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Research on Antenna Cabin Structure Optimization Based on Response Surface and Multi-island Genetic Algorithm

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Research on Antenna Cabin Structure Optimization Based on Response Surface and Multi-island Genetic Algorithm

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Abstract. This paper focuses on the characteristics of high efficiency and high accuracy in the optimization design of the antenna bay structure. The polynomial response surface model is used to replace the computationally intensive target characteristic analysis model in the original genetic algorithm and a multi-island genetic algorithm is combined with the sequential quadratic programming. In this method, the square steel structure of the antenna module is optimized, which not only ensures the search for the global optimal solution, but also improves the calculation efficiency. The optimized results meet the rigid strength requirements of the antenna module under working wind load, and the weight of the antenna module is reduced by 33.5%, which greatly saves costs.

1. Introduction

The antenna module is a carrier and support for antenna arrays, cooling equipment, electronic equipment, etc.; it is an important equipment for ensuring the accuracy of radars and is an important place for on-line repair and maintenance of radar equipment[1]. In order to ensure the accuracy of radar array work, the antenna module needs to meet strict rigidity requirement [2] under the wind load, but at the same time the weight of the module must also meet certain requirements; therefore, the optimization of the structure of the antenna module is very important.

The structural optimization of the antenna bay frame has a large number of design variables. If the calculation of the finite element model is repeated, the cost is too high. At the same time, the multiple design variables cause the complexity and nonlinearity of the optimization process, making it difficult to achieve optimal global optimization results; how to ensure High efficiency and high accuracy in the optimization design are the key to the problem [3].

Therefore, this paper first adopts the method of random super-Latin experiment design to obtain the sensitivity coefficients of each design variable to the weight of the antenna cabin and deformation under wind load; based on this, a polynomial response surface model is established to replace the original calculation model and parallel. Iterative calculations greatly increase the efficiency of optimization. In the optimization problem, a combination of numerical optimization techniques and exploratory optimization techniques is used. The multi-island genetic algorithm is used for global search and the sequential quadratic programming algorithm is used for local search to ensure the accuracy of the calculation.

2. Structural Optimization Design Model

The antenna module acts as a carrier and support for the antenna array and uses a lightweight steel skeleton structure. Viewed from the side, the cross-section is approximately trapezoidal and is divided into 10 layers. The schematic diagram of the antenna tank structure is shown in the Figure 1.

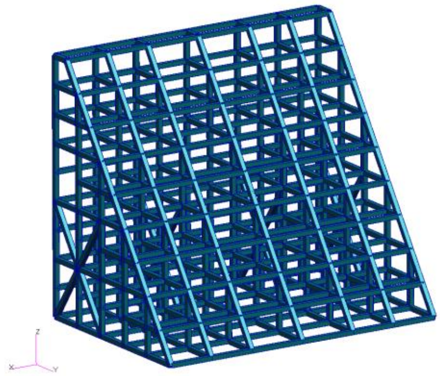


Figure 1. Antenna cabin structure

The skeleton adopts a rectangular steel structure. Three parameters are extracted for each section, which are W, H, and T. Each parameter is shown in Figure 2. According to its hierarchical structure, there are a total of 9 layers and a total of 27 design variables.

Optimize the design model：

$$\text{Min } M(x)$$

$$\text{s.t. } D1(x) \leqslant D\max;\ D2(x) \leqslant D\max \qquad (1)$$

where M(x) is the weight function of the antenna module, D1(x) is the displacement function under positive blow load, and D2(x) is the displacement function under the side blow load. x=(W1, H1, T1,..., Wi, Hi, Ti,..., W9, H9, T9) denotes the design variable vector, i denotes the ith truss section parameters.

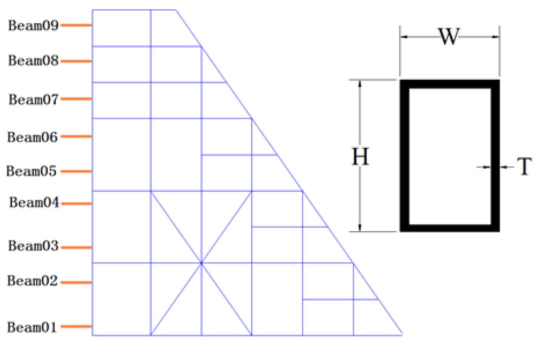


Figure 2. Schematic diagram of design variables

3. Optimization Design Method

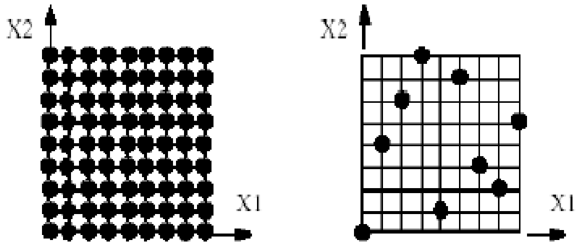
Due to too many design variables, experimental design was used to establish a polynomial response surface model. The polynomial response surface model is used instead of the calculation model to overcome the problem of excessive calculation and effective solution to numerical calculation noise. The optimization method uses a multi-island genetic algorithm and a sequential quadratic programming algorithm.

