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Sidelobe Reductions of Antenna Arrays via an Improved Chicken Swarm Optimization Approach

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ABSTRACT Antenna arrays are able to improve the directivity performance and reduce the cost of wireless communication systems. However, how to reduce the maximum sidelobe level (SLL) of the beam pattern is a key problem in antenna arrays. In this paper, three kinds of antenna arrays that are linear antenna array (LAA), circular antenna array (CAA) and random antenna array (RAA) are investigated. First, we formulate the SLL suppression optimization problems of LAA, CAA and RAA, respectively. Then, we propose a novel method called improved chicken swarm optimization (ICSO) approach to solve the formulated optimization problems. ICSO introduces four enhanced strategies including the local search factor, weighting factor and global search factor into the update method of conventional chicken swarm optimization (CSO) algorithm, respectively, for achieving better beam pattern optimization results of antenna arrays. Moreover, a variation mechanism is proposed to enhance the population diversity so that further improving the performance of the algorithm. We conduct simulations to evaluate the performance of the proposed ICSO for the maximum SLL suppressions of LAAs, CAAs and RAAs, and the results show that ICSO obtains lower maximum SLLs for different antenna array cases with different numbers of antenna elements compared to several other algorithms.

INDEX TERMS Beam pattern, sidelobe level, antenna array optimization, swarm intelligence optimization, chicken swarm optimization.

I. INTRODUCTION

Antenna arrays are important technologies for modern wireless communication systems because they can provide high gains and spectral efficiency [1], [2]. Moreover, by using beamforming technique, directional beams with low sidelobes and interferences of the antenna arrays can be achieved, so that improving the performance of the communication systems and long-distance wireless power transmissions [3], [4]. A communication system can achieve the signal with lower interference and higher directionality by using antenna arrays [5], [6]. The fifth generation (5G) communications are rapidly developed, and the massive multi-input-multi-output (MIMO) and beamforming technologies that with high spectral efficiency are proposed to enhance the capacity of the system [7], [8]. Both of these two technologies are based on antenna arrays.

There are many different shapes of antenna arrays used in practical systems, and the linear antenna array (LAA) and circular antenna array (CAA) can be regarded as the most commonly used ones [9]. Both of LAA and CAA are able to perform the beams with high gains to the desired receivers, which can enhance the communication performance and suppress the interferences. Different from LAA, CAA can generate the mainlobe of beam pattern towards any desired directions of the space. However, the feed network of CAA is more complex than that of LAA.

Moreover, the collaborative beamforming (CB) technology, which is constructed with the virtual node random antenna array (RAA), is successfully introduced in

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distributed wireless networks [10]–[12], for extending the communication distance of a node with limited hardware resources [13]–[15]. Furthermore, CB can be also regarded as a promising approach for improving the performance of the device to device (D2D) communication [16], Internet of Things (IoT) [17]–[19], and unmanned aerial vehicle (UAV) networks [20].

The high sidelobe levels (SLLs) of beam patterns will be occurred if the LAA and CAA are not optimized [7], [21]. For the RAA-based CB transmission, the element nodes are always with random distribution and this may cause higher maximum SLLs of the beam patterns [22], which means the increasing of interferences. Therefore, it is necessary to optimize the beam patterns of the abovementioned antenna arrays, especially to suppress the maximum SLLs.

Selecting an optimal set of parameters so that achieving the expected beam pattern is called antenna array beam pattern synthesis [23]. However, the relationships among these parameters are not simple, causing the beam pattern optimizations of antenna arrays to become very complex non-linear optimization problems. Therefore, how to optimize the beam patterns as well as reduce the maximum SLLs of antenna arrays is of great significance.

Swarm intelligence algorithms are effective method for the SLL suppression optimizations of antenna arrays. For example, the genetic algorithm (GA), particle swarm optimization (PSO), firefly algorithm (FA) and cuckoo search (CS) are widely used to optimize the beam patterns of antenna arrays. Among these kind of algorithms, the chicken swarm optimization (CSO) algorithm can attract the intelligence of chicken swarms and it is simple to be implemented. Moreover, CSO has better performance in certain optimization problems due to the population hierarchy mechanism. Thus, it has been applied in many engineering optimization fields. However, this algorithm may have some drawbacks as follows. First, the solution update method of roosters in CSO is not effective which may cause the algorithm lack of the exploitation ability. Second, the hens and chicks are relatively far away from the optimal locations. Thus, they need more efficient exploration ability. However, the solution update methods of hens and chicks in conventional CSO algorithm are simple, which may be not suitable for the complex optimization problems. Third, according to the mechanism of CSO, the hens and chicks should be updated towards the roosters, which may cause the solutions of population are very similar so that reducing the population diversity. Moreover, since the swarm intelligence algorithms do have certain drawbacks, they may be fit for just a finite number of optimization problems, while unfit for others. In addition, according to no free lunch (NFL) theorem, no such kind of algorithm is perfect for solving all optimization problems. Thus, these conditions above motive us to propose an improved version of conventional CSO algorithm for solving the SLL suppression optimization problems of antenna arrays.

The main contributions of this paper are introduced as follows:

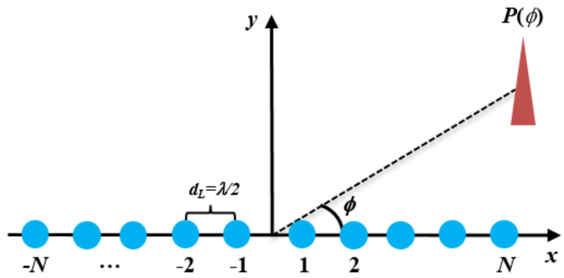

FIGURE 1. Geometry model of LAA.

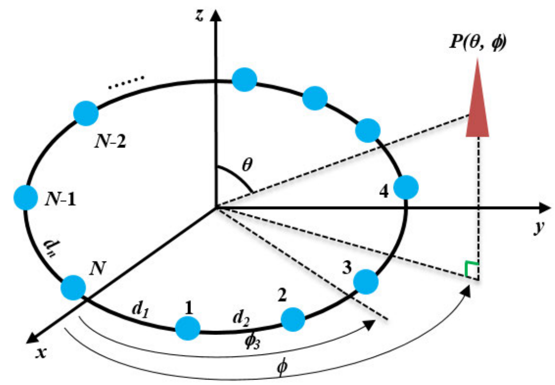

FIGURE 2. Geometry model of CAA.

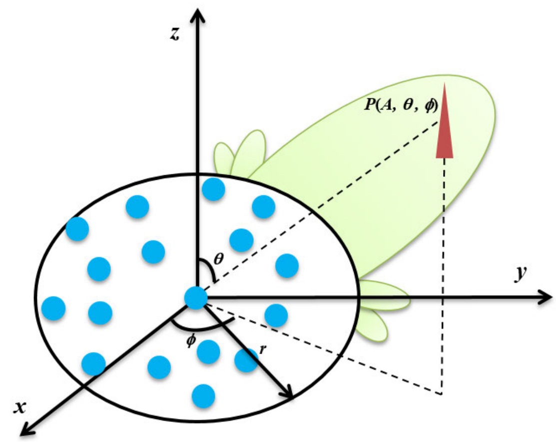

FIGURE 3. Geometry model of RAA.

- We design the fitness functions and formulate the SLL suppression optimization problems of LAA, CAA and RAA, respectively, to reduce the maximum SLLs of beam patterns.
- To overcome the drawbacks of conventional CSO algorithm above, we propose a novel swarm intelligence approach called improved chicken swarm optimization (ICSO) algorithm to solve the formulated sidelobe suppression optimization problems. First, ICSO introduces the solution update method of bat algorithm (BA) as the local search operator to give a more effective searching method of the algorithm. Second, we propose a weighting factor to adjust the step size dynamically according to the number of appeared times of the

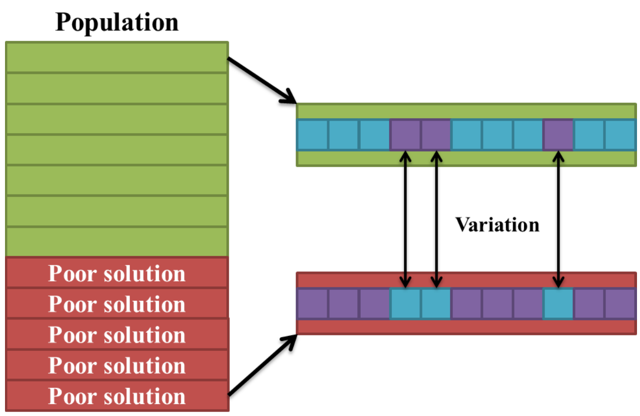

FIGURE 4. Sketch map of variation mechanism.

hen solutions with the same fitness values, which may improve the global search performance of the hen solutions. Third, we propose a global search factor which is able to establish contact between the chicks and roosters directly, so that guiding the chick solutions to move toward the roosters. Finally, a variation mechanism is proposed to improve the population diversity of the algorithm. By using these introduced improved factors, ICSO is able to balance the exploration and exploitation so that avoiding the premature convergence.

- We conduct extended simulations to further verify the effectiveness and performance of the proposed ICSO algorithm for the SLL reductions of LAAs, CAAs and RAAs.

A. ROADMAP

The rest of this paper is as follows. Section II introduces the related work. Section III gives the models and array factors of LAA, CAA and RAA. Section IV formulates the sidelobe reduction optimization problems of different antenna arrays. Section V describes the proposed ICSO approach. Section VI shows the extended simulation results and the overall paper is concluded in Section VII.

II. RELATED WORK

The swarm intelligence optimization and evolutionary algorithms for optimizing the beam pattern optimizations of antenna arrays are reviewed in this section.

For the LAA beam pattern optimizations, the authors in reference [24] propose to use the classical genetic algorithm (GA) to optimize the beam pattern of a non-uniform LAA. In reference [25], the researchers optimize the beam patterns of LAA and CAA by adopting the particle swarm optimization (PSO) algorithms, the excitation currents are determined by PSO for achieving better beam patterns. Sharaqa and Dib [26] utilize the biogeography-based optimization (BBO) method to minimize the maximum SLL of the LAA and elliptical antenna array, respectively, and three optimization cases that are element amplitude, elements position and element phase optimizations are considered in their work. The authors in reference [27] proposes an enhanced firefly algorithm (EFA) for synthesis of LAA for both equally and unequally spaced arrays. Singh et al. proposes a modified spider monkey optimization (MSMO) for the synthesis of LAA. Reference [28] uses a novel bat flower pollination (BFP) for synthesis of unequally spaced LAA. In reference [9], the cuckoo optimization algorithm (COA) is used to select a set of optimal parameters of the elements so that providing the desired radiation patterns. Moreover, the ant lion optimization (ALO) algorithm is introduced to optimize the excitation currents and element positions for jointly controlling the sidelobes and nulls of beam patterns [23]. In addition, the authors in references [29], [30] and [31] use the flower pollination algorithm (FPA), improved flower pollination algorithm (IFPA), and enhanced flower pollination algorithm (EFPA), respectively, to optimize beam patterns of LAAs for obtaining the reduced maximum SLLs and nulls.

There are also several previous work that are proposed for the CAA optimizations. For example, reference [32] uses firefly algorithm (FA) to synthesize the beam patterns of CAA and concentric circular antenna array (CCAA), and this work achieves the beam patterns with lower maximum SLL while keeping the fixed mainlobe beamwidth. Reference [33] proposes a novel binary spider monkey optimization (binSMO) approach for thinning of CCAA, which aims to reduce the maximum SLL and cost. The authors in reference [34] apply the ant colony optimization (ACO) algorithm to optimize the beam pattern of the CAA, in which a cost function is designed by the authors for getting the maximum SLL reduction and providing the desired beam patterns towards the destinations. Moreover, algorithm fusion can combine the advantages of various algorithms to improve the optimization performance. Reference [35] proposes an improved invasive weed optimization algorithm to minimize the interference of linear sparse array, and the positions of antenna elements are controlled for their optimization purposes. Reference [36] proposes a novel hybrid artificial bee colony and differential evolution (ABC-DE) algorithm for synthesizing the beam patterns of time-modulated antenna arrays. Moreover, in our previous work [5], [7] and [37], a BBO with local search (BBOLS) algorithm, a cuckoo search-chicken swarm optimization (CSCSO) algorithm and an improved discrete CS (IDCS) algorithm are proposed to optimize the beam patterns of LAA, CAA and CCAA, respectively.

