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Optimized radii and excitations with concentric circular antenna array for maximum sidelobe level reduction using wavelet mutation based particle swarm optimization techniques

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Abstract In this paper, a Particle Swarm Optimization with Constriction Factor and Inertia Weight Approach with Wavelet Mutation (PSOCFIWA-WM) is applied to the process of synthesizing three-ring Concentric Circular Antenna Arrays (CCAA) without and with central element feeding, focused on maximum sidelobe level reductions. Sidelobe level (SLL) is a critical radiation pattern parameter in the task of reducing background noise and interference in the most recent wireless communication systems. To improve the radiation pattern with maximum SLL reduction, an optimum set of antenna element parameters as excitation weights and radii of the rings are to be developed. The extensive computational results show that the method of PSOCFIWA-WM provides a maximum sidelobe level reduction of 96.06% with respect to the uniformly excited case for the particular CCAA containing 4, 6, and 8 numbers of elements in the three successive rings along with central element feeding.

Keywords Concentric circular antenna array · Non-uniform excitation · Sidelobe level · Particle swarm optimization · Wavelet mutation

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1 Introduction

Antenna arrays have considerable interest in various applications including radar, sonar, imaging, biomedicine, and mobile communications [1–6]. The array geometries that have been studied include mainly uniform linear arrays, uniform rectangular (URA), and circular arrays (UCA). A linear array has excellent directivity and it can form the narrowest main-lobe in a given direction, but it does not work equally well in all azimuthal directions. A major disadvantage of the URA is that an additional major lobe of the same intensity appears on the opposite side. An obvious advantage results from the symmetry of the circular array structure. Since a circular array does not have edge elements, directional patterns synthesized with a circular array can be electronically rotated in the plane of the array without a significant change of the beam shape [3]. Concerning the two geometries, the URA and the planar uniform circular array (PUCA) with similar areas, slightly greater directivity was obtained with the use of the PUCA [4]. On the other hand, a circular array is a high side-lobe geometry. For mitigating high side-lobe levels, a concentric circular antenna array (CCAA) [7–9] contains many concentric circular rings of different radii sharing the same center and different numbers of elements in each ring are utilized. It has several advantages including the flexibility in array pattern synthesis and design both in narrowband and broadband beam-forming applications [9–12]. CCAA are also used for direction finding and applications requiring main beam symmetry. CCAA provide almost invariant azimuth angle coverage.

Over the past few decades [13–20] many synthesis methods are concerned with suppressing the SLL while preserving the gain of the main beam. Uniformly excited and equally spaced antenna arrays have high directivity but they usually suffer from high side lobe level. Compared with the uniformly excited array, the non-uniformly excited array with optimal excitations and optimal radii of the rings have more degree of freedom and is able to lower the peak sidelobe with smaller number of elements. So, the optimizing parameters would be large in number and discrete, resulting in highly non-linear, discontinuous and non-differentiable array factors of CCAA design.

Classical optimization methods have several disadvantages such as: (i) highly sensitive to starting points when the number of solution variables and hence the size of the solution space increase, (ii) frequent convergence to local optimum solution or divergence or revisiting the same sub-optimal solution, (iii) requirement of continuous and differentiable objective cost function (gradient search methods), (iv) requirement of the piecewise linear cost approximation (linear programming), and (v) problem of convergence and algorithm complexity (non-linear programming). Particle Swarm Optimization (PSO) [21–27], an evolutionary algorithm based on the swarm intelligence, which does not suffer from above disadvantages may be adopted. The original conception comes from the birds' flocking or fish schooling. PSO algorithm can be used to solve complex near-global optimization problems. Currently, the algorithm and its variations are applied to solve many practical problems [23–27]. In this work, for the optimization of complex, highly non-linear, discontinuous, and non-differentiable array factors of CCAA design, Particle Swarm Optimization with Constriction Factor and Inertia Weight Approach (PSOCFIWA), and its modified version with Wavelet mutation are adopted.

However, for maintaining the diversity from one generation of the population to the next, mutation takes an important role in the evolution process. The presence of mutation can help to reach the near-global optimal solution but a too vigorous mutation in every iteration step may slow down or even destroy the convergence of the algorithm. On doing the mutation operation, one can have the solution space to be more widely explored in the early stage of the search by setting a larger searching space and it is more likely to obtain a fine-tuned near-global solution in the later stage of the search by setting a smaller searching space, The above requirement can be fulfilled by Wavelet [28–30]. The Wavelet is a tool to model seismic signals by combining dilations and translations of a simple, oscillatory function (mother Wavelet) of a finite duration. Its properties enable us to improve further the optimization performance of PSOCFIWA through mutation. Thus, PSOCFIWA-WM, a new variant of PSOCFIWA is proposed in this work. PSOCFIWA-WM yields near-global solution and provides a much faster convergence than PSOCFIWA. Moreover, Wavelet mutation helps to achieve higher solution stability. Thus, optimal CCAA design achieved by PSOCFIWA-WM would have the near-global optimized set of non-uniform current excitation weights and radii of the rings.

In this paper we study mostly uniform CCAA that have an inter-element spacing d ($d \in [\lambda/2, \lambda]$) in the same array. The beam pattern, sidelobe level and beamwidth are examined for two cases; the first with no central element feeding and the other with the existence of such element. It is found that the existence of the central element can appreciable reduce the sidelobe level with minimal beamwidth increase.

