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Article

Data-Driven Co-Optimization of Blade Selection and Sequencing for Aeroengine Rotors under Industrial Assembly Constraints

Chunyu Shao[1,2], Haixu Yu[1,2], Like Zhang[1,2], Quanyi Ge[1,2], Bobo Fang[1,2], Ruirui Li[1,2*], Chuanzhi Sun[1,2], Yongmeng Liu[1,2*], Jiubin Tan[1,2*]

[1] Center of Ultra-precision Optoelectronic Instrument Engineering, Harbin Institute of Technology, Harbin 150080, China

[2] Key Lab of Ultra-precision Intelligent Instrumentation Engineering (Harbin Institute of Technology), Ministry of Industry and Information Technology, Harbin 150080, China

[*] Corresponding author email: liruirui@hit.edu.cn, lym@hit.edu.cn, jbtan@hit.edu.cn

Abstract: During the rotor assembly of aeroengines, the combined effect of blade mass moment variations and fixed tenon slot constraints makes single-phase rotor unbalance optimization strategies insufficient for real-world industrial assembly scenarios. This often leads to excessive residual unbalance after assembly, resulting in engine vibrations and compromised operational stability. To address the lack of blade selection strategies and low qualification rates due to tenon slot constraints in industrial settings, this paper proposes a co-optimization method for blade selection and sequencing under industrial assembly constraints. A two-stage data-driven optimization framework is developed. In the first stage, a Dynamic Replacement Roulette Selection (DRWS) algorithm is introduced for global multi-set blade selection, improving blade utilization and avoiding selection failure caused by excessive moment dispersion. In the second stage, under fixed tenon slot constraints, blade sequencing is optimized using a Constrained Adaptive Genetic Algorithm (CAGA), effectively suppressing residual unbalance. Experimental results demonstrate that the proposed method achieves a blade utilization rate of 92.4% on 145 samples, with well-balanced group sets. Under tenon slot constraints, the residual unbalance is reduced from 58 g·mm and 94 g·mm (random assembly) to 7 g·mm and 10 g·mm, respectively. This study offers a novel solution and technical support for improving assembly precision and enabling intelligent decision-making in aeroengine rotor assembly lines.

Keywords: aircraft engine rotor; intelligent assembly; blade selection optimization; data-driven optimization; residual unbalance control

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1 Introduction

Aircraft engines provide propulsion for aircraft and are among the most critical components of an aircraft[1]. The vibration issues caused by rotor imbalance at high rotational speeds are a primary factor leading to performance degradation and reduced lifespan of aircraft engines[2,3]. Therefore, effectively reducing the imbalance after rotor assembly is a crucial issue in the field of aircraft engine assembly. Rotor imbalance is primarily caused by assembly errors of rotor blades and machining errors of the bladed disk. Traditional balancing methods, such as grinding the balancing surface or adding mass weights, can reduce imbalance to some extent. However, these methods may introduce residual stress, affecting the rotor's fatigue strength and service life. Additionally, methods such as coating and patching have stringent material property requirements, limiting their applicability.

In recent years, researchers worldwide have found that optimizing the installation sequence of rotor blades on the bladed disk is an effective approach to reducing rotor imbalance and has gradually become a research hotspot. For example, Sun et al. [4] proposed a pointer network-based mass moment balancing method for single-stage rotor blades, significantly improving assembly accuracy. Piskin et al. [5] employed an ant colony algorithm to optimize rotor imbalance, achieving better results than traditional methods. Maesschalck et al. [6] investigated the impact of blade tip clearance on engine performance and developed an optimization program for blade arrangement based on capacitive probe data. Amiouny et al. [7] optimized the static balance of turbine fans using the loaded point mass method, significantly reducing rotor imbalance. Mason et al. [8] formulated the turbine balancing problem as a variant of the quadratic assignment problem and used a domain search algorithm to optimize blade positions. Pan et al. [9] improved the genetic algorithm, achieving remarkable results in assembly sequence optimization. Zhang et al. used a discrete particle swarm algorithm to sort mass-mismatched blades, optimizing vibration reduction for mistuned bladed disks. Their method reduced the maximum amplitude by 23.9% and vibration localization by 46.3%[10]. Choi addressed the NP-hard problem of turbine blade balancing by developing a heuristic algorithm based on number partitioning, significantly improving computational accuracy while maintaining time efficiency, providing an effective solution for large-scale blade balancing problems[11]. Sinanoğlu developed an assembly sequence planning system based on neural networks, using a backpropagation algorithm to train the network to predict the optimal assembly order, with its parallel structure enhancing algorithm efficiency[12]. Zhang et al. proposed a reinforcement learning-based semi-physical simulation method for fan rotor assembly, using a multi-stage phase optimization model to reduce overall rotor imbalance, verifying the feasibility of the approach[13]. Li et al. established an Assembly Sequence Matching Planning (ASMP) model, integrating blade balance deviation control techniques to reduce the optimization decision time in the rotor assembly process[14]. Xu et al. proposed a data-driven rotor assembly optimization method, combining the Harris Hawk Optimization algorithm and Simulated Annealing (HHOSA), and utilizing LSTM to predict rotor imbalance. The method reduced imbalance after sorting by 98.3%, significantly improving optimization results[15]. Sun et al. developed a cloud-adaptive genetic algorithm that optimizes the unbalance of asymmetric rotors by improving selection and crossover operators, achieving significantly higher precision than traditional genetic algorithms[16]. Zhang et al. improved the Harris Hawk algorithm and established an assembly sequence model for single-stage disk-shaped blades in engine rotors, as well as a phase assembly model for multi-stage disks, effectively reducing the unbalance of multi-stage rotor assemblies[17]. Wang et al. proposed a prediction method for low-pressure rotor unbalance, integrating a mechanistic model with a bidirectional recurrent neural network[18]. Sun et al. developed a deep reinforcement learning-based pointer network model for end-to-end optimization of blade sequencing, significantly reducing unbalance while improving search efficiency[19]. Zhao et al. proposed a small-world network genetic algorithm, improving selection and crossover operations to reduce unbalance in turbine rotor optimization[20]. Sun et al. optimized the high-pressure compressor assembly using an improved genetic algorithm, generating the initial population through a sector-interleaved distribution, which significantly reduced unbalance[21].