For the optimizations of RAAs, reference [38] proposes a method that based on PSO algorithm to optimize the locations of the nodes, thereby reducing the maximum SLL. The authors in [39] propose a PSO-gravitational search algorithm-explore (PSOGSA-E) approach to calculate the optimal excitation currents of the antenna elements to get lower maximum SLLs of the beam patterns of RAAs. Reference [40] proposes to utilize a simplified version of PSO algorithm called WSA to minimize the maximum SLL as well as improving the capacity. Our previous work [41] and [42] use FA-based

TABLE 1. Introductions of functions in CEC 2017.

	No.	Functions	Optimum
Unimodal Functions	1	Shifted and Rotated Bent Cigar Function	100
	2	Shifted and Rotated Sum of Different Power Function	200
	3	Shifted and Rotated Zakharov Function	300
Simple Multimodal Functions	4	Shifted and Rotated Rosenbrock's Function	400
	5	Shifted and Rotated Rastrigin's Function	500
	6	Shifted and Rotated Expanded Scaffer's F6 Function	600
	7	Shifted and Rotated Lunacek Bi_Rastrigin Function	700
	8	Shifted and Rotated Lunacek BiRastrigin Function	800
	9	Shifted and Rotated Levy Function	900
	10	Shifted and Rotated Schwefel's Function	1000
Hybrid Functions	11	Hybrid Function 1 (N=3)	1100
	12	Hybrid Function 2 (N=3)	1200
	13	Hybrid Function 3 (N=3)	1300
	14	Hybrid Function 4 (N=4)	1400
	15	Hybrid Function 5 (N=4)	1500
	16	Hybrid Function 6 (N=4)	1600
	17	Hybrid Function 6 (N=5)	1700
	18	Hybrid Function 6 (N=5)	1800
	19	Hybrid Function 6 (N=5)	1900
	20	Hybrid Function 6 (N=6)	2000
Composition Functions	21	Composition Function 1 (N=3)	2100
	22	Composition Function 2 (N=3)	2200
	23	Composition Function 3 (N=4)	2300
	24	Composition Function 4 (N=4)	2400
	25	Composition Function 5 (N=5)	2500
	26	Composition Function 6 (N=5)	2600
	27	Composition Function 7 (N=6)	2700
	28	Composition Function 8 (N=6)	2800
	29	Composition Function 9 (N=3)	2900
	30	Composition Function 10 (N=3)	3000
Search Range = $[-100, 100]^D$, D = 30, *Iteration* = 500			

and CS-based strategies, respectively, for the beam pattern optimizations of RAA-based CB.

III. MODELS AND ARRAY FACTORS

In this section, the geometric models and array factors (AFs) of different shapes of antenna arras are introduced.

A. LAA MODEL AND AF

The geometry of a LAA is shown in Fig. 1. As can be seen, the LAA is consisted of $2N_{LAA}$ isotropic antenna elements which are placed on the x-axis. According to the superposition principle of electromagnetic wave, the AF of LAA is as follows [26]:

$$AF_{LAA}\left(I^L, \phi\right) = \sum_{n=-N_{LAA}}^{N_{LAA}} I_n^L \cos\left(kd_n^L \cos(\phi) + \varphi_n^L\right) \quad (1)$$

where k is the wave number and $k = \frac{2\pi}{\lambda}$. I_n^L, d_n^L and φ_n^L are the excitation current, spacing between the nth and $(n+1)$th elements and phase of the nth antenna element, respectively. Due to the symmetry of LAA, the AF of LAA can be simplified as follows (assume $\varphi_n^L = 0$) [26]:

$$AF_{LAA}\left(I^L, \phi\right) = 2\sum_{n=1}^{N_{LAA}} I_n^L \cos\left(kd_n^L \cos(\phi)\right) \quad (2)$$

Moreover, I_n^L is normalized to its maximum value in this work, thus the values of I_n^L range from 0 to 1. In addition, d^L is equal and it is set as $\frac{\lambda}{2}$.

B. CAA MODEL AND AF

As shown in Fig. 2, the N_{CAA} elements of a CAA are placed on a circle in the x-y plane, and the radius of the circle is r. Moreover, ϕ and θ in the figure are the azimuth angle and elevation angle measured from the positive x axis and z axis,

TABLE 2. Key parameter setups of different optimization algorithms.

Algorithm	Values of the parameters
CSO [25]	$RN = 0.2 * N, HN = 0.6 * N,$ $CN = N - RN - HN, MN = 0.1 * N$
BBO [3]	$Pmodify = 1, Ep = 1, Mp = 0.01$
PSO [14]	$c_1 = 2, c_2 = 2, w_{pso} = 0.5$
HBA [47]	$A = 0.95, r = 0.85, f_{max} = 1, f_{min} = 0,$ $\alpha = 0.9, \gamma = 0.9, INV = 10, LT = 5, MLT = 2$
ESRFA [48]	$\beta = 1.0, \alpha_t = 0.25, \gamma = 1.0,$ $r_f = 0.6, r_t = 0.1, nt = 0.5$
NMCSA [49]	$\alpha_0 = 0.3, p_0 = 0.5$
HBBOG [50]	$Pmodify = 1, Ep = 1, Mp = 0.01$
ICSO	$RN = 0.2 * N, HN = 0.6 * N,$ $CN = N - RN - HN, MN = 0.1 * N$ $A_0 = 1, r_0 = 0.3$

respectively. Similar to the LAA case, the AF of CAA is as follows [32]:

$$AF_{CAA}(I^C, \theta, \phi) = \sum_{n=1}^{N_{CAA}} I_n^C \exp(j[kr\sin(\theta)\cos(\phi - \phi_n) + \alpha_n]) \tag{3}$$

$$kr = \frac{2\pi}{\lambda} r = \sum_{i=1}^{N_{CAA}} d_i^C \tag{4}$$

$$\phi_n = \frac{2\pi \sum_{i=1}^{N_{CAA}} d_i^C}{kr} \tag{5}$$

$$\alpha_n = -kr\sin(\theta_0)\cos(\phi_0 - \phi_n) \tag{6}$$

where $k = \frac{2\pi}{\lambda}$ is the wave number, λ is the wavelength, d_n^C represents the arc distance between the nth and (n-1)th elements. Moreover, I_n^C and α_n represents the excitation current and phase of nth antenna element, respectively. For simplicity, I_n^C is normalized to its maximum value so that it ranges from 0 and 1. d_n^C is normalized to λ and thus it is from 0 to λ.

C. RAA MODEL AND AF

Compared to LAA and CAA, RAA can be regarded as a special antenna array since the elements of a RAA are usually distributed nodes such as the IoT nodes or sensor nodes. Fig. 3 shows a RAA consists with N_{RAA} nodes. These array nodes are distributed randomly in a disk area which has a radius of R for performing the CB transmissions. Usually, one of these nodes is selected as the source node (donated as S_{node}) to manage and proceed the CB transmission progress [41]. Refer to previous work, the polar coordinate system is used to represent the CB nodes. Thus, $\mathbf{r} = [r_1, r_2, \ldots, r_{N_{RAA}}] \in [0, R]$ and $\psi = [\psi_1, \psi_2, \psi_3, \ldots, \psi_{N_{RAA}}] \in [-\pi, \pi]$. By use this coordinate system, the location of kth node can be represented as (r_k, ψ_k). In this paper, we assume a far field communication scene, and the AF of RAA is approximated as [39]:

$$AF_{RAA}\left(I^R, \phi, \theta\right) = \sum_{k=1}^{N_{RAA}} I_k^R e^{j\frac{2\pi}{\lambda} r_k[\cos(\theta - \psi_k)]} \tag{7}$$

TABLE 3. Statistical results of different algorithms for solving f_1, f_2, f_3, f_4, f_5 and f_6 of 30 independent runs.

Functions	Algorithm	Mean	SD	Best
f_1	CSO	2.14E+10	4.67E+09	1.44E+10
	BBO	1.27E+09	2.68E+08	4.15E+08
	PSO	2.15E+09	2.85E+08	1.70E+09
	HBA	5.04E+10	8.37E+09	3.32E+10
	ESRFA	5.04E+10	7.21E+09	2.86E+10
	NMCSA	**1.23E+07**	**7.81E+06**	**2.23E+06**
	HBBOG	1.25E+10	2.45E+09	7.92E+09
	ICSO	8.58E+09	2.62E+09	3.89E+09
f_2	CSO	2.19E+10	4.92E+09	1.23E+10
	BBO	**8.74E+08**	4.20E+08	**2.99E+08**
	PSO	2.21E+09	2.79E+08	2.04E+10
	HBA	4.21E+10	7.37E+09	3.09E+10
	ESRFA	4.93E+10	9.76E+09	2.92E+10
	NMCSA	8.36E+10	**1.06E+06**	8.36E+10
	HBBOG	1.20E+10	3.62E+09	6.74E+09
	ICSO	3.03E+10	5.38E+09	1.41E+09
f_3	CSO	6.37E+04	7.94E+03	4.36E+04
	BBO	2.25E+05	4.77E+04	6.98E+04
	PSO	**5.79E+04**	1.87E+04	**2.47E+04**
	HBA	2.76E+05	8.81E+04	1.43E+05
	ESRFA	9.42E+04	**7.64E+03**	7.22E+04
	NMCSA	1.41E+05	2.90E+04	9.15E+04
	HBBOG	9.97E+04	4.93E+04	6.48E+04
	ICSO	7.14E+04	1.19E+04	4.94E+04
f_4	CSO	3.18E+03	1.41E+03	1.23E+03
	BBO	7.02E+02	6.66E+01	5.54E+02
	PSO	6.75E+02	2.84E+01	6.16E+02
	HBA	4.70E+03	8.97E+02	1.78E+03
	ESRFA	1.14E+04	3.37E+03	2.73E+03
	NMCSA	**5.34E+02**	**1.04E+01**	**5.06E+02**
	HBBOG	1.79E+03	4.19E+02	1.10E+03
	ICSO	9.81E+02	2.45E+02	6.26E+02
f_5	CSO	8.07E+02	2.77E+01	7.26E+02
	BBO	6.74E+02	**2.30E+01**	6.13E+02
	PSO	6.90E+02	3.43E+01	8.32E+02
	HBA	8.75E+02	3.42E+01	8.21E+02
	ESRFA	9.58E+02	2.60E+01	8.06E+02
	NMCSA	7.30E+02	2.76E+01	1.01E+03
	HBBOG	8.17E+02	2.58E+01	7.73E+02
	ICSO	**6.61E+02**	2.97E+01	**6.18E+02**
f_6	CSO	6.65E+02	8.48E+00	6.41E+02
	BBO	6.12E+02	**1.67E+00**	**6.04E+02**
	PSO	6.34E+02	1.24E+01	6.20E+02
	HBA	6.75E+02	9.85E+00	6.52E+02
	ESRFA	6.95E+02	8.74E+00	6.73E+02
	NMCSA	6.34E+02	5.16E+00	6.25E+02
	HBBOG	6.62E+02	1.02E+01	6.41E+02
	ICSO	**6.04E+02**	7.81E+00	6.10E+02

where λ represents the wavelength, I_k^R is the excitation current of kth node. Similar to LAA and CAA cases, I_k^R is also normalized to its maximum value and thus $I_k^R \in [0, 1]$.

IV. PROBLEM FORMULATION

The fitness functions of suppressing the maximum SLLs are designed in this section, and corresponding SLL reduction optimization problems are formulated.

A. PROBLEM 1: REDUCING THE MAXIMUM SLL OF LAA

In this work, our purpose is to optimize the beam patterns of LAA by determining an optimal set of excitation currents of antenna elements so that achieving a lower maximum SLL.

TABLE 4. Statistical results of different algorithms for solving f_7, f_8, f_9, f_{10}, f_{11} and f_{12} of 30 independent runs.