The paper is arranged as follows; in Sect. 2, the CCAA geometry and its design equations are stated. In Sect. 3 the brief introduction for the PSO based algorithms is given, while in Sect. 4 the sidelobe levels and beamwidths as determined by computational experiments with the optimization techniques are presented, and finally the conclusions are given in Sect. 5.

2 Design equation

Geometrical configuration is a key factor in the design process of an antenna array. For CCAA, the elements are arranged in such a way that all antenna elements are placed in multiple concentric circular rings, which differ in radii and in number of elements. Figure 1 shows the general configuration of CCAA with M concentric circular rings, where the mth ($m = 1, 2, \dots, M$) ring has a radius r_m and the corresponding number of elements is N_m. If all the elements in all the rings are assumed to be isotropic sources, the radiation pattern of this array may be written in terms of its array factor only.

Referring to Fig. 1, the array factor, $AF(\theta, \phi, I)$ for the CCAA may be written as (1) [25]:

$$AF(\theta, \phi, I) = \sum_{m=1}^{M} \sum_{i=1}^{N_m} I_{mi} \exp[j(kr_m \sin\theta \cos(\phi - \phi_{mi}) + \alpha_{mi})] \quad (1)$$

where I_{mi} denotes current excitation of the ith element of the mth ring. $k = 2\pi/\lambda$, λ being the signal wave-length. θ and ϕ symbolize the zenith angle from the positive z axis and the azimuth angle from the positive x axis to the orthogonal projection of the observation point respectively. It may be noted that the array factor is always a periodic function of ϕ with a period of 2π radian, whatever be the value of θ. The azimuth angle to the ith element of the mth ring is ϕ_{mi}. As the elements in each ring are assumed to be uniformly distributed, we have.

$$\phi_{mi} = 2\pi\left(\frac{i-1}{N_m}\right); \quad m = 1, \dots, M;\ i = 1, \dots, N_m \quad (2)$$

The term α_{mi} is the phase difference between the individual elements in the array which is a function of angular separa-

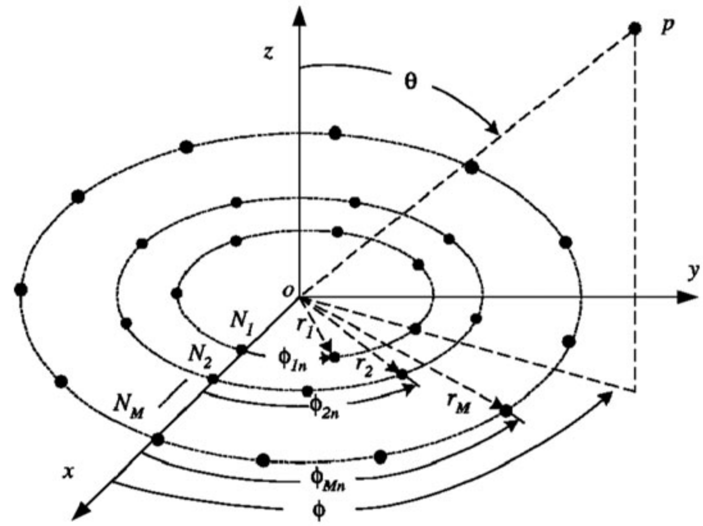


Fig. 1 Concentric circular antenna array (CCAA)

tion ϕ_{mi} and ring radii r_m.

$$\alpha_{mi} = -kr_m \sin\theta_0 \cos(\phi_0 - \phi_{mi})$$
$$m = 1, \ldots, M;\ i = 1, \ldots, N_m \quad (3)$$

where θ_0 and ϕ_0 are the values of θ and ϕ ($\theta, \phi \in [-\pi, \pi]$) respectively where the highest peak of the main lobe is obtained.

In this work, the elevation angle is assumed to be 90 degrees i.e. $\theta = 90^0$. The array factor, $AF(\theta, \phi, I)$ of (1) for the CCAA in *x*–*y* plane can now be rewritten as (4):

$$AF(\phi, I) = \sum_{m=1}^{M} \sum_{i=1}^{N_m} I_{mi} \exp[jkr_m(\cos(\phi - \phi_{mi}) - \cos(\phi_0 - \phi_{mi}))] \quad (4)$$

Normalized absolute array factor, $AF(\phi, I)$ in dB can be expressed as follows:

$$AF(\phi, I)|_{dB} = 10\log_{10}\left[\frac{|AF(\phi, I)|}{|AF(\phi, I)|_{\max}}\right]^2 = 20\log_{10}\left[\frac{|AF(\phi, I)|}{|AF(\phi, I)|_{\max}}\right] \quad (5)$$

After defining the array factor, the next step in the design process is to formulate the objective function which is to be minimized. The objective function "Cost Function" (*CF*) may be written as (6):

$$CF = W_{F1} \times \frac{|AF(\phi_{msl1}, I_{mi}) + AF(\phi_{msl2}, I_{mi})|}{|AF(\phi_0, I_{mi})|} + W_{F2} \times (FNBW_{computed} - FNBW(I_{mi} = 1)) \quad (6)$$

