Hindawi
International Journal of Antennas and Propagation
Volume 2023, Article ID 7735267, 10 pages
https://doi.org/10.1155/2023/7735267

Research Article

Synthesis of Thinned Planar Concentric Circular Antenna Arrays Using a Modified Artificial Bee Colony Algorithm

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Received 14 December 2021; Revised 6 March 2022; Accepted 11 May 2022; Published 22 July 2023

Academic Editor: Stefano Selleri

The artificial bee colony (ABC) algorithm is a biomimetic optimization algorithm based on the intelligent foraging behavior of a bee colony. It has obvious advantages in dealing with complex nonlinear optimization problems. However, the random neighborhood search leads to the ABC algorithm being good at exploration but neglected in exploitation. Therefore, a modified artificial bee colony algorithm (MABC) is proposed in this paper. The modified artificial bee colony algorithm is applied to the thinned optimization of large multiple concentric circular antenna arrays. The aim is to make the thinned array obtain the narrow beam pattern with the best peak sidelobe level (PSLL) in the vertical plane. The elements in the concentric circular antenna arrays are uniformly excited and isotropic. Two different cases have been considered in this study for thinning of concentric circular antenna arrays using MABC, one with fixed uniform interelement spacing and another with optimum uniform interelement spacing. In both the cases, the thinning percentage of the array is kept equal to or more than 50%. Simulation results of the proposed thinned arrays are compared with a fully populated array to illustrate the effectiveness of our proposed method.

1. Introduction

In the array antenna, an array composed of a group of array elements arranged on a ring at equal intervals is called a circular array. It is a very practical array configuration. Compared with other array antennas, a circular array antenna has many advantages, such as all-azimuth scan capability, flexible beam, and invariant beam pattern in every φ-cut. Moreover, circular antenna arrays are less sensitive to mutual coupling as compared with linear and rectangular arrays since these do not have edge elements. They are widely used in sonar, radar, mobile, and commercial satellite communication systems. They can be used for beam forming in the azimuth plane, for example, at the base stations of the mobile radio communication system [1, 2]. The concentric circular antenna array (CCAA) is a planar array antenna composed of circular arrays with different radii with a fixed point as the center. The CCAA can not only provide narrow beam and all-azimuth scan capability but also achieve high gain and is more flexible in antenna pattern synthesis and design. Therefore, CCAAs are more popular than other antenna array configurations in recent years [3–9]. One of the main purposes of designing a concentric circular antenna array is the reduction of the peak sidelobe level to reduce interference [4]. In order to achieve this goal, many optimization methods have been used to design a CCAA with the lowest peak sidelobe level.

The main contents of the optimal design of the concentric circular array include ring radius, the number and spacing of array elements on rings with different radii, as well as the amplitude and phase of array elements. There are usually two methods to reduce the PSLL of a CCAA. One method is to keep the distance between the array elements uniform and employing radially tapered amplitude distribution among the elements. However, this method increases the complexity of the feed network and reduces the maximum power input [1]. Another method is to make the distribution of array elements aperiodic by changing the radius of the circle and the spacing of array elements on the premise that the excitation of each array element is uniform. However, this optimization method has a high degree of freedom and a large amount of calculation [10].

Thinned array means randomly arranging array elements on a uniform grid or randomly closing some elements from an evenly spaced periodic array. Through the thinned optimization of the array, not only the peak sidelobe level of the array pattern is reduced but also the volume and cost of the array antenna are reduced with the reduction of the number of array elements. In addition, the thinned distribution of array elements increases the distance between adjacent array elements and the influence of mutual coupling between array elements is effectively reduced. In recent years, thinned array antennas are widely used in satellite receiving antennas, ground-based high frequency radar, and radio astronomical interferometer array design.

Thinned concentric circular arrays have been studied by a large number of scholars because of their excellent radiation performance. With the increase of the size of the array, the traditional mathematical analysis methods have been unable to obtain the optimal radiation characteristics of the array. The intelligent optimization algorithm provides a new solution, such as genetic algorithm (GA) [10–12], particle swarm optimization algorithm (PSO) [13, 14], difference algorithm (DE) [15], biogeography-based optimization (BBO) [16], etc., which is used to optimize thinned concentric circular arrays. Haupt [10] applies a genetic algorithm to the sparse optimization of concentric circular antenna arrays. He thinly optimized a uniformly spaced concentric circular array with 279 elements. The radius and number of rings, the number of array elements, and the radius of nonuniformly spaced rings are discussed. The results show that the sparse optimization of the array pattern by a genetic algorithm can effectively reduce the peak sidelobe level of the array pattern. Chen et al. [12] proposed an optimization method of the thinned concentric circular array based on a modified real genetic algorithm. In this method, the number of array elements, aperture, and minimum array element spacing are fixed. Finally, the effectiveness and reliability of the method are verified by numerical simulations. Pathak et al. [14] present an optimization method based on the modified particle swarm optimization (PSO) algorithm for thinning large multiple concentric circular ring arrays of uniformly excited isotropic antennas that will generate a pencil beam in the vertical plane with a minimum relative sidelobe level (SLL). Ghosh and Dass have used DE with differential evolution with global and local neighborhood (DEGL) for synthesis of planar circular arrays [15]. Singh and Kamal have used biogeography-based optimization (BBO) and firefly algorithm (FA) for thinning of concentric circular antenna arrays [16].

