Optimal Design of Microwave Devices by Fitness-estimation-based Particle Swarm Optimization Algorithm

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Abstract — As important parts of modern communication systems, microwave devices play a decisive role in communication quality. When optimizing the complex microwave devices, the global optimization algorithm is generally used exploiting full-wave electromagnetic simulation software. The full-wave electromagnetic simulation software evaluates the performance of the microwave device. Based on this evaluation result, the global optimization algorithm is used to design the microwave device. This ordinary method can achieve high accuracy, but the main disadvantage is time-consuming. It takes a long time and sometimes takes days or even weeks. In order to improve the efficiency of the optimization of microwave devices, this research presents a method called fitness-estimation-based particle swarm optimization (fePSO). According to the explicit evolution formula of particle swarm optimization (PSO), the particles fitness predictive model is constructed. From the third generation, the fitness value is estimated by the predictive model, so as to replace the time-consuming full-wave electromagnetic simulation when optimizing complex microwave devices. Thereby it can greatly reduce the evaluation time of the fitness, shorten the entire optimization process, and improve the design efficiency. This method is validated by optimizing Yagi microstrip antenna (MSA) and hairpin SIR band-pass filter. The results show that the efficiency can be increased by about 90% with the assurance of design accuracy, so the purpose of rapid optimization has been achieved.

Index Terms — Antenna, filter, particle swarm optimization.

I. INTRODUCTION

With the rapid development of modern communication systems, microwave devices, as an important part of communication systems, play an important role in civil and military communications. Therefore, the demand for various microwave devices with complex structures is also growing. In order to meet the needs of development of microwave devices, it is an important research area to improve the performance of microwave devices through optimization. When optimizing complex microwave devices, global optimization algorithms are used exploiting full-wave electromagnetic simulation software [1]. The commonly used global optimization algorithms include genetic algorithm (GA) [2], particle swarm optimization (PSO) [3], etc. The commonly used full-wave electromagnetic simulation softwares include High Frequency Structure Simulator (HFSS), IE3D, Computer Simulation Technology (CST), etc. In this process, full-wave electromagnetic simulation software evaluates the performance of microwave devices. The evaluation result is as fitness of global optimization algorithm to design microwave devices. Although this method can achieve high precision, it is very time-consuming. It may take days or even weeks to design a microwave device that meets the design specifications, and it has high requirements for the computer performance. Therefore, it has some limitations when designing complex microwave devices. Under this research background, how to reduce the computing time to design microwave devices has become a hot topic.

In order to solve this problem, machine learning methods have been applied in designing and optimizing microwave devices. Through constructing surrogate models and reducing the evaluation number of full-wave electromagnetic simulation, the methods can decrease the optimizing time. Currently, the most common and popular methods are artificial neural network (ANN), support vector machine (SVM) and Gaussian process (GP), etc. Zhang described the design process of radio frequency and microwave devices from theory to practice using ANN in [4]. In [5], ANN was proposed to predict the resonant frequency of a single-feed corner-sliced circularly polarized microstrip antenna (MSA). In [6], the authors used the particle behavior parallelization of PSO to accelerate ANN training, and modeled the resonant frequency of rectangular MSA under compute unified device architecture (CUDA). Yi et al. in [7] proposed a knowledge-based neural network (KBNN) based on Advanced Design System (ADS) and applied

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it to design filters. Angiulli proposed SVM-based microwave device modeling in [8]. Al Sharkawy et al. in [9] proposed a new CAD system for the detection of breast cancer in mammograms. The discrete wavelet transform (DWT), the contourlet transform, and the principal component analysis (PCA) were all used for feature extraction; while the SVM was used for classification. Sun et al. in [10] proposed a SVM combined with a hybrid kernel function (HKF) for accurately modeling the resonant frequencies of the compact microstrip antenna (MSA). Kayabasi in [11] presented a SVM based analysis and synthesis models for the equilateral triangular ring microstrip antennas (ETRMAs) that operated at ultrahigh band applications. Villier modeled ultra-wideband and dual-frequency coplanar waveguides fed slot antennas using GP [12-13]. Chen et al. in [14] proposed a KBNN based on GP and applied it to design microstrip antenna. In general, the construction of these prediction models consists of two parts, sampling and modeling. These prediction models usually don't have a direct formula, so it is not built by looking for model parameters. Instead, it approximates the function by learning a large number of samples. The correctness of the model has a great relationship with the sample selection. As the dimension increases, the difficulty of constructing a prediction model also increases. ANN training requires a large number of samples and the model structure is not easy to be determined, and it usually suffers problems of over-fitting or under-fitting. For SVM and GP, it is difficult to find a suitable kernel function and optimal hyper parameters.