3.1 Test Design Method

The test design is mainly used to determine the design points in the design space that must be tested numerically. In principle, all design variables within the limits of the design variables can be selected; for the sake of efficiency, select a limited number of discrete values (called layers) for each design variable. The test design methods include: central composite test design, full factorial test design, orthogonal test design, uniform test design, and Latin Hypercube test design [4].

The full assay is evaluated at all levels for all combinations of all factors for the experimental design, allowing any number of factors and levels. This method provides a wealth of information for accurately assessing the effects of factors and interactions. There are 27 design variables in the antenna module. Even if only 2 layers are selected for each design variable, the full factorization method needs to calculate 227=1.34×108 times, which is costly to calculate.

Therefore, this paper adopts the random Latin hypercube method, which can greatly reduce the number of sample points. The random Latin hypercube design was the earliest full-space experimental design used in computer simulation experiments. This experimental design is an m × k matrix (m is the number of levels for each variable, k is the number of design variables), each column of data is a random arrangement of m levels, which has an effective space filling capacity; for example, a 2-factor by 9-level study, Figure 3, shows that 81 points are needed for the full factorial, whereas the Latin hypercube design requires only 9 points.



（a）Full analysis due to design（b）Latin super legislation

Figure 3. Full factorial design and latin hypercube design

3.2 Polynomial Response Surface Model Construction

Response surface model is the use of statistics and mathematics knowledge, through a simple expression, the actual analysis of the code for approximation processing to obtain a simpler model, but also conducive to the analysis of the calculation method. The whole process of the response surface method mainly includes: selecting the response surface approximation function model (polynomial model), determining a set of test data points for evaluating the response function, constructing the response approximation function based on the test result, and performing the prediction performance of the response approximation function. Evaluation, final response surface methodology applied to the optimization design [5].

In practical problems, the true response function relationship between input and output cannot be determined in advance, but any function can be approximated by polynomials. Therefore, in common practical problems, polynomial regression can always be used for analysis and calculation regardless of the actual relationship between input and output.

The polynomial response surface model can be written as：

$$y^{(p)} = c_0 + \sum_{1\le j\le n_v} c_j x_j^{(p)} + \sum_{1\le j\le k\le n_v} c_{(n_v-1+j+k)} x_j^{(p)} x_k^{(p)} \tag{2}$$

Where $y^{(p)}$ is the response of the p^{th} analysis; $x_j^{(p)}$ and $x_k^{(p)}$ are the design values of the p^{th} n_v dimensional design point; c_0,c_j,$c_{(nv-1+j+k)}$ is an unknown underestimated polynomial parameter.

After calculating the underestimated parameters of the response surface equation, it is also necessary to perform statistical tests on the response surface equations to evaluate their approximation to the true response.

The complex correlation coefficient R2 is defined as：

$$R^2 = 1 - \frac{S_{SSE}}{S_{SSY}} = \frac{S_{SSR}}{S_{SSY}} \tag{3}$$

SSSY is the sum of the squared total deviations, SSSR is the regression sum of squares, and SSSE is the sum of the remaining squares. The value of R^2 is between 0 and 1. The larger the value, the more accurate the approximation of the response equation. However, a value of R^2 close to 1 does not necessarily mean a good degree of approximation. This is because the increase in the number of variables in the response equation tends to increase the value of R^2 but does not necessarily increase the prediction accuracy of the equation. Therefore, the modified complex correlation coefficient R^2_{Adj} is defined as:

$$R^2_{Adj} = 1 - \frac{S_{SSE} / (n_s - n_t - 1)}{S_{SSY} / n_s} \tag{4}$$

The approximation degree of the response equation is measured by calculating the value of R^2_{Adj}. If the values of R^2 and R^2_{Adj} are greatly different, then there is likely to be an excess of the variable in the response equation, and if it is approximate, the equation is explained. The more accurate the approximation.

3.3 Optimization Methods

The optimization algorithms in iSIGHT are mainly divided into numerical optimization techniques and exploratory optimization techniques. Numerical optimization techniques usually assume that the parameter space is unimodal, convex, and continuous. Exploratory optimization techniques avoid the search focused on local areas, and these techniques search the global optimal design points across the entire parameter space. The numerical optimization technology can quickly find the local optimum, and the exploratory optimization technology can find the global optimum but the efficiency is low in the later period. Therefore, a search strategy composed of two technologies can take into account both the global optimum and the later efficiency.

