Optimization for Hot-film Anti-icing Structure by BPNN and GA

Jie Liu* and Peng Ke2

1Department of Civil Helicopter Research and Development, China Helicopter Research and Development Institute, 35th Center Avenue, Binhai District, Tianjin, China
2Department of Transportation Science and Engineering, Beihang University, 37th Xueyuan Road, Haidian District, Beijing, China
*Email: liujie0430@buaa.edu.cn

Abstract. A coupled method combining the Back Propagation Neural Network (BPNN) and Genetic Algorithm (GA) was developed to optimize a 2D design of aero-engine inlet anti-icing structure, which has a cover on the film heating ejection slot. The optimal goal is to maximize the heating effectiveness which was used to assess the performance of hot-air film. The film-heating ejection angle and the cover opening angle were selected as the design variables to be optimized. The training and testing samples employed in BPNN were obtained by numerical simulation, after which the objective function of GA was predicted. With a given flow rate of bled air, the optimal values of the two design variables were achieved as 22.6° and 15.1°, respectively. Compared to the previous optimal result of other researchers, the heating performance was improved by 16.7% with rapid progress. The result of this study illustrates that this hybrid optimal method can meet the accuracy requirements with high time-efficiency for optimization problems in aeronautics engineering.

1. Introduction
Ice accretion on aircraft for both rotor and fixed wing could cause serious effects on flight safety, such as mass imbalance and components damage [1-3]. Related requirements have been made in airworthiness regulatory to guarantee safe operation like FAR 33.68, FAR 25.1093, FAR 25.1419 as well as similar regulations in FAR29.

Hot air ice protection system is extensively used in the aeronautic industry, whose ability has been demonstrated to meet requirements of airworthiness regulations. The hot-film anti-icing system evolved from traditional impact heat transfer models. Through the aero-engine’s jet-hole, the hot air is bled and ejected out to form a hot-film covering the rear region of the outer structure wall. It can improve the utilization of hot bleed air by combing the internal impact of heat transfer and the external film-heating. Whereas the heat performance is still needed to be improved to reduce the effect caused on aero-engines by bleeding hot air [4-6].

Some researchers have studied the working principle of the hot-film anti-icing system of the aero-engine inlet vane, and found some structural factors could obviously affect the heating performance, the film-heating ejection angle, for instance. [7,8]. Moreover, the installation of a cover at the exit of slot could further improve the attachment of the hot-film to the rear region of out wall. Therefore, the
film-heating ejection angle as well as the cover opening angle were defined as design variables to find the optimal structure with the highest heating performance.

For the complexity of the anti-icing structure, such as the existence of jet-slot and cover, the flow field could be affected significantly, especially when taking characteristics of droplet impingement into consideration in further investigation. Thus, the functional relationship between the optimization objective and design variables is obviously nonlinear. Besides, discrete feature points were selected to evaluate the heating performance of the hot-film anti-icing system. Given the characteristics aforementioned, the traditional gradient-based methods cannot be applied, and there is a need to develop a new optimal method.

Many optimization problems with high complexity can be solved by GA through individuals’ evolution. Besides, it does not depend highly on the function continuity and the derivatives existence. BPNN can acquire a functional relationship using limit samples, which can serve as the input of GA. The combination optimization method using GA and ANN (Artificial Neural Network) shows good perspectives in many fields and attract more and more attention in recent years [9-12] Among those, Darvishvand [13] optimized the design of 3D radiant furnaces using this coupled method, where the uniform thermal conditions on a 3D irregular shape body’s surfaces were obtained. Krzywanski [14] et al. adopted the BPNN-GA method to optimize a tri-bed twin-evaporator adsorption chiller to realize the highest cooling capacity. Compared to the conventional method, the results showed that the computational time was significantly reduced.

In this study, an efficient optimization algorithm is established coupling BPNN and GA based on CFD results. The framework of optimization process is shown as figure 1.

![Figure 1. Framework of overall solution.](image)

2. CFD Numerical Simulation

CFD numerical simulation was done with the two dimensional hot-film anti-icing structure for the aero-engine inlet vane.

2.1. Structure of the Object

The object structure is shown in figure 2(a). The dimension is almost constant along the span wise due to good symmetry. Thus, half of the structure is chosen for the numerical simulation.
Figure 2. Model of the anti-icing structure of inlet vane.