The artificial bee colony (ABC) algorithm is a type of the popular swarm intelligence optimization algorithm. It is widely concerned because of its easy implementation, few parameters, and strong global search ability [17]. In this paper, ABC is applied for the thinning of concentric ring arrays. In recent years, the artificial bee colony algorithm has been successfully applied to the field of antenna array synthesis. In 2014, Chatterjee and Mandal [18] thinly optimized the isotropic hexagonal array by the ABC algorithm and obtained the radiation pattern with high gain and low sidelobe. Zhang et al. [19] proposed an adaptive variable differential artificial bee colony (AVDABC) algorithm, which adaptively determines the number of decision variables to be mutated. In each iteration, different search equations are assigned to the selected decision variables. The feasibility of the algorithm is verified by the design of thinned nonuniform antenna array and Yagi antenna. Wang et al. [20] proposed an artificial bee colony algorithm with similarity-induced search method (ABCSIM). This method adaptively adjusts the search step size. Employed bees are used to search in large steps, while onlooker bees are used to explore in small steps. Scout bees can search for potential high-quality solutions in their neighborhood. The algorithm is verified in the design of the antenna array.

Because of the inherent operation mechanism, the standard artificial bee colony algorithm is good at exploration and neglected to exploitation. In the standard artificial bee colony algorithm, the solutions generated by each generation are obtained by a random search, which directly leads to the weak exploitation ability of the algorithm. Moreover, the information of the optimal solution in the process of running the algorithm has not been fully utilized, which contains a lot of valuable information. In addition, the random neighborhood search leads to the rapid loss of population diversity, which makes the algorithm easy to be precocious and fall into local optimization.

In this paper, two modifications are made to the artificial bee colony algorithm. First of all, the location information of the global optimal solution is introduced into the neighborhood search operator to guide the bee colony to find food, which not only makes full use of the optimal solution information of the previous generation but also enhances the exploitation ability and search accuracy of the algorithm. Second, in order to improve the lack of population diversity, a genetic model is embedded in the algorithm to enrich the population diversity through genetic crossover and mutation. Through these two improvements, the contradiction between the exploration and exploitation of the ABC algorithm is effectively balanced and the optimization accuracy and speed of the algorithm are improved. The excellent performance of the modified artificial bee colony algorithm is verified on a set of widely used numerical functions. Finally, the modified artificial bee colony algorithm is applied to the sparse optimization of large multiconcentric circular antenna arrays. For concentric circular antenna arrays of the same size, narrower antenna beams and lower peak sidelobe levels (PSLL) can be obtained by using fewer elements, which is very valuable for improving the communication quality and anti-jamming ability of communication equipment. In addition, compared with the same type of a method, this method can obtain a lower peak sidelobe level.

The next section discusses the optimization model and array configuration of thinned concentric circular arrays. Section 3 introduces the artificial bee colony algorithm and the modified artificial bee colony algorithm in detail. At the same time, the numerical function optimization test of the improved artificial bee colony algorithm is carried out and compared with other algorithms. Section 4 gives the design examples and results. Section 5 gives the conclusion.

2. Thinned Planar Concentric Circular Array

Consider a concentric circular array as shown in Figure 1. The array has N elements uniformly distributed in the plane x–y. The array elements are distributed in a number of concentric rings with different radii. Figure 1 shows the general configuration of the CCAA with M concentric circular rings, where the mth ($m = 1, 2, \ldots, M$) ring has a radius rm and the corresponding number of elements is Nm. Assuming that all array elements are isotropic sources, then the antenna array factor of the geometric shape considered can be expressed as follows:

$$F = \sum_{m=1}^{M} \sum_{n=1}^{N_m} w_m e^{\mathrm{jkr}_m \left[\cos\varphi_{\mathrm{mn}} u + \sin\varphi_{\mathrm{mn}} v - \alpha_{\mathrm{mn}}\right]}, \quad (1)$$

where N_{m} = number of elements in ring m; M = number of rings; $k = 2\pi/\lambda$; λ = wavelength; w_m = element weights for ring m; ($r_m\cos\varphi_{\mathrm{mn}}$, $r_m\sin\varphi_{\mathrm{mn}}$) = element location; $u = \sin\theta\cos\varphi$; $v = \sin\theta\sin\varphi$; $\varphi_{\mathrm{mn}} = 2\pi(n-1)/N_{\mathrm{m}}$; $\alpha_{\mathrm{mn}} = \sin\theta_0\cos(\varphi_0 - \varphi_{\mathrm{mn}})$; and θ_0 is the value of θ where the peak of the main lobe is obtained. All the elements in the same ring have the same weight.

