Optimization Design of Metamaterial Absorbers Based on an Improved Adaptive Genetic Algorithm

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Abstract **─** Most reported metamaterials are designed empirically by parameter sweep, which is time-consuming and ineffective. We propose an optimization method of designing metamaterial absorbers based on an improved adaptive genetic algorithm (IAGA), with the aim to get wideband absorption. Firstly, an IAGA optimization model is presented, of which the crossover probability is adaptively adjusted by introducing a nonlinear function, and the mutation probability is adaptively adjusted using complementary idea. Then, a wideband triple-layer metamaterial absorber in THz region is designed and optimized using IAGA, getting about 40.4% increasing of relative bandwidth compared with the results of reference [19]. A further comparison between IAGA and standard genetic algorithm (SGA) indicates that the IAGA is an effective method in improving convergence speed and stability, and can be used to optimize structure parameters of metamaterial absorbers with desired characteristics.

Index Terms **─** Absorber, adaptive genetic algorithm, metamaterial, optimization.

I. INTRODUCTION

In recent years, metamaterials have been investigated extensively by researchers all over the world. Metamaterials are artificially synthesized periodic structures with lattice constant that is much smaller than the wavelength of the incident electromagnetic wave, thus can be considered as effectively homogeneous media [1]. The effective parameters ($\varepsilon(\omega)$ and $\mu(\omega)$) can be tuned and controlled by the design of the resonance structure of unit cell. Thus, metamaterials can achieve many interesting and exotic electromagnetic properties or phenomena, and can apply to absorbers, frequency selective surfaces (FSS), gradient meta-surfaces, electromagnetic band gap structures(EBG) and artificial magnetic conductors(AMC) [1-8], etc. In 2008, the concept of prefect metamaterial absorber was proposed by Landy et al. [5], of which the perfect absorption mainly arises from locally enhanced fields because of the strong electromagnetic resonance. The electric and magnetic responses can be tuned independently so as the impedance matches to that of free space by varying the geometry of metamaterial absorbers.

However, most reported metamaterial unit cells are obtained empirically based on intuition, experience or a large number of simulation, which is time-consuming, ineffective and expensive [1-3,5,7]. Usually, in the design process of a new device, optimization methods play important roles in assisting the designer to find the best solution efficiently. These methods vary in the design variables on which they performed. There are three main categories of methods. The first one is the parameter optimization method, which uses design parameters to get a solution whose geometry has been pre-defined by the designer; The second one is the shape optimization method, which changes the boundary between each sub-domain whose topology is defined by the designer; The third one is the topology optimization method, which uses parameters to describe material distribution inside a design space. All the above optimization methods are built on mature optimization algorithms such as genetic algorithm (GA), particle swarm optimization algorithm (PSO), and ant colony algorithm (ACA). GA is one of the earliest algorithms which applied to the optimization design of metamaterials [4-14]. In GA, the biology evolutionary steps are simulated by taking biological evolution process as the background, and the concepts of propagation, hybridization, variation, competition and selection are introduced. As GA uses a lot of evaluations during the process of optimization, many studies are aimed to decrease the time cost [15-16]. Dealing with the shortcomings of slow convergence speed and easily premature of GA, Srinivas put forward adaptive genetic algorithm (AGA) whose crossover and mutation probability can automatically change according to the fitness [17]. However, when AGA is used to solve

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practical metamaterial optimization problems [18], the optimization process may be interrupted unexpectedly or even failed to achieve optimal results.

In this paper, we propose a metamaterial absorber design method based on an improved adaptive genetic algorithm (IAGA) technique, with the aim to wideband high-efficiency absorption. Firstly, an IAGA optimization model for wideband absorption is proposed. Then the effectiveness of the new technique is evidenced by a design example using IAGA and the comparison between IAGA and SGA.

II. IMPROVED ADAPTIVE GENETIC ALGORITHM

A. Adaptive genetic algorithm

AGA can adjust crossover and mutation probability adaptively based on individual fitness in the evolutionary process to improve the convergence. The crossover and the mutation probability, P_c and P_m are calculated as follows [17]:

$$P_c = \begin{cases} \frac{k_1(f_{max}-f)}{f_{max}-f_{avg}} & , f \geq f_{avg} \\ k_2 & , f < f_{avg} \end{cases}, \tag{1a}$$

$$P_m = \begin{cases} \frac{k_3(f_{max}-f')}{f_{max}-f_{avg}} & , f' \geq f_{avg} \\ k_4 & , f' < f_{avg} \end{cases}, \tag{1b}$$

where f_{max} and f_{avg} are respectively the largest and the average fitness of the current population, f is the fitness of individual being selected to participate in crossover, f' the fitness of individual being selected to participate in mutation, and k_1, k_2, k_3, k_4 the constants between 0 and 1, which are based on experience and practical problem [17].

