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Research Article

Optimal Pattern Synthesis of Linear Array and Broadband Design of Whip Antenna Using Grasshopper Optimization Algorithm

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Antenna arrays with high directivity, low side-lobe level, and null control in desired direction and whip antenna with wider bandwidth both need to be optimized to meet different needs of communication systems. A new natural heuristic algorithm simulating social behavior of grasshoppers, grasshopper optimization algorithm (GOA), is applied to electromagnetic field as a new effective technology to solve the antenna optimization problem for the first time. Its algorithm is simple and has no gradient mechanism, can effectively avoid falling into local optimum, and is suitable for single-objective and multiobjective optimization problems. GOA is used to optimize the side lobe suppression, null depth, and notch control of arbitrary linear array and then used to optimize the loading and matching network of 10-meter HF broadband whip antenna compared with other algorithms. The results show that GOA has more advantages in side-lobe suppression, null depth, and notch control of linear array than other algorithms and has better broadband optimization performance for HF whip antenna. The pattern synthesis and antenna broadband optimization based on GOA provide a new and effective method for antenna performance optimization.

1. Introduction

In communication systems, especially in point-to-point communication systems, antennas are required to have fairly strong directionality. The antenna array [1, 2] is mainly used to enhance directivity, improve gain coefficient, or to obtain the required directional characteristics. Generally, antenna arrays need to maintain narrow first null beam width (FNBW) and low side-lobe level (SLL) to achieve high directivity and avoid unnecessary interference. However, the above requirements of FNBW and SLL are contradictory, and arrays with narrower FNBW and lower SLL cannot be realized simultaneously. In many applications, gain and beam width must be sacrificed to achieve lower SLL, so limiting the FNBW to get lower SLL can be used as an index to further optimize the performance of antenna array. On the other hand, in many applications, the antenna is also required to work effectively in a wide frequency range. That is because the broadband antenna [3] has high transmission rate, high processing gain, and strong multipath resolution, which improves the existing spectrum utilization rate, and the system is relatively simple to implement with low complexity and low cost. Broadband technology has become an important development direction in the field of wireless communication.

In terms of electromagnetic field problems and antenna optimization, population-based algorithms inspired by nature are the most popular in stochastic optimization methods [4, 5]. Many swarm intelligent algorithms have been successfully applied to antenna array pattern synthesis or antenna broadband optimization, such as genetic algorithm (GA) [6, 7], ant colony optimization (ACO) [8, 9], particle swarm optimization (PSO) [10–12], invasive weed optimization (IWO) [13], cat swarm optimization (CSO)

[14], spider monkey optimization (SMO) [15], butterfly mating optimization (BMO) [16, 17], social group optimization (SGO) [18], grey wolf optimization (GWO) [19], quadratic programming method (QPM) [20], flower pollination algorithm (FPA) [21], ant lion optimization (ALO) [22], firefly algorithm (FA) [23–25], cuckoo search (CS) [26, 27], chaotic adaptive butterfly mating optimization (CABMO) [28], modified spider monkey optimization (MSMO) [29], enhanced firefly algorithm (EFA) [30], bat flower pollination (BFP) algorithm [31], gravitational search algorithm (GSA) [32], and so on. For antenna broadband optimization, there are also GA [33, 34], evolutionary algorithm (EA) [35], real frequency technology [36], IWO [37–39], etc. The above algorithms all show their stronger robustness and search ability to solve the electromagnetic optimization problems.

In this paper, a new nature-inspired algorithm, grasshopper optimization algorithm (GOA), is applied to linear antenna array optimization and antenna broadband optimization. GOA is inspired from the lifestyle of grasshopper swarm, developed by Saremi et al. in 2017 [40, 41]. GOA has simple algorithm without gradient mechanism, which can effectively avoid falling into local optimum, and has very few parameters to adjust, which minimizes the adjustment of empirical parameters. These characteristics make GOA get some good applications; paper [42] presents a parameter adaptive VMD method based on GOA to analyze vibration signals of rotating machinery and proves that this method is effective for fault diagnosis of mechanical vibration signals. In [43], a hybrid method based on GOA is proposed to optimize the parameters of support vector machine (SVM) model and find the best feature subset, which is verified that this method is superior to other methods in classification accuracy, while minimizing the number of selected features. GOA has been applied in many fields since it was put forward, but it has not involved electromagnetic field and antenna optimization so far. Paper [44] proposes an improved version of the grasshopper optimization algorithm (GOA) based on the opposition-based learning (OBL) strategy called OBLGOA for solving benchmark optimization functions and engineering problems. In this paper, GOA is introduced into electromagnetic field for the first time and applied to array pattern synthesis and antenna broadband optimization. The effectiveness and stability of this algorithm for solving antenna electromagnetic problems are proved.

In order to successfully introduce GOA into the field of antenna optimization, the advantages of GOA for single and multi-objective optimization, array antenna, and cell antenna optimization are proved by suppressing the maximum SLL, controlling the null or notch of linear array and broadband optimization of whip antenna. Six examples from two aspects can more fully reflect the ability of GOA in antenna optimization than other methods in the existing literature. The second part of this paper will briefly introduce the optimization principle of GOA. The third part briefly describes the principle of pattern synthesis of linear array and broadband optimization of whip antenna and then cites six examples to prove its ability to optimize antenna performance, including suppression of the maximum sidelobe level (SLL), the depth of null depression and the notch of linear array, and design for the loading and matching network of broadband antenna. The fourth part concludes the paper.

2. Grasshopper Optimization Algorithm

GOA is a kind of natural heuristic algorithm; its design inspiration comes from the social behavior of grasshopper in nature. The grasshopper swarm moves slowly and slowly in its infancy but has a wide range of activities in its adulthood. These two characteristics make two trends in the search process of natural heuristic algorithm: exploration and grasshopper, which, as well as target search, are naturally accomplished by grasshoppers. In order to solve the optimization problem for avoiding grasshoppers reaching comfort zone quickly and the population not converge to a specific point, the mathematical model for simulating grasshopper swarm behavior is revised as follows [40]:

$$X_i^d = c\left(\sum_{\substack{j=1\\ j\neq i}}^{N} c\frac{\mathrm{ub}_d - \mathrm{lb}_d}{2} s\left(\left|x_j^d - x_i^d\right|\right)\frac{x_j - x_i}{d_{ij}}\right) + \widehat{T}_d , \quad (1)$$

$$s(r) = f e^{(-r/l)} - e^{-r}, \quad (2)$$

$$c = c_{\max} - \frac{1(c_{\max} - c_{\min})}{L}, \quad (3)$$

where X_i^d is defined as the location of i-th grasshoppers in the D-th dimension solution space; ub_d and lb_d are the upper and lower bounds of the dimension solution space; $|x_j^d - x_i^d|$ is the distance between i-th grasshopper and j-th grasshopper; $(x_j - x_i)/d_{ij}$ is the unit vector of the distance between i-th grasshopper and j-th grasshopper; $s(r)$ is the force function of social activities; f and l are the attraction intensity and the attraction length between grasshoppers; and $\widehat{T}_d$ is the value of the $D-$ th dimension in the target (best solution found so far). c is used to reduce the decline coefficients of comfort zone, exclusion zone, and attraction zone, $c_{\max}$, $c_{\min}$ are the maximum and minimum values, l is the current iteration times, and L is the maximum iteration times respectively.

Equation (1) cleverly simulates the interaction between grasshoppers in a swarm. The next position of grasshoppers is determined by their current position, target position, and the position of all other grasshoppers, which is different from PSO whose next position is based on current position, personal best and global best; GOA requires all search agents to participate in defining the next location of each search agent. The first component of the equation takes into account the position of grasshoppers relative to other grasshoppers, the second component simulates the trend of grasshoppers transferring to food sources, and the parameter c simulates the deceleration of grasshoppers approaching food sources and slowing down to eat.