The fitness inheritance method is another approach to predict the fitness, that is, the fitness of the children inherits that of the parents in a certain way. In [15], Smith proposed that in the evolutionary process of GA, inherited fitness could be used instead of the true fitness. The fitness of some individuals in the population was directly assigned to the average value of their parents' fitness, reducing the actual evaluation of the number of evaluations. Salami and Hendtlass [16] proposed a fast evolutionary algorithm. The fitness of the offspring was directly assigned by the weighted average of the fitness of the parent. Sun [17] proposed a fitness inheritance and estimation technique to reduce the number of fitness evaluations by using different linear combinations of historical location fitness and directly assigning recent historical location fitness. Xiao [18] proposed a novel fitness estimation based particle swarm optimization algorithm with an adaptive penalty function approach (FEPSO-AP) to handle the problem of expensive computational cost of truss analysis. Cui [19] proposed a fast PSO algorithm based on the change of particle velocity and position. Only when the confidence of the particle fitness was lower than a certain threshold, the true fitness was needed to calculate. Different from the sample prediction model, the inheritance prediction model does not need a large number of sample selection, it can save a large number of sample acquisition time. Simultaneously, it can avoid the prediction model error caused by the improper sampling.

As we all know, PSO is a typical swarm intelligence optimization algorithm that is simulated bird swarm in search of food processes, which was proposed by Kennedy, a social psychologist, and Eberhart, an electrical engineer [1, 20-21]. The theory is that collaboration among the particles generates group intelligence to guide search. PSO considers each individual as a particle without weight and volume in space and flies at a certain speed in the search space with reference to the flight experience of the group and the flight experience of the particle itself. As an effective parallel search method, the algorithm preserves the global search strategy based on population, and does not need to rely on the feature information of the problem itself. It adopts a simple velocity-shift evolution model to avoid complicated genetic operations. PSO has the advantages of simple operation, fewer parameters to be adjusted and faster convergence, which are quite effective for the optimization of nonlinear problems, combinatorial problems and hybrid nonlinear problems [22]. PSO algorithm has many successful applications in designing microwave devices, such as filters [23-25] and antennas [26-27]. The evolutionary process of PSO is an iterative optimization process. As the number of iterations increases, individuals in the population gradually converge to the optimal solution of the problem. If the individual fitness prediction model can be constructed according to the characteristics of the algorithm, not only the time consumption of sampling can be avoided, but also the optimization ability of the algorithm can be kept while greatly reducing the calculation times of the real fitness. Therefore, based on the PSO evolutionary formula, this paper constructs a PSO algorithm with predictive mechanism to design complex microwave devices with high efficiency.

The specific content of this paper is structured as follows. Section II presents a brief introduction of the standard PSO and theory of the proposed fitness-estimation-based PSO (fePSO). In Section III, the method is introduced in the optimization of microstrip Yagi MSA. In Section IV, the method is introduced in the optimization of hairpin-type SIR band-pass filter. Finally, summarizes are provided in section V.

II. THE FePSO ALGORITHM

A. Standard PSO algorithm

In PSO, the state vector of each particle usually contains the position and velocity. At the beginning of the search, the state of particles is given randomly within the search range. During the search there are two important pieces of information that be retained, one is the best location named *pbest* for each particle, the other is the best location named *gbest* for the entire population. The best location is measured by fitness function. Each particle is driven toward its best location and the optimal location of the population. There are fewer parameters to be adjusted, but these parameters directly affect the performance and convergence. One of the parameters is the inertia weight factor ω. A large ω can jump out of the local optimum, which is in favor of looking for the global optimum. A small ω is beneficial to the local optimization and accelerates the convergence of the algorithm.

