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Optimal design of E-shaped microstrip antenna in terms of self-renewing fitness estimation of particle swarm optimization algorithm

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Abstract

When the method of global optimization algorithm call the full-wave electromagnetic simulation software can not meet the requirements of efficient of designing microstrip antennas, this paper proposes a self-renewing fitness estimation method of PSO (SFEPSO) to improve the design efficiency. Firstly, construct the prediction model of the fitness based on the explicit evolutionary formula of the PSO algorithm. Then from the third generation of the algorithm, the fitness is given by the prediction model replaces the full-wave electromagnetic simulation. The model will be proofread every eight generations. If the prediction model accuracy is lower than the set threshold, the true fitness of this generation will be recalculated, and a new prediction model will be re-established by this generation particles and the latest generation particles with real fitness in the iterative history. Lastly, continuously update the prediction model during the optimization iteration process until the design specifications are met. Compared with the traditional optimization method, this method greatly reduces the evaluation time and improves the design efficiency. This method is verified by the E-shaped microstrip antenna. The results show that the purpose of rapid optimization can be achieved while ensuring the accuracy of the designing.

1. Introduction

When designing complex antennas, the method of full-wave electromagnetic simulation software call the global optimization algorithm is generally used [1], but this method requires a lot of time in the analysis. In order to improve the design efficiency, the machine learning aided design method [2, 3, 4] is gradually emerging. This fitness prediction method includes sampling and modeling. The function is approximated by learning a large number of samples, but the correctness of the constructed model depends on the selection of samples, and there are also problems such as dimensional disasters. The fitness inheritance method is another fitness prediction method [5, 6], that is, the fitness of the subclass inherits the fitness of parents in a certain way. Usually, the method has a direct preset formula and it doesn't require a large number of sample selections, so it can avoid prediction model errors caused by inappropriate sampling. This paper constructs a fitness prediction model based on the evolution formula of PSO (Particle swarm optimization), which not only avoids the time required for sample selection, but also maintains the optimization ability of the algorithm, and greatly reduces the number of calculations of true fitness.

2. Fitness estimation of PSO algorithm

The position and velocity update formula of the standard PSO algorithm is

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

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

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.

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

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

From (2), we know that

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

Thus,

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

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

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

Formula (6) is the position update formula of particles in the fitness estimation method of PSO (FEPSO). And we can find 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. So the (k+1)th generation fitness $f\left(x_{i,d}^{(k+1)}\right)$ of particle i can be linearly weighted by the fitness of these four locations. The (k+1)th generation fitness $f\left(x_{i,d}^{(k+1)}\right)$ of particle i can be calculated as follows:

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

$$\alpha = \frac{1}{\frac{1}{d_i^i(k)} + \frac{1}{d_i^i(k-1)} + \frac{1}{d_i^{pi}(k)} + \frac{1}{d_i^{pg}(k)}} \quad (8).$$

Where, $f\left(x_{i,d}^{(k-1)}\right)$, $f\left(x_{i,d}^{(k)}\right)$ and $f\left(x_{i,d}^{(k+1)}\right)$ are respectively denote the fitness of the $k-1$ 、 k 、 $k+1$ generation particles. $d_i^i(k)$, $d_i^i(k-1)$, $d_i^{pi}(k)$ and $d_i^{pg}(k)$ are 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 $gbest_{i,d}^{(k)}$.

3. Gaussian variation

Gaussian variation is that a Gaussian variation matrix with a mean of 0 and a standard deviation of 1 is generated by a Gaussian distribution function, and the obtained results multiply each dimension of the original particle as an update step. Since the peak of the Gaussian distribution curve is located at the position of the mean value, the Gaussian mutation will focus on the local area near the original particle, and the convergence ability of the algorithm is improved. The Gaussian variation formula is

$$stepsize = normrnd(0,1,D) \quad (9).$$

$$X_i^{t+1} = X_i^t + stepsize \oplus X_i^t \quad (10).$$

Where *stepsize* is the step, *normrnd(0,1,D)* is the Gaussian distribution function, D is the dimension.

4. Self-renewing fitness estimation of PSO algorithm

The steps of the optimal design microstrip antennas by SFEPAO method are as follows:
(1) The antenna to be optimized is modeled in HFSS;

(2) PSO algorithm population initialization, including the population size, inertia weight, cognitive coefficient and social coefficient;

(3) For the first two generations of the population, calculate the fitness of each particle using the HFSS model which is the fitness function;

(4) According to the position and fitness of the first two generations of particles, calculate the fitness of the next generation particles by equation (1), and update the position of the particles by equation (2);

(5) Repeat step 4), after iterations reached per 8 times, judged whether the position of the optimal particle of this generation is the same as that of the previous 8 generations. If it is different, go to step 6). If it is the same, add a Gaussian variation operator to the optimal particles of this generation and go to step 6);

(6) Call HFSS to judge whether the optimal particle has reached the design index. If reached, the algorithm ends. If not, proceed to step 7);

(7) Judged whether the error between the HFSS exact value and the predicted value is less than the threshold. The threshold in this paper is 1.3 times the average absolute error between the predicted value and the accurate value of the third generation particles. If the error is less than the threshold, return to step 5). If not, calculate the fitness of all particles of this generation by HFSS, and predicted and updated by the particles of the latest generation with real fitness and this generation particles with new true fitness by formulas 1) and 2), then return to step 5) ;

(8) The algorithm ends until the optimal particle reaches the design specification.

