, to overcome the limitations in Lee et al.'s method, Bucci et al. in [3] developed a far-field power pattern-based method for identifying on-off faults in planar arrays. They used a modified genetic algorithm to find the optimal amplitude distribution, allowing for easy identification of faulty elements with minimal computational effort. Patnaik et al. employed an artificial neural network (ANN) to discover failures in a 5-element binomial array and a 16-element microstrip array in [4, 5], respectively, to reduce computational effort. It has been observed that the adoption of ANN improves the computational effort at the expense of a lengthy training period, resulting in a more modest approach of defect detection. Vakula and Sarma [6] also worked on understanding the type of fault in linear antenna array using neural networks. However, it was found out that neural network-based approaches have certain disadvantages, such as the fact that training requires numerous layers and input nodes, resulting in enormous computations and training time. Hence, Iglesias et al. [7] developed a case-based reasoning system for fault diagnosis in moderate and large linear antenna arrays, reducing computational cost while improving detection accuracy. Consequently, Rajagopalan et al. [8] developed a support vector machine-(SVM-) based fault detection method for antenna arrays, potentially replacing neural networks. They found that adding training sets improved outcomes and reduced errors, but high noise levels decreased accuracy. Further, Vakula and Sarma [9] conducted a comparative study on neural network-based methods, finding ANN is time-consuming but outperforms radial basis function (RBF) and probabilistic neural network (PNN) in locating faulty elements. In [10], Acharya et al. utilized bacterium foraging technique to optimize fault detection in linear antenna arrays, determining the optimum excitation amplitude for faulty far-field radiation patterns. Again in [11], Khan et al. showed the application of firefly algorithm (FF) in identifying fault in nonuniformly excited linear antenna array. In [12], a comparative study by Mishra et al. on fault finding in antenna arrays using neural networks and genetic algorithms found both methods computationally intensive. Harrou and Nounou in [13] proposed an exponentially weighted moving average control scheme for detecting faults in linear antenna arrays, including full faults and partial faults. Again, Muralidharan et al. [14] developed a fast Fourier transform- (FFT-) based method for detecting antenna array fault position and level from degraded far-field pattern samples. In [15], a modified version of the method using iterative fast Fourier transform (IFFT) has been reported by Yadav and Singh, whereas in [16], Puri V. and Puri S. have shown the application of particle swarm optimization (PSO) in detecting defective element in space borne planar array. Further, Zhu et al. proposed a signal-processing scheme for faulty phased arrays, utilizing beamforming, direction of arrival (DOA) estimation, and array diagnosis [17]. The method effectively detects array defects and is verified using numerical results. Harrou and Sun in [18, 19] proposed a generalized likelihood ratio (GLR) test-based statistical fault detection method for potential faults in linear antenna arrays. Khan et al. in [20] developed a hybrid method for fault detection in nonuniformly excited linear arrays, improving slow convergence of differential evolution- (DE-) based compressed sensing techniques. They also used the parallel coordinate decent algorithm (PCD) [21] for fault prediction in linear antenna arrays and the cuckoo search algorithm [22] for antenna array fault diagnosis. In [23], Chen and Tsai have proposed fault detection in planar antenna array using a statistical process control method called as cumulative sum scheme. In [24], Lee uses uniform linear array redundancy for reliable DOA estimation in sensor failures, using sparse array interpolation, sparse signal recovery, and penalized-weight alternating methods in computer simulations. Chen et al. in [25] developed a fault finding and location approach using two different complexity deep neural networks. The basic network detects faults at low cost, while the precise network locates problems. This reduces energy consumption and operation costs but requires slower systems. Toshev [26] simply presents X-band array approach for accurate localization of excitation errors in phased antennas at Fresnel distances. Later, Ameya and Kurokawa [27] reported another usage of neural networks in creating fault detection in planar antennas. The method employs a shallow neural network that has been trained to retain sufficient accuracy by learning the relationship between array antenna excitation coefficients and electric near-field distribution. Nielsen et al. [28] reported on the application of deep neural networks in generating remote diagnosis of antenna arrays used in satellite communication. Xiong et al. used compressed sensing to study defect detection in a beam-steered planar array [29]. Capability of simulated annealing-based fault detection in linear antenna has been reported by Boopalan et al. in [30]. Again in [31], Zainud-Deen et al. developed particle swarm optimization (PSO) algorithm for detecting and correcting failed elements in linear arrays, finding pattern deterioration more near the center, but with higher complexity. A comprehensive review of fault-finding algorithms for planar arrays has been carried out by Boopalan et al. in [32].