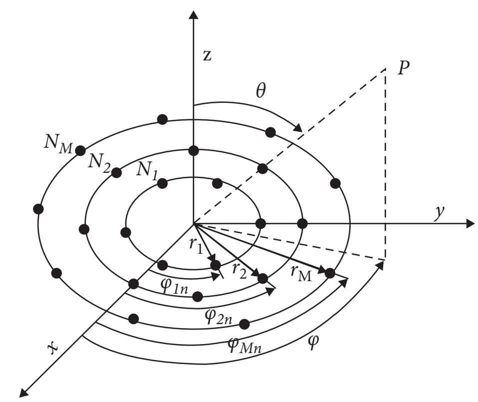

Figure 1: Configuration of the concentric circular antenna array (CCCA) with isotropic array elements in a x–y plane.

3. Modified Artificial Bee Colony Algorithm

The artificial bee colony (ABC) algorithm was proposed by Karaboga [21] in 2005. It is a global intelligent optimization algorithm, inspired by the foraging behavior of honey bee swarm. The optimization idea of the artificial bee colony algorithm is to find the optimal solution from all feasible solutions. This algorithm first showed excellent performance in numerical optimization problems [22]. The algorithm has the characteristics of good robustness, few parameters, and strong exploration ability. It is widely used to deal with constrained optimization, binary optimization problems, multiobjective optimization problems, and many practical applications.

As is known, the proper balance of exploration and exploitation during the search process is very important for the swarm intelligence algorithms. Exploration is the process of visiting entirely new regions of a search space, while exploitation is the process of visiting those regions of a search space within the neighborhood of previously visited points. The ABC algorithm is a global intelligent optimization algorithm that simulates bee foraging. The ABC algorithm also has some shortcomings. First of all, the algorithm randomly generates the feasible solution in each generation and the optimal solution information is not involved in the generation of the feasible solution. This directly leads to the good at exploration and it neglects exploitation. In addition, the random neighborhood search leads to the rapid loss of population diversity, which makes the algorithm easy to be precocious and fall into local optimization. So, balancing the contradiction between exploration and exploitation is an essential work of ABC algorithm research [23, 24].

3.1. Standard Artificial Bee Colony Algorithm. In the artificial bee colony algorithm, bees are divided into three categories: employed bees, onlooker bees, and scout bees. The three bees search for honey sources in nature. The exchange of information among bees is the most important occurrence in the formation of the collective knowledge. In order to understand the basic behavior characteristics of foragers better, when the employed bee finds the honey source, it has three options. One is to give up the honey source and it becomes an unemployed bee. The other is to collect honey alone. The third kind is that the employed bees make a neighborhood search for the honey source in its memory and transmits the information with the location and quality of the honey source in the specified position in the hive to the onlooker bees waiting in the hive by the way of "swing dance" [21]. The onlooker bees choose a honey source from the honey source which was found by the employed bees. The more nectar the honey source has, the more likely it is to be chosen by the onlooker bees. When honey sources are exhausted, employed bees will turn into scout bees, looking for new sources of food in nature. The quality of the honey source is expressed by fitness function, which is related to the value of objective function. The process of bees looking for a good source of honey is the process of finding the best solution. The ABC algorithm mainly includes four stages.

3.1.1. Population Initialization Stage. In this stage, SN initial feasible solutions are randomly generated. $X_i = x_{i,1}, x_{i,2}, \ldots x_{i,D}$, $\quad i \in \mathrm{SN}$, where X_i is the i-th solution of the population, SN is the size of the population, and D is the dimension of the solution vector. In the artificial bee colony algorithm, each initial solution X_i is generated according to the following .

$$X_{i,j} = X_{\min,j} + \mathrm{rand}(0,1) \times \left(X_{\max,j} - X_{\min,j}\right). \tag{2}$$

3.1.2. Employed Bee Stage. Employed bees search around the known honey sources and try to find honey sources with a higher content of nectar. The search formula is as follows.

$$\mathrm{NEW\_}X_{i,j} = X_{i,j} + \varphi_{i,j}\left(X_{i,j} - X_{k,j}\right), \tag{3}$$

where i and k are randomly selected and satisfy i, $k \in SN$, where $i \neq k$, j is a random integer of [0, D] and $\varphi_{i,j}$ is a random integer of [−1, 1]. The greedy rule is adopted to retain the better individuals to the next generation when the nectar content of the new nectar source $NEW\text{-}X_{i,\ j}$ is better than that of the previous nectar source $X_{i,\ j}$, $X_{i,\ j} = NEW - X_{i,\ j}$, otherwise, the bees continue to search the neighborhood of the honey source $X_{i,\ j}$ according to equation (3).

3.1.3. Onlooker Bee Stage. After completing the neighborhood search of the known honey source, the employed bee brings the information with the location and quality of the honey source back to the hive. They use this information to recruit onlooker bees. The onlooker bees will choose a better honey source for further neighborhood search. In order to select honey sources better, a selection probability P_i is defined for each honey source.

$$P_i = \frac{\mathrm{fit}(i)}{\sum_{i=1}^{\mathrm{SN}} \mathrm{fit}(i)}, \tag{4}$$

where $\mathrm{fit}(i)$ is the fitness function value of individual X_i,

3.1.4. Scout Bee Stage. Employed bees were used to conduct neighborhood searches on honey sources. When the number of searches exceeded the "limit" and still no better honey source was found, we thought that the honey source had been exhausted. At this time, the employed bees are converted into scout bees, and the honey source location is randomly initialized according to (2).

