Design of Multilayer Wideband Microwave Absorbers using Improved Grey Wolf Optimizer

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Abstract – In this paper, an improved heuristic algorithm based on the disturbance and somersault foraging grey wolf optimizer (IDSFGWO) is proposed to optimize the design of multilayer wideband microwave absorbers for normal incidence. The multilayer absorber is designed to reduce maximum reflection coefficient by choosing suitable layers of materials from a predefined database. Three improvement strategies are given to enhance the performance of GWO, including tent map, nonlinear perturbation, and somersault foraging. The optimization results show that the reflection coefficients optimized by IDSFGWO are better than those of other algorithms for multilayer absorber design.

Index Terms – absorbing material, GWO, multilayer microwave absorbers, reflection coefficient.

I. INTRODUCTION

Microwave absorbers have important applications in stealth technology [1], wave anechoic chamber [2], imp-roving electromagnetic environment, and protecting daily safety [3–4]. Traditional single microwave absorbers are limited by their low electromagnetic parameters, narrow absorber band, and thick absorber structure. Multilayer microwave absorbers can complement and correlate the absorbing properties of each material and broaden the absorbing bandwidth to a certain extent [5]. Reasonable optimization of the absorbing structure can improve the absorptivity of a multilayer microwave absorber.

Over the years, primitive optimization algorithms like simplex algorithms [6], penalty function method [7], and multi-objective programming method [8] have been used. Simplex method is often used to find the optimal solution of objective function in linear constraint problems. Penalty function method is to transform the constrained optimization problem into a series of unconstrained optimization problems to solve. Multi-objective programming is a mathematical method for solving multi-objective decision-making problems based on linear programming. Recently, nature-inspired heuristic algorithms have been effectively applied to the design of absorbers [9–10], most notably the particle swarm optimization and the genetic algorithm [11–13]. They are accepted by researchers due to their higher probability of global optimal solution, higher robustness, and faster convergence speed.

This paper proposes the improved grey wolf optimizer (GWO) to design multilayer wideband microwave absorbers. Three enhancement strategies are provided to improve the performance of GWO. The tent map is used to initialize the populations. The nonlinear perturbation factor is adopted to balance mining and exploration capabilities. The somersault foraging strategy is introduced to prevent the algorithm from converging to local optima during the later stage. The reflection coefficient of incident electromagnetic waves on the surface of multilayer flat structures is calculated by the improved GWO through simulation experiments. It is shown that IDSFGWO has a certain advantage in designing multilayer microwave absorbers.

II. PHYSICAL MODEL OF MULTILAYER ABSORBER

The physical model of a multilayer microwave absorber is shown in Fig. 1. It is a multilayer system consisting of N layers of different materials backed by a perfect electric conductor (PEC). The total reflection coefficient of the multilayer microwave absorber can be calculated by using the equivalent transmission line method [14–15]. Each layer of media in Fig. 1 is considered as a transmission line. The equivalent transmission line model of the cascade of N different uniform transmission lines is shown in Fig. 2.

The input impedance of the Nth transmission line can be considered as the input impedance of the transmission line with a terminal short, which is expressed as

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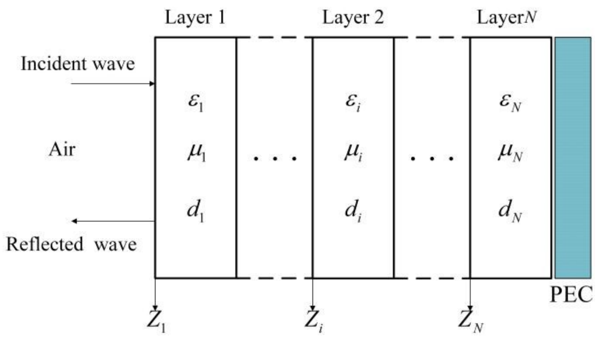

Fig. 1. Structure of multilayer microwave absorber.