The mathematical model of the GOA requires grasshoppers to move towards the target gradually during the iteration process, avoiding convergence to the target too quickly, so as to fall into local optimum. GOA saves the most promising target in the search space in each iteration and requires grasshoppers to move towards it gradually. This is to find a better and more accurate target as the best approximation of the real global optimum in the search space. Like other evolutionary algorithms, GOA uses fitness function to guide grasshoppers to search their optimal location in D-dimensional space in order to meet the requirements of objective function. At each stage of the algorithm, the position vector corresponding to the optimal fitness value is taken as the global optimal position vector, and this information is transmitted to other grasshoppers around, so that grasshoppers can adjust their steps and position vectors accordingly until they reach the target position of food. The main optimization process of GOA is shown in Figure 1.

Compared with other algorithms, GOA has the following characteristics: GOA improves the average survival rate of grasshoppers, which shows that the algorithm can effectively improve the initial random population of grasshoppers. Grasshopper can effectively find the promising area in a given search space and can solve the practical problem of unknown search space. In the initial stage of optimization, they face sudden large-scale changes, which helps them search on a global scale, and in the final optimization step, they tend to move locally, which enables them to make use of the search space. Different comfort zone coefficients need grasshoppers to balance exploration and exploitation gradually, which helps GOA not fall into local optimum and approach global optimum precisely. In the iterative process, the accuracy of the target is improved, so the global optimal approximation is more accurate in proportion to iterations. The exploitation of GOA is satisfactory when it comes to the single peak test function; the exploratory nature of GOA is very high when it comes to multimodal test function, and the exploration and exploitation are properly balanced by GOA when it comes to solving the challenging problems involving composite test function. In solving a series of current or new optimization problems, GOA may be significantly superior to several existing algorithms.

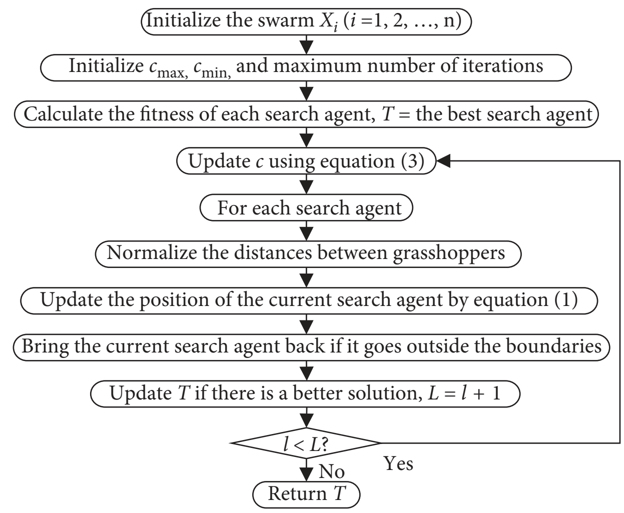

Figure 1: Flowchart of the GOA.

3. Design Examples

In the antenna optimization problem, there are many factors that can be used to evaluate the reliability of the algorithm for the actual engineering application, such as directivity, gain, SLL, size, and weight. In order to achieve better directionality of linear array and broadband of whip antenna, this section will apply GOA to pattern synthesis of linear antenna array and broadband optimization design of whip antenna. The simulation platform is Windows 7, with Intel core i5 processor and the MATLAB version R2014a.

4. Linear Antenna Array Synthesis

When a linear array guides the main lobe in the user direction with enhanced gain, it often forms side lobes and nulls in directions other than the main lobe. SLL needs to be as low as possible to reduce interference, and it is also very important to place null position in a certain direction to avoid electromagnetic pollution. The radiation direction of the antenna array depends on its structure, the distance between the elements, the excitation magnitude, and phase of each element. For linear array geometry, suppression of SLL and placement of nulls in desired directions can be achieved in two ways: one is to optimize the distance between elements while maintaining uniform excitation and the other is to use nonuniform excitation of elements and periodic placement of antenna elements.

This section will optimize the position or the excitation magnitudes of array elements and take the maximum SLL, main lobe size, null depth, or notch control of linear array pattern as single or multiple optimization objectives so as to achieve the desired synthesis of linear array pattern.

Figure 2 shows the geometric position distribution of a linear array of $2N$ elements; due to the symmetry of element distribution, the array factor can be expressed as

$$\mathrm{AF}(\theta) = 2\sum_{n=1}^{N} a_n \cos\left(kz_n \cos(\theta) + \beta_n\right), \tag{4}$$

where $k = 2\pi/\lambda$ is wave number and a_n, z_n, and β_n are the excitation magnitude, position, and phase of the $n-$th element, respectively. For the convenience of calculation and comparison, the magnitude of uniform excitation is usually 1 $(a_n = 1)$, and there is no phase difference between each element $(\beta_n = 0)$.

4.1. Element Position Optimization with FNBW Constraint

Example 1. In the first example, GOA is used for maximum SLL reduction of a 10-element linear array, the excitation is

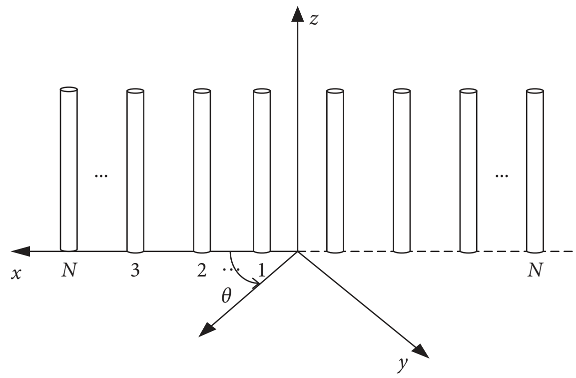

Figure 2: Geometric position distribution of $2N$-element linear array.

uniform ($a_n = 1$), each element position (spacing between adjacent elements) of a 10-element linear array is taken as the optimization variable of GOA to minimize the maximum SLL in $\theta \in [0^\circ, 78^\circ] \cup [102^\circ, 180^\circ]$, and its search space is [0, 1]. The objective function is as follows:

$$\text{fitness} = \min\{F(\overline{z})\} = \min\left\{\max\left[20\log\left(\frac{|\mathrm{AF}^{\overline{z}}(\theta)|_{\theta\in S}}{\max\left(|\mathrm{AF}^{\overline{z}}(\theta)|_{\theta\in S}\right)}\right)\right]\right\}, \tag{5}$$

where $\overline{z}$ is the position vector of array element. $S = [0^\circ, 78^\circ] \cup [102^\circ, 180^\circ]$ is the interval of side lobes for this 10-element antenna array.

To obtain a lower maximum SLL in $[0^\circ, 78^\circ] \cup [102^\circ, 180^\circ]$, this example uses GOA to optimize the unit position of 10-element linear array. The size of population is 30, the maximum number of iterations is 500, and the spatial dimension of solution is 5. After 20 times optimization, the convergence characteristics of GOA for 10-element linear array are shown in Figure 3, the distribution of maximum SLL for 20 runs of GOA for 10-element linear array is shown in Figure 4, and the best array factor is obtained as shown in Figure 5, which is compared with conventional and PSO [10], CSO [14], and SMO [15] optimized arrays. The maximum SLL and the position of each element of the linear array optimized by each algorithm are shown in Table 1. The results show that the maximum SLL obtained by GOA is −21.31 dB, which is 8.41 dB, 3.90 dB, 1.32 dB, and 1.06 dB lower than conventional method, PSO, CSO, and SMO, respectively. The performance comparison of PSO, CSO, and GOA for 10-element linear array in 20 runs is shown in Table 2; the best SLL, worst SLL, and average SLL of GOA are all better than that of PSO and CSO, and the standard deviation (SD) is relatively small and is 0.1150. GOA can obtain lower maximum SLL and has good stability, which shows that GOA has better optimization ability than other algorithms for this design example.