The film-heating ejection angle ($\alpha$) and the cover opening angle ($\beta$) are defined as design variables. Considering droplet impingement characteristics as well as limited by the structure, the constraints are set to: $\alpha \in [5^\circ, 150^\circ]$ and $\beta \in [10^\circ, 30^\circ]$. The optimization objective is identified to be reached when hot-film achieves its highest heating efficiency, assuming that the amount of bleed air has been determined. Thus, the front most position of the structure’s is (-0.0025m, 0m), and the backmost is (-0.1661m, 0m).

Numerical simulations were conducted with the control variable method. Heat conduction of solid was not considered since it does not influence the change rule of the heating performance obviously. Besides, the simulation of droplet impingement and ice accretion are not presented here due to focusing on the establishment of overall optimal process.

The definition of heating effectiveness $\eta_t$ is as equation (1), in which $T_{aw}$, $T_2$, $T_{\infty}$ are the temperature of the adiabatic wall, the hot bleed air, and the cold air flow.

$$\eta_t = \frac{T_{aw} - T_{\infty}}{T_2 - T_{\infty}}$$ (1)

2.2. Independence Check of Mesh
The 2D structured grid when $\alpha=150^\circ$, $\beta=10^\circ$ is shown in figure 3 for instance. The calculation domain contains the inner thermo-jet field and the outer main cold airflow field. The grid around the junction of two fields aforementioned and the outer wall is locally encrypted, thus features of the hot-film can be better captured. Grids with different density have been used to conduct the grid independence check, as shown in figure 4. The grid with 70,000 cells is selected due to the comprehensive consideration between calculation cost and accuracy. The accuracy requirement of enhanced wall treatment $y^+<1$ near the outer wall can be met at each position except the tail end.

Figure 3. Example of meshing. Figure 4. Heating effectiveness with different mesh density.

2.3. Governing Equations and Boundary Conditions
Three conservation equations are solved with the assumption of compressible and statistically steady turbulent flow. RNG $k-\varepsilon$ turbulence model is adopted with the enhanced wall treatment. Besides, the fluid material is recognized as ideal-gas solved with the pressure-base coupled solver. Meanwhile, all of the convective terms are discretized with a second-order upwind interpolation scheme. The
governing equations aforementioned are solved using ANSYS Fluent. In addition, boundary conditions are illustrated as table 1.

**Table 1.** Settings of boundary conditions.

| Type of boundary | Cold airflow inlet | Hot-jet inlet | Outlet |
|------------------|--------------------|---------------|--------|
| Mach             | 0.314              | Depend on the blowing ratio | --    |
| Temperature, K   | 253                | 413           | 253    |
| Pressure, Pa     | 101325             | 202000        | 101325 |

For there is a certain similarity between the research object and a one-line thermo-jet confined channel, the latter was chosen in the verification of the simulation settings’ accuracy. Related work is contained in previous research of authors [15].

3. **BPNN Fitting**

BPNN consists of the input layer, the hidden layer and the output layer, which is a kind of multi-layer feed forward neural network. It can model complex physical phenomena with high computational speed as well as accurate prediction [9,12], thus overcoming the disadvantage of time-consuming experimental studies and simulation approaches. The most important thing is that BPNN can process fuzzy information, even when the functional relationship is uncertain [13,14]. The schematic diagram is shown as figure 5.

![Figure 5. Schematic diagram of BPNN.](image)

After extracting the outer wall temperature, the 18 groups of heating effectiveness are calculated according to equation (1). These can serve as training and testing samples in the prediction process using BPNN, which is illustrated as follows.

**3.1. Fitting of a Continuous $x - \eta_i$ curve**

For a certain set of $(\alpha, \beta)$, the distance $x$ and corresponding heating effectiveness $\eta_i$ are selected as input and output, respectively. Thus, a continuous $x - \eta_i$ curve can be obtained with discrete data points. Therefore, the internal change rule of the heating effectiveness along the outer wall can be explored. In addition, nine feature positions from 0m to 0.16m in 0.02m intervals (named as $P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8, P_9$ respectively) are selected that the heating performance can be better compared. The corresponding $\eta_i$ calculated by the network result of this step is given in table 2.

