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A Novel Method for Frequency Selective Surface Design Using Deep Learning with Improved Particle Swarm Algorithm

Riqiu Cong
Dalian University of Technology
Dalian, China
congriqiu@163.com

Ning Liu*
Dalian University of Technology
Dalian, China
liun@dlut.edu.cn

Xiang Gao
Lianyungang JARI Electronics Co., Ltd
Lianyungang, China
568481055@qq.com

Chunbo Zhang
Aerospace Institute of Advanced Material & Processing Technology
Beijing, China
950869@qq.com

Kaihua Yang
Aerospace Institute of Advanced Material & Processing Technology
Beijing, China
20879651@qq.com

Xianjun Sheng
Dalian University of Technology
Dalian, China
sxianjun@dlut.edu.cn

***Abstract*—This paper presents a design method for frequency selective surface (FSS) based on the deep neural network and improved particle swarm algorithm (IPSO). In the proposed method, the forward prediction network (FPN) based on the fully connected network is established to fast predict the transmission coefficient of FSS. Combined with the FPN, the IPSO is used to optimize the structural parameters of FSS. Compared with the traditional iterative optimization method based on full-wave simulation, this method greatly improves the optimization efficiency of FSS. For example, a band-stop FSS is optimized with the proposed method in 210.6s, and the optimization efficiency increases by more than 99%. Simulation results show that the transmission coefficient errors of key frequency points between optimization results and objectives are less than 1 dB. And the deviation of the center frequency and the bandwidth of the target frequency bands is less than 0.81% and 4.1%, respectively.**

Keywords—frequency selective surface, deep neural network, forward prediction network, improved particle swarm algorithm

I. Introduction

Frequency selective surface (FSS) is a two-dimensional periodic array structure, which is usually acted as a spatial filter to construct hybrid radome, antenna reflector, EM shelter, and so on [1]. Usually, the filtering property of FSS is affected by not only its structural topology and parameters but also the incident angle, polarization, and energy of the EM waves. Hence, it is difficult to design an FSS with specific frequency response requirements. Especially, in practical applications, the rapid design method with high design accuracy is highly desired.

Motivated by this practical requirement, different methods have been investigated. Typically, the design methods can be divided into two categories. One is the equivalent circuit model-based design method [2-4] and the other is the full-wave simulation-based iterative optimization method [5-8]. The first kind of design method is only suitable for specific structural topology, such as cross dipole, square loop, Jerusalem cross, and so on. Compared with the first kind of design method, the optimization iterative design method is suitable for any structural topology in theory. Hence, the full-wave simulation-based iterative optimization method is the most widely applied design method for FSS structures. For example, the binary particle swarm optimization algorithm combined with the full-wave simulation software is adopted to design bandpass FSS in [5]. The genetic algorithm is applied in [6] to acquire the structural topology and parameters from the desired resonant frequency and bandwidth. Although the full-wave simulation-based iterative optimization method has the merits including good versatility and high accuracy, the design process is usually time-consuming.

Nowadays, with the rapid development of machine learning theory, various deep learning algorithms are also applied to solve the design problem of metasurface and FSS [9-15]. For example, the convolutional neural network is used to predict the optical response of the plasmonic 2D structure in [10]. A deep learning approach for inverse design of the metasurface for dual-polarized waves is proposed in [11]. Compared with the full-wave simulation-based iterative optimization method, with the aid of the deep learning algorithm, the design efficiency has been improved greatly. However, the design accuracy of this method is mainly limited by the deep learning network. Especially, for the inverse network, the design accuracy is even worse for practical applications.

In this paper, a rapid FSS design method based on the combination of the forward prediction network (FPN) and the improved particle swarm optimization (IPSO) algorithm is proposed. By replacing the full-wave simulation method with the FPN, the calculation time of the transmission coefficient is shortened greatly. And with the aid of the nonlinear adaptive inertia weight and dynamic adjustment of learning factors, the iterative optimization process can be converged faster, which also accelerates the design process. Hence, compared with these aforementioned design methods, the proposed method has the merits of high design efficiency and accuracy.