3.2. Modified Artificial Bee Colony Algorithm. The standard ABC algorithm does not fully use the location information of the optimal solution after each iteration. This information is considered to be very valuable. In this paper, a global neighborhood search operator is proposed (as shown in (5)). The operator contains the location information of the global optimal solution $X_{Gbest,j}$, which guides the bee colony to find food. This advantage is that the honey source $X_{Gbest,j}$ can be fully exploitation and utilized. At the same time, searching around the optimal solution is helpful to speed up the convergence of the algorithm. β takes the random number between [0, 1].

$$\mathrm{NEW\_}X_{i,j} = X_{i,j} + \varphi_{i,j}\left(X_{\mathrm{Gbest},j} - X_{k,j}\right) + \beta\left(X_{\mathrm{Gbest},j} - X_{i,j}\right). \tag{5}$$

Although the optimal solution information of the current generation is introduced into the neighborhood search operator, the random neighborhood search method has not changed. (5) enhances the exploitation ability and speeds up the convergence of the algorithm. However, it makes the whole colony search in the direction of the local extremum, thus falling into the local optimization. To jump out of the local optimization, it is necessary to provide further vitality to the algorithm and constantly develop new feasible solutions. Therefore, we have established a genetic model. First, 50% of the optimal solution is retained at the end of each iteration. Second, the retained solution was recombined according to formula (6). Finally, crossover and mutation are performed on the newly generated solution. The crossover and mutation schematic diagram is shown in Figure 2. Through this genetic model, the search scope is further expanded and the diversity of feasible solutions is enriched.

$$X_{i,j} = X_{k1,j} + \gamma\left(X_{k2,j} - X_{k3,j}\right), \tag{6}$$

where X_{k1}, X_{k2}, and X_{k3} are three solutions selected from the retained feasible solutions by random probability selection. j represents the position of an array element in the plane array. γ takes the random number between [0, 1]. The flowchart of the MABC algorithm is as shown in Figure 3.

3.3. Modified Artificial Bee Colony Algorithm Test. The effectiveness of the MABC algorithm is proved by a set of numerical functions (as shown in Table 1). These benchmark functions contain different problems, where *f1–f4* are continuous unimodal functions and *f5–f7* are multimodal functions. Table 1 also shows the parameter value range and theoretical minimum value of the numerical function. The MABC algorithm, ABC [22] algorithm, GABC [25] algorithm, and GA [11] algorithm are used in the optimization of seven numerical functions. GA represents a genetic algorithm, ABC represents the standard artificial algorithm, GABC represents the artificial bee colony algorithm after the introduction of the global optimal solution, and MABC represents the bee colony algorithm after the introduction of the global optimal solution and embedded genetic model. Each algorithm runs 20 times independently. In order to better evaluate the advantages and disadvantages of the algorithm, the average and standard deviation in the statistical sense are taken. Table 2 lists the performance of several algorithms when the dimension $D = 30$ and the maximum number of iterations $g = 3000$. From the analysis in Table 2, we can see that the average value and standard deviation of the results optimized by MABC algorithm are better than those of other algorithms. So, the MABC algorithm performs well.

4. Design Examples and Optimization Simulation

Each solution in the search space consists of a set of optimization parameters representing the honey source. In this paper, all array elements are isotropic sources. Therefore, all

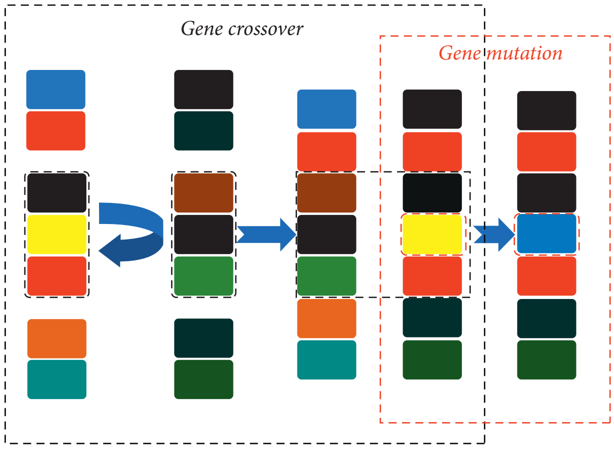

Figure 2: Schematic diagram of genetic crossover and mutation.