In practical optimization design of metamaterials, standard adaptive genetic algorithm (SAGA) may cease unexpectedly or fail to achieve convergence solution. By analysis, we find that SAGA is prone to be interrupted during the process of evolution under improper setting of crossover and mutation probability. Specifically, the main problems are as follows.

(1) In the initial evolution stage of SAGA, the initial individual fitness may have a little difference,

$$f \approx f_{avg} \approx f_{max}, \tag{2}$$

so the standard deviation of fitness of current population can be expressed as:

$$\sigma_f = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i - f_{avg})^2} \approx 0, \tag{3}$$

where N is the current population size. In this situation, the adaptive crossover and the adaptive mutation probability cannot be calculated by Eq. (1) since arithmetic error. This may lead to abnormal interruption of the computing process and divergence of the algorithm.

(2) Theoretically, in the late evolution stage of SAGA, the algorithm gradually converges to the optimal solution,

$$\lim_{N\to\infty} f \approx f_{best}, \tag{4}$$

such trend is what we expect. However, in the actual convergence process, there will be the same problem as what was mentioned in case (1). In this case, the algorithm get stagnated or even interrupted, which makes it converge fast to a local optimum.

(3) From the schema theorem of GA, the low order, short length, and high fitness mode can generate a global optimal solution ultimately with the genetic operators [11]. As the algorithm evolution proceeds, various individual similarity increases. However, the mutation operator is still in working, which will create new individuals of a higher order, resulting in oscillation problem.

To solve the above problems of using SAGA in metamaterial optimization design, we propose an IAGA as described in the next section.

B. Improved adaptive genetic algorithm

To deal with the divergence problem of SAGA, the elite preservation strategy is employed. This strategy preserves the elite individual from each previous generation to the next generation. Meanwhile, a duplicate of elite individual participates in crossover and mutation operation, which ensures the integrity of the elite individual. Based on this strategy, we propose a new adaptive method in which adaptive adjustment will occur in the process of making a new generation. The improved method includes two aspects: Firstly, we employ a nonlinear adjustment function, exponential function, to adjust crossover and mutation probability adaptively in real-time, which can solve the divergence problem in the early evolution stage. Secondly, we adjust mutation probability adaptively based on complementary idea, which reduces the order of populations, increase the search space of the algorithm, and solve convergence oscillation problem in the late evolutionary stage.

1) Exponential adjustment function

Exponential adjustment function (Eq. (5)) is a variation of the standard exponential function, where constants α and β are adjustment factor used to adjust the decline rate of the function; G is the generation number of GA:

$$h(G) = 1/(1+e^{(\frac{G-\alpha*\beta}{\alpha})}). \tag{5}$$

Graphically, as shown in Fig. 1, at the initial stage, $h(G)$ is almost invariant; whereas with increasing G, $h(G)$ decreases gradually, which can be used to adjust the crossover and the mutation probability, to improve the convergence stability of the algorithm. The constant α controls the spread and shrink of $h(G)$. The greater α, the faster declines of $h(G)$. The constant β controls the shift of $h(G)$, and $h(G)$ right shifts with increasing β.

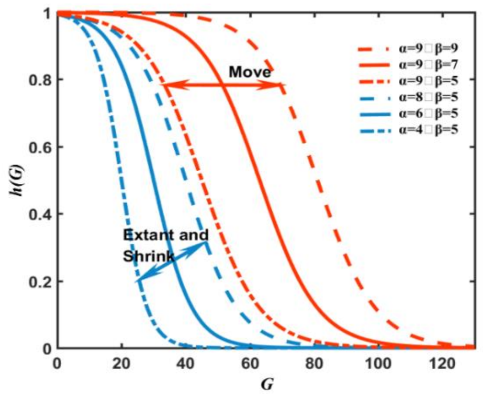

Fig. 1. The exponential adjustment function $h(G)$.

