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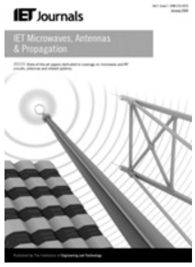

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Synthesis of thinned planar concentric circular antenna arrays using biogeography-based optimisation

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Abstract: This study presents a novel optimisation algorithm biogeography-based optimisation (BBO) for thinning large multiple concentric circular ring arrays. The objective is to achieve an array of uniformly excited isotropic antennas that will generate a narrow beam with minimum relative sidelobe level (SLL). BBO is a new comprehensive force based on the science of biogeography. Biogeography is the schoolwork of geographical allotment of biological organisms. BBO utilises migration operator to share information between the problem solutions. The problem solutions are known as habitats and sharing of features is called migration. In this study, the authors propose pattern synthesis method to reduce the SLLs with narrow beamwidth (BW) by making the ring array thinned using the BBO algorithm. The thinning percentage of the array is kept equal to or more than 50% and the BW is kept equal to or less than that of a fully populated, uniformly excited and $0.5\lambda_w$, spaced concentric circular ring array of same number of elements and rings. The results obtained are compared with previous published results of modified particle swarm optimisation and differential evolution with global and local neighbourhoods.

1 Introduction

Circular antenna arrays have significant interest in a variety of applications which comprise sonar, radar, mobile and commercial satellite communications systems [1–4]. A circular array is an arrangement of a number of elements usually omni-directional arranged on a circle [1] and can be employed for beam forming in the azimuth plane such as at the base stations of the mobile radio communications system [2–4]. Circular arrays have become popular in recent years over other array geometries because they have the capability to perform the scan in all directions without a considerable change in the beam pattern and provide 360° azimuth coverage. Moreover, circular arrays are less sensitive to mutual coupling as compared with linear and rectangular arrays since these do not have edge elements [1]. Concentric circular antenna array (CCAA) that contains many concentric circular rings of different radii and number of elements has a number of advantages including the flexibility in array pattern synthesis and design both in narrowband and broadband beam forming applications [2–4]. CCAA is also used in direction-of-arrival applications since it gives almost invariant azimuth angle coverage.

One of the most important types of CCA is uniform concentric circular antenna (UCCA) in which the inter-element spacing in individual ring is kept almost half of the wavelength and all the elements in the array are uniformly excited [2]. Uniform antenna arrays exhibit high directivity; however, they usually have high sidelobe level (SLL) [1, 2]. In order to reduce the SLL, the positions of antenna element are altered and array is made aperiodic with uniform amplitude excitations. The other method to reduce the SLL is by employing equally spaced arrays with radially tapered amplitude distribution [3, 4]. However, uniform excitation is required in order to reduce the complexity in designing a feed network and to maximise the power input.

Thinning an array means turning off some of the elements from a uniformly spaced or periodic array to achieve a radiation pattern with low SLLs. Thinning is employed in several fields that include satellite-receiving antennas which operate against a jamming environment, ground-based high-frequency radars and design of interferometer array for radio astronomy [5]. Thinning a large array will not minimise SLL further but also reduces the number of antennas in the array and thus cutting down the cost considerably. Hence, the synthesis of arrays using thinning is under active research by many groups. Owing to the complexity in synthesis problem, it cannot be solved by analytical methods. Therefore several global optimisation algorithms such as genetic algorithms (GA) [6], particle swarm optimisation (PSO) [7] and differential evolution (DE) [8] etc. have been introduced to solve these problems. Haupt has used GA for thinning of linear arrays [9, 10]. Orthogonal GA has been utilised by Zhang *et al.* for thinning of linear arrays [11]. Ant colony optimisation (ACO) has been used for achieving minimum SLL by employing thinning [12]. Mahanti *et al.* have employed real coded GA for synthesis of linear antenna arrays [13]. Ghosh and Dass have used DE with differential evolution with global and local neighbourhood (DEGL) for synthesis of planar circular array [14]. Mahanti *et al.* have used modified PSO (MPSO) for thinning of circular arrays [15]. Chatterjee and Mahanti have compared the performance of gravitational search algorithm (GSA) and MPSO for thinning of scanned concentric ring arrays [16].

