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Suppressing Sidelobe Level of the Planar Antenna Array in Wireless Power Transmission

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ABSTRACT The power pattern synthesis, as well as the sidelobe level (SLL) suppression of the planar antenna arrays for the wireless power transmission is investigated. An improved chicken swarm optimization (ICSO) algorithm is proposed for reducing the maximum SLL of the power pattern. ICSO introduces the global search, the local search, and the duplicate solution removing operators to enhance the accuracy and the convergence rate of the conventional CSO algorithm, thereby making it suitable for the power pattern optimizations. Simulations are conducted to verify the performance of the proposed algorithm, and the results show that ICSO obtains the lowest maximum SLL compared with other algorithms. Moreover, the power pattern performances of different algorithms are tested by the electromagnetic simulations, and the results show that the proposed ICSO has the best optimization ability.

INDEX TERMS Wireless power transmission, power pattern, energy beamforming, sidelobe level, chicken swarm optimization.

I. INTRODUCTION

The long-range and high efficiency wireless power transmission (WPT) is a promising technology for a wide range of applications in many fields [1], and it is one of the feasible technologies for the solar satellite [2]. Different from other wireless power transfer technologies using near-field coupling or laser beaming, WPT based on radio-frequency (RF) has certain advantages such as the longer transmission distance [3]. In general, there are two important components in a RF-based WPT system that are the transmitting antenna and the rectifying antenna. Thus, the fundamentals of a WPT system are similar to those of the traditional communication and radar systems [4].

Two important factors that are the transmission distance and the energy efficiency should be considered in the RF-based WPT system [1]. Thus, to enhance the transmission distance while keeping a certain level receiving efficiency has been taken into account [5]. For improving the receiving efficiency, most current research commit to improve the RF-to-DC conversion efficiency of the receiving antenna. However, the transmission systems as well as the antennas are also very important because they can determine the transmission range and the efficiency directly [4].

Improving the beam directivity of an antenna can enhance the energy efficiency of the RF-based WPT system. Both the directional antennas and antenna arrays are able to achieve this goal. For example, the Fabry-perot cavity antenna (FPCA) is a kind of directional antennas with high gain and it is excited by a localized source sandwiched between a partially reflecting surface and a metallic ground plane, as shown in Fig. 1. Moreover, due to the high directivities and simple structures, the FPCAs are more suitable for the wireless and satellite communications or radar systems, compared to the omnidirectional antennas. Similar with the microwave communication systems, the FPCAs are able to be used in the RF-based WPT system [6], [7]. However, using FPCAs in the microwave-based WPT system may have several disadvantages compared to the systems that based on the antenna arrays. First, several references, e.g., [8], [9], have reported that the back lobe of a FPCA is relatively high so that wasting energy in the WPT system. Second, the beam control performance such as the beam tracking is

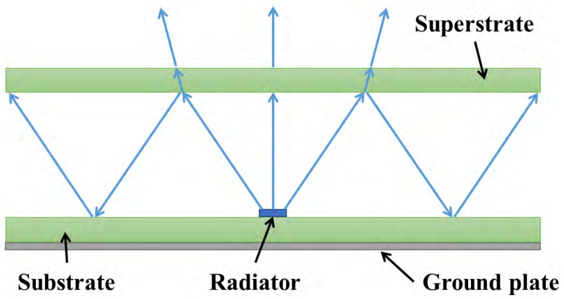

FIGURE 1. Sketch map of a FPCA.

necessary in some WPT applications, e.g., to charge a moving vehicle or a mobile phone, the transmitter needs to adjust the direction of the mainlobe of the beam so that obtaining the best charging efficiency, and this can be achieved by adjusting the excitation currents and the phases of the antenna array. However, it is much more difficult to control the beam by using FPCAs [10]. Third, the size of a FPCA is relatively large [11], and thus it may not suitable for some applications. For example, to charge a pacemaker of a person, the energy transmitter cannot be too large because it is unavailable in the indoor environment. On the contrary, using the patch antenna array which has a small size structure may be a better way.

Therefore, it motived us to use the antenna arrays to construct the transmitter of the RF-based WPT system. The energy transmission efficiency can be improving by using the energy beamforming technology based on the antenna arrays [12]. The transmission module of a WPT system can use an antenna array to generate a narrow power beam with lower sidelobe, to make most of the energy focus on the receiving direction, thereby improving the transmission distance and the efficiency. However, power pattern synthesis of an antenna array is a complex non-linear problem [3]. Moreover, there is a trade-off between the sidelobe and the mainlobe of the power pattern, and this means that the mainlobe beamwidth may be extended while only considering to reduce the sidelobe, thereby causing the decreased energy transmission efficiency. Thus, to find an efficient and effective approach to synthesize the power pattern is of great significance.

The power pattern synthesis for energy beamforming is similar with the radiation beamforming for information transmission because both of them are based on antenna arrays. Thus, the optimization method for radiation beamforming can be learned for energy beamforming. There are several conventional and classical antenna array sidelobe level suppression methods such as the Taylor synthesis method [13], the Chebyshev synthesis method [14] and the convex optimization method [15], and using the swarm intelligence optimization as well as the evolutionary computation algorithms is also a common method for the sidelobe suppressions of the antenna arrays. However, in some applications of the antenna array-based WPT systems, the swarm intelligence optimization algorithms have advantages compared to the conventional antenna array synthesis methods and hence they are more suitable for these applications. For example, for a WPT system with large scale antenna array (thousands of antenna elements), using the conventional Chebyshev synthesis method needs several restrictive conditions. Moreover, the time cost of this method is large. In addition, it needs to relax some constraints by using the convex optimization method in the antenna array beam pattern synthesis problem. Thus, it is unavailable in practical applications. However, the swarm intelligence optimization methods are able to be used in almost any applications without considering the constraints of the optimization problem. Therefore, these methods can be regarded as the practical approaches and thus we will consider to use them as the optimizer in this paper.

A. MAIN CONTRIBUTIONS

The main contributions of this paper are as follows:

(1) We formulate an optimization problem to synthesize the power pattern and reduce the maximum sidelobe level (SLL) of the planar antenna array (PAA) for wireless power transmission.

(2) We propose an improved chicken swarm optimization (ICSO) algorithm to solve the proposed optimization problem, thereby achieving a better power pattern with lower maximum SLL.

(3) We conduct simulations to verify the performance of the proposed ICSO algorithm for the power pattern synthesis. Moreover, electromagnetic (EM) simulations are conducted to test the performances of different approaches in the EM environment.

B. PAPER ORGANIZATION

The remaining part of this paper is organized as follows. Section II discusses the related work. Section III shows the system models and formulates the optimization problem. Section IV proposes the ICSO algorithm. Section V presents the simulation results and Section VI concludes the paper. Table 1 lists the main abbreviations used in this paper.

II. RELATED WORK

The evolutionary computation and the swarm intelligence algorithms are effective methods for solving the beam pattern optimization problems in radiation beamforming [16]. Compared with other methods, the swarm intelligence algorithms have some advantages such as simple operation, fast convergence and better global convergence. Thus, they have become the focus of more and more researchers. For example, Li et al. [17] utilize an improved biogeography-based optimization (BBO) to optimize the beam pattern of the linear antenna array (LAA) as well as the circular antenna array (CAA). However, the performance of the algorithm for the high-dimensional optimization problem is not presented. Todnatee and Phongcharoenpanich [18] synthesize the radiation pattern of a LAA with a lower SLL by using the genetic algorithm (GA). A maximum SLL of −20 dB is achieved by using the proposed approach. However, the stability of the algorithm is not evaluated. Sharaqa and Dib [19] utilize

TABLE 1. Main abbreviations.

Abbreviation	Expansion
SLL	Sidelobe level
PAA	Planar antenna array
WPT	Wireless power transmission
ICSO	Improved chicken swarm optimization
CSO	Chicken swarm optimization
RF	Radio-frequency
DC	Direct current
FPCA	Fabry-perot cavity antenna
EM	Electromagnetic
BBO	Biogeography-based optimization
LAA	Linear antenna array
CAA	Circular antenna array
GA	Genetic algorithm
FA	Firefly algorithm
PSO	Particle swarm optimization
IWO	Invasive weed optimization
CS	Cuckoo search
BCE	Beam collection efficiency
ABC	Artificial bee colony
DE	Differential evolution
AF	Array factor
GWO	Grey wolf optimizer
IUMCH	Improved update method of chicks and hens
IUMR	Improved update method of the roosters

the firefly algorithm (FA) to optimize the set of weights and positions for CAA. Although FA has better performance for the SLL reduction of the CAA compared to some well-known algorithms like particle swarm optimization (PSO), the CPU time of FA is larger. Li et al. [20] propose to use the invasive weed optimization (IWO) to reduce the maximum SLL of the conical conformal array, and they discover that the IWO algorithm has the better efficiency and stability. However, the convergence rate of this approach is not always fast in some cases. Moreover, Sun et al. [21] use a cuckoo search (CS)-based algorithm to suppress the SLL of the large scale antenna array used in 5G communications, the maximum SLL and the total transmission power are jointly reduced by the proposed method. However, the effectiveness of the introduced improved factors is not mentioned.