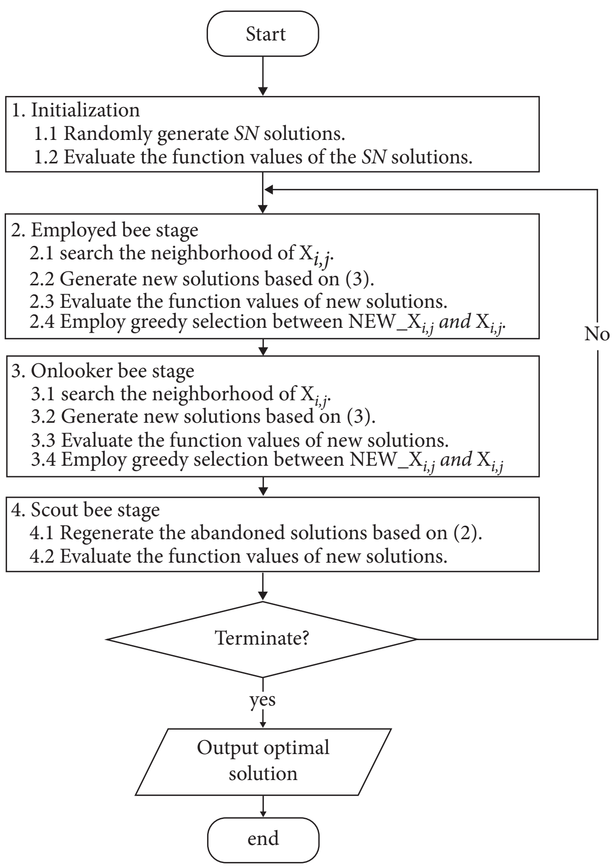

Figure 3: Flowchart of the ABC algorithm.

array elements have two states, namely, “on” or “off,” depending on whether the array elements are connected to the feed network. In the “open” state of the element, amplitude and phase excitation are applied through the feed network; in the “off” state, it can be assumed that the passive end of the array element is connected to the matching load or open circuit. The purpose of a thinned array is achieved through the selection of “on” and “off” of array elements. Because thinning is carried out in a fixed position, whether the array element is left behind can be expressed by a binary bit. When the array element is “on” at “1,” and the array element at “0” is “off” (it means the array element is thinned).

Consider a planar array of M ($M=10$) concentric circular rings (As shown in Figure 4). Each ring in the array has $8\,m$ ($m=1, 2, \ldots, M$) equally spaced isotropic elements. The total number of elements is 440.

The distance between adjacent elements is d_c (λ is the wavelength). The distance between the adjacent rings is $d_r = 4\lambda/2\pi$. So, the radius of each ring can be approximately expressed as follows:

$$r(m) = 8m \times \frac{\mathrm{dc}}{2\pi}. \tag{7}$$

The aim is to make the thinned array obtain the narrow beam pattern with the best peak sidelobe level (PSLL) in the vertical plane. Therefore, according to the definition of the maximum peak sidelobe level, the equation for calculating the maximum sidelobe level of the concentric circular array pattern is as follows:

$$\mathrm{MSLL} = \max\left\{\left|\frac{F(\theta_{0,}\varphi)}{\max\left(F(\theta_{0,}\varphi)\right)}\right| \varphi \in S, \quad \theta = \theta_0.\right. \tag{8}$$

In the equation, $F(\theta_0, \varphi)$ denotes the normalized pattern function and S denotes the sidelobe interval of the pattern. The fitness function can be defined in the following.

$$\mathrm{fit}(i) = \min_{X_i}\left\{\mathrm{MSLL} + \left(\mathrm{BW}_0 - \mathrm{BW}_d\right)^2\right\}, \tag{9}$$

where X_i is a solution to the optimization problem. In this paper, X_i is a binary string with a total length of 440, which represents the position of the array elements (as shown in the (10)). BW_0 and BW_d are obtained and desired value of half-power beamwidth.

$$X(i) = \left(x_{i1}, x_{i2}, x_{i3}, \ldots x_{i439}, x_{i440}\right). \tag{10}$$

Case 1. In the first case, the positions of the array elements are fixed as shown in Figure 4. The distance between adjacent elements is $d_c = 0.5\lambda$ (λ is the wavelength). Uniform excitation is used for array elements. For such a uniformly excited concentric circular array with 440 elements, its peak sidelobe level is -17.37 dB and the half-power beamwidth is approximately 4.5°.

The artificial bee colony algorithm is used to thinly optimize such an array. All array elements have only two states, “on” or “off”. Keep the number of elements t closed greater than 220. The parameters for MABC taken are as follows:

Total number of bees $SN = 60$.

Number of employed bees = 25.

Number of onlooker bees = 25.

Number of scout bees = 5.

Maximum number of generations = 150.

Table 1: Numerical function.

Numerical function	Expression	Range	Minimum value
Sphere	$f_1(x) = \sum_{i=1}^{D} x_i^2$	$[-100, 100]^D$	0
Elliptic	$f_2(x) = \sum_{i=1}^{D} (10^6)^{i-1/D-1} x_i^2$	$[-100, 100]^D$	0
SumSquare	$f_3(x) = \sum_{i=1}^{D} \mathrm{i}x_i^2$	$[-10, 10]^D$	0
Exponential	$f_4(x) = \exp(0.5 * \sum_{i=1}^{D} x_i)$	$[-10, 10]^D$	0
Rosenbrock	$f_5(x) = \sum_i^{D-1} [100(x_{i+1} - x_i^2)^2 - (x_i - 1)^2]$	$[-5, 10]^D$	0
Rastrigin	$f_6(x) = \sum_i^{D} [x_i^2 - 10\cos(2\pi x_i) + 10]$	$[-5.12, 5.12]^D$	0
Himmelblau	$f_7(x) = 1/\mathrm{D} \sum_i^{D} [x_i^4 - 16x_i^2 + 5x_i]$	$[-5, 5]^D$	−78.33236

Table 2: Algorithm comparison.