Existing fault detection methods related to neural networks take a huge amount of runtime, which was solved using evolutionary algorithm. But, it is also observed that evolutionary algorithm-based methods have some major limitations like lesser accuracy and higher computational complexity. To solve these problems, a method is reported in this article. Here, a hybrid method using differential evolution algorithm to approximate faulty far-field radiation patterns in linear arrays has been investigated. The later stage of the method calculates precise faulty patterns using binary sequencing of array elements. The effectiveness of the method has been illustrated using two design instances of 12- and 20- element Dolph Tschebyscheff linear antenna array with faults at random elements. Details of the proposed hybrid method in detecting faulty elements have been discussed in the later section. The simulation setup along with results has also been provided to prove the effectiveness of the method.

2. Proposed Method

The proposed method employs an evolutionary algorithm-based technique to create estimated excitation amplitude weights in tune with the reference faulty pattern for a nonuniformly excited linear antenna array. A threshold weight is determined using maximum value of semioptimized weights. Then, binary sequencing is used to determine whether the optimized weight is larger than the threshold weight, in which case the array state will be 1, otherwise 0. Another array factor is calculated and checked for error based on the newly generated array state. This step is repeated until the error is zero. Therefore, the exact location of defects can be detected by computing the quantity and position of 0 s in the final array state. The major steps of the proposed method are illustrated in Figure 1.

2.1. Evolutionary Algorithm-Based Pattern Approximation. The number of elements (N), interelement spacing (d), and beam steering angle (θ_s) are defined in step 1. In step 2, the evolutionary algorithm uses these design parameters to build an estimated radiation pattern of a nonuniformly excited array with a fault. In this article, differential evolution (DE) approach has been used as a representative algorithm. DE mainly consists of three steps, which are mutation, crossover, and selection. DE begins, like any other evolutionary algorithms, with a population of N D-dimensional search variable vectors. In a swarm of N particles in a D-dimensional search space, the i^{th} particle's position at iteration t is given by $x_i(t) = (x_i^1(t), x_i^2(t), \cdots, x_i^D(t))$. In each generation or iteration