Inspired by the radiation beam pattern optimizations, the swarm intelligence optimization algorithms have been gradually applied to the energy efficiency optimization problem of the energy beamforming in WPT. Li et al. [5] introduce an antenna array optimization method for WPT based on PSO, the spacing between the array elements is optimized by the method, to improve the beam collection efficiency (BCE). However, the accuracy of the solution is not good. As we known, the wireless terminals, e.g., the cell phones, are often in the mobile state, and thus, the antenna array should has the ability to adjust the mainlobe direction quickly. Therefore, the fast convergence ability of the algorithm is very important. Algorithm fusion is an effective way to achieve the purpose above because it can combine the advantages of each algorithm. For example, Yang et al. [22] propose a hybrid algorithm based on artificial bee colony (ABC) algorithm and differential evolution (DE) algorithm called ABC-DE to inherit their advantage, and it is used for the synthesis of the time-modulated arrays. Sun *et al.* [23] propose an algorithm named CSCSO that combines the CS algorithm and the chicken swarm optimization (CSO) algorithm to optimize the beam pattern of virtual node antenna array. In our previous work [24], a BBO-FA approach is proposed to design the beam pattern of a CAA, and this algorithm achieves the best optimization results among several benchmarks. However, the performance of BBO-FA for the large scale antenna array is not evaluated.

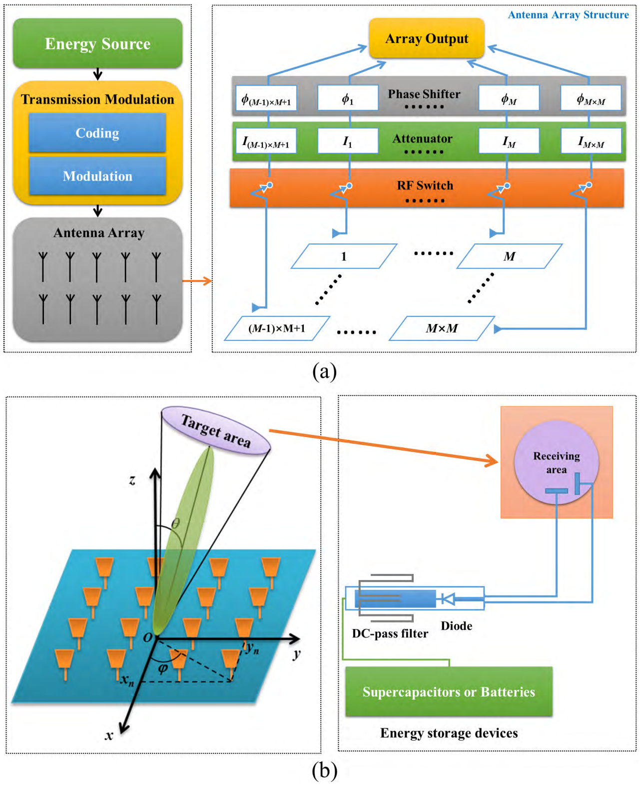

FIGURE 2. Sketch map of the WPT system. (a) Transmission module of the antenna array-based WPT system. (b) Geometric structure of the PAA for WPT.

Recently, a novel optimization method called CSO is proposed. This algorithm has promising performance because it absorbs the advantages of many swarm intelligence optimization algorithms, and chickens' diverse movements are helpful to the algorithm to break the balance of the randomness and determinacy to find the optima [25]. Moreover, CSO is able to solve the optimization problem by using the hierarchical mechanism extracted from the group intelligence of the chickens. In this paper, we propose a hybrid CSO-based algorithm to optimize the power pattern of the PAA for energy beamforming in WPT.

III. SYSTEM MODEL, ARRAY FACTOR AND PROBLEM DESCRIPTION

A. SYSTEM MODEL AND ARRAY FACTOR

Fig. 2 shows the common sketch map of an antenna array-based WPT system, and the transmission module of the system is shown in Fig. 2(a). As can be seen, the transmission module usually contains the energy source, the transmission modulation model and the transmission antenna array. Moreover, the transmission antenna array usually have three main modules that are the RF- switches, the attenuators and the phase shifters, and the non-uniform excitations can be achieved by using the attenuators in an actual antenna array [26]. In addition, Fig. 2(b) shows the geometric structure of a PAA with $M \times M$ elements for WPT, and the schematic diagram of the rectenna is also shown in this figure. Different from the wireless information transmission system, the receiver of the antenna array-based WPT system is usually an area instead of a point, as shown in Fig. 2(b).

The array factor (AF) of the PAA can be mathematically formulated as follows [5]:

$$F(u, v) = \sum_{i=1}^{M*M} I_i \exp[jk(ux_i + vy_i + \phi_i)] \tag{1}$$

where I_i is the excitation current of the ith array element, (x_i, y_i) is the position of the ith array element in the plane coordinate system, λ is the wavelength, k is the wave number ($k = 2\pi/\lambda$) and ϕ_i is the phase of the ith element. $u = \sin\theta\cos\varphi$, $v = \sin\theta\sin\varphi$, θ and φ are the elevation and azimuth angles of the edge of the target area relative to the origin of the coordinate, respectively. Assume $\phi_i = 0$, then Eq. (1) can be simplified as follows:

$$F(u, v) = \sum_{i=1}^{M*M} I_i \exp[jk(ux_i + vy_i)] \tag{2}$$

correspondingly, the power pattern can be expressed as [5]:

$$P_{\Omega_1,\Omega_2}(u, v) = |F(u, v)|^2 \tag{3}$$

where Ω_1 and Ω_2 are the receiving and the visible areas, respectively.

B. PROBLEM DESCRIPTION

1) PROBLEM FORMULATION

In this paper, the goal is to find a set of optimal excitation currents $\vec{I}$ ($I_i \in \vec{I}$ is normalized to 1 and hence $I_i \in [0, 1]$) such that the PAA is able to generate a narrow power pattern toward the receiver with lower maximum SLL. This is because if the maximum SLL of the PAA is reduced, there will be more energy concentrates upon the mainlobe according to the energy conservation principle, and then the BCE will be increased. Thus, the optimization problem can be achieved as follows:

$$\min \Gamma(\vec{I}) = 10\lg \frac{\max_{u,v\in(\Omega_2-\Omega_1)} P(u, v)}{\max_{u,v\in(\Omega_2)} P(u, v)} \tag{4a}$$

$$\text{s.t. } 0 \leqslant I_i \leqslant 1 \tag{4b}$$

$$-1 \leqslant u \leqslant 1 \tag{4c}$$

$$-1 \leqslant v \leqslant 1 \tag{4d}$$

$$\theta_{\text{null}_2} - \theta_{\text{null}_1} \leqslant \eta \tag{4e}$$

where θ_{null_1} and θ_{null_2} are the angles of the first nulls in $[-\pi, 0]$ and $[0, \pi]$, respectively, and these two angles determine the beamwidth of the mainlobe. Constraint (4b) gives the ranges of the excitation current weights of the antenna elements. Since $u = \sin\theta\cos\varphi$ and $v = \sin\theta\sin\varphi$, the ranges of these two variables are limited in constraints (4c) and (4d), respectively. Moreover, constraint (4e) determines the beamwidth of the mainlobe. In addition, the solution of the formulated optimization problem is expressed as $I = (I_1, I_2, \ldots, I_{M*M})^{\mathrm{T}}$.

As can be seen from the formulated optimization problem above, the denominator represents the maximum value of the power pattern in the visible area and it is actually the value of the mainlobe. Thus, the denominator can be regarded as a fixed value. Therefore, minimizing Eq. (4a) can be converted to minimize the maximum power pattern in the region that outside the receiving area of the visible area ($\Omega_2 - \Omega_1$). Note that different from the wireless communications for the information transmission, the receiver of the microwave-based wireless power transmission (WPT) system is usually a region instead of a point (see Fig. 2), and the reason is that using a receive region which within the mainlobe beamwidth can collect more transferred energy. Moreover, using a receive region is a more practical way in real-world applications since it is difficult for the beam to accurately aim at the receive point. In conventional antenna arrays for the wireless communications, there is a trade-off between the sidelobe and the mainlobe beamwidth which means that the decreased maximum SLL will cause a broadened mainlobe. However, in antenna array-based WPT system, the broadened mainlobe will not damage the BCE as long as the mainlobe beamwidth is within the receiving region. Therefore, we only consider to suppress the maximum SLL in the cost function and this will make the energy concentrate in the mainlobe so that the BCE can be improved correspondingly.