II. Design Method and Results

A. Overview of the Design Method

Firstly, the FPN is established to realize the fast mapping of FSS structural parameters to the transmission coefficient, which can replace the full-wave simulation of FSS. Then, according to the design goal, the IPSO is used to iteratively optimize the structural parameters of the FSS. In the iterative process, the FPN is used to fast predict the transmission coefficient of FSS to improve optimization efficiency. Finally, the optimal structural parameters will be obtained until the iterative result converges. The flow chart of the proposed method is shown in Fig. 1.

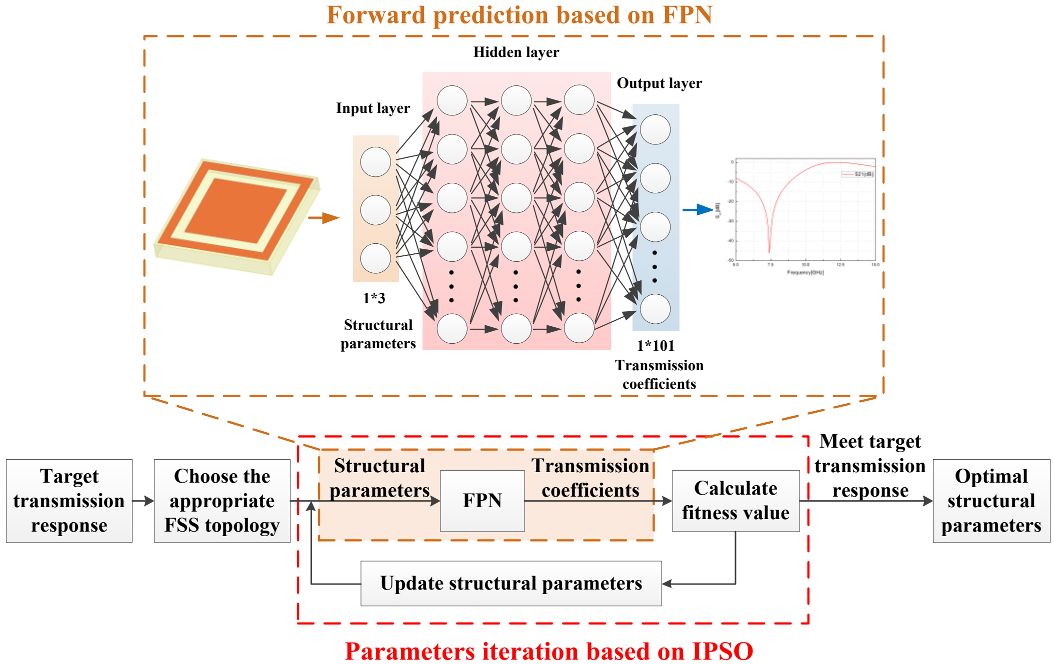


Fig. 1. Flow chart of the proposed method

B. Forward Prediction Based on FPN

1) Data acquisition: Firstly, electromagnetic simulation software HFSS is used for data acquisition. A band-stop FSS topology, as shown in Fig. 2, is taken for data acquisition and network training, some structural parameters of it are fixed: the size of unit P is 8 mm, the thickness of the dielectric layer h is 1 mm and the relative permittivity ε_r of the dielectric layer is 2.65. Other structural parameters are set as the parameters to be optimized. In which, the inner side length of the square loop $2L_1$ changes in the range of [5.6mm, 6.4mm], the outer side length of the square loop $2L_2$ varies in the range of [6.8mm, 7.6mm], and the side length of the internal patch $2L_3$ is in the range of [4mm, 5mm]. By determining the three structural parameters [L_1, L_2, L_3], the unit structure can be locked and the transmission coefficient can be calculated by HFSS software. Using the co-simulation between Matlab and HFSS, 4000 data sets are generated. Each group of data includes the structural parameters [L_1, L_2, L_3] and the transmission coefficient curve, that is, the magnitude of S_{21} at each frequency point within 5-15GHz with a step of 0.1GHz. A ratio of 8:1:1 is taken to divide data sets into training data sets, verification data sets, and test data sets.