Function		ABC	GABC	GA	MABC
$f_1(x)$	Mean	2.42e − 15	5.12e − 16	1.23e − 13	3.73e − 23
	Std	3.20e − 15	4.35e − 17	1.63e − 13	4.16e − 23
$f_2(x)$	Mean	4.52e − 8	4.19e − 16	4.47e − 12	4.99e − 21
	Std	4.83e − 8	4.25e − 16	5.77e − 12	1.21e − 20
$f_3(x)$	Mean	7.32e − 15	5.25e − 15	8.10e − 11	3.57e − 20
	Std	8.18e − 15	6.18e − 15	7.82e − 11	6.93e − 20
$f_4(x)$	Mean	7.18e − 21	7.18e − 23	0	0
	Std	7.21e − 21	7.07e − 23	0	0
$f_5(x)$	Mean	4.75e − 01	9.71e − 02	4.16e − 05	1.91e − 07
	Std	5.81e − 01	1.01e − 01	5.01e − 05	2.11e − 07
$f_6(x)$	Mean	1.34e − 13	0	0	0
	Std	1.97e − 13	0	0	0
$f_7(x)$	Mean	−78.332	−78.332	−78.332	−78.33233
	Std	0	3.13e − 15	1.0974e − 14	0

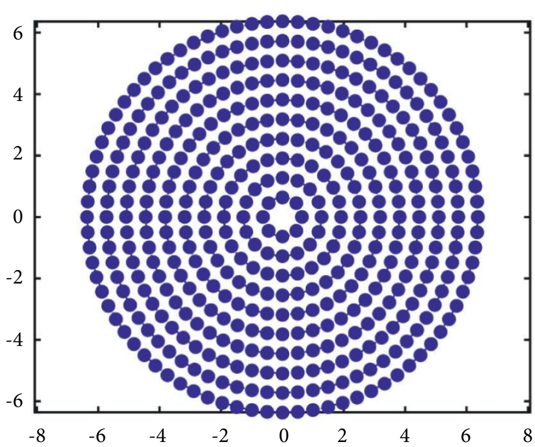

Figure 4: Ten-ring concentric circular antenna array of isotropic array elements.

The stopping criterion for the MABC algorithm is the maximum number of generations. The objective function adopts the (9). The simulation is run for 15 times, and the best result obtained by the MABC algorithm is listed in Table 3. The results of the MABC algorithm are compared with the results of fully populated uniform array, BBO [16], FA [1], and SOS [4] thinned arrays which are also given in Table 3. The PSLL achieved by MABC is -28.81 dB and BW of 4.6°, while 236 elements are switched off. The PSLL achieved by uniform fully populated array, BBO, FA, and SOS are −17.37 dB, −26.55 dB, −26.15 dB, and −26.07 dB, respectively. Hence, the PSLL achieved by MABC is lower by 11.44 dB, 2.26 dB, 2.66 dB and 2.74 dB than the PSLL obtained by fully populated array, BBO, FA, and SOS thinned arrays, respectively. The convergence characteristics of the MABC algorithm are shown in Figure 5. The thinned concentric circular antenna arrays are shown in Figure 6. The radiation pattern for the MABC optimized concentric circular antenna arrays is shown in Figure 7. For comparison, the radiation pattern of fully arrays is also drawn in the same figure. The optimal amplitude excitations obtained by the MABC algorithm are shown in Table 4.

Table 3: Results obtained by different methods with fixed $d_c = 0.5\lambda$ (interelement arc spacing).

Array	PSLL (dB)	BW (deg)	d_c	Switched off elements
Fully array	−17.37	4.5	0.5λ	0
BBO [16]	−26.55	4.6	0.5λ	224
FA [1]	−26.15	4.6	0.5λ	226
SOS [3]	−26.07		0.5λ	236
MABC	−28.81	4.6	0.5λ	236

Case 2. In the second case, the interelement arc spacing (dm) of each ring is made uniform and the same but is not fixed. The objective function and the parameters for MABC are the same as in the previous case. Similarly, the expected number of turn-off elements is equal to or more than 220. The interelement arc spacing is allowed to vary between $[0.5\lambda, \lambda]$. The optimized results of the MABC algorithm are shown in Table 5. For comparison, the results of fully populated uniform array, BBO, FA, and SOS thinned arrays are also given in Table 5.

When taking the optimal spacing $d_c = 0.5801\lambda$, the PSLL value of the array optimized by the MABC algorithm is −33.62 dB, while 236 elements are switched off, which is better than other arrays. The PSLL achieved by uniform fully populated array ($d_c = 0.5\lambda$), BBO ($d_c = 0$), $.5296\lambda$ FA ($d_c = 0.5732\lambda$), and SOS ($d_c = 0.5903\lambda$) are −17.37 dB, −26.60 dB, −30.19 dB, and −31.18 dB, respectively. Hence, the PSLL achieved by MABC is lower by 16.25 dB, 7.02 dB, 3.43 dB, and 2.44 dB than the PSLL obtained by fully populated array ($d_c = 0.5\lambda$), BBO ($d_c = 0.5296\lambda$), FA ($d_c = 0.5732\lambda$), and SOS ($d_c = 0.5903\lambda$) thinned arrays, respectively. In this case, the aperture of the array is slightly higher than that of fully populated array, BBO, and FA, but the beamwidth is kept almost unchanged. At the same time, the array optimized by the MABC algorithm closes more elements and achieves better radiation performance than other methods. The convergence characteristics of the MABC algorithm with fixed interelement arc spacing ($d_c = 0.5801\lambda$)