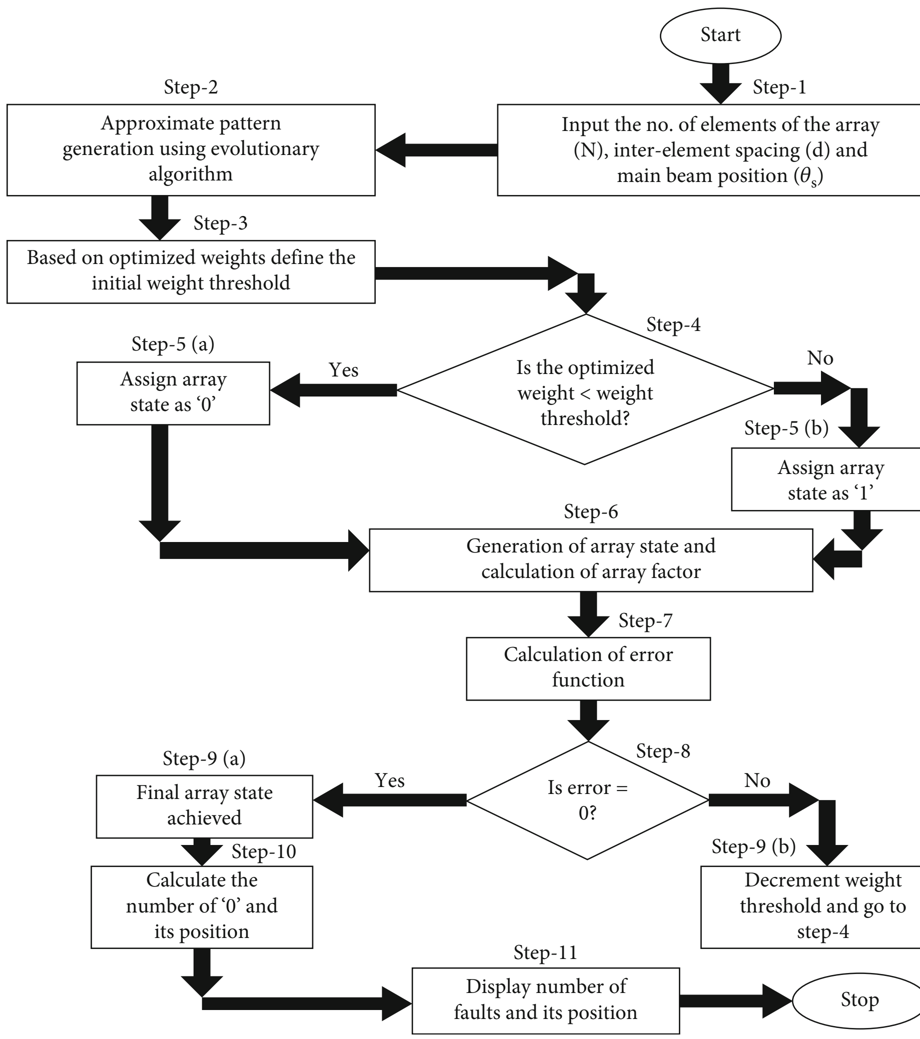

Figure 1: Major steps of the proposed method.

of the algorithm, a donor vector $v_i(t)$ is created to modify each population member $x_i(t)$. Three random parameter vectors ($r1$, $r2$, and $r3$) are chosen from the current population. A scalar number F scales the difference of any two vectors, adding the scaled difference to the third vector and subsequently creating the donor vector $v_i(t)$. The generation process expression is given by

$$v_i^{\mathrm{d}}(t+1) = x_{r1}^{\mathrm{d}}(t) + F.\left(x_{r2}^{\mathrm{d}}(t) - x_{r3}^{\mathrm{d}}(t)\right). \quad (1)$$

The mutation operator is given by

$$F = F_{\max}.e^{c.t}. \quad (2)$$

In (2), parameter c is represented as $c = \log 10(F_{\min}/F_{\max})/t$. A crossover technique is then used to expand the potential diversity of the population. Based on the crossover rate (CR), the donor vector exchanges its components to form a trial vector which is given by

$$u_i^{\mathrm{d}}(t) = v_i^{\mathrm{d}}(\mathrm{t}+1), \text{rand } (1) \le \mathrm{CR}, \quad (3)$$

$$u_i^{\mathrm{d}}(t) = v_i^{d}(\mathrm{t}), \text{rand } (1) > \mathrm{CR}. \quad (4)$$

The crossover rate is defined by (5) where T is the total number of iterations.

$$\mathrm{CR} = \mathrm{CR}_{\min} + (\mathrm{CR}_{\max} - \mathrm{CR}_{\min}).\left(\frac{t}{T}\right). \quad (5)$$

The algorithm creates an offspring vector $u_i(t)$ for each trial vector $x_i(t)$. To maintain population size, the next step involves selection to determine which of the target vector and the trial vector survives in the next generation which is mathematically given as (6) and (7). This is because DE involves the principle of "survival of the fittest" in its selection process.