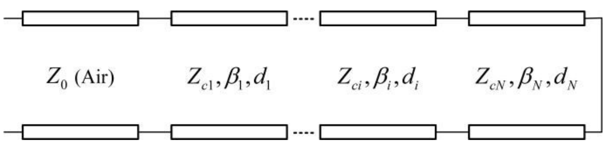

Fig. 2. Equivalent circuit of multilayer microwave absorber.

follows:

$$\mathrm{Z}_i = j\mathrm{Z}_c \tan(\beta d), \tag{1}$$

where, Z_c is the characteristic impedance, β is the propagation constant, d is the length of transmission line. Z_c and β are calculated in the TE mode as follows:

$$\beta = k_0\sqrt{\varepsilon_r\mu_r - \sin^2\theta}, \tag{2}$$

$$\mathrm{Z}_c = \frac{\omega\mu}{\beta}, \tag{3}$$

while in TM mode Z_c and β are expressed as follows:

$$\beta = k_0\sqrt{\varepsilon_r\mu_r - \sin^2\theta}, \tag{4}$$

$$\mathrm{Z}_c = \frac{\beta}{\omega\varepsilon}, \tag{5}$$

where, ε_r and μ_r are the relative permittivity and relative permeability of the materials, ε and μ are the permittivity and permeability of the materials.

The input impedance of the left adjacent transmission line can be expressed as follows:

$$\mathrm{Z}_i = \mathrm{Z}_c\frac{\mathrm{Z}_1 + j\mathrm{Z}_c\tan(\beta d)}{\mathrm{Z}_c + j\mathrm{Z}_1\tan(\beta d)}, \tag{6}$$

where, Z_1 is the terminal load of the left adjacent transmission line. It is also the input impedance of the Nth transmission line represented by Eq. (1).

Repeat the above process from right to left in turn. Then the reflection coefficient of the interface between air and medium is expressed as

$$R = \frac{\mathrm{Z}_{10} - \mathrm{Z}_{c0}}{\mathrm{Z}_{10} + \mathrm{Z}_{c0}}, \tag{7}$$

where, Z_{c0} is the characteristic impedance of the air corresponding to the transmission line, Z_{10} is the load impedance of the air corresponding to the transmission line.

For TE mode, Z_{c0} is defined as follows:

$$\mathrm{Z}_{c0} = \frac{\mathrm{Z}_0}{\cos\theta}. \tag{8}$$

For TM mode, Z_{c0} is defined as

$$\mathrm{Z}_{c0} = \mathrm{Z}_0\cos\theta, \tag{9}$$

where, Z_0 is the wave impedance in vacuum.

Finally, the total reflection coefficient of the multilayer microwave absorber is obtained:

$$RL = 20\log_{10}\left|\frac{\mathrm{Z}_{10} - \mathrm{Z}_{c0}}{\mathrm{Z}_{10} + \mathrm{Z}_{c0}}\right|. \tag{10}$$

III. GREY WOLF OPTIMIZER

A. Basic grey wolf optimizer

GWO is a new heuristic algorithm based on the predatory characteristics of grey wolves. It optimizes the search by imitating the leadership level and hunting mechanism of grey wolves. The leadership hierarchy of the grey wolf population divides the wolves into $\alpha\beta\delta\omega$, and the mathematical model includes stalking, encircling, and hunting [16]-[18].

1) Encircling prey

$$\vec{X}(t+1) = \vec{X_P}(t) - \vec{A}\cdot\left|\vec{C}\cdot\vec{X_P}(t) - \vec{X}(t)\right|, \tag{11}$$

where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X_P}(t)$ is the position vector of the prey, and $\vec{X}(t)$ indicates the position vector of a grey wolf.

The vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2\vec{a}\cdot\vec{r}_1 - \vec{a}, \tag{12}$$

$$\vec{C} = 2\vec{r_2}, \tag{13}$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations, and $\vec{r_1}$, $\vec{r_2}$ are random vectors in [0,1].

The factor $\vec{a}$ is defined as follows:

$$a = 2\left(1 - t/t_{\max}\right), \tag{14}$$

where $t_{\max}$ is the maximum number of iterations.