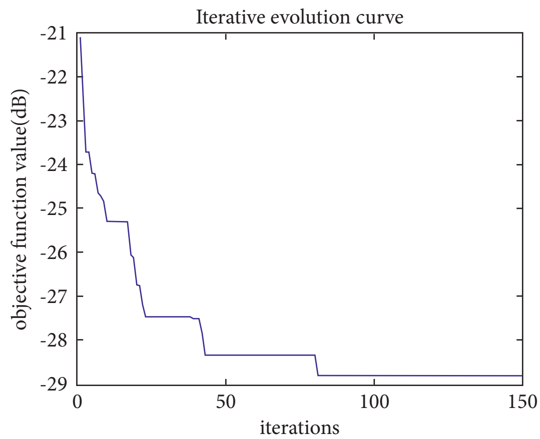

Figure 5: Convergence characteristics of MABC.

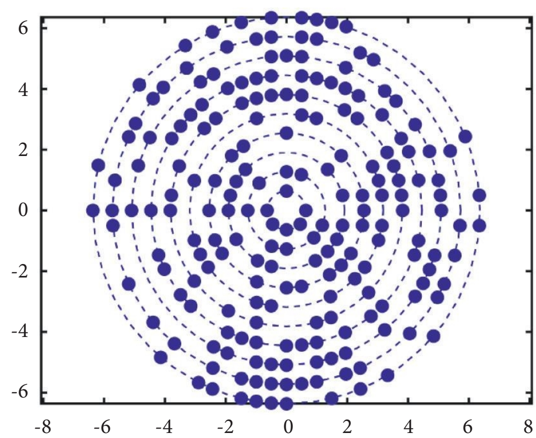

Figure 6: Thinned concentric circular antenna arrays of MABC.

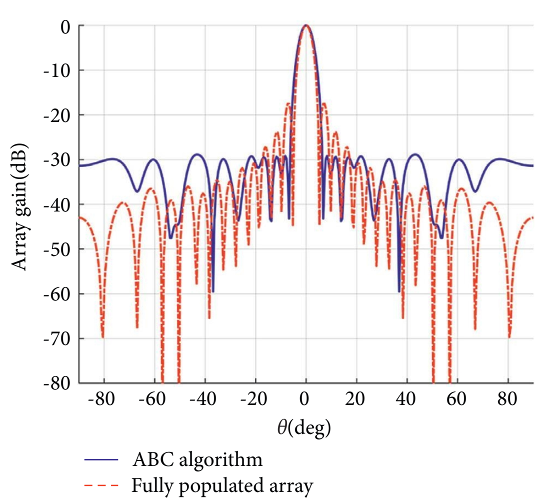

Figure 7: Radiation pattern for the MABC optimized concentric circular antenna arrays and comparison of the radiation pattern of fully array.

are shown in Figure 8. The thinned concentric circular antenna arrays are shown in Figure 9. The radiation pattern for the MABC optimized concentric circular antenna arrays is shown in Figure 10. For comparison, the radiation patterns of fully populated array and the radiation pattern obtained by the MABC algorithm in the first case are also drawn in the same figure. The optimal amplitude excitations obtained by the MABC algorithm are shown in Table 6.

Table 4: Excitation amplitude distributions using MABC with fixed $d_c = 0.5\lambda$.

		MABC
Ring number	1	10101111
	2	0001101010011011
	3	010100000111101011001111
	4	11001000100110101011001011011101
	5	01110000110010000001000111000110001011011
	6	111110011001111101100101100001001010001100100000
	7	00101101011111011110111100001001101100111011101011000110
	8	11101010110010011100011000010100100000000000110111011100100111100
	9	000010000000110011011010010110110010110001001010010111111011000100110101
	10	0100010000000000011110101010100010000010010000000000010011011110010101000100000001

Table 5: Results obtained by different methods with the inter-element arc spacing (d_c) of each ring is made uniform and the same but is not fixed.

Array	PSLL (dB)	BW (deg)	d_c	Switched off elements
Fully array	−17.37	4.5	0.5λ	0
BBO [16]	−26.60	4.4	0.5296λ	230
FA [1]	−30.19	4.4	0.5732λ	226
SOS [3, 16]	−31.18		0.5903λ	232
MABC	−33.62	4.5	0.5801λ	236

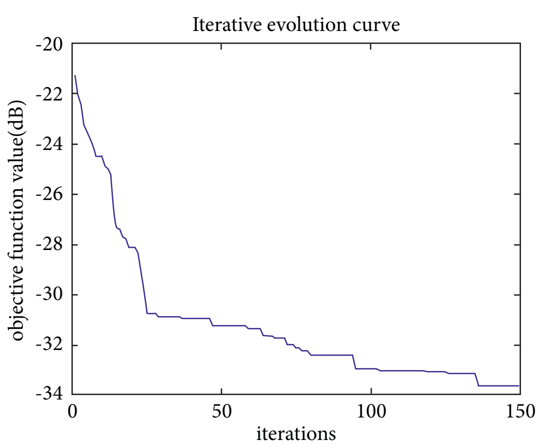

Figure 8: Convergence characteristics of MABC with fixed interelement arc spacing ($d_c = 0.5801\lambda$).