Introducing the exponential adjustment function, the crossover probability P_c of IAGA can be expressed as:

$$P_c = \begin{cases} \frac{1}{1+exp((G-\alpha*\beta)/\alpha)}*[k_0+\frac{(k_1-k_0)*(f_{max}(G)-f_{avg}(G-1))}{f_{max}(G)-f_{avg}(G)}] & ,f_{avg}(G)\geq f_{avg}(G-1) \\ k_2 & ,f_{avg}(G)<f_{avg}(G-1) \end{cases}, \quad (6)$$

where $f_{avg}(G)$ and $f_{max}(G)$ are respectively, the mean fitness and the largest fitness of all individuals in generation G; the constants k_0, k_1, and k_2 control the range of adaptive crossover probability within the scope of $[h(G)*k_0, h(G)*k_1]\cup k_2$. It should be noted that, Eq. (6) is coincident with Eq. (1) in a particular case: $h(G)=0$ and $k_0=0$. As scale factor, such an adjustment function can increase the overall coordination in the evolutionary process of SAGA, and adaptively decrease the crossover and mutation probability, reducing the probability of convergence oscillation problem in the late evolution stage.

Equation (6) indicates that in the initial stage of evolutionary algorithm, the effect of exponential adjustment function $h(G)$ on P_c is small, so the adaptive range of P_c is $[k_0, k_1]$. With G increasing, $h(G)$ decreases gradually and decrease crossover probability slightly in a nonlinear manner. In this paper, the parameters are fixed at $k_0=0.5, k_1=k_2=0.8$ as the experience value in which the GA works well for most of practical problems, and thus the adaptive crossover probability range is [0.5,0.8].

2) Adaptive adjustment strategy based on the complementary idea

Adaptive adjustment of mutation operator is implemented with complementary idea. SGA mutation operator is based on a fixed number of individuals. But this is different from the real ecological environment, of which mutation number is stochastic. We adaptively adjust the number of mutation individuals to simulate the stochastic mutation operation of the real ecological environment, according to complementary idea. The specific steps are as follows.

(1) Use the elite preservation strategy to determine *nEliteKids*, which means the number of preservation individuals. This principle allows the best individuals from the current generation to carry over to the next.

(2) Use Eq. (6) to calculate crossover probability and then determine the number of crossover individuals:

$$nXoverKids = [P_c * populationsize]. \quad (7)$$

(3) Determine the number of mutation individuals in accordance with the complementary idea:

$$nMutateKids = populationsize - nXoverKids - nEliteKids, \quad (8)$$

where *populationsize* is the population size that denotes the number of individuals in current generation.

According to schema theorem of GA, we analyze the convergence characteristic [11, 22] of IAGA. Suppose the crossover probability range is $[h(G)_{min}*k_0, k_1]$, where $h(G)_{min}$ is the minimum value of exponential adjustment function. The adaptive mutation probability can be estimated with complementary idea according to Eq. (7) and Eq. (8):

$$P_m = \frac{nMutateKids}{populationsize} = 1 - P_c - \frac{nEliteKids}{populationsize}. \quad (9)$$

Equation (9) indicates that the range of P_m is $[1-\frac{nEliteKids}{populationsize}-k_1, 1-\frac{nEliteKids}{populationsize}-h(G)_{\min}*k_0]$ and P_m will increase with decreasing P_c. According to theoretical analysis based on the genetic algorithm schema theorem, the changes of P_m versus P_c will reduce the populations order and accelerate the convergence speed.

From the analysis in section 2.2, we can get that the IAGA can adaptively adjust the crossover and mutation probabilities. The mutation probability increases with decreasing crossover probability, which helps to reduce the populations order, create new structures, and extend the algorithm search space; on the other hand, the mutation probability can be adaptively reduced when the crossover probability increases, thereby improving the convergence speed and stability. Particularly, in the late stage of IAGA, not only the crossover and mutation probability can be ensured properly, but also low order individual can be effectively avoided, leading to a better stability of the algorithm at the convergence value since the adjustment function $h(G)$.

III. OPTIMIZATION DESIGN OF WIDEBAND METAMATERIAL ABSORBERS

A. Initial design

A polarization insensitive and wide-band THz metamaterial absorber is selected as the optimizing object, with the goal of achieving the maximum absorption bandwidth. The metamaterial absorber structure in Ref. [19] is shown in Fig. 2. The metamaterial absorber consists of two metallic pattern layers separated by a FR4 substrate. The metallic parts are copper with frequency independent conductivity σ=5.8×10^7 S/m and thickness $ft = 0.017\mu m$. The geometry parameters are denoted by a, b, c, u, n, w, h.