2) HP-HARDNESS

The formulated problem shown in Eqs. (4a)-(4e) is a continuous optimization problem and it is NP-hard. The proofs are as follows.

For ease of analysis, we first transform the continuous optimization problem (the solutions are the continuous values between 0 and 1) into a discrete optimization problem (the solution can be only chosen as several candidate values between 0 and 1), that is, the excitation currents are selected from a set with finite numbers of elements, the set can be defined as $S = \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0\}$. Next, we will verify that the transformed problem is a combinatorial optimization problem.

The goal of the combinatorial optimization problem is to find the optimal subset of a given universal set with finite elements with certain characteristics, so that achieving the best solutions of the optimization problem. The combinatorial optimization problem can be represented by the following three parameters (F, G, D) [27], where F is the cost function (Eq. (4a)), G represents the feasible solution region, and it is a set of constraint functions (Eqs. (4b)-(4e)), and D is the domain of solution which represents the regions of the solutions. Thus, the transformed version of the formulated problem can be regarded as a combinatorial optimization problem. The combinatorial optimization problem is NP-hard [28], and the transformed version of the formulated problem is a simplified form of the original problem. Thus, the formulated problem in Eqs. (4a)-(4e) is NP-hard.

IV. ALGORITHM

A. OPTIMIZATION FRAMEWORK

For different applications, the specific optimization procedures for suppressing the maximum SLL of the antenna array-based WPT system may be different. However, the optimization frameworks are similar. However, the specific optimization procedures of different WPT systems are not the same so that the design criteria of the antenna array for WPT should depend on the applications and it may not have absolute parameter values. For example, the antenna array structure of the WPT system for charging the mobile phones is different from the one that for the space solar power satellite, hence there cannot be a standardized procedure for them. However, they can have similar optimization steps. Thus, a common optimization framework for the power pattern synthesis of the antenna array-based WPT system is proposed and the main steps are as follows:

Step 1: Determine the type and structure of the antenna array.

Step 2: Construct the maximum SLL suppression optimization framework based on the selected antenna array.

Sub-step 2-1: Formulate the sidelobe suppression optimization problem according to the system requirements.

Sub-step 2-2: Use the proposed ICSO algorithm to solve the optimization problem formulated in section III-B.

Step 3: Allocate the obtained excitation currents to the antenna array.

The proposed ICSO algorithm mentioned in sub-step 2-2 will be introduced in detail in the following sections.

B. CONVENTIONAL CSO

CSO is an optimization algorithm inspired by the behavior of the chickens and it is based on the following rules [25]:

(1) A number of groups exist in the chicken swarm, and each group contains a rooster, several hens and chicks.

(2) The best individual in a randomly selected group will be retained to the next generation.

(3) The percentages of various levels of chicken swarms are fixed, and the number of the hens is the greatest.

(4) The number of the available chickens n is fixed. The hierarchical order, dominance relationship, and mother-child relationship in a group will remain unchanged. These statuses can be only updated in every G time step.

In CSO, the identity of chickens (roosters, hens and chicks) depends on the fitness values. The chickens with the best fitness values will be determined as the roosters, whereas the chickens with the worst fitness value will be identified as the chicks, and the rest chickens will be identified as the hens. Moreover, in the group, each chicken is considered as a solution. Thus, to move a chicken is to generate a new solution. The optimal solution is retained in the end, which is the ultimate goal of the algorithm.

According to the hierarchy mechanism of CSO, the solution update methods of different group are different. For the roosters, the solution update method is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} * (1 + N(0, \sigma^2)) \tag{5}$$

$$\sigma^2 = \begin{cases} 1, & \text{if } f_i \le f_k, \\ \exp\left(\dfrac{(f_k - f_i)}{|f_i| + \varepsilon}\right), & \text{otherwise } k \in [1, rNum],\ k \ne i. \end{cases} \tag{6}$$

where $N(0, \sigma^2)$ is a normal distribution with a mean of 0 and a variance of σ^2, k is another rooster which is different from i. $rNum$ is the number of roosters. f_i and f_k are the fitness values of roosters i and k, respectively.

The hens need to follow the roosters to forage for food, and there is a competitive relationship within and between groups. This condition can be formulated as follows:

$$\begin{aligned} x_{i,j}^{t+1} &= x_{i,j}^{t} + S1 * Rand * (x_{r1,j}^{t} - x_{i,j}^{t}) \\ &\quad + S2 * Rand * (x_{r2,j}^{t} - x_{i,j}^{t}) \end{aligned} \tag{7}$$

$$S1 = \exp((f_i - f_{r1})/(abs(f_i) + \varepsilon)) \tag{8}$$

$$S2 = \exp((f_{r2} - f_i)) \tag{9}$$

where $Rand$ is a random number between [0, 1]. $r1$ represents the index of the rooster ($r1 \in [1, \ldots, N]$) which is in the same group with ith hen and $r2$ represents the index ($r2 \in [1, \ldots, N]$) of the rooster or hen randomly chosen from the swarm, $r1 \ne r2$.

The chicks can only follow their mother hens to forage for food. Thus, the location update method of the chicks can be defined as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL * (x_{m,j}^{t} - x_{i,j}^{t}) \tag{10}$$

where m is the mother hen of ith chick. FL is a adjust parameter between 0 and 2.

The main steps of the conventional CSO algorithm are as follows [25]:

Step 1: Initialize the number of population pop, and define the related parameters including the maximum iteration $MaxG$ and the cycle of redefining relationship G.

Step 2: Generate pop chickens randomly, calculate the fitness values of pop chickens, and set $t = 1$.

Step 3: If t mod $G = 1$, sort the solutions and determine the hierarchal order in the population. Then, divide the population into different groups and determine the relationship between the mother hens and the chicks.

Step 4: Update the location (solution) of each individual by using the corresponding solution update methods in Eqs. (5)-(10), $t = t + 1$.

Step 5: Evaluate the fitness values of the new generated solutions. For each individual, if it is better than the previous one, accept the update.

Step 6: If $t > MaxG$, the algorithm should be terminated. However, if the maximum iteration $MaxG$ is not arrived, the algorithm should return to Step 3 for a loop.

C. ICSO

The conventional CSO can use the hierarchy mechanism to improve the population utilization of the algorithm. However, the solution update method of each group is not very efficient, thereby causing the algorithm lacks the exploration. Therefore, we introduce three improved factors of each solution update method to enhance their searching abilities. Moreover, a filter operator is introduced to remove the repeated solutions, thereby improving the diversity of the population. The main steps of the proposed ICSO is shown in Algorithm 1 and the details are as follows.

1) THE IMPROVED SOLUTION UPDATE METHOD OF THE HENS AND CHICKS

The hens and the chicks are at a disadvantage location in the population which means the fitness values of the hens and the chicks are worse than the roosters. In conventional CSO, the solution update method of the hens is consisting of two parts. The first part represents the hens are following the rooster in their own group and the second part represents that they are also following other roosters or hens in the swarm. However, this method is too simple so that it does not have sufficient ability to find a better solution. Similar situation will happen in the position update method of the chicks.

To overcome the shortcomings, the attraction mechanism of the FA [29] is introduced to the solution update method of the hens and chicks. For the hens, we use the attraction mechanism of FA to replace the part that the hens follow the roosters in their own group. For the chicks, we use the attraction mechanism of FA to improve the part that the chicks follow their mother hens.

Accordingly, the new solution update method of the hens is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \beta * (x_{r1,j}^{t} - x_{i,j}^{t}) + \alpha\xi + S2 * Rand * (x_{r2,j}^{t} - x_{i,j}^{t}) \tag{11}$$

$$\beta = e^{-\gamma * r^2} \tag{12}$$

$$r = \|x_{r1} - x_i\| = \sqrt{\sum_{j=1}^{d} (x_{r1,j} - x_{i,j})^2} \tag{13}$$

where β is the attractive force, γ is the light absorption coefficient ($\gamma \in [0.1, 10]$) and r is the Cartesian distance of $r1$ and i, α is a random number between [0, 1]. ξ is a number obtained by uniform distribution, and other parameters are the same with Eq. (7).

