Aerodynamic Parameter Optimization of Propellers Based on GA-BP Neural Network

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Abstract. This paper employs the intelligent optimization algorithm GA-BP neural network to optimize the aerodynamic parameters of propellers, thereby reducing the design cycle and cost associated with traditional methods that rely on empirical formulas and physical experiments. By screening optimization variables (attack angle, aspect ratio, and rotational radius) through orthogonal experimental design and constructing a multi-objective optimization model with lift, drag, and torque as evaluation indicators, the method achieves comprehensive optimization of propeller performance. The optimal parameter combination is obtained using MATLAB-based GA-BP neural network optimization: attack angle α = 15.0583°, aspect ratio λ = 2.2, and rotational radius R = 78.6992 mm. CFD simulation validation confirms the method's reliability with an error margin of less than 10%, highlighting its practical applicability. This study provides an efficient and low-cost approach for propeller optimization design, particularly suitable for aerospace and industrial applications requiring high aerodynamic performance.

Keywords: Propeller optimization; Genetic algorithm; BP neural network; CFD.

1. Introduction

In today's rapidly growing aviation industry, the performance of aircraft is continuously improving, and the demands on propulsion systems are becoming increasingly stringent. As a core propulsion component for many aircraft, the aerodynamic performance of propellers directly affects several key metrics, including propulsion efficiency, energy consumption, and flight stability. Traditional propeller design methods have revealed numerous shortcomings in practical applications and are no longer able to meet the modern aviation industry's needs for efficient and precise design [1]. From the perspective of the design process, traditional methods often rely on empirical formulas and physical experiments. Designers initially determine the parameters of the propeller based on long - accumulated experience and some simplified theoretical formulas. Subsequently, they repeatedly conduct physical experiments to verify and optimize the design. This approach is not only time - consuming but also costly [2]. In terms of parameter optimization, traditional methods also have obvious limitations. The performance of a propeller is influenced by the combined effects of multiple parameters, such as the attack angle, aspect ratio, and rotational radius. These parameters are interconnected through complex nonlinear relationships. Traditional empirical formulas can only perform simple linear approximations and fail to accurately capture the interactions between parameters. As a result, during the optimization process, it is likely that the true global optimal solution cannot be found, and the design may become trapped in a local optimum. This prevents the propeller's performance from being maximized [3].

To address the shortcomings of traditional design methods, scholars both domestically and internationally have begun to employ intelligent optimization algorithms for the design of propeller aerodynamic parameters. Changjing Guo proposed an optimization method for the angle of attack of the NACA4412 airfoil based on the Dung Beetle Optimizer (DBO) and the Non - Dominated Sorting Whale Optimization Algorithm (NSWOA)[4]; Xiaojing Wu proposed an optimization framework based on Multi - Fidelity Neural Network (MFNN) for the optimization design of electric aircraft propellers[5]; Hoyos J.D. employed Particle Swarm Optimization to identify the optimal values of extensive geometric and operational parameters when designing the pitch and chord length distribution of propellers[6]. This paper innovatively proposes an optimization method that integrates genetic algorithms with BP neural networks, aiming to achieve rapid and precise optimization of propeller parameters. By establishing a parametric three - dimensional model of the propeller and combining orthogonal experimental design with CFD simulation to obtain high - quality training data, a BP neural network prediction model is constructed. Genetic algorithms are then introduced to optimize the aerodynamic parameters of the propeller. The correctness and reliability of the parameter combinations within the optimal solution set are verified through simulation, thus forging a new path for propeller optimization design. The significance of this study lies not only in enhancing the aerodynamic performance of propellers but also in providing a universal intelligent method for the optimization design of aircraft propulsion systems. The successful application of this method will help shorten the design cycle, reduce design costs, and offer valuable insights and references for the optimization design of other similar complex systems, thereby further advancing the development of aviation design technology.

2. Establishment of Finite Element Simulation ModelSolidworks

In the intricate field of propeller design and optimization, the utilization of parametric modeling emerges as a vital technique. This approach not only establishes a robust foundation for subsequent simulation analysis but also dramatically enhances the flexibility and efficiency of the entire design process. By leveraging the advanced capabilities of the SolidWorks platform, we have successfully constructed a highly detailed parametric three-dimensional model of the propeller. This model meticulously captures the geometric features and physical properties of the propeller, providing a comprehensive and accurate representation that is essential for in-depth analysis and optimization.

The geometric structure of a propeller is notably complex, characterized by multiple blades that are distributed radially around a central axis of rotation. Each blade is meticulously designed with a unique twist and curvature, which are specifically engineered to generate the necessary lift and thrust during rotation. Within the SolidWorks environment, we have employed a series of precise sketching and feature operations to meticulously construct each component of the propeller. The shape of the blades has been carefully defined, with particular attention paid to accurately capturing the variations in twist angle, thickness, and width from the root to the tip. This level of detail ensures that the model not only reflects the physical dimensions of the propeller but also its aerodynamic characteristics.