FNBW is an abbreviated form of first null beamwidth, or, in simple terms, angular width between the first nulls on either side of the main beam. *CF* is computed only if $FNBW_{computed} < FNBW(I_{mi} = 1)$ and the corresponding solution of current excitation weights is retained in the active population otherwise not retained. ϕ_{msl1} is the angle where the maximum sidelobe ($AF(\phi_{msl1}, I_{mi})$) is attained in the lower band and ϕ_{msl2} is the angle where the maximum sidelobe ($AF(\phi_{msl2}, I_{mi})$) is attained in the upper band. After experimentation, best proven values of W_{F1} and W_{F2} are fixed as 18 and 1 respectively. W_{F1} and W_{F2} are so chosen that optimization of SLL remains more dominant than optimization of $FNBW_{computed}$ and *CF* never becomes negative. In (6) the two beamwidths, $FNBW_{computed}$ and $FNBW(I_{mi} = 1)$ basically refer to the computed first null beamwidths in radian for the non-uniform excitation case and for uniform excitation case respectively. Minimization of *CF* achieves maximum reductions of SLL both in lower and upper bands dominantly. The evolutionary optimization techniques employed for optimizing the current excitation weights resulting in the minimization of *CF* and hence reduction in SLL are described in the next section.

3 Optimization techniques employed

3.1 Particle swarm optimization (PSO)

PSO is a flexible, robust population-based stochastic search/optimization technique with implicit parallelism, which can easily handle with non-differential objective functions, unlike traditional optimization methods. Standard PSO is less susceptible to getting trapped on local optima unlike GA, Simulated Annealing etc. Kennedy, Eberhart and Shi [21, 22] developed standard PSO concept similar to the behavior of a swarm of birds. Standard PSO is developed through simulation of bird flocking in multidimensional space. Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest). This information corresponds to personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gbest) among pbests. Namely, each agent tries to modify its position using the following information:

- The distance between the current position and pbest.
- The distance between the current position and gbest.

Mathematically, velocities of the particles are modified according to the following equation:

$$\begin{aligned} V_i^{k+1} &= w \times V_i^k + C_1 \times rand_1 \times (pbest_i - S_i^k) \\ &\quad + C_2 \times rand_2 \times (gbest - S_i^k) \end{aligned} \tag{7}$$

where V_i^k is the velocity of agent i at iteration k; w is the inertia weighting function; C_i is the weighting factor; $rand_i$ is the random number between 0 and 1; S_i^k is the current position of agent i at iteration k; pbest$_i$ is the pbest of agent i; gbest is the gbest of the group. The searching point in the solution space can be modified by the following equation:

$$S_i^{k+1} = S_i^k + V_i^{k+1} \tag{8}$$

The first term of (7) is the previous velocity of the agent. The second and third terms are used to change the velocity of the agent. Without the second and third terms, the agent will keep on "flying" in the same direction until it hits the boundary. Namely, it corresponds to a kind of inertia and tries to explore new areas. The values of w, C_1 and C_2 are given in the next section.

3.1.1 *Particle swarm optimization with constriction factor and inertia weight approach (PSOCFIWA)*

For PSOCFIWA [24, 25], the velocity of (7) is manipulated in accordance with (9).

$$\begin{aligned} V_i^{k+1} &= CFa \times \big(w^{k+1} \times V_i^k \\ &\quad + C_1 \times rand_1 \times (pbest_i - S_i^k) \\ &\quad + C_2 \times rand_2 \times (gbest - S_i^k)\big) \end{aligned} \tag{9}$$

Normally, $C_1 = C_2 = 1.5$–2.05 and constriction factor (CFa) varies from 0.6–0.73. The best values of C_1, C_2, and CFa are found to vary with the design sets. In Inertia Weight Approach (IWA), inertia weight (w^{k+1}) at $(k+1)$th cycle is as given in (9).

$$w^{k+1} = w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} \times (k+1) \tag{10}$$

where $w_{\max} = 1.0$; $w_{\min} = 0.4$; $k_{\max}$ = Maximum number of iteration cycles. The solution updating is the same as (8).

3.2 PSOCFIWA with wavelet mutation (PSOCFIWA-WM)

3.2.1 *Basic wavelet theory: a concept*

Certain seismic signals can be modeled by combining translations and dilations of an oscillatory function with a finite duration called a "Wavelet". Wavelet transform can be divided in two categories: continuous Wavelet transform and discrete Wavelet transform. The continuous Wavelet transform $W_{a,b}(x)$ of function $f(x)$ with respect to a mother Wavelet $\psi(x) \in L^2(\Re)$ is given by the following equation [28–30].

$$\begin{aligned} &W_{a,b}(x) = \frac{1}{\sqrt{C_\psi}} \int_{-\infty}^{+\infty} f(x)\psi_{a,b}^*(x)dx \\ &\text{where } \psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \\ &x \in \Re,\ a, b \in \Re,\ a > 0 \end{aligned} \tag{11}$$

In (11), (*) denotes the complex conjugate, a is the dilation (scale) parameter, and b is the translation (shift) parameter. It is to be noted that a controls the spread of the Wavelet and b determines its control position. A set of basis functions $\psi_{a,b}(x)$ is derived from scaling and shifting the mother Wavelet. The basis function of the transform is called the daughter Wavelet. The mother Wavelet has to satisfy the following admissibility condition.

$$C_\psi = 2\pi \int_{-\infty}^{+\infty} \frac{|\overline{\psi}(\omega)|^2}{\omega} d\omega < \infty \tag{12}$$

where $\overline{\psi}(\omega)$ is the Fourier is transform of $\psi(\omega)$ and given by the following equation:

$$\overline{\psi}(\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} \psi(x) \times e^{-j\omega x} dx \tag{13}$$

Most of the energy $\psi(x)$ is confined to a finite domain and is bounded.