Functions	Algorithm	Mean	SD	Best
f_7	CSO	1.15E+03	4.41E+01	1.06E+03
	BBO	1.01E+03	2.96E+01	9.57E+02
	PSO	1.03E+03	**1.41E+01**	1.00E+03
	HBA	1.95E+03	2.15E+02	1.37E+03
	ESRFA	1.46E+03	8.33E+01	1.12E+03
	NMCSA	1.03E+03	3.40E+01	9.42E+02
	HBBOG	1.11E+03	4.25E+01	1.03E+03
	ICSO	**1.00E+03**	4.80E+01	**8.83E+02**
f_8	CSO	1.05E+03	**2.46E+01**	1.01E+03
	BBO	9.67E+02	2.75E+01	9.31E+02
	PSO	9.92E+02	3.36E+01	1.09E+03
	HBA	1.16E+03	3.40E+01	1.12E+03
	ESRFA	1.18E+03	3.09E+01	1.08E+03
	NMCSA	1.03E+03	3.35E+01	1.28E+03
	HBBOG	1.07E+03	2.60E+01	1.03E+03
	ICSO	**9.33E+02**	2.50E+01	**8.98E+02**
f_9	CSO	7.31E+03	1.89E+03	5.00E+03
	BBO	4.06E+03	1.52E+03	2.20E+02
	PSO	6.10E+03	1.98E+03	1.32E+04
	HBA	1.22E+04	1.95E+03	9.48E+03
	ESRFA	1.35E+04	1.75E+03	1.06E+04
	NMCSA	1.09E+04	2.89E+03	1.35E+04
	HBBOG	6.98E+03	1.72E+03	3.50E+03
	ICSO	**3.78E+03**	**1.19E+03**	**1.34E+03**
f_{10}	CSO	8.12E+03	8.04E+02	6.53E+03
	BBO	5.76E+03	5.04E+02	4.51E+03
	PSO	8.53E+03	5.15E+02	7.66E+03
	HBA	7.55E+03	**3.83E+02**	6.66E+03
	ESRFA	8.29E+03	5.90E+02	6.67E+03
	NMCSA	**5.45E+03**	5.79E+02	3.94E+03
	HBBOG	8.56E+03	9.52E+02	6.45E+03
	ICSO	6.88E+03	1.29E+03	**3.82E+03**
f_{11}	CSO	3.68E+03	8.82E+02	2.42E+03
	BBO	1.48E+04	4.76E+03	3.34E+03
	PSO	1.75E+03	1.28E+02	1.53E+03
	HBA	1.71E+04	8.49E+03	6.03E+03
	ESRFA	1.17E+04	2.92E+03	6.22E+03
	NMCSA	1.98E+03	**5.67E+01**	1.27E+03
	HBBOG	4.06E+03	1.05E+03	2.19E+03
	ICSO	**1.35E+03**	7.10E+02	**1.27E+03**
f_{12}	CSO	2.65E+09	1.42E+09	7.62E+08
	BBO	1.68E+08	4.98E+07	4.14E+07
	PSO	2.84E+08	6.73E+07	1.73E+08
	HBA	4.89E+09	1.44E+09	1.80E+09
	ESRFA	9.48E+09	3.85E+09	3.56E+09
	NMCSA	**3.17E+06**	**2.85E+06**	**1.98E+05**
	HBBOG	1.43E+09	5.83E+08	7.16E+08
	ICSO	4.49E+08	4.10E+08	1.24E+08

TABLE 5. Statistical results of different algorithms for solving f_{13}, f_{14}, f_{15}, f_{16}, f_{17} and f_{18} of 30 independent runs.

Functions	Algorithm	Mean	SD	Best
f_{13}	CSO	7.63E+08	8.43E+08	7.60E+07
	BBO	2.35E+08	4.60E+07	4.29E+07
	PSO	1.25E+08	4.07E+07	3.46E+07
	HBA	4.67E+09	2.02E+09	1.74E+09
	ESRFA	6.78E+09	4.24E+09	4.26E+08
	NMCSA	**4.01E+04**	**2.42E+04**	3.77E+05
	HBBOG	5.19E+08	2.97E+08	1.49E+08
	ICSO	8.69E+07	1.05E+08	**8.24E+03**
f_{14}	CSO	9.30E+05	8.87E+05	1.19E+05
	BBO	7.07E+06	4.60E+07	6.21E+04
	PSO	2.13E+05	1.48E+05	3.35E+04
	HBA	7.50E+06	2.02E+09	1.05E+06
	ESRFA	5.02E+06	4.24E+09	4.22E+05
	NMCSA	1.27E+06	2.42E+04	1.57E+03
	HBBOG	7.65E+05	2.97E+08	3.10E+05
	ICSO	**8.56E+01**	**1.05E+08**	**1.52E+03**
f_{15}	CSO	2.07E+07	4.45E+07	4.15E+06
	BBO	9.69E+07	2.70E+07	4.43933E6
	PSO	1.87E+07	5.82E+06	7.03E+06
	HBA	1.43E+08	1.50E+08	4.01E+06
	ESRFA	5.00E+07	6.37E+07	3.73E+05
	NMCSA	**5.78E+03**	9.80E+06	5.18E+03
	HBBOG	8.54E+06	1.13E+07	7.89E+05
	ICSO	2.12E+06	**2.43E+03**	**2.04E+03**
f_{16}	CSO	3.89E+03	2.74E+02	3.32E+03
	BBO	3.26E+03	3.24E+02	2.46E+03
	PSO	3.56E+03	2.79E+02	2.86E+03
	HBA	4.14E+03	3.81E+02	3.39E+03
	ESRFA	5.24E+03	7.25E+02	3.97E+03
	NMCSA	2.87E+03	2.80E+02	2.22E+03
	HBBOG	4.38E+03	2.95E+02	3.81E+03
	ICSO	**2.64E+03**	**1.85E+02**	**2.20E+03**
f_{17}	CSO	2.57E+03	1.96E+02	2.32E+03
	BBO	2.60E+03	1.95E+02	2.26E+03
	PSO	2.62E+03	2.34E+02	2.07E+03
	HBA	3.39E+03	4.12E+02	2.61E+03
	ESRFA	3.64E+03	9.77E+02	2.38E+03
	NMCSA	**2.15E+03**	**1.24E+02**	1.90E+03
	HBBOG	3.01E+03	2.67E+02	2.29E+03
	ICSO	2.18E+03	1.65E+02	**1.83E+03**
f_{18}	CSO	4.34E+06	3.12E+06	5.98E+05
	BBO	1.56E+07	4.02E+06	1.70E+06
	PSO	2.73E+06	1.33E+06	7.99E+05
	HBA	2.91E+07	3.04E+07	3.06E+06
	ESRFA	4.49E+07	4.13E+07	2.61E+06
	NMCSA	4.32E+06	5.18E+06	**5.64E+03**
	HBBOG	8.33E+06	5.70E+06	1.63E+06
	ICSO	**3.52E+04**	**2.34E+04**	1.13E+05

For this goal, we can design a fitness function as follows:

$$F_{LAA}(I_i^L) = 20 \log_{10} \frac{|AF_{LAA}(\phi_{SL})|}{|\max AF_{LAA}(\phi_{ML})|} \tag{8}$$

The maximum SLL reduction optimization problem of LAA can be formulated as:

$$\min F_{LAA}(I_i^L) \tag{9a}$$

$$\text{s.t. } 0 \leqslant I_i^L \leqslant 1, \quad \forall i \in N \tag{9b}$$

$$\phi_{ML} = \arg\max |AF_{LAA}(\phi)|, \quad \phi \in [-\pi, \pi] \tag{9c}$$

$$\phi_{SL} \in [-\pi, \phi_{FN1}) \cup (\phi_{FN2}, \pi] \tag{9d}$$

where θ_{FN1} and θ_{FN2} are the two first nulls in $[-\pi, \phi_{ML})$ and $(\phi_{ML}, \pi]$, respectively, and the first null beamwidth (FNBW) of the beam pattern can be determined by them.

B. PROBLEM 2: REDUCING THE MAXIMUM SLL OF CAA

For the CAA beam pattern optimization, our goal is to select optimal I^C and d^C of each antenna element so that obtaining a reduced maximum SLL. Similar to the LAA case, the fitness function for reducing the maximum SLL of CAA can be designed as follows:

$$F_{CAA}(I_i^C, d_i^C) = 20 \log_{10} \frac{|AF_{CAA}(\theta, \phi_{SL})|}{|\max AF_{CAA}(\theta, \phi_{ML})|} \tag{10}$$

TABLE 6. Statistical results of different algorithms for solving f_{19}, f_{20}, f_{21}, f_{22}, f_{23} and f_{24} of 30 independent runs.

Functions	Algorithm	Mean	SD	Best
f_{19}	CSO	3.68E+07	7.98E+07	3.81E+06
	BBO	9.43E+07	1.52E+07	1.60E+07
	PSO	2.73E+07	1.30E+07	6.90E+06
	HBA	1.24E+09	7.20E+08	2.44E+08
	ESRFA	1.55E+08	1.46E+08	4.84E+06
	NMCSA	**3.22E+03**	9.81E+06	9.08E+03
	HBBOG	3.22E+03	1.28E+07	2.31E+06
	ICSO	2.97E+06	**2.95E+03**	**2.02E+03**
f_{20}	CSO	2.76E+03	1.86E+02	2.48E+03
	BBO	2.92E+03	2.42E+02	2.42E+03
	PSO	2.74E+03	2.58E+02	2.55E+03
	HBA	3.18E+03	**1.31E+02**	2.68E+03
	ESRFA	2.99E+03	1.74E+02	2.64E+03
	NMCSA	2.52E+03	1.39E+02	3.68E+03
	HBBOG	2.93E+03	1.85E+02	2.58E+03
	ICSO	**2.41E+03**	1.59E+02	**2.13E+03**
f_{21}	CSO	2.57E+03	2.77E+01	2.52E+03
	BBO	2.48E+03	2.48E+01	2.41E+03
	PSO	2.49E+03	4.21E+01	2.65E+03
	HBA	2.65E+03	4.33E+01	2.62E+03
	ESRFA	2.75E+03	7.25E+01	2.40E+03
	NMCSA	2.48E+03	1.06E+02	2.78E+03
	HBBOG	2.60E+03	2.43E+01	2.54E+03
	ICSO	**2.44E+03**	**2.15E+01**	**2.38E+03**
f_{22}	CSO	5.33E+03	1.21E+03	3.93E+03
	BBO	6.56E+03	1.91E+03	**2.50E+03**
	PSO	6.97E+03	3.64E+03	2.54E+03
	HBA	9.12E+03	4.15E+02	7.94E+03
	ESRFA	7.68E+03	1.41E+03	4.84E+03
	NMCSA	4.84E+03	1.94E+03	2.69E+03
	HBBOG	**3.88E+03**	**3.53E+02**	3.28E+03
	ICSO	5.96E+03	2.39E+03	2.69E+03
f_{23}	CSO	3.02E+03	4.65E+01	2.96E+03
	BBO	**2.84E+03**	3.71E+01	**2.76E+03**
	PSO	2.85E+03	3.87E+01	2.89E+03
	HBA	3.20E+03	8.40E+01	3.07E+03
	ESRFA	3.82E+03	2.13E+02	3.31E+03
	NMCSA	2.87E+03	5.74E+01	3.65E+03
	HBBOG	3.07E+03	4.31E+01	2.95E+03
	ICSO	2.85E+03	**3.14E+01**	2.80E+03
f_{24}	CSO	3.18E+03	5.24E+01	3.03E+03
	BBO	3.09E+03	4.46E+01	2.95E+03
	PSO	3.28E+03	1.19E+02	3.07E+03
	HBA	3.30E+03	1.02E+02	3.13E+03
	ESRFA	4.09E+03	3.11E+02	3.63E+03
	NMCSA	4.44E+02	1.69E+02	3.98E+03
	HBBOG	3.26E+03	4.38E+01	3.17E+03
	ICSO	**3.01E+03**	**3.50E+01**	**2.94E+03**

By using this fitness function, the corresponding maximum reduction optimization problem of CAA can be formulated as:

$$\min F_{CAA}(I_i^C, d_i^C) \tag{11a}$$
$$\text{s.t. } 0 \leqslant I_i^C \leqslant 1, \quad \forall i \in N \tag{11b}$$
$$0 \leqslant d_i^C \leqslant 1, \quad \forall i \in N \tag{11c}$$
$$\phi_{ML} = \arg\max |AF_{CAA}(\phi)|, \quad \phi \in [-\pi, \pi] \tag{11d}$$
$$\phi_{SL} \in [-\pi, \phi_{FN1}) \cup (\phi_{FN2}, \pi] \tag{11e}$$

TABLE 7. Statistical results of different algorithms for solving f_{25}, f_{26}, f_{27}, f_{28}, f_{29} and f_{30} of 30 independent runs.