Example 2. The second example uses GOA to realize maximum SLL reduction and null placement of a 32-element linear array and sets the each element position as the optimization variables of GOA, and its search space is [0, 1], so that a minimum null is controlled in a specific direction ($\theta = 81^\circ$ and $\theta = 99^\circ$), and the maximum SLL is minimized in $\theta \in [0^\circ, 86^\circ] \cup [94^\circ, 180^\circ]$, and the excitation is uniform ($a_n = 1$). The objective function is as follows:

$$\text{fitness} = \min\{F(\overline{z})\} = \min\left\{\max\left[20\log\frac{|\mathrm{AF}^{\overline{z}}(\theta)|_{\theta\in S}}{\max\left(|\mathrm{AF}^{\overline{z}}(\theta)|_{\theta\in S}\right)}\right] + 20\log\frac{|\mathrm{AF}^{\overline{z}}(\theta)|_{\theta=81^\circ}}{\max\left(|\mathrm{AF}^{\overline{z}}(\theta)|_{\theta\in S}\right)}\right\}. \tag{6}$$

On the premise of obtaining a lower maximum SLL, this example uses GOA to optimize each position of 32-element linear array to achieve a lower nulling depth in a specific direction ($\theta = 81^\circ$ and $\theta = 99^\circ$). The size of the population is set to 30, the maximum number of iterations is 500, and the solution space dimension is 16. After 20 times optimization, the best array factor is as shown in Figure 6, which is compared with CSO [14], PSO [10], QPM [20], MSMO [29], EFA [30], and BFP [31] optimized. The maximum SLL and the position of each unit of linear array are optimized by each algorithm as shown in Table 3. From the calculation results, we can see that the maximum SLL obtained by GOA is −24.61 dB, and the depth of null in direction $\theta = 81^\circ$ is −90 dB; the maximum SLL of GOA is 0.62 dB, 0.71 dB, 0.76 dB, 6.01 dB, 6.41 dB, 6.81 dB, and 11.11 dB lower than BFP, EFA, MSMO, PSO, CSO, QPM optimized, and conventional array, respectively, and the depth of null is 28 dB, 30 dB, 30 dB, 30 dB, 10 dB, 45 dB, and 71 dB lower than that of BFP, EFA, MSMO, PSO, CSO, QPM optimized, and conventional array, respectively. It is obvious that GOA has great advantages in suppressing maximum SLL and null depth, which shows that GOA has better optimization ability than other algorithms for this design example.

4.2. Element Excitation Optimization with FNBW Constraint

Example 3. The third example uses GOA to realize maximum SLL reduction of a 10-element linear array, sets the distance between each element as 0.5λ, and takes the excitation magnitudes as the optimization variables of GOA to minimize the maximum SLL in $\theta \in [0^\circ, 76^\circ] \cup [104^\circ, 180^\circ]$, and its search space is [0, 1]. The objective function is as follows:

$$\text{fitness} = \min\{F(\overline{z})\} = \min\left\{\max\left[20\log\left(\frac{|\mathrm{AF}^{\overline{a}}(\theta)|_{\theta\in S}}{\max\left(|\mathrm{AF}^{\overline{a}}(\theta)|_{\theta\in S}\right)}\right)\right]\right\}, \tag{7}$$

where $\overline{a}$ is the magnitude vector of linear array. S is the SLL interval; $S = [0^\circ, 76^\circ] \cup [104^\circ, 180^\circ]$ is selected for this 10-element linear array.

To obtain a lower maximum SLL in $[0^\circ, 76^\circ] \cup [104^\circ, 180^\circ]$, this example uses GOA to optimize each excitation magnitude of 10-element linear array. The size of population is 30, the maximum number of iterations is 500, and the spatial dimension of solution is 5. After 20 times optimization, the convergence characteristics of GOA

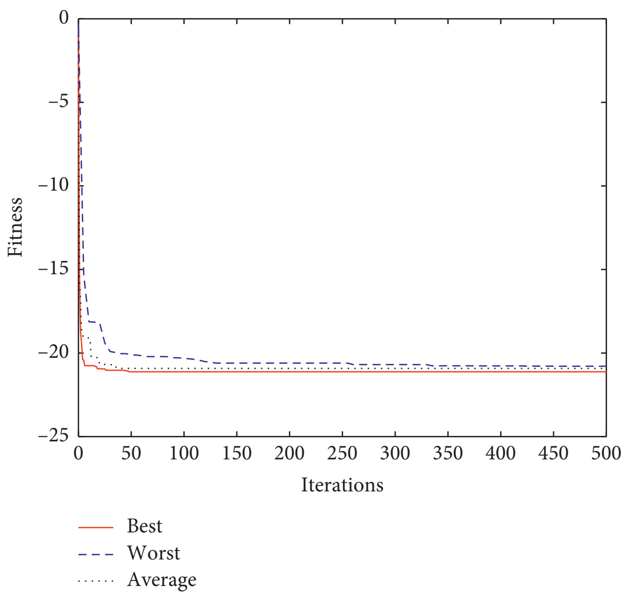

Figure 3: Convergence characteristics of GOA for 10-element linear array in example 1.

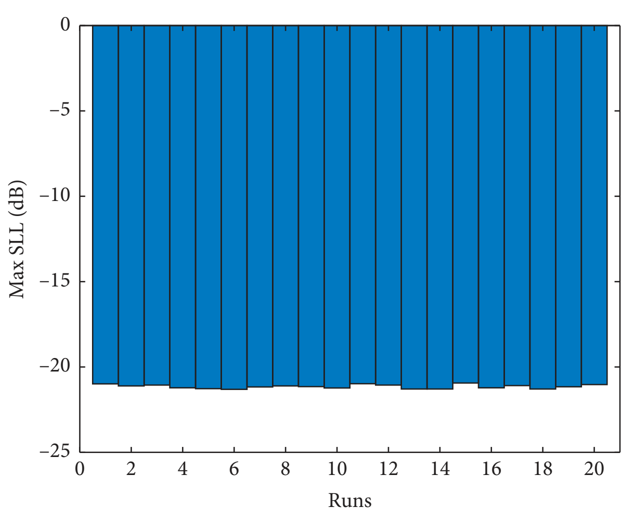

Figure 4: Distribution of maximum SLL for 20 runs of GOA for 10-element linear array in example 1.

for 10-element linear array are shown in Figure 7, the distribution of maximum SLL for 20 runs of GOA for 10-element linear array is shown in Figure 8, and the best array factor is obtained as shown in Figure 9, which is compared with conventional and PSO [12], FPA [21], and ALO [22] optimized arrays. The maximum SLL and the excitation magnitude of each element of the linear array optimized by each algorithm are shown in Table 4. The results show that the maximum SLL obtained by GOA is −27.36 dB, which is 14.46 dB, 2.74 dB, 2.04 dB, and 1.28 dB lower than that by conventional method, PSO, FPA, and ALO respectively. The performance comparison of FPA and GOA for 10-element linear array in 20 runs is shown in Table 5(paper [22] does not give the worst SLL, the average value, and the SD of

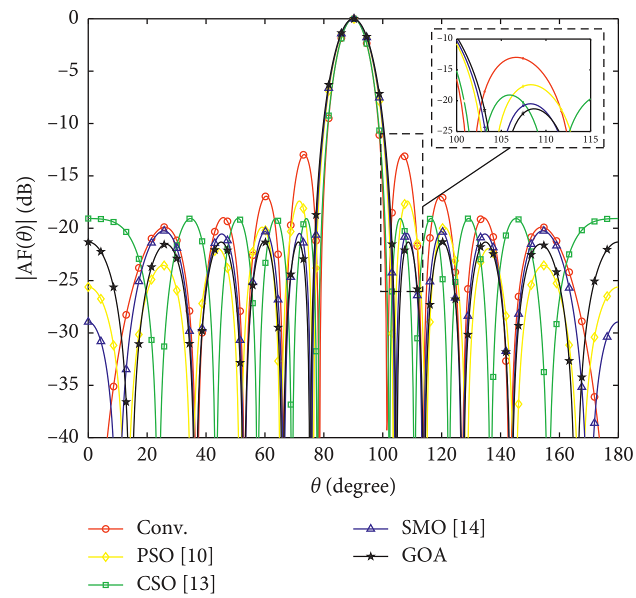

Figure 5: Array factors of 10-element linear array for example 1.