3.2.2 *Association of wavelet based mutation with PSOCFIWA (PSOCFIWA-WM)*

It is proposed that every element of the particle of the population will have a chance to mutate, governed by a user defined probability $p_m \in [0, 1]$. For each element, a random number between 0 and 1 will be generated such that if it is less than or equal to p_m, the mutation will take place on that element. Among the population, a randomly selected ith agent and its jth element (within the limits $[S_{j,\min}, S_{j,\max}]$)

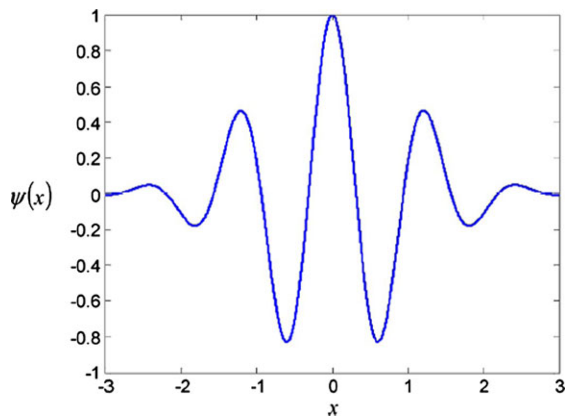


Fig. 2 Morlet Wavelet, $\psi(x)$

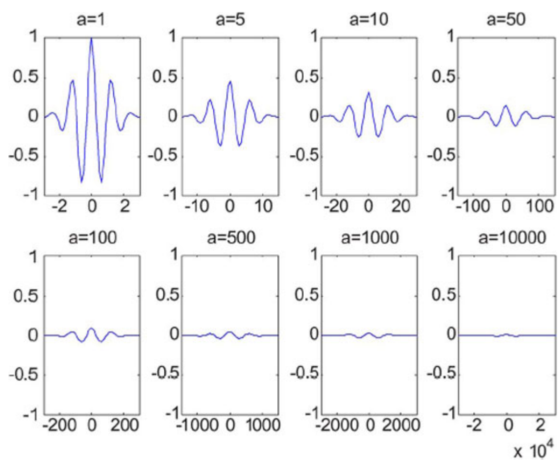


Fig. 3 Various dilated morlet wavelets (x-axis: x, y-axis: $\psi_{a,0}(x)$)

at kth iteration ($S_{i,j}^{(k)}$) will undergo mutation as given in the following equation:

$$S_{i,j}^{(k)} = \begin{cases} S_{i,j}^{(k)} + \sigma \times (S_{j,\max} - S_{i,j}^{(k)}), & \text{if } \sigma > 0 \\ S_{i,j}^{(k)} + \sigma \times (S_{i,j}^{(k)} - S_{j,\min}), & \text{if } \sigma \le 0 \end{cases}$$

$$\text{where } \sigma = \psi_{a,0}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x}{a}\right) \tag{14}$$

A Morlet Wavelet (mother Wavelet) defined in the following equation may be shown as in Fig. 2.

$$\psi(x) = e^{\frac{-x^2}{2}} \cos(5x) \tag{15}$$

Thus,

$$\sigma = \frac{1}{\sqrt{a}} e^{\frac{-(\frac{x}{a})^2}{2}} \cos\left(5\left(\frac{x}{a}\right)\right) \tag{16}$$

Different dilated Morlet Wavelets are shown in Fig. 3. From this figure it is clear that as the dilation parameter a increases, the amplitude of $\psi_{a,0}(x)$ will be scaled down. In order to enhance the searching performance, this property will be utilized in mutation operation.

As over 99% of the total energy of the mother Wavelet function is contained in the interval $[-2.5, 2.5]$ (Property II), x can be randomly generated from $[-2.5 \times a, 2.5 \times a]$. The value of the dilation parameter a is set to vary with the value of k/K in order to meet the fine-tuning purpose, where k is the current iteration number and K is the maximum number of iterations. In order to perform a local search when k is large, the value of a should increase as k/K increases to reduce the significance of the mutation. Hence, a monotonic increasing function governing a and k/K may be written as given in the following equation [30]:

$$a = e - \ln(g) \times \left(1 - \frac{k}{K}\right)^{\xi_{\omega m}} + \ln(g) \tag{17}$$

where $\xi_{\omega m}$ is the shape parameter of the monotonic increasing function, and g is the upper limit of the parameter a. The value of a is between 1 and 10000.

A perfect balance between the exploration of new regions and the exploitation of the already sampled regions in the search space is expected in PSOCFIWA-WM. This balance, which critically affects the performance of the PSOCFIWA-WM, is governed by the right choices of the control parameters, e.g. swarm size (n_p), the probability of mutation (p_m), and the shape parameter of WM ($\xi_{\omega m}$). Changing the parameter $\xi_{\omega m}$ will change the characteristics of the monotonic increasing function of WM. The dilation parameter a will take a value to perform fine tuning faster as $\xi_{\omega m}$ increases. In general, if the optimization problem is smooth and symmetric, it is easier to find the solution, and the fine tuning can be done in early iteration. Thus, a larger value of $\xi_{\omega m}$ can be used to increase the step size (σ) for the early mutation.