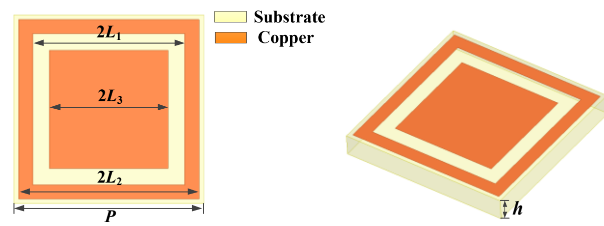


Fig. 2. Schematics of FSS unit structure

2) Network configuration: A fully connected network is selected to build FPN. [L_1, L_2, L_3] as input parameters, transmission coefficient curve as output parameters. The hyperparameters of the network are listed in Table I.

TABLE I. HYPERPARAMETERS OF FPN

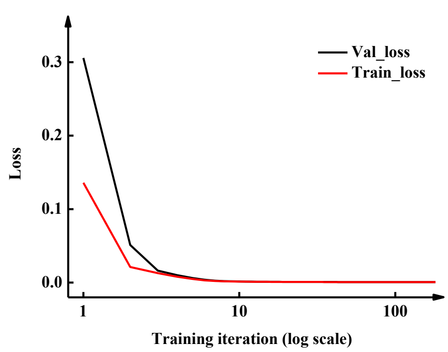
Hyperparameters	FPN
Activation Function	LeakyReLU (0.05)
Loss Function	MSE
Optimizer	Adam(lr = 1e-4)
Batch size	32
Number of Layers	5
Number of neurons in each layer	3,(50,100,200),101

Mean square error (MSE) is selected to be the loss function of FPN. The loss is expressed as the following formula:

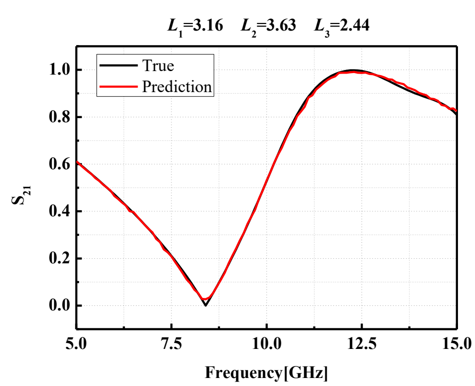
$$loss = \frac{1}{N}\sum_{i=1}^{N}(y_{true}^{i} - y_{pred}^{i})^2 \tag{1}$$

where N is the number of frequency points, y_{true} and y_{pred} are the true value and the predicted value of the transmission coefficient, respectively. Compared with the transmission coefficient curve in the log domain, the one in the linear domain has smoother features, which is easy to be trained with better results. Therefore, the transmission coefficient curve in the linear domain is selected as the output data in the network training.

3) Results: Completed with 200 iterations of training, the loss curve converges and the loss value reaches 7e-4 finally. The loss curve is shown in Fig. 3 (a). The test data, not used for the network training can be used to verify the generalization performance of the network. A set of test data [3.16, 3.63, 2.44] selected randomly is used as the input of the FPN together with the true value obtained with full-wave simulation software HFSS is shown in Fig.3(b). As observed, the predicted transmission coefficient agrees with the simulated one with high accuracy, which demonstrates the viability of the established FPN.