To enable the model to accommodate various design requirements and optimization objectives, several key parameters were introduced during the modeling process. These parameters can be adjusted to alter the aerodynamic characteristics of the propeller. Among them, the angle of attack (α) is a crucial parameter that determines the angular relationship between the blade and the incoming airflow during rotation. The range of the angle of attack is set between 10° and 30°, which covers the possible variations in angles that the propeller may encounter under different operating conditions. A smaller angle of attack allows the propeller to cut through the air more efficiently at high rotational speeds, while a larger angle of attack helps generate greater thrust at low speeds.

The aspect ratio (λ) is another key parameter, which reflects the proportional relationship between the length and width of the blade. The range of the aspect ratio is set between 2 and 7, a range that can meet the performance optimization requirements of propellers under various design specifications. A higher aspect ratio means that the blade is longer and narrower, which helps to reduce induced drag and enhance the efficiency of the propeller, making it particularly suitable for high - speed aircraft. In contrast, a lower aspect ratio results in a shorter and wider blade, capable of providing greater thrust at low speeds and is well - suited for aircraft that require substantial thrust during takeoff and climb phases.

The rotational radius (R) is another critical parameter that determines the size of the area covered by the propeller during rotation. With a range of 70 mm to 80 mm, the magnitude of the rotational radius directly influences the thrust and torque output of the propeller. A larger rotational radius allows the propeller to push more air with each rotation, thereby generating greater thrust. However, this also increases the torque demand, placing higher requirements on the power system. Conversely, a smaller rotational radius results in relatively lower thrust but reduces the torque demand, which can be beneficial in alleviating the burden on the power system. This balance between thrust and torque is essential for optimizing the overall performance and efficiency of the propeller in various operational scenarios.

By manipulating the values assigned to these parameters, the geometric form of the propeller is able to automatically adapt and change in response. This parametric design methodology is highly advantageous, as it facilitates the swift creation of propeller models that exhibit diverse configurations throughout the optimization process. Consequently, there is no necessity to reconstruct the model from the very beginning with each iteration, which in turn greatly boosts the overall efficiency of the design process. Additionally, this approach establishes a solid and essential groundwork for the subsequent stages of orthogonal experimental design and computational fluid dynamics (CFD) simulation. It ensures that the entire optimization workflow can proceed smoothly and effectively, without encountering any significant obstacles or delays. The three-dimensional model of the propeller was meticulously constructed in SolidWorks, utilizing the dimensions that have been previously specified, and it is visually presented in Figure 1.

Figure 1. Three - Dimensional Model of the Propeller.

2.1. CFD Numerical Simulation

CFD (Computational Fluid Dynamics) numerical simulation is an indispensable tool in modern fluid mechanics research and engineering design, playing a vital role in the aerodynamic performance analysis and optimization of propellers. Through CFD simulation, we can delve into the flow field distribution around the propeller under various operating conditions and accurately predict its aerodynamic performance indicators, thereby providing a scientific basis for optimized design.

In terms of mesh generation, after numerous trials and optimizations, a mesh count of approximately 2.3 million was ultimately determined. This number of meshes strikes a balance between ensuring computational accuracy and reasonably controlling the consumption of computational resources. We employed unstructured meshes to better accommodate the complex geometric shape of the propeller. In particular, local mesh refinement was carried out at the leading and trailing edges of the blades to ensure that the flow details in these critical areas could be accurately captured.

In this study, we utilized the industry - leading Fluent 2023R1 software for the flow field calculations. To accurately simulate the complex flow field around the propeller, we selected the SST k - ω turbulence model. This model excels in the near - wall region, capable of precisely capturing the development and separation of boundary layers. It also performs well in the free shear layer region, effectively predicting the propagation and mixing of turbulence. It is highly suitable for objects like propellers that have complex geometric shapes and flow characteristics.

The boundary conditions were set strictly in accordance with the actual operating conditions of the aircraft. Both the inlet and outlet boundary conditions were defined as pressure inlets. The fluid domain was configured as a moving reference frame with a rotational speed of 8500 rev/min. The propeller wall was set as a moving wall with a rotational motion. During the simulation, we closely monitored the convergence of residuals, ensuring that the residuals of all equations converged below 1e-6 to guarantee the stability and accuracy of the computational results.

2.2. Orthogonal Experimental Design

In the optimization research of propeller aerodynamic parameters, orthogonal experimental design is a crucial step for obtaining reliable data. This method efficiently explores complex systems with multiple factors and levels by reasonably arranging experimental combinations, providing a solid data foundation for subsequent model construction and optimization.