4 CCAA design sets and setting of algorithm parameters

The optimization techniques described in the previous section are individually implemented to optimize the radiation pattern for non-uniformly excited CCAA. For all sets of experiments, the number of current excitation elements for the inner most ring is N_1, for outermost ring is N_3; whereas the middle ring consists of N_2 number of current excitation elements. Several cases are considered with different number of antenna elements in the three-ring CCAA (N_1, N_2, N_3) designs for both without and with central element feeding are (2, 4, 6), (3, 5, 7), (4, 6, 8), (5, 7, 9), (6, 8, 10), (7, 9, 11), (8, 10, 12), (9, 11, 13), (10, 12, 13), and (11, 13, 15). (Each CCAA is required to have optimal current excitation weights and also to maintain fixed but different from ring to ring

Table 1 SLL and FNBW for uniformly excited ($I_{mi} = 1$) CCAA sets

Set No.	No. of elements in each rings (N_1, N_2, N_3)	Without central element (Case (a))		With central element (Case (b))	
		SLL (dB)	*FNBW* (deg)	SLL (dB)	*FNBW* (deg)
I	2, 4, 6	−12.56	128.4	−17.0	140.0
II	3, 5, 7	−13.8	107.2	−15.0	116
III	4, 6, 8	−11.23	90.3	−12.32	95.4
IV	5, 7, 9	−11.2	78.2	−13.24	81.6
V	6, 8, 10	−10.34	68.4	−12.0	71.1
VI	7, 9, 11	−10.0	61.0	−11.32	63.0
VII	8, 10, 12	−9.6	54.8	−10.76	56.4
VIII	9, 11, 13	−9.28	50.0	−10.34	51.3
IX	10, 12, 14	−9.06	46.0	−10.0	47.0
X	11, 13, 15	−8.90	42.0	−9.8	43.2

optimal inter-element spacing in each ring with the help of optimal radii.) For all the cases, $\phi_0 = 0^0$ is considered so that the peak of the main lobe is obtained at the origin.

Each particle vector of PSOCFIWA and PSOCFIWA-WM consists of real-coded sub-stings of current excitation weights and three radii within their respective maximum and minimum limits. Number of sub-strings of current excitation weights depends on the total number of current excitation elements. The current excitations for the array elements, $(I_{11}, I_{12}, \ldots, I_{mi})$ are normalized to be called as current excitation weights using $\max(I_{mi}) = 1$. So, for current excitation weights, the maximum and minimum limits are 1 and 0 respectively. The limits of the radius of a particular ring of CCAA are decided by the product of number of elements in the ring and the inequality constraint for the inter-element spacing, d ($d \in [\frac{\lambda}{2}, \lambda]$).

The best algorithm parameters set after several experiments are: (i) Population of particle vectors (swarm size) = 120, (ii) Maximum number of iteration cycles = 100, (iii) $C_1 = C_2 = 1.5$, (iv) For Wavelet Mutation, rigorous trial runs with respect to the dependence of a on (k/K), p_m, $\xi_{\omega m}$ and g is performed to determine the individual best values of p_m, $\xi_{\omega m}$ and g as 0.15, 2.0 and 10000 respectively.

4.1 Computational results

PSOCFIWA and PSOCFIWA-WM based optimal results are produced in Tables 2–5 to show the improvement in PSOCFIWA based results. Table 1 depicts SLL values and *FNBW* values for all corresponding uniformly excited $((I_{mi}) = 1)$ CCAA with $d = \lambda/2$ inter-element spacing in each ring. Figure 4 shows a comparison between the radiation patterns for uniformly excited CCAA with $d = \lambda/2$ and the same CCAA with optimal current excitation weights with optimal radii obtained by PSOCFIWA. The radiation pattern behavior shown in Fig. 4 indicates that a uniformly excited $((I_{mi}) = 1)$ CCAA with $d = \lambda/2$ in each ring has a radiation pattern with −11.23 dB SLL for the particular CCAA containing 4, 6, and 8 number of antenna elements in the three successive rings without central element feeding and the SLL for the same set with central element feeding and uniform excitation with $d = \lambda/2$ is −12.32 dB. All sidelobes are suppressed to a level less than −31.16 dB and −36.88 dB for the above set without and with central element feeding respectively, as a result of the optimization by PSOCFIWA. In this case, it is observed in Fig. 4 that the PSOCFIWA provides maximum sidelobe level reductions of 89.92% and 94.08% with respect to the corresponding uniform case for without and with central element feeding respectively.

Similarly, Fig. 5 also illustrates the array factors obtained for the CCAA having $N_1 = 4$, $N_2 = 6$, $N_3 = 8$ elements as compared to uniformly excited CCAA with uniform inter-element spacing $d = \lambda/2$ in each ring. For the above set, the PSOCFIWA-WM generates a set of optimal current excitation weights and radii as shown in Tables 4, 5, that provide a radiation pattern with −34.7 dB and −40.4 dB for the above set without and with central element feeding respectively, i.e. maximum sidelobe level reductions of 93.29% and 96.06% with respect to the corresponding uniform case for without and with central element feeding respectively are achieved.