From the research status of scholars worldwide, it can be observed that traditional rotor unbalance optimization methods typically adopt a single-stage strategy, directly optimizing blade array arrangements. However, in practical turbine rotor assembly, when blades from a batch are randomly grouped into multiple sets, excessive variations in mass moment differences and mass moment dispersion within the same set may lead to scenarios where no blade arrangement can satisfy the rotor unbalance requirements. Such issues not only waste a significant number of blade resources but also reduce assembly efficiency. Therefore, in actual production, selecting appropriate blade sets is crucial for optimizing subsequent arrangement sequences. Additionally, certain rotor blades may need to be individually replaced due to manufacturing defects or other factors to ensure that the turbine rotor meets the required balance standards after assembly. Meanwhile, to prevent multiple reassembly operations from damaging the remaining blades and disks, the already assembled blades must remain fixed. This fixed tenon slot constraint further increases the complexity of optimization, making it difficult for traditional methods to effectively address the challenge.

In summary, although the aforementioned studies have made significant progress in rotor unbalance control, they still face limitations in handling multi-set blade selection and fixed tenon slot constraints. In particular, during actual assembly, when the tenon slot positions of the rotor disk are fixed and cannot be adjusted, traditional optimization methods struggle to meet assembly requirements. To address these challenges, this paper proposes an intelligent co-optimization-driven method for blade selection and unbalance control in disk-separated aeroengine rotors. First, a multi-set blade selection algorithm is employed to eliminate inherent mass moment differences among blades. Second, blade array arrangement optimization is applied to minimize residual unbalance, achieving efficient optimization under fixed tenon slot constraints. The main contributions of this paper include: (1) Proposing a two-stage co-optimization strategy that first eliminates inherent mass differences in the blade assembly process and then compensates for residual unbalance, providing a novel solution for aeroengine rotor assembly optimization. (2) Introducing a multi-set blade selection method based on the Dynamic Replacement Roulette Wheel Selection (DRWS) algorithm, which overcomes the local optima issue of traditional roulette selection algorithms, significantly improving blade selection efficiency and resource utilization. (3) Developing a fixed tenon slot-constrained rotor unbalance control method based on the Constrained Adaptive Genetic Algorithm (CAGA), which incorporates an elitist strategy and adaptive crossover-mutation probabilities to optimize blade sequencing under real-world tenon slot constraints.

This study presents an innovative solution for blade assembly and unbalance control in disk-separated turbine rotors, with broad application prospects. By applying intelligent co-optimization theory, this approach not only enhances blade selection efficiency and resource utilization but also effectively reduces rotor assembly unbalance, improving the stability and service life of aeroengines.

2 Intelligent Co-Optimization-Driven Theoretical Framework for Aeroengine Rotor Blade Assembly

2.1 Two-phase Collaborative Optimization Strategy

The unbalance of an aeroengine rotor is a critical factor affecting its performance and service life. In particular, in turbine rotors with a disk-separated structure, assembly errors between the rotor blades and the rotor disk can directly cause the overall rotor unbalance to exceed technical requirements. Therefore, effectively reducing unbalance during the assembly process has become a key issue in improving aeroengine assembly quality.

Traditional single-stage optimization strategies control the overall rotor unbalance solely by optimizing rotor blade arrangement. This strategy has significant limitations in actual production, especially under multi-set blade selection and fixed tenon slot constraints, making it difficult to balance assembly efficiency and optimization effectiveness simultaneously. To address this, this paper proposes a two-stage co-optimization strategy that sequentially tackles blade selection and arrangement optimization, significantly improving rotor assembly quality. The schematic diagram of the two-stage collaborative optimization strategy for blade selection and imbalance control in the disk-segmented aircraft engine rotor is shown in Fig. 1.

In the first stage, a multi-set blade selection algorithm is employed to filter blade sets from the candidate blade pool that meet the requirements for mass moment variation and dispersion. The primary objective of this stage is to maximize blade resource utilization, reduce blade waste, and ensure the reliability of the selection results. This optimization stage provides high-quality input for the subsequent blade array arrangement.

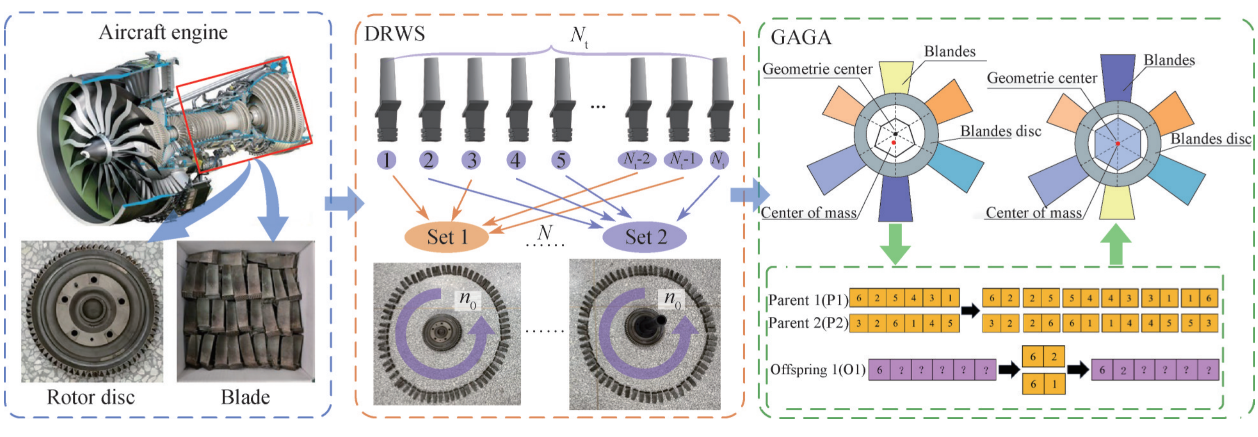


Fig.1 Schematic diagram of the two-stage collaborative optimization strategy

In the second stage, a rotor unbalance control method based on blade array arrangement is applied to the selected blade sets, further optimizing the installation sequence to reduce residual unbalance. Particularly under fixed tenon slot constraints, the introduction of CAGA effectively addresses optimization challenges that traditional methods struggle to resolve. The CAGA algorithm enhances global search capability through an elitist strategy and adaptive crossover-mutation probabilities, ensuring high-quality optimization results even under complex constraints.