Sequential quadratic programming in numerical optimization techniques is used to solve the nonlinear mathematical programming problem with constraints [6]. The main advantage of this algorithm is that it is easy to use with a very robust algorithm. Mathematical convergence and numerical performance are The assumptions of the applicable situation are superior to other mathematical programming algorithms.

Exploratory optimization methods include: simulated annealing algorithm[7] and multi-island genetic algorithm[8].

The simulated annealing algorithm is obtained by simulating the physical process of metal annealing. When the metal is heated to a certain temperature, it melts. At this time, the molecules can move freely. The slow and regular cooling of the metal allows the atoms to be arranged in the most stable and energy-minimized position. Minimizing the energy of the metal, this process minimizes the objective function. The global minimum solution corresponds to the most stable state of matter.

The genetic algorithm mainly uses the law of "survival of the fittest" in the process of biological evolution to imitate the genetic propagation mechanism in the process of biological evolution, and encodes the individual who optimizes the problem space, and then selects, crosses, and mutates the encoded individual population. Iteratively seeks a combination of optimal solutions or better solutions from new populations.

The fitness function is the only criterion for assessing the pros and cons of an individual. The genetic algorithm determines the individual's chance of reproduction based on the degree of fitness. Individuals with a higher fitness value have a greater chance of reproduction than those individuals with a smaller fitness value, resulting in an average new population. The fitness value is higher than the average fitness value of the old group.

The biggest difference between the multi-island genetic method and traditional genetic algorithm is that each population is divided into several subpopulations, also known as islands. The traditional genetic algorithms were performed in the respective sub-populations, and some individuals were selected to “immigrant” to other islands on a periodic basis. Such operations became “immigrants”. There are two parameters that control the immigration process: the immigration interval (the number of progeny to be procreated after each immigration); the immigration rate (percentage of immigration individuals). In this way, populations are separated and more kinds of solutions are generated. The diversity of the solutions improves the ability and convergence of the global search. In order to avoid convergence before the algorithm matures, large groups are used to improve the quality of search, but

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large groups increase the amount of calculation of individual adaptive evaluation, thereby reducing the convergence rate.

Simulated annealing algorithms and genetic algorithms have many similarities. They all need to generate new design points through mutation from the old design points. The simulated annealing algorithm is simpler than the genetic algorithm because it only checks one design point in the search space each time, and the genetic algorithm checks a set of design points. In addition, the simulated annealing algorithm has fewer parameters than the genetic algorithm. Therefore, the simulated annealing algorithm is very suitable for the discrete design space, while the genetic algorithm can be calculated in parallel.

The optimization problem of the size of the skeleton section of the antenna module should be a multi-modal nonlinear problem. Considering that there are many design variables, the global optimization algorithm is used to explore the multi-island genetic algorithm, and the local search uses the second algorithm in the numerical optimization algorithm. Planning method. This not only guarantees the search for the global optimal solution, but also guarantees the local convergence efficiency. The local optimization adopts the sequential quadratic programming algorithm, and local optimization is performed. At the same time, the finite element model calculation is used to locally update the polynomial response surface model, which ensures the accuracy of the calculation model.

4. Design Optimization

The finite element model was established using Patran, and the model was parameterized by the iSIGHT integrated PCL [9]. Super Latin sampling method was adopted. Polynomial response surface model was established through experimental design. Finally, the optimal algorithm was obtained using a combination of multi-island genetic algorithm and sequential quadratic programming algorithm.

4.1 Finite Element Modeling and Calculation Parameters of Antenna Cabin

The finite element model was established based on the structural dimensions, and the units were in Newton and millimeter units. The finite element model is shown in Figure 1. The antenna module was built using beam elements.

The antenna module is mainly calculated as whether the stiffness meets the accuracy requirement at a wind speed of 25m/s. When the given wind speed is a steady wind speed, the wind pressure calculation formula is (g is the gravity acceleration):

$$q = K_R (K_g K_h)^2 \frac{g}{16} V^2 \tag{5}$$

K_R is the coefficient of wind resistance, which is mainly determined by the shape and direction of the object. Here, when the wind is blowing, it is 1.4. Kg is a gust factor. When the given wind speed is a steady wind speed, the national army standard is 1.42; Kh is a height factor, and it is 1.15. When the 25m/s is a steady wind speed, q=1.429 kN/m 2.

The initial value of the skeleton beam section is taken as W=500mm, H=500mm, and T=10mm.The initial weight M = 481.6 tons.

The design constraints are: positive blow at 25m/s and deformation of the antenna module ≤ 14.8mm under the side blow load.

4.2 Experimental design

Using the Super-Latin method, 5000 sample points were selected and the numerical range was ±60% of the initial value.

The sensitivity of each input and each other to the deformation of the antenna module under blow load is shown in Figure 4. It can be seen that the thickness of the first layer skeleton steel has the most significant influence on the deformation of the antenna module, reaching 5.33%.