Table 1: The maximum SLL of linear array and the location of each element after optimization.

Algorithms	Max SLL (dB)	Optimized element positions (units: λ)				
Conv.	−12.90	0.2500	0.7500	1.2500	1.7500	2.2500
PSO [10]	−17.41	0.2515	0.5550	1.0650	1.5000	2.1100
CSO [14]	−19.99	0.2081	0.6679	1.1347	1.7238	2.4036
SMO [15]	−20.25	0.236	0.528	1.007	1.471	2.126
GOA	−21.31	0.3360	0.4196	1.0126	1.4166	2.1000

Table 2: The comparison of algorithms' performance for 10-element linear array in 20 runs.

Algorithms	PSO	CSO	GOA
Best SLL (dB)	−17.41	−19.99	−21.31
Worst SLL (dB)	−17.07	−19.01	−20.94
Average (dB)	−17.11	−19.28	−21.15
SD (dB)	—	—	0.1150

ALO); the best SLL, worst SLL, and average SLL of GOA are all better than that of FPA, and the standard deviation (SD) is relatively small and is 0.0528. GOA obtains lower maximum SLL and has good stability, which shows that GOA has better optimization ability than other algorithms for this design example.

Example 4. The fourth example uses GOA to realize maximum SLL reduction of a 16-element linear array, sets the distance between each element as 0.5λ, and takes the excitation magnitudes as the optimization variables of GOA to minimize the maximum SLL in $\theta \in [0^\circ, 81^\circ] \cup [99^\circ, 180^\circ]$, and its search space is [0, 1]. The objective function is the same as equation (7), while $S = [0^\circ, 81^\circ] \cup [99^\circ, 180^\circ]$ for this 16-element linear array.

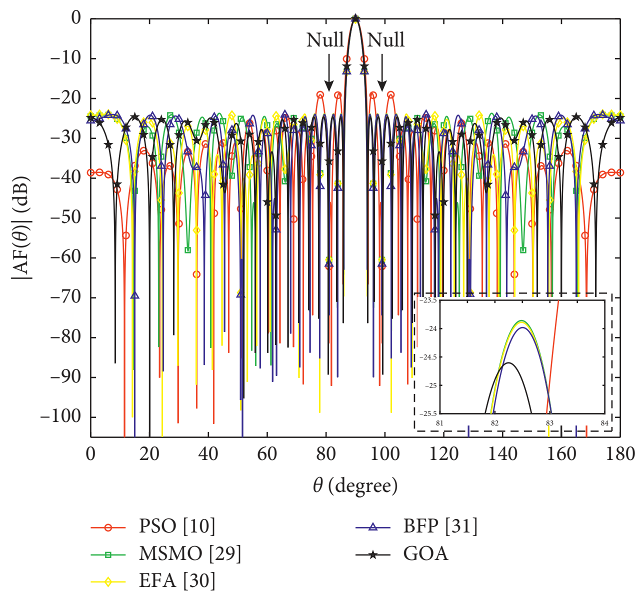

Figure 6: Array factor of 32-element linear array for example 2.

To obtain a lower maximum SLL in $[0^\circ, 81^\circ] \cup [99^\circ, 180^\circ]$, this example uses GOA to optimize each excitation magnitude of 16-element linear array. The size of population is 30, the maximum number of iterations is 500, and the spatial dimension of solution is 8. After 20 times optimization, the convergence characteristics of GOA for 16-element linear array are shown in Figure 10, the distribution of maximum SLL for 20 runs of GOA for 16-element linear array is shown in Figure 11, and the best array factor is obtained as shown in Figure 12, which is compared with FA [13, 23–25], CS [13, 26, 27], IWO [13], and CABMO [28] optimized arrays. The maximum SLL and the excitation magnitude of each element of the linear array optimized by each algorithm are shown in Table 6. The results show that the maximum SLL obtained by GOA is −28.10 dB, which is 3.83 dB, 3.09 dB, 2.23 dB, and 1.71 dB lower than FA, CS, CABMO, and IWO, respectively. The performance comparison of GOA and other algorithms for 16-element linear array in 20 runs is shown in Table 7; the best SLL, worst SLL, and average SLL of GOA are all better than those of other algorithms, and the standard deviation (SD) is relatively small and is 0.1396. GOA obtains lower maximum SLL and has good stability, which shows that GOA has better optimization ability than other algorithms for this design example.

Example 5. The fifth example uses GOA to realize maximum SLL reduction and notch (i.e., continuous multiple nulls) placement of a 20-element linear array, sets the distance between each element as 0.5λ, and takes the excitation magnitudes as the optimization variables of GOA, and its search space is $[0, 1]$ so that the antenna array not only meets the minimum maximum SLL in $\theta \in [0^\circ, 82^\circ] \cup [98^\circ, 180^\circ]$ but also has a notch with the minimum maximum SLL in the specific direction interval $\theta \in [50^\circ, 60^\circ] \cup [120^\circ, 130^\circ]$, so the objective function is as follows:

$$\text{fitness} = \sum_i \frac{1}{\Delta\theta_i} \int_{\theta_{l_i}}^{\theta_{u_i}} \left|\text{AF}(\theta)^2\right| d\theta + \sum_j \left|\text{AF}\left(\theta_j\right)^2\right|, \quad (8)$$

where $\Delta\theta_i = \theta_{u_i} - \theta_{l_i}$, $[\theta_{l_i}, \theta_{u_i}]$ is the angle range of optimized SLL and θ_j determines the angle direction of notch. The first part of (8) is to optimize the maximum SLL, and the second part is to control the position of the notch.

On the premise of obtaining a lower maximum SLL, this example uses GOA to optimize the excitation magnitudes of 20-element linear array to achieve a lower notch in a specific direction $\theta \in [50^\circ, 60^\circ] \cup [120^\circ, 130^\circ]$. The size of the population is set to 30, the maximum number of iterations is 500, and the spatial dimension of the solution is 10. After 20 times optimization, the best array factor is as shown in Figure 13, which is compared with real-coded genetic algorithm (RCGA) and the SMO algorithm in [15], and the maximum SLL of linear array and the excitation magnitude of each element are optimized by each algorithm as shown in Table 8 (the optimal value of RCGA's excitation magnitudes is not given in paper [15]). The results show that the maximum SLL obtained by GOA is −27.7 dB, and the maximum SLL of notch in $\theta \in [50^\circ, 60^\circ] \cup [120^\circ, 130^\circ]$ is −61.2 dB; the maximum SLL of GOA is 3.6 dB and 8.5 dB lower than that of SMO and RCGA, respectively, and the maximum SLL of notch is 4.5 dB and 5.4 dB lower than that of SMO and GCGA, respectively. It is obvious that GOA has greater advantages in suppressing the maximum SLL and the depth of notch, and the optimization ability of the GOA is higher than that of other algorithms for this design example.