2) Hunting

The first three best candidate solutions obtained so far oblige the other search agents to update their positions according to the position of the best search agents. So the updating equations for the wolves positions are proposed as follows:

$$\begin{cases} \vec{X_1} = \vec{X_\alpha} - \vec{A_1}\cdot\left|\vec{C_1}\cdot\vec{X_a} - \vec{X}\right| \\ \vec{X_2} = \vec{X_\beta} - \vec{A_2}\cdot\left|\vec{C_2}\cdot\vec{X_\beta} - \vec{X}\right| \\ \vec{X_3} = \vec{X_\delta} - \vec{A_3}\cdot\left|\vec{C_3}\cdot\vec{X_\delta} - \vec{X}\right| \end{cases}, \tag{15}$$

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3}, \tag{16}$$

where, $\overrightarrow{X_\alpha}\overrightarrow{X_\beta}\overrightarrow{X_\delta}$ are the first three best solutions in the swarm at a given iteration t, $\overrightarrow{A_1}\overrightarrow{A_2}\overrightarrow{A_3}$ are defined as in Eq. (12), and $\overrightarrow{C_1}\overrightarrow{C_2}\overrightarrow{C_3}$ are defined using Eq. (13).

B. Improved grey wolf optimizer

The basic grey wolf optimizer uses randomly generated data in the initial population stage, resulting in poor population diversity and poor optimization results. A chaotic map is used to generate a random chaotic sequence generated by a simple deterministic system, which has the characteristics of nonlinearity, ergodicity, and randomness. When solving the optimization problem, chaotic maps can maintain the diversity of the population and improve the global search ability. The existing chaotic maps include Logistic map, Chebyshev map, Tent map, etc. [19–20]. Tent map has better ergodic uniformity than other maps. So Tent map is selected to initialize the grey wolf population. The Tent map expression is defined as follows:

$$X_{t+1} = \begin{cases} \frac{X_t}{u} & X_t \in [0,u) \\ \frac{1-X_t}{1-u} & X_t \in [0,u) \end{cases}, \tag{17}$$

where, the value of parameter u is 0 to 1. The obtained chaotic sequence has uniform distribution when u is 0.5.

Due to the linear change of the convergence factor a, the first half and the second half of the convergence of the algorithm have the same decline. Thus, the grey wolf optimizer cannot effectively complete both global search in the early stage and local search in the late stage. Adjusting linear to nonlinear is a general improvement [21]. The improved nonlinear perturbation factor can balance the capability of local and global search effectively [22]. The nonlinear perturbation factor E is defined as follows:

$$E = randn \cdot (\sin^k(\frac{\pi}{2} \cdot \frac{t}{t_{\max}}) + \cos(\frac{\pi}{2} \cdot \frac{t}{t_{\max}}) - 1), \tag{18}$$

$$\overrightarrow{A} = (2\overrightarrow{a} \cdot \overrightarrow{r}_1 - \overrightarrow{a}) + E, \tag{19}$$

where $randn$ represents a random number subject to Gaussian normal distribution, k represents a constant that determines the peak value of the disturbance factor.

In order to avoid the situation that the basic GWO is prone to fall into the local optimum in the later stage of optimization, the somersault feeding strategy is introduced. This strategy is inspired by the behavior of manta rays that take the current optimal solution as the turning fulcrum and roll to the other side of the mirror relationship with their current position [23]. The mathematical expression of somersault for aging strategy is defined as follows:

$$X_i^d(t+1) = X_i^d(t) + S \cdot (r_1 X_{best}^d - r_2 X_i^d(t)) \;\; i = 1, \cdots, N, \tag{20}$$

where, S is the flip factor, X_{best}^d is the location of prey, N is the population number, d is a dimension, and r_1,r_2 are random numbers in [0,1].

In each iteration of the GWO, the fitness value of the current grey wolf is compared with the fitness value of the grey wolf after jumping the fulcrum to determine whether to carry out the somersault feeding strategy. If the grey wolf has fallen into the local optimum at this time, the optimization result will be replaced. As the grey wolf optimizer iterates to the later stage, each wolf is getting closer to the optimal solution. The effect of jumping out of the local optimum is more obvious. The somersault foraging bebavior of grey wolves is shown in Fig. 3. The flow chart of improved GWO is shown in Fig. 4.