The new solution update method of the chicks is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \beta * (x_{m,j}^{t} - x_{i,j}^{t}) + \alpha\xi \tag{14}$$

where m represents the mother hen of the chick.

Algorithm 1 ICSO

Initialize the parameters:
(1)The number of population: *pop*;
(2)The d-dimensional search space: d;
(3)The maximum iteration: *MaxGeneration*;
(4)The cycle of redefining relationship: G;
(5)The percent of roosters, hens and mother hens: *rPercent*, *hPercent* and *mPercent*;
(6)The speed of roosters;
for $i = 1$ *to pop* **do**
    $x_i = rand(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{id})$;
    Calculate the fitness value of x_i;
end
for $t = 1$ *to MaxGeneration* **do**
    if t *mod* $G == 1$ **then**
        Define the hierarchical order and relationship;
    end
    for $i = 1$ *to pop* **do**
        if *i is a rooster* **then**
            update x_i using Eq. (15);
        else
            if *i is a hen* **then**
                update x_i using Eq. (11);
            else
                update x_i using Eq. (14);
            end
        end
    end
    Limit the bound of the new solution;
    end
    Calculate the fitness value of the limited solution;
    If the new solution is better, reserve it, otherwise, abandon it, reserve the original solution;
    Replace the duplicate solution using the operator proposed in Algorithm 2;
end

2) THE IMPROVED SOLUTION UPDATE METHOD OF THE ROOSTERS

In CSO, the roosters are in the dominant positions with the best fitness values which means they are more closer to the optimal location. However, they will be updated according to the normal distribution so that the solution update method of the roosters has certain randomness and blindness. Thus, to improve the exploitation performance of the roosters, we introduce the solution update method of the leader wolf of grey wolf optimizer (GWO) [30] as the globe search operator to improve their searching performance. Moreover, the solution update mechanism of PSO is also introduced to speed up the convergence rate. The improved solution update method of the roosters is as follows:

$$x_{i,j}^{t+1} = gbest - S * D + X_v \tag{15}$$

$$D = \left| C * gbest - x_{i,j}^{t} \right|, \quad C = 2r_3 \tag{16}$$

$$S = 2Ar_4 - A \tag{17}$$

$$X_v = \omega * v_{i,j}^{t} + r_5 * rand * (pbest - x_{i,j}^{t}) + r_6 * rand * (gbest - x_{i,j}^{t}) \tag{18}$$

where S is the convergence factor and D is the distance between the current solution and the global optimal solution. $r3$ and $r4$ are the numbers between [0, 1], C is the wobble factor, A decreases linearly to 0 with the iteration increasing, $v_{i,j}^{t}$ is the speed of ith rooster at the tth generation. $pbest$ and $gbest$ are the local optimal value and the global optimal value. $rand$ is a random number between [0, 1]. $r5$ and $r6$ are the learning factors and they are temporarily set to 2. $\omega = (0.5 + rand)/2$ is the inertial weight, and thus ω is a number between 0.25 and 0.75.

3) DUPLICATE SOLUTION REMOVING OPERATOR

The situation that the two solutions are exactly the same may happen during the solution update process, thereby reducing the performance of the algorithm due to the low diversity of the population. A duplicate solution removing operator is introduced to overcome this issue. The solutions will be sorted according to their fitness values, then the proposed operator will find the duplicate solution and generate new solutions randomly to replace them, thereby making the algorithm more efficient. The steps of the duplicate solution removing operator are shown in Algorithm 2.

Algorithm 2 Duplicate Solution Removing Operator

```
for i = 1 to pop do
    Sort each dimension of x_i in descending order,
    then obtain a new solution ẋ_i;
    for j = i + 1 to pop do
        Sort each dimension of x_j in descending
        order, then obtain a new solution ẋ_j;
        if ẋ_i == ẋ_j then
            Select a dimension from ẋ_j and change its
            value randomly;
        end
    end
end
```

D. SLL SUPPRESSION OF POWER PATTERN WITH ICSO

In this section, how to use the proposed ICSO to optimize the formulated problem is presented. The goal of our work is to find a set of better excitation currents of the PAA so that achieving a lower SLL of the power pattern. Thus, the excitation currents I of each antenna element can be regarded as the solution of the proposed ICSO algorithm. Normally, these excitation currents of the PAA can be expressed as a matrix. However, to make it suitable as the solution format in ICSO algorithm, the solution (excitation current matrix) of the formulated problem should be converted to a one-dimensional matrix. The conversion process is as follows:

$$x = \begin{bmatrix} I_{1,1}, I_{1,2}, I_{1,3}, \ldots, I_{1,n-1}, I_{1,n} \\ I_{2,1}, I_{2,2}, I_{2,3}, \ldots, I_{2,n-1}, I_{2,n} \\ \vdots \\ I_{n,1}, I_{n,2}, I_{1,3}, \ldots, I_{n,n-1}, I_{n,n} \end{bmatrix}$$
$$\Rightarrow x = (I_{1,1}, I_{1,2}, I_{1,3}, \ldots, I_{n,n-1}, I_{n,n}) \tag{19}$$

where $I_{i,j}$ is the excitation current of antenna element in the PAA matrix with line i and column j, n is the dimension of the matrix. Then, the population of ICSO can be expressed as:

$$X_{\text{pop}} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_{pop} \end{bmatrix} = \begin{bmatrix} I_{1,1}^{1}, I_{1,2}^{1}, I_{1,3}^{1}, \ldots, I_{n,n-1}^{1}, I_{n,n}^{1} \\ I_{1,1}^{2}, I_{1,2}^{2}, I_{1,3}^{2}, \ldots, I_{n,n-1}^{2}, I_{n,n}^{2} \\ I_{1,1}^{3}, I_{1,2}^{3}, I_{1,3}^{3}, \ldots, I_{n,n-1}^{3}, I_{n,n}^{3} \\ \vdots \\ I_{1,1}^{pop}, I_{1,2}^{pop}, I_{1,3}^{pop} \ldots, I_{n,n-1}^{pop}, I_{n,n}^{pop} \end{bmatrix} \tag{20}$$

where pop is the population size.

Using the proposed ICSO to solve the formulated problem can be described as follows. First, the initial population X_{pop} will be generated randomly. Second, the algorithm determines the solution roles in the population and different hierarchies of the solutions will be updated by the corresponding solution update method shown in Eqs. (11)-(18). Then, use Algorithm 2 to remove the duplicate solutions so that improving the diversity of the population. Finally, if the algorithm meets the stop criteria, the optimal solution will be obtained and it can be expressed as:

$$x_{\text{optimized}} = \arg \min_{m=1,\ldots,n*n} f(x_m) \tag{21}$$

where $x_{\text{optimized}}$ is the best set of the excitation currents.

E. ALGORITHM COMPLEXITY

The cycle times of the proposed ICSO algorithm according to Algorithms 1 and 2 can be roughly written as $pop + rNum + MaxGeneration * (rNum + hNum + cNum + pop + pop * (pop - 1)/2)$, where pop is the number of population. $rNum$ is the number of roosters, $MaxGeneration$ is the maximum iteration, $hNum$ and $cNum$ are the numbers of hens and chicks. Thus, the time complexity of the proposed ICSO with the respect to the number of population and iteration is $O(pop^2 * MaxGeneration)$.

V. SIMULATION RESULTS

In this section, the proposed ICSO algorithm for optimizing the power pattern of WPT is evaluated by Matlab. The CPU used for the simulation is CORE i5, the RAM is 4G and the operation system is Windows 10. First, the parameters of the proposed ICSO are tuned for achieving the best performance. Second, the effectiveness of the introduced improved factors of ICSO is verified. Then, the SLL of the power patterns of the 10×10 and 20×20 PAAs are optimized by ICSO and the other benchmark algorithms. Finally, the EM simulations are conducted to verify the effectiveness of the proposed ICSO algorithm for the practical antenna arrays.