The core advantage of the two-stage co-optimization strategy lies in its phased and goal-oriented optimization approach. In the first stage, blade selection eliminates inherent mass moment differences among blades, providing high-quality input for subsequent optimization. In the second stage, further optimization of the blade array arrangement, especially under fixed tenon slot constraints, achieves efficient residual unbalance control. This strategy not only significantly enhances assembly efficiency but also effectively reduces rotor unbalance, improving the assembly precision and stability of the aeroengine rotor.

Overall, the two-stage co-optimization strategy improves rotor assembly accuracy and efficiency by sequentially solving blade selection and arrangement optimization problems, providing reliable technical support for high-performance aeroengine rotor assembly.

2.2 Multi-Set Blade Selection Method Based on DRWS Algorithm

2.2.1 Multi-Set Blade Selection Model for Disk-Separated Rotor Structures

By optimizing the multi-group blade selection algorithm and refining the assembly strategy between the blades and the disk, the extreme difference in blade mass moments is reduced, the dispersion of mass moments is minimized, and the overall mass uniformity among blade groups is improved. This optimization lays a solid foundation for subsequent blade sequencing and rotor unbalance reduction, ensuring that the assembly meets quality requirements. To prevent the impact of blade-disk selection on subsequent rotor unbalance optimization, which could lead to excessive unbalance deviation, it is imperative to establish a multi-group blade selection model for the turbine rotor with a disk-blade separation structure. This model will guide the blade-disk selection process.

Based on the assembly model of an aircraft engine turbine rotor, the number of blade-disk groups under different blade selection configurations is obtained. The optimization function for blade selection in a turbine rotor with a disk-blade separation structure is expressed as Equation (1):

$$f\left(r,\sigma\right)=N\left(r,\sigma\right) \tag{1}$$

Where N — the number of blade−disc groups in a disk-separated turbine rotor, r — the extreme difference in blade mass moments, and σ — the dispersion of blade mass moments.

Based on Equation (1) and the optimization model for blade selection in a turbine rotor with a disk-blade separation structure, an optimal multi-group blade selection scheme is sought for a specific type of aircraft engine turbine rotor. The optimization objective is to minimize the number of remaining blades in the selection pool while maximizing the number of turbine rotor groups assembled from the selected rotor blades and the disk. The selection criteria for rotor blades, based on the assembly requirements of this model, are given by Equation (2):

$$\begin{cases} d_{g,m}=\max\left(m_g\right)-\min\left(m_g\right)\leq r \\ d_{l,m}=\dfrac{\max\left(m_l\right)-\min\left(m_l\right)}{\min\left(m_l\right)}\leq\sigma \end{cases} \tag{2}$$

Where: m_g—Blade mass moment, $d_{g,m}$—Blade mass moment difference, $d_{l,m}$—Blade mass moment dispersion.

The optimization objective of multi-group blade selection is to minimize the number of remaining blades in the selection pool while maximizing the number of assembled turbine rotor groups. The number of remaining blades in the selection pool is given by Equation (3):

$$N_{rb}=N_t-n_0\cdot N \tag{3}$$

2.2.2 Multi-Group Blade Selection Algorithm Based on DRWS

The traditional roulette wheel selection algorithm tends to fall into local optima when performing multi-group blade selection, leading to the inability of the remaining blades to form standard-compliant groups. As the number of complete groups increases, the possible combinations of remaining blades decrease, reducing the probability of selecting a suitable blade, which may ultimately prevent the attainment of the optimal solution. Therefore, this paper proposes a multi-group blade selection algorithm based on DRWS to address this issue.

This algorithm adjusts the selection strategy for remaining blades to avoid the predicament in the traditional roulette wheel algorithm, where remaining blades fail to meet the selection criteria. Specifically, if a candidate blade can form a standard-compliant combination with the previous complete group, it can replace a blade in that group, updating the remaining blade pool and preventing local optima.

The specific steps of the multi-group blade selection algorithm based on DRWS are as follows:

1.Blade Pair Selection and Standard Evaluation

For N_t rotor blades, a pairwise combination method is used to evaluate whether the mass moment of inertia dispersion of each pair of blades is less than or equal to σ, and whether the maximum range of the mass moment of inertia is less than or equal to r.

2. Establishment of Selection Resource Pool and Initial Blade Selection

All blades are selected from the candidate pool, and those meeting the criteria are temporarily stored. When the temporary pool reaches the set threshold, the selected blades are grouped and stored in the group library.

3.Blade Selection and Probability Calculation

By pairing the blades in pairs, $C_{N_t}^2$blade pairs can be generated, and the number of pairs that meet the selection criteria formed by each blade and the remaining blades can be counted. The selection probability of each blade is based on statistical results, with the cumulative probability calculated as follows:

$$P_k=\frac{C_k}{\sum_{i=1}^{n}C_i} \tag{4}$$

Here, C_k indicates the number of blade pairs for the kth blade that meet the selection criteria, and n is the total number of blades.

