

Efficient Topology-based Optimization Method of Broadband Absorbing Material

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2 Abstract

Metamaterial has been applied as a new type of radar absorbing material. In the face of more and more complex material structures, optimization algorithm has become a mainstream direction of structure design. However, the electromagnetic simulation often needs a lot of time, in order to improve efficiency, it is necessary to reduce the number of simulations as much as possible. This paper combined surrogate model and Genetic Algorithm to propose a topology-based optimization method for metamaterial, then designed a broadband absorbing structure. This optimization method uses a less complex surrogate model instead of the electromagnetic model, which can greatly reduce the time of optimization, to design the metamaterial structure that meets the requirements of wave absorbing performance. Compared with the previous literature, this method has some advantages. At the same time, this topology design method can also be applied to other optimization designs.

Keywords—Topological Structure, Genetic Algorithm, Surrogate Model, Kriging Interpolation

3 Introduction

3.1 Research Background

With the continuous development of marine precision guidance technology and detection radar, the anti-radar detection materials have also achieved unprecedented development. Vigorously develop stealth technology is very important for improving the battlefield survival and penetration capabilities of weapons and equipment. In reducing target radar echoes with certain radar characteristics, shape design and the use of absorbing materials are the most common ways. The radar stealth based on shape design (abbreviated as shape stealth) is direct and effective means to achieve target stealth. Its principle is to use system engineering theory to optimize the shape and structure of stealth targets, so that the reflected radar wave energy of the target deviates from the radar emission direction, thereby effectively reducing the average Radar Cross Section (RCS) [1] of the target.

However, the shape stealth has obvious limitations. First, the excessive requirements on the shape may affect the hydrodynamic performance of the equipment and reduce the containment space; Second, the target is at a certain angle. Therefore, the decrease of the RCS in this domain will inevitably increase the RCS in some other corner domains. With the development of intensively distant radio communication and over-the-horizon radar systems in the range of high frequencies (HF) [2],[3], it is impossible to reduce the target RCS at the same time in the full three-dimensional range. Therefore, if we want to fundamentally be

endowed the target with excellent stealth performance, it must rely on materials intrinsic stealth function, that is, the development of radar absorbing materials.

Metamaterial has been applied as a new type of absorbing material. But at present, the most common metamaterial designs are based on the resonance mechanism, and their performance is mainly determined by the structure type, parameters, and the properties of the component material. Due to the structure type diversity and the sensitivity, it is not enough for the design to simply rely on physical models and human experience. Therefore, using a mature optimization algorithm has become an important way for metamaterial design.

The essence of metamaterials absorbing electromagnetic waves is to form electromagnetic resonance through structural design, so that the electric and magnetic fields are significantly enhanced, so that the incident electromagnetic waves are consumed by the electrical and magnetic losses of the material. To obtain broadband absorbing performance, it is necessary to ensure that the corresponding frequency band on the other hand, from the perspective of "circuit", the resistive metamaterial resonant unit introduces reactance based on equivalent resistance. The electromagnetic response is opposite to that of the traditional ground matrix, so as to obtain a broadband impedance matching and achieve a strong wave absorption performance. [4],[5]

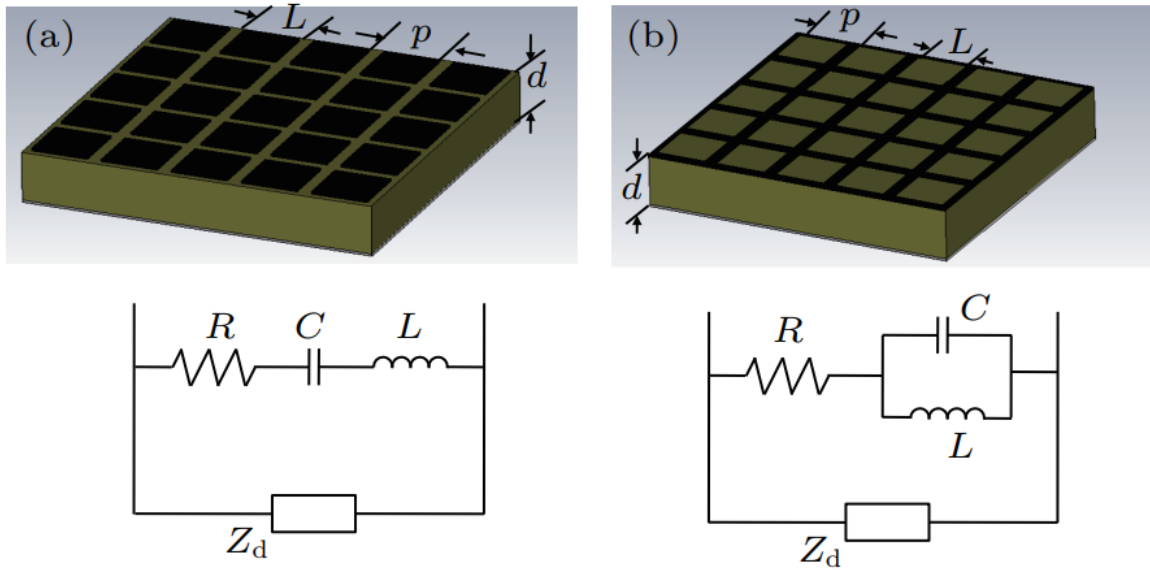


Fig. 1. Metamaterials and equivalent circuit models

The equivalent circuit of the resistive metamaterial with loss characteristics is shown in Figure 1, which is divided into two types: capacitive and inductive. To produce strong resonance, it is composed of structural unit, matrix and reflective layer, and the dielectric matrix can be equivalent to a segment Transmission line.

3.2 Relative Work

As a novel optimization design method, topology optimization [4],[5] overcomes the shortcomings that mentioned above. In [6], the author proposes an optimization-design method for the Frequency Selective Surface (FSS) based on the Genetic Algorithm (GA) incorporated with a geometry-refinement technique. In [7], it proposed a hybrid algorithm called HIGAPSO, which combine PSO and GA algorithms to improve the convergence speed and the optimum search ability. In [8], the author developed the topology optimization method based on GA, which further

improve the convergence speed. The current research on this field is generally based on improve GA algorithm. However, simply using GA will generate a huge number of electromagnetic simulations and consume a lot of time.

This paper combined GA with the surrogate model to design an efficient and fast optimization method based on the topology optimization design [9],[10]. In order to verify the effectiveness of this algorithm, this method is used to optimize the structure of a metamaterial absorber based on topological structure. Compared this result with the result by GA. The results show that the use of the surrogate model/GA can ensure the quality of the solution while reducing the optimization process. It significantly reduces the time required for optimization by reducing the number of electromagnetic simulations. Furthermore, this optimization design method is transferable and can be applied to other structures and models.

4 Basic Theory

4.1 Genetic Algorithms

Genetic Algorithm originated from the computer simulation research of biological systems [11-13]. It draws on Darwin's theory of evolution and Mendel's theory of genetics. It is not limited by function derivation and continuity for complex problems, but directly. It is a probabilistic global search algorithm that can automatically guide the optimization of the search space, adjust the search direction, and seek the optimal solution efficiently and in parallel by operating on the structural object.

The genetic algorithm generally consists of the following parts [14-16]:

(1) Encoding and decoding

(2) The fitness function is used to describe the degree of adaptation of the individual to the environment. The selection of this function has a decisive influence on the probability of the individual in the current group to inherit his own genes to the next generation. Generally, the larger the value of the individual fitness function is, the better the individual performance, the greater the possibility of inheritance to the next generation.

(3) Genetic operators include crossover, mutation and replication. The replication operator is the process of generating a new population based on the pros and cons of individuals. Individuals with high fitness are more likely to produce one or more offspring in the next generation.

(4) The control parameters of the algorithm include the population size M , the mating rate P_c and the mutation rate P_m .