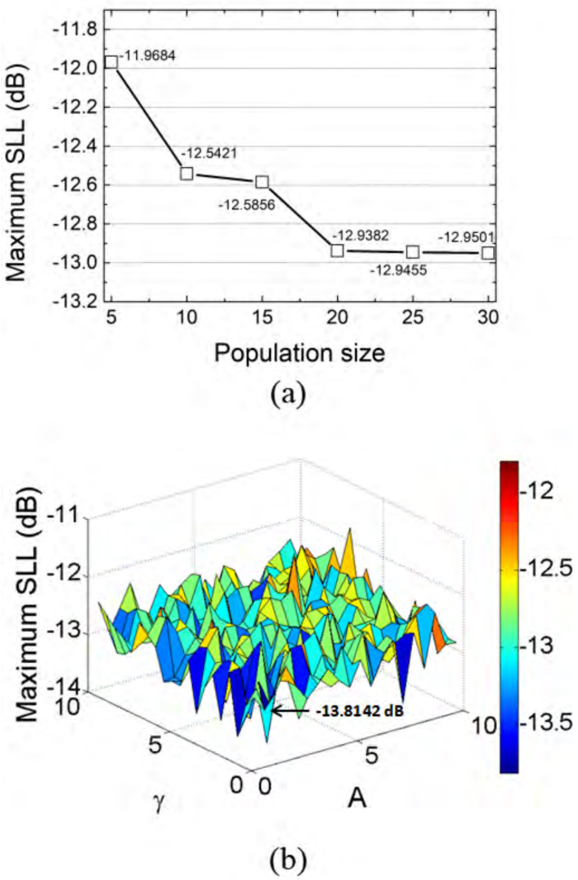

FIGURE 3. Parameter tuning results. (a) Maximum SLL obtained by different population sizes. (b) Joint tuning of γ and A.

A. PARAMETER TUNINGS

To achieve a better performance of ICSO, the population size and the other two key parameters are tuned. In swarm intelligence algorithms, the population size will affect the performance of the algorithm directly. Large population size will make the algorithm have more individuals to search in the searching space. However, the computational cost will be higher correspondingly. Thus, a tuning test is done for determining the population size. In this test, the population sizes vary from 5 to 30. Fig. 3(a) shows the maximum SLLs of different population sizes. As can be seen, the algorithm can achieve the lowest maximum SLL when the population size is 30. However, this value is very similar to the population sizes of 20 and 25, and hence we will choose to use 20 as the population size in the simulation so that reducing the computation cost.

Moreover, different parameter setups of an algorithm will result in different qualities of the solutions. Therefore, the parameters of the proposed ICSO algorithm for optimizing the power pattern need to be determined. γ and A are both random numbers between 0.1 and 10 in ICSO. Therefore, we dynamically adjust the values of γ and A, and Fig. 3(b) shows the maximum SLLs that related to the different combinations of γ and A. It can be seen from the figure that when

TABLE 2. Parameter setups of different algorithms.

Algorithm	Values of the parameters
BBO [17]	$I = 1, E = 1$
CSO [25]	$RN = 0.2 * N, HN = 0.6 * N, CN = N - RN - HN,$ $MN = 0.1 * N, G = 2, FL \in [0.5, 0.9]$
PSO [5]	$C1 = 2, C2 = 2,$ $W = 0.95 - CurCount * 0.55 / LoopCount$
FA [29]	$\alpha = 0.25, \beta = 0.5, \gamma = 1$
CS [21]	$pa = 0.25, \alpha = 0.01, \beta = 3$
GA [31]	$pc = 0.8, pm = 0.05$
ICSO	$RN = 0.2 * N, HN = 0.6 * N, CN = N - RN - HN,$ $MN = 0.1 * N, G = 2, A = 1.5, \gamma = 1,$ $r1 = 2, r2 = 2, \omega \in [0.25, 0.75]$

$\gamma = 1$ and $A = 1.5$, the algorithm can achieve the lowest maximum SLL.

B. EFFECT VERIFICATION OF THE IMPROVED FACTORS

Tests are conducted to verify the introduced improved factors of the proposed ICSO algorithm. First, we use the conventional CSO and the CSO with the improved update method of chicks and hens (IUMCH) to optimize the power pattern of the 10 × 10 PAA. Fig. 4(a) shows the convergence rate during the optimization process. It can be seen from the figure that by using the IUMCH, the convergence rate and the accuracy of the solution can be effectively improved. This is because by introducing the absorption mechanism of FA, the local search performance of the solution update method of the hens and chicks are improved.

Moreover, to verify the effectiveness of the improved update method of the roosters (IUMR), the conventional CSO and the CSO with IUMR are used to optimize the power pattern of the 10 × 10 PAA, respectively. Fig. 4(b) shows the convergence rate during the optimization process obtained by these two approaches. As can be seen, by using the introduced improved factors of the roosters, the search ability, especially the convergence rate of the conventional CSO algorithm is improved effectively. This is because the global search ability is enhanced by introducing the solution update method of PSO, hence the current solution can establish a connection with the global best solution.

Accordingly, by combining IUMCH and IUMR, the accuracy and the convergence rate of the conventional CSO can be effectively improved.

C. SLL SUPPRESSION OF THE POWER PATTERN

In this section, the power patterns of the PAA are optimized by the proposed ICSO and other benchmark algorithms include BBO, CS, FA, GA, PSO and the conventional CSO. The parameter setups of these algorithms are shown in Table 2. In BBO, I and E are the maximum immigration and emigration rates, respectively. In PSO, $C1$ and $C2$ are the learning factors, W is the inertial weight, *CurCount* is the current iteration and *LoopCount* is the maximum iteration. In FA, α is the step-size parameter, β is the attractive force and γ is the light absolution coefficient. In CS, *pa* is the discovery rate of alien eggs, α and β are the parameters used in Lévy flight. In GA, *pc* and *pm* are the crossover and the

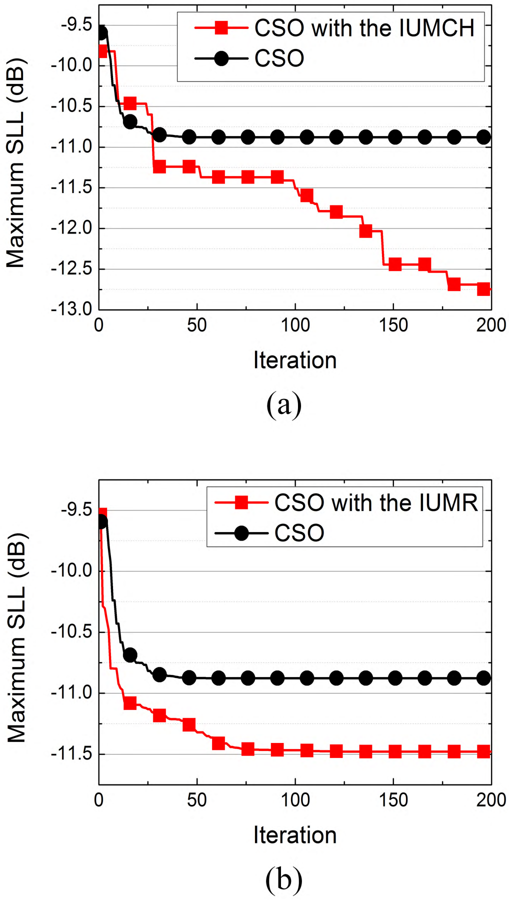

FIGURE 4. Effectiveness of the improved factors. (a) CSO with IUMCH. (b) CSO with IUMR.

mutation probabilities, respectively. In CSO and ICSO, N, RN, HN, CN and MN are the number of the population, the roosters, the hens, the chicks and the mother hens, $r1$ and $r2$ are the learning factors. The other parameters have been introduced in Section IV.

1) 10 × 10 PAA

Figs. 5(a) and 5(b) show the 3D power patterns of the 10 × 10 PAA obtained by the uniform excitation currents and by the excitation currents optimized by the proposed ICSO algorithm. In this case, the solution dimension of the optimization problem is 100. It can be seen intuitively from the figure that the maximum SLL is effectively reduced by using ICSO. The numerical results of the maximum SLLs obtained by different algorithms are shown in Table 3. Moreover, Fig. 6 shows the convergence rates of different optimization methods and the results indicate that the proposed ICSO has the best performance among these algorithms. In addition, the CPU running time of different algorithms are listed in Table 4.

2) 20 × 20 PAA

In some WPT applications, the PAA needs more elements to generate a narrower beam to the receivers.