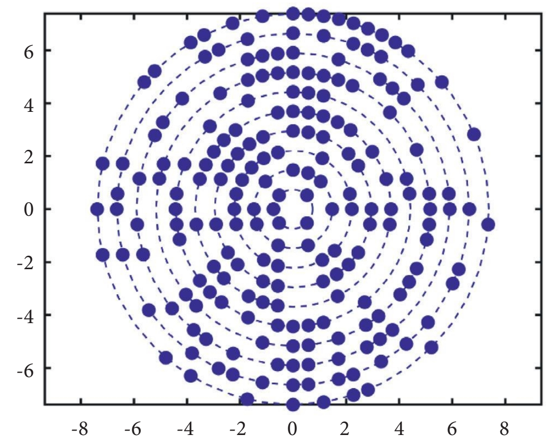

Figure 9: Thinned concentric circular antenna arrays with fixed interelement arc spacing ($d_c = 0.5801\lambda$).

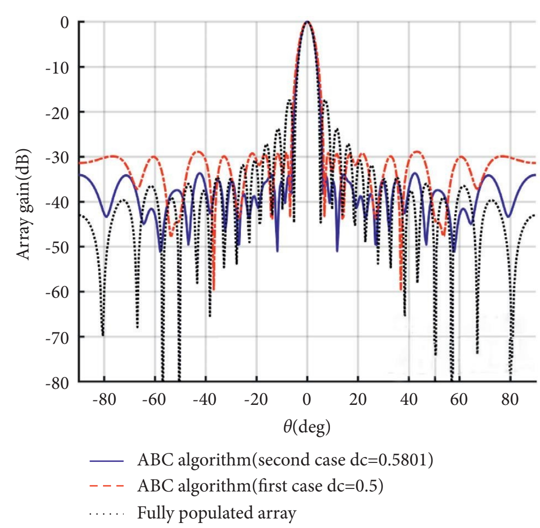

Figure 10: Radiation pattern for the MABC optimized concentric circular antenna arrays with fixed interelement arc spacing ($d_c = 0.5801\lambda$) compared with the results of the fully populated array and the radiation pattern obtained by the ABC algorithm ($d_c = 0.5\lambda$) in the first case.

In this section, two different cases are mainly considered. A concentric circular antenna array with 10 rings is thinned by using MABC. Under the same optimization conditions, the optimization results obtained by the MABC algorithm are compared with BBO, FA, SOS algorithms. It can be seen that the concentric circular array optimized by the MABC algorithm not only maintains the same beam width but also further reduces the peak sidelobe level, which is very valuable to improve the anti-interference ability of the antenna.

Table 6: Excitation amplitude distributions using MABC with fixed $d_c = 0.5801\lambda$.

		ABC
Ring number	1	01011101
	2	1011101011010100
	3	110010011111110011001100
	4	10011011101111100101101100111101
	5	1010101111110011111001001101110001000001
	6	011000000011100100100101111001110101111001000000
	7	11001001001111111101000001100000001100001011010110111011
	8	1100000011100100111100001011001001010001011010011101011100000000
	9	100000000100111010100101100000000101100100010001011010110110101010011000
	10	00000100010011111111101010110011000001001001000000010100010010101100001000000001

5. Conclusions

Due to the lack of exploitation ability, the traditional bee colony algorithm directly leads to the rapid loss of population diversity. At the same time, the optimal solution information of each generation cannot be effectively shared in the population. In view of these two shortcomings, first, the information of the optimal solution of each generation is retained in the neighborhood search operator, and then, the genetic evolution mechanism is introduced into the bee colony algorithm. Through the modification of the artificial bee colony algorithm, not only the contradiction between exploration and exploitation is effectively balanced but also the diversity of population is enriched. The feasibility of the algorithm is proved by the benchmark function test. Finally, the MABC algorithm is applied to the sparse optimization of large multiconcentric circular antenna arrays with isotropic elements to generate pencil beams in the vertical plane. Two cases are presented in this paper. One method is to obtain a thinned array with fixed element spacing and the other is to optimize the element spacing. In both cases, the MABC algorithm achieves better antenna radiation characteristics than other algorithms. Moreover, the concentric circular array optimized by the MABC algorithm turns off more elements, which will greatly reduce the cost of designing the array. The experimental results show that the improved bee colony algorithm proposed in this paper is an effective means to improve the radiation performance of the antenna and has a certain reference and practical value when the sparse array is widely used today.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This paper was supported by the guiding project of scientific research plan of the Department of Education of Hubei Province (Grant No. B2020234), the Philosophy and Social Science Research Project of the Department of Education of Hubei Province (Grant No. 20G064), the Project of China Society of Logistics (Grant No. 2021CSLKT3-097), the Project of National Business Education and Scientific Research of 14th Five-Year Plan (Grant No. SKJYKT-210548), and the PhD Project of Wuhan Business University (Grant No. 2018KB003).

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