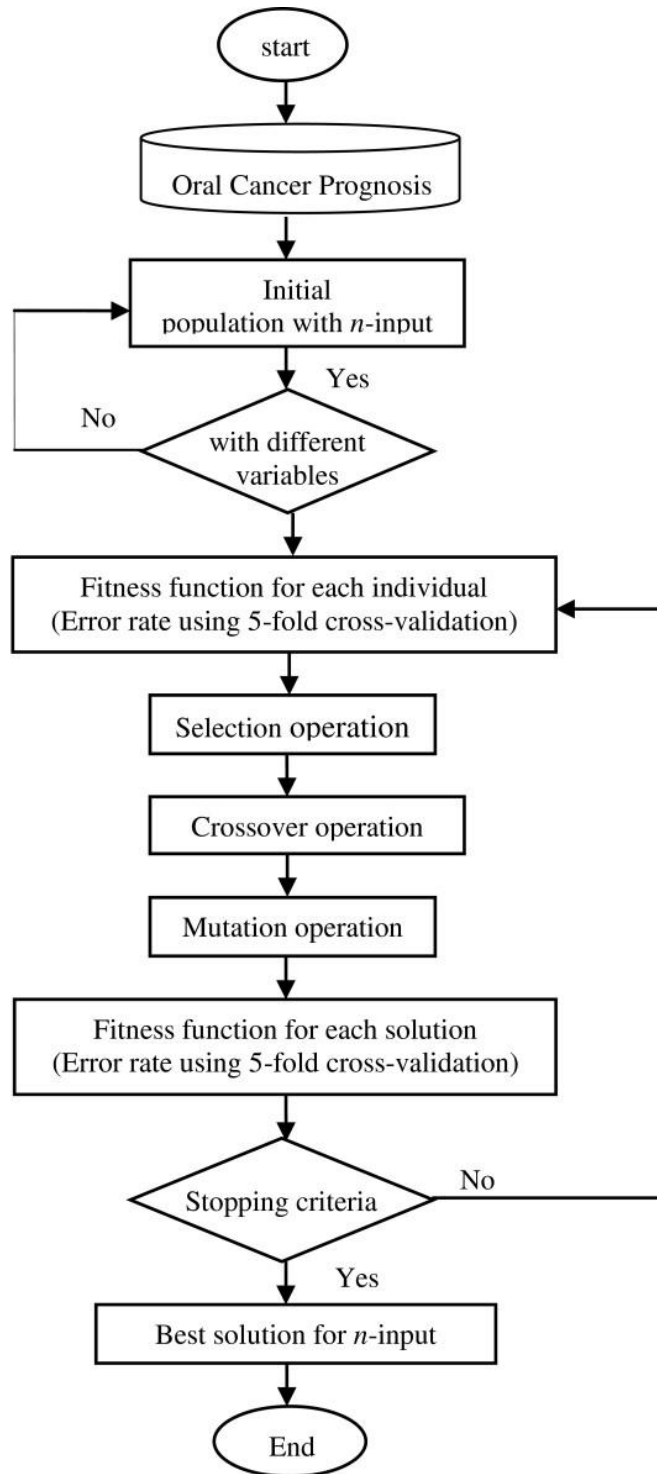


Fig. 2. Genetic algorithm feature selection flowchart

The basic steps of using genetic algorithm to solve engineering optimization design problems are as follows [17-19]:

(1) Coding Determine the optimization parameters, and then code them according to the selected code system. Each code represents a chromosome individual and represents a solution to the optimization problem. When coding, a reasonable code length should be set according to the solution accuracy of the problem.

(2) Initialization Generate a set of initial populations. The number of its individuals is called the size of the initial population; the individuals of the initial population should be randomly generated to ensure the fairness of its diversity and competition.

(3) Estimation of fitness According to the optimization problem, determine the objective function and fitness function, calculate the objective function value of everyone in the population and its corresponding fitness function value, and provide the basis for the evolutionary selection of the population. The choice of fitness function is very important.

(4) Selection According to the fitness function value of each chromosome in the population, select the individuals of the population with a certain algorithm (such as the roulette algorithm), and add the operation result to the next generation population. Selection is a random process. Individuals with poor genes (that is, low fitness function) will not necessarily be eliminated, but they have a high probability of being eliminated. Individuals

with good genes (high fitness function) may be repeatedly selected. This achieves the survival of the fittest.

(5) Crossover Select two individuals at random and let them exchange some genes randomly according to a certain probability to form two new individuals.

(6) Variation Randomly select an individual from the population and mutate a certain bit of its chromosome according to a certain probability. The selection and crossover operators provide the genetic algorithm with the search ability, and the mutation operator provides the necessary disturbance for the algorithm to avoid the occurrence of local extremum problems, so that the algorithm optimization is global.

(7) End If the genetic algebra (number of iterations) reaches the preset value or the operation ends when it converges to the preset condition, otherwise return to step (3).

4.2 High Frequency Structure Simulator

HFSS (High Frequency Structure Simulator) is a three-dimensional electromagnetic simulation software launched by Ansoft Company. It has been acquired by ANSYS Company. It is the world's first commercialized three-dimensional structure electromagnetic field simulation software. After more than 20 years of development, HFSS With its high simulation speed and unmatched simulation accuracy, it has become an industry-recognized electronic design industry standard for 3D electromagnetic field design and

analysis. HFSS provides a simple and intuitive user design interface, an accurate and adaptive field solver, a powerful post-processor with unprecedented electrical performance analysis capabilities and can calculate the S-parameters and full-wave electromagnetic fields of three-dimensional passive structures of any shape. Using HFSS, it is possible to calculate: (1) basic electromagnetic field numerical solution and boundary problem, near and far field radiation problems; (2) port characteristic impedance and transfer constant; (3) S-parameters and normalized S-parameters of corresponding port impedances; (4) The eigenmode or resonance solution of the structure. Moreover, Ansoft High Frequency Solution, composed of Ansoft HFSS and Ansoft Designer, is currently the only high frequency design solution based on physical prototypes, providing fast and accurate design methods from system to circuit to component level, covering All aspects of high frequency design.

The application direction of HFSS

(1) RF and microwave device design

Compared with digital circuit designers, microwave designers have long recognized that high-frequency design requires special measures and tools to correctly identify and handle electromagnetic effects, which is why HFSS has become the authoritative standard for microwave/RF device design.

(2) Antenna unit, antenna array and feed design

HFSS software has a powerful antenna design function, it can calculate various antenna parameters, such as gain, directivity, far-field pattern and 3dB bandwidth, and can plot polarization characteristics, including spherical field component, circular polarization field component, Ludwig No. 3. Define field components and axial ratios, etc.

(3) High frequency IC design

Accurate extraction of parameters for the analysis of interconnected structure characteristics is required, and HFSS is the only software that can implement this function conveniently and efficiently.

(4) Design of electric vacuum device

In the design of electric vacuum devices such as traveling wave tubes, klystrons, and gyrotrons, the HFSS eigenmode solver combines periodic boundary conditions to obtain the normalized phase velocity-frequency relationship accurately for the dispersion characteristics of the device, and the electromagnetic field distribution in the structure provides a powerful design tool for the design of such devices.

4.3 Introduction of MATLAB and M function files

MATLAB is the abbreviation of Matrix Laboratory, which means Matrix Laboratory. It is a high-tech computing environment released by MathWorks Corporation of the United States, mainly facing scientific computing, visualization, and interactive programming. It integrates many powerful functions such as numerical analysis, matrix calculation, scientific

data visualization, and modeling and simulation of nonlinear dynamic systems in an easy-to-use window environment for scientific research, engineering design, and many sciences that must perform effective numerical calculation. Domain provides a comprehensive solution and is largely free from the editing mode of traditional non-interactive programming languages (such as C, Fortran), representing today's advanced level of international scientific computing software.

To meet the user's development needs, in addition to the prefabricated functions and toolboxes, MATLAB software also supports users to write their own function format files, that is, M function files. In the M function file, users can program themselves to achieve variable definition, main program construction, calling sub-functions, and cyclic interrupt operations in general programming languages. Compared with some other commonly used programming languages, M function files written in MATLAB have the following characteristics:

(1) M function files all start with the function declaration guided by "function", and at the same time give the variable name that the function connects with the outside world.

(2) Whenever a sub-function needs to be called during the running of the program, the system will open an independent workspace for the function, which is called the function workspace, and the residual variables in it will be cleared in time when the function call ends.

(3) The function workspace will be generated quickly with the call of the M file, and the function has a high ability to recognize the format of the variable, which is necessary for various software interfaces. At the same time, this also lays the foundation for using MATLAB to control the operation of HFSS in the following text.

4.4 Kriging interpolation

Kriging interpolation method [20], also known as spatial autocovariance optimal interpolation method, is an optimal interpolation method named after D.G. Krige, a South African mining engineer. Kriging interpolation is widely used in groundwater simulation, soil mapping and other fields, and is a very useful geostatistical gridding method. It first considers the variation distribution of the function value in the spatial position and determines the range that affects the value of a point to be interpolated, and then uses the sampling points within this range to estimate the value of the point to be interpolated. This method can mathematically provide an optimal linear unbiased estimate of the object under study. It considers the geometric characteristics such as the shape, size, and the spatial position of the information sample and the spatial position between the blocks to be estimated, as well as the spatial structure of the grade, in order to achieve linear, unbiased and minimum estimation variance estimation, and assign each sample to each sample. With a certain coefficient, the weighted average is finally performed to estimate the block grade. When there are many data points, the reliability of the interpolation results is higher. Nowadays, kriging interpolation as a surrogate model has been widely used

in many aspects, such as optimization, design space search, information visualization, prototyping, and sensitivity analysis. Below, we will briefly introduce the principle of kriging interpolation.

In short, the kriging interpolation model consists of two parts, first, a regression function based on sample point data, plus an error vector based on a Gaussian random process. A kriging interpolation model for an unknown point can be expressed as:

$$Y(x) = f(x) + Z(x) \quad (8)$$

where $f(x)$ represents the regression function, and $Z(x)$ represents a Gaussian random process with a mean value of 0 and a variance of σ^2 .