In this paper, BBO is applied for the thinning of concentric ring array. BBO is a population-based evolutionary technique introduced in [17]. It has been applied for the design of linear antenna arrays for obtaining the maximum SLL reduction and null placement in desired directions in [18]. Results obtained using BBO for the linear arrays are encouraging. The BBO method produced a lower value of SLL and better null placement as compared with PSO [19]. BBO has also been used for the optimisation of Yagi-Uda [20]. BBO has been able to provide very good results for circular antenna [21]. The novel technique has also been applied in other areas, such as the power flow problem [22], optimisation of gear trains [23] and satellite image classification problems [24]. In this paper, BBO is applied for thinning large multiple concentric circular ring arrays of isotropic antennas for reducing the maximum SLL and at the same time keeping the beamwidth (BW) as small as possible. The same problem has been dealt by Ghosh and Dass [14] and Mahanti *et al.* [15] using DEGL and MPSO, respectively. So, the results of this work are compared with a fully populated array, MPSO and DEGL optimised array. To the best of our knowledge, BBO has not been applied for the thinning of concentric circular before. It is well known in general that if the SLL is reduced, the BW is increased [25]. Therefore the aim of the optimisation in this paper is to minimise the SLL whereas maintaining minimum possible BW.

The rest of the paper is organised as follows: Section 2 discusses the geometry and general design for the CCAA. In Section 3, the BBO algorithm is explained. Section 4 presents design examples and the results and in Section 5 conclusions are presented.

2 Thinned planar circular array

Thinning an array means selectively turning off some elements in a uniformly spaced or periodic array in order to have an antenna with low-SLLs. In this work, antenna positions are kept fixed and the elements can have only two states either ‘on’ or ‘off’. An antenna in an ‘on’ state only contributes to the total array pattern. On the other hand, an antenna is in ‘off’ state if the element is either passively terminated to a matched load or is open circuited and hence it does not contribute to the total array pattern. Thinning an array to produce low sidelobes is much simpler than the more general problem of non-uniform spacing the elements. Non-uniform spacing has an infinite number of possibilities for placement of the elements [9].

In CCAA, the elements are arranged in such a manner that all antenna elements are positioned in multiple concentric circular rings, which vary in radii and in number of elements. Fig. 1 shows the general configuration of CCAA with M concentric circular rings, where the mth ($m = 1, 2, \ldots, M$) ring has a radius r_m and the corresponding number of elements is N_m. Assuming that all the elements (in all the rings) are isotropic sources, then the far-field pattern [15] of this array can be written as

$$E(\theta, \phi) = \sum_{m=1}^{M} \sum_{n=1}^{N_m} A_{mn} \exp\left[\mathrm{j}(kr_m \sin\theta(\cos(\phi - \phi_{mn}))\right] \quad (1)$$

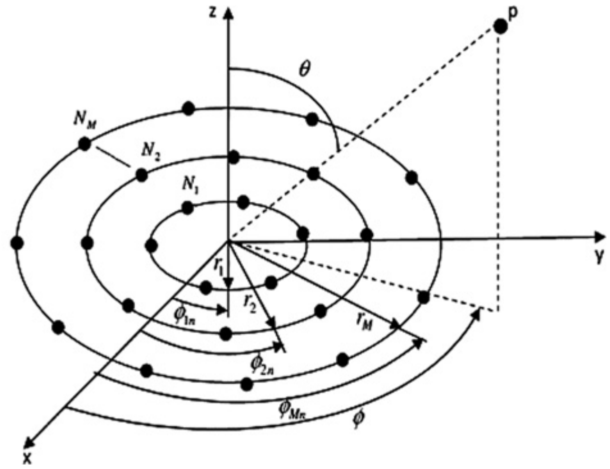

Fig. 1 *Multiple concentric circular ring arrays of isotropic antennas in the XY plane*

where k = wave number $= 2\pi/\lambda_w$, λ_w is the signal wavelength, r_m is the radius of the mth ring $= N_m d_m / 2\pi$, d_m = inter element arc spacing of the mth ring $\phi_{mn} = 2\pi((n-1)/N_m$ is the angular position of the nth element of the mth ring, A_{mn} is the current amplitude excitation of the nth element of the mth ring, ϕ and θ are the azimuth and zenith angle, respectively. All the elements have same excitation phase of zero degree.