The PSO can be described in mathematical language. Assuming that the particles search space is *n*-dimension, and the entire particle swarm $\boldsymbol{x}=\left(x_1,x_2,\cdots,x_m\right)^T$ contains *m* particles. The location of the particle *i* is $\boldsymbol{x}_i=\left(x_{i,1},x_{i,2},\cdots,x_{i,n}\right)^T$. At this time, the particle velocity is $\boldsymbol{v}_i=\left(v_{i,1},v_{i,2},\cdots,v_{i,n}\right)^T$ and the best individual particle is $\boldsymbol{p}_i=\left(p_{i,1},p_{i,2},\cdots,p_{i,n}\right)^T$. When particles find the best individual locations and the global best location, we can use equation (1) and (2) to update their velocity and positions:

$$\begin{aligned} v_{i,d}^{(k+1)} &= \omega v_{i,d}^{(k)} + c_1 rand()(pbest_{i,d}^{(k)} - x_{i,d}^{k}) \\ &\quad + c_2 rand()(gbest_{i,d}^{(k)} - x_{i,d}^{(k)}) \end{aligned}, \tag{1}$$

$$x_{i,d}^{(k+1)} = x_{i,d}^{(k)} + v_{i,d}^{(k+1)}, \tag{2}$$

where c_1 and c_2 are accelerating constants; $rand()$ is used to generate a random number between (0,1); $v_{i,d}^{(k)}$ and $x_{i,d}^{(k)}$ are the velocity and positions of the *d*th dimension of particle *i* in the *k* iteration; $pbest_{i,d}^{(k)}$ is the best individual position of a particle and $gbest_{i,d}^{(k)}$ is the best position of the global particles.

B. The description of the proposed fePSO algorithm

For particle *i* in the population, the standard PSO velocity update formula (1) is substituted into the position update formula (2), we have:

$$\begin{aligned} x_{i,d}^{(k+1)} &= x_{i,d}^{(k)} + \omega v_{i,d}^{(k)} \\ &\quad + c_1 rand()(pbest_{i,d}^{(k)} - x_{i,d}^{k}) \\ &\quad + c_2 rand()(gbest_{i,d}^{(k)} - x_{i,d}^{(k)}) \end{aligned}. \tag{3}$$

From (2), we know that:

$$x_{i,d}^{(k)} = x_{i,d}^{(k-1)} + v_{i,d}^{(k)}. \tag{4}$$

Thus,

$$v_{i,d}^{(k)} = x_{i,d}^{(k)} - x_{i,d}^{(k-1)}. \tag{5}$$

Substituting (5) into (3), after rearrangement, it becomes:

$$\begin{aligned} x_{i,d}^{(k+1)} &= (1+\omega - c_1 rand() - c_2 rand())x_{i,d}^{(k)} \\ &\quad -\omega x_{i,d}^{(k-1)} + c_1 rand()\, pbest_{i,d}^{(k)} \\ &\quad + c_2 rand()\, gbest_{i,d}^{(k)} \end{aligned}. \tag{6}$$

From (6), we know that the (*k*+1)-th generation position $x_{i,d}^{(k+1)}$ of particle *i* can be obtained by linear combination of $x_{i,d}^{(k)}$, $x_{i,d}^{(k-1)}$, $pbest_{i,d}^{(k)}$ and $gbest_{i,d}^{(k)}$. Thus, the (*k*+1)-th generation fitness $f\left(x_{i,d}^{(k+1)}\right)$ of particle *i* can be obtained by these four locations fitness linearly weighted, where weight coefficients can be determined by the distances from the (*k*+1)-th generation position $x_{i,d}^{(k+1)}$ of particle *i* to $x_{i,d}^{(k)}$, $\boldsymbol{x}_{i,d}^{(k-1)}$, $pbest_{i,d}^{(k)}$ and $gbest_{i,d}^{(k)}$. Suppose $d_i^{(k)}$, $d_i^{(k-1)}$, $d_{ip}^{(k)}$ and $d_{ig}^{(k)}$, respectively, denote the distances from the (*k*+1)-th generation position $x_{i,d}^{(k+1)}$ of particle *i* to $x_{i,d}^{(k)}$, $\boldsymbol{x}_{i,d}^{(k-1)}$, $pbest_{i,d}^{(k)}$ and $gbest_{i,d}^{(k)}$. The (*k*+1)-th generation fitness $f\left(x_{i,d}^{(k+1)}\right)$ of particle *i* can be calculated as follows:

$$\begin{aligned} f(x_{i,d}^{(k+1)}) &= \frac{1}{\alpha}\frac{1}{d_i^{(k)}} f(x_{i,d}^{(k)}) + \frac{1}{\alpha}\frac{1}{d_i^{(k-1)}} f(x_{i,d}^{(k-1)}) \\ &\quad + \frac{1}{\alpha}\frac{1}{d_{ip}^{(k)}} f(pbest_{i,d}^{(k)}) \\ &\quad + \frac{1}{\alpha}\frac{1}{d_{ig}^{(k)}} f(gbest_{i,d}^{(k)}) \end{aligned}, \tag{7}$$

where

$$\alpha = \frac{1}{d_i^{(k)}} + \frac{1}{d_i^{(k-1)}} + \frac{1}{d_{ip}^{(k)}} + \frac{1}{d_{ig}^{(k)}}. \tag{8}$$

Obviously, if the fitness of the particle *i* in (*k*-1)-th generation and *k*-th generation are known, the fitness in (*k*+1)-th generation can be predicted by the formula (7). Like the standard PSO, the best position of population in this method is also selected from the best position of all individuals.