5. Optimization of HF Broadband Antenna

Because of the wide application of frequency hopping and spread spectrum technology in shortwave communication system, the requirement of broadband antenna is getting higher and higher. Generally, lumped element loading and network matching can be used to solve. Component loading can smooth the input impedance and reduce the VSWR, but it increases the antenna loss and reduces the gain and efficiency. Therefore, the VSWR and gain are generally used as performance indicators to measure the degree of antenna optimization in the study of antenna loading and broadband matching network optimization. $\Gamma(\omega_i)$ is the reflection coefficient at frequency ω_i and $\text{VSWR}(\omega_i)$ is the VSWR at frequency ω_i.

$$\Gamma(\omega_i) = \frac{Z_q(\omega_i) - Z_0}{Z_q(\omega_i) + Z_0},$$
$$\text{VSWR}(\omega_i) = \frac{1 + |\Gamma(\omega_i)|}{1 - |\Gamma(\omega_i)|}, \quad (9)$$

where $Z_q(\omega_i)$ is impedance, called driving point impedance; Z_0 is characteristic impedance of feeder, and it is usually $50\,\Omega$; and ω_i $(i = 1, 2, \ldots, N)$ represents the frequency points in the frequency band.

5.1. Antenna Structure. In order to further verify the efficiency of GOA in antenna optimization, this section will take

Table 3: The maximum SLL of linear array and the location of each element after optimization.

Algorithms	SLL (dB)	Null (dB)	Optimized element positions (units: λ)							
Conv.	−−13.5	−19	0.25	0.75	1.25	1.75	2.25	2.75	3.25	3.75
			4.25	4.75	5.25	5.75	6.25	6.75	7.25	7.75
QPM [20]	−17.8	−45	0.245	0.725	1.125	1.595	1.980	2.335	2.685	3.055
			3.460	3.925	4.445	5.030	5.665	6.325	7.005	7.675
CSO [14]	−18.2	−80	0.288	0.683	1.193	1.520	1.977	2.325	2.689	3.136
			3.485	3.954	4.382	4.925	5.482	6.209	7.041	7.750
PSO [10]	−18.6	−60	0.265	0.685	1.175	1.555	1.985	2.330	2.665	3.055
			3.430	3.900	4.380	4.950	5.550	6.240	7.050	7.755
MSMO [29]	−23.85	−60	0.216	0.631	1.014	1.470	2.015	2.386	2.784	3.310
			3.824	4.417	4.919	5.504	6.298	7.148	7.998	8.847
EFA [30]	−23.90	−60	0.239	0.557	1.092	1.483	1.953	2.386	2.817	3.257
			3.869	4.422	4.888	5.499	6.299	7.145	7.995	8.845
BFP [31]	−23.99	−62	0.282	0.583	1.147	1.419	1.928	2.340	2.907	3.337
			3.770	4.386	4.978	5.558	6.257	7.141	8.047	8.851
GOA	−24.61	−90	0.287	0.574	1.024	1.384	1.906	2.220	2.778	3.173
			3.656	4.168	4.753	5.333	5.999	6.831	7.766	8.571

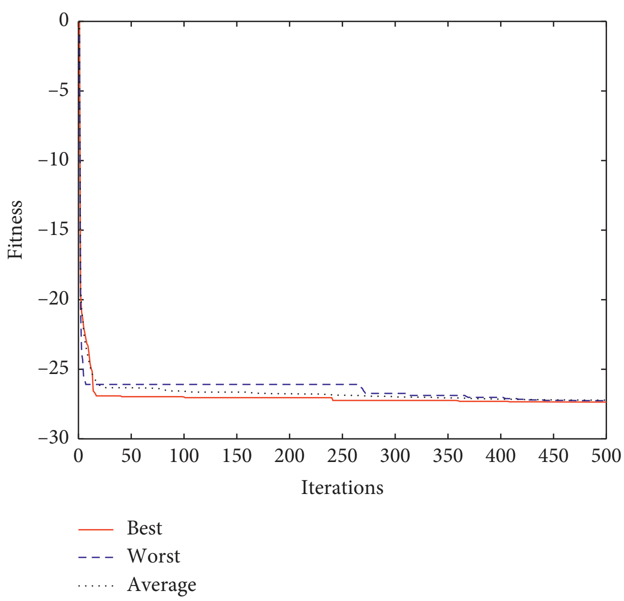

Figure 7: Convergence characteristics of GOA for 10-element linear array in example 3.

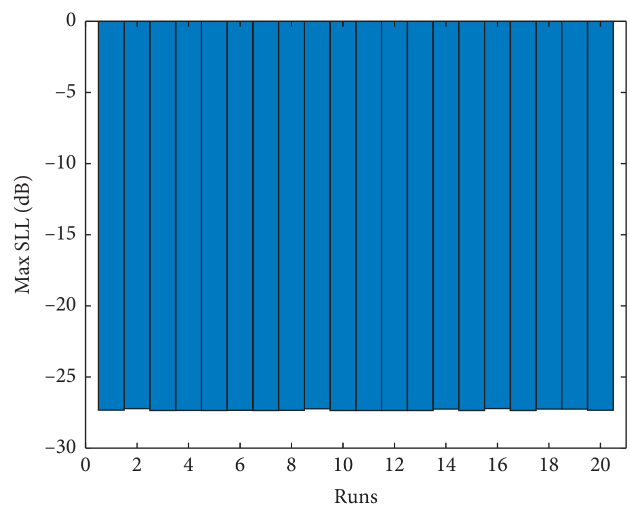

Figure 8: Distribution of maximum SLL for 20 runs of GOA for 10-element linear array in example 3.

the element values of load and matching network as optimization variables on the basis of 10-meter HF whip antenna. As shown in Figure 14, two centralized loading points are set on the whip body of the 10-meter antenna, and the upper loading point is set on the upper part of the whip body (25% from the top), and the lower loading point is set on the bottom of the whip body, both adopting the RLC parallel loading structure. The selection of component parameters for each loading point branch will be determined by GOA. The objective function of optimization calculation is to minimize the maximum VSWR and maximize the minimum gain of each sampling frequency point in the band [33, 34, 45].

$$F = \min\left\{\sum_{i=1}^{n}\left[W_i\left(\mathrm{VSWR}\left(\omega_i\right)-1\right)^2 + A_i\left(G_0 - G\left(\omega_i\right)\right)\right]\right\}, \tag{10}$$

where $G(\omega_i)$ refers to the gain of the antenna at frequency ω_i, G_0 is a rated gain, A_i is an adjusting parameter whose function is to weigh the broadband impedance characteristics and gain characteristics of the antenna, and W_i is the weighted value of the VSWR at each frequency point, whose value depends on the relative importance to $\mathrm{VSWR}(\omega_i)$. On the one hand, it retains a good VSWR; on the other hand, it rejects bad VSWR. Obviously, the smaller the value of the objective function, the better the optimization effect.

A matching network is added at the bottom of the antenna, which combines transmission line transformer and lumped parameter matching network; it is a network topology with "Γ" shape composed of transformer cascade lumped parameter elements. As shown in Figure 14, the elements mainly choose low-consumption capacitance and inductance. The two branches of the "LC" matching network consist of a series LC and a parallel LC structure, and the component parameters of each band will be determined by GOA too. The objective function should minimize the

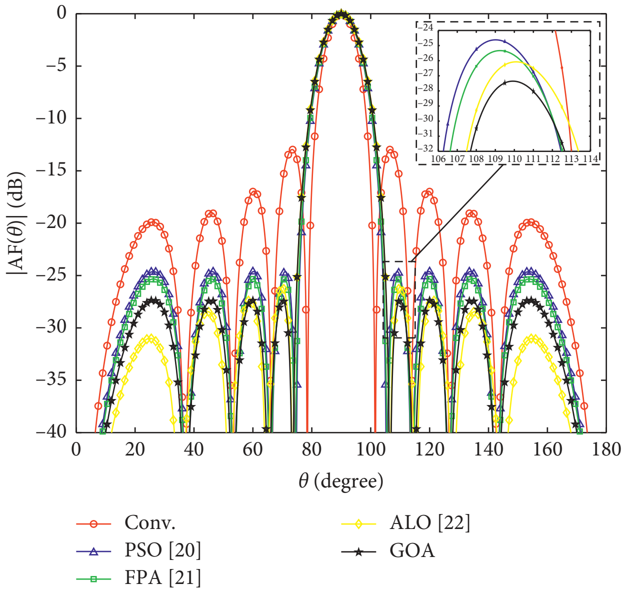

FIGURE 9: Array factor of 10-element linear array for example 3.