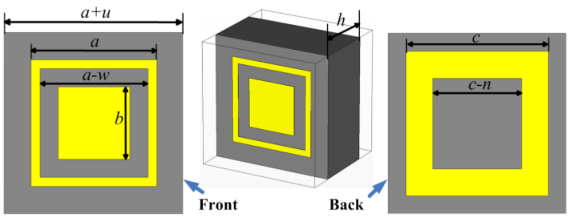

Fig. 2. The absorber unit cell structure in Ref. [19] and the geometry parameters.

1) Calculation of the absorption

The absorption can be calculated using:

$$A(\omega) = 1 - R(\omega) - T(\omega), \tag{10}$$

where $A(\omega)$, $R(\omega)$, and $T(\omega)$ are the absorption, reflectivity, and transmissivity, respectively.

This metamaterial absorber can be modeled as a two-port network. Electromagnetic waves are incident in port 1 and exit through port 2. The reflectivity and transmissivity can be calculated by S-parameters of S_{11} and S_{21}:

$$R(\omega) = |S_{11}|^2, \tag{11}$$

$$T(\omega) = |S_{21}|^2. \tag{12}$$

2) The fitness function

The metamaterial absorber optimization design is a multi-objective optimization problem [20,21], so the working band, the bandwidth and the absorption should be considered synchronously in calculating the fitness function. In the simulation frequency range $[F_{min}, F_{max}]$ (where F_{max} and F_{min} are the upper and lower limit frequencies), the optimization goal is to make the absorption bandwidth as wide as possible and meanwhile the absorption meets a certain minimum requirement. Considering these two optimization goals, we set the absorption not less than 80%, and the fitness function is:

$$f = 1 - \frac{\sum_{i=1}^{n} \Delta F_i}{F_{max} - F_{min}}, \tag{13}$$

where ΔF_i is the frequency interval distance which the absorption is not less than 80% continually. Equation (13) indicates that, the wider bandwidth, the smaller fitness value we will get, supposing the absorption is more than 80%.

3) The structure and algorithm parameters and their constraints

To ensure getting the reasonable structure, we employ an inequality to constraint the geometric parameters, as follows:

$$\begin{cases} -a+b<0 \\ -a+c-u<0 \\ -a+b+w<0 \\ -c+n<0 \\ a,b,c,u,n,w,h>0 \end{cases} . \tag{14}$$

Population size is generally in 20-40 preferably. In this paper, the population size is fixed at 20 as the minimum size in which the GA works well for most of practical problems, and its size makes it possible to perform faster computation, and the maximum generation is 30. The initial individual parameters assume the parameters in Ref. [19] and the rest initial individuals are created randomly to satisfy the constraint conditions.

B. Numerical simulation

The VBA interfaces provided by commercial electromagnetic simulation software CST and MATLAB are employed to establish an interactive simulation system [9, 20, 21]. Joint simulation flow chart with IAGA is shown in Fig. 3. The calculation configurations, in CST, are as follows: periodic boundary conditions, 2μm near-field distance, frequency-domain solver, and the frequency range $3.5-6THz$.

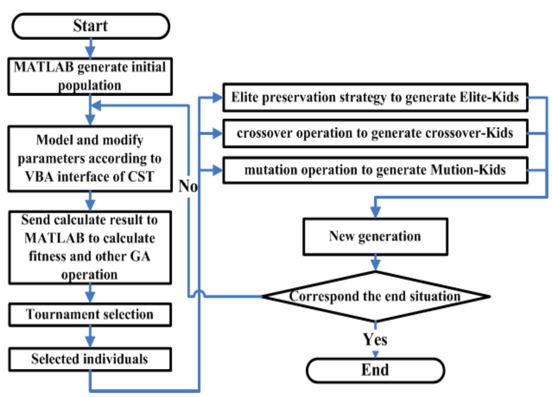

Fig. 3. Joint simulation flow chart.

C. Comparison and discussion

1) Optimization results

After 30 generations of evolution, the steady optimal individual results are obtained, as shown in Table 1 and Fig. 4.