4.Roulette Wheel Selection Algorithm

Based on the previously calculated probabilities, the roulette wheel selection algorithm is used for blade selection. In each iteration, a blade is chosen and combined with the already selected blades; the differences in mass moments and their dispersion are computed. Only blades that meet the criteria are selected. If a blade fails to meet the criteria, it is reselected until an acceptable blade is chosen. This process continues until all blades in the set satisfy the selection standards, resulting in a complete group set.

5.Dynamic Replacement Strategy

As the number of complete group sets increases, it becomes increasingly difficult to select remaining blades from the candidate pool. When a new blade that meets the criteria cannot be selected, a blade from a completed group (denoted as r_{ca}) is randomly chosen, and a new blade from the candidate pool (denoted as r_{as}) is selected using the roulette wheel algorithm. r_{as} is then validated by combining it with the already selected blades (excluding r_{ca}) and computing the mass moment differences and dispersion. If the criteria are met, the replacement is executed; otherwise, r_{as} is reselected.

6.Termination

When the number of iterations reaches the preset limit, the algorithm terminates and outputs the final grouping information, including the number of complete sets and the blade numbers in each set.

The flowchart for the multi-group blade selection algorithm based on DRWS is shown in Fig. 2.

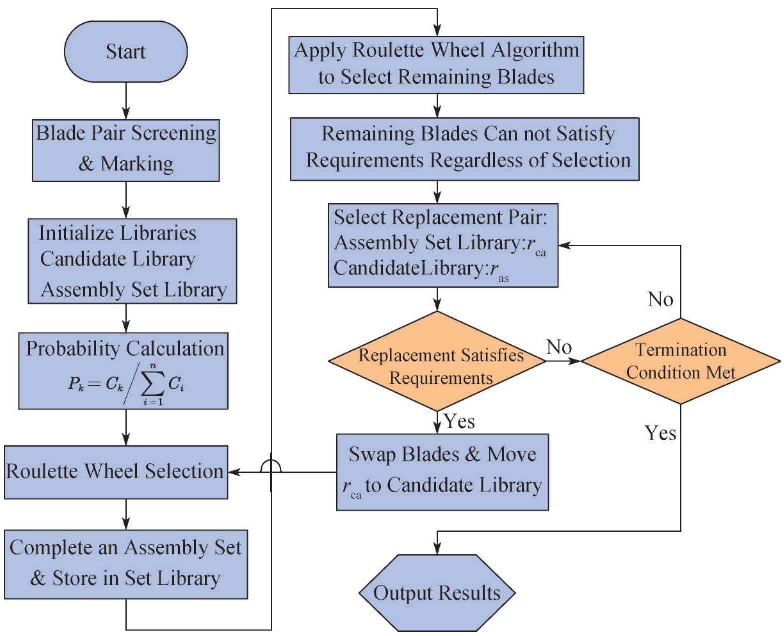


Fig.2 Flowchart of the Multi-Set Blade Selection Algorithm Based on DRWS

2.3 Fixed Tenon Slot-Constrained Rotor Unbalance Control Method Based on CAGA

2.3.1 Rotor Unbalance Control Model Based on Blade Array Arrangement

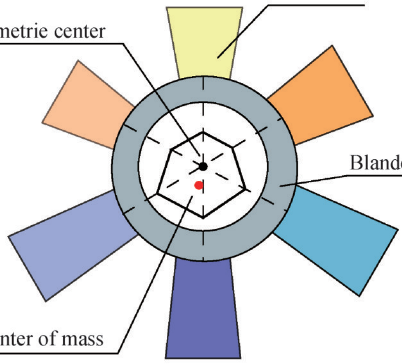
For turbine rotors with a disk-and-blade separation structure, optimizing the blade assembly sequence to reduce or even eliminate rotor unbalance is an effective solution. However, the large number of rotor blades and the high mass moment of some blades pose significant challenges for adjusting the assembly sequence. Moreover, in practical assembly, some blades may be fixed, which necessitates that the algorithm accommodates such constraints. Therefore, it is essential to develop a rotor unbalance control method based on optimizing the blade array arrangement.

Rotor unbalance is essentially caused by the displacement of the rotor's center of mass from its axis after assembly, with contributing factors including uneven mass distribution or geometric errors in the rotor disc, the blade array arrangement, and assembly errors of the blades. While assembly errors and uneven mass distribution in the disc are uncontrollable, adjusting the blade array arrangement can effectively reduce or even eliminate rotor unbalance. Therefore, establishing a rotor unbalance control model based on blade array arrangement is of great significance.

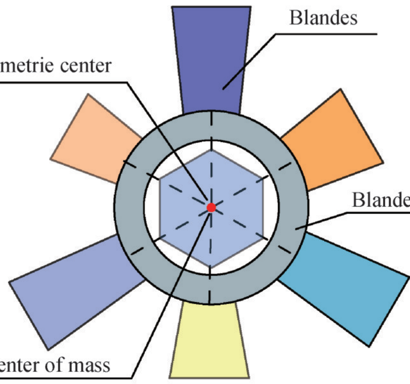
Fig. 3 depicts the impact of blade arrangement on rotor center-of-mass deviation. In Fig. 3(a), a randomly arranged blade configuration causes a significant shift in the rotor's center from its axis, leading to excessive unbalance that exceeds the specified limits, rendering the assembly unqualified. In contrast, after optimization (Fig. 3(b)), the center-of-mass deviation is significantly reduced, minimizing overall unbalance and ensuring a qualified assembly.

To control rotor unbalance and prevent it from exceeding specified limits, it is necessary to adjust the blade array arrangement to optimize the overall unbalance of the turbine rotor, thereby guiding the assembly process of disk-and-blade separation rotors.

In practical assembly, the initial assembly success rate is typically low, often requiring multiple adjustments.