3 Biogeography-based optimisation

BBO is a recently developed population-based evolutionary algorithm based on the theory of biogeography. Biogeography is the study of the distribution of the species in nature. The species migrate to different habitats for their survival and better living conditions. BBO imitates this migration phenomenon for solving real-world optimisation problems. In common with the GA, the PSO and many other algorithms, BBO is motivated by natural phenomenon. In along the biogeography, a habitat (H) is defined as any ecological area which is geographically isolated from other habitats. Each habitat has its measure of goodness for living which is known as the suitability index (SI). Habitats that are well suited as residences for biological species have a high SI. The SI of a habitat depends upon a number of factors, such as rainfall, temperature, diversity of species, population of the species and security. These factors are known as suitability index variables (SIV). The habitats with a high SI have a large population as they are fit for living whereas the habitats with low SI are not apt or friendly for living and have a thin population. High SI habitats have a low immigration rate λ and high emigration rate μ simply because they are highly populated and can not easily support new species. For the same reason, low SI habitats have a high immigration rate λ, and low emigration rate μ which allows more species to move into these habitats. The habitats with a high SI have many species that emigrate to nearby habitats. The high SI habitats are less dynamic than the low SI habitats. The influx of species to the low SI habitats may raise its SI because the suitability of a habitat is proportional to its biological diversity. If SI remains low, the habitat may become extinct. Here, Fig. 2 illustrates a model of species abundance in a single habitat. Let us consider the immigration graph of Fig. 2.

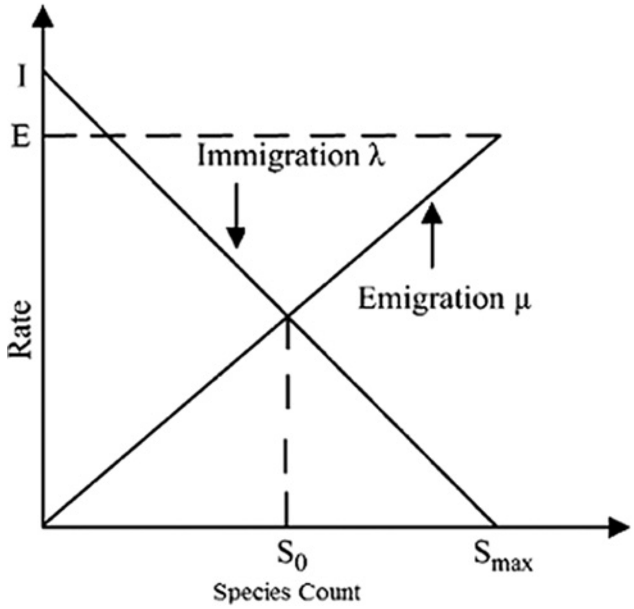

Fig. 2 *Linear migration relationships for a habitat*

The maximum possible immigration rate to the habitat is SI, which occurs when there are zero species in the habitat. If a habitat has less number of species, then much larger amount of species from other habitat can come into that habitat, thus immigration rate is higher at that time. With the increase in the number of species, the habitat becomes densely populated, and fewer species are able to successfully survive after immigration to the habitat, and therefore immigration rate decreases. The largest possible number of species that the habitat can maintain is $S_{\max}$, at which point the immigration rate becomes zero, because no more species can immigrate to that habitat after that species count. Now consider the emigration graph. If there are no species in the habitat, then there is no species in that habitat that emigrate other habitat, so the emigration rate must be zero. As the number of species increases, the habitat becomes more crowded, more species are able to leave the habitat to explore other possible residences and the emigration rate increases. The maximum emigration rate is E, which occurs when number of species is $S_{\max}$. The equilibrium number of species is S_0, at which point the immigration and emigration rates are equal. The immigration and emigration lines in Fig. 2 have been shown as straight lines but, in general, they might be more complicated curves. However, the simple model gives us a general description of the process of immigration and emigration. In the BBO algorithm, calculation of emigration rate and immigration rate is important as these play a vital role to select habitats that SIVs will undergo migration operation.

Mathematically, the concept of migration between habitats can be represented by a probabilistic model. Now, let P_S be probability that the habitat contains exactly S species at time t. P_S changes from time t to time $t + \Delta t$ as [17]

$$P_S(t + \Delta t) = P_S(t)(1 - \lambda_S \Delta t - \mu_S \Delta t) + P_{S-1}\lambda_{S-1}\Delta t + P_{S+1}\mu_{S+1}\Delta t \qquad (2)$$

where λ_S and μ_S are the immigration and emigration rates when there are S species in the habitat. This equation holds because in order to have S species at time $(t + \Delta t)$ one of the following conditions must be satisfied:

1. There were S species at time t, and no immigration or emigration occurred between t and $t + \Delta t$.
2. There were $(S - 1)$ species at time t, and only one species immigrated.
3. There were $(S + 1)$ species at time t, and only one species emigrated.

