Optimization of Helicopter Rotor Airfoil Wind Tunnel Test Model Based on Intelligent Algorithm

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Abstract. The helicopter rotor wing wind tunnel test model is the basic equipment for helicopter wind tunnel test research. On the premise of meeting the requirements of corresponding strength, stiffness, natural frequency and stability, the model mass needs to be light enough to meet the requirements of heave vibration test. To this end, this paper proposes the structure of aluminum alloy skeleton + carbon fiber reinforced composite skin, and in order to obtain good performance, the following steps are used to optimize the parameters of the test model structure: 1. Establish an RBF neural network approximation model; 2. Use multiple island genetic algorithm (MIGA) and the sequential quadratic programming algorithm (SQP) are combined to optimize the thickness of the skeleton and composite materials. The optimization results show that the quality of the model is reduced by 34.05% under the condition that the corresponding requirements of strength, stiffness, natural frequency and stability are met.

Keywords: Carbon fiber reinforced composite; Finite element analysis; Intelligent algorithm; Multi-objective optimization, Wind tunnel test.

1. Introduction
Helicopter rotor dynamic stall is a serious un-steady aerodynamic phenomenon, the mechanism is very complicated, and the airfoil dynamic stall is its concentrated manifestation, in-depth understanding of the rotor airfoil dynamic stall characteristics is conducive to study how to improve rotor performance, more accurately predict rotor aerodynamics.

At present, wind tunnel testing is the main means to understand the rotor blade airfoil dynamic stall characteristics and flow mechanism. Therefore, the establishment of rotor blade airfoil dynamic wind tunnel test technology to research helicopter rotor blade dynamic stall characteristics. It will play a vital role in promoting the research and development of high-load, high-speed, and high-mobility helicopters.

To meet the needs of rotor airfoil dynamic stall research. As one of the key equipment for the dynamic test research of the helicopter rotor airfoil, on the premise of meeting the requirements of strength, stiffness, and natural frequency, the helicopter rotor airfoil wind tunnel test model must optimize the quality of the model and obtain better heave oscillation dynamic performance.

The optimization design of composite materials has been extensively studied. For example, Thompson et al. [1,2] combined finite element analysis with the feasible direction method, optimized the structural quality with the ply thickness as the optimization variable, and the strength and the specified point deflection as the constraints. Park et al [3] proposed the optimization method of symmetrical laminates based on a genetic algorithm. Jin Dafeng et al [4] proposed the optimization of plywood composite
plywood cutting structure based on genetic algorithm, and Narita [5] studied the optimization of plywood composite laminate sequence. But at present, there is still a lack of optimization design work for the helicopter rotor airfoil wind tunnel test model, especially the multiobjective optimization that comprehensively considers static, stiffness, natural frequency, stability conditions, and quality. The helicopter rotor airfoil wind tunnel test model uses a new type of carbon fiber reinforced composite skin, rib + aluminum alloy skeleton structure layout. Make the model with lighter weight, suitable strength, stiffness, and other characteristics. However, in engineering applications, the model aluminum alloy framework thickness, ply thickness, and ply angle distribution are relatively complex, and it is necessary to select an appropriate method to optimize. This article intends to propose the following design optimization ideas: establish a finite element analysis model to analyze the quality, strength, stiffness, natural frequency, and stability of the model under the conditions of initial aluminum plate thickness, layer thickness, and layer angle; the RBF neural network approximate model and two intelligent algorithms are used to optimize the thickness of the front beam aluminum and the thickness of the composite material.

2. Analysis of Finite Element Model

2.1. Geometric Model
The helicopter rotor airfoil wind tunnel test model (Figure 1) is composed of main components such as front and rear crossbeams, front and rear longitudinal beams, skin, and left and right end connecting flanges. The model has a total length of 1950mm and a chord length of 300mm. The front crossbeam and the left and right flange materials are 7075 aluminum alloy, and the rest are made of T800 carbon fiber-reinforced composite material.

![Figure 1. 3D geometric model](image)

2.2. Meshing
In order to ensure the accuracy of the calculation, this device uses a 4-node quadrilateral element to divide each component (see Figure 2).