5. E-shaped microstrip antenna design

This paper introduces a common E-shaped microstrip antenna. The structure is shown in Figure 1. It achieves a wide-band effect by slotting on a rectangular microstrip antenna. The antenna is coaxially fed, and the patch is located at the center of the dielectric substrate and the dielectric material is vacuum, G_L , G_W and H are the length, width and height of the dielectric substrate. The overall size of the dielectric substrate is 120mm*100mm*15mm. L =70mm and W =50mm are length and width of the patch. The two slots are the same size, L_S and W_S are the length and width of the slot. P_S is the distance from the centerline of the slot to the centerline of the patch. X_0 is the position of the feed point.

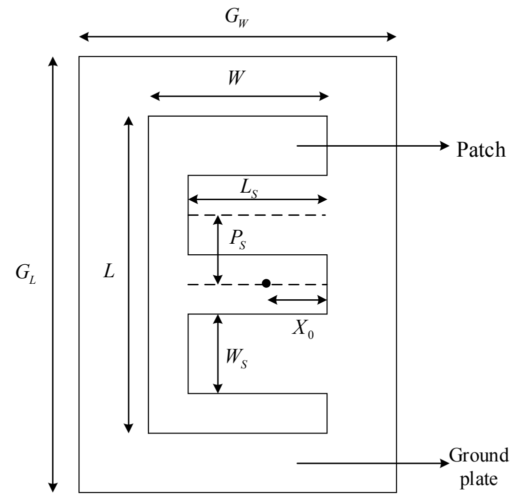

Figure 1. Structure of E-shaped patch microstrip antenna

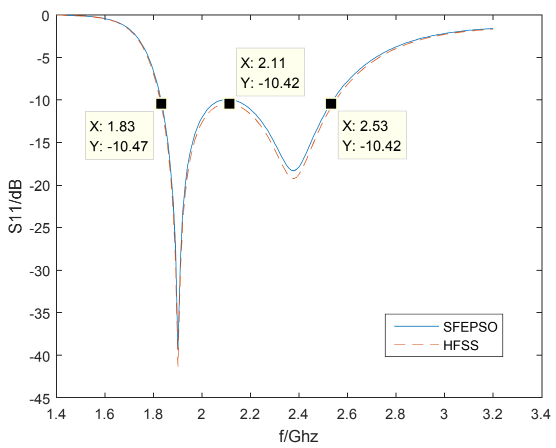

Figure 2. S_{11} of E-shaped patch microstrip antenna

The antenna design specification is -10dB bandwidth covering 1.9GHz~2.4GHz. The parameter $\boldsymbol{v}$ =[L_S W_S P_S X_0] is the optimization object, where L_S=[30, 0], W_S =[2, 10], P_S =[5, 15] and X_0=[4, 12]. The fitness function is

$$Fit = \left| y_{\max} - 10 \right| \qquad (11).$$

$$y_{\max} = \left| \max(y_{@1.9GHz} : y_{@2.4GHz}) \right| \qquad (12).$$

Where $y_{@1.9GHz}$ and $y_{@2.4GHz}$ are the S_{11} of frequency points at 1.9 GHz and 2.4 GHz. $y_{\max}$ is the maximum S_{11} in the 1.9 GHz to 2.4 GHz band.

In the algorithm, the number of particles is N=20 and the maximum number of iterations is num=200. The acceleration constant $c_1 = c_2 = 2$, and the inertia weight $\omega = 1$. The total optimization time is 2.25 hours. The S_{11} that satisfies the design specifications is shown in Figure 2. And the optimal size is $\boldsymbol{v}$ = [46.6087 10 9.04469 7.7518].

6. Conclusion

When optimal design the microstrip antenna, the method of full-wave electromagnetic simulation software called the global optimization algorithm usually takes a lot of time. The SFEPSO method proposed in this paper is derived by the explicit evolution formula of PSO algorithm, that is, the fitness of the offspring is obtained by a weighted average of the parents. Therefore, it is only necessary to calculate the true fitness of the first and second generations. The fitness of the third generation particles can be weighted by the position and fitness of the first and second generation particles. The fitness of the fourth generation particles can be weighted by the position and fitness of the second and third generation particles. In the optimization and the iteration process, the model is proofed every eight generations. If the prediction model accuracy is lower than the set threshold, the true fitness of this generation will be recalculated, and a new prediction model will be re-established by this generation particles and the latest generation particles with real fitness in the iterative history. In this paper, the E-shaped patch microstrip antenna is optimized. It can be seen from the simulation results that this method can achieve better optimization effect with a shorter time. This method provides theoretical guidance for the rapid design microstrip antennas.

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8. References

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