In an optimization problem, the value of an unknown point can be expressed by Kriging as:

$$f_p(x) = \mu + \varepsilon(x) \quad (9)$$

where μ represents the mean value of the response function at the surrounding base points, $\varepsilon(x)$ represents the error value when take 0 as the expected value. Here the error value is given in the form of a correlation function, which is determined by the distance between the desired point and the surrounding base point. Here is a Gaussian correlation function of the form:

$$R(x^i, x^j) = \exp \left[\sum_{k=1}^N \theta_k |x_k^i - x_k^j|^2 \right]$$

Among them, θ_k is the correlation coefficient used to adjust the model, and x_k^i and x_k^j are the k th elements of the vectors x^i and x^j , respectively. The surrogate model R_s based on kriging interpolation is defined as:

$$R_s(x) = [R_{s,1}(x), R_{s,2}(x), \dots, R_{s,m}(x)]^T$$

Here,

$$R_{s,j}(x) = \bar{\mu}_j + r^T(x)R^{-1}(f_j - \overline{I\mu_j})$$

Here I is an $N \times 1$ unit vector,

$$f_j = [R_{cd,j}(x^2), R_{cd,j}(x^2), \dots, R_{cd,j}(x^N)]^T$$

r is the correlation vector of point x and other base points,

$$r^T(x) = [R(x, x^1), R(x, x^2), \dots, R(x, x^N)]^T$$

where R is the correlation matrix between base points:

$$R = \begin{bmatrix} R(x^1, x^1) & R(x^1, x^2) & \dots & R(x^1, x^N) \\ R(x^2, x^1) & R(x^2, x^2) & \dots & R(x^2, x^N) \\ \dots & \dots & \dots & \dots \\ R(x^N, x^1) & R(x^N, x^2) & \dots & R(x^N, x^N) \end{bmatrix}$$

The mean $\bar{\mu}$ is given by:

$$\bar{\mu} = (I^T R^{-1} I)^{-1} I^T R^{-1} f_j$$

The correlation coefficient θ_k can be obtained by maximizing the following formula

$$- [N \ln(\bar{\sigma}^2) + \ln|R|]/2$$

where the variables σ^2 and $|R|$ are both functions of θ_k

$$\bar{\sigma}^2 = (f_j - \overline{I\mu_j})^T R^{-1} (f_j - \overline{I\mu_j}) / N$$

If the algorithm uses this model to completely judge the quality of new solution, it needs a lot of sampling points to get an extremely high accuracy, which will undoubtedly take more time. To solve this problem, this paper will screen the newly generated solutions in each generation, select the individuals with the best performance among them, and then use accurate electromagnetic simulation to calculate.

5 Surrogate Model/GA algorithm

5.1 Principle of Surrogate Model/GA algorithm

The core of the surrogate model method is not simply to use the surrogate model to replace the electromagnetic simulation for fitness calculation. In order to use the surrogate model to completely judge the quality of a new individual for electromagnetic simulation, the surrogate model needs to have extremely high accuracy in the entire design space, and the higher the accuracy of the surrogate model, the more sampling data is required. Many more electromagnetic simulations are required when building the model. This undoubtedly consumes more time, and the advantages of the surrogate model are not obvious. However, if the initial sampling points are too few or the location is not ideal, some characteristics of the real problem may not be reflected in the model.

In order to solve this problem, we do not simply use the surrogate model to replace the electromagnetic simulation but use the surrogate model to screen the newly generated offspring individuals, select the individuals with smaller fitness, and then use the accurate electromagnetic simulation for the individual. authenticating. That is, use the surrogate model as a screening tool to select the "most promising" individuals and then validate them.

For new individuals of each generation, first use the surrogate model to calculate their fitness values and sort all new individuals from small to large. Next, select the first individual after sorting, and judge whether the individual is already included in the database (if it is, select the second

individual, if the second individual is still included in the database, select the third individual, and so on), if the individual is not included in the database, the parameters of the individual are simulated using HFSS and the results are added to the database.

There are two advantages to this: (1) new simulation data is constantly added to the existing database, and the surrogate model is built using the database, so the surrogate model will become more and more accurate; (2) each generation only a detailed simulation of an individual takes less time.

5.2 Process of Surrogate Model/GA algorithm

The steps of surrogate model/GA in this article are as follows:

- Step 1. Set the basic parameters: including the binary variables to be optimized and some parameters of GA.
- Step 2. Initialize the database: extract sampling points and use electromagnetic simulation to calculate.
- Step 3. Compare with termination condition: if the termination condition is met, then output the best result in the database; if it is not met, continue to Step 4.
- Step 4. Form the population: sort all the solutions in the database, then take Np best solutions to form a population.
- Step 5. Generate the offspring: do the cross-mutation operation of GA on the previous generated population.

Step 6. Establish surrogate model: use the sampling solutions in the current database to build a surrogate model.

Step 7. Update database: record the best individual selected by surrogate model, calculate its fitness value using electromagnetic simulation. Add the solution to the database and then return to Step3.

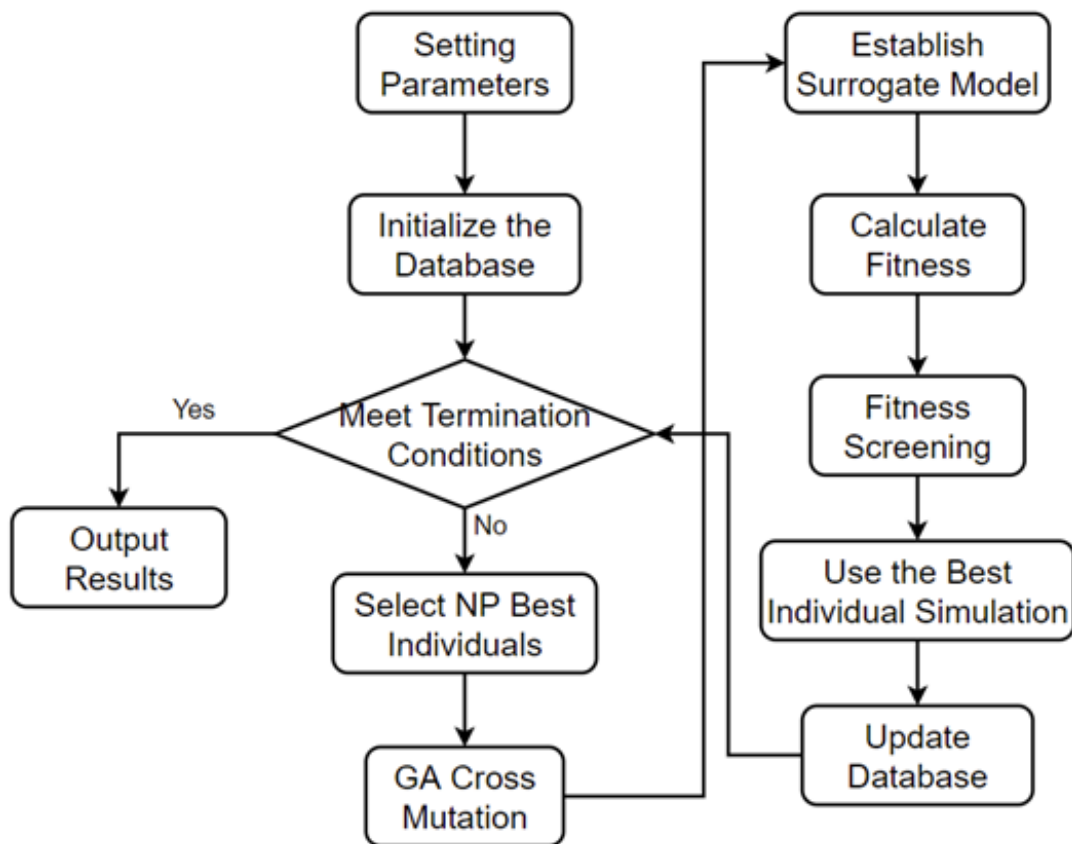


Fig. 3. The combined simulation system flow chart of MATLAB and HFSS

In the process of implementing the surrogate model/DE algorithm, some control parameters need to be set in advance. The main parameters involved include the following categories:

(1) GA control parameters: including scale factor F , crossover probability CR and population size NP . According to the recommendation of the literature, the scale factor should be selected in $F \in [0.4,1]$, and the crossover probability is more effective in the interval $CR \in [0.5,0.95]$. The population size NP depends on the number of parameters to be optimized. Assuming that the number of parameters to be optimized is n , it is more appropriate to select NP in the range of $[4n, 10n]$.

(2) Surrogate model related parameters: The database must be updated in the optimization process of each generation, so a new surrogate model must be established before the screening process. When the algorithm is just started, the number of sampling points in the database is only the number of sampling points α at the time of initialization, and α sampling points are used when building the surrogate model. As the algorithm progresses, new electromagnetic simulation results are added to the database as sampling points. When the current algebra is not too large, there are not many sampling points in the database. At this time, we can use all the sampling points in the database to build the surrogate model; when the algebra increases to a very large number, the speed of using all the sampling points to build the surrogate model It may be very slow, so we set a parameter τ here, which represents the maximum number of sampling points used when building the surrogate model.