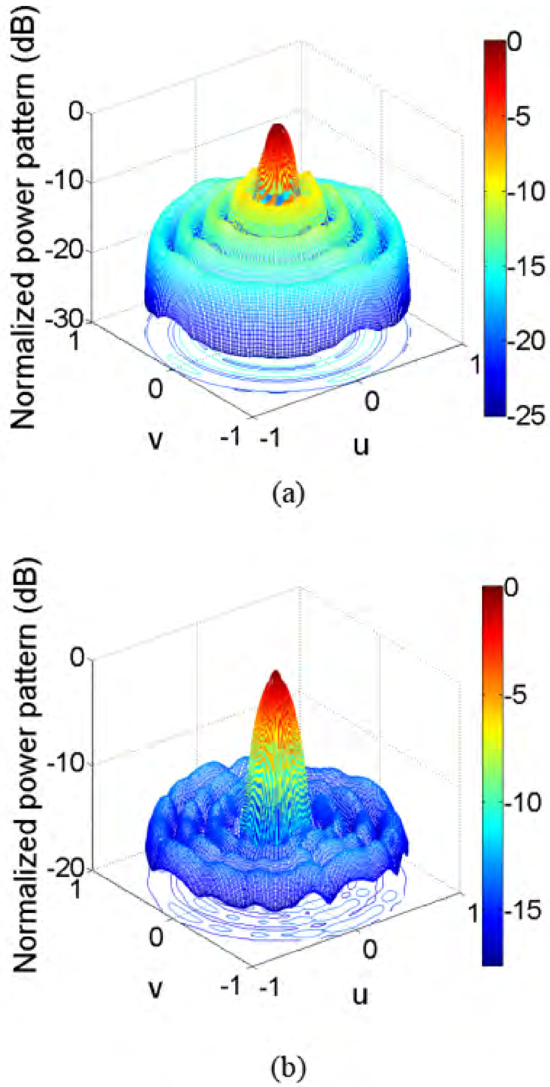

FIGURE 5. Power patterns of the 10 × 10 PAA obtained by different methods. (a) Uniform excitation currents. (b) Excitation currents obtained by ICSO.

TABLE 3. Maximum SLL obtained by different algorithms for 10 × 10 PAA.

Algorithm	Maximum SLL (dB)
Uniform	-8.8354
BBO	-12.1964
CSO	-10.8768
CS	-12.2771
FA	-11.8273
PSO	-11.1282
GA	-11.1524
ICSO	-12.8466

Thus, a 20 × 20 PAA for WPT is constructed to evaluate the performance of the proposed ICSO for the high dimension optimization problem. In this case, the solution dimension is 400. Figs. 7(a) and 7(b) shows the 3D power patterns obtained by the uniform excitation currents and by the excitation currents optimized by the proposed ICSO algorithm,

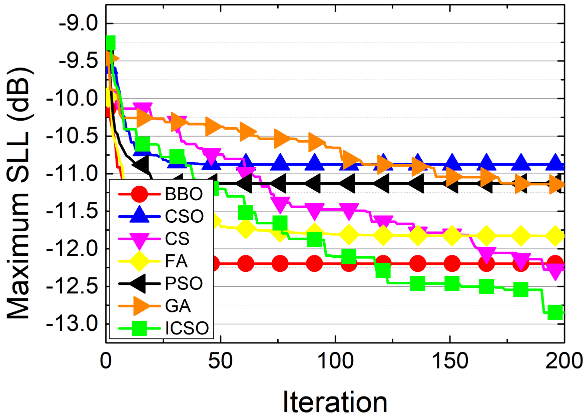

FIGURE 6. Convergence rates of different algorithms for 10 × 10 PAA.

TABLE 4. Runtime of different algorithms for 10 × 10 PAA.

Algorithm	Runtime (s)
BBO	689.90
CSO	177.19
CS	358.60
FA	181.01
PSO	372.65
GA	234.19
ICSO	192.67

TABLE 5. Maximum SLL obtained by different algorithms for 20 × 20 PAA.

Algorithm	Maximum SLL (dB)
Uniform	-8.1351
BBO	-11.8056
CSO	-11.8456
CS	-11.3946
FA	-10.2625
PSO	-10.8479
GA	-9.9776
ICSO	-12.4862

respectively. Correspondingly, the numerical results of the maximum SLLs obtained by different algorithms are listed in Table 5. It can be seen from the figure and the table that the proposed ICSO algorithm achieves the lowest maximum SLL of -12.4862 dB among all the algorithms. Moreover, the convergence rates of different approaches are shown in Fig. 8 and it can be seen that the proposed ICSO also has the best performance in terms of the accuracy and the convergence.

D. SLL SUPPRESSION BY CONSIDERING THE PHASE OF THE ANTENNA ELEMENT

To set the phases of the antenna elements as zero for simplification is a common way in the research field of the PAA-based WPT system [32]–[35]. However, the phase of an antenna element can be regarded as a new degree of freedom of the optimization problem and this can extend the searching space so that improving the accuracy of the solution. Thus, we will consider the effects of the phase.

In this section, Eq. (1) (with phase) is used to construct the fitness function in section III-B. Thus, in this

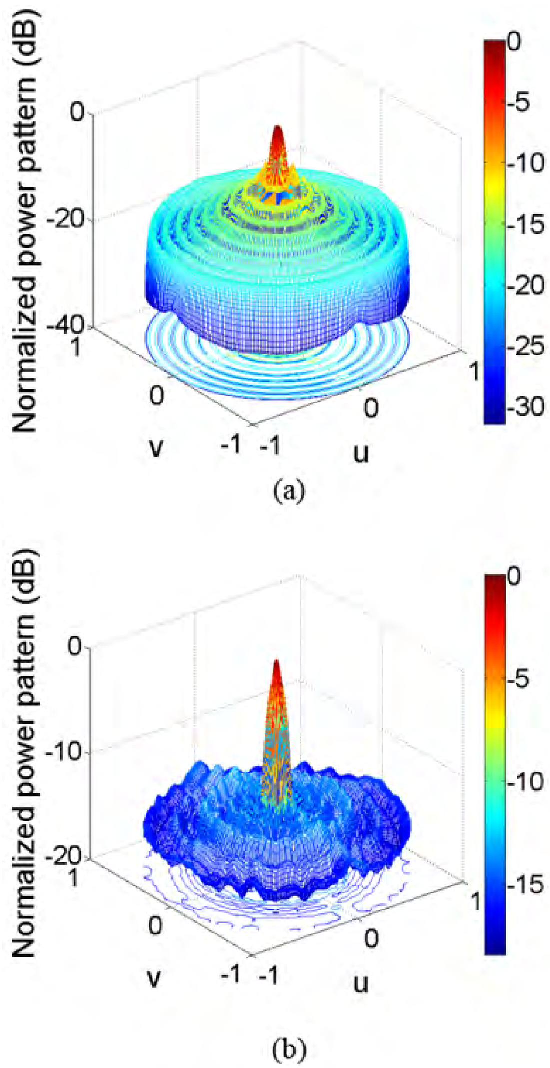

FIGURE 7. Power patterns of the 20 × 20 PAA obtained by different methods. (a) Uniform excitation currents. (b) Excitation currents obtained by ICSO.

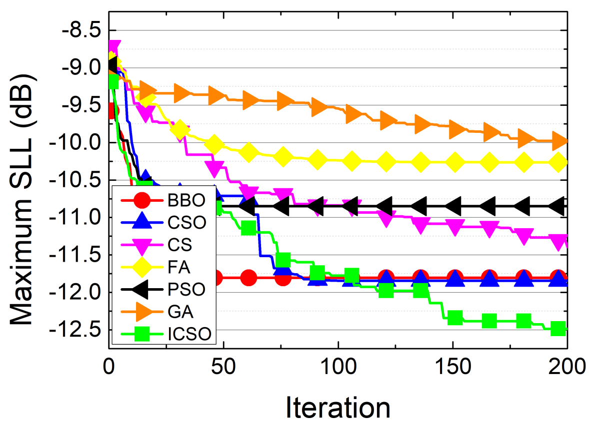

FIGURE 8. Convergence rates of different algorithms for 20 × 20 PAA.

case, a solution of the formulated optimization problem shown in Eqs. (4a) to (4e) can be expressed as $x = \{I_1, I_2, \ldots, I_{M*M}, \phi_1, \phi_2, \ldots, \phi_{M*M}\}$. Fig. (9a) shows the