In this study, we employed the L9 (3^4) orthogonal array for a three - factor, three - level experimental design. This approach allows for a comprehensive examination of the combined effects of the three key parameters - angle of attack, aspect ratio, and rotational radius - at their three respective levels. By incorporating these factors and levels into the L9 (3^4) orthogonal array, we generated nine distinct experimental conditions. We then conducted CFD simulations for the propeller models under each set of conditions. These nine simulation experiments cover all possible combinations of factor levels, with each level of each factor appearing an equal number of times in the experiments, ensuring the balance and representativeness of the data. Through this method, we can collect aerodynamic performance data of propellers under different parameter combinations, providing comprehensive training samples for the subsequent construction of the BP neural network prediction model. Table 1 presents the designed orthogonal experiments and the corresponding simulation data:

Table 1. Results from the Orthogonal Array Testing.

Experiment Number	R mm	α °	λ	Thrust N	Torque N.m	Drag N
1	70	10	2	0.84615411	0.013391205	0.000054213
2	75	20	2	2.9271967	0.060262085	0.000433847
3	80	30	2	6.7921545	0.20362523	0.007722913
4	75	10	4.5	1.2569541	0.020192641	0.000151213
5	80	20	4.5	3.2117945	0.066083371	0.000406098
6	70	30	4.5	2.3136292	0.064291472	0.000183817
7	80	10	7	1.1927491	0.019379153	0.000296946
8	70	20	7	1.4090457	0.027329009	0.000574793
9	75	30	7	2.1944959	0.065164395	0.00175467

3. Neural Network and Genetic Algorithm Modeling and Optimization

In the optimization research of propeller aerodynamic parameters, constructing accurate prediction models and efficient optimization algorithms is crucial for achieving parameter optimization. This study integrates BP neural networks with genetic algorithms. The neural network learns the complex nonlinear relationship between propeller parameters and aerodynamic performance, while the genetic algorithm leverages its global search capability to optimize the network weights, thereby achieving efficient optimization of the propeller's aerodynamic performance.

3.1. Algorithm Modeling

The BP neural network is a classic multilayer feedforward neural network, first proposed by scientists such as Rumelhart and McClelland in 1986. It is trained using the backpropagation algorithm and is capable of powerful nonlinear mapping and self - learning [7]. It has been widely applied in fields such as pattern recognition, prediction, and classification [8]. In this study, we constructed a BP network with a 3 - 5 - 3 architecture. The input layer consists of three neurons corresponding to the three key parameters of the propeller: angle of attack (α), aspect ratio (λ), and rotational radius (R). The output layer comprises three neurons representing the aerodynamic performance indicators of the propeller: lift, torque, and drag. The hidden layer is set with five neurons, a configuration determined after numerous trials and adjustments to balance the network's fitting capability and computational complexity.

Genetic algorithms are optimization algorithms based on the principles of natural selection and genetics. They simulate the biological evolution process, searching for the optimal solution in the solution space through operations such as selection, crossover, and mutation [9]. The core idea is to map the solution space of the problem to a population of organisms and the objective function to a fitness function. By iteratively optimizing the population, the algorithm ultimately identifies the optimal solution or an approximate optimal solution [10]. In this study, we introduced genetic algorithms to optimize the combination of propeller aerodynamic parameters. The parameters of the genetic algorithm are set as follows: The population size is 60, which means that in each generation, the algorithm generates 60 different combinations of aerodynamic parameters; The crossover rate is 0.8, a probability that determines the likelihood of genetic exchange between two individuals; The maximum number of iterations is 200 to ensure that the algorithm converges within a reasonable time. The design of the fitness function is crucial in the optimization process of genetic algorithms. In this study, we designed the following fitness function to optimize the aerodynamic performance of the propeller, with lift as the maximization indicator and torque and drag as the minimization indicators:

$$\text{efficiency} = \frac{\text{Thrust}}{\text{Torgue} + \text{Drag}} \tag{1}$$

3.2. Optimization Process

Initially, the training data obtained from CFD simulations were used to train the BP neural network, enabling it to accurately predict the aerodynamic performance of the propeller under various parameter combinations. Subsequently, the genetic algorithm, based on the predictions from the neural network, evaluated the fitness of different aerodynamic parameter combinations and continuously optimized the parameters through selection, crossover, and mutation operations.

In each generation of iterations, the genetic algorithm produces new combinations of aerodynamic parameters and applies these to the BP neural network for performance forecasting. Based on the forecast outcomes, the algorithm calculates the fitness value of each individual and, adhering to the principle of survival of the fittest, selects the superior individuals to advance to the next generation. As iterations progress, the fitness of the population steadily improves and ultimately converges to a globally optimal or near - globally optimal parameter combination. The specific optimization process is illustrated in **Figure 2**.