If time Δt is small enough so that the probability of more than one immigration or emigration can be ignored, then taking the limit of (2) as $\Delta t \to 0$ gives

$$\dot{P}_S = \begin{cases} -(\lambda_S + \mu_S)P_S + \mu_{S+1}P_{S+1}, & S = 0 \\ -(\lambda_S + \mu_S)P_S + \lambda_{S-1}P_{S-1} + \mu_{S+1}P_{S+1}, & 1 \le S < S_{\max} - 1 \\ -(\lambda_S + \mu_S)P_S + \lambda_{S-1}P_{S-1}, & S = S_{\max} \end{cases} \qquad (3)$$

Define $n = S_{\max}$ and $[P_0, \ldots, P_n]^{\mathrm{T}}$ for notational simplicity. The P_S equations (for $S = 0, \ldots, n$) can be arranged into single matrix equation given by

$$\dot{P} = \boldsymbol{W}P$$

where the matrix $\boldsymbol{W}$ is given by (see (4))

For the straight-line graph of Fig. 2, the equation for emigration rate and immigration rate can be written as

$$\lambda_S = I\left(1 - \frac{S}{n}\right) \qquad (5)$$

$$\mu_S = \frac{ES}{n} \qquad (6)$$

where I_b is the maximum possible immigration rate, E_b is the maximum possible emigration rate and $n = S_{\max}$ is the maximum number of species.

When $E = I$, combining (5) and (6) gives

$$\lambda_S + \mu_S = E \qquad (7)$$

The BBO technique imitates nature's way of distributing species, and is analogous to general problem solutions. Suppose that there is an optimisation problem with some candidate solutions. The problem can be of any field of life

$$\boldsymbol{W} = \begin{bmatrix} -(\lambda_0 + \mu_0) & \mu_1 & 0 & \cdots & 0 \\ \lambda_0 & -(\lambda_1 + \mu_1) & \mu_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \lambda_{n-2} & -(\lambda_{n-1} + \mu_{n-1}) & \mu_n \\ 0 & \cdots & 0 & \lambda_{n-1} & -(\lambda_n + \mu_n) \end{bmatrix} \qquad (4)$$

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provided that there is a quantifiable measure of the suitability of a given solution. In BBO, for an N_{var}-dimensional optimisation problem, a habitat is a $1 \times N_{\text{var}}$ array. The population consists of $NP = n$ parameter vectors or habitats, where NP is the total number of habitats. Habitats consist of solution features named SIV, corresponding to GA genes. A good solution is equivalent to the high SI habitat whereas a poor solution is given by the low SI habitat. The value of the SI of a habitat in BBO is similar to the fitness of solution in the other optimisation algorithms. In this work, BBO is used to generate discrete numbers, that is, 0 or 1 as such the variable values or SIVs in a habitat are represented as binary numbers. The set of all such vectors is the search space from which the optimum solutions are to be found. The value of the SI is found by evaluating the cost of function at the variables $[\text{SIV}_1, \ldots, \text{SIV}_{N_{var}}]$. Therefore we have

$$\text{SI} = f(\text{Habitat}) = f(\text{SIV}_1 \ldots - \text{SIV}_{N_{var}}) \tag{8}$$

where f (Habitat) represents the value of cost or objective function. The emigration and immigration rates of each solution are used to probabilistically share information between habitats. Each solution is modified depending on the probability P_{mod} which is a user-defined parameter. In BBO, if a given solution is selected for modification, then its immigration rate λ is used to probabilistically decide whether or not to modify each SIV in that solution. If a given SIV is selected for modification, then emigration rates μ of other solutions are used to select which of the solutions should migrate a randomly selected SIV to solution S_i. Similar to other population-based optimisation algorithms, elitism is introduced in the BBO to prevent the best p solutions from being corrupted by the migration operation. To this end, p best solutions are kept aside from the migration operation by setting their immigration rate λ equal to zero and therefore these are retained in the population from one generation to the next.