TABLE 4: The maximum SLL of linear array and the location of each element after optimization.

Algorithms	Max SLL (dB)	Optimized excitation magnitudes (normalized)				
Conv.	−12.90	1.0000	1.0000	1.0000	1.0000	1.0000
PSO [12]	−24.62	1.0000	0.9010	0.7255	0.5120	0.4088
FPA [21]	−25.33	1.0000	0.8979	0.7178	0.5002	0.3833
ALO [22]	−26.08	1.0000	0.8959	0.6957	0.4935	0.2966
GOA	−27.36	1.0000	0.8892	0.6962	0.4684	0.3208

TABLE 5: The comparison of algorithms' performance for 10-element linear array in 20 runs.

Algorithms	FPA	GOA
Best SLL (dB)	−25.33	−27.36
Worst SLL (dB)	−25.30	−27.22
Average (dB)	−25.31	−27.32
SD (dB)	0.0630	0.0528

average VSWR in the frequency band, which can be given by the following formula:

$$F = \min\left[\frac{1}{n}\sum_{i=1}^{n} \mathrm{VSWR}(\omega_i)\right]. \quad (11)$$

5.2. Antenna Optimization. GOA is adopted to optimize the element values of the antenna, setting $D = 6$, $\mathrm{lb}_d = 1$, $\mathrm{ub}_d = 1000$, $L = 100$, and $N = 30$, and its search space is [0, 1000]. After 100 iterations of optimization, the element optimization value is shown in Table 9. GOA's loading optimization behavior (6 grasshoppers) is shown in Figure 15; when the number of iterations reaches 65, all the trajectory of 6 grasshoppers converges. The convergence curve of objective function is shown in Figure 16; when the number of iterations has not reached 40, the GOA optimized antenna objective function has achieved convergence effect, which fully illustrates that the convergence speed and cost time of GOA optimized broadband antenna are considerable.

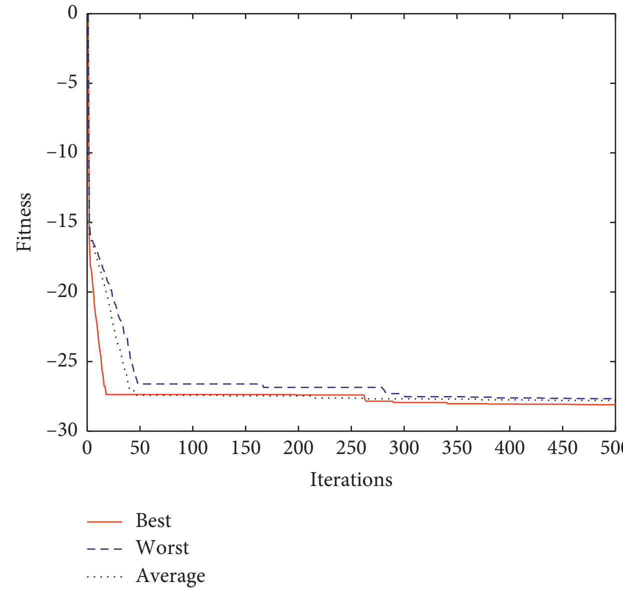

FIGURE 10: Convergence characteristics of GOA for 16-element linear array in example 4.

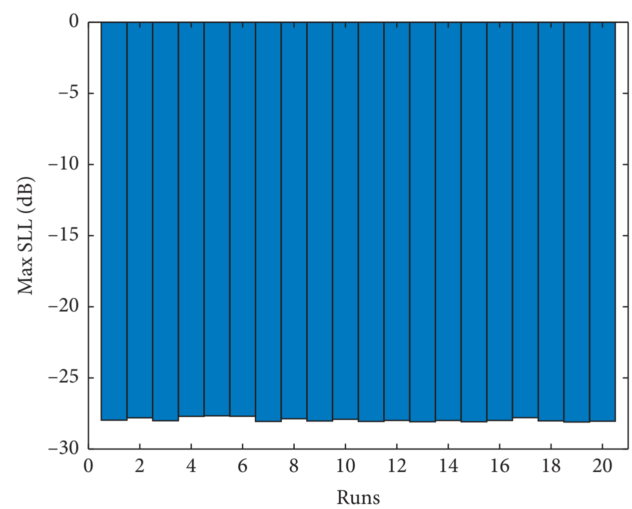

FIGURE 11: Distribution of maximum SLL for 20 runs of GOA for 16-element linear array in example 4.

5.3. Scaling Antenna Measurement and Analysis. In order to better verify the effectiveness of the broadband optimizing ability of GOA, a 10 : 1 scaling model is designed for the HF broadband antenna. To further smooth input impedance and realize impedance matching between antenna and feeder, two "RLC" loading networks are added at 0.75 m and 0 m, and a "τ"-type broadband matching network is added at the bottom of antenna, which is composed of broadband transmission line transformer and "LC" network, as shown in Figure 17.

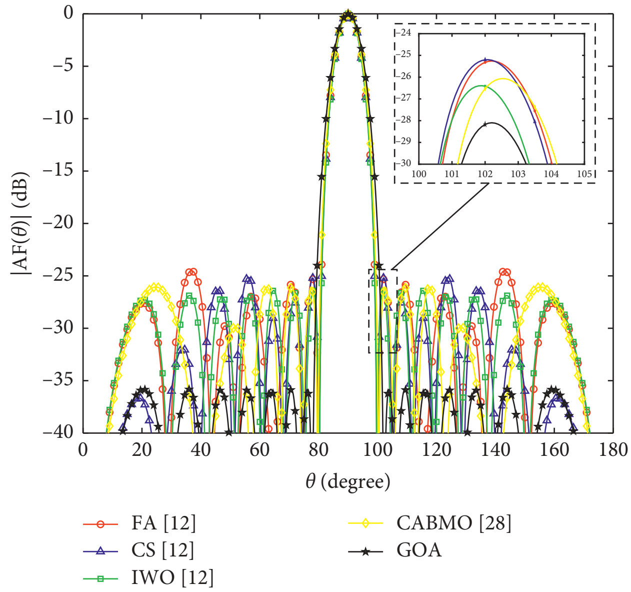

Figure 12: Array factor of 16-element linear array for example 4.

Table 6: Excitation magnitudes of 16-element linear array after optimization.

Algorithms	Max SLL (dB)	Optimized excitation magnitudes (normalized)							
FA [13]	−24.27	1.000	0.907	0.880	0.753	0.596	0.500	0.366	0.397
CS [13]	−25.01	1.000	0.866	0.791	0.801	0.567	0.366	0.353	0.336
CABMO [28]	−25.87	1.000	0.808	0.641	0.62	0.661	0.484	0.366	0.301
IWO [13]	−26.39	1.000	0.976	0.931	0.793	0.660	0.644	0.400	0.409
GOA	−28.10	1.000	0.958	0.874	0.756	0.627	0.485	0.367	0.349

Table 7: The comparison of algorithms' performance for 16-element linear array in 20 runs.