(a) Convergence curves of loss



(b) Comparison between prediction data and true data

Fig. 3. Results of FPN's training and prediction

C. Improved Particle Swarm Optimization (IPSO) Algorithm

In order to obtain the optimized structural parameters, the particle swarm optimization (PSO) algorithm is adopted. In the process of optimization, each particle is a potential solution and the optimal solution can be found by self-learning and group learning of particles. For the D-dimension problem, each particle has two vectors: One is the velocity vector expressed by $V_i = (v_{i1}, \ldots, v_{id}, \ldots, v_{iD})$. The other is the location vector represented by $X_i = (x_{i1}, \ldots, x_{id}, \ldots, x_{iD})$, which represents the information of the potential solution. During the iteration, X_i is updated to approach the optimal solution by dynamic tuning V_i. The iterative update equations, at iteration m, are described as follows:

$$v_{ij}(m+1) = wv_{ij}(m) + c_1 rand_1(p_{ij}(m) - x_{ij}(m)) + c_2 rand_2(p_{gj}(m) - x_{ij}(m)) \tag{2}$$

$$x_{ij}(m+1) = x_{ij}(m) + v_{ij}(m+1) \tag{3}$$

where ω is the inertia weight, $rand_1$ and $rand_2$ are the random numbers in [0, 1], $p_{ij}(m)$ is the position with the best fitness of i_{th} particle, $p_{gj}(m)$ is the position with the best fitness of all particles. Based on the above mentioned, the PSO with fixed inertia weight and learning coefficients is called basic PSO (BPSO). When solving some complex problems, BPSO will face some challenges, including that particles can not converge to the global optimum position, and slow convergence will appear. To overcome these problems, nonlinear adaptive inertia weight and dynamic adjustment learning coefficient are introduced into BPSO to establish the proposed IPSO. The details of the improvements are as follows.

1) Nonlinear adaptive inertia weight ω: Inertia weight ω plays an important role in balancing the local and the global search capabilities. Global search capabilities can be reinforced with a large ω. On the contrary, local search ability can be enhanced with a small ω. The expected solution is that the algorithm has a fast convergence ability at the beginning of iterations, and it is more likely to have a strong local convergence at the latter iterations. Therefore, a nonlinear adaptive inertia weight is proposed, which can be expressed as follows:

$$\omega_i^d = \begin{cases} \omega_{\min} + (\omega_{\max} - \omega_{\min})\dfrac{f(x_i^d) - f_{\min}^d}{f_{average}^d - f_{\min}^d}, & f(x_i^d) \le f_{average}^d \\ \omega_{\max}, & f(x_i^d) > f_{average}^d \end{cases} \tag{4}$$

where $f(x_i^d)$ is the fitness value of the ith particle, f_{average} and $f_{\min}$ are the average and minimum of the all particles' fitness at iteration d. $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of ω, respectively. It can be seen that ω can be tuned adaptively, which will be decreased when the particle fitness value tends to the optimal solution, otherwise ω will be increased to accelerate the searching process.

2) Dynamic adjustment of learning coefficients c_1, c_2: Learning coefficients c_1 and c_2 represent the self and social cognition of particles, respectively, which reflect the global search and global convergence capability of particles. That is to say that large c_1 is beneficial for the enhancement of the global search ability of particles. On the contrary, large c_2 is conducive to the global convergence of particles. It is expected that particles have the ability to jump out of the local optimum at the latter iterations. Therefore, a kind of dynamically adjusted scheme of learning coefficient is introduced. That is to say, c_1 is set as a constant, and c_2 is reduced gradually with the increase of the iteration number. This strategy can avoid the occurrence of the premature phenomenon to promote the global search capability of particles. The update equation of c_2 can be expressed as follows:

$$c_2 = c_{2e}\left(\frac{c_{2s}}{c_{2e}}\right)^{1/(1+w_c G/G_{\max})} \tag{5}$$

where w_c is a proportionality coefficient, which determines the decline rate of c_2, c_{2s} and c_{2e} represent the starting and ending values of c_2, respectively, and $G_{\max}$ is the maximum number of iterations.

In a word, these improvement strategies can balance global optimization ability and local optimization ability. Compared with BPSO, the efficiency and accuracy of optimization problems will be enhanced.