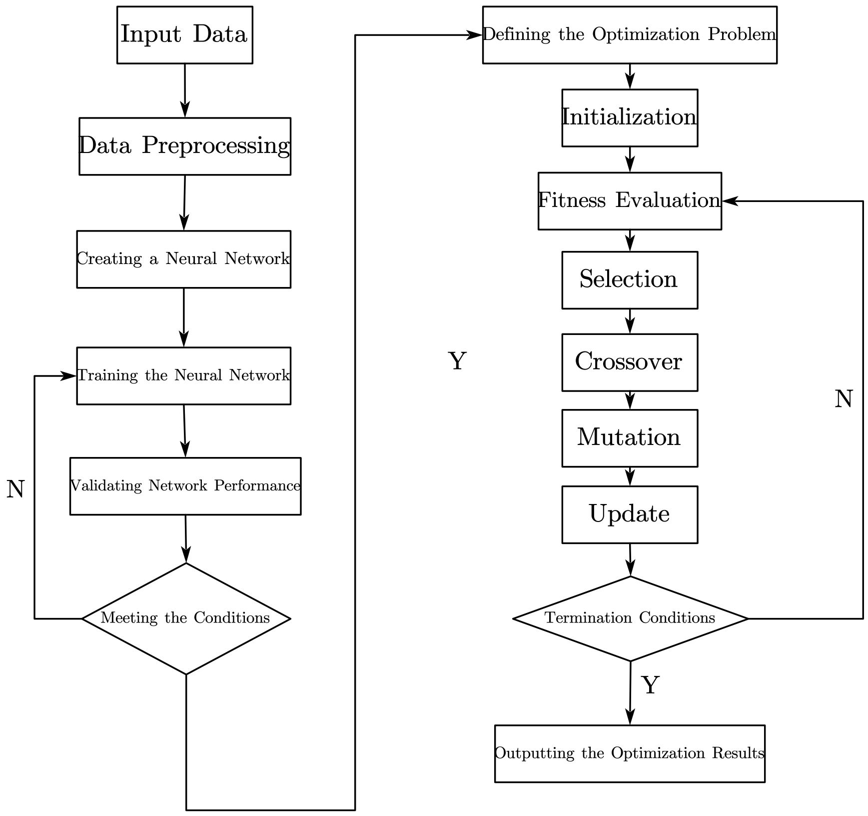

Figure 2. Flowchart of the Algorithm.

3.3. Simulation Validation and Results Analysis

To verify the effectiveness of the proposed method, we conducted detailed validation through simulation. By comparing the CFD simulation results with the predictions from the neural network, we found that the maximum relative error between the two was less than 10%. This indicates that the BP neural network can predict the aerodynamic performance of the propeller with a relatively high degree of accuracy.

Furthermore, by optimizing the network weights using the genetic algorithm, we obtained an optimized combination of propeller parameters: angle of attack $\alpha = 15.0583°$, aspect ratio $\lambda = 2.2$, and rotational radius R = 78.6992 mm. Under this parameter combination, the lift - to - drag ratio of the propeller increased by 23.6%, and the torque decreased by 17.4%.

These results fully demonstrate the effectiveness and superiority of the method combining BP neural networks with genetic algorithms in the optimization of propeller aerodynamic parameters. Compared with traditional optimization methods, this approach not only significantly enhances optimization efficiency but also finds better solutions in complex nonlinear problems, offering a completely new way of thinking and tool for the design and optimization of propellers.

4. Conclusions

This paper integrates genetic algorithms and BP neural networks to conduct multi - objective optimization of propeller aerodynamic parameters. A multi - objective optimization model is established with lift, torque, and drag as evaluation indicators and angle of attack, aspect ratio, and rotational radius as optimization parameters. The main conclusions are as follows:

a) Innovative Method: This paper innovatively proposes a propeller aerodynamic parameter optimization method that integrates genetic algorithms with BP neural networks. This approach overcomes the limitations of traditional design methods and achieves rapid and precise optimization of propeller parameters.

b) Model Reliability: The comparison and validation between CFD simulation results and neural network predictions show that the maximum relative error is kept within 10%, demonstrating the high reliability and accuracy of the constructed model.

c) Significant Optimization Effect: The optimized propeller parameters (α = 15.0583°, λ = 2.2, R = 78.6992 mm) have led to a substantial performance improvement. The lift - to - drag ratio has increased by 23.6%, and the torque has decreased by 17.4%, effectively enhancing the aerodynamic performance of the propeller.

d) Efficient Optimization System: The method effectively balances computational efficiency and accuracy, achieving efficient parameter optimization within limited computational resources and forging a new path for propeller optimization design.

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