It must be mentioned that in formula (7) distances $d_i^{(k)}$, $d_i^{(k-1)}$, $d_{ip}^{(k)}$, and $d_{ig}^{(k)}$ have an very important impact on the fitness value $f\left(x_{i,d}^{(k+1)}\right)$. If one of them is too small, its reciprocal will be very large, and it will be the main part of the fitness value. Moreover, if one of them is zero, the expression (7) has no meaning. So, we have to avoid this happened. Usually, we should give a certain threshold. If the distance is less than the threshold, the algorithm will be terminated. Of course, as we all know as the PSO algorithm evolutes, the $x_{i,d}^{(k+1)}$ will approaches the $gbest_{i,d}^{(k)}$. In this situation, the termination is normal. Otherwise, the termination is abnormal, which we should avoid it. In this paper, the threshold is 0.0001.

C. Proposed PSO algorithm

The flowchart of the fePSO algorithm is shown in Fig. 1, and the main steps of the proposed algorithm for optimizing complex microwave devices are as follows.

(1) Modeling the microwave device in HFSS;

(2) PSO initialization, including population size, inertia weight, cognitive coefficient and social coefficient, number of iterations;

(3) For the first two generations of the population, calculate particles fitness using the model in HFSS, which is the true fitness, and update particles velocity and positions according to formula (1) and (2);

(4) According to the previous two generations particles position and fitness, we can calculate the next generation particle fitness using formula (7), which is the estimated fitness, and then update the particles position using formula (6);

(5) Return to step (4) until the number of iterations is reached, then the algorithm stops.

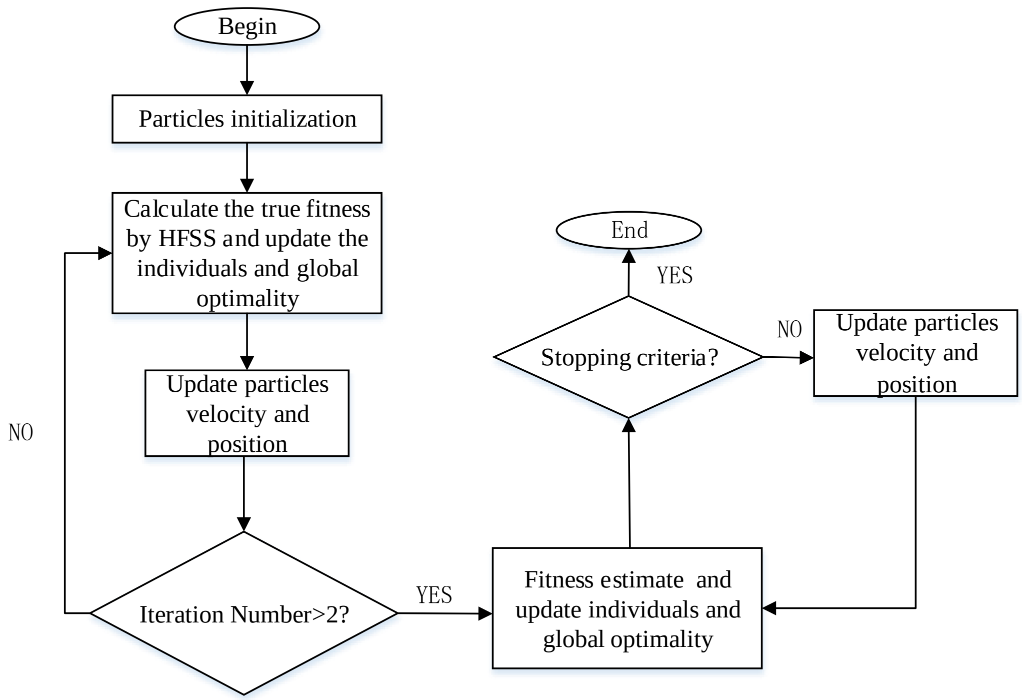


Fig. 1. Flowchart of the proposed fePSO algorithm.