The SI of a habitat can change suddenly because of some cataclysmic events owing to which the species count in a habitat changes rapidly from its equilibrium value. Therefore these random events can result in an abrupt change in the SI of a habitat. This is modelled in the BBO as SIV mutation. The species count probabilities are used to determine the mutation rate. The probabilities of each species count are determined by the differential equation in (3). Every habitat member has an associated probability, which represents the chances that it exists as a solution for a given problem. The solutions having high SI and low SI are equally improbable. On the other hand, solutions with medium SI are relatively probable. If a given solution S has a low probability P_s, then it is surprising that it exists as a solution. It is, therefore likely to mutate to some other solution. Conversely, a solution with a high probability is less likely to mutate to a different solution. This can be realised as a mutation rate m that is inversely proportional to the solution probability

$$m_S = m_{\max}\left(1 - \frac{P_S}{P_{\max}}\right) \tag{9}$$

where $m_{\max}$ is a user-defined parameter and P_s is a function of S. This mutation scheme is likely to increase the diversity of the population. Without this variation, the highly probable solutions will have a tendency to be more dominant in the population. This mutation operation makes both low and high SI solutions likely to mutate, which gives a chance of improving both types of solutions in comparison to their earlier value. Elitism is introduced so that the best solutions are retained in the population. Elitism helps in reverting back to an old solution (solution before mutation) if a solution is ruined by the mutation process [17]. The migration and mutation operations are shown in Figs. 3 and 4.

The migration of species among a group of neighbouring habitats, combined with mutation of the individual species, will have a propensity over many generations to produce habitats that attract and keep large numbers of species through immigration. Habitats with low SI lose species through the extinction or emigration and will sometimes become uninhabited. The BBO algorithm emulates this behaviour in a manner that causes an 'optimal' habitat to come out from the original population of habitats.

BBO has certain features which are similar to other biology-based algorithms. As with GAs and PSO, BBO shares information between solutions. GA solutions 'die' at the end of each generation, whereas PSO and BBO solutions survive forever (although their characteristics change as the optimisation process progresses). PSO solutions are more likely to bunch together in similar groups, whereas GA and BBO solutions do not necessarily have any built-in tendency to cluster.

BBO differs from other popular evolutionary algorithms in certain aspects. Although BBO is a population-based optimisation algorithm, it does not involve reproduction or the generation of 'children.' This undoubtedly differentiates it from reproductive strategies such as GAs and evolutionary strategies. BBO also clearly diverges from ACO, in respect that ACO generates a new set of solutions with each iteration whereas BBO, in contrast, preserves its set of solutions from one iteration to the next, relying on migration to probabilistically adapt those solutions. BBO

```
for i= 1 to NP do
  Select Hi with probability based on λi
  if Hi is selected then
    for j=1 to NP do
      Select Hj with probability based on μj
      if Hj is selected
        Randomly select a SIV from Hj
        Replace a random SIV in Hi with selected SIV of Hj
      end if
    end for
  end if
end for
```

Fig. 3 *Algorithm for migration process of the BBO*

```
for i=1 to NP
  for j=1 to Nvar do
    Use λi and μi to compute the probability Pi using (3)
    Select a SIV Hi (j) with probability based on priori
    probability m
    if Hi (j) selected then
      Replace Hi (j) with a randomly generated SIV
    end if
  end for
```

Fig. 4 *Algorithm for mutation process of the BBO* has the most in common with strategies such as PSO and DE. In PSO and DE approaches, solutions are retained from one iteration to the next, but each solution is capable of learning from its neighbours and adapt itself as the algorithm progresses. PSO gives each solution as a point in space, and represents the change over time of each solution as a velocity vector, nevertheless, PSO solutions do not alter directly but it is rather their velocities that change and which indirectly causes in position (solution) changes. On the other hand, DE changes its solutions directly, but changes in a particular DE solution are based on differences between other DE solutions. BBO solutions are changed directly via migration from other solutions (habitats). That is, BBO solutions directly share their attributes (SIVs) with other solutions. In this respect, BBO is different from PSO and DE.

4 Design examples

In this work, a planar array of ten concentric circular rings is considered. Each ring in the array has $8\,m$ equi-spaced isotropic elements (a total of 440), where m stands for the ring number counted from the innermost ring 1. Two cases are considered similar to that reported in [15]. The objective function is given as

$$F = \mathrm{SLL}_{\max} + (\mathrm{BW}_{\mathrm{o}} - \mathrm{BW}_{\mathrm{d}})^2 + (T_{\mathrm{o}}^{\mathrm{off}} - T_{\mathrm{d}}^{\mathrm{off}})^2 H(T) \quad (10)$$

where $\mathrm{SLL}_{\max}$ is the value of maximum SLL, BW_{o}, BW_{d} are obtained and desired value of half-power BW respectively, $T_{\mathrm{o}}^{\mathrm{off}}$, $T_{\mathrm{d}}^{\mathrm{off}}$ are obtained and desired value of number of switched off elements. $H(T)$ is the Heaviside step functions defined as follows

$$H(T) = \left\{ \begin{matrix} 0 & \text{if} & T > 0 \\ 1 & \text{if} & T \le 0 \end{matrix} \right\} \quad (11)$$

$$T = (T_{\mathrm{o}}^{\mathrm{off}} - T_{\mathrm{d}}^{\mathrm{off}}) \quad (12)$$

In the first example, inter-element arc spacing (d_m) in all the rings is fixed at $0.5\lambda_{\mathrm{w}}$. For such a fully populated and uniformly excited array, the maximum SLL is calculated to be −17.37 dB and half-power BW is approximately 4.5°. Such a fully populated array is shown in Fig. 5.