D. Overview of the Optimization Method Based on IPSO with FPN

1) The process of optimization: Considering the prediction accuracy, the FPN can be adopted to replace the full-wave simulation for the acceleration of the optimization process. In this paper, the IPSO algorithm combined with the FPN is selected to optimize the structural parameters. The optimization process is as follows: Firstly, the structural parameters of the FSS are extracted and the number of parameters is determined as particle dimension; Secondly, initialize the particle parameters, and the parameters are used as the input parameters of FPN. The transmission coefficient curve is obtained through the prediction of FPN. Thirdly, the fitness value of each particle is calculated to determine whether the target transmission coefficient is satisfied by the corresponding particle or not. If the target transmission coefficient is satisfied, the optimal particle parameters are obtained with the corresponding particle. Otherwise, the fitness value is set as feedback to promote the evolution of the particles. Under some special circumstances, it is difficult to find the particle which meets the requirements of transmission coefficient in the space of solutions. Therefore, the maximum number of iterations is set. Once the maximum number of iterations is reached, the optimal particle in all particles is obtained. The optimization flow chart is shown in Fig. 4.

2) Optimization target and system configuration: Based on the FSS topology shown in Fig. 2 and the optimization flow chart shown in Fig. 4, an FSS with specific transmission coefficient requirements is designed for verification. The optimization target is:

$$\begin{cases} S_{21} < -15\text{dB}, & 9\text{GHz} < f < 10\text{GHz} \\ S_{21} > -0.5\text{dB}, & 12\text{GHz} < f < 14\text{GHz} \end{cases} \tag{6}$$

where S_{21} represents the transmission coefficient. The fitness function is established according to the target:

$$F = (S_{21}^{9\text{GHz}}+15)^2 + (S_{21}^{10\text{GHz}}+15)^2 + (S_{21}^{12\text{GHz}}+0.5)^2 + (S_{21}^{14\text{GHz}}+0.5)^2 \tag{7}$$

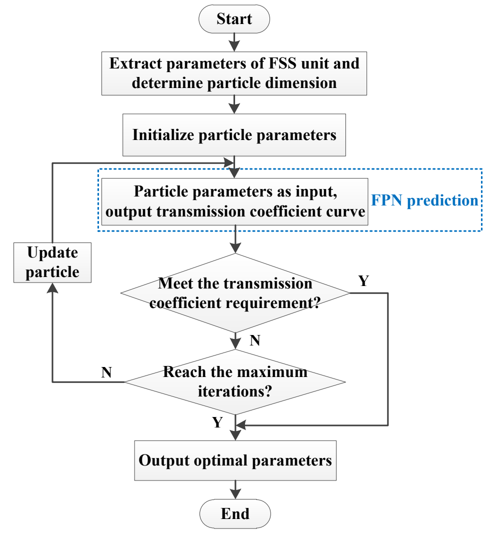


Fig. 4. Flow chart of parameters optimization

Finally, BPSO and IPSO are adopted to acquire the optimized structural parameters and the configuration parameters of the two algorithms are listed in Table II.

TABLE II. CONFIGURATION OF BPSO AND IPSO

Parameters	BPSO	IPSO
Inertia weight *w*	$w = 0.8$	$w_{\max} = 0.9$, $w_{\min} = 0.4$
Particles number	15	15
Iterations	200	200
c_1	2	2
c_2	2	$c_{2s} = 2$, $c_{2e} = 0.1$, $w_c = 50$

3) Results of optimization: As shown in Fig. 5, both the BPSO and IPSO algorithms converge within 200 iterations. And the optimal results are: the best fitness value of BPSO and IPSO are F=0.207 and F=0.154, and the optimal particle parameters are [3.012, 3.404, 2.369] and [3.02, 3.4, 2.359]. The best fitness value obtained from IPSO is 25.6% smaller than the one from BPSO. Moreover, it takes 210.6s and 272.4s for the optimization process of IPSO and BPSO, respectively. Considering the efficiency and precision of the optimization, the IPSO is more suitable for FSS optimization than BPSO.

