Optimization research of film cooling structure with fan-sharped hole

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Abstract. In order to improve the film cooling efficiency, the fan-shaped film cooling holes are optimized. The length of the straight hole section (\(L_m\)), the forward angle(\(\alpha\)) and the backward angle (\(\beta\)) were selected as the design variables. The area-averaged film cooling efficiency within the range of \(X/D=50\) (\(X\) is the downstream distance of the hole, \(D\) is the hole diameter)was taken as the objective function. The Co-kriging surrogate model was established according to the sample points by Latin Hypercube method and the finite element calculation results by calculating two meshing with different quality. The genetic algorithm was adopted to find the optimal fan-shaped hole structure. Under the condition that blowing ratio is 1.5, the optimized \(L_m\), \(\alpha\) and \(\beta\) are 2.6\(D\), 41°, and 14°, respectively, the cooling efficiency increased by 45% compared with the reference structure. The results show that a smaller straight hole section and a larger backward expansion angle can effectively inhibit the generation of kidney-shaped vortex pairs and improve the film cooling efficiency.

1. Introduction

With the continuous development of aero-engines, higher requirements are put forward for the cooling of the hot end components, because of the inlet gas temperature of the turbine is getting higher and higher. The research of the "Advanced Core Aircraft Military Engine" (ACME) had been carried out by UK in 2020. Till then the thrust-to-weight ratio will reach 20 and the turbine inlet temperature will increase to 2403K. For a series of problems caused by high temperature, solutions are proposed from two aspects. On the one hand, improve the heat resistance of materials and develop high-performance heat-resistant alloys; on the other hand, adopt advanced cooling technology. Film cooling is one of the most widely used cooling methods. Through the small holes on the blade surface, the cooling medium is injected into the main stream in the form of a jet to form a film with the blade surface to protect the wall[1][2].

In recent years, Fan-sharped hole is analyzed by many experimental and numerical simulation. Compared with circular film cooling holes, fan-shaped film cooling holes have higher cooling efficiency[3][4]. However, the factors that affect the film cooling efficiency are more complex due to the large number of geometric parameters of the hole. Lee et al[5]applied response surface surrogate model and a hybrid evolutionary algorithm for multi-objective optimization of fan-shaped film cooling holes. Lee and Kim[6] studied a method by linking Kriging surrogate model and sequential programming for optimizing the fan shaped cooling hole.
2. Description of the computation model

2.1 Geometry model

Fig. 1 shows that the geometry of the computation domain and the fan-shaped hole geometric parameters. The calculation area is composed of the main flow channel, the cold air channel and the air film hole with fan-shaped holes. The diameter of the pure cylindrical part is D=10mm, the sum of the hole length of the straight hole section and the hole length of the expansion section is 8D, the main flow channel length is 76D, the cross-sectional size is 9D, the cold air channel length is 50D, and the cross-sectional size is 7D. In order to verify the accuracy of the model data, the boundary conditions are set the same as his Fraas [7].

Fig. 1. Geometry model of the fan-shaped hole

2.2 Design variables and objective function

The detailed parameters of the fan-shaped hole is shown in Fig. 2. Three geometrical parameters, including the length of the straight hole section \( L_m \), the forward angle \( \alpha \) and the backward angle \( \beta \) are selected as design variables. The lower and upper limits of these three parameters are listed in Table 1.

Fig. 2. The detailed parameters of the fan-shaped hole

The area-averaged film cooling efficiency within the range of \( X/D=50 \) (X is the downstream distance of the hole) was taken as the objective function. Area-averaged adiabatic film cooling effectiveness \( \eta_{avg} \) is defined as:

\[
\eta_{avg} = \frac{1}{50} \int_{-4D}^{4D} \int_{0D}^{50D} \eta_{ad}(x,y) dxdy
\]

\[
\eta_{ad} = \frac{(T_{aw} - T_{aw})}{(T_{aw} - T_c)}
\]

Table 1 Design variables and the design space

| Design variable | Lower bound | Upper bound |
|-----------------|-------------|-------------|
| \( L_m/D \)     | 2           | 5           |
| \( \alpha \)    | 35°         | 50°         |
| \( \beta \)     | 5°          | 15°         |
3. Methods for solving optimization problems

The Co-Kriging surrogate model is constructed from multiple sets of high-fidelity data and low-fidelity data that do not interfere with each other. This method can reduce the time and computational cost required to construct a Kriging surrogate model using only high-confidence samples[8].