The objective is to find the optimal set of 'on' and 'off' elements that will produce a narrow beam in the XZ plane keeping the half-power BW unchanged, fixing the number of switched off elements to be equal to 220 or more and reducing the maximum SLL further. The parameters for BBO taken are as follows:

- Number of habitats or population : $NP = 100$
- Iterations or generations = 150
- Mutation probability: $m_{\max} = 0.005$
- Habitat modification probability $P_{\mathrm{mod}} = 1$
- Elitism parameter $p = 2$
- Maximum migration rates $E = 1$ and $I = 1$

The number of habitats for BBO is equal to the population size and it is taken as 100. Each habitat consists of 440 SIVs made up of element amplitudes, that is

$$X = (A_1, A_2, \ldots, A_{440}) \quad (13)$$

The BBO algorithm is applied to the ring antenna problem which consists of a migration operator followed by mutation. The duplicate solutions are removed at each generation and restored with random mutations. The elitism operation is applied for preserving two fittest habitats from each generation. The stopping criterion for BBO is the maximum number of generations. The simulation is run for 25 times, and the best result obtained by BBO is listed in Table 1. The consistency of BBO algorithm in 25 runs is listed in Table 2. The results of BBO are compared with the results of fully populated uniform array, DEGL [14] and MPSO [15] thinned arrays which are also given in Table 1. The maximum SLL achieved by BBO is −26.55 and BW of 4.6° while 224 elements are switched off. The maximum SLL achieved by uniform array, MPSO and DEGL are −17.37, −23.22 and −21.91 dB, respectively. Hence, the maximum SLL achieved by BBO is lower by 9.18, 3.33 and 4.64 dB than the maximum SLL obtained by fully populated, MPSO and DEGL thinned arrays, respectively. The convergence characteristics of BBO are shown in Fig. 6. The thinned ring array is shown in Fig. 7. The radiation pattern for the BBO optimised ring antenna array

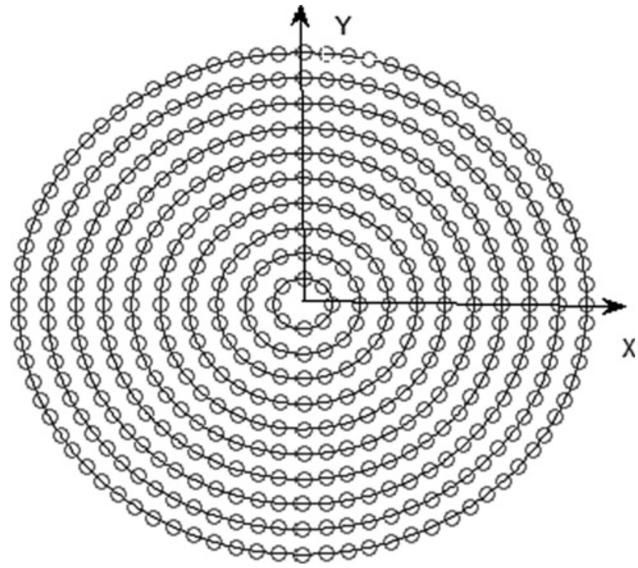

Fig. 5 *Ten-ring concentric circular ring array of isotropic antennas*

Table 1 Results obtained by different methods with fixed $d_m = 0.5\lambda_{\mathrm{w}}$

Array	SLL, dB	BW, deg	Inter-element arc spacing	Number of switched off elements
fully populated	−17.37	4.5	$0.5\lambda_{\mathrm{w}}$	0
MPSO [15]	−23.22	4.6	$0.5\lambda_{\mathrm{w}}$	231
DEGL [14]	−21.91	4.6	$0.5\lambda_{\mathrm{w}}$	220
BBO	−26.55	4.6	$0.5\lambda_{\mathrm{w}}$	224