(4) The number of sampling points when initializing the database α , according to the complexity of the optimization problem, $\alpha \in [3n, 5n]$ is more appropriate.

6 Optimization Design of Wave Absorbing Materials Based on Topology Structure

6.1 HFSS Macro Command Introduction

Although the GA differential evolution algorithm provides us with a powerful global search engine, there are still many problems to be solved in how to apply the GA algorithm to the actual antenna optimization. Among them, the most critical problem is how to solve the fitness function. In the literature [6], MATLAB is used for modelling, and the method of moments is used to solve the model by programming. However, it is obviously very inconvenient to model in MATLAB, and only simple models can be built using MATLAB, but it is powerless for electromagnetic structures with complex structures and materials. However, if MATLAB is used for genetic operations and HFSS is used to achieve model establishment and simulation, it means that every time a new generation of design parameters is generated, it is necessary to continuously return to the HFSS drawing interface to modify the model and obtain a new fitness function., and then input it into MATLAB. In the face of thousands of fitness calculations in the general genetic algorithm, this complicated operation is undoubtedly unimaginable. The HFSS macro command provides an effective solution.

HFSS macros are a fast, efficient way to repeat the same job. It uses VBScript language to record macro commands. VBScript is the abbreviation of Microsoft Visual Basic Script Edition. It is designed based on the Visual Basic scripting language and is the scripting language of Microsoft Visual Basic. In other words, it is a set of visual programming

tools based on the Basic pattern launched by Microsoft. In this environment, the scripting language is not compiled into binary files, but the source code is directly translated and executed by the host. The program written under this condition is not directly compiled into an executable file in *.exe format, but directly converts the information. After sending the source program corresponding to the script program, the user can directly execute the script without knowing many complicated links. That is, it can automate a wide variety of tasks. By using macros, we can quickly complete repetitive tasks, such as creating and solving problems with variable parameters. Therefore, once the simulation model is determined, the establishment of the model in the optimization process only needs to call the vbs script file. For the same model, through repeated execution, the designer can modify it only by changing some variables in the script file. The script function that comes with HFSS allows users to record every step of the operation from model building to simulation solution in a vbs script file. After all the operations are completed, when the user needs to build the same model next time, just use With the Run Script function in HFSS, the script file can automatically complete a series of operations for modelling and solving. However, in the process of using the genetic algorithm to optimize the design of absorbing materials, we need to export the solution results to MATLAB to calculate the fitness value, and then write the design parameters of the offspring population into the vbs script program. To meet this requirement, the HFSS-MATLAB-Api toolbox is used here.

6.2 Introduction to HFSS MATLAB Api Toolbox

Through the HFSS-MATLAB-Api toolbox, we can link HFSS and MATLAB to realize the combination of electromagnetic simulation and optimization algorithm. Below, we jointly use MATLAB and HFSS, and use the differential evolution algorithm to carry out the steps of antenna optimization design.

The HFSS-MATLAB-Api toolbox is a MATLAB library toolbox. It consists of a series of M function files. Using these functions, we can easily complete the following tasks in the MATLAB environment: (1) Create a HFSS vbs script file, which includes model establishment, parameter settings, simulation settings, etc.; (2) run the script file (automatically start HFSS software for simulation calculation); (3) export the calculated data to MATLAB for post-processing. The initial version of the HFSS-MATLAB-Api toolbox was released by Vijay Ramasami in May 2003 [22], and after that, James Mc Donald et al. improved some of its functions and further improved the function of the toolbox. The toolbox now covers many commonly used functions, roughly including the following four modules: 3D modelling, solution settings, boundary (excitation port) settings and general functions. Each function module is composed of many M functions, and each M function has a specific function. The two more important functions are introduced below:

(1) hfssExportNetworkData

Generate the corresponding vbs script command to export the network parameters obtained by the HFSS simulation to the specified data file.

(2) hfssExecuteScript

Execute the generated vbs script file, that is, run HFSS for simulation. At the same time, you can also set whether to automatically close HFSS after the operation is completed. Using these two functions, we can easily use MATLAB to control the operation of HFSS and the export of parameters. For parametric modelling of the antenna, we can use the 3D modelling functions in the HFSS-MATLAB-Api toolbox. For example, the function hfssBox.m is used to build a cube or cuboid. In addition, this function also allows holes to be included in the cuboid, and the coordinates, radius and axis of the holes can be set. This setup is very convenient when a coaxial feed is required.

6.3 Model Structure

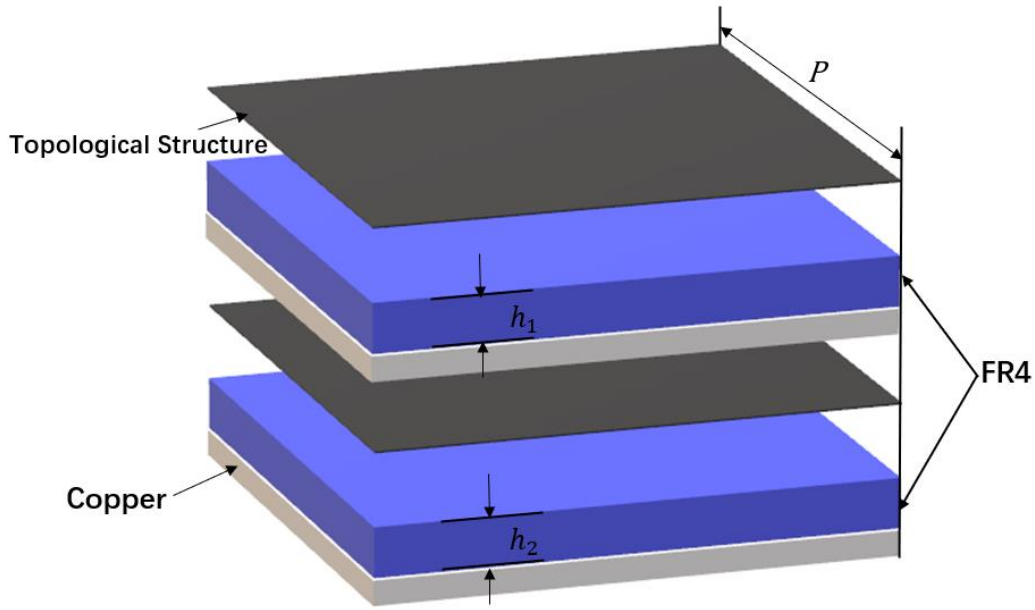


Fig. 4. Absorber Structure

In this paper, according to the design method of resistive frequency selection surface, a lightweight, broadband sandwich structure is designed. The structure is shown in Figure 4. The topological structure is designed by binary coding on the dielectric substrate (epoxy-based glass fiber, hereinafter referred to as FR4) loaded with the metal backplane.

The key to metamaterial topology optimization design is encoding. The longer the encoding, the less conducive to the convergence of the optimization algorithm, that is, the less likely it is to find the optimal solution within a limited range. Metamaterial discretization encoding includes two parts: topology encoding and parameter encoding. The topology encoding adopts the method shown in Figure 5. Due to the polarization-independent characteristics of the material, the binary encoding of the axisymmetric structure is used to divide the surface of the metamaterial unit into $M \times M$ Grid and the code length is $M \times M$, each

small square is filled with 0 or 1, where 0 represents no surface structure, and 1 represents this square structure filled with corresponding materials. Due to the axisymmetric binary code, the code length can be shortened as $(M \times M)/4$ [23].

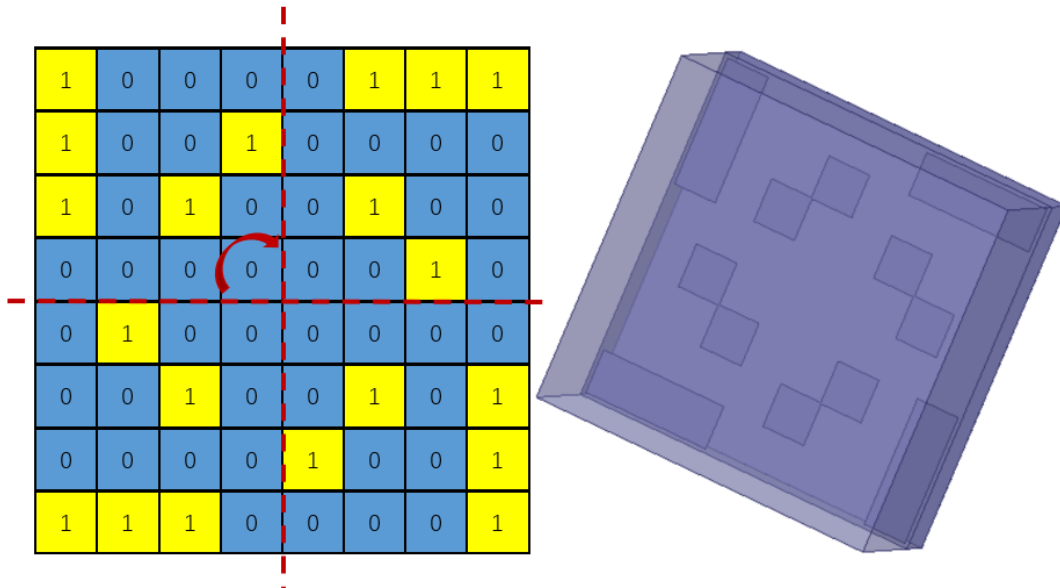


Fig. 5. Schematic of the coding method of topological optimization design

Parameter encoding is to encode the size of the periodic unit structure, the thickness of the substrate, the square resistance of the resistor, and other parameters in accordance with the rules of binary encoding, and the encoding length is N .