First the Co-Kriging model builds up by low-fidelity data and high-fidelity data. We assume that each sampling point corresponds to a stochastic process in low-fidelity model, which is based on Kriging model. For sampling point \( x \) with \( m \) dimensions, the stochastic process for low-fidelity prediction is \( Y_c \). Normally prediction value can be both one dimensional or multidimensional. In this paper, prediction value is one-dimensional that denotes empirical correlation result:

\[
Y_c(x) = \mu_c + Z_c(X)
\]

Where \( \mu_c \) denotes mean value for the model, \( Z_c(x) \) denotes a stochastic process which follows Gaussian distribution. Normally high-fidelity data is more accurate but harder to obtain in comparison with low-fidelity data. Similarly the stochastic process for the prediction of a high-fidelity sampling point, which is RANS simulation result in this work, consists two parts:

\[
Y_h(x) = \mu_h + Z_h(x)
\]

Now we get the complex covariance matrix composed of low-fidelity and high-fidelity sampling points as follows:

\[
C = \begin{pmatrix}
a & b \\ p & q
\end{pmatrix}
\]

\[
a = \sigma_c^2 \psi_c(X_c, X_c)
\]

\[
b = \rho \sigma_c^2 \psi_c(X_c, X_c)
\]

\[
p = \rho \sigma_c^2 \psi_c(X_c, X_c)
\]

\[
q = \rho^2 \sigma_c^2 \psi_c(X_c, X_c) + \sigma_d^2 \psi_d(X_c, X_c)
\]

The high fidelity prediction at an untried point \( x \), which denotes RANS simulation result in this work, can be written as

\[
\hat{y}_c = \hat{\mu}_c + c^T C^{-1} (y - 1_{co} \hat{\mu})
\]

(10)

\[
\hat{\mu}_c = 1_{co}^T C^{-1} y / 1_{co}^T C^{-1} 1_{co}
\]

(11)

Noted that in co-Kriging method, \( Z_d(x) \) is composed with the low-fidelity stochastic process \( Z_c(x) \) multiplied by a scalar plus another stochastic process \( Z_d(x) \):

\[
Z_h(x) = \rho Z_c(x) + Z_d(x)
\]

(12)

3.1 High fidelity method

According to Fraas [14] research on fan-shaped holes, the boundary conditions of the computational domain are set as follows: the inlets of the main flow and the secondary flow are set as velocity inlets, where the main flow Reynolds number is \( 13 \times 10^4 \), the temperature is 510K, the turbulence is 8.3, and the secondary flow The speed is determined by the blowing ratio, and the air-conditioning temperature is 300K. Periodic boundary conditions are used on both sides of the main flow channel and the cold air channel, symmetrical boundary conditions are used on the upper side of the main flow channel, and non-slip adiabatic boundary conditions are set on the remaining surfaces. The calculation working medium is an ideal incompressible gas.

The turbulence model adopts the Realizable k-ε model, the wall function adopts the enhanced wall function, and the coupling of pressure and velocity adopts the SIMPLE algorithm. The discrete format
of density, momentum, turbulent kinetic energy, turbulent dissipation rate and energy adopts the second-order upwind style; the convergence criterion of the solution is that the residual values are all less than $10^{-5}$. To reach the requirements of enhanced wall function, $y^+$ is kept between 1 and 2.