Table 2 Performance of BBO algorithm with fixed $d_m = 0.5\lambda$

best SLL (dB)	−26.55
mean SLL (dB)	−25.97
worst SLL (dB)	−25.6
SD (dB)	0.21

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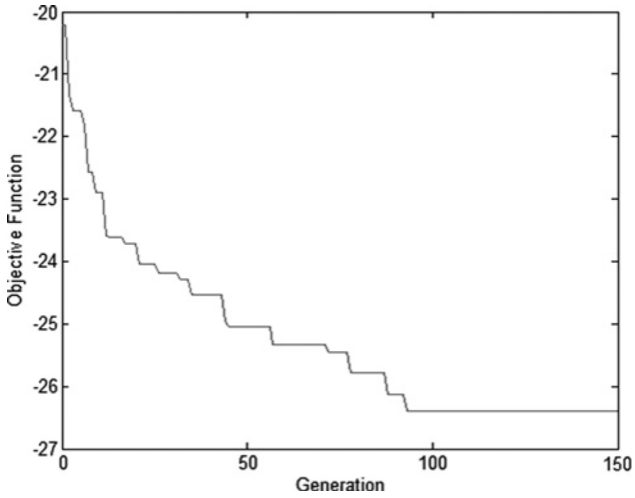

Fig. 6 *Convergence characteristics of BBO*

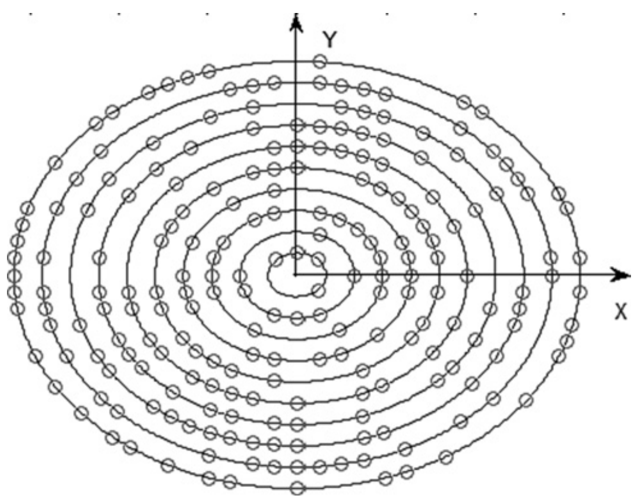

Fig. 7 *Thinned array obtained by BBO*

is shown in Fig. 8. For comparison radiation pattern of MPSO and fully populated array are also drawn in the same figure. The optimal amplitude excitations obtained by BBO are shown in Table 3.

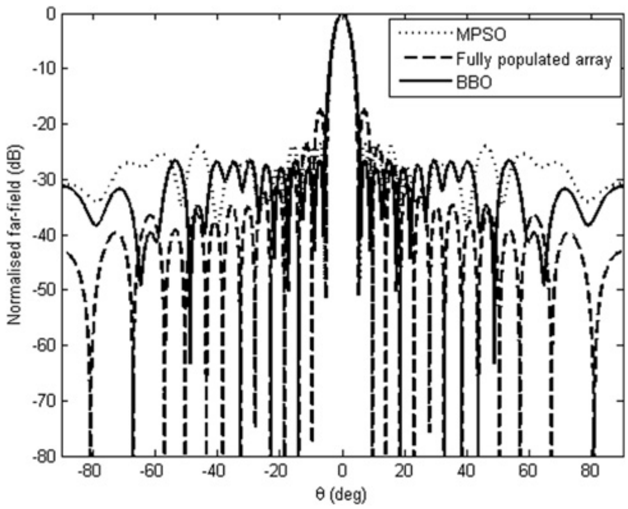

Fig. 8 *Radiation pattern for ring antenna array obtained using BBO results as compared with the results of the fully populated and the MPSO array*

In the second example, the inter-element arc spacing (d_m) of each ring is made uniform and same but not fixed. The objective is the same as in the previous example, that is, to generate a narrow beam in the *XZ*-plane with reduced SLL. The desired half-power BW is kept at 4.5° and the desired number of switched off elements is made equal to 220 or more. The inter-element arc spacing is allowed to vary between [$0.5\lambda_w$, $1\lambda_w$]. The parameters for BBO are also same as in the previous example. The optimised results of the BBO algorithm are shown in Table 4. For comparison, the results of fully populated uniform array, DEGL [14] and MPSO [15] thinned arrays are also given. The maximum SLL obtained by BBO optimised array is −26.6 dB which is better than other arrays in Table 4. The SLL of BBO optimised array is lower by 9.23, 1.79 and 2.75 dB than fully populated uniform array, DEGL and MPSO optimised arrays, respectively. The BW and SLL of BBO optimised antenna are better than the uniform and DEGL array with small increase in aperture size. The BW of MPSO array is narrower than other listed antennas but its aperture size is quite larger than the other antennas. The radiation pattern of the BBO thinned array is shown in Fig. 9 along with the radiation patterns of fully populated array and MPSO thinned arrays. The optimised amplitude excitations of elements obtained by BBO are given in Table 5.