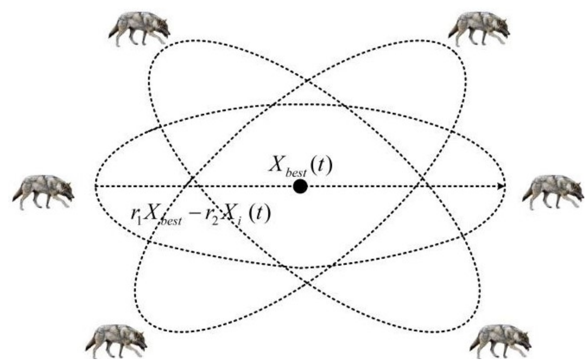

Fig. 3. Somersault foraging behavior of grey wolf.

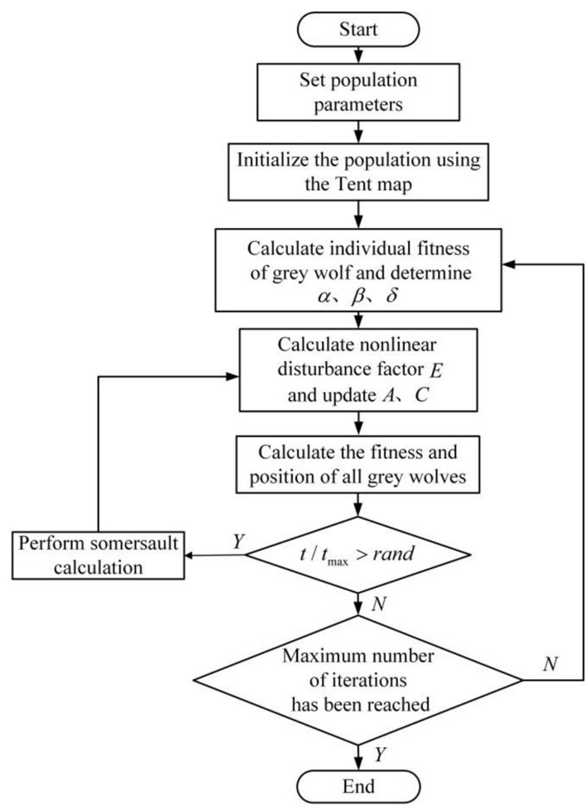

Fig. 4. Flow chart of improved grey wolf optimizer.

C. Objective function

Generally, the reflection coefficient is used to measure the absorbing effect. The reflection coefficient of the electromagnetic wave is closely related to the electromagnetic parameters of each layer of materials, the thickness of the layer, the arrangement of the layer and the incident frequency of the electromagnetic wave [24–25]. The optimization design is to optimize the selection and arrangement of layer thickness and materials type of each layer under the constraints of given number of layers, maximum thickness and band-width. The optimization goal is to minimize the maximum value of reflection coefficient.

Therefore, the maximum reflection coefficient in a specific frequency band is taken as the objective function. The objective function is represented as follows:

$$F_{obj} = 20\log_{10}(\max|R|) \tag{21}$$

IV. SIMULATION EXPERIMENT AND RESULT ANALYSIS

A. Database of absorbing materials

Absorbing materials convert the incident electromagnetic wave into heat energy or other forms of energy through various loss mechanisms, so as to absorb and attenuate the electromagnetic wave.

The single absorption principle database selected by many scholars limits the ability of the algorithm to search the optimal solution. There are 16 kinds of materials selected for this optimization design, which are divided into 4 categories: lossless dielectric materials, lossy magnetic materials, lossy dielectric materials, and relaxation magnetic materials, basically covering all types of electromagnetic materials. The database of absorbing materials is shown in Table 1.

Real and imaginary parts of permeability and permittivity for corresponding materials can be calculated using following equations.

For lossy magnetic materials:

$$\mu'(f) = \mu'(1GHz)/f^a, \tag{22}$$

$$\mu''(f) = \mu''(1GHz)/f^b. \tag{23}$$

For lossy dielectric materials:

$$\varepsilon'(f) = \varepsilon'(1GHz)/f^a, \tag{24}$$

$$\varepsilon''(f) = \varepsilon''(1GHz)/f^b. \tag{25}$$

For relaxation-type magnetic materials:

$$\mu'(f) = \frac{\mu_m f_m^2}{f^2 + f_m^2}, \tag{26}$$

$$\mu''(f) = \frac{\mu_m f_m f}{f^2 + f_m^2}. \tag{27}$$

Finally, the complex permittivity and permeability can be calculated as

$$\mu = \mu' - j\mu'', \tag{28}$$

$$\varepsilon = \varepsilon' - j\varepsilon''. \tag{29}$$

Table 1: Database of absorbing materials

Lossless Dielectric Materials ($\mu'=1, \mu''=0$)				
#	ε'			
1	10			
2	50			
Lossy Magnetic Materials ($\varepsilon'=15, \varepsilon''=0$)				
#	$\mu'(1GHz)$	a	$\mu''(1GHz)$	b
3	5	0.974	10	0.961
4	3	1.000	15	0.957
5	7	1.000	12	1.000
Lossy Dielectric Materials ($\mu'=1, \mu''=0$)				
#	$\varepsilon'(1GHz)$	a	$\varepsilon''(1GHz)$	b
6	5	0.861	8	0.569
7	8	0.778	10	0.682
8	10	0.778	16	0.861
Relaxation-type Magnetic Materials ($\varepsilon'=15, \varepsilon''=0$)				
#	μ_m	f_m		
9	35	0.8		
10	35	0.5		
11	30	1.0		
12	18	0.5		
13	20	1.5		
14	30	2.5		
15	30	2.0		
16	25	3.5		

B. Results and analysis

The application of the IDSFGWO to optimize multilayer microwave absorber is discussed and analyzed with the help of two design examples, including a 5-layer microwave absorber and a 7-layer microwave absorber. The simulation experiment considers the case of vertical incidence of electromagnetic waves.

Particle swarm optimization (PSO) is a classic heuristic intelligent algorithm which is based on the collaborative manner in which a swarm of insects, a herd of animals, a flock of birds, or a school of fish search for food [26]. The PSO algorithm is easy to execute and it has been seen to perform well on the design of broadband microwave absorbers [27].

WOA is a heuristic intelligent optimization algorithm that seeks the optimal solution by simulating the behavior of whale populations [28]. Both WOA and GWO can be used to solve nonlinear, nonconvex, and high-dimensional optimization problems. GWO performs well when dealing with large-scale problems or constrained optimization problems. WOA performs well when rapid convergence and high precision are required [29].

Example A: 5-layers microwave absorber

The design is a multilayer absorbing structure with 5 layers. The specified frequency range is 2-12 GHz,

Table 2: The best optimization result of 5-layer microwave absorber

Algorithm	IDSFGWO		GWO		PSO		WOA	
Layers	Type and Thickness (mm)							
1	16	0.1962	16	0.2220	8	1.5941	16	0.2826
2	8	1.9755	16	0.0671	9	0.3662	1	0.1906
3	7	1.8286	6	1.9910	8	1.2310	7	2.0000
4	13	0.7471	5	1.6768	7	1.1402	3	2.0000
5	7	1.3248	12	2.0000	12	1.2028	5	2.0000
Total thickness (mm)	6.0722		5.9569		5.5343		6.4732	
Maximum reflection coefficient (dB)	-34.2194		-28.0019		-14.7287		-23.1191	

the frequency step is set to 0.1 GHz. The maximum total thickness of the microwave absorber is limited to 10 mm. Each algorithm is run 20 times independently in the experiment. The maximum number of iterations is 1000 times. The optimal design optimization results of the four algorithms after 20 runs are shown in Table 2.

The maximum reflection coefficient optimized by the IDSFGWO is significantly better than the other three algorithms. The maximum reflection coefficient result of GWO is equivalent to WOA and better than PSO. Although the total thickness optimized by the IDSFGWO is worse than the PSO algorithm, it is thinner than the WOA algorithm. In addition, relaxation materials appear most frequently in the optimization results in Table 2. It indicates that the absorbing properties of relaxation materials are more likely to meet the requirements of multilayer microwave absorbers. The results of the selection of materials show that the mixed composition of magnetic and dielectric multilayer structure is conducive to better absorption of electromagnetic waves. A reasonable combination of electromagnetic media is expected to achieve the performance requirements of strong absorption of microwave absorber.

The reflection coefficient curves corresponding to the optimization results in Table 2 are shown in Fig. 5. The optimized maximum reflection coefficient of the IDSFGWO is -34.2194 dB. The peak value of -43.6407 dB is reached at 3.8 GHz. The numerical results show that IDSFGWO achieves a better absorption effect. The reflection coefficients optimized by both GWO and IDSFGWO are below -28 dB in the frequency range of 2-12 GHz. It reflects a better absorption performance compared with the rest of the algorithms.