The above reductions of SLL can be easily determined by referring to Table 1 and Tables 2, 3, 4, 5. PSOCFIWA-WM yields consistently better optimal results than PSOCFIWA.

The minimum *CF* values are plotted against the number of iteration cycles to get the convergence profiles for PSO based techniques. Figure 6 shows the convergence profiles for PSOCFIWA and PSOCFIWA-WM for Set No. III CCAA. PSOCFIWA yield suboptimal higher values of *CF* but PSOCFIWA-WM yields true optimal (least) *CF* values consistently in all cases. With a view to the above fact, it may finally be inferred that the performance of PSOCFIWA-WM technique is better than that of PSOCFIWA. All optimization programs are written in MATLAB 7.5 version on core (TM) 2 duo processor, 3.00 GHz with 2 GB RAM.

The CCAA model using isotropic sources in this work will be useful for the calculation of the radiation patterns of any practical antenna by simply multiplying the proposed array factor by the array factor of single such antenna using Pattern multiplication theorem [5].

Table 2 Current excitation weights, radii, *CF*, SLL and FNBW for optimally excited CCAA sets (Case (a)) using PSOCFIWA

Set No.	$(I_{11}, I_{12}, \ldots, I_{mi})$; (r_1, r_2, r_3) in λ					*CF*	SLL (dB)	*FNBW* (deg)
III	0.9731	1.0000	1.0000	1.0000	0.6842	1.15	−31.16	74.3
	0.6365	0.9143	0.6883	0.6872	0.9137			
	0.6037	1.0000	0.6558	0.3301	0.6598			
	1.0000	0.5707	0.1862;					
	0.3385	0.5809	0.9825					
V	0.4256	0.7281	0.3679	0.7213	0.3864	2.39	−24.92	60.1
	0.7212	1.0000	0 0.9319	1.0000	0.8668			
	0 0.8535	1.0000	0.4616	0.6344	0.9680			
	0	0	0.1622	1.0000	0.5467			
	0.5582	0.3460;						
	0.4805	0.7234	1.1608					
VII	0.5047	0.7723	0.4207	1.0000, 1.0000	0	2.62	−24.52	60.5
	0.6304	1.0000	0.5897	0.4000	0.1816			
	1.0000	1.0000	0.5354	0.2338	0.2843			
	0.7795	0.9798	0.4236	0 0.7926	0.2780			
	0.5493	0.3813	0.6452	0	0.6617			
	0	0.5092	0.2532;					
	0.6688	0.9652	1.3327					

Table 3 Current excitation weights, radii, *CF*, SLL and FNBW for optimally excited CCAA sets (Case (b)) using PSOCFIWA

Set No.	$(I_{11}, I_{12}, \ldots, I_{mi})$; (r_1, r_2, r_3) in λ					*CF*	SLL (dB)	*FNBW* (deg)
III	0.4124	0.7748	0.8370	0.7863	0.7963	0.57	−36.88	86.4
	1.0000	1.0000	0.9210	1.0000	1.0000			
	1.0000	0.5387	1.0000	0.5680	0.3426			
	0.5786	1.0000	0.5485	0.3991;				
	0.3376	0.5207	0.9793					
V	1.0000	0.9796	1.0000	0.6388	1.0000	1.15	−29.46	64.4
	1.0000	0.4391	0.8441	0.1797	0.8168			
	1.0000	1.0000	0.4176	0.7032	1.0000			
	0.3300	1.0000	1.0000	0.4447	0.2162			
	0.3409	1.0000	0.8096	0.3148	0.2698;			
	0.4547	0.7410	1.1566					
VII	1.0000	0.7922	1.0000	0.6768	0.8687	1.87	−26.4	60.5
	0.3921	1.0000	0.4983	1.0000	1.0000			
	0.7203	0.4846	0.7811	1.0000	1.0000			
	0.2393	0.4808	1.0000	1.0000	0.5573			
	0.4321	1.0000	0.2565	0.4101	0.3630			
	0.7667	0 1.0000	0.1471	1.0000	1.0000;			
	0.6179	0.9009	1.3474					

Table 4 Current excitation weights, radii, *CF*, SLL and FNBW for optimally excited CCAA sets (Case (a)) using PSOCFIWA-WM

Set No.	$(I_{11}, I_{12}, \ldots, I_{mi})$; (r_1, r_2, r_3) in λ					*CF*	SLL (dB)	*FNBW* (deg)
III	0.9873	1.0000	0.9997	1.0000	0.5488	0.85	−34.70	91.4
	0.6244	0.8523	0.5471	0.5789	0.8233			
	0.5139	0.8390	0.5418	0.3631	0.5399			
	0.8687	0.5464	0.3551;					
	0.3272	0.5969	0.9932					
V	0.5351	0.5678	0.7606	0.5075	0.5102	2.03	−27.14	62.46
	0.6465	0.6918	0 0.7210	0.9565	0.7635			
	0 0.6463	0.9478	0.4941	0.6648	0.6766			
	0.5399	0.4933	0.5208	0.6358	0.5508			
	0.4671	0.4642;						
	0.5064	0.7787	1.1845					
VII	0.6602	0.2828	0.5378	0.9875	0.7343	1.90	−27.54	53.29
	0.4022	0.4818	1.0000	0.5089	0.3606			
	0.0597	0.6740	0.9245	0.5923	0.1030			
	0.1157	0.5992	1.0000	0.7768	0.2435			
	0.8709	0.2266	0.6679	0.5689	0.5610			
	0.3182	0.9455	0.2538	0.6775	0.7301;			
	0.7413	1.0739	1.4209					