(a) Centroid eccentricity under random blade arrangement



(b) Centroid eccentricity after optimized blade arrangement

Fig.3 Effect of blade array arrangement on rotor centroid eccentricity

This is primarily due to improper blade position planning, which results in the rotor unbalance after assembly failing to meet the expected target or even exceeding the standard range. Additionally, due to the nature of mass blade production, some blades may have excessive manufacturing or machining errors, making them incompatible with the rotor disc. In such cases, certain blades must remain fixed, while the arrangement of other blades needs to be adjusted to minimize rotor unbalance. At this point, the rotor unbalance optimization function under fixed tenon slot constraints can be expressed as:

$$u = f(s, w) \tag{5}$$

Where u represents the unbalance of the turbine rotor with a disk-and-blade separation structure, s denotes the fixed tenon slot constraint, and w represents the blade array arrangement sequence.

2.3.2 Unbalance Control Method Based on CAGA

In the actual assembly process of turbine rotors, some rotor blades may have manufacturing defects that make it impossible to meet the rotor unbalance requirements regardless of the arrangement sequence. In such cases, these specific blades must be replaced to ensure that the assembled turbine rotor meets the unbalance standards. Furthermore, to prevent damage to the remaining blades and the rotor disc due to repeated adjustments, the already assembled blades should remain fixed. Therefore, this study proposes a rotor unbalance control method under fixed tenon slot constraints to address the blade array arrangement optimization problem encountered in practical turbine rotor assembly.

Taking a certain type of aero-engine turbine rotor as the research object, this study solves the rotor unbalance control model under fixed tenon slot constraints as defined in Equation (5). The algorithm searches the solution space for the optimal solution of the rotor unbalance control model, obtaining the optimal blade array arrangement sequence under fixed tenon slot constraints to optimize the overall unbalance of the assembled turbine rotor. This section proposes an improved CAGA to address the rotor unbalance control problem under fixed tenon slot constraints. Compared with traditional genetic algorithms, CAGA introduces an adaptive mechanism in population selection, crossover, and mutation operations, enhancing global search capability and avoiding local optima.

The specific steps are as follows:

(1) Problem Modeling and Encoding

To optimize the rotor imbalance after assembly, the blade array arrangement is first encoded into chromosomes for the genetic algorithm using real-number encoding, with each blade corresponding to one gene. The numbers corresponding to the fixed tenon slots remain unchanged throughout the iterations to ensure that the positions of the blades at fixed tenon slots are maintained.

(2) Initial Population Generation

The initial population is generated using random numbers to ensure that the blade arrangement sequences have sufficient randomness and meet practical assembly requirements. During generation, numbers corresponding to fixed tenon slots are first removed from the random array to prevent repeated occurrence of fixed tenon slot numbers within a blade arrangement sequence.

(3) Fitness Function Design

The fitness function is used to evaluate the magnitude of the rotor imbalance after assembly. Based on Equation (5), a fitness function for the overall rotor imbalance of a disk-separated turbine rotor under fixed tenon slot constraints is defined. This function quantifies the impact of the blade array arrangement on rotor assembly, enhancing the efficiency of comparing different blade arrangements, and guides the population toward minimizing the overall rotor imbalance through optimization of the fitness function.

(4) Adaptive Crossover and Mutation Operations

To avoid duplicate blade numbers, a pairwise crossover method is employed. First, the two parent blade arrangement sequences are converted into a linear representation by pairing each blade number with its subsequent number to form a two-element substring, ensuring that the sequence forms a closed loop, as shown in Fig. 4.Then, these two-element substrings are sorted in ascending order based on their first element, and the sorted substrings are merged into a set, as shown in Fig. 5.

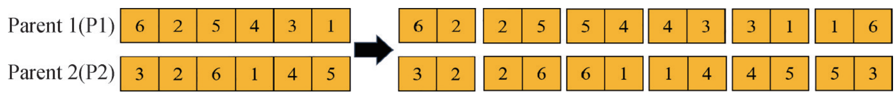


Fig.4 Decomposition and Combination of Parent Blade Arrangement Sequences

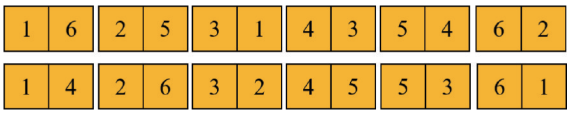


Fig.5 Sorted Set of Substrings

When generating the offspring blade arrangement sequence, the first blade number is selected from the parent sequence. Subsequently, the algorithm sequentially selects the next blade number from the sorted substring set. If a blade number has already appeared in the offspring sequence, it is removed from the candidate set. Next, by counting the frequency of each remaining number in the substring set, the number with the fewest occurrences is selected as the new blade number. If multiple numbers have the same minimum frequency, one is chosen randomly. If the candidate set becomes empty, a blade number is randomly chosen from the unused numbers until the offspring blade arrangement sequence is completely generated, as illustrated in Fig. 6.

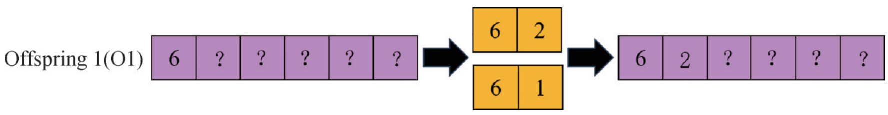


Fig.6 Random Selection When Frequencies are Equal

This crossover method aims to preserve and optimize local continuity in the solution while introducing diversity. In this way, the algorithm explores the solution space and gradually approaches the optimal solution. The mutation operation employs a random mutation strategy, where individual mutations are randomly applied to selected members of the population. Specifically, this involves identifying and swapping the blade numbers at two designated positions in the selected individual, a strategy that effectively prevents the population from deviating from the proper iteration direction and losing high-quality individuals with low fitness values, while also helping the algorithm escape local optima.