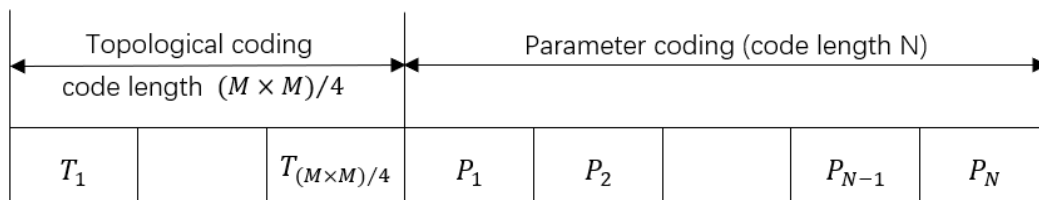


Fig. 6. The Structure of the binary code

The total length of the encoding is $(M \times M)/4 + N$. The topology code used in this paper is 16 bits, the parameter code is 14 bits, and a total of 30 bits are coded. The decoding process of parameter encoding is:

$$Sub_H = Sub_{H_{min}} + 0.2 * (8 * P_1 + 4 * P_2 + 2 * P_3 + P_4) \quad (1)$$

$$R = R_{min} + 16 * P_5 + 8 * P_6 + 4 * P_7 + 2 * P_8 + P_9 \quad (2)$$

$$p = p_{min} + 16 * P_{10} + 8 * P_{11} + 4 * P_{12} + 2 * P_{13} + P_{14} \quad (3)$$

$$tpbits = T(1:16) \quad (4)$$

where Sub_H , R , p represent the binary code of the periodic unit structure, the thickness of the substrate and the square resistance of the resistor value respectively; $Sub_{H_{min}}$, R_{min} , p_{min} , are the minimum value of the unit structure parameter, here I set $Sub_{H_{min}} = 3$, $R_{min} = 35$ and $p_{min} = 6$.

Set the reflectance of the absorbing composite material to $R(w)$, transmittance $T(w)$, and absorbance $A(w)$, according to the equivalent circuit theory:

$$R(w) = |S_{11}|^2, T(w) = |S_{21}|^2 \quad (5)$$

$$A(w) = 1 - R(w) - T(w) = 1 - |S_{11}|^2 - |S_{21}|^2 \quad (6)$$

where S_{11} represents the reflection coefficient and S_{21} represents the transmission coefficient. In this paper, because the reflective back plate is loaded at the bottom of the material, the transmittance $T(\omega) = 0$. Therefore, the absorption rate can be expressed as:

$$A(\omega) = 1 - R(\omega) = 1 - |S_{11}|^2 \quad (7)$$

To improve the absorbing performance of the absorbing composite material, the reflection coefficient S_{11} of the material must be sufficiently small. Therefore, the problem of solving the material absorption rate is transformed into the problem of solving the reflection coefficient S_{11} .

7 Simulation

7.1 Simulation Design

To verify the effectiveness of the algorithm, the surrogate model/GA is used in this section to optimize the topological absorbing material introduced above.

To confirm the effect of the initial database size on the simulation, I ran simulations with different initial database sizes and settled on the capacity of 30. The simulation results are as follows

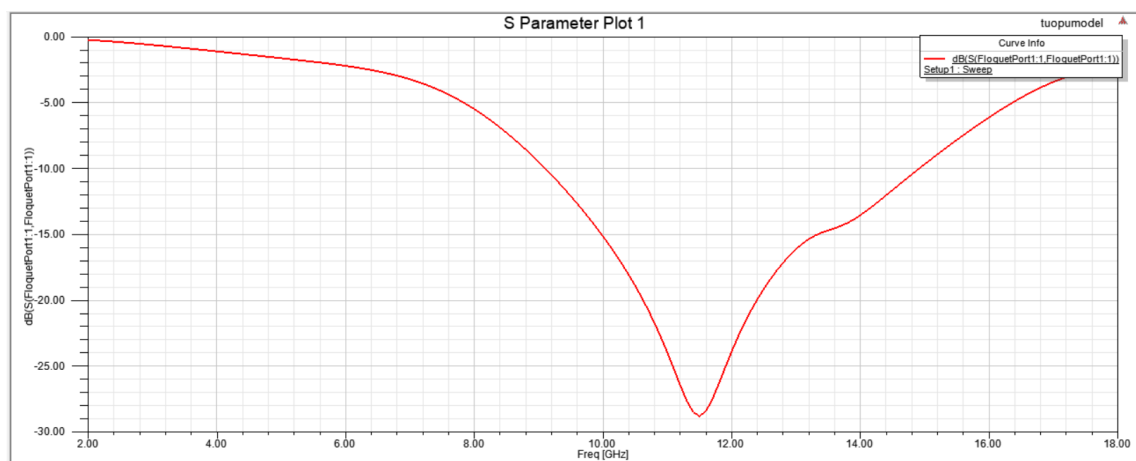


Fig. 7. Optimized S11 curve(capcity25)

Within capacity of 25:

Time consuming: 01:00:15

Fitness value: 0.6398

Working frequency: 9GHz-15GHz

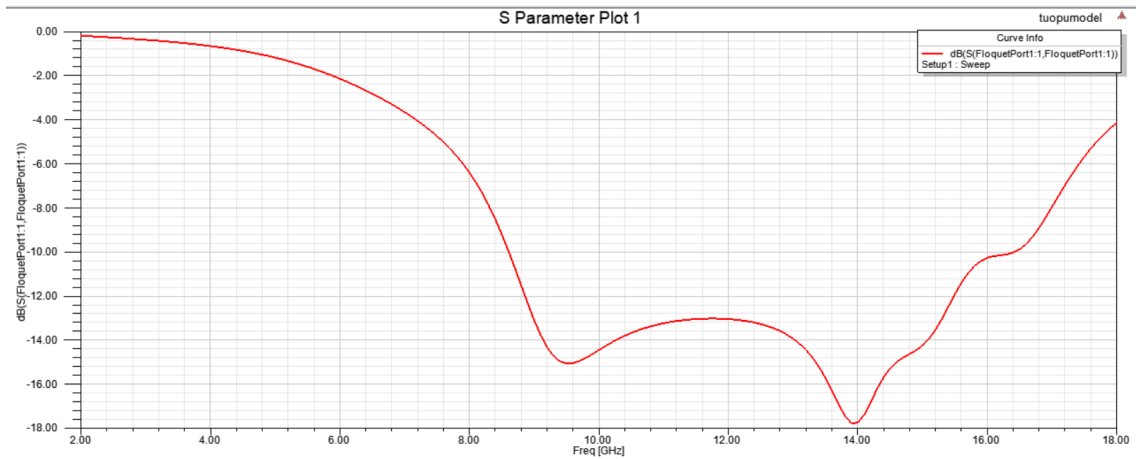


Fig. 8. Optimized S11 curve(capcity30)

Within capacity of 25:

Time consuming: 01:46:30

Fitness value: 0.515528

Working frequency: 8.6GHz-16.4GHz

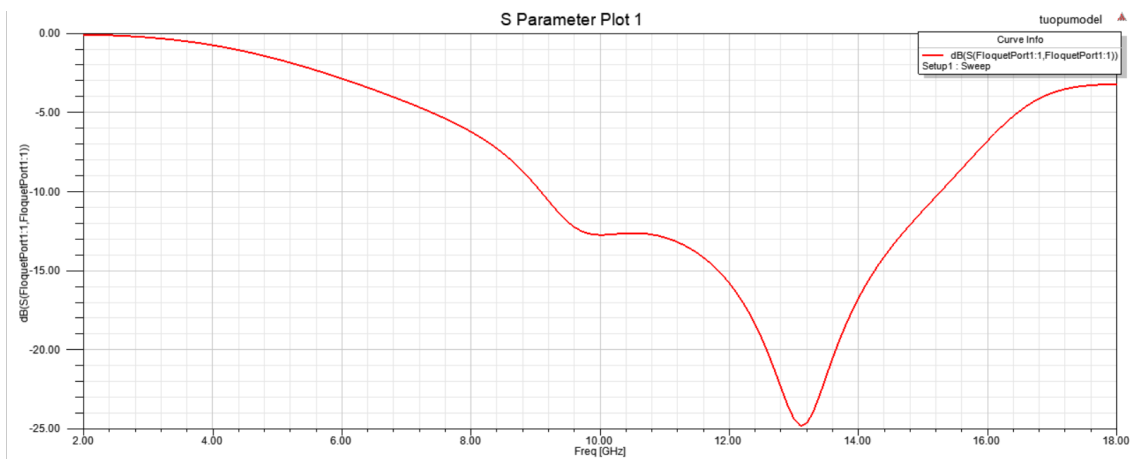


Fig. 9. Optimized S11 curve(capacity35)

Within capacity of 35:

Time consuming: 01:23:52

Fitness value: 0.615

Working frequency: 9GHz-15.2GHz

The relevant parameters are set as follows:

TABLE I. PARAMETER SETTINGS (SURROGATE MODEL/GA)

| | |
|---|-----|
| Initial sampling point | 30 |
| Maximum sampling point of surrogate model | 75 |
| Population size | 20 |
| Differential caling factor | 0.8 |
| Crossover probability | 0.8 |
| The maximum number of evaluations | 100 |

This part is aimed to compare with the non-surrogate model, so here also uses original evolutionary algorithms to optimize the same structure. The fitness function adopts the same setting as the upper and lower limits of the parameters to be optimized.