2.3. Definition of Material Properties and Boundary Conditions
The material of the front crossbeam and flange is 7075, and the rest of the components are made of T800 carbon fiber reinforced composite materials. The material properties are shown in Tables I and II. The applied load is composed of two aspects: 1) the model bears the inertial load; 2) the aerodynamic load of the model.

![Figure 2. Meshing diagram](image)
Table 1. Carbon fiber reinforced composite material properties

| Elastic modulus/GPa | Shear modulus/GPa | Poisson’s ratio |
|---------------------|------------------|-----------------|
| $E_1$               | $E_2$            | $E_3$           | $G_{12}$ | $G_{13}$ | $G_{23}$ | $v_{12}$ | $v_{13}$ | $v_{23}$ |
| 195                 | 8.58             | 8.58            | 4.6      | 4.6      | 2.9      | 0.33     | 0.33     | 0.48     |

| Tensile strength/MPa | Compression strength/MPa | Shear strength/MPa |
|----------------------|--------------------------|-------------------|
| $X_t$                | $Y_t$                    | $Z_t$             | $X_c$    | $Y_c$    | $Z_c$    | $S_{12}$ | $S_{13}$ | $S_{23}$ |
| 3071                 | 88                       | 88                | 1747     | 271      | 271      | 143      | 143      | 143      |

Table 2. Material properties

| Material | Modulus(GPa) | Poisson’s ratio | Density(kg · m$^{-3}$) |
|----------|--------------|-----------------|------------------------|
| 7075     | 72           | 0.33            | 2810                   |

2.4. Finite Element Static Analysis and Results
According to the strength theory, when the stress value reaches the yield limit of the material, the material will yield failure.

The strength condition is expressed as $\sigma \leq [\sigma]$, $\sigma$ is the equivalent stress, $[\sigma]$ is the allowable stress of the material. The allowable stress of material 7075 is: $[\sigma] = \frac{\sigma_y}{2} = 252.5$ MPa.

2.5. Strength Analysis
It can be seen from Figure 3 that the maximum equivalent stress value $\sigma = 131.51$ MPa of the model is less than the allowable stress of the material. So the whole model is safe.

2.6. Stiffness Analysis
It can be seen from Figure 4 that the maximum displacement of the model is 5.6187 mm.

2.7. Modal Analysis and Results
The natural frequency and mode of each order are shown in Table 3.

2.8. Stability Analysis and Results
It can be seen from Figure 5 that the buckling analysis of the model corresponds to the absolute value of the corresponding buckling load factor 4.638.

2.9. Failure Analysis and Results
Using the Tsai–Wu failure criterion and failure analysis, it can be seen from Figure 6 that the maximum failure index is 0.8143.

Figure 3. Stress contours of the model.  
Figure 4. Deformation contours of the model.
Figure 5. Displacement cloud diagram of eigenvalue buckling analysis.

Figure 6. Contours of composite failure factors.

Table 3. Result of mode analysis

| Mode | 1      | 2      | 3      | 4      |
|------|--------|--------|--------|--------|
| Frequency | 59.944 | 153.55 | 247.57 | 251.0 |

3. Thickness Optimization

First, define the optimization problem, select variables and optimization targets to determine the variable range and response value; then, carry out design of experiment, generate the above finite element analysis sample points to fit an approximate model; and finally, use the optimization algorithm to find the optimization results.

3.1. Approximate Model and Verification

In order to solve the problem that the numerical simulation software takes a lot of time and cost in the object calculation process, the RBF neural network approximate model is used to simulate the input and output relationship of the finite element model. The input parameters are shown in Table 4, a total of 14 variables. The output parameters include model quality mass and finite element calculation results: maximum equivalent stress $s_{\text{max}}$, maximum deformation displacement value $d_{\text{max}}$, first-order natural frequency $f_{req1}$, buckling load factor $\lambda$ and failure index $F$.

The approximate model error analysis result (Table 5) shows that the RBF neural network approximate model has good performance in fitting the helicopter rotor wing wind tunnel test model.