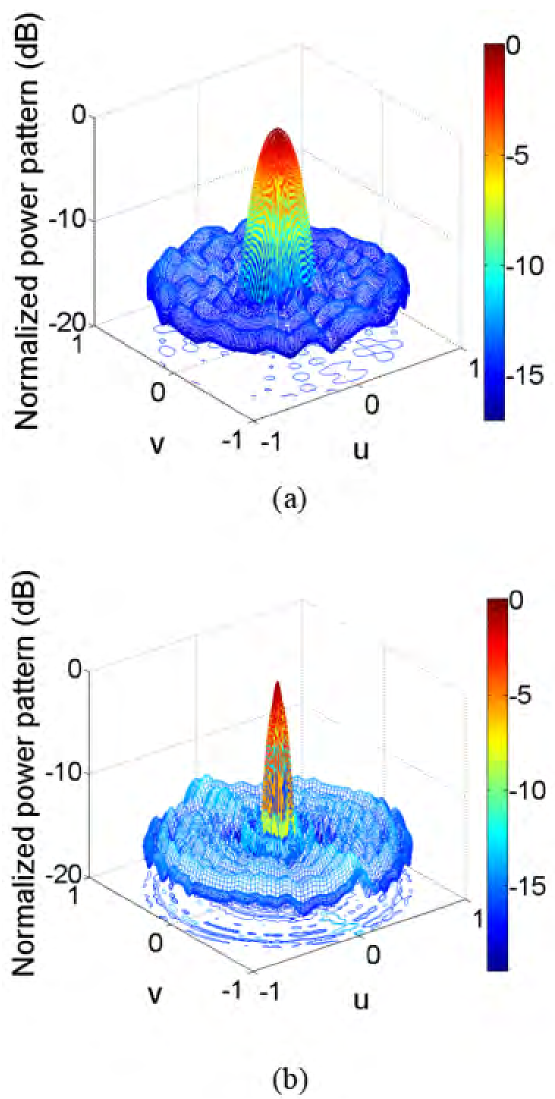

FIGURE 9. Power patterns obtained with phase optimized. (a) 10 × 10 PAA. (b) 20 × 20 PAA.

power pattern obtained by the proposed ICSO algorithm for 10 × 10 PAA with considering the phase, and the result of the 20 × 20 PAA is shown in Fig. (9b), respectively. The numerical results of the obtained maximum SLLs of these two cases are listed in Table 6. As can be seen, the results that considering the phase are lower than that of the results without considering the phase. This is because that the new degree of freedom extends the solution space and hence the algorithm may find a better solution. However, it may take much more extra iterations.

E. PERFORMANCE ANALYSIS OF ICSO

The previous simulations show that the proposed ICSO algorithm has better performances in terms of the accuracy and the convergence rates. However, According to the "no free lunch" theory [36], an algorithm should have pros and cons. Thus, the disadvantages of the proposed ICSO algorithm is analyzed in this section.

TABLE 6. Maximum SLLs obtained by ICSO with and without phase optimizations.

Scale	Only Amplitude (dB)	Amplitude and Phase (dB)
10 × 10 PAA	-12.8466	-13.2532
20 × 20 PAA	-12.4862	-12.7651

The first drawback is that the number of the parameters of the proposed algorithm is more than some other algorithms, and this will cause the algorithm to be difficult to find the optimal performance for specific optimization problems. Thus, we need to select the parameters of the algorithm very carefully so that achieving a better performance of the proposed algorithm. Hence, a parameter tuning test of the proposed algorithm is conducted in this paper.

The second one is that the convergence rate in the earlier iterations are not fast. This is because that by using the hierarchy mechanism of CSO, the quality of solution mainly depends on the solutions in the high hierarchy (group). However, in the earlier iterations, the solutions are usually located far away from the optimal locations, and only several roosters have better locations. As we mentioned, the solution update methods of the conventional CSO algorithm are not efficient, although we introduced several improved factors to the solution update methods of the conventional CSO algorithm, the number of the roosters are limited in the population. Thus, this is why the proposed algorithm has poor convergence rate in the earlier iteration.

The third disadvantage should be the complexity and the CPU running time. The complexity of the proposed algorithm is analyzed in section IV-E, and it is larger than the benchmarks due to the introduced duplicate solution removing operator. However, and the main time cost operation of an algorithm is the fitness function evaluation, and times of the fitness function evaluation operations of the ICSO algorithm are the least among all the algorithms, according to the algorithm structures. Thus, although the proposed ICSO algorithm has a large complexity, the performance of the CPU running time is not the worst. However, the solution update methods of the solutions are also time cost operations, and different solution update methods must consume different time. In the proposed algorithm, several new factors are introduced including the square root operation. Thus, from the above analysis, the performance of CPU running time of the proposed ICSO is neither the best nor the worst among benchmark algorithms.

F. EM SIMULATIONS

In this paper, although the spacing between the elements are set to be 0.5 λ to avoid the effect of the mutual coupling, this phenomenon cannot be completely ignored. The EM simulations can be regarded as an effective way to evaluate the performance of an optimization method in the practical real-world environments. Thus, we design a 10 × 10 PAA for EM simulations based on ANSYS Electromagnetics 2016 (HFSS), to verify the power pattern performances obtained by

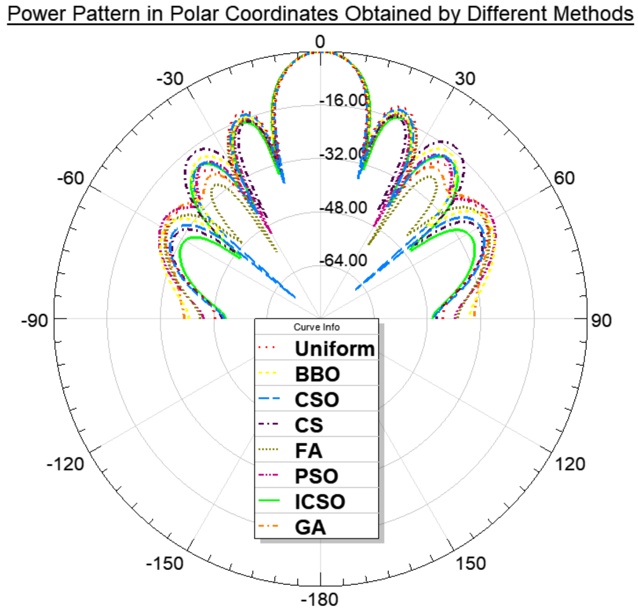

FIGURE 10. Power patterns in polar coordinates obtained by different methods for 10 × 10 PAA.

TABLE 7. Maximum SLLs obtained by different algorithms for 10 × 10 PAA in EM simulations.

Algorithm	Maximum SLL (dB)
Uniform	-12.1607
BBO	-13.8783
CSO	-13.0748
CS	-15.2239
FA	-13.8941
PSO	-14.7157
ICSO	-15.3882
GA	-14.4439

different algorithms in the realistic EM environment. It has been demonstrated by several references (e.g., [37], [38]) that the power pattern or the beam pattern optimizations in an ideal condition are able to provide a general overview of the effectiveness of the proposed algorithm. Thus, similar to [37] and [38], we use the optimized excitation current obtained by Matlab without considering the mutual coupling into HFSS, to test that whether the solution obtained by the ideal conditions is effective for the practical conditions.

Fig. 10 shows the polar coordinate form power patterns of the planar antenna arrays with different excitation currents obtained by the uniform excitations, BBO, CSO, CS, FA, PSO, GA and ICSO, respectively. Table 7 shows the numerical results of the maximum SLLs of these algorithms. As can be seen, the proposed ICSO obtains the best performance in EM simulations, which verifies the conclusions about the EM simulations of [37] and [38].

VI. CONCLUSIONS

In this paper, an ICSO algorithm is proposed to suppress the maximum SLL of the power patterns for WPT. ICSO introduces the global search, the local search and the duplicate solution removing operators to enhance the performance of the conventional CSO, thereby making it suitable for the power pattern optimizations. The parameters of the ICSO algorithm are tuned for achieving the optimal performance. Simulations results show that the proposed ICSO can obtain the lowest maximum SLL compared with BBO, CSO, CS, FA, PSO and GA. Moreover, the effectiveness of the improved factors is verified by simulations and the results show that the convergence rate and accuracy of ICSO can be improved by the introduced improved factors. In addition, the power pattern performances obtained by different algorithms are tested by EM simulations and the results show that the proposed ICSO algorithm has the best performance in the realistic EM environment.

REFERENCES

[1] A. Massa, G. Oliveri, F. Viani, and P. Rocca, "Array designs for long-distance wireless power transmission: State-of-the-art and innovative solutions," *Proc. IEEE*, vol. 101, no. 6, pp. 1464–1481, Jun. 2013.

[2] J. O. McSpadden and J. C. Mankins, "Space solar power programs and microwave wireless power transmission technology," *IEEE Microw. Mag.*, vol. 3, no. 4, pp. 46–57, Dec. 2002.

[3] T. Moriyama, L. Poli, and P. Rocca, "On the design of clustered planar phased arrays for wireless power transmission," *IEICE Electron. Express*, vol. 12, no. 4, p. 20150028, 2015.

[4] L. Liu, R. Zhang, and K.-C. Chua, "Multi-antenna wireless powered communication with energy beamforming," *IEEE Trans. Commun.*, vol. 62, no. 12, pp. 4349–4361, Dec. 2014.