$$x_i(t+1) = u_i(t) \text{ if } f(u_i(t)) < f(x_i(t)), \quad (6)$$

$$x_i(t+1) = x_i(t) \text{ if } f(x_i(t)) < f(u_i(t)). \quad (7)$$

Array factor used by DE for nonuniformly excited linear antenna array expression given by (8) has been used in the optimization process.

$$\mathrm{AF}(\theta)_{\text{faulty}} = \sum_{n=1}^{N} a_{\mathrm{n}} \times e^{j(n-1)\mathrm{kd}(\sin\theta - \sin\theta_s)}. \quad (8)$$

In (8), N is the number of array elements, a_{n} is the normalized excitation amplitude weight of the N^{th} array element which is zero for a faulty element and a nonzero value for a nonfaulty element, $k = 2\pi/\lambda$ is the wave number, d is the interelement spacing in terms of λ, θ is the angular position which varies from $-\pi/2$ to $+\pi/2$, and θ_s is the main beam position of the array. The fitness function used in the faulty pattern approximation is given by

$$\text{Fitness} = \sum_{i=1}^{M} \left| \mathrm{AF}(\theta_i)_{\text{ref}} - \mathrm{AF}(\theta_i)_{\text{Cal}} \right|. \quad (9)$$

In (9), M represents the number of samples between $\theta = -\pi/2$ and $\theta = \pi/2$, and $\mathrm{AF}(\theta_i)_{\text{ref}} = \mathrm{AF}(\theta_i)_{\text{faulty}}$ and $\mathrm{AF}(\theta_i)_{\text{Cal}}$ are the reference and calculated array factors of the linear antenna array under investigation. Further, normalized excitation weights (a'_n) of each array element have been considered as optimization parameters and take any value between "1" and "0."

2.2. Binary Sequence-Based Pattern Approximation. The threshold weight by using the maximum and minimum values of the optimized weights acquired in step 2 is defined in step 3. The threshold weight has been set in such a way that only a few execution stages are necessary to achieve the desired array state. Further, the array factor expression corresponding to a particular binary sequence representing an array element state can be represented by

$$\mathrm{AF}(\theta)_{\text{bin}} = \sum_{n=1}^{N} \mathrm{BN}(n) \times {a'}_n \times e^{j(n-1)\mathrm{kd}(\sin\theta - \sin\theta_s)}. \quad (10)$$

In (10), $\mathrm{BN}(n)$ and a'_n represent array state and the correct excitation weight of nth array element, respectively. The array state can either be 1 or 0 which in turns represents nonfaulty and faulty element, respectively. Comparison between the optimized excitation weight and threshold weight for each element has been carried out in step 4. If the optimum weight is less than threshold weight, then array state has been assigned "0"; otherwise, it has been assigned as "1." This process of assignment and array pattern calculation has been carried out in step 5 and step 6, respectively, using array factor expression of (10). Step 7 involves the calculation of error function using

$$\text{Error} = \text{sum}\left(\text{abs}\left(\mathrm{AF}(\theta)_{\text{faulty}} - \mathrm{AF}(\theta)_{\text{bin}}\right)\right). \quad (11)$$

Analysis of error function value has been carried out in step 8. Accordingly, in step 9(b), if error value has been found to be a nonzero value, then weight threshold has been decremented and process flow goes to step 4. However, zero value of the error function represents desired array state which corresponds to step 9(a). Subsequently, in step 10, numbers of "0" are identified along with their position using final array state. Finally, the results are displayed in step 11, showing number of faults and their respective positions in the array.

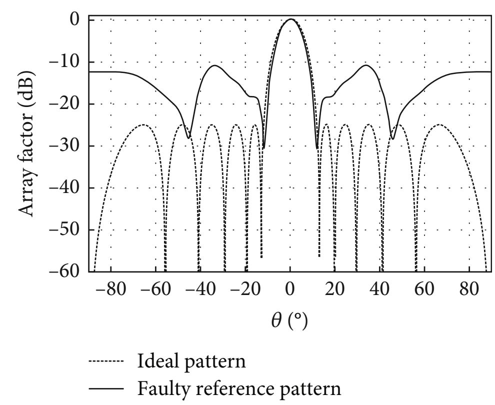

Figure 2: Comparison of ideal and faulty reference array factor of 12-element array.