Functions	Algorithm	Mean	SD	Best
f_{25}	CSO	3.73E+03	3.75E+02	3.25E+03
	BBO	3.09E+03	6.76E+01	2.95E+03
	PSO	3.04E+03	2.82E+01	2.99E+03
	HBA	4.90E+03	7.52E+02	3.73E+03
	ESRFA	4.78E+03	4.38E+02	4.10E+03
	NMCSA	3.06E+03	**1.32E+01**	2.98E+03
	HBBOG	3.24E+03	8.50E+01	3.12E+03
	ICSO	**2.93E+03**	7.59E+01	**2.90E+03**
f_{26}	CSO	8.02E+03	7.48E+02	5.91E+03
	BBO	5.85E+03	**5.03E+02**	5.17E+03
	PSO	5.17E+03	1.28E+03	**3.52E+03**
	HBA	9.12E+03	7.04E+02	7.48E+03
	ESRFA	1.07E+04	1.21E+03	8.50E+03
	NMCSA	**4.83E+03**	1.10E+03	3.53E+03
	HBBOG	6.38E+03	8.94E+02	5.12E+03
	ICSO	5.86E+03	7.25E+02	4.06E+03
f_{27}	CSO	3.44E+03	6.23E+01	3.35E+03
	BBO	3.28E+03	1.72E+01	3.24E+03
	PSO	3.29E+03	2.74E+01	3.25E+03
	HBA	3.62E+03	2.33E+02	3.32E+03
	ESRFA	4.53E+03	5.06E+02	3.73E+03
	NMCSA	3.25E+03	1.22E+01	3.23E+03
	HBBOG	3.20E+03	**8.18E-05**	**3.20E+03**
	ICSO	**3.26E+03**	2.30E+01	3.23E+03
f_{28}	CSO	4.55E+03	4.39E+02	3.82E+03
	BBO	3.45E+03	5.95E+01	3.33E+03
	PSO	3.40E+03	2.80E+01	3.35E+03
	HBA	6.07E+03	7.96E+02	4.88E+03
	ESRFA	6.32E+03	7.33E+02	5.02E+03
	NMCSA	3.33E+03	1.81E+01	**3.29E+03**
	HBBOG	**3.30E+03**	**5.35E-05**	3.30E+03
	ICSO	3.63E+03	1.92E+02	3.42E+03
f_{29}	CSO	4.89E+03	2.27E+02	4.50E+03
	BBO	4.22E+03	1.59E+02	3.64E+03
	PSO	4.53E+03	2.19E+02	4.00E+03
	HBA	5.75E+03	7.79E+02	4.80E+03
	ESRFA	6.91E+03	1.10E+03	5.17E+03
	NMCSA	4.08E+03	**1.49E+02**	3.69E+03
	HBBOG	4.71E+03	3.69E+02	4.02E+03
	ICSO	**3.95E+03**	2.44E+02	**3.60E+03**
f_{30}	CSO	6.85E+07	5.19E+07	2.00E+07
	BBO	3.91E+07	2.64E+06	2.04E+06
	PSO	2.62E+07	9.86E+06	1.16E+07
	HBA	8.55E+08	5.60E+08	1.19E+08
	ESRFA	7.67E+08	5.79E+08	2.14E+07
	NMCSA	1.14E+07	**1.11E+05**	**3.21E+04**
	HBBOG	4.56E+07	3.25E+07	6.31E+06
	ICSO	**1.49E+05**	1.27E+07	3.64E+05

C. PROBLEM 3: REDUCING THE MAXIMUM SLL OF RAA

For reducing the maximum SLL of RAA, we aim to find a set of optimal I^R for getting a lower maximum SLL. Similar to the LAA and CAA cases, the fitness function of reducing the maximum SLL of RAA can be designed as:

$$F_{RAA}(I^R) = 20\log_{10}\frac{|AF_{RAA}(\theta, \phi_{SL})|}{|\max AF_{RAA}(\theta, \phi_{ML})|} \tag{12}$$

Accordingly, we can formulate the maximum SLL reduction optimization problem of RAA as follows:

$$\min F_{RAA}(I_i^R) \tag{13a}$$
$$\text{s.t. } 0 \leqslant I_i^R \leqslant 1, \quad \forall i \in N \tag{13b}$$

TABLE 8. *p*-test comparisons of different algorithms.

Function	CSO	BBO	PSO	HBA	ESRFA	NMCSA	HBBOG	ICSO
f_1	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	NA	3.0199E-11	3.0199E-11
f_2	3.0199E-11	NA	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.02E-11
f_3	3.0199E-11	1.5846E-06	NA	9.9258E-06	3.0199E-11	9.9186E-11	2.8716E-10	3.0199E-11
f_4	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	NA	3.0199E-11	3.0199E-11
f_5	3.6897E-11	3.1119E-07	3.0199E-11	3.0199E-11	3.0199E-11	1.8567E-09	3.0199E-11	NA
f_6	3.0199E-11	2.2273E-09	3.0199E-11	3.0199E-11	3.0199E-11	2.8790E-06	3.3384E-11	NA
f_7	8.1014E-10	1.9527E-05	3.0199E-11	3.0199E-11	3.3384E-11	8.1875E-05	1.7290E-06	NA
f_8	3.0199E-11	1.7479E-05	3.0199E-11	3.0199E-11	3.0199E-11	3.8202E-10	3.0199E-11	NA
f_9	3.0199E-11	3.0199E-11	3.0199E-11	7.3891E-11	2.6099E-10	5.4941E-11	3.0199E-11	NA
f_{10}	4.0772E-11	8.7663E-06	3.3384E-11	3.0199E-11	3.0199E-11	NA	3.0199E-11	7.2208E-06
f_{11}	2.6695E-09	2.3715E-10	3.0199E-11	3.0199E-11	3.0199E-11	8.9934E-11	1.0702E-09	NA
f_{12}	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	NA	3.0199E-11	3.0199E-11
f_{13}	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	NA	3.0199E-11	3.0199E-11
f_{14}	2.4157E-05	2.7829E-07	1.7666E-07	1.4643E-10	9.8329E-08	3.0199E-11	2.3885E-04	NA
f_{15}	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	NA	3.0199E-11	3.4742E-10
f_{16}	4.5043E-11	7.2208E-06	3.3384E-11	3.3384E-11	3.0199E-11	8.1200E-06	3.0199E-11	NA
f_{17}	1.1937E-06	1.6947E-09	4.9752E-11	3.0199E-11	4.0772E-11	NA	2.1544E-10	2.7071E-06
f_{18}	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.3384E-11	3.0199E-11	NA
f_{19}	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	NA	3.0199E-11	3.0199E-11
f_{20}	1.5465E-09	3.1967E-09	4.9752E-11	3.0199E-11	5.4941E-11	4.4272E-06	1.2057E-10	NA
f_{21}	3.0199E-11	8.3146E-07	3.0199E-11	3.0199E-11	3.0199E-11	1.0907E-05	3.0199E-11	NA
f_{22}	2.8314E-08	3.9881E-04	3.0199E-11	3.0199E-11	3.0199E-11	7.8446E-01	NA	8.2357E-06
f_{23}	3.0199E-11	3.0199E-11	3.0199E-11	1.1077E-06	3.0199E-11	3.0199E-11	3.0199E-11	NA
f_{24}	6.0658E-11	1.8368E-06	3.6897E-11	3.0199E-11	3.0199E-11	1.1738E-05	3.0199E-11	NA
f_{25}	4.0772E-11	7.3940E-06	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	1.1737E-09	NA
f_{26}	2.3715E-10	2.9205E-07	3.0199E-11	3.0199E-11	3.0199E-11	NA	1.2493E-05	1.9527E-06
f_{27}	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	NA
f_{28}	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	3.0199E-11	8.4848E-09	NA	3.0199E-11
f_{29}	6.0658E-11	1.6238E-08	1.3289E-10	3.0199E-11	3.0199E-11	2.4157E-05	5.4617E-09	NA
f_{30}	6.1210E-10	1.1674E-05	9.5873E-06	3.0199E-11	5.4941E-11	3.3384E-11	4.8011E-07	NA

$$\phi_{ML} = \arg\max |AF_{RAA}(\phi)|, \quad \phi \in [-\pi, \pi] \tag{13c}$$

$$\phi_{SL} \in [-\pi, \phi_{FN1}) \cup (\phi_{FN2}, \pi] \tag{13d}$$

V. ALGORITHM

In this section, we propose an ICSO algorithm which is improved from the conventional CSO for solving the formulated SLL reduction optimization problems shown in Section IV. ICSO algorithm introduces three improved factors that are global search, weighting and local search factors for achieving better optimization performance. Moreover, we propose a variation mechanism in ICSO algorithm to improve the population diversity of the algorithm. The details of ICSO are presented as follows.

A. CHICKEN SWARM OPTIMIZATION

CSO [43] is a kind of swarm intelligence algorithm inspired by the behaviors of chickens. A chicken swarm has the hierarchy order, and the chickens perform different behaviors when they are forging for food. Moreover, competitions are existed among different chickens with different hierarchy orders. The conventional CSO algorithm are based on four idealized rules and they are introduced as follows [43]:

- The algorithm divides the chickens into different groups of roosters, hens and chicks. Moreover, the roosters can lead other members to search for food.
- The fitness values of solutions (chickens) will determine the hierarchy order of chickens in the swarm. Specifically, the chickens with some best fitness values will be the roosters, the chickens with some worst values will act as chicks, and the rest chickens will act as hens.
- In the algorithm, the hierarchal orders of the chickens are dynamic, and they will be updated during the iterative process.
- The number of active chickens (donated as N) is fixed. Moreover, the percentages of groups that with different hierarchal orders are also permanent.

In CSO algorithm, a solution can be represented by a chicken, and generating a new solution can be regarded as the progress of moving a chicken. The ultimate purpose of the algorithm is to retain the optimal solution generated in each iteration to the end. Moreover, the number of rooters, hens, chicks and mother hens are RN, HN, CN and MN, respectively, and the positions of the N chickens in the tth iteration of the algorithm can be represented as $x_i^t = (x_{i,1}^t, x_{i,2}^t, \ldots, x_{i,j}^t)$ $(i \in [1, \ldots, N], j \in [1, \ldots, D])$, where D is the dimension of the searching space.

The update method of roosters in conventional CSO algorithm is as follows:

$$x_{new_i}^t = x_i^t \times (1 + Randn(0, \sigma^2)) \tag{14}$$

$$\sigma = \begin{cases} 1 & \text{if } f_i \leq f_k \\ \exp \dfrac{f_k - fi}{|f_i + \varepsilon|} & \text{otherwise} \end{cases} \tag{15}$$

where $Randn(0, \sigma^2)$ is a function of Gaussian distribution with the mean of zero and standard deviation of σ^2, f is the fitness function value and k is the serial index of rooster.

The hens will follow the roosters within the same group to search for food. According to this phenomenon, the solution update method of hens can be described as follows:

$$x^t_{new_i} = x^t_i + \exp\frac{f_i - f_{ri}}{|f_i| + \varepsilon} \times Rand \times (x^t_{r1} - x^t_i) + exp(f_{r2} - f_{r1}) \times Rand \times (x^t_{r2} - x^t_i) \quad (16)$$

where $Rand$ is a random number that generated from 0 and 1. $r1$ and $r2$ ($r1 \neq r2$) are the index of the roosters and hens in the same group, respectively.

For the chicks, they can search for food just near their mother hens. Thus, the solution update method of chicks is designed as follows:

$$x^t_{new_i} = x^t_i + FL \times (x^t_m - x^t_i) \quad (17)$$

where x^t_m is the position of mth hen in the tth iteration. FL is an adjusted parameter which represents the individual differences of the chicks.

The steps of CSO can be found in [25].

B. ICSO

It has been reported that the conventional CSO approach has certain advantages compared to some other swarm intelligence algorithms [43]. However, due to the complexity and hardness of the formulated maximum SLL reduction optimization problem [37], we find that the conventional CSO algorithm can not achieve reasonable results. The reasons may as follows: First, the position update method of roosters in conventional CSO is not effective because it only uses a Gauss distribution to generate the step size, which may cause the algorithm lack of the exploitation ability. Second, compared to the roosters, the hens and chicks are relatively far away from the optimal locations. Thus, they should have more efficient exploration ability. However, the solution update methods of hens and chicks in conventional CSO algorithm are very simple, which may be not suitable for the complex antenna array optimization problems. Finally, according to the mechanism of conventional CSO algorithm, the hens and chicks should be updated towards the roosters since the roosters have the dominant positions in the population. However, this mechanism may cause the solutions of population to be very similar and even cause them to be unchanged compared to themselves after the update, thereby reducing the population diversity.

Thus, this motivated us to propose a novel ICSO approach to further enhance the performance of CSO, so that making it more suitable for solving the formulated maximum SLL reduction optimization problems of different antenna arrays. Algorithm 1 presents the main steps of ICSO and the details of the improved factors are introduced in the following subsections.