III. OPTIMAL DESIGN OF YAGI MSA BASED ON THE PROPOSED fePSO ALGORITHM

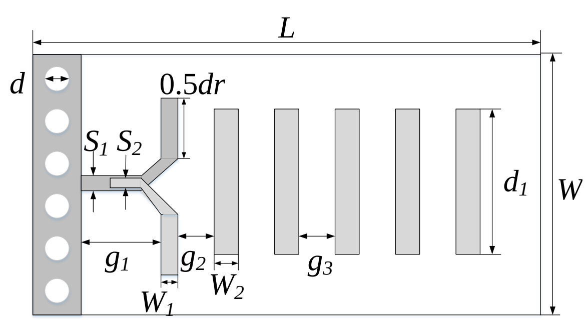
Yagi-Uda antenna was developed by two Japanese scholars Shintaro Uda and Hidetsugu Yagi in 1920, and it is called "Yagi Antenna" for short [28]. Yagi antenna is composed of a feeder oscillator and several passive parasitic oscillator side by side, and it is a commonly used for radar, television and meter, decimeter band end-fire antenna in communication. In 1989, Huang designed a Yagi MSA for mobile satellite equipment [29]. Yagi MSA has get high attention due to its small size, light weight, compact structure, easy processing and integration features. In 1998, Qian proposed a Yagi MSA with broadband characteristics [30]. The broadband impedance matching was performed on the antenna through microstrip line to a broadband balun structure with coplanar strip line [31], and it used a truncated floor acting as a reflector. As a result, it gained 17% relative bandwidth and 6.5 dB gain. The Yagi MSA is widely used in tunnels, narrow mines due to its high gain and wide beam width. In this section, we will optimize a Yagi MSA by the proposed fePSO algorithm.

The structure of the Yagi MSA is shown in Fig. 2 (a) and its HFSS model is shown in Fig. 2 (b). The antenna uses a tapered microstrip balun for feeding, and uses a tapered structure to connect the microstrip line and the excitation array. There is a reflection array, an excitation array and a lead array on the substrate. The parameters related to the performance of the antenna include the length of the reflection element W, the diameter of the cylinder d, the length of the excitation element d_r and the width W_1, the length and width of the lead element d_1 and W_2, the distance between the excitation element and the reflection element g_1, the distance between the excitation element and the lead element g_2, the distance between the lead elements g_3, the width of the feed microstrip line S_2 and the width of the ground plane S_1. The dielectric board material is FR4, which length is L, width is W, thickness is h, the relative dielectric constant ε_r = 4.4 and dielectric loss tangent $\tan\delta = 0.02$.

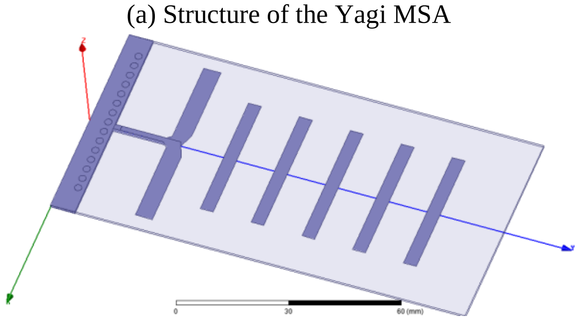
The design specifications of the antenna is that the center frequency is 2.45GHz covering 2.4 ~ 2.483GHz WiFi frequency band. Totally, there are 12 variables except the dielectric board. We select 4 variables to optimize, and the other fixed sizes are shown in Table 1. The optimized size parameters are $\boldsymbol{v}=[d_r\ g_1\ g_2\ g_3]$, where the range of each parameter is d=[40, 45], g_1=[15, 20], g_2=[8, 14], $g_2 = g_3$.

Table 1: Fixed parameters of the Yagi MSA

Names	**Value (mm)**
W	60
d	2
W1	4.96
d1	37
W2	3.7
S2	1.5
h	0.8
L	120



(a) Structure of the Yagi MSA



(b) Model of the Yagi MSA in HFSS

Fig. 2. The Yagi MSA.

Select 24 groups $\boldsymbol{v}=[d_r\ g_1\ g_2\ g_3]$ as the initial population using orthogonal design method, which means the number of particles is 24. The maximum number of iterations is 500. For the first two generations of the population, calculate reflection coefficient S_{11} in HFSS, which is the true fitness, and update particles velocity and positions according to equation (1) and (2), where $c_1=c_2=2$, $\omega=1$. According to the previous two generations particles position and fitness, we can calculate the next generation particle fitness using equation (7) and update the particles position using equation (6). When the number of iterations is reached, we may save the optimal size combination. Then, we model the Yagi MSA with the optimal sizes into HFSS to calculate exact solution for comparison.