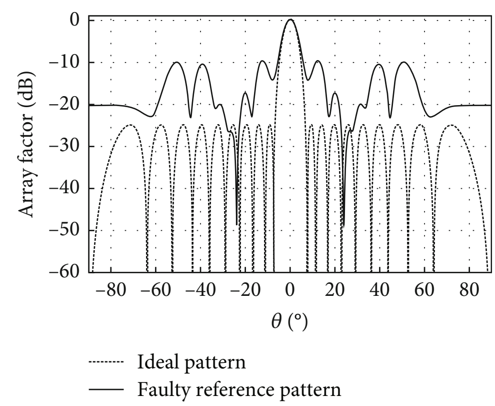

Figure 3: Comparison of ideal and faulty reference array factor of 20-element array.

3. Simulated Results

Effectiveness of the proposed method has been illustrated through fault detection in 12- and 20- element Dolph Chebyshev linear antenna array. It must be noted that choice of excitation distribution is representative only and can be used with any distribution like Taylor distribution. Interelement spacing (d) for each design instance has been kept at 0.5λ where λ is the operating wavelength. Such value of interelement spacing ensures that there are no grating lobes. Further, the array elements have been considered to be isotropic in nature. A 12-element array with fault at 3rd and 7th elements has been considered as the first case. Subsequently, a 20-element array with fault at 3rd, 5th, 6th, 13th, 15th, 16th, and 18th elements has been considered as the second case. Comparison between ideal and faulty reference far-field array pattern of these 12 and 20 elements has been illustrated in Figures 2 and 3, respectively.

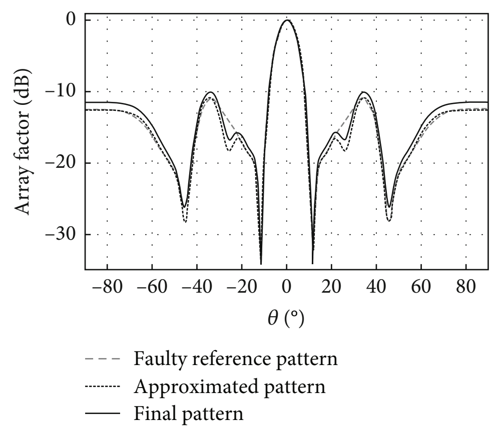

Figure 4: Comparison between reference, approximated, and final array factor of 12-element array.

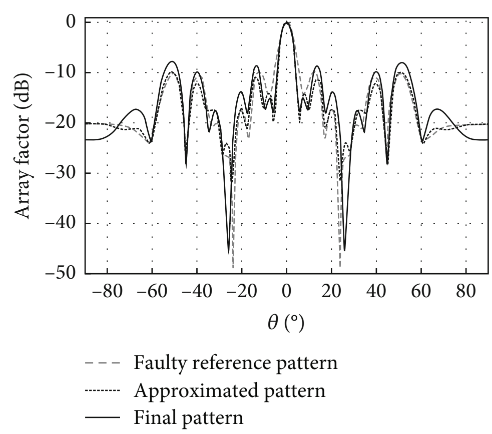

Figure 5: Comparison between reference, approximated, and final array factor of 20-element array.

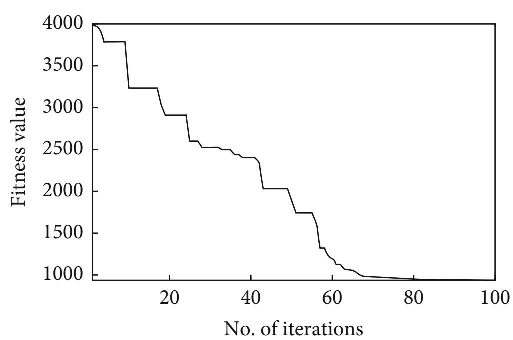

Figure 6: Fitness curve for approximated radiation pattern for 12-element array.