Furthermore, the probabilities for crossover and mutation are adjusted adaptively, closely linked to each individual's fitness value. A lower crossover probability helps maintain population stability, and a reduced mutation probability makes the convergence process more controllable. In later iterations, maintaining population stability is crucial; hence, this adaptive mechanism meets that requirement. However, in the early stages, excessively low crossover and mutation probabilities may hinder the development of superior individuals, potentially causing the algorithm to become trapped in local optima. Based on the above considerations, the adaptive adjustment formulas for crossover and mutation probabilities are given in Equations (6) and (7):

$$P_c=\begin{cases} k_1-\dfrac{k_1(q_{\max}-q')}{q_{\max}-q_{avg}} & q'\le q_{avg} \\ k_2 & q'>q_{avg} \end{cases} \tag{6}$$

$$P_m=\begin{cases} k_3-\dfrac{k_3(q_{\max}-q')}{q_{\max}-q_{avg}} & q'\le q_{avg} \\ k_4 & q'>q_{avg} \end{cases} \tag{7}$$

where P_c— represents the crossover probability; P_m— represents the mutation probability; $q_{\max}$— represents the maximum fitness value among individuals in the population; q_{avg}— represents the average fitness value in the population; q' — represents the higher fitness value of the two individuals involved in crossover; q— represents the fitness value of the mutated individual; and k_1, k_2 , k_3 , k_4 — are constants.

By integrating the specific implementations of crossover and mutation operations with the adaptive adjustment mechanism, the algorithm can rapidly explore the solution space in the early stages and maintain population stability in later stages, thereby effectively avoiding local optima and enhancing global search capability.

(5) Population Screening and Elitism Strategy

To ensure that the optimization direction remains aligned with the desired objective, an elitist strategy is employed for population screening. In each generation, the individuals with the lowest fitness values are directly carried over to the next generation, ensuring that the best solutions are preserved. Consequently, the blade arrangement sequences with lower unbalance continue to guide the evolution of the population toward further unbalance reduction, leading to algorithmic convergence. First, a set of offspring blade arrangement sequences meeting the preset population size is generated through crossover and mutation operations, as shown in Fig. 7.

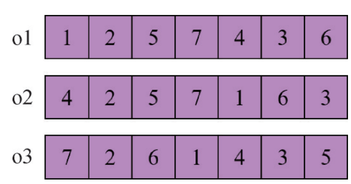


Fig.7 Offspring Blade Arrangement Sequence Set

Then, the offspring blade arrangement sequences are merged with the parent blade arrangement sequences to form the overall blade arrangement sequence set, as shown in Fig. 8.

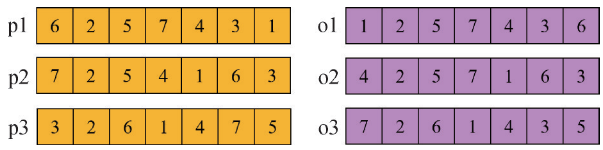


Fig.8 Merged Set of Parent and Offspring Blade Arrangement Sequences

After merging, each blade arrangement sequence in the set is sorted in ascending order based on its corresponding unbalance value, and the top 50% of individuals are retained as the parent population for the next generation. This selection of low-unbalance individuals guides the evolution and convergence of the population as the algorithm proceeds with further iterative crossover and mutation, as illustrated in Fig. 9.

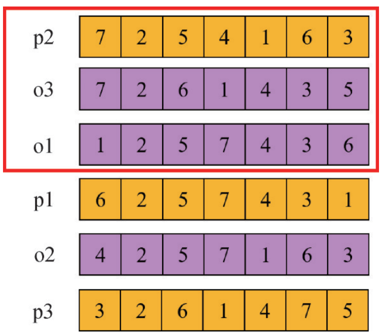


Fig.9 Retention of Superior Blade Arrangement Sequences

(7) Iteration and Termination Conditions

To enhance computational efficiency and avoid redundant calculations, the genetic algorithm employs an iterative termination mechanism. Specifically, the algorithm is set to terminate after 100 iterations. At termination, the current lowest fitness value and the corresponding blade arrangement sequence are output as the final solution.

3 Simulation Validation

To verify the effectiveness of the two-stage collaborative optimization strategy proposed in this paper for the assembly of aircraft engine rotor blades, simulation verification is conducted for both the multi-group blade matching and the blade sequencing optimization under fixed tenon slot constraints. The results are compared with those of traditional methods to validate the effectiveness of the proposed approach.

3.1 Simulation Verification of Multi-Group Blade Matching Method Based on DRWS

In this section, a dataset of 200 turbine rotor blade mass moments is used as the test database for the algorithm. The specific data are shown in Table 1:

Table 1 Turbine Rotor Blade Database

Blade Number	Mass Moment (g·mm)
1	35490.43
2	35491.81
…	…
199	35466.98
200	35470.07

The blades in the candidate blade pool are selected using both the traditional roulette wheel selection method and the DRWS method for multi-group blade matching. According to the assembly requirements of this rotor model, the selection criteria for blades are set as follows: the maximum difference in blade mass moments must not exceed 900 g·mm, the dispersion of blade mass moments must not exceed 0.05, and each group must contain 47 rotor blades.

The effectiveness of the traditional roulette wheel selection method for multi-group blade matching is analyzed first. For the test database composed of the 200 generated turbine rotor blade mass moment data, the matching results obtained using the traditional roulette wheel selection method are shown in Table 2:

Table 2 Blade Matching Results Obtained Using the Traditional Roulette Wheel Selection Method

Group Number	Blade Number	Mass Moment Range(g·mm)	Mass Moment Dispersion
1	84 143 15 118 171⋯38 6 12 28	812.66	0.0253
2	32 117 5 92 127⋯19 126 113 42	799.04	0.0248
3	53 101 47 71 147⋯64 31 52 109	882.74	0.0277
4	94 155 100 85 10⋯138 180 106 195	884.93	0.0275
Set Value	_	900	0.05

It can be seen that this method successfully selects four complete blade groups from the candidate blade pool that match the rotor disk. Theoretically, when selecting 47 blades per group from the 200 rotor blades, a maximum of four groups can be selected, minimizing the number of remaining blades in the candidate pool and maximizing the utilization of blade resources. Furthermore, the selected four blade groups do not exceed the set selection criteria, meeting the requirements for subsequent rotor unbalance optimization through blade sequencing.