In this example, the fitness function of the fePSO is given by:

$$Fit = \max\left|S_{11@2.45GHz}\right|. \tag{9}$$

According to the proposed fePSO algorithm and equation (9), we get the optimal result, which is $\boldsymbol{v}$ = [41.6252 18.3370 12.1976 12.1976].

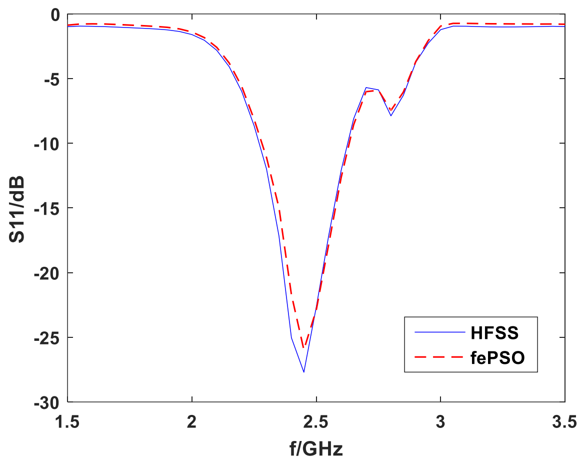
After optimization, the accuracy of the model is evaluated using the average absolute error (ABE). Assume $y_{pred,i}$ is calculated by equation (7), and its precision value computed by HFSS is y_i. We select T data points for each group of data, so the ABE is given by:

$$ABE = \frac{1}{T}\sum_{i=1}^{T}\left|y_{pred,i} - y_i\right|. \tag{10}$$

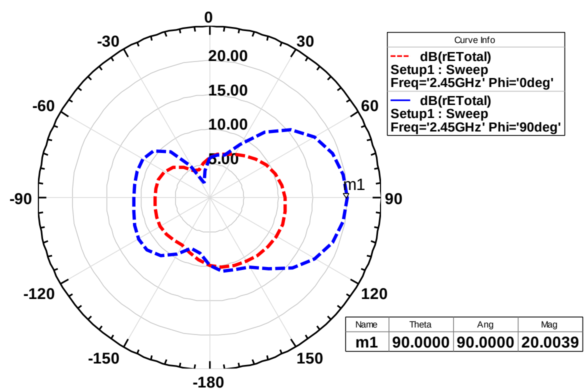
Table 2: ABE of different test samples

Test Sample Number	**ABE**
1	0.2013
2	0.2955
3	0.1981
4	0.2480
5	0.3314

In order to demonstrate the accuracy of formula (7), in this example, we select five sets of sizes randomly in the 3rd generation as test samples for comparison with computing results by HFSS, and the results are in Table 2. There are 41 points selected for the S_{11}, that is, T = 41 in (10), then the ABE is calculated. It can be seen from Table 2 that the ABE of the five test samples are around 0.2. Also, according to (10), we compute the ABE of the optimized result, which is 0.2610. Therefore, we can conclude that the results given by the fePSO algorithm are very close to the accuracy values in HFSS, which means the method is effective.



(a) S_{11} of the optimized Yagi MSA



(b) Pattern of the optimized Yagi MSA

Fig. 3. Optimal results of the Yagi MSA.

The performance of the optimized Yagi MSA is given in Fig. 3. From Fig. 3 (a) we know that the resonant frequency is 2.45GHz, the attenuation is -27dB, and covers the WiFi frequency band from 2.4 to 2.483GHz with -10dB. Figure 3 (b) shows the radiation pattern. It can be seen that the maximum gain of the optimized Yagi MSA can reach 20dB at 2.45 GHz, which meets the requirements. Therefore, the fePSO algorithm can be used to optimize the Yagi MSA, and the performance is excellent.

When optimizing the Yagi MSA by using standard PSO exploiting HFSS, it takes about 150s for a particle, therefore 24 particles need around 1800000s after 500 iterations. When optimizing the Yagi MSA by GP, establishing a precise GP model needs at least 28 sets of data after many trials. Only calculating HFSS to acquire 28 sets of data requires 4004s. But before modeling, it needs tedious manual extraction and arrangement of the data. When establishing a precise ANN model for the Yagi MSA, it requires more than 28 sets of data, the total time will be more time-consuming than optimization by GP model. Moreover, the training time either GP or ANN is necessary. However, it only needs 7210s using the proposed fePSO algorithm after 500 iterations. Therefore, the optimization of the Yagi MSA using the fePSO algorithm can greatly shorten the optimization time.