Algorithm 1 ICSO

Input: N solutions
Output: Best solution x_{best}
Parameter initialization;
Design objective function $f(x)$;
Evaluate the value of each $f(x)$ in the population;
while $t < t_{max}$ **do**
  if $t\%G == 0$ **then**
    Rank the solutions of the population according to $f(x)$;
    Determine the hierarchal order for each solution;
    Divide the solutions into different groups;
    Determine the relationship between the chicks and mother hens in a group;
  else
    for $i = 1$ *to* N **do**
      if *ith solution is a rooster* **then**
        Determine r^t_i;
        Update x_i using Eq. (20);
      end
      if *ith solution is a hen* **then**
        Calculate w according to Eq. (21);
        Update x_i using Eq. (22);
      end
      if $i == chick$ **then**
        Update x_i using Eq. (23);
      end
      Evaluate the new solutions x_{new_i};
      if $f(x_i) > f(x_{new_i})$ **then**
        Accept the updated solution x_{new_i};
      else
        Update the solution x_i using Algorithm 2;
      end
    end
  end
end
return x_{best};

1) LOCAL SEARCH FACTOR FOR IMPROVING THE UPDATE METHOD OF ROOSTERS

Theoretically, the rooster solutions are nearer to the optimal position due to their better positions in the searching space. However, the solution update method of roosters in conventional CSO algorithm is actually with the Gaussian distribution, which is not a very effective way for exploiting the solution space. Moreover, this may cause the algorithm fall into local optima. To solve this issue, the solution update method of BA [44] is introduced as a local search factor for the rooster solutions, which may enhance the local search performance of the algorithm so that improving the exploitation ability of the algorithm.

The loudness A_i and the pulse emission rate r_i of BA are the two key parameters of BA, and they will be updated during the iterative procedure of the algorithm. The update methods of these two parameters are as follows:

$$A_i^{t+1} = \alpha A_i^t \tag{18}$$

$$r_i^{t+1} = r_i^0 \left(1 - \exp(-\lambda_{BA} t)\right) \tag{19}$$

where α and λ_{BA} are constants. As $t \rightarrow \infty$, $A_i^t \rightarrow 0$ and $r_i^t \rightarrow r_i^0$. The initial loudness A_0 can be chosen as $A_0 \in [1, 2]$, while the initial emission rate $r_0 \in [0, 1]$, respectively.

By combining the solution update method of BA, the improved solution update method of roosters in ICSO are described as follows:

$$x_{new_i}^t = \begin{cases} x_{best} + 0.01 * randn(1, N) & Rand \leq r_i^t \\ x_i^t * randn(0, \sigma^2) + \varepsilon * A^t & Rand > r_i^t \end{cases} \tag{20}$$

where x_{best} is the current global best solution that selected from the population, ε is random number generated between -1 to 1, and $A_t = < A_i^t >$ is an average loudness of all the bats at the tth iteration.

2) WEIGHTING FACTOR FOR IMPROVING UPDATE METHOD OF HENS

Compared to the roosters, the hen solutions in CSO algorithm are relatively far away from the optimal solution. Thus, we propose a weighting factor w for the solution update method of the hens so that it is able to dynamically adjust the step size, thereby achieving a better performance of the algorithm. w is designed as follows:

$$w = \exp(\frac{R}{K})^P \tag{21}$$

where R is the number of appeared times of the hen solutions with the same fitness values and K is a constant with the value of 5 and this value is determined by the parameter tuning experiments. Moreover, P is the step index. It can be seen from Eq. (21) that the update method of hen solutions are related to the number of appeared times of the same fitness values during the optimization process. Specifically, a big value of R may indicate that the algorithm is fall into local optima, and thus w should be chosen as a big value. Otherwise, w should have a small value. By using w, the solution update method of hens is as follows:

$$\begin{aligned} x_{new_i}^t = w \times x_i^t + \exp\frac{f_i - f_{ri}}{|f_i| + \varepsilon} \times Rand \times (x_{r1}^t - x_i^t) \\ + exp(f_{r2} - f_{r1}) \times Rand \times (x_{r2}^t - x_i^t) \end{aligned} \tag{22}$$

3) GLOBAL SEARCH FACTOR FOR IMPROVING UPDATE METHOD OF CHICKS

In conventional CSO, the solution update method of chicks only associates with their corresponding mother hens, and this may lead the chick solutions to deviate from the optimal solution. To solve this problem, we propose a global search factor that establishes contact between the chicks and roosters directly, so that guiding the chick solutions to move toward the roosters, which may extend the searching ranges of solutions. To achieve this goal, the improved update method of chicks is designed as follows:

$$x_{new_i}^t = x_i^t + FL * (x_m^t - x_i^t) + Rand * (x_r^t - x_i^t) \tag{23}$$

where x_r^t is the position of rooster within the same group.

4) VARIATION MECHANISM FOR POOR SOLUTIONS

To enhance the population diversity, a variation mechanism is proposed to variate some poor solutions of the population after each iteration. Note that the poor solutions are the ones that do not get better values in the current iteration compared to last iteration. The poor solutions in each iteration may not contribute useful evolutionary information to the algorithm, which wasts resources in terms of the computing. Thus, we aim to variate these poor solutions by using the better solutions of the population. This is because a better solution may be nearer to the optimal solution and thus it may contain useful evolutionary information for the algorithm.

Fig. 4 shows the sketch map of the variation mechanism. The key steps of variation mechanism are to select which dimensions of the poor solution should be variated, and what are the values of these dimensions after the variation. To achieve these goals, the roulette wheel selection method [45] is introduced. The probability $p(i)$ of each solution being inherited into the next iteration and the cumulative probability $q(i)$ of each solution are as follows:

$$p(i) = \frac{F_i}{\sum_{i=1}^{N} F_i} \tag{24}$$

$$q(i) = \sum_{j=1}^{i} p(j) \; i \in (1, 2, 3, \ldots, N) \tag{25}$$

The detailed variation mechanism based on roulette wheel selection method are shown in Algorithm 2.

C. ANALYSIS OF THE PROPOSED ICSO

In this section, the theoretical justifications about the effectiveness of the improved factors of ICSO are analyzed.

First, the solution update method of roosters in conventional CSO algorithm is actually the Gauss distribution method, which is not effective and may easy to fall into local optima. Moreover, since the roosters are closer to the optimal positions, they need stronger exploitation ability to search better locations in the solution space. Thus, we propose to use the solution update method of bat algorithm (BA) as the local search operator because this method can not only connect relationships between each candidate solution and the global best solution, but also give a more effective searching method of the algorithm. In addition, by introducing the solution update method of BA, different search steps are fully combined, which may further improve the local search ability of the rooster location update methods.

Second, since the hens are farther away from the optimal locations, we consider that the search steps of hens should be larger. However, with the algorithm proceeds iteratively,

Algorithm 2 Variation Mechanism

Input: x_i^t
Output: $x_{new_i}^t$
for $j = 1$ *to* D **do**
  // *Rand* is a random number between 0 and 1.
  if $Rand \leq q(i)$ **then**
    // p_{select} is the probability of solution that is selected for variated.
    $p_{select} = p(1)$;
    // $i_{selected}$ is the index of the selected solution for information sharing.
    $i_{selected} = 1$;
    while $Rand > p_{select}$ & $i_{selected} < N$ **do**
      $i_{selected} = i_{selected} + 1$;
      $p_{select} = p_{select} + p(i_{selected})$;
    end
    $x_{i,j}^{t+1} = x_{i_{selected},j}^t$;
  else
    $x_{i,j}^{t+1} = x_{i,j}^t$;
  end
end
return x_i^{t+1};

the hens may be approaching to the optimal position, and then the searching step should be smaller. Moreover, if the hen solutions with the same fitness values appear for several times, the algorithm may fall into local optima. Thus, we consider to propose a weighting factor to adjust the step size dynamically according to the number of appeared times of the hen solutions with the same fitness values, which may improve the global search performance of the hen solutions.

Third, the solution update method of chicks in conventional CSO algorithm only associates with their corresponding mother hens, and this may lead the chick solutions to deviate from the optimal solution. Moreover, the chick solutions are with the worst fitness values, which means that they are the farthest away from the optimal location. Thus, the solution update method of the chicks should be guided so that they can move toward the better direction. To overcome these short comings, we proposed a global search factor which is able to establish contact between the chicks and roosters directly, so that guiding the chick solutions to move toward the roosters.

Finally, if some of the solutions in the population do not change to better values compared to themselves after the update, then these solutions can be regarded as the ones that do not contribute useful evolutionary information to the algorithm, which wastes resources in terms of the computing. Thus, we propose a variation mechanism to variate these solutions so that improving the population diversity.

Accordingly, by using the abovementioned improved factors, the proposed ICSO algorithm may perform better than the conventional CSO algorithm.

D. COMPLEXITY

The complexity of the proposed ICSO is analyzed in this section. For a swarm intelligence algorithm, the main computational cost is the evaluations of the fitness function. We assume that the maximum iteration of the algorithm is t, then the complexity of ICSO is $O(N \cdot t)$ because it has only one internal loop, as shown in Algorithm 1. Thus, the cost of the proposed ICSO algorithm is not expensive since the complexity is linear with t.

VI. SIMULATION RESULTS

We conduct simulations by the Matlab platform to evaluate the ICSO algorithm for the SLL reduction optimization problems of different antenna arrays. First, we use some common test functions to evaluate the performance of ICSO. Second, ICSO and other comparison algorithms are used for solving the formulated SLL reduction optimization problems and results are presented. Moreover, tests are conducted to verify the stability of ICSO for the sidelobe suppression optimization problems and the numerical statistical results are given. Next, the effectiveness of the proposed improved factors are verified. Finally, we conduct electromagnetism (EM) simulations to evaluate the performance of ICSO under the consideration of mutual coupling.

A. PERFORMANCE EVALUATION OF ICSO

In this section, we use the standard CEC 2017 function set [46] to evaluate the performance of the proposed ICSO approach, and the introductions of these test functions are shown in Table 1.

We use a computer with CORE i5 CPU and 4 GB RAM for the simulations. Moreover, the conventional CSO, BBO and PSO, and the recently proposed hybrid bat algorithm (HBA) [47], enhanced scattering repulsive firefly algorithm (ESRFA) [48], novel modified cuckoo search algorithm (NMCSA) [49] and hybrid algorithm based on BBO and GWO (HBBOG) [50] are selected as the comparison algorithms for this test. The number of decision variable, the maximum number of iteration and population size are set as 30, 500 and 20, respectively. The other parameters of different algorithms are shown in Table 2. In addition, the tests are repeated for 30 times independently to avoid random bias.

1) ACCURACY

Tables 3, 4, 5, 6 and 7 shows the numerical statistical results calculated by different algorithms from the 30 independent trials, the best results for each function are highlighted in bold font. As can be seen, the proposed ICSO gets the best mean values on $f_5, f_6, f_7, f_8, f_9, f_{11}, f_{14}, f_{16}, f_{18}, f_{20}, f_{21}$ and $f_{24}, f_{25}, f_{27}, f_{29}$ and f_{30}. Moreover, ICSO obtains the most numbers of best results for solving these test functions. Thus, ICSO has the overall best performance for solving the test functions of CEC 2017 test function set compared to other algorithms.