**Table 2.** Calculated data.

| $\alpha$ | $\beta$ | $\eta_1$ | $\eta_2$ | $\eta_3$ | $\eta_4$ | $\eta_5$ | $\eta_6$ | $\eta_7$ | $\eta_8$ | $\eta_9$ |
|----------|---------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| 5°       | 10°     | 0.6037   | 0.3569   | 0.2904   | 0.2511   | 0.2216   | 0.1990   | 0.1817   | 0.1677   | 0.1583   |
| 5°       | 15°     | 0.8841   | 0.4632   | 0.3599   | 0.3033   | 0.2619   | 0.2293   | 0.2052   | 0.1851   | 0.1714   |
5° 20° 0.8644 0.4066 0.3073 0.2630 0.2194 0.2005 0.1776 0.1595 0.1518
5° 25° 0.8310 0.3312 0.2412 0.1968 0.1721 0.1533 0.1405 0.1306 0.1252
5° 30° 0.7820 0.3125 0.2174 0.1794 0.1548 0.1409 0.1266 0.1205 0.1147
30° 10° 0.8729 0.4486 0.3429 0.2866 0.2492 0.2228 0.2016 0.1861 0.1751
30° 15° 0.9189 0.3922 0.3121 0.2653 0.2377 0.2069 0.1929 0.1716 0.1649
30° 20° 0.7453 0.3328 0.2471 0.2040 0.1804 0.1619 0.1480 0.1375 0.1322
30° 25° 0.7825 0.3213 0.2156 0.1745 0.1448 0.1242 0.1203 0.1152
30° 30° 0.6558 0.3220 0.2023 0.1630 0.1409 0.1267 0.1179 0.1090 0.1076
90° 10° 0.0404 0.5044 0.3653 0.3044 0.2581 0.2337 0.2110 0.1910 0.1781
90° 15° 0.0457 0.6247 0.4747 0.3785 0.3032 0.2617 0.2262 0.1929 0.1805
90° 20° 0.0576 0.5741 0.3581 0.2729 0.2249 0.1909 0.1618 0.1499 0.1355 0.1285
90° 25° 0.0665 0.5027 0.2972 0.2226 0.1909 0.1471 0.1350 0.1214 0.1193
90° 30° 0.0710 0.4866 0.2675 0.2043 0.1673 0.1471 0.1350 0.1214 0.1193
150° 10° 0.0068 0.7030 0.4917 0.3824 0.3055 0.2548 0.2160 0.1900 0.1712
150° 15° 0.0118 0.7590 0.4122 0.2930 0.2332 0.1970 0.1737 0.1571 0.1433
150° 20° 0.0070 0.6608 0.3248 0.2353 0.1880 0.1663 0.1441 0.1327 0.1249

3.2. Fitting of $\langle \alpha, \beta \rangle - \eta_t$ Curve at Feature Points

Trained with the dataset in table 2, a two-input nine-output BPNN can be obtained. Thus, the internal relationship between $\eta_t$ and its corresponding set of $\langle \alpha, \beta \rangle$ can be found. Instead of traditional optimal methods, it does not need to conduct extremely time-consuming simulations with a lot of data.

3.3. Verification of BPNN

Comparison between the BPNN fitting results and the numerical simulation data has been made. The verification within and beyond 18 groups of sampling are elaborated respectively in the following contents.

Firstly, (30°,15°) and (90°,20°) were selected for instance in the verification of the fitting accuracy within sampling. It is illustrated in figure 6 that, the predicted $\eta_t$ at feature points match well with the CFD data. The relative error is less than $3e^{-5}$.

Secondly, two conditions namely (60°,18°) and (120°,24°) were selected to further verify the fitting accuracy beyond sampling. The film heating effectiveness of feature points were predicted by BPNN trained in section 3.2, and corresponding simulations were conducted. Figure 7 indicates the comparison of the fitting results and simulation data. The overlap ratio indicates that the fitting accuracy of BPNN is adequate enough to be employed in prediction of the objective function in constrains of design variables.
Figure 6. Comparison between CFD and fitting within samples.

Figure 7. Comparison between CFD and fitting beyond samples.

4. GA Optimization

GA is inspired by natural selection and evolution theories. It can attain the extremum results making use of group search, thus being considered as one of the most efficient optimization algorithms. Starts from numerous points simultaneously, the search process is of high efficiency, robustness and quick reaction capability [16]. Instead of having expensive cost in computational aspect than traditional techniques to some extent, GA has reliable ability to detect the global optima thus it has been adopted in aerodynamic optimization researches progressively [17]. The main factors affecting the solving efficiency and result accuracy are listed.

- method of chromosome encoding.
- fitness function of individual evaluation.
- genetic operators and its probability.
- population size, iterations, etc.