Algorithms	FA	CS	CABMO	IWO	GOA
Best SLL (dB)	−25.34	−26.08	−25.87	−26.57	−28.10
Worst SLL (dB)	−24.26	−25.01	—	−25.35	−27.67
Average (dB)	−24.61	−25.28	—	−26.41	−27.94
SD (dB)	0.3180	0.2293	0.5347	0.0550	0.1396

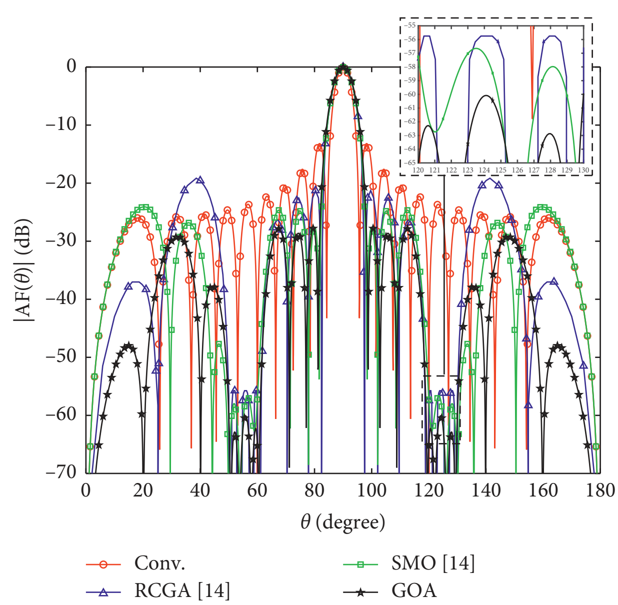

Figure 13: Array factor of 20-element linear array for example 5.

Table 8: Excitation magnitudes of 20-element linear array after optimization.

Algorithms	Max SLL (dB)	Notch depth (dB)	Optimized excitation magnitudes (normalized)									
RCGA [15]	−−19.2	−55.8	—	—	—	—	—	—	—	—	—	—
SMO [15]	−24.1	−56.7	1.000	0.999	1.000	0.836	0.643	0.654	0.477	0.597	0.258	0.215
GOA	−27.7	−61.2	1.000	0.986	0.990	0.796	0.736	0.563	0.527	0.447	0.243	0.151

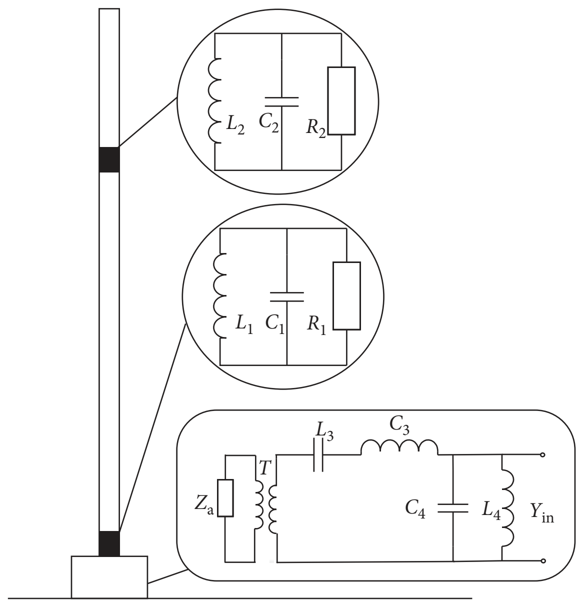

Figure 14: Antenna optimization diagram.

Table 9: The element optimization values.

$R1$ (Ω)	$L1$ (μH)	$C1$ (pF)	$R2$ (Ω)	$L2$ (μH)	$C2$ (pF)	$L3$ (nH)	$C3$ (μF)	$L4$ (μH)	$C4$ (pF)	T
112	1.86	980	317	323	2.20	31.5	392	2.20	0.40	2.3

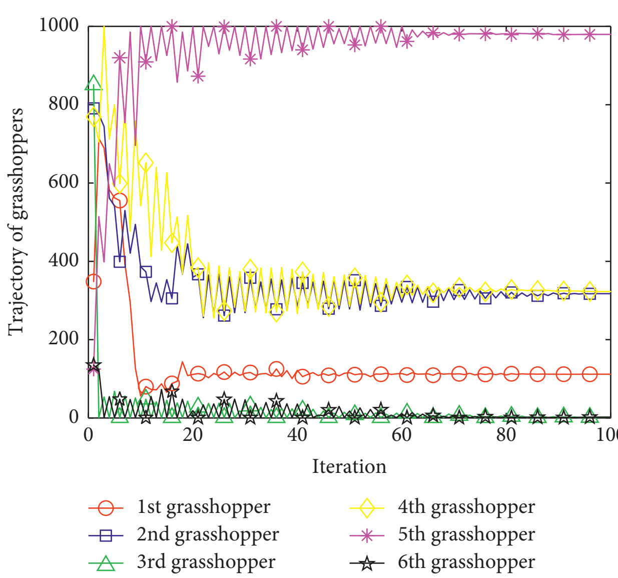

Figure 15: The trajectory behavior of 6 grasshoppers.

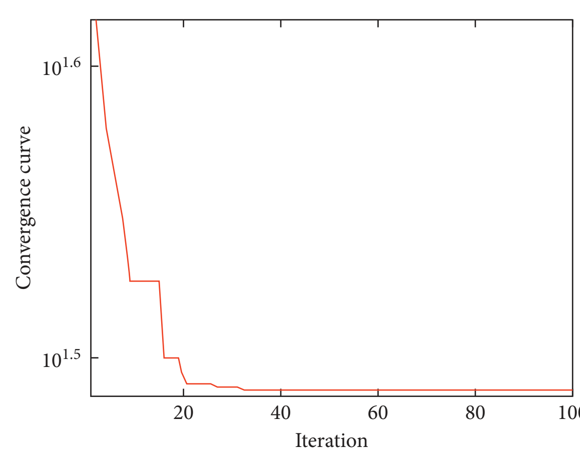

Figure 16: The convergence curve of objective function.

Under the optimization, the antenna VSWR and gain are shown in Figures 18 and 19 (where gain represents the antenna gain on the maximum direction). In terms of VSWR, the optimized value of GOA are better than that of IWO [35], whose frequency points with VSWR less than 3 account for 99% (96% for IWO), less than 2 account for 72% (61% for IWO), and less than 1.5 account for 36% (14% for IWO), and the measured and simulated values are basically consistent and slightly better than the simulated values. Moreover, compared with IWO optimized results, it can be seen that the gain optimized by GOA is greater than −9 dB (−10.2 dB for IWO), which is increased by at least 1 dB in low

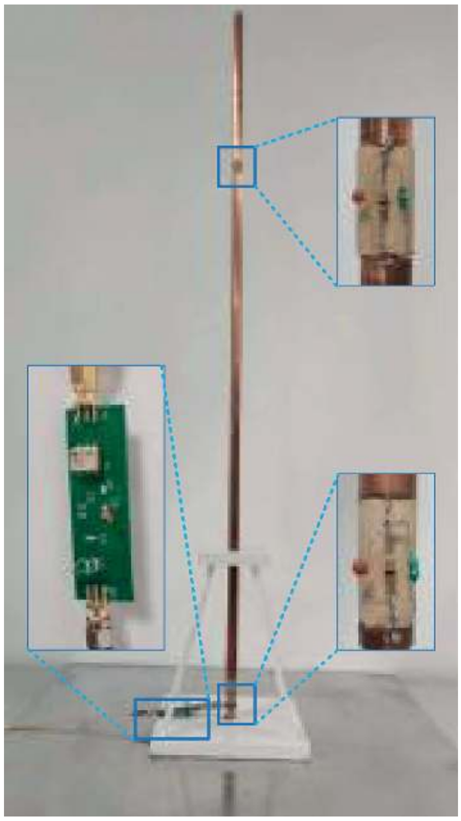

Figure 17: Scaling model of HF broadband antenna.