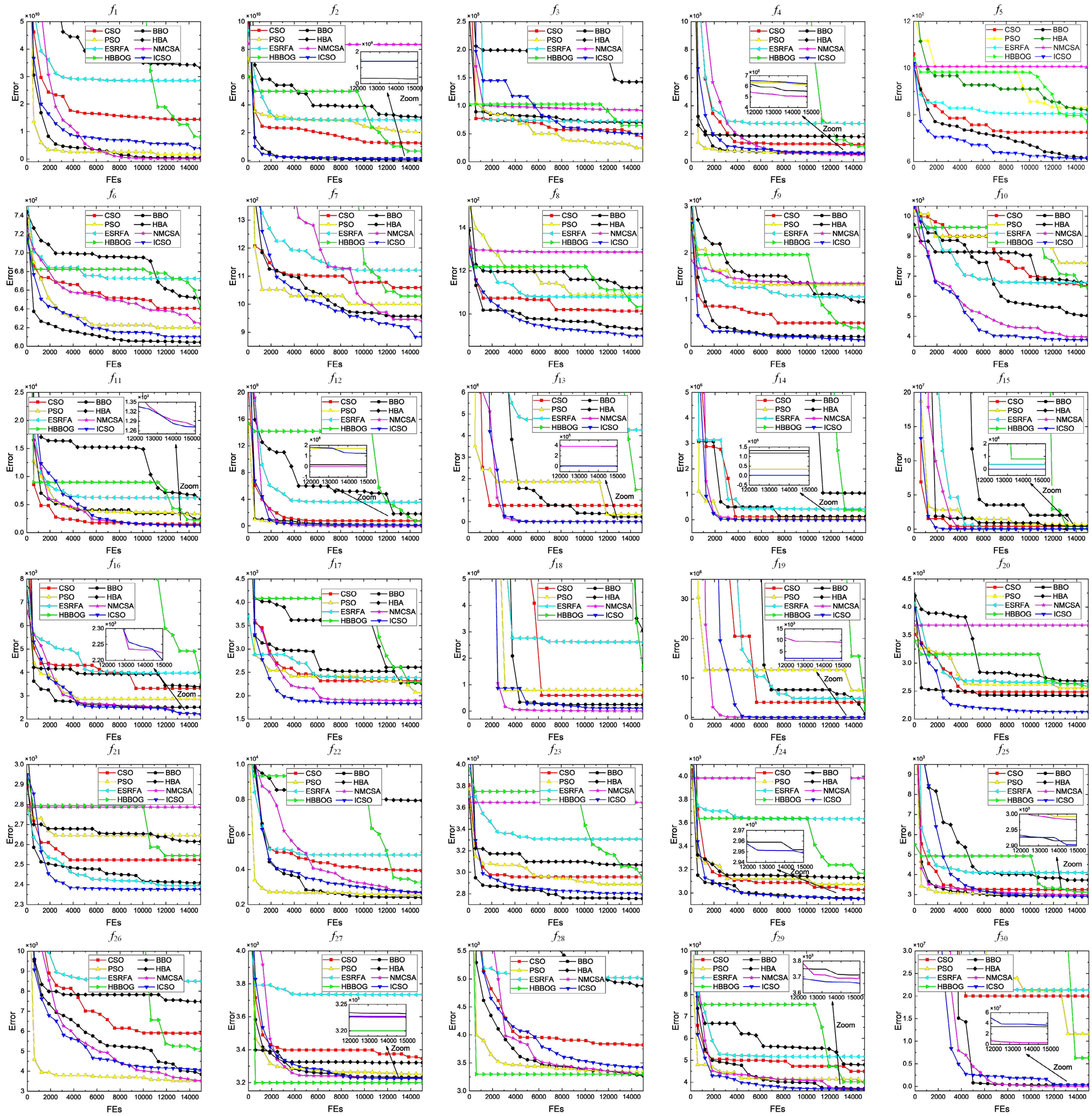

FIGURE 5. Convergence rates of different algorithms for solving the 30 test functions in CEC 2017.

2) CONVERGENCE RATE

Correspondingly, Fig. 5 shows the convergence rates during the process of solving the above mentioned test functions of different algorithms. Note that these curves are the best results selected from the 30 trials. As can be seen, the proposed ICSO algorithm has faster convergence rates on most of the test cases, especially for solving the hybrid functions.

3) STATISTICAL TEST RESULTS

Since the swarm intelligence algorithms are usually stochastic, it is necessary to perform statistical tests to evaluate the performance of the proposed ICSO algorithm. In this section, we use the Wilcoxon nonparametric rank-sum test [27] to verify the statistical significance of ICSO for solving the CEC 2017 test functions. In this test, two different populations are compared and their differences are analyzed. Moreover, this test uses a p value to determine the statistical significance level of any two algorithms. In this paper, we adopt $p \leq 0.05$ to imply a significant difference among the algorithms, and the results of p values for different algorithms are shown in Table 8. Note that NA represents that this is the algorithm with best performance for solving the certain function, and the other values are the results that are compared to the

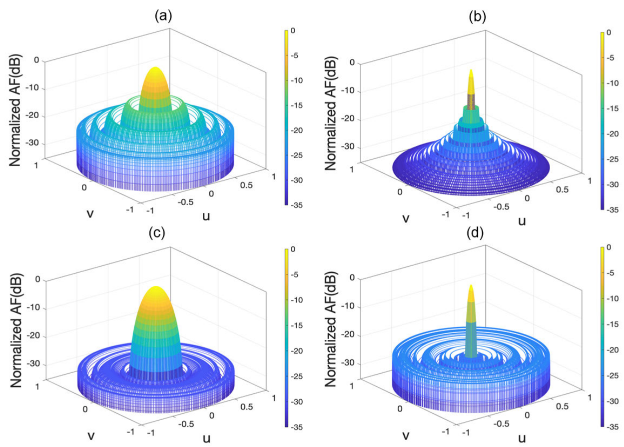

FIGURE 6. 3D beam patterns of LAA obtained by uniform excitation currents and ICSO. (a) Uniform excitation currents for 16-element LAA. (b) Uniform excitation currents for 64-element LAA. (c) ICSO for 16-element LAA. (d) ICSO for 64-element LAA.

TABLE 9. Numerical results obtained by different algorithms of 16-element LAA case.

	Maximum SLL (dB)	Mainlobe beamwidth (°)
Uniform	-13.1700	14.51
CSO	-20.4854	17.11
BBO	-24.9822	20.82
PSO	-26.5908	21.22
HBA	-19.3917	17.11
ESRFA	-21.8585	17.61
NMCSA	-22.1510	17.70
HBBOG	-21.5930	17.71
ICSO	-29.2361	21.32

TABLE 10. Numerical results obtained by different algorithms of 64-element LAA case.

	Maximum SLL (dB)	Mainlobe beamwidth (°)
Uniform	-13.2400	3.50
CSO	-20.3600	4.10
BBO	-22.4635	4.70
PSO	-19.7671	3.70
HBA	-19.8276	4.10
ESRFA	-18.5209	3.90
NMCSA	-23.2228	4.50
HBBOG	-19.6818	4.30
ICSO	-24.7676	4.70

best algorithm. Moreover, if there are more than one NAs for a function, then these algorithms have no significant differences for solving this function. It can be seen from the table that the proposed ICSO algorithm has the best performance for more than half of the 30 test functions. However, the performance of ICSO needs to be further evaluated in the sidelobe suppression optimization problems.

B. BEAM PATTERNS

In this section, we use the proposed ICSO and other abovementioned algorithms to solve the formulated SLL reduction optimization problems of LAA, CAA and RAA. The maximum number of iteration for each algorithm is 400 and the population size is set as 30. Moreover, the parameter setups of different algorithms are listed in Table 2, which are the same with their corresponding references.

In the simulations, each kind of antenna array is tested with the element numbers of 16 and 64, respectively, to evaluate the algorithm performances for different dimensions of solutions. Moreover, these simulations are repeated for 30 times independently for each test case and we present the median results.

TABLE 11. Numerical results obtained by different algorithms of 16-element CAA case.

	Maximum SLL (dB)	Mainlobe beamwidth (°)
Uniform	-7.9200	32.80
CSO	-12.6474	36.40
BBO	-12.5180	37.40
PSO	-13.5119	33.20
HBA	-11.3342	32.20
ESRFA	-10.8663	37.00
NMCSA	-14.3552	35.60
HBBOG	-13.9971	36.80
ICSO	-14.7656	36.20

TABLE 12. Numerical results obtained by different algorithms of 64-element CAA case.

	Maximum SLL (dB)	Mainlobe beamwidth (°)
Uniform	-8.0490	8.60
CSO	-13.2504	9.80
BBO	-13.2167	10.60
PSO	-13.4982	5.80
HBA	-12.8752	5.20
ESRFA	-11.3553	6.00
NMCSA	-13.5194	12.60
HBBOG	-13.5446	11.20
ICSO	-14.6640	12.00

1) LAA

Figs. 6(a) and 6(c) show the three dimensional (3D) beam patterns obtained by the uniform excitation currents and the proposed ICSO algorithm, respectively, for the 16-element LAA case. For the 64-element case, the 3D beam patterns obtained by the uniform excitation currents and ICSO algorithm are shown in Figs. 6(b) and 6(d), respectively. Moreover, Figs. 7(a) and 7(c) show the two dimensional (2D) beam pattern optimization results obtained by CSO, BBO, PSO, HBA, ESRFA, NMCSA, HBBOG and the proposed ICSO for the cases of 16-element and 64-element LAAs, respectively. We note that the beam pattern synthesis process are based on the entire 3D beam patterns, and the selected 2D planes are to show the results of different algorithms in a clearer way.

Moreover, Tables 9 and 10 show the numerical results in terms of the maximum SLLs and mainlobe beamwidth obtained by the uniform antenna array and abovementioned algorithms for 16-element and 64-element LAAs, respectively. Since the sidelobe and mainlobe are often tradeoffs, which means that reducing the sidelobe may widen

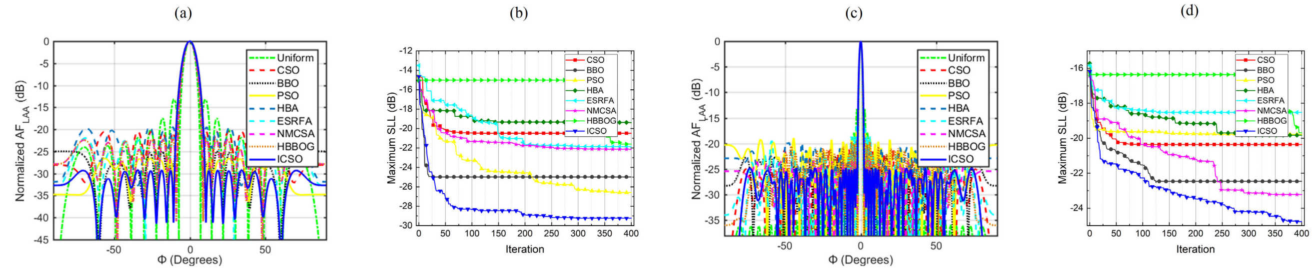

FIGURE 7. **2D beam patterns and convergence rates obtained by different algorithms of LAA case. (a) Beam patterns of 16-element LAA. (b) Convergence rates of 16-element LAA. (c) Beam patterns of 64-element LAA. (d) Convergence rates of 64-element LAA.**

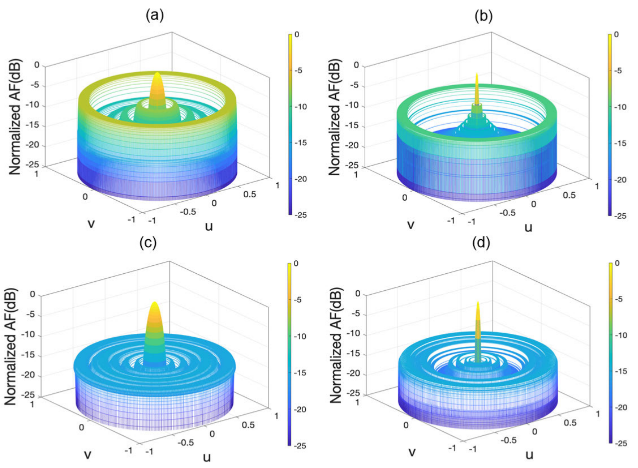

FIGURE 8. **3D beam patterns of CAA obtained by uniform array and ICSO. (a) Uniform array for 16-element CAA. (b) Uniform array for 64-element CAA. (c) ICSO for 16-element CAA. (d) ICSO for 64-element CAA.**

the mainlobe. Thus, the mainlobe beamwidth is presented. It can be seen from the figures and tables that ICSO has better optimization results than all other comparison algorithms in both 16-element and 64-element LAA cases. Moreover, it can be also observed that the mainlobe beamwidth of the 64-element LAA is much narrower than that of the 16-element case. This is because that with the increasing number of the antenna elements, the mainlobe of the beam pattern will be narrower, and it will be also reflected in the CAA and RAA cases.

In addition, Figs. 7(b) and 7(d) show the convergence rates obtained by different algorithms of 16-element and 64-element LAA cases, respectively. As can be seen, the convergence rate and accuracy of the proposed ICSO are much better than that of other comparison algorithms. The reason may be that the introduced improved factors are able to enhance the performance in terms of both local and global searches of the algorithm so that it can achieve better optimization results.