The algorithm's matching performance is then tested multiple times. Using the same candidate blade pool, the multi-group blade matching algorithm based on the traditional roulette wheel selection method is run 20 times. The obtained results are shown in Table 3:

Table 3 Results of 20 Runs of the Multi-Group Blade Matching Algorithm Using the Traditional Roulette Wheel Selection Method

Independent Runs	Completed Sets	Independent Runs	Completed Sets
1	3	11	3
2	3	12	3
3	4	13	3
4	3	14	3
5	3	15	4
6	4	16	3
7	3	17	3
8	3	18	3
9	3	19	4
10	3	20	3

From the above results, it can be seen that after 20 tests of this algorithm, only 20% of the runs successfully selected four blade groups, meeting the requirement of maximizing blade resource utilization. In the remaining 16 runs, only three sets of compliant blade groups were successfully selected, leading to significant blade resource waste. This indicates that the algorithm has not yet achieved the optimal target and still has room for improvement.

Subsequently, the effectiveness of the DRWS-based multi-group blade selection method proposed in this paper was analyzed. The same dataset of 200 turbine rotor blade mass moments was used as the algorithm's test database. The blades in the test database were selected using the DRWS method, with selection criteria and other parameters remaining unchanged. The algorithm results are shown in Table 4:

Table 4 Selection Results of the DRWS-Based Algorithm

Group Number	Blade Number	Mass Moment Range(g·mm)	Mass Moment Dispersion
1	129 23 110 45···176 118 192 10	796.04	0.0247
2	34 97 168 171···179 25 58 42	898.05	0.0279
3	160 13 26 122···44 107 2 131	891.13	0.0281
4	48 184 163 12···177 31 116 158	682.31	0.0211
Set Value	-	900	0.05

It can be observed that this method also successfully selected a complete set of four blade groups, all meeting the predefined criteria. Subsequently, the method's selection results were further validated through multiple runs. The optimized multi-group blade selection algorithm was executed 20 times, and the results are summarized in Table 5:

Table 5 Results of 20 Runs of the DRWS-Based Multi-Group Blade Selection Algorithm

Independent Runs	Completed Sets	Independent Runs	Completed Sets
1	4	11	4
2	4	12	4
3	4	13	4
4	3	14	4
5	4	15	3
6	3	16	4
7	4	17	4
8	4	18	4
9	4	19	3
10	3	20	4

As shown in Table 5, out of 20 runs of the multi-group blade selection algorithm, 15 runs successfully selected a complete set of four blade groups. This demonstrates that the DRWS-based multi-group selection algorithm not only exhibits considerable stability but also achieves high selection efficiency, ensuring optimal selection results. For the same database, the DRWS method proposed in this paper increased the full utilization rate of blade resources from 20% to 75%, compared to the traditional roulette-wheel selection method.

3.2 Simulation Verification of Rotor Unbalance Control Method Based on CAGA Under Fixed Tenon Slot Constraints

Based on the previously completed multi-group blade matching, the effectiveness of the proposed CAGA method in optimizing rotor unbalance under fixed tenon slot constraints is verified. Compared to full-array blade sequencing, this study focuses on verifying whether the rotor unbalance after algorithm optimization can meet the required range under fixed tenon slot constraints. By randomly generating an initial population of 100 and conducting 50 iterative tests, the impact of different numbers of fixed tenon slot constraints on the optimization results and convergence of the algorithm is analyzed. The simulation results are shown in Fig. 10, and Table 6 presents the algorithm results under different numbers of fixed tenon slot constraints.

From Fig. 10 and Table 6, it can be seen that the fixed tenon slot constraint rotor imbalance control method based on CAGA exhibits good convergence and optimization performance. As the number of fixed tenon slots increases, the algorithm's computation time gradually increases from 31.76 seconds to 54.61 seconds. This is because the increase in fixed tenon slots adds to the computational load, as the blade array arrangement needs to account for the effect of blades on the rotor's center of gravity, and the constraints on the fixed tenon slot blades also increase computational complexity. Nevertheless, under all testing conditions, the final fitness function values (rotor imbalance) are all below 5 g·mm, meeting technical requirements, indicating the effectiveness of this method in optimizing rotor imbalance.

Table 6 Algorithm operation results under different numbers of fixed tenon slot constraints

Fixed tenon slot number	Computation time (s)	Fitness function value (g·mm)
4	31.76	1.05
4、16	39.54	1.23
4、16、28	44.87	2.11
4、16、28、37	54.61	2.30