IV. OPTIMAL DESIGN OF SIR MICROSTRIP BANDPASS FILTER BASED ON THE PROPOSED fePSO ALAGORITHM

In microwave communications, microstrip bandpass filter directly affects the performance of the system. There are many kinds of microwave bandpass filters, such as capacitive gap coupling transmission line bandpass filters, comb bandpass filters, interdigital filters and half-wavelength resonators parallel coupled bandpass filters. Straddy Impedance Resonator (SIR) parallel coupled bandpass filter is a unique parallel coupled bandpass filter. It was first proposed by Mitsuo Makimoto and Sadahiko Yamashita in 1980 [32], which is an essential components between the low-noise final amplifier and Mixer. Compared with the traditional microstrip filters, the hairpin SIR microstrip bandpass filter has the advantages of small size, easy integration and low cost. By controlling the coupling and non-coupling segments, the position of the parasitic passband can be controlled. The problem of harmonic suppression is solved, so it has been widely used in the L-band and S-band.

The structure of the L-band hairpin SIR microstrip band-pass filter is shown in Fig. 4 (a), and the HFSS model is shown in Fig. 4 (b). The parameters for a single resonator are as follows: l_1 and l_c are the length of the different microstrip lines; w_t and w_c are the width of the different microstrip lines; l_2 is the width of a single resonator unit and l-l_2 is the spacing of adjacent resonator units; The thickness of dielectric substrate is h and the relative dielectric constant $\varepsilon_r = 9.5$.

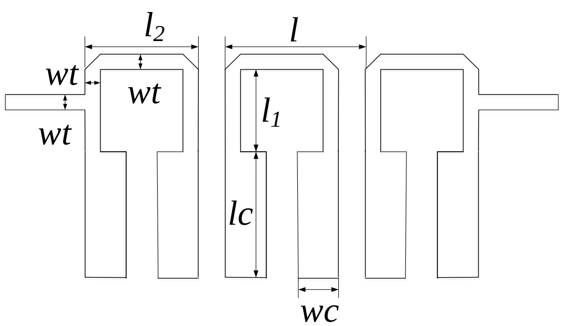
The design specifications of the SIR microstrip bandpass filter are that the center frequency is 1.2GHz, -3dB bandwidth is greater or equal to 50MHz, $S_{21} \leq -40$ dB in 1.05GHz and 1.35GHz. In this example, two sizes are selected for optimization. The optimized size parameter is $\boldsymbol{v}=[w_t\, l_1]$, where the range of each parameter is w_t=[0.5, 0.9], l_1=[6.5, 8.5]. Other dimensions are fixed, as shown in Table 3.

Select 24 groups $\boldsymbol{v} = [w_t\, l_1]$ as the initial population using orthogonal design, in which the number of particles is 24. The maximum number of iterations is 500. For the first two generations of the population, calculate transmission coefficient S_{21} in HFSS, which is the true fitness, and update particles velocity and positions according to equation (1) and (2), where $c_1=c_2=2$, $\omega=1$. According to the previous two generations particles position and fitness, we can calculate the next generation particle fitness using equation (7) and update the particles position using equation (6). When the number of iterations is reached, we get the optimal size combination. After that, the SIR microstrip band-pass filter with the optimized parameters is modeled in HFSS to calculate its exact solution for comparison.

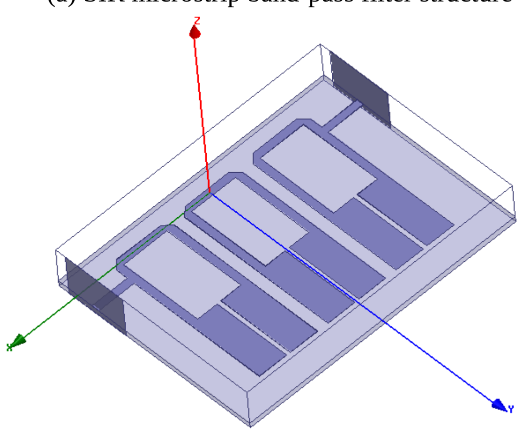
In this example, the fitness function of the fePSO for the filter is given by:

$$Fit = \left(S_{21@1.185GHz} < 3\right) \& \& \left(S_{21@1.235GHz} < 3\right) \\ \& \& \left(S_{21@1.05GHz} > 40\right) \& \& \left(S_{21@1.35GHz} > 40\right). \tag{11}$$

According to the proposed fePSO algorithm and equation (11), we get the optimal result, which is $\boldsymbol{v}$ = [0.8074 8.3717].