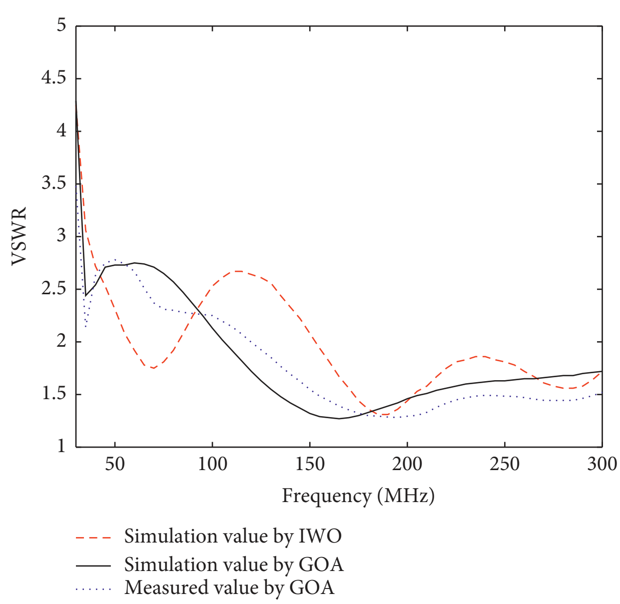

Figure 18: The VSWR of 10 : 1 scaled optimized whip antenna.

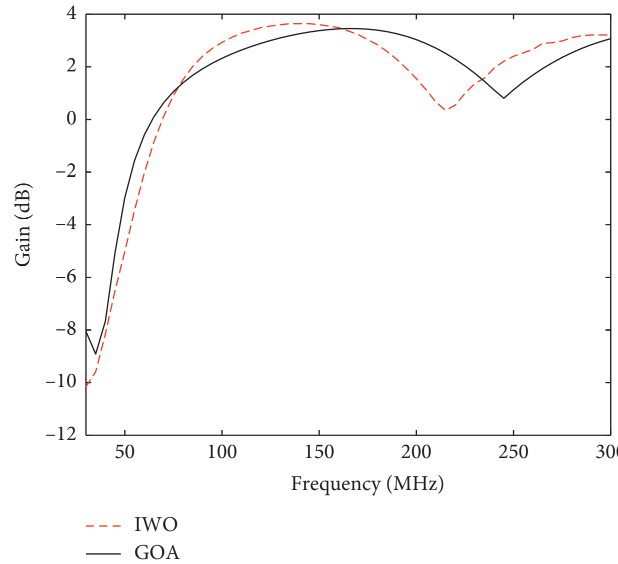

Figure 19: The gain of 10 : 1 scaled optimized whip antenna.

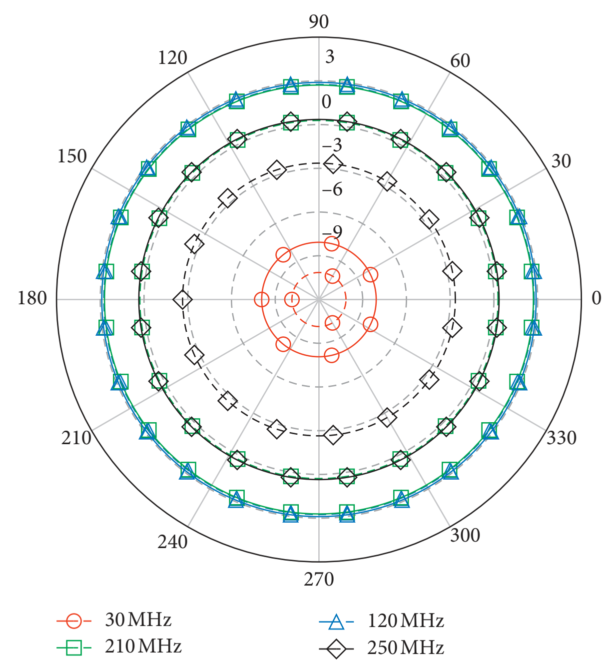

Figure 20: H-plane pattern (solid line for GOA; dashed line for IWO).

frequency; although there are less decreased points in medium frequency, the rest of the frequency points are basically better, so GOA is better able to balance the gain of each frequency point.

The optimized field pattern is shown in Figures 20 and 21 (H-plane and E-plane). Under the two algorithms, both H-plane patterns of the antenna remain circular in all frequency bands and both E-plane patterns remain the half shape of "∞" in the low and middle frequency bands, with a upward warping phenomenon gradually in the high-frequency bands. However, the maximum direction of the E-plane pattern optimized by IWO deviates from the horizontal direction at 210 MHz, while that optimized by GOA deviates from the horizontal direction only at 250 MHz. This shows that under the GOA optimization of the antenna, the upward warping of the E-plane pattern of the antenna is

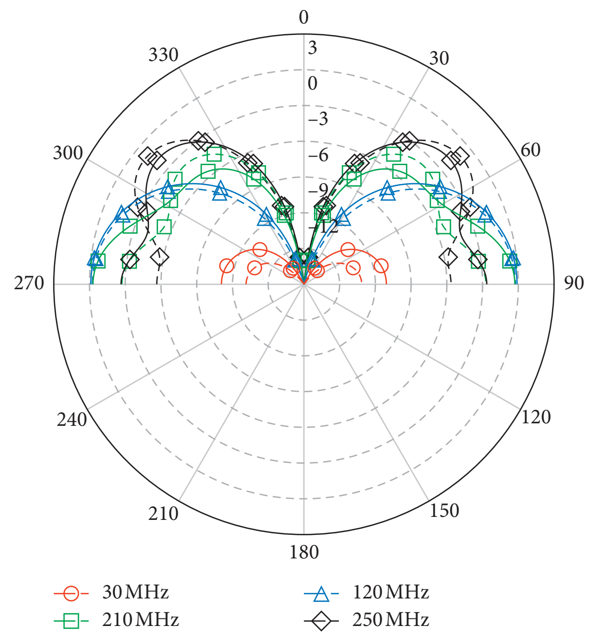

Figure 21: E-plane pattern (solid line for GOA; dashed line for IWO).

suppressed to a certain extent, which will be more conducive to the radiation of the antenna. For broadband optimization of antenna, GOA can balance the gain of the whole frequency band more reasonably, can effectively reduce the VSWR of the band, and can also effectively restrain the upward warping of the pattern, which indicates that the algorithm has more advantages in optimizing the multitarget antenna problem in this design example.

6. Conclusions

In this paper, GOA is applied to antenna optimization in electromagnetic field for the first time. In order to prove that the algorithm is a new and effective method to solve the problem of antenna optimization, the algorithm is applied to multiple linear array pattern synthesis and broadband optimization of whip antenna. On the one hand, under the same conditions, with the element position and excitation magnitude as the optimization variables and SLL suppression, null depth, and notch control of arbitrary linear array as the optimization objectives, the GOA algorithm is superior to PSO, CSO, SMO, QPM, FPA, ALO, CS, CABMO, IWO, RCGA, MSMO, EFA, BFP, and other algorithms in reducing SLL, convergence speed, and stability through five simulation examples. On the other hand, in order to realize the wideband of the shortwave antenna, taking the standing wave ratio and gain of the antenna as the objective function and taking the loading network and matching network parameters of the 10-meter shortwave broadband whip antenna as the optimization variables, the simulation and experiment show that the GOA algorithm is superior to IWO in the aspect of optimizing the impedance wideband of the antenna, which verified the feasibility of its application in the broadband optimization of the shortwave whip antenna. GOA is a natural heuristic algorithm to simulate the social behavior of grasshopper population, which is simple and has no gradient mechanism and can effectively avoid falling into local optimum. It is helpful to get better results of pattern synthesis and antenna broadband optimization based on GOA than other algorithms, and it also reduces the calculation cost of antenna optimization.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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