Table 5 Current excitation weights, radii, *CF*, SLL and FNBW for optimally excited CCAA sets (Case (b)) using PSOCFIWA-WM

Set No.	$(I_{11}, I_{12}, \ldots, I_{mi})$; (r_1, r_2, r_3) in λ					*CF*	SLL (dB)	*FNBW* (deg)
III	0.8230	0.3073	0.6584	0.3034	0.6191	0.41	−40.40	95.4
	0.9665	1.0000	1.0000	0.9887	0.9754			
	0.9906	0.5120	0.5599 0.5224	0	0.4944			
	0.5327	0.4951	0.0055;					
	0.3313	0.5103	0.8743					
V	1.0000	1.0000	0.9004	0.8323	1.0000	1.29	−29.22	61.88
	0.9615	0.8660	0.5715	0.2435	0.7012			
	0.7271	0.6479	0.2854	0.6052	0.6899			
	0.3366	0.9061	1.0000	0.3099	0.4124			
	0.3330	0.9777	0.9902	0.3553	0.5128;			
	0.5112	0.7941	1.2199					
VII	1.0000	0.4153	1.0000	0.5718	1.0000	1.52	−27.77	55.01
	0.7573	0.9752	0.4530	1.0000	0.7132			
	0.1473	0.1414	1.0000	1.0000	0.9622			
	0.1574	0.1328	0.9701	1.0000	0.9373			
	0.2020	1.0000	0.5629	0.5830	0.4990			
	0.4129	0.5989	0.9499	0.3832	0.7377			
	0.7309;							
	0.7044	0.9948	1.3978					

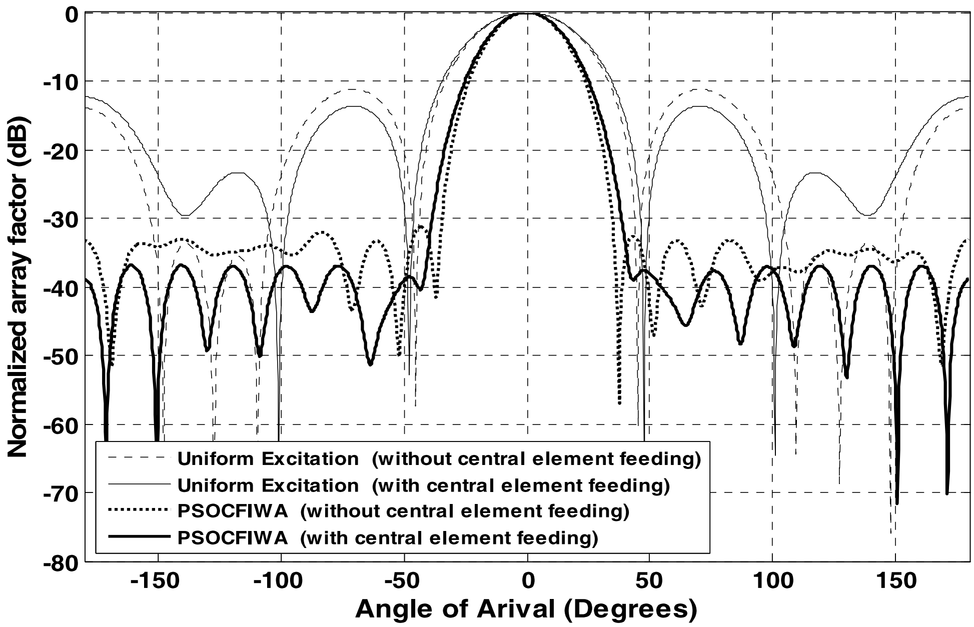


Fig. 4 Radiation patterns for a uniformly excited CCAA and corresponding PSOCFIWA based optimized non-uniformly excited CCAA for the Set. No. III ($N_1 = 4$, $N_2 = 6$, $N_3 = 8$ elements)