TABLE II. PARAMETER SETTINGS (GA)

| | |
|-----------------------------|-----|
| Evolutionary algorithm used | GA |
| Population size | 20 |
| Differential scaling factor | 0.8 |

| | |
|-----------------------------------|-----|
| Crossover probability | 0.8 |
| The maximum number of evaluations | 100 |

The goal of verification is which can get better results after passing same time. The average time of an electromagnetic simulation is about 50-70s, so the same time passed here is converted to the same number of simulations, which is set 100 times.

| | | | | | | | | | | | |
|----------|---|----------|---|----------|---|----------|---|----------|---|----------|---|
| T_1 | 1 | T_{11} | 1 | P_5 | 0 | T_1 | 1 | T_{11} | 0 | P_5 | 0 |
| T_2 | 0 | T_{12} | 0 | P_6 | 1 | T_2 | 0 | T_{12} | 1 | P_6 | 0 |
| T_3 | 0 | T_{13} | 1 | P_7 | 0 | T_3 | 1 | T_{13} | 0 | P_7 | 1 |
| T_4 | 0 | T_{14} | 1 | P_8 | 0 | T_4 | 0 | T_{14} | 0 | P_8 | 1 |
| T_5 | 0 | T_{15} | 0 | P_9 | 1 | T_5 | 0 | T_{15} | 1 | P_9 | 1 |
| T_6 | 0 | T_{16} | 0 | P_{10} | 1 | T_6 | 1 | T_{16} | 0 | P_{10} | 1 |
| T_7 | 0 | P_1 | 0 | P_{11} | 0 | T_7 | 0 | P_1 | 0 | P_{11} | 1 |
| T_8 | 1 | P_2 | 0 | P_{12} | 0 | T_8 | 0 | P_2 | 0 | P_{12} | 1 |
| T_9 | 0 | P_3 | 1 | P_{13} | 0 | T_9 | 0 | P_3 | 0 | P_{13} | 1 |
| T_{10} | 1 | P_4 | 1 | P_{14} | 0 | T_{10} | 1 | P_4 | 0 | P_{14} | 0 |

Fig. 10. The optimized binary code by GA(left); The optimized binary code by surrogate model/GA(right)

Both simulations are executed on the same computer, which average time of an electromagnetic simulation is about 50-70s. The specific performance parameters of this computer are as follows:

- CPU model: Intel(R) Core (TM) i7-10875H CPU @2.30GHz,
- RAM: 32GHz,

- Graphics cards: NVIDIA GeForce RTX 2600.

I will briefly introduce the establishment of the model and the setting of the port with a few pictures. The setting of the ports is shown in the following figures:

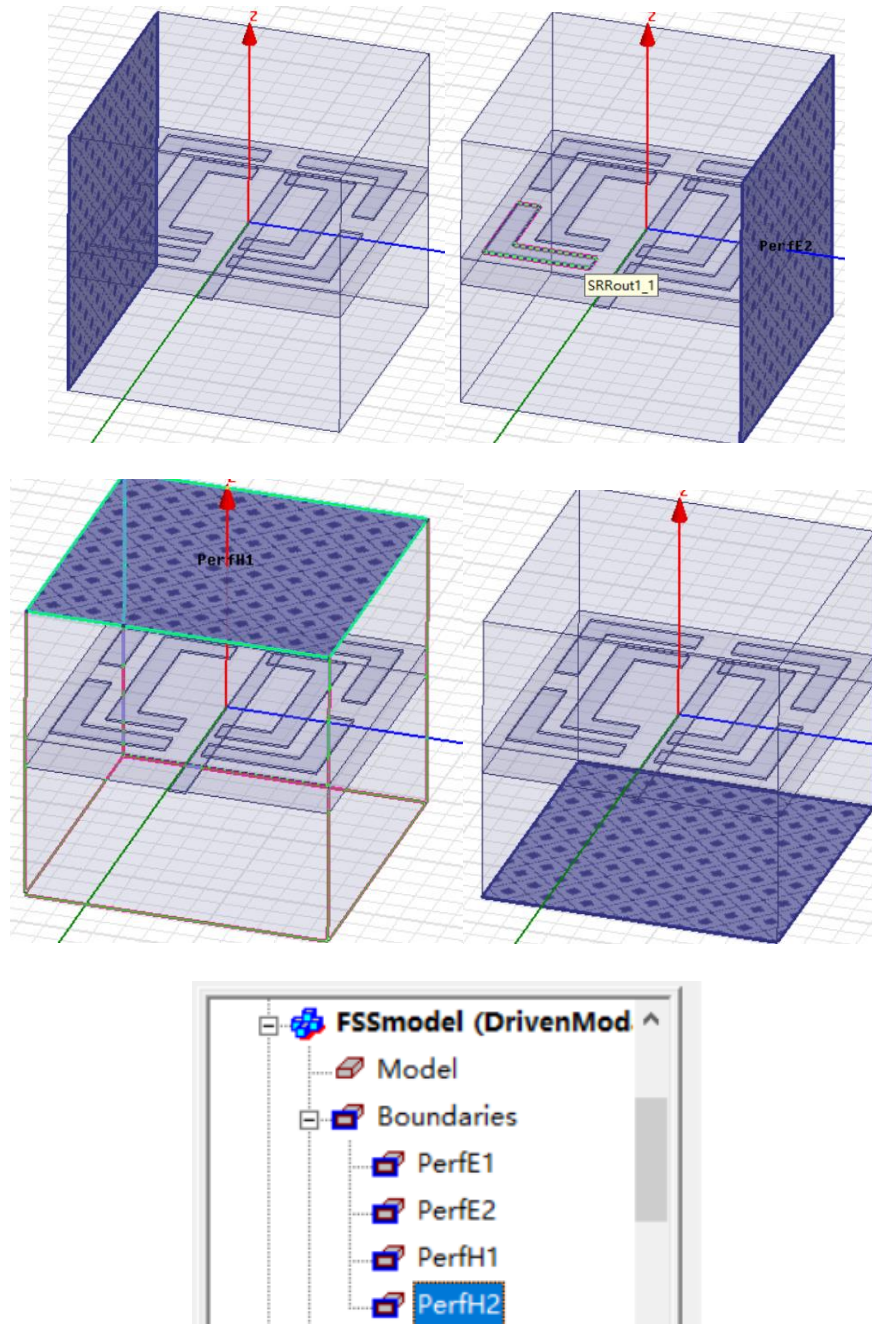


Fig. 11. Boundaries Settings

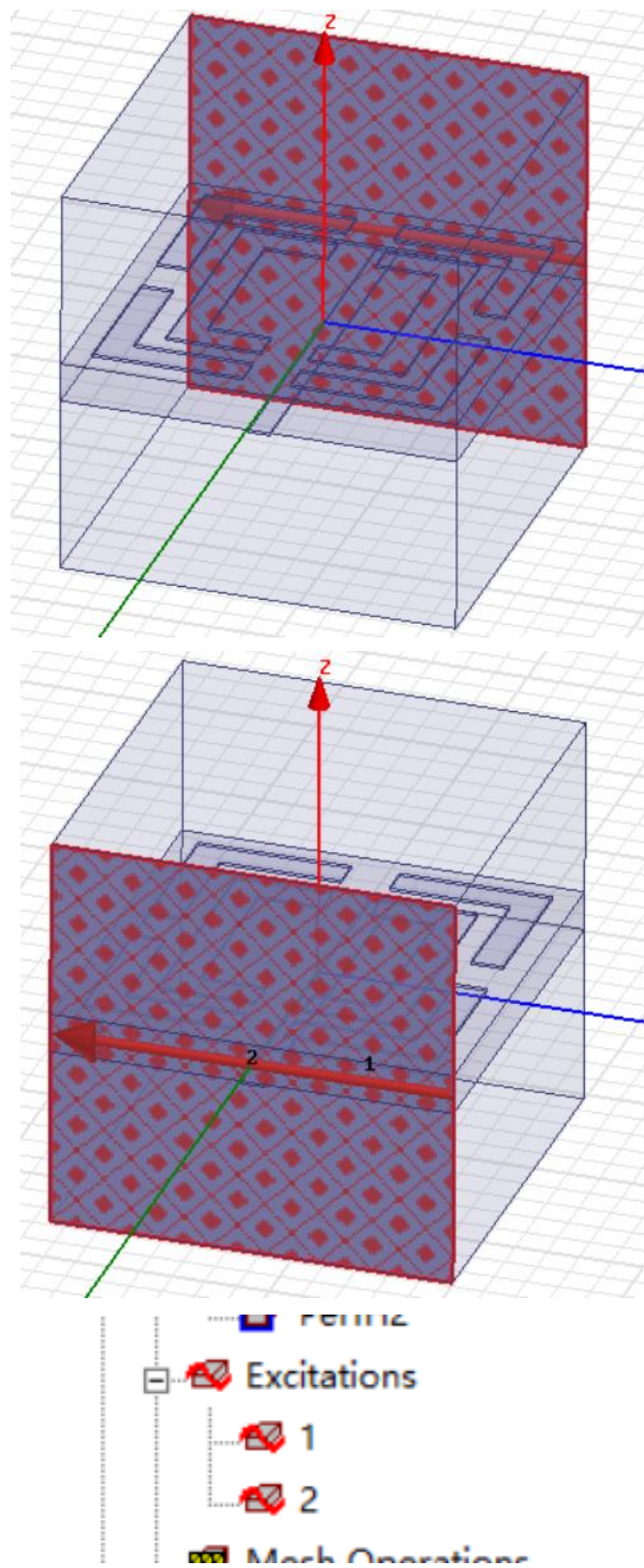


Fig. 12. Excitations Settings

7.2 Simulation Results

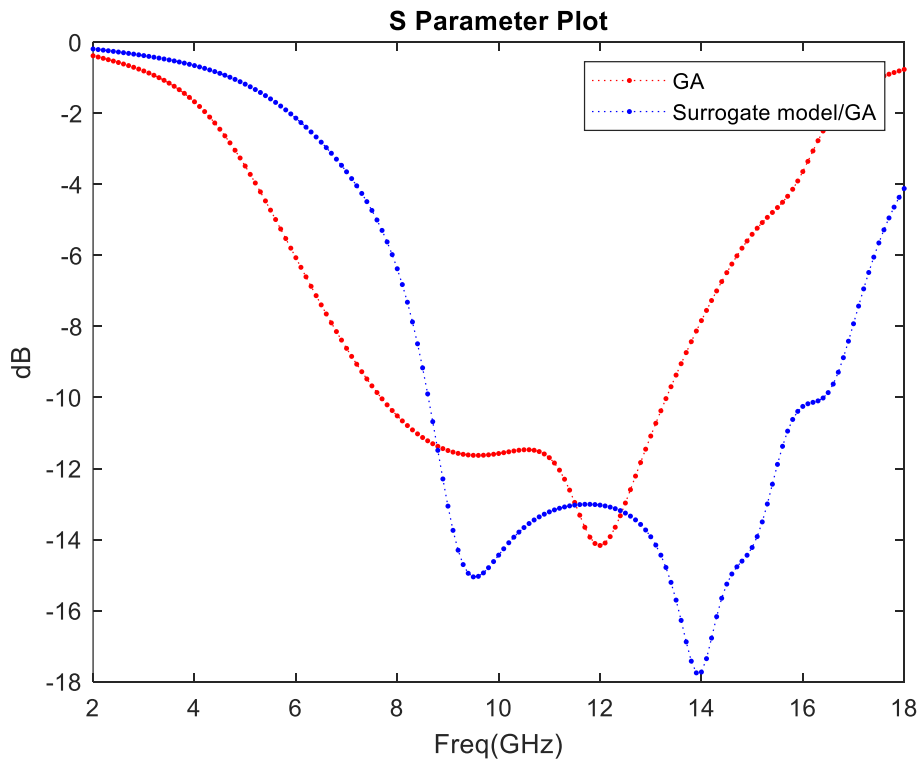
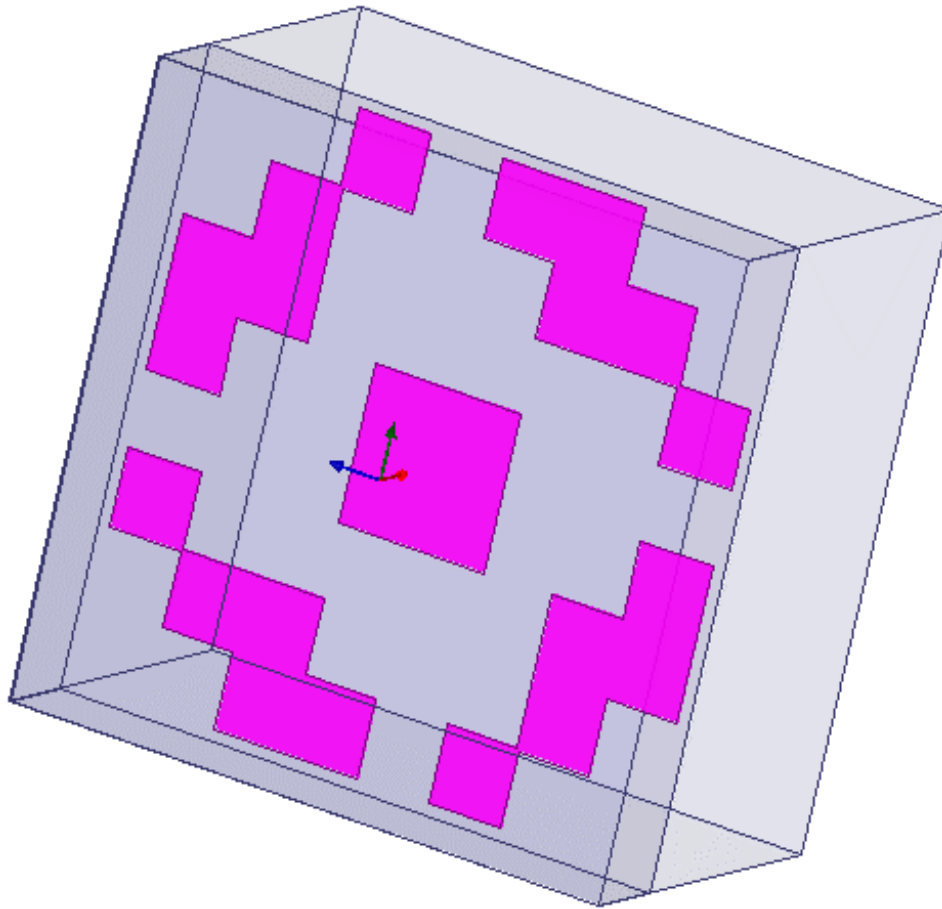
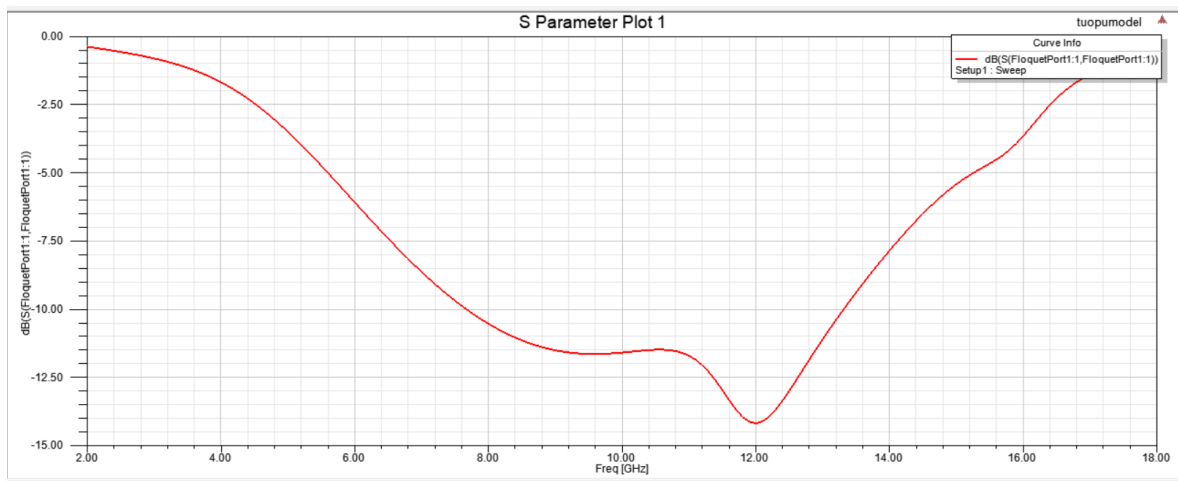
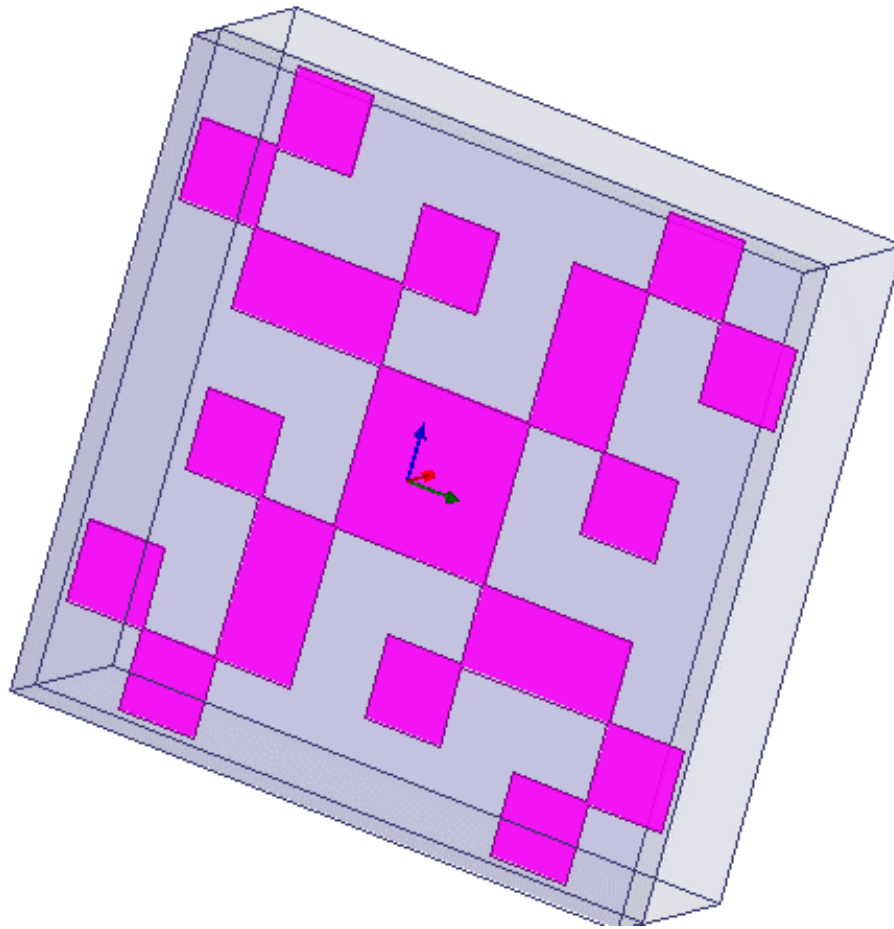