Table 3 Excitation amplitude distributions (A_{mn}) using BBO with fixed $d_m = 0.5\lambda_w$

		BBO
ring number	1	01110001
	2	1001000011011100
	3	111111011011110010001001
	4	11100000010100101110001101101001
	5	0111111100111010111001101111010001001101
	6	100101001111110000100000011011011110100110010100
	7	00001000101111101001010100010110111010110110010001101010
	8	0000010010101110001010010010100000010110011111111001100001010111
	9	110001111010001111011100000010101001011101001100001011111101001010000000
	10	01001100000110000000100001111011001001111111001010101101011001000110100001001110 1
		elements state in each ring (0 or 1)

Table 4 Results obtained by different methods with optimised d_m

Array	SLL, dB	BW, deg	Inter-element arc spacing	Number of switched off elements
fully populated	−17.37	4.5	$0.5000\lambda_w$	0
MPSO [15]	−23.85	4.0	$0.6266\lambda_w$	227
DEGL [14]	−24.81	4.5	$0.5285\lambda_w$	220
BBO	−26.6	4.4	$0.5296\lambda_w$	230

Table 5 Excitation amplitude distributions (A_{mn}) using BBO with optimised d_m

		BBO
ring number	1	11010101
	2	0110100111001100
	3	111111111010111110111010
	4	01010011000011101011000100101111
	5	0001101011100000111001100011011000001000
	6	001001100100000001011101011000111101111001010100
	7	00111010001111011101101000110100010001111001100110000000
	8	0001100111111000101101011001100001010110000100100100111110111100
	9	001010101100010110110110000000101100111011101010010111101001000100011000
	10	01100110001011110000101011001000000110010110000001000101101101010010010000111011
		elements state in each ring (0 or 1)

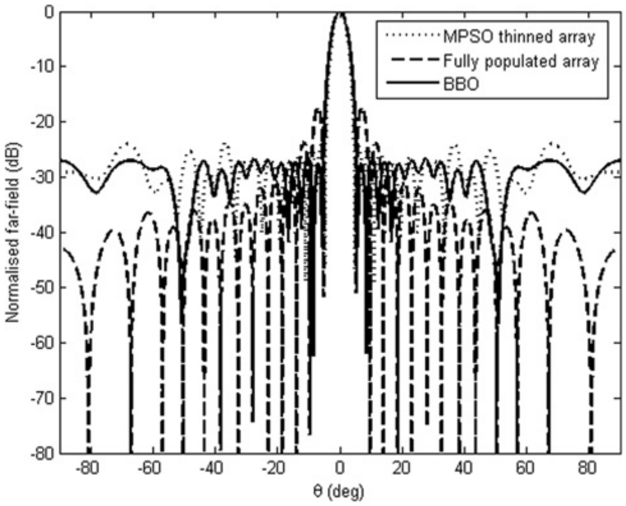

Fig. 9 *Radiation pattern for ring antenna array obtained using BBO results as compared with the results of the fully populated and the MPSO array*

5 Conclusions

In this paper, the BBO technique is applied for thinning large multiple concentric circular ring antenna arrays of isotropic elements to generate a pencil beam in the vertical plane with reduced SLL. Two cases are presented in the paper. One is to obtain a thinned array with fixed inter-element array spacing and second with optimised inter-element array spacing. In both cases, BBO obtained an array which has lower SLL than MPSO and DEGL thinned array for same or narrow BW. Both synthesised arrays consist of 220 or more switched off elements, that is, a reduction of 50% or more of the total elements used in the case of a fully populated array whereas the SLL is also considerably reduced. This will reduce the cost of designing the arrays substantially. There is a very good agreement between the desired and synthesised specifications. BBO is simple to implement and easy to comprehend. It has again demonstrated to be an effective technique for antenna optimisation. It can be further applied to thinning of other antenna arrays of different shapes and geometries.

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