2) CAA

For the CAA case, the excitation currents and distance between the elements are both regarded as the solutions of the algorithm and hence they will be jointly optimized. Thus, different from the LAA optimization case, the solution dimension of the CAA optimization case will be twice of the number of antenna elements. Figs. 8(a) and 8(c) show the 3D beam patterns of 16-element CAAs obtained by uniform array and ICSO, respectively, and the 3D beam patterns of 64-element CAAs obtained by these two abovementioned approaches are shown in 8(b) and 8(d). Fig. 9(a) shows the 2D beam patterns of uniform array, CSO, BBO, PSO, HBA, ESRFA, NMCSA, HBBOG and ICSO for the 16-element CAA optimization case, and Fig. 9(c) shows the beam pattern optimization results of the 64-element CAA. Similar to LAA case, the mainlobe beamwidth is much narrower than the 16-element CAA. Moreover, the numerical results of these two optimization cases obtained by different approaches are shown in Tables 11 and 12. In addition, the convergence rates of different algorithms for the two optimization samples are shown in Figs. 9(b) and 9(d). As can be seen, ICSO is able to jump out from local optima and this may be due to the introduced improved factors. Moreover, the solution dimension in 64-element CAA is 128 which can be regarded as a high dimensional solution. Thus, the proposed ICSO is effective for both the low and high dimensional beam pattern optimization problems.

3) RAA

Figs. 10(a) and 10(b) show the antenna element distributions of the 16-element and 64-element RAAs, respectively. These antenna elements are distributed randomly on a plane. Moreover, the radius r of the RAA is normalized to λ such that $\tilde{r} = r/\lambda$. In this simulation, $\tilde{r}$ is set as 1.

Fig. 11(a) and 11(c) show the 3D beam patterns of a RAA with 16 antenna elements obtained by uniform array and ICSO, respectively. Moreover, the 3D beam patterns of 64-element RAA obtained by uniform array and ICSO are shown in Figs. 11(b) and 11(d), respectively. Moreover, Figs. 12(a) and 12(c) show the 2D beam patterns of 16-element and 64-element RAAs obtained by uniform array, CSO, BBO, PSO, HBA, ESRFA, NMCSA, HBBOG and ICSO, and the numerical results in terms of the maximum SLLs and mainlobe beamwidth for these two cases are shown in Tables 13 and 14. As can be seen, although all algorithms can reduce

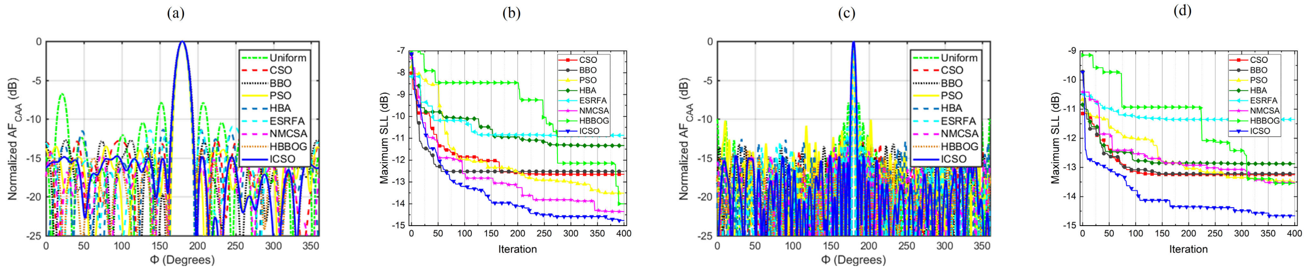

FIGURE 9. 2D beam patterns and convergence rates obtained by different algorithms of CAA case. (a) Beam patterns of 16-element CAA. (b) Convergence rates of 16-element CAA. (c) Beam patterns of 64-element CAA. (d) Convergence rates of 64-element CAA.

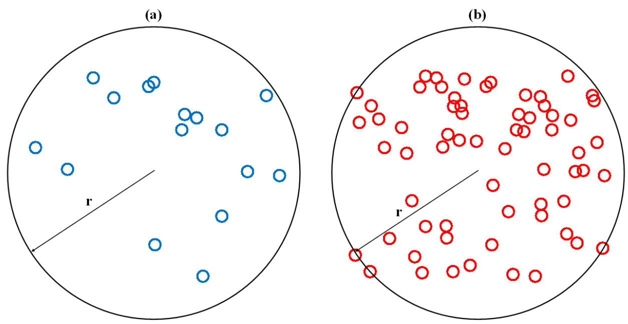

FIGURE 10. Random antenna element distributions of the RAA. (a) 16-element RAA. (b) 64-element RAA.

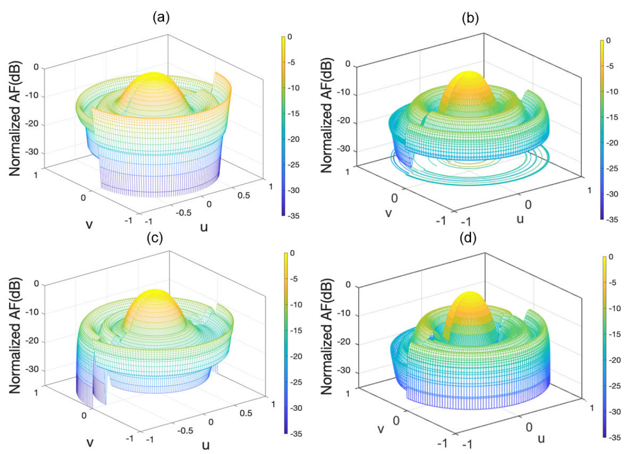

FIGURE 11. 3D beam patterns of RAA obtained by uniform array and ICSO. (a) Uniform excitation currents for 16-element RAA. (b) Uniform excitation currents for 64-element RAA. (c) ICSO for 16-element RAA. (d) ICSO for 64-element RAA.

TABLE 13. Numerical results obtained by different algorithms of 16-element RAA case.

	Maximum SLL (dB)	Mainlobe beamwidth (°)
Uniform	-5.4030	65.00
CSO	-11.0116	61.00
BBO	-11.0896	60.00
PSO	-10.6109	62.00
HBA	-10.2081	65.00
ESRFA	-9.5133	63.00
NMCSA	-11.1869	63.00
HBBOG	-11.2222	60.00
ICSO	-11.3617	60.00

TABLE 14. Numerical results obtained by different algorithms of 64-element RAA case.

	Maximum SLL (dB)	Mainlobe beamwidth (°)
Uniform	-10.3000	52.00
CSO	-12.1970	46.00
BBO	-13.0224	44.00
PSO	-11.5660	43.00
HBA	-11.8547	44.00
ESRFA	-11.5003	50.00
NMCSA	-12.1773	45.00
HBBOG	-12.3164	44.00
ICSO	-14.0973	46.00

the maximum SLL, ICSO gets the best sidelobe suppression performance in these cases. In addition, the convergence rates during the optimization process are presented in Figs. 12(b) and 12(d), respectively.

C. STABILITY VERIFICATION

To further evaluate the stabilities of the proposed ICSO approach for sidelobe suppression optimizations of different antenna arrays, a test with 30 independent trials are established.

Fig. 13(a) shows the maximum SLLs of different trials obtained by different algorithms for the 16-element LAAs, and Fig. 13(b) shows the trial results of the 64-element LAAs. Moreover, the numerical statistical results of these two cases are shown in Tables 15 and 16, respectively. It can been from the figures that the maximum SLLs obtained by ICSO are lower than CSO, BBO, PSO, HBA, ESRFA, NMCSA and HBBOG for all runs. Moreover, the mean values and standard deviations (SDs) achieved by ICSO is lower than that of other comparison algorithms. Therefore, the stability performance of ICSO may be the best for the LAA case compared to other approaches.

Figs. 13(c) and 13(d) show the stability test results of the 16-element and 64-element CAAs obtained by different algorithms. As can be seen, CSO, BBO, PSO, HBA, ESRFA, NMCSA and HBBOG have similar performance for the SLL

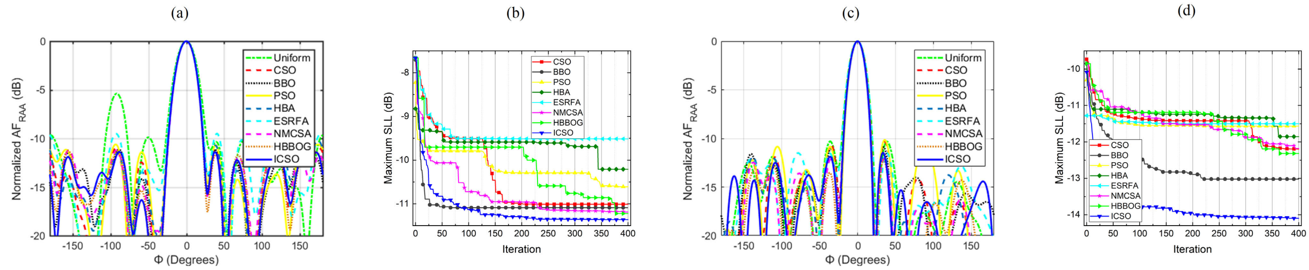

FIGURE 12. 2D beam patterns and convergence rates obtained by different algorithms of RAA case. (a) Beam patterns of 16-element RAA. (b) Convergence rates of 16-element RAA. (c) Beam patterns of 64-element RAA. (d) Convergence rates of 64-element RAA.

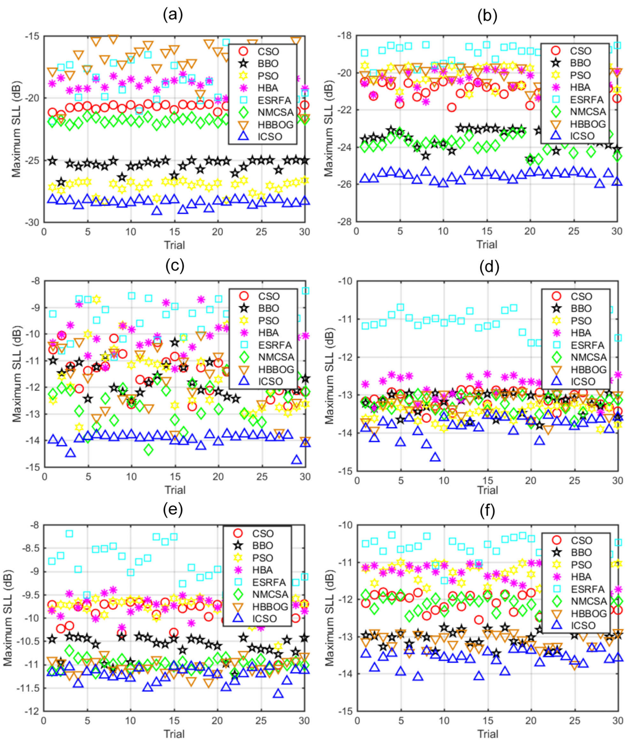

FIGURE 13. Numerical statistical results of different algorithms for stability tests. (a) 16-element LAA. (b) 64-element LAA. (c) 16-element CAA. (d) 64-element CAA. (e) 16-element RAA. (f) 64-element RAA.

reduction of the 16-element CAA, while ICSO can achieve much lower maximum SLLs than these benchmark algorithms. A similar situation also appears in Fig. 13(d), which shows that the proposed ICSO has the lowest maximum SLLs compared with other algorithms on 64-element CAAs. The numerical statistical results for the 16-element and 64-element CAAs are shown in Tables 17 and 18, respectively. As can be seen, the proposed ICSO approach has better performance in terms of the mean values and SDs compared to other algorithms, which indicates that ICSO also has superiority for the sidelobe reductions of CAAs.

For RAA case, the intuitive stability test results of 16-element and 64-element samples are shown in Figs. 13(e) and 13(f), respectively. Moreover, tables 19 and 20 present the numerical statistical results of different algorithms for the tests. Similar to the previous LAA and CAA cases, the mean values obtained by the proposed ICSO are better than other comparison algorithms. However, the SDs achieved by ICSO are not optimal, but they are very close to the optimal values.

Accordingly, by using the local search, weighting, global search and variation factors, the exploration and exploitation can be balanced, which may achieve better performance in terms of stability.

D. PERFORMANCE VERIFICATION OF IMPROVED FACTORS

In this section, we conduct several test cases to verify the effectiveness of the proposed four improved factors. In this tests, we use the conventional CSO algorithm, CSO with local search factor, CSO with weighting factor, CSO with global search factor, CSO with variation mechanism and ICSO to solve the sidelobe suppression optimization problems of 16-element LAA, CAA and RAA, respectively, and the convergence curves obtained by these methods are shown in Figs. 14(a), 14(b) and 14(c). We note that these tests are repeated 30 times to avoid random bias, and the average convergence rates are presented. As can be seen, these introduced improved factors can effectively enhance the performance of conventional CSO algorithm so that making it more suitable for the sidelobe reduction optimization problems.