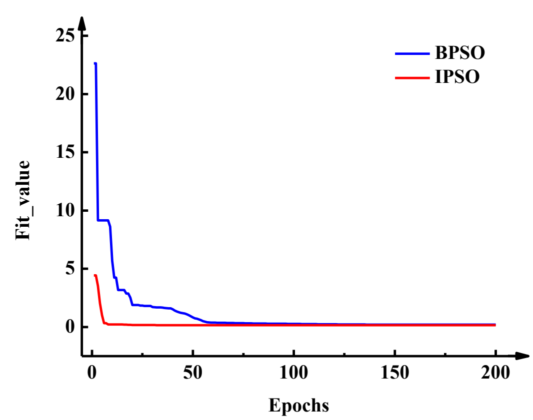


Fig. 5. Curves of fitness value

In order to verify the accuracy of the results obtained from IPSO, the optimal FSS is simulated in HFSS software. As indicated in Fig. 6, the optimized FSS can meet the requirements of the target frequency band with high accuracy. The key frequency points and their transmission coefficient are listed in Table III. It can be found that the transmission coefficient errors of key frequency points are less than 1 dB. Meanwhile, the −15 dB bandwidth is from 9.028 to 10.045 GHz. Compared with the target requirements, its center frequency deviation is only 0.089%, and its bandwidth increases by 1.7%. Also, the −0.5 dB bandwidth is from 12.068 to 14.142 GHz. Its center frequency deviation is 0.807%, and its bandwidth increases by 4.1%. The differences between the simulated results and the target frequency response requirements are mainly caused by the prediction error of the FPN.

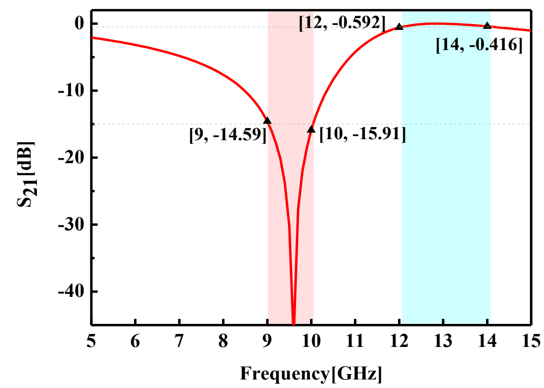


Fig. 6. Transmission coefficient curve of optimal FSS

TABLE III. THE KEY FREQUENCY POINTS AND THEIR TRANSMISSION COEFFICIENT

Target frequency points (GHz)	Optimal frequency points (GHz)	Deviations of frequency points (GHz)	Target transmission coefficient of target frequency points (dB)	Optimal transmission coefficient of target frequency points (dB)	Errors of transmission coefficient (dB)
9	9.028	0.028	-15	-14.59	0.41
10	10.045	0.045	-15	-15.91	0.91
12	12.068	0.068	-0.5	-0.592	0.092
14	14.142	0.142	-0.5	-0.416	0.084

It is worth pointing out that the optimization process is completed within only 210.6s with the proposed method. As for the traditional full-wave simulation-based method, it will take an average of 20s for each simulation calculation of FSS in HFSS software and the entire optimization process will cost about 16.7h through 200 iterations. Hence, compared with the traditional method, the efficiency of the proposed method improves by about 99.65%.

III. CONCLUSION

In this paper, the FPN is used to realize the fast prediction of the FSS transmission coefficient with high accuracy. By replacing the full-wave simulation method with the FPN, a fast design method based on the combination of FPN and IPSO algorithm is developed. An FSS is designed for verification and compared with the traditional method based on the full-wave simulation, the design efficiency improves by 99.65% with high design accuracy. Considering the merits of high accuracy and efficiency, the proposed method is a good candidate for fast FSS design.

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