3.2 Low fidelity method
Compared with high-fidelity data, low-fidelity data uses the same calculation method, but changes the number of grids. The total mesh elements are approximately 0.5 million, about one-fifth of the high-fidelity model, as shown in Fig.4.

3.3 Optimization method
After the construction of multi-fidelity model, the optimum hole geometry is found by GA. The genetic algorithm simulates the phenomenon of reproduction, crossover, and gene mutation that occur in natural selection and natural genetic processes. In each iteration, a set of candidate solutions are retained, and a better individual is selected from the solution group according to a certain index, using genetic operators. Making a new combination of these individuals to produce a new generation of candidate solution groups, repeat the process until a certain convergence index is met, and have a good global optimization ability [9][10]. In this research, the global optimization point is found by GA. Co-kriging surrogate model serves as the evaluation method for GA. The optimization problem can be defined as:

$$\min F(L_m, \alpha, \beta) = -\eta_{\text{avg}}$$

$$2D \leq L_m \leq 5D$$

$$35^\circ \leq \alpha \leq 50^\circ$$

$$5^\circ \leq \beta \leq 15^\circ$$

4. Results and analysis
In the present study, in front of the 36 groups are the low-fidelity date and at the back of the 12 groups are the high fidelity date. Both of them are used for the training samples for Co-kriging surrogate model. These samples are listed in Table 2.

| NO. | Lm/D | $\alpha$ | $\beta$ | $\eta$ |
|-----|------|----------|---------|--------|
| 1   | 2    | 35       | 5       | 0.0927 |
| 2   | 2    | 38       | 8       | 0.1004 |
| 3   | 2    | 41       | 11      | 0.1176 |
| 4   | 2    | 44       | 14      | 0.1104 |
| 5   | 2    | 47       | 17      | 0.1331 |
| 6   | 2    | 50       | 20      | 0.1372 |
The Co-Kriging surrogate model was used to train the sample points. The basic values $L_m$, $\alpha$ and $\beta$ (3.8D, 44° and 5°) respectively as the reference structure. Table 3 shows the geometric parameters of the sector hole before and after optimization.

| Item        | $L_m/D$ | $\alpha$ | $\beta$ | $\eta$ |
|-------------|---------|----------|---------|--------|
| Reference   | 3.8     | 44       | 5       | 0.0942 |
| Optimized   | 2.6     | 41       | 11      | 0.1383 |

Figure 5 shows the distribution of film cooling efficiency before and after optimization. The downstream cooling efficiency close to the air film hole is relatively high; along the mainstream direction, the cooling efficiency continues to decrease, and the spanwise coverage of the air film continues to shrink. In addition, at the downstream of the film hole, the pressure distribution of the two cooling holes in the span direction is low in the center and high on both sides. This is due to the characteristics of the cooling airflow flow structure in the fan-shaped film hole. The distribution characteristics of the fan-shaped film cooling holes after optimization are more obvious. Under the condition of a blowing ratio of 1.5, after optimization, the cooling efficiency of the downstream area of the fan-shaped hole from 10D to 15D is significantly improved, and the cold air spreading and overflowing capacity is strengthened.

![Figure 5](image_url)

Fig.5 Distribution of film cooling efficiency on adiabatic surface
fit the wall surface well, and the cooling effect on the wall surface is poor. Due to the existence of the kidney-shaped vortex, the cold air cannot fit the wall surface well, and the cooling effect on the wall surface is poor.

![Velocity contours in the hole](image)

**Fig. 6 Velocity contours in the hole**

5. Conclusion

Co-kriging surroated model and genetic algorithm based optimization for improving film cooling effectiveness of a fan-shaped hole was carried out. Surrogate model is an effective tool during optimization for film cooling holes. At $M=1.5$, compared with the reference structure, the optimized film cooling hole has a larger forward expansion angle, which can better inhibit the formation of kidney vortices and effectively improve the cooling efficiency. At the same time, the Co-kriging surrogate model can greatly save calculation time and cost, and has a good application prospect.

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