Table1: Metamaterial absorber structure parameters

Parameters/μm	a	b	c	u	n	w	h
Before	9.75	9.00	12.10	8.25	1.00	0.25	5.00
After	8.63	7.40	12.93	5.50	4.98	0.16	5.25

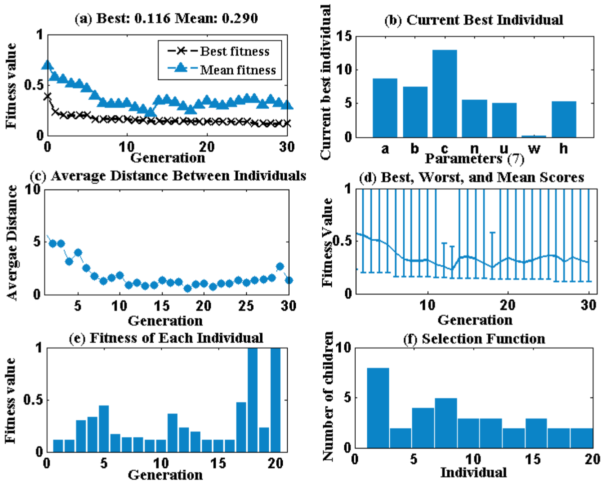

Fig. 4. The results of IAGA: (a) the best fitness value (cross mark) and the average fitness value (triangle mark) of each generation; (b) the best individual obtained from final optimization results; (c) the mean distance of all individuals in each generation (Hamming distance); (d) the optimum fitness value, the worst fitness value and average fitness value of each generation; (e) each individual fitness value of the current generation; (f) offspring quantity of the initial population.

2) Comparison with reference

As shown in Fig. 5, after the optimization, both the two resonances move to a higher position, due to the overall reduced size (Table 1). Compare to the results of Ref. [19], the absorption bandwidth increases, resulting in that the bandwidth with absorption more than 80% are increased from the original 0.805 THz to 1.604 THz with the relative bandwidth increasing of 40.4% [24]. These results demonstrate the feasibility of IAGA.

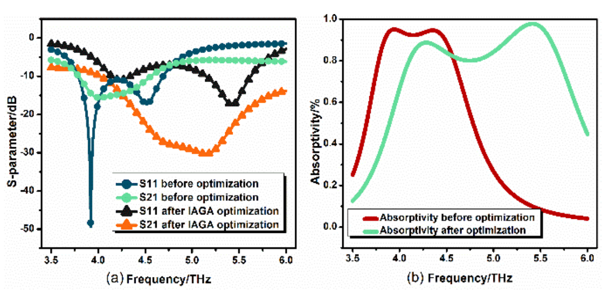

Fig. 5. (a) The S-parameter and (b) the absorption of before and after optimization.

3) Comparison between IAGA and SGA

Adopting the same structure as that of above metamaterial absorber, a real-coded SGA is employed to make a comparison with IAGA. Shown as Fig. 6, the IAGA optimal fitness value is less than SGA, which proves that the former algorithm has better global search capability. It is also found that the convergence speed of IAGA is much higher.

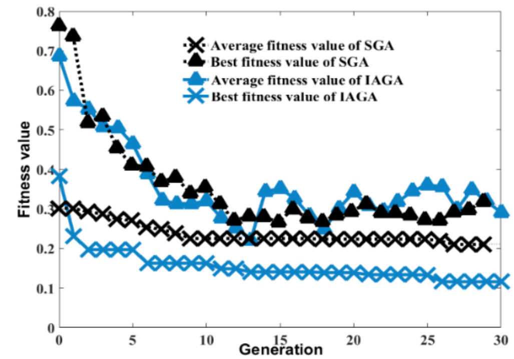

Fig. 6. Average fitness value and best fitness value of IAGA and SGA.

IV. CONCLUSION

An optimization method of designing metamaterial absorbers based on an improved adaptive genetic algorithm (IAGA) is proposed and is verified by example of THz metamaterial absorber. Firstly, a nonlinear self-adjustment function is employed to adjust crossover and mutation probability in real-time, which can solve the possible oscillation problem in the middle/late stage and the divergence problem in the early stage of SAGA. Secondly, mutation operator with the complementary idea is adjusted to decrease the population order and to create the new structure for population, improving the algorithm search space, convergence speed and stability. Lastly, the feasibility of the IAGA is verified by making comparisons with SGA, proving that the IAGA owns advantages of easy mobility, large search space, fast convergence speed and less design time. However, the IAGA has disadvantage of depending on the adjustment parameters and there is no experiment of the THz metamaterial absorber since experimental condition limitation, which is our next research direction. This method can also be extended to multi-object optimization problems such as the design of left-handed metamaterials, frequency selective surfaces, transmission line (TL) metamaterials, etc.

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