E. EFFECT OF MUTUAL COUPLING

In this work, our main objective is to propose a novel swarm intelligence optimization technique for effectively synthesizing the beam patterns of antenna arrays, hence the effectiveness of mutual coupling is not considered when formulating and solving the sidelobe suppression optimization problems for simplification. However, it is necessary to evaluate the effect of mutual couping since it exists in practical antenna arrays [21], [51]. Thus, the EM simulations are constructed to verify if the proposed ICSO algorithm is also useful for the sidelobe reductions of antenna arrays with the existence of mutual coupling.

The EM simulations are conducted based on ANSYS Electromagnetics (HFSS), and we design 16-element LAA, CAA and RAA in this software, respectively. Then, the optimized parameters including excitation currents and spacing

TABLE 15. Stability test results achieved by different algorithms of 16-element LAA case.

Algorithm	CSO	BBO	PSO	HBA	ESRFA	NMCSA	HBBOG	ICSO
Worst	-20.49	-24.99	-26.64	-18.11	-15.55	-21.47	-15.19	**-28.21**
Best	-21.40	-26.65	-28.28	-20.19	-21.86	-22.17	-21.59	**-28.95**
Median	-20.65	-25.30	-26.87	-19.03	-19.14	-21.77	-16.64	**-28.41**
Mean	-20.76	-25.44	-27.05	-19.00	-18.89	-21.80	-17.12	**-28.44**
SD	0.27	0.43	0.44	0.52	1.47	**0.19**	1.64	**0.19**

TABLE 16. Stability test results achieved by different algorithms of 64-element LAA case.

Algorithm	CSO	BBO	PSO	HBA	ESRFA	NMCSA	HBBOG	ICSO
Worst	-20.49	-22.99	-19.64	-19.83	-18.52	-23.22	-19.68	**-25.34**
Best	-21.83	-24.66	-20.88	-21.64	-19.93	-24.94	-21.39	**-26.02**
Median	-20.65	-23.32	-19.83	-20.15	-18.95	-23.57	-20.19	**-28.41**
Mean	-20.85	-23.43	-19.94	-20.37	-19.04	-23.75	-20.23	**-25.54**
SD	0.40	0.44	0.29	0.51	0.43	0.51	0.45	**0.18**

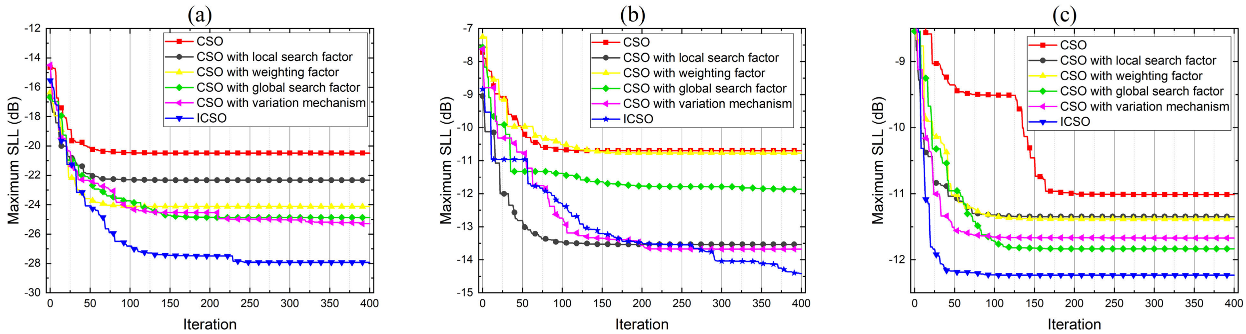

FIGURE 14. Convergence rates obtained by different improved factors for sidelobe suppression optimization tests. (a) LAA case. (b) CAA case. (c) RAA case.

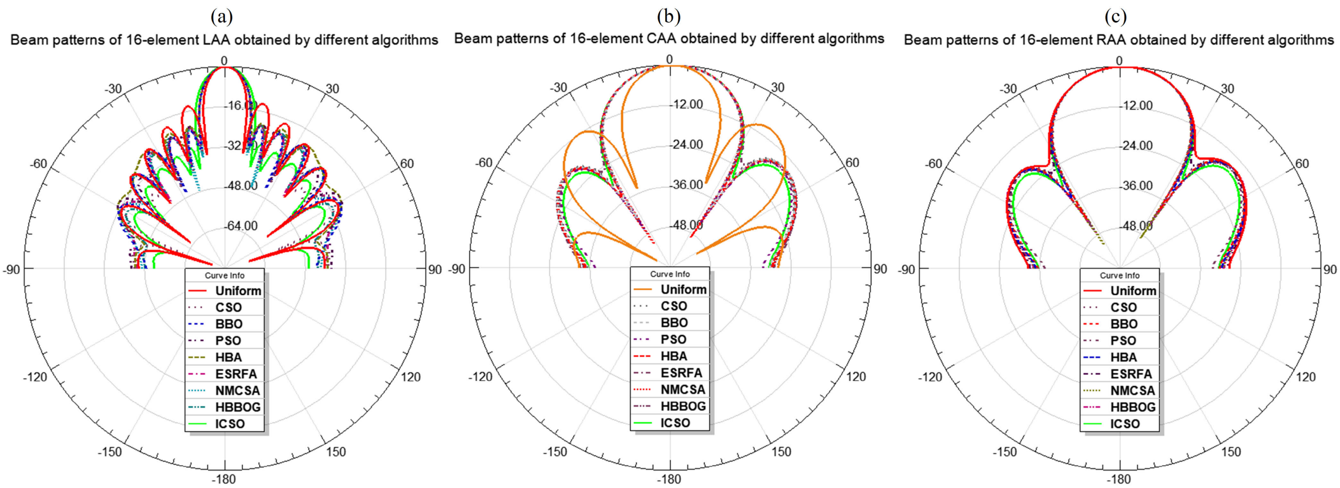

FIGURE 15. EM simulation results obtained by different algorithms for antenna arrays. (a) 16-element LAA. (b) 16-element CAA. (c) 16-element RAA.

achieved in the ideal condition (without considering mutual coupling) are input into HFSS, to verify if these ideal environment solutions are effective for the antenna arrays in more practical environments. Figs. 15(a), 15(b) and 15(c) show the 2D beam pattern results obtained by different algorithms in EM simulations, and the numerical results in terms of maximum SLLs are shown in Table 21. As can be seen, the proposed ICSO algorithm gets the lowest maximum SLLs in these three antenna arrays compared to other approaches. Thus, similar to the conclusions in Refs. [6] and [52], the beam pattern optimizations in ideal condition may provide general overviews of different optimization algorithms.

TABLE 17. **Stability test results achieved by different algorithms of 16-element CAA case.**

Algorithm	CSO	BBO	PSO	HBA	ESRFA	NMCSA	HBBOG	ICSO
Worst	-10.07	-10.33	-8.72	-8.71	-8.38	-11.37	-10.05	**-13.79**
Best	-12.73	-12.52	-13.51	-11.33	-10.87	-14.36	-14.00	**-14.77**
Median	-11.32	-11.76	-11.66	-10.08	-9.25	-12.41	-11.47	**-14.06**
Mean	-11.43	-11.65	-11.61	-10.02	-9.39	-12.57	-11.65	**-14.11**
SD	0.74	0.58	1.21	0.67	0.65	0.75	1.15	**0.24**

TABLE 18. **Stability test results achieved by different algorithms of 64-element CAA case.**

Algorithm	CSO	BBO	PSO	HBA	ESRFA	NMCSA	HBBOG	ICSO
Worst	-12.87	-12.95	-13.23	-12.46	-10.72	-12.99	-12.91	**-13.53**
Best	-13.64	-13.80	-14.05	-13.24	-11.77	-13.72	-14.05	**-14.66**
Median	-13.05	-13.15	-13.38	-12.63	-11.01	-13.27	-13.17	**-13.70**
Mean	-13.12	-13.18	-13.41	-12.73	-11.06	-13.32	-13.24	**-13.78**
SD	0.21	0.21	**0.19**	0.23	0.31	0.25	0.28	**0.19**

TABLE 19. **Stability test results achieved by different algorithms of 16-element RAA case.**

Algorithm	CSO	BBO	PSO	HBA	ESRFA	NMCSA	HBBOG	ICSO
Worst	-9.68	-10.40	-9.57	-9.40	-8.20	-10.70	-10.79	**-11.04**
Best	-11.01	-11.23	-10.61	-10.21	-9.51	-11.19	-11.38	**-11.77**
Median	-9.87	-10.57	-9.83	-9.75	-8.75	-11.00	-11.08	**-11.16**
Mean	-10.01	-10.64	-9.89	-9.75	-8.79	-10.99	-11.06	**-11.25**
SD	0.343	0.23	0.26	0.22	0.35	**0.21**	0.25	0.22

TABLE 20. **Stability test results achieved by different algorithms of 64-element RAA case.**

Algorithm	CSO	BBO	PSO	HBA	ESRFA	NMCSA	HBBOG	ICSO
Worst	-11.80	-12.75	-11.01	-11.03	-10.27	-11.88	-12.32	**-13.32**
Best	-12.54	-13.58	-11.70	-11.89	-11.50	-12.75	-13.73	**-14.10**
Median	-11.98	-12.95	-11.17	-11.23	-10.45	-12.11	-13.05	**-13.58**
Mean	-12.02	-12.99	-11.25	-11.33	-10.54	-12.17	-13.10	**-13.59**
SD	**0.19**	0.21	**0.19**	0.28	0.27	0.24	0.28	0.23

F. DISCUSSION OF RESULTS

As we known, the exploration and exploitation may be regarded as the two most important abilities of a swarm intelligence as well as evolutionary computing algorithm, and these two performances may decide if an algorithm is performing better or not. Generally, the exploration is to explore the whole solution searching space which is usually represented the global search ability. Moreover, the exploitation is often meant for the local search ability. Thus, these two processes should be balanced so that the algorithm can achieve better optimization results.

In ICSO algorithm, the roosters are with better fitness functions, thus they need a stronger local search ability to exploit new and better candidate solutions, and this can be achieved by the proposed BA-based local search operator. Moreover, the hens and chicks are relatively farther away from the optimal location. Therefore, they need larger searching step sizes so that they can search for a wider region of solution space, and this can be achieved by the proposed weighting and global search factors of hens and chicks. Accordingly, by using the abovementioned improved factors, the exploration and exploitation can be balanced in the proposed ICSO, thereby it is able to achieve better beam pattern optimization results of different antenna arrays and this can be directly reflected in the results of Section VI-D.

TABLE 21. **Numerical results obtained by different algorithms for reducing the maximum SLLs of 64-element LAA and CAA in EM simulations.**

	Max SLL (dB) (LAA)	Max SLL (dB) (CAA)	Max SLL (dB) (RAA)
Uniform	-18.1859	-9.2350	-15.0058
CSO	-23.2514	-15.3096	-15.3096
BBO	-24.0824	-15.1701	-16.0694
PSO	-22.3310	-16.3082	-15.7849
HBA	-21.9380	-16.1339	-15.0416
ESRFA	-25.5990	-16.1428	-15.6162
NMCSA	-24.5919	-15.5973	-15.0380
HBBOG	-22.7540	-15.9680	-15.3232
ICSO	-30.1509	-17.1247	-16.7627

However, ICSO has certain drawbacks in terms of the parameters. The conventional CSO algorithm has several parameters. However, by introducing the improved factors, the proposed ICSO algorithm has more parameters than CSO. Since a swarm intelligence algorithm may perform different performances under different parameter selections, it is often important to tune the key parameters for different applications. However, since this work mainly aims to propose the proposal of a novel swarm intelligence optimization technique, the parameter tuning and selection will be considered in our future works.

VII. CONCLUSION

In this paper, suppressing the maximum SLLs of different antenna arrays are investigated. We formulate the SLL reduction optimization problems of LAA, CAA and RAA, and then propose an ICSO algorithm which includes four improved mechanisms to solve the formulate optimization problems. Simulations are conducted and the results indicate that the maximum SLL performance optimized by ICSO approach are better than that of several conventional algorithms like CSO, BBO, PSO, and some recently proposed improved algorithms such as HBA, ESRFA, NMCSA and HBBOG. Moreover, the convergence rate and stability of ICSO are the best for each optimization case. In addition, the effectiveness of the proposed improved factors are verified. Finally, the performance of ICSO for reducing the SLL of different antenna arrays with considering the mutual coupling is evaluated by EM simulations.

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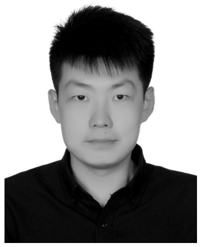

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