Figure 6 shows the convergence curves of the four algorithms for the absorption optimization. It can be found that the convergence accuracy of the IDSFGWO is significantly higher than the other three algorithms.

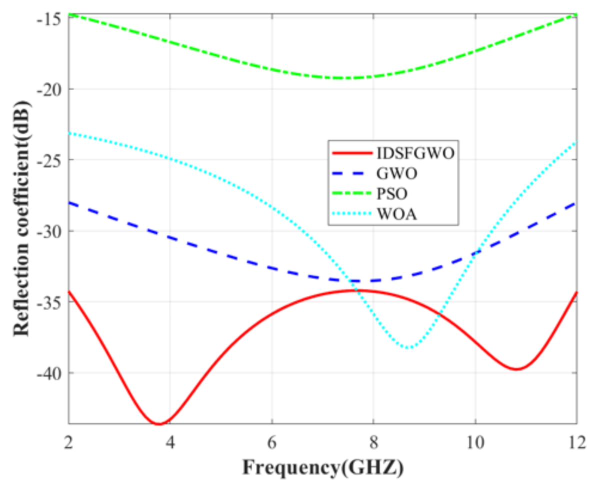

Fig. 5. Convergence curve for 5-layer design.

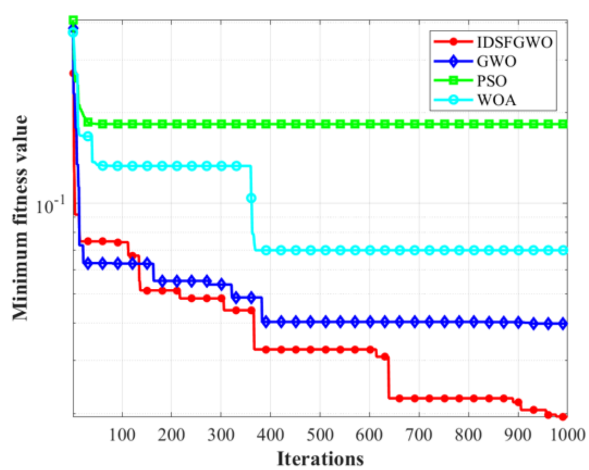

Fig. 6. Convergence curve for 5-layers design.

IDSFGWO has a strong convergence performance and eventually converges to a minimum after 1000 iterations.

Table 3: Comparison results of maximum reflection coefficient(in dB) of 5-layers design

Algorithm	Best	Worst	Mean	Standard Deviation
IDSFGWO	-43.6407	-34.2194	-37.4532	1.4507
GWO	-33.5502	-28.0019	-31.3174	1.7568
PSO	-19.2381	-14.7287	-17.3531	2.8072
WOA	-38.2401	-23.1191	-29.0179	4.6701

The statistical results of the optimal, worst, mean, and standard deviation values of the maximum reflection coefficient for each algorithm are given in Table 3. It can be seen that the IDSFGWO obtains a small optimal value of the reflection coefficient. The standard deviation value of IDSFGWO is also smaller than the other three algorithms. This indicates that the IDSFGWO obtains better absorption performance and also has better stability.

Example B: 7-layers microwave absorber

The four algorithms above are still used to optimize the design of the 7-layers microwave absorber. The maximum total thickness of microwave absorber is still limited to 10 mm. To observe the optimization results of four optimization algorithms for multilayer microwave absorber in a wider band range, the absorbing band width is widened to 0.1-20 GHZ.

The best design results obtained after 20 independent runs are also given, as well as the reflection coefficient curve, convergence curve, and the comparative results of maximum reflection coefficient. The optimization results of 7-layers are analyzed in comparison with the optimization results of 5-layers. According to the refle-ction coefficient curves, the absorption bandwidth of 7-layers is significantly better than 5-layers with the same reflection coefficient. It shows that more layers of microwave absorber has a good effect on broadening the absorbing bandwidth. However, it is also seen that the absorption peak of the optimized absorption of the IDSFGWO becomes smaller. The reflection coefficient curve is smoother than 5-layers. Therefore, multilayer microwave absorber broadening the absorbing bandwidth will also weaken the absorbing performance in part of the frequency band.