(a) SIR microstrip band-pass filter structure



(b) SIR microstrip band-pass filter model in HFSS

Fig. 4. The SIR microstrip bandpass filter.

Table 3: Fixed parameters of the SIR microstrip bandpass filter

Names	**Value (mm)**
wc	2.76
lc	7.25
l_2	5.2
l	7
h	0.254

In order to demonstrate the accuracy of formula (7), in this example, we select five sets of sizes randomly in the 3rd generation as test samples for comparison with computing results by HFSS, and the result is in Table 4. There are 61 points selected for the S_{21}, that is, T = 61 in (10), then the ABE is calculated. It can be seen from Table 4 that the ABE of the five test samples are around 0.5. Also, according to (10), we compute the ABE of the optimized result, which is 0.6792. Therefore, we can conclude that the results given by the fePSO algorithm are very close to the accuracy values in HFSS, which means the method is effective.

Table 4: ABE of different test samples

Test Sample Number	**ABE**
1	0.4792
2	0.5602
3	0.4125
4	0.7939
5	0.4489

From the optimized result in Fig. 5 we can see that the SIR microstrip bandpass filter center frequency is 1.2GHz and the 3dB cutoff bandwidth reached 50MHz. At 1.05 GHz and 1.35 GHz, the decay have reached 40dB. It can meet the design requirements.

When optimizing a SIR microstrip bandpass filter by using standard PSO exploiting HFSS, it takes about 40s for a particle in HFSS and 24 particles need around 480000s after 500 iterations. When optimizing design the SIR microstrip band-pass filter by GP, we find it needs at least 10 sets of data after many trials for establishing a precise GP model. Only calculating HFSS to acquire 10 sets of data requires 400s. Also, we need some time to train the GP. When establishing a precise ANN model of the SIR microstrip band-pass filter, it requires more than 10 sets of data, the total time will be more time-consuming than optimization by GP model. However, it only needs 1930s using the proposed fePSO algorithm after 500 iterations. The optimization of the SIR microstrip bandpass filter using the fePSO algorithm can greatly increase the optimization design efficiency.

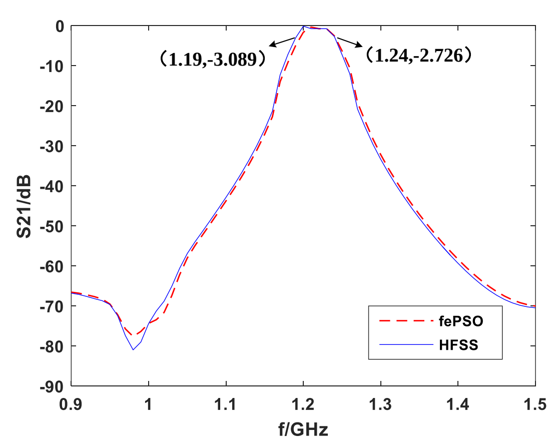


Fig. 5. S_{21} of the optimized SIR bandpass filter.

V. CONCLUSION

When optimizing complex microwave devices, it takes a lot of time to use global optimization algorithms exploiting full-wave electromagnetic simulation software. The most commonly used fitness prediction methods such as neural networks, support vector machines and Gaussian processes require sample acquisition and training. And the choice of sample affects the correctness of the constructed model. The fitness estimation method proposed in this paper is derived from the explicit evolutionary formula of particle swarm optimization, that is, the fitness of the offspring is obtained through the weighted average of the fitness of the parents. Therefore, only the first and the second generation true fitness are needed. The third generation fitness can be obtained by weighting the position and fitness of the first and the second generation particles, and the fourth generation fitness can be obtained by weighting the position and fitness value of the second and the third generation particle, and so on. When optimizing the microwave devices, only the first two generations of particles need to be solved in the full wave electromagnetic simulation software, and then the prediction formula is used in the subsequent iterative optimization, which can greatly improve the optimization efficiency. In this paper, the Yagi microstrip antenna and hairpin SIR bandpass filter are optimized respectively. From the results, it can be seen that this method can achieve good optimization design in a short time, so this method provide theoretical guidance for the optimal design of complex microwave devices.

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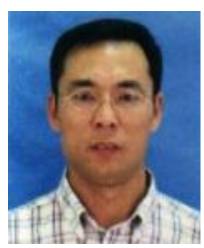

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