Fig. 13. The corresponding S11 curve of the optimized absorbing material by GA (blue) and surrogate model/GA (red)



(a)





(b)

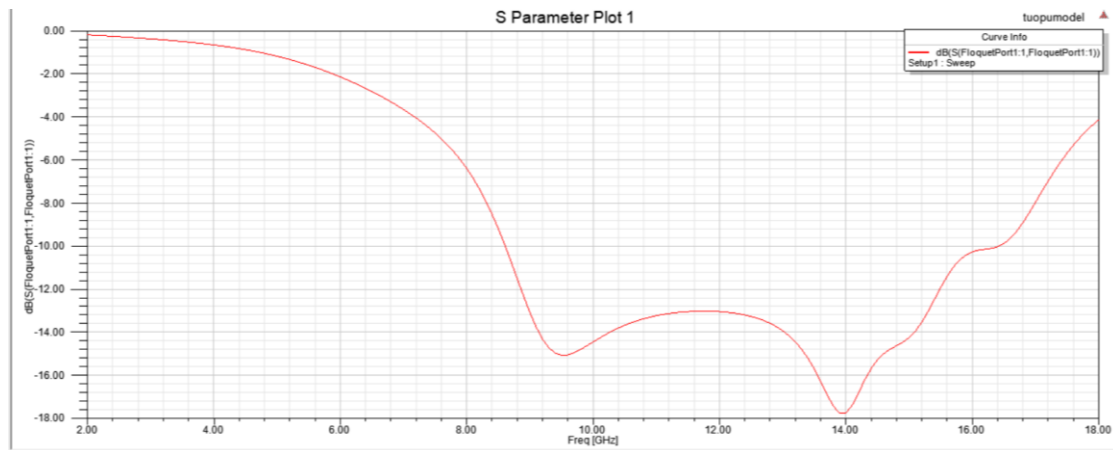


Fig. 14. (a) The optimized structure by GA; (b) The optimized structure by surrogate model/GA

The optimized structures are shown in the Figure. 14. In Figure. 13, the blue line shows that the S11 values of the structure optimized by GA are less than -10dB in 7.6 ~ 12.5GHz. The red line shows that the S11 values of the structure optimized by surrogate model/GA are less than -10dB in 8.6 ~ 16.4GHz.

TABLE III. COMPARISON OF TWO METHODS

| | Time Consuming | Absorbing Frequency Band |
|---------------------------|-----------------------|---------------------------------|
| GA | 63 min | 7.6~12.5GHz(4.9GHz) |
| Surrogate model/GA | 59 min | 8.6~16.4GHz(7.8GHz) |

When using GA, the simulation must be done in each evaluation, which means electromagnetic simulation is used 20 times in each generation. Therefore, 100 times simulation means the optimization has only been carried out for 5 generations. While in surrogate model/GA electromagnetic simulation is used only during model establishment and verification of each generation. The optimization can carry out for 100 generations. It shown in Figure. 15 this method has found the best design parameters in the 76th generation.

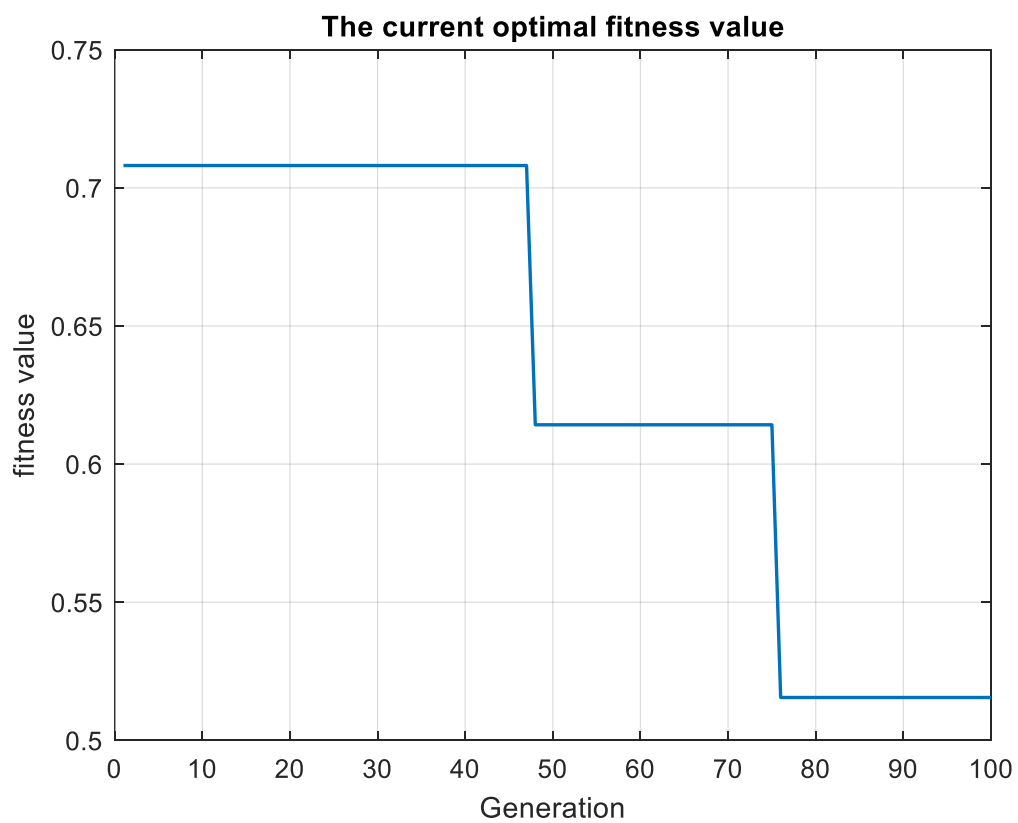


Fig. 15. The evolution curve of surrogate model/GA

8 Conclusion

This paper proposed an efficient topology-based optimization method for broadband absorbing material called surrogate model/GA. This method combined GA and surrogate model. Using surrogate model to evaluate the performance of different structures can avoid excessive electromagnetic simulations. In section IV, use this method to optimize a topology-based metamaterial structure and designed an absorbing material that could work between 8.6 ~ 16.4GHz. Compared with only use GA with the same optimization time, the use of the surrogate model/GA has a certain improvement in the quality, the range of absorbing wave band has been expanded by 1.6 times larger. It could be clearly seen that the use of this method greatly improves the optimization efficiency of topology-based absorbing material.

The model in the article is just an example, this method can be applied to more complex topology-based structures. It is also practical in the design of other metamaterials such as Frequency Selective Surfaces (FSS) and electromagnetic band gap structures. The future work will include applying this method in other models and choosing different surrogate models for different problems.

In future research, there are still many issues that could be further explored. For example, the surrogate model used in this article is the Kriging interpolation. In fact, there are many other excellent surrogate models to choose, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Radial Basis Functions (RBF), and so on. For

different problems, choosing different surrogate models may further improve optimization efficiency and accuracy.

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