[5] X. Li, J. Zhou, and X. Du, "Planar arrays synthesis for optimal wireless power transmission," *IEICE Electron. Express*, vol. 12, no. 11, p. 20150346, 2015.

[6] B. Han, X.-X. Yang, and H.-G. Xue, "A millimeter-wave Fabry–Pérot antenna with high-gain and circular polarization operation," in *Proc. Antennas Propag.*, 2014, pp. 40–43.

[7] Q. Wu *et al.*, "Enhanced wireless power transfer using magnetostatic volume modes in anisotropic magnetic metamaterials," in *Proc. IEEE Int. Conf. Ind. Electron. Sustain. Energy Syst.*, Feb. 2018, pp. 415–420.

[8] D. Kim, "Novel dual-band Fabry–Pérot cavity antenna with low-frequency separation ratio," *Microw. Opt. Technol. Lett.*, vol. 51, no. 8, pp. 1869–1872, May 2009.

[9] L. Li, S. Lei, and C.-H. Liang, "Metamaterial-based Fabry-Pérot resonator for ultra-low profile high-gain antenna," *Microw. Opt. Technol. Lett.*, vol. 54, no. 11, pp. 2620–2623, 2012.

[10] K. Lu and K. W. Leung, "Differential Fabry–Pérot resonator antennas," *IEEE Trans. Antennas Propag.*, vol. 61, no. 9, pp. 4438–4446, Sep. 2013.

[11] O. Roncière, B. A. Arcos, R. Sauleau, K. Mahdjoubi, and H. Legay, "Radiation performance of purely metallic waveguide-fed compact Fabry–Pérot antennas for space applications," *Microw. Opt. Technol. Lett.*, vol. 49, no. 9, pp. 2216–2221, 2007.

[12] Y. Zeng, B. Clerckx, and R. Zhang, "Communications and signals design for wireless power transmission," *IEEE Trans. Commun.*, vol. 65, no. 5, pp. 2264–2290, May 2017.

[13] K.-J. Oh, H.-Y. Lee, S.-J. Kim, Y. Chung, and C. Cheon, "A study on wideband adaptive beamforming using taylor weighting and LSMI algorithm," *Trans. Korean Inst. Electr. Eng.*, vol. 62, no. 3, pp. 380–386, 2013.

[14] Y. P. Saputra, F. Oktafiani, Y. Wahyu, and A. Munir, "Side lobe suppression for x-band array antenna using Dolph–Chebyshev power distribution," in *Proc. Asia–Pacific Conf. Commun.*, 2016, pp. 86–89.

[15] X. Zhao, Q. Yang, and Y. Zhang, "Design of non-uniform circular antenna arrays by convex optimization," in *Proc. Eur. Conf. Antennas Propag.*, 2016, pp. 1–4.

[16] G. Sun, Y. Liu, Z. Chen, Y. Zhang, A. Wang, and S. Liang, "Thinning of concentric circular antenna arrays using improved discrete cuckoo search algorithm," in *Proc. Wireless Commun. Netw. Conf.*, 2017, pp. 1–6.

[17] H. Li, Y. Liu, G. Sun, A. Wang, and S. Liang, "Beam pattern synthesis based on improved biogeography-based optimization for reducing sidelobe level," *Comput. Elect. Eng.*, vol. 60, pp. 161–174, May 2017.

[18] S. Todnatee and C. Phongcharoenpanich, "Iterative ga optimization scheme for synthesis of radiation pattern of linear array antenna," *Int. J. Antennas Propag.*, vol. 2016, pp. 1–8, Jun. 2016.

[19] A. Sharaqa and N. Dib, "Circular antenna array synthesis using firefly algorithm," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 24, no. 2, pp. 139–146, 2014.
[20] Y. Li, F. Yang, J. Ouyang, and P. Yang, "Synthesis of conical conformal array antenna using invasive weed optimization method," *Appl. Comput. Electromagn. Soc. J.*, vol. 28, no. 11, pp. 1025–1030, 2013.
[21] G. Sun, Y. Liu, J. Li, Y. Zhang, and A. Wang, "Sidelobe reduction of large-scale antenna array for 5G beamforming via hierarchical cuckoo search," *Electron. Lett.*, vol. 53, no. 16, pp. 1158–1160, 2017.
[22] Y. Jing, L. Wen-Tao, S. Xiao-Wei, X. Li, and Y. Jian-Feng, "A hybrid ABC-DE algorithm and its application for time-modulated arrays pattern synthesis," *IEEE Trans. Antennas Propag.*, vol. 61, no. 11, pp. 5485–5495, Nov. 2013.
[23] G. Sun *et al.*, "A sidelobe and energy optimization array node selection algorithm for collaborative beamforming in wireless sensor networks," *IEEE Access*, vol. 6, pp. 2515–2530, 2018.
[24] G. Sun, Y. Liu, S. Liang, A. Wang, and Y. Zhang, "Beam pattern design of circular antenna array via efficient biogeography-based optimization," *AEU Int. J. Electron. Commun.*, vol. 79, pp. 275–285, Sep. 2017.
[25] X. Meng, Y. Liu, X. Gao, and H. Zhang, "A new bio-inspired algorithm: Chicken swarm optimization," in *Proc. Int. Conf. Swarm Intell.*, 2014, pp. 86–94.
[26] S. Horst, D. E. Anagnostou, G. E. Ponchak, E. Tentzeris, and J. Papapolymerou, "Beam-shaping of planar array antennas using integrated attenuators," in *Proc. 57th Electron. Compon. Technol. Conf. (ECTC)*, 2007, pp. 165–168.
[27] C. Blum, J. Puchinger, G. R. Raidl, and A. Roli, "Hybrid metaheuristics in combinatorial optimization: A survey," *Appl. Soft Comput.*, vol. 11, no. 6, pp. 4135–4151, 2011.
[28] P. Belotti, C. Kirches, S. Leyffer, J. Linderoth, J. Luedtke, and A. Mahajan, "Mixed-integer nonlinear optimization," *Acta Numer.*, vol. 22, pp. 1–131, 2013.
[29] X-S. Yang, "Firefly algorithm, stochastic test functions and design optimisation," *Int. J. Bio-Inspired Comput.*, vol. 2, no. 2, pp. 78–84, 2010.
[30] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014.
[31] J. H. Holland, "Adaption in natural and artificial systems," *Quart. Rev. Biol.*, vol. 6, no. 2, pp. 126–137, 1975.
[32] X. Li, B. Duan, J. Zhou, L. Song, and Y. Zhang, "Planar array synthesis for optimal microwave power transmission with multiple constraints," *IEEE Antennas Wireless Propag. Lett.*, vol. 16, pp. 70–73, Feb. 2017.
[33] G. Sun, Y. Liu, H. Li, J. Li, A. Wang, and Y. Zhang, "Power-pattern synthesis for energy beamforming in wireless power transmission," *Neural Comput. Appl.*, vol. 30, pp. 2327–2342, Oct. 2018.
[34] G. Oliveri, L. Poli, and A. Massa, "Maximum efficiency beam synthesis of radiating planar arrays for wireless power transmission," *IEEE Trans. Antennas Propag.*, vol. 61, no. 5, pp. 2490–2499, May 2013.
[35] X. Li, J. Zhou, B. Duan, Y. Yang, Y. Zhang, and J. Fan, "Performance of planar arrays for microwave power transmission with position errors," *IEEE Antennas Wireless Propag. Lett.*, vol. 14, pp. 1794–1797, Nov. 2015.
[36] Y.-C. Ho, "The no free lunch theorem and the human-machine interface," *IEEE Control Syst.*, vol. 19, no. 3, pp. 8–10, Jun. 1999.
[37] S. Jayaprakasam, S. K. A. Rahim, C. Y. Leow, T. O. Ting, and A. A. Eteng, "Multiobjective beampattern optimization in collaborative beamforming via NSGA-II with selective distance," *IEEE Trans. Antennas Propag.*, vol. 65, no. 5, pp. 2348–2357, May 2017.
[38] G. Sun, Y. Liu, Z. Chen, S. Liang, A. Wang, and Y. Zhang, "Radiation beam pattern synthesis of concentric circular antenna arrays using hybrid approach based on cuckoo search," *IEEE Trans. Antennas Propag.*, vol. 66, no. 9, pp. 4563–4576, Sep. 2018.

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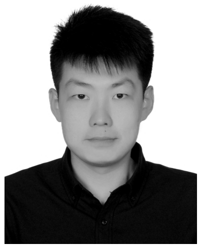

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