Comparison between reference, approximated, and final restored far-field array pattern for 12 and 20 elements has been illustrated in Figures 4 and 5, respectively.

Fitness curve corresponding to approximated array patterns using DE for 12 and 20 elements has been shown in Figures 6 and 7, respectively.

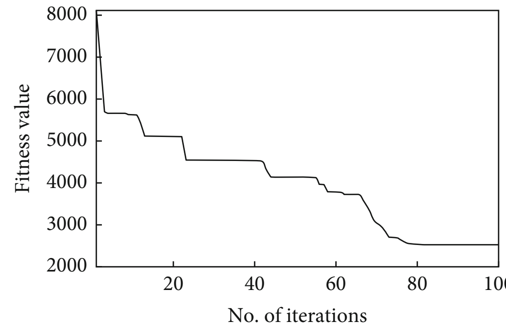

Figure 7: Fitness curve for approximated radiation pattern for 20-element array.

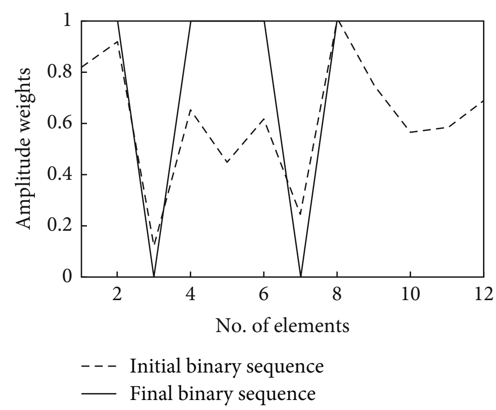

Figure 8: Comparison of initial and final binary sequence-based excitation weights for 12-element array.

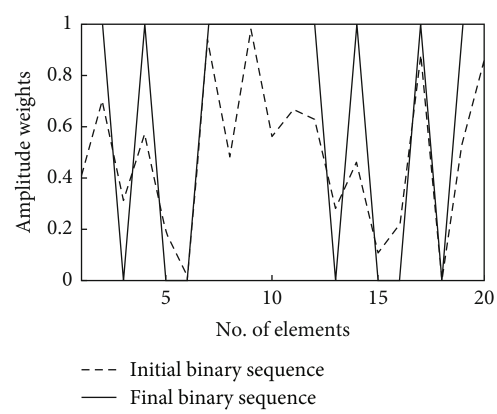

Figure 9: Comparison of initial and final binary sequence-based excitation weights for 20-element array.

Final excitation weights after using binary sequence method for 12 and 20 elements have been represented in Figures 8 and 9, respectively.

Form the illustrations, it has been observed that the proposed method can detect faults perfectly at the given random locations. Table 1 shows the comparative study of parametric setup between conventional DE and the method proposed in this article.

Table 1: Comparative parametric setup for DE algorithm.

Optimization method	Array size	Failure type	Run cycles required	Iterations required	Particles required
Differential evolution (DE) method	12 elements	3^{rd}, 7^{th}	10	1000	100
	20 elements	3^{rd}, 5^{th}, 6^{th}, 13^{th}, 15^{th}, 16^{th}, 18^{th}	10	1000	100
Hybrid method (proposed)	12 elements	3^{rd}, 7^{th}	1	100	10
	20 elements	3^{rd}, 5^{th}, 6^{th}, 13^{th}, 15^{th}, 16^{th}, 18^{th}	1	100	10

Table 2: Results of fault detection using different optimization algorithms.