The best design results of the 7-layers microwave absorber are shown in Table 4. The reflection coefficient curve of the 7-layers microwave absorber is shown in Fig. 7. The convergence curve of the 7-layers microwave absorber is shown in Fig. 8. The comparative results of the maximum reflection coefficient of the 7-layers microwave absorber are shown in Table 5.

Table 4: The best design result of 7-layers design

Algorithm	IDSFGWO		GWO		PSO		WOA	
Layers	Type and Thickness (mm)							
1	16	0.1824	16	0.4331	16	0.3546	1	0.1420
2	8	1.3370	5	0.1995	1	0.3664	7	0.3073
3	6	1.2994	13	1.4285	7	0.3221	1	1.4285
4	4	0.0403	1	0.0130	16	1.4285	14	0.4135
5	16	0.4294	2	0.4031	12	0.8721	1	0.8741
6	1	0.6216	9	0.1387	7	0.4952	4	1.4285
7	3	0.3607	13	0.0322	6	1.2276	1	0.3201
Total thickness (mm)	4.2708		2.6481		5.0665		4.9140	
Maximum reflection coefficient (dB)	-30.4597		-21.5203		-19.7793		-17.7929	

Table 5: Comparison results of maximum reflection coefficient(in dB) of 7-layers design

Algorithm	Best	Worst	Mean	Standard Deviation
IDSFGWO	-35.0045	-30.4597	-33.1925	1.4287
GWO	-38.2451	-21.5203	-28.4008	5.1299
PSO	-23.2331	-19.7793	-21.9631	1.0417
WOA	-20.6594	-17.7929	-19.5723	0.9028

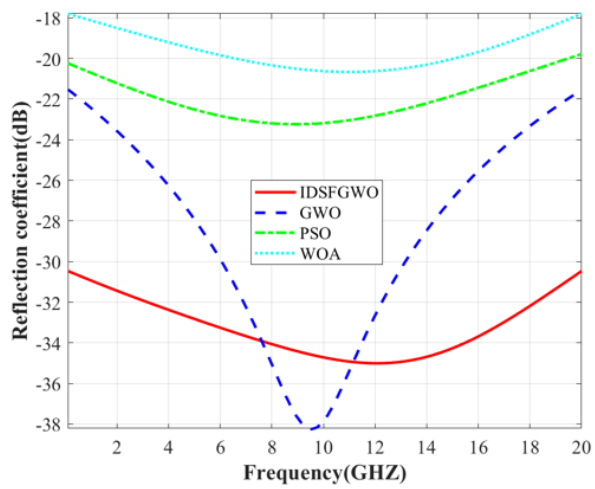

Fig. 7. Reflective coefficient curve of 7-layers design.

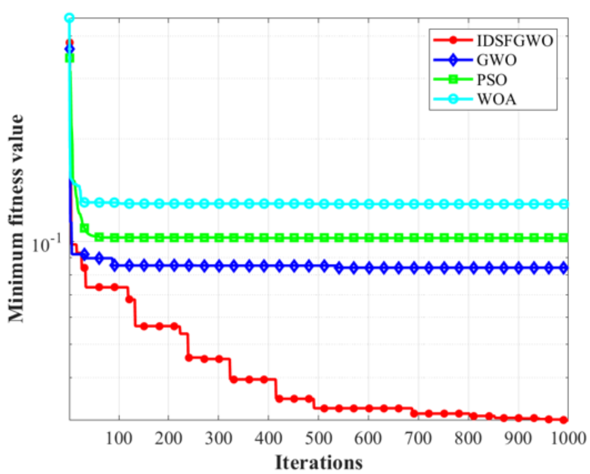

Fig. 8. Convergence curve for 7-layers design.

V. CONCLUSION

In this paper, an improved grey wolf optimizer combining three strategies is proposed to solve the problem of multilayer wideband microwave absorber design in the case of vertical incidence. Through this method, a set of coatings with the smallest reflection coefficient and thin thickness in a specific frequency range can be optimized. The simulation results show that IDSFGWO has better convergence accuracy, stronger optimization ability, and a more stable optimization process when solving the optimization problem of mul-tilayer wideband microwave absorbers.

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