Table 4. Input parameter values and range results

| Input Parameters                      | Lower Bound | Value | Upper Bound |
|--------------------------------------|-------------|-------|-------------|
| -45° skin thickness                  | 2           | 3     | 4           |
| 0° skin thickness                    | 2           | 3     | 4           |
| 45° skin thickness                   | 2           | 3     | 4           |
| 90° skin thickness                   | 2           | 3     | 4           |
| -45° longitudinal beams thickness    | 4           | 6     | 8           |
| 0° longitudinal beams thickness     | 4           | 6     | 8           |
| 45° longitudinal beams thickness    | 4           | 6     | 8           |
| 90° longitudinal beams thickness    | 4           | 6     | 8           |
| -45° rear crossbeams thickness      | 4           | 6     | 8           |
| -45° rear crossbeams thickness      | 4           | 6     | 8           |
| -45° rear crossbeams thickness      | 4           | 6     | 8           |
| Front crossbeam thickness           | 3           | 8     | 8           |
| Flange thickness                    | 5           | 12    | 12          |
### Table 5. Error calculation result

| Evaluation Index | $R^2$ |
|------------------|-------|
| $s_{\text{max}}$ | 0.964 |
| $d_{\text{max}}$ | 0.996 |
| $f_{\text{req}}$ | 0.996 |
| $\lambda$ | 0.999 |
| $FI$ | 0.925 |
| mass | 1 |

### 3.2. Combinatorial Optimization

On the premise of meeting the requirements of strength, stiffness, natural frequency and stability, with the goal of minimum mass, the optimization strategy of the combination of MIGA algorithm and SQP algorithm is used to optimize the thickness of the composite material ply and the metal material.

Define the input parameter $x_i$, a total of 14 variables, as design parameters, and define the output variable parameter $y_j$ as the response. Define the objective function: $\min(mass)$. Define constraints:

- $d_{\text{max}} \leq 10 \text{ mm}$,
- $FI \leq 1.0$,
- $s_{\text{max}} \leq 252.5 \text{ mm}$,
- $f_{\text{req}} \geq 40 \text{ Hz}$,
- $\lambda \geq 2.5$.

Input the approximate model according to the value of the initial scheme, and iterate through the 1001 steps of the MIGA algorithm and 405 steps of the SQP algorithm. The optimized results are shown in Tables 6 and 7, and the model quality optimization process is shown in Figures 8 and 9.

#### Table 6. Values after design parameter optimization

| Input Parameters               | Initial Value | MIGA Algorithm | SQP Algorithm |
|--------------------------------|---------------|----------------|---------------|
| -45° skin thickness            | 3             | 2              | 4             |
| 0° skin thickness              | 3             | 4              | 4             |
| 45° skin thickness             | 3             | 2              | 4             |
| 90° skin thickness             | 3             | 4              | 4             |
| -45° longitudinal beams thickness | 6           | 5              | 6             |
| 0° longitudinal beams thickness | 6             | 6              | 4             |
| 45° longitudinal beam thickness | 6             | 5              | 6             |
| 90° longitudinal beam thickness | 6             | 7              | 6             |
| -45° rear crossbeams thickness  | 6             | 6              | 7             |
| 0° rear crossbeams thickness   | 6             | 5              | 6             |
| 45° rear crossbeams thickness  | 6             | 6              | 7             |
| 90° rear crossbeams thickness  | 6             | 7              | 7             |
| Front crossbeam thickness      | 8             | 3              | 3             |
| Flange thickness               | 12            | 6.40           | 5.72          |

#### Table 7. Optimization results

| Output Parameters | Initial Value | MIGA Algorithm | SQP Algorithm |
|-------------------|---------------|----------------|---------------|
| $s_{\text{max}}$  | 131.5         | 247.9          | 252.2         |
| $d_{\text{max}}$  | 5.62          | 7.78           | 7.46          |
| $f_{\text{req}}$  | 59.94         | 56.98          | 56.1          |
| $\lambda$         | 4.64          | 4.67           | 5.95          |
| $FI$              | 0.814         | 0.94           | 0.728         |
| mass              | 12.567        | 8.322          | 8.288         |

It can be seen from Table 7 that under the premise of meeting the requirements of strength, stiffness, natural frequency and stability, the mass is reduced by 33.74% after optimization by the MIGA algorithm, and the total mass is reduced by 34.05% after combination optimization.
4. Conclusion
Under the premise of satisfying the corresponding strength, stiffness, natural frequency, and stability requirements, the RBF neural network approximate model and two intelligent algorithms are used to optimize the thickness of the flange, front beam, and composite layer thickness. The optimization result reduced the model quality by 34.05%.

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