Optimization method	Array size	Fault position	Run cycles required	Detection efficiency	Average processing time (s)
Differential evolution (DE) method	12 elements (design instance-I)	3^{rd}, 7^{th}	10	50%	594.03
	20 elements (design instance-II)	3^{rd}, 5^{th}, 6^{th}, 13^{th}, 15^{th}, 16^{th}, 18^{th}	10	71.4%	972.21
Hybrid method (proposed)	12 elements (design instance-I)	3^{rd}, 7^{th}	1	100%	4.53
	20 elements (design instance-II)	3^{rd}, 5^{th}, 6^{th}, 13^{th}, 15^{th}, 16^{th}, 18^{th}	1		28.92

Table 3: Summary of excitation amplitudes.

Design instance	Excitation weight using DE	Proposed method		
		Initial binary sequence	Final binary sequence	Final excitation weight
Design instance-I	0.992, 0.96, 0, 0.843, 0.746, 0.198, 0.98, 1.18, 0.499, 0.13, 0.71, 0.55	0.82, 0.92, 0.124, 0.65, 0.48, 0.62, 0.24, 1.01, 0.75, 0.56, 0.68, 0.72	1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1	1.49, 1.16, 0, 1.77, 1.985, 2.098, 0, 1.985, 1.77, 1.49, 1.16, 1.49
Design instance-II	1.01, 0.89, 0, 0.65, 0.297, 0, 1.338, 0.78, 1.08, 1.6, 0.56, 0.595, 0, 0.6, 0.134, 0, 0.85, 0, 0.156, 1.44	0.41, 0.7, 0.31, 0.57 0.19, 0.02, 0.934, 0.48, 0.98, 0.564, 0.67, 0.63, 0.28, 0.46, 0.11, 0.22 0.87, 0.05, 0.56, 0.86	1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1	1.265, 0.587, 0, 0.814, 0, 0, 1.098 1.163, 1.21, 1.23, 1.23, 1.21, 0, 1.098, 0, 0, 0.814, 0, 0.587, 1.265

The comparative results from using conventional differential evolution method as well as the hybrid optimization method for the 12-element and 20-element nonuniformly excited Dolph Tschebyscheff linear arrays are listed in Table 2. The processing time taken for each of the optimization methods is recorded as well for different types of failure in Table 2.

Table 3 summarizes the excitation weights obtained using DE algorithm and the proposed method. From Table 3, it has been observed that for the first design instance of 12-element nonuniformly excited linear array, DE has detected the fault at 3^{rd} element and fails to detect the fault at 7^{th} element which leads to detection efficiency of 50%. For the second design instance, DE has detected fault at 3^{rd}, 6^{th}, 13^{th}, 16^{th}, and 18^{th} element which accounts for detection efficiency of 74.2%. However, the proposed method has outperformed the DE-based method with 100% detection efficiency for both the design instances.

From Tables 1–3, it can be clearly observed that the hybrid method needs lesser run cycles, particles, and iterations to detect fault locations and that too with a better efficiency than conventional DE. It can also be observed that the processing time of the hybrid method is much lesser than the previous existing methods. Consequently, the proposed method can be used for fault detection in nonuniformly excited linear antenna array.

4. Conclusion

The present article proposes a binary sequence-based evolutionary algorithm-inspired approach of fault detection in a nonuniformly excited linear antenna array. To approximate the faulty radiation pattern, the differential evolution method was applied as a representative evolutionary algorithm. Following that, binary sequencing with optimized excitation weights was used to generate the final array pattern. The effectiveness of the proposed method has been demonstrated using a 2-element fault in a 12-element linear antenna array and a 7-element fault in a 20-element linear antenna array. The simulation results show that the method successfully detects flaws in both 12-element and 20-element linear antenna array of isotropic radiators using only $1/10^{th}$ number of run cycle, particles, and iterations compared to the previous approaches. This approach can also be expanded to include beam-steered linear antenna array and planar antenna array layouts as well.

Data Availability

Database is not publicly available. However, data will be made available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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