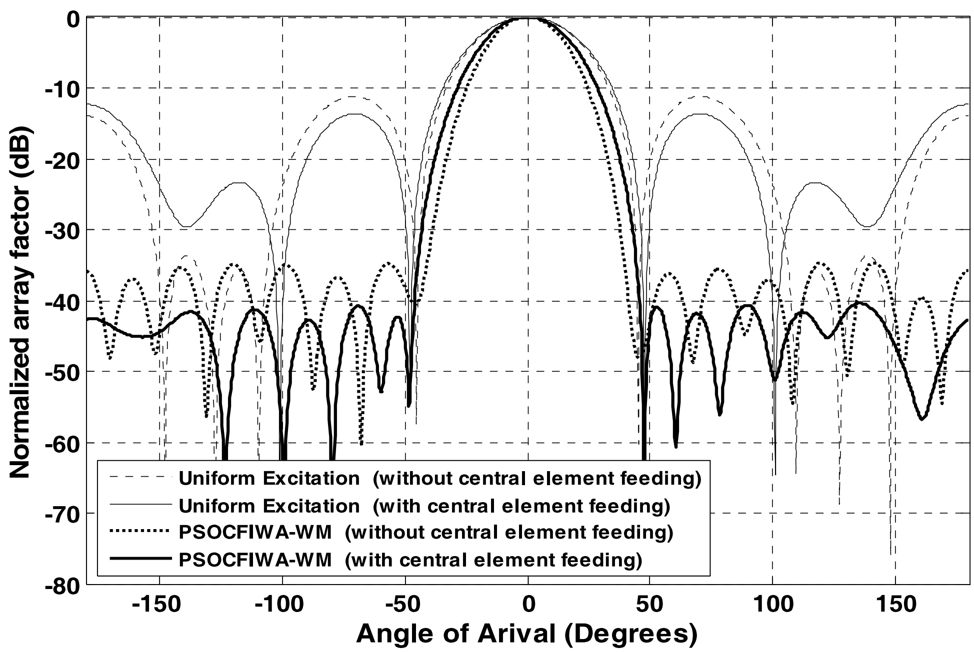
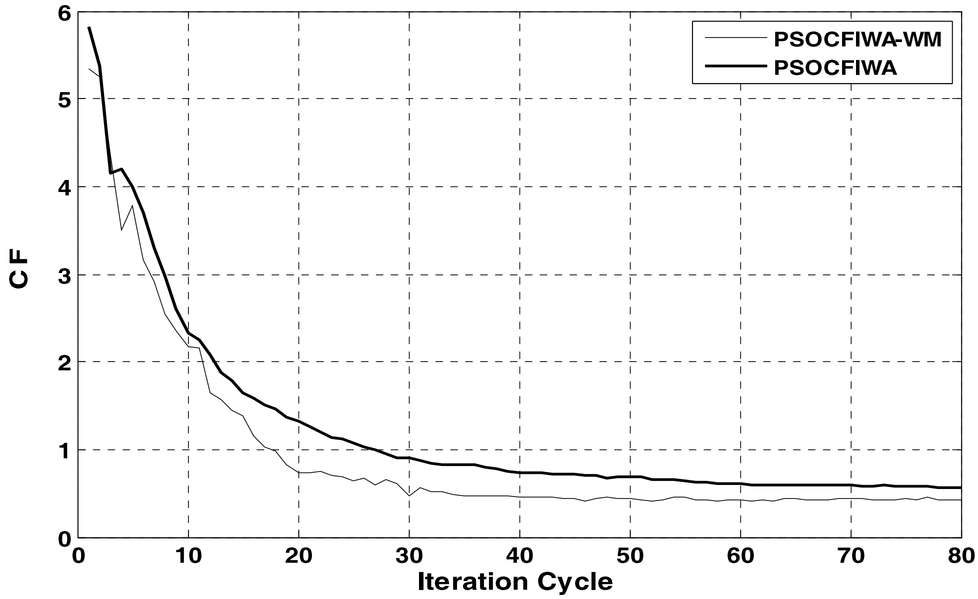


Fig. 5 Radiation patterns for a uniformly excited CCAA and corresponding PSOCFIWA-WM based optimized non-uniformly excited CCAA for the Set. No. III ($N_1 = 4$, $N_2 = 6$, $N_3 = 8$ elements)

5 Conclusions

In this paper, the PSO based techniques are used to adjust the radius of each ring and excitation of each element in the three-ring CCAA to obtain optimal sidelobe level suppression. The PSOCFIWA and PSOCFIWA-WM algorithms can efficiently handle the design of non-uniformly excited CCAA by generating radiation patterns with maximum SLL reductions. PSOCFIWA-WM proves to be much more effective algorithm by reducing notably the sidelobe levels as compared to the case of uniform current excitation with $d = \lambda/2$ inter-element spacing. This paper has the following conclusions: (1-) In CCAA, the central element plays a very important role to improve the performance of radiation pattern. (2-) The existence of the central element in the CCAA having $N_1 = 4$, $N_2 = 6$, $N_3 = 8$ elements reduces the sidelobe level to 96.06% with respect to the uniform current excitation with $d = \lambda/2$ inter-element spacing. (3-) It is shown that the proposed PSOCFIWA-WM technique outperforms significantly the other counterpart PSOCFIWA in terms of solution quality and solution robustness. Thus, the proposed Particle Swarm Optimization with Constriction Factor and

Fig. 6 Convergence curves for PSOCFIWA and PSOCFIWA-WM in case of optimized non-uniformly excited CCAA for the Set. No. III ($N_1 = 4$, $N_2 = 6$, $N_3 = 8$ elements), with central element feeding



Inertia Weight Approach with Wavelet Mutation is a good evolutionary optimization technique for the near-global optimization of any other antenna array problem.

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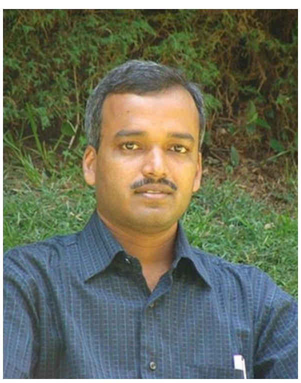

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