The flow chart of GA is illustrated as figure 8.

![Flow chart of GA](image)

Figure 8. Solution frame of GA.

4.1. Definition of Evaluation Index

The fitness function needs to be defined after population initialization to evaluate the performance of different individuals. For the hot-film anti-icing structure optimization, the following indexes can be considered as fitness function based on different design objectives.

- The maximum arithmetic mean heating effectiveness of several feature positions. These positions uniformly distribute from the leading-edge to the tail end of the structure. It can represent the overall best heating performance of the whole region.
- The single-point maximum heating effectiveness. It represents the existence of highest heating performance at a certain position.
- The maximum average heating effectiveness behind the slot. It represents the best protection of the area behind the jet-slot, which is within the focus area of ice protection problems. However, the region in front of the slot could not be considered using this evaluation index.
- The maximum weighted-average heating effectiveness within the droplet impingement limit. This can protect the icing region but needs to determine the droplet impingement limit first.

In this study, the fourth is selected as the evaluation index for better consideration of the realistic droplet impingement problem. Because the profile of the inlet vane is similar to an NACA0012 airfoil to some extent, the droplet impingement limit could be determined refer to that of the airfoil.
The droplet impingement limit of a NACA0012 airfoil with 0.15m in chord length is about 0.042m. Thus, the feature points \( P_1, P_2, P_3 \), are in the range of the droplet impingement limit, whose weight is given as 20% each. Considering the backflow beyond the droplet impingement limit could still freeze, the weight of \( P_4, P_5, P_6 \) is given as 10% each as these points may exist in the backflow area. Besides, the remaining 10% is divided equally by the other points.

Therefore, the weight of nine selected feature points can be defined as:

\[
\mathbf{w}_i = \begin{cases} 
20\% & i = 1, 2, 3 \\
10\% & i = 4, 5, 6 \\
3.3\% & i = 4, 5, 6
\end{cases}
\]

(2)

4.2. Parameter Setting of Algorithm

According to the evaluation index selected in section 4.1, the fitness function is defined as equation (3).

\[
f = \sum_{i=1}^{9} [\eta_i(i) \times \mathbf{w}_i] \quad i = 1, ..., 9
\]

(3)

Considering droplet impingement characteristics as well as structure limit, the constraints are set to:

\[
\alpha \in [5^\circ, 150^\circ], \quad \beta \in [10^\circ, 30^\circ]
\]

(4)

The single-point crossover GA based on binary coding is adopted. The maximum number of iteration is set as 100 with a population which has 100 individuals after several attempts. The probability of crossover and mutation are set as 0.5 and 0.05, respectively. The precision is defined as 0.1° taking the design accuracy and time-consuming problem into consideration comprehensively.

4.3. Optimal results and CFD verification

The final optimal design is obtained as the film-heating ejection angle \( \alpha = 22.6^\circ \) and the cover opening angle \( \beta = 15.1^\circ \), the temperature distribution of which is displayed in figure 9.

![Figure 9. Temperature contour of the optimal design.](image)

The iteration convergence is illustrated as figure 10, from which it can be seen that the fitness value does not change after 22 iterations or so. Furthermore, CFD simulation was done to compare the heating effectiveness of the optimal design with Lu’s simulation results [18], in which the optimal values of the same design variables are \( \alpha = 5^\circ \) and \( \beta = 20^\circ \), as shown in figure 11. The heating performance of the optimal condition in this study is better, indicating that the BPNN-GA method can improve the optimization efficiency.
5. Conclusions
An integrated BPNN-GA optimization method is developed in this research, where a feedforward neural network was built using 18 groups of samples generated by CFD simulation, the maximum relative error of which is about $3e^{-5}$. The optimal design for a hot-film anti-icing structure of aero-engine inlet vane is obtained after repeatability checking, where the film-heating ejection angle and the cover opening angle are 22.6° and 15.1°, respectively. Compared to the optimal result obtained in Lu’s research, the optimal heating performance has been improved by 16.73%.

BPNN-GA is verified to be accurate and time-efficient rather than solving time-consuming CFD simulation for each possible design point. It should be noted that, the inlet vane structure was taken as an example to demonstrate the feasibility of using the BPNN-GA couple method to conduct the optimization work on engineering problems. This method is of strong utilizability and can be applied to optimization problems in many other engineering fields, such as the optimal design of component structure and intelligent selection of system performance parameters of both fixed-wing or rotor aircraft.

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