The polynomial response surface equation is constructed based on the calculation results. The approximating degree index of the response surface equation to the true response is: the complex correlation coefficient R and the modified complex correlation coefficient Radj. The response surface equations R^2=0.959 and R^2_{Adj} =0.955 calculated from equations (3) and (4) are all close to 1, indicating that the response surface polynomial fits well with the sample points.

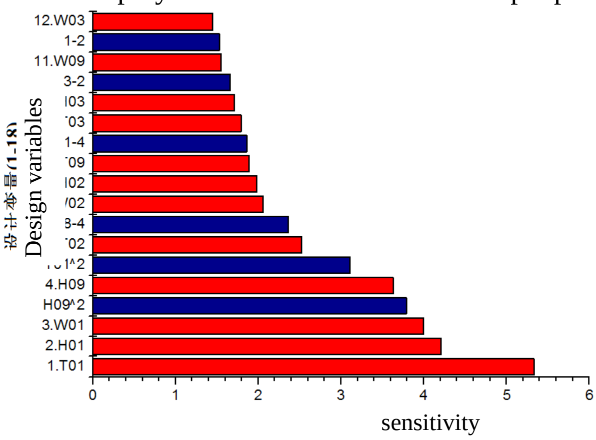

Figure 4. Top 18 sensitivity factors

4.3 Structural Optimization Design Process

Based on the experimental design model, after 43649 iterations, the convergence of the design constraints, optimization goals, and design variables is shown in Figures 5 and 6. It can be seen that in the initial stage of optimization, the global individual population is selected and crossed. Variations and other operations, through iterative search from the new population containing the optimal solution combination, in the latter iteration through the sequential quadratic programming for local search convergence. Since the calculation used is based on the approximate model established by the polynomial response surface and the parallel genetic algorithm is used in the multi-island genetic algorithm, although the number of iterations is more than 40,000, the entire optimization time is only 15 minutes and the calculation efficiency is very high. Figure 5 and Figure 6 show the convergence curves of the deformation of the antenna module under the weight and positive load.

After the final optimized parameters are listed in Table 1, the optimized skeleton weight is 320 tons, and the initial state is 481.6 tons, and the weight loss is 161.6 tons, accounting for 33.5% of the original skeleton weight.

Table 1. List of optimized parameters

Variable Code number	Value /mm	variable Code number	Value /mm	variable Code number	Value /mm
Beam01W	700	Beam04W	207	Beam07W	502
Beam01T	7	Beam04T	7	Beam07T	7
Beam01H	700	Beam04H	290	Beam07H	259
Beam02W	700	Beam05W	207	Beam08W	510
Beam02T	7	Beam05T	7	Beam08T	7
Beam02H	658	Beam05H	235	Beam08H	293
Beam03W	225	Beam06W	361	Beam09W	430
Beam03T	7	Beam06T	7	Beam09T	7
Beam03H	700	Beam06H	260	Beam09H	686

It can be seen from Table 2 that the stiffness of the optimized antenna array has decreased, and the maximum deformation is 14.5 mm, which satisfies the accuracy constraints. After optimization, the maximum bending stress of the antenna frame is -56.2 Mpa, which is based on the stability of the profile pipe. The maximum moment of inertia of the pressure beam I = 8.99 × 10 8 mm 4, area A = 284 mm2, radius of gyration of the profile Mm, L/ρ=11. Conservatively estimate the end support coefficient C = 1, the critical stress curve in reference [10], then the σcr of the rod = 274Mpa, the residual strength coefficient is greater than 2, which meets the stability requirements.

Table 2. Comparison of antenna bay strength before and after optimization

Operating conditions	Pre-optimization plan		Optimized plan	
	Antenna module deformation/mm	Antenna skeleton strength/Mpa	Antenna module deformation/mm	Antenna skeleton strength/Mpa
Weight	6.63	-36.0	7	-36
25m/s Front	10.6	-47.6	14.2	-56.2
25m/s Side	6.77	-38.3	14.5	-38.3

5. Conclusion

In this paper, a typical antenna module structure is optimized based on response surface and multi-island genetic algorithm. The following conclusions are obtained:

(1) The polynomial response surface model is used instead of the original calculation model. The random super-Latin method is used to carry out the combined sampling of 27 design variables. The exact polynomial response surface model is established through experimental design, and the calculation efficiency is significantly higher.

(2) Taking into account the large number of design variables and the wide design field, in order to avoid focusing on the local area search, an optimization method combining the multi-island genetic algorithm and the sequential quadratic programming algorithm is adopted, thus ensuring the global optimal solution. The search also ensures local convergence efficiency.

Finally, an optimized weight reduction of 33.5% was achieved for the antenna bay frame structure, which will result in significant economic benefits.

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