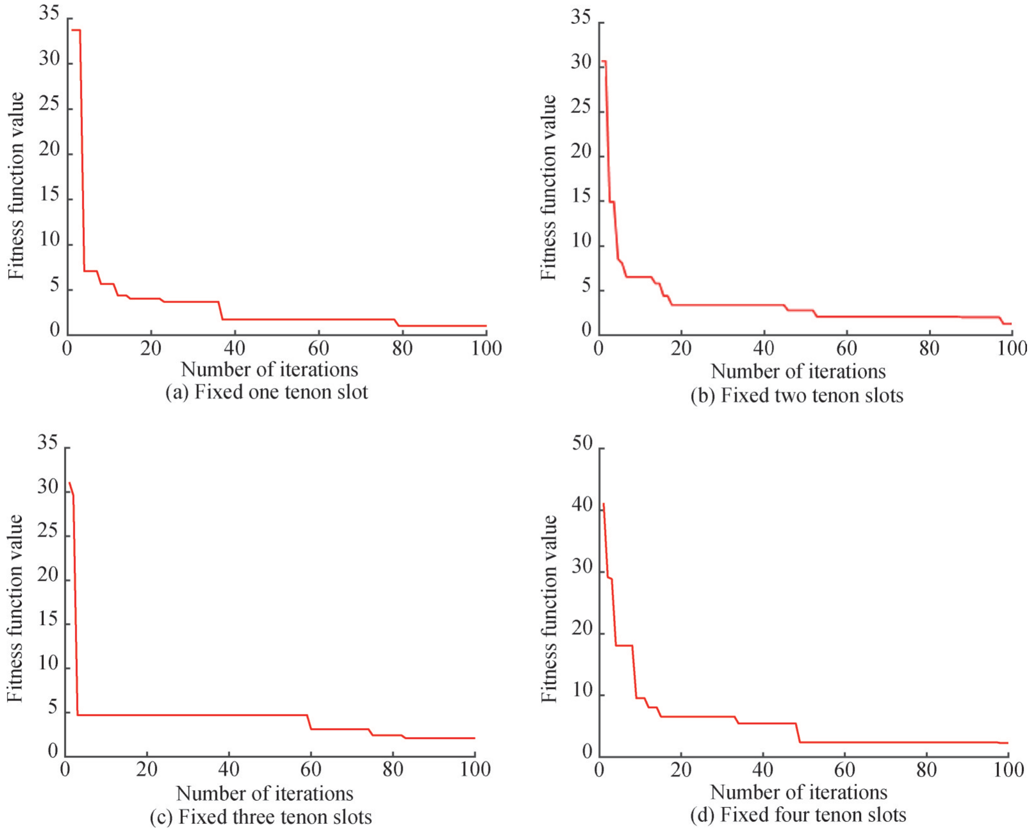


Fig.10 Genetic algorithm fitness function values under different numbers of fixed tenon slot constraints

4 Experimental Verification

A turbine rotor with a disk separation structure from a certain model of aircraft engine is used as the experimental specimen, as shown in Fig. 11. It includes 2 turbine rotor discs (each disc requires the installation of 67 blades) and 145 rotor blades.

The blade selection and imbalance control method driven by intelligent collaborative optimization for the disk separation structure of the aircraft engine rotor is applied to optimize the selection and arrangement of the rotor blades for this model, verifying the effectiveness of the algorithm described in this paper. Firstly, a multi-set blade selection method based on DRWS is used to classify the 145 blades in the blade library according to the selection standards, calculating whether the range and dispersion of each set after selection meet the selection criteria. Subsequently, for the disk separation structure turbine rotor, based on the actual situation, the rotor blade positions on the disc are adjusted under the conditions of whether the fixed tenon slot constraint is given, using a

(a) Rotor disc 1 (b) Rotor disc 2 (c) Rotor blades

Fig.11 Disk separation structure turbine rotor experimental specimen

fixed tenon slot constraint rotor imbalance control method based on CAGA to optimize the rotor imbalance after assembly. After assembly, the rotor imbalance is measured using a vertical balancing machine based on the optimization results, and compared with the rotor imbalance obtained from random assembly, verifying the effectiveness of the rotor imbalance control algorithm based on blade array arrangement.

4.1 Verification experiment of the multi-set blade selection method based on DRWS

The 145 blades from the blade library of the turbine rotor of this aircraft engine model are used as experimental subjects, and the multi-set blade selection method based on DRWS is employed to select blades according to the selection standards. The blade numbers and their corresponding standard mass moment data from the blade library are shown in Table 7.

The blades from the blade library are selected using the multi-set blade selection algorithm based on DRWS.

Table 7 Turbine rotor blade database (g·mm)

Blade number	Mass moment	Blade number	Mass moment
1	35380.4	74	35380.1
2	35381.8	75	34461.9
3	35363.1	76	35403.2
4	34487.2	77	34507.0
…	…	…	…
71	34443.0	144	35388.3
72	34463.9	145	35366.8
73	35447.7		

The selection criteria for rotor blades are set as follows: the range of blade mass moments should not exceed 900 g·mm, the dispersion of the blade mass moments should not exceed 0.05, and each set contains 67 rotor blades. The selection results are shown in Table 8:

Table 8 Rotor blade selection results

Group Number	Blade Number	Mass Moment Range /(g·mm)	Mass Moment Dispersion
1	84 143 15 118 171⋯38 6 12 28	812.6	0.025
2	32 117 5 92 127⋯19 126 113 42	799.0	0.024
Set Value		900	0.05

From the results in Table 8, it can be seen that the multi-set blade selection algorithm selects two complete sets of blades from the blade library, which match the selection criteria and the rotor discs. The matching result is shown in Fig. 12.

From a theoretical perspective, selecting 67 blades per set from the 145 rotor blades allows for a maximum of two sets to be selected, meaning the remaining number of blades in the blade library is minimized, and the blade resources are utilized to the greatest extent. Furthermore, the mass moment range and dispersion for each set of blades selected by the multi-set blade selection algorithm were calculated and verified to not exceed the set values of the selection criteria. This demonstrates that the two selected blade sets can each be assembled with the rotor discs, laying the foundation for subsequent adjustments to the blade arrangement sequence to optimize the overall imbalance of the turbine rotor and improve the overall mass uniformity between each blade set.

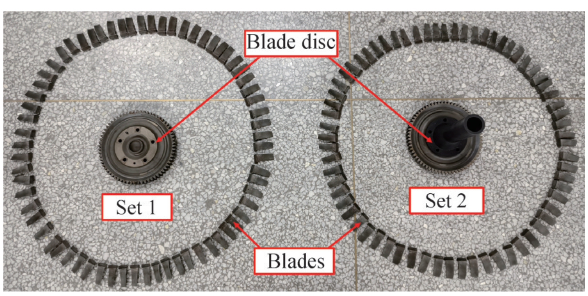


Fig.12 Two complete blade sets that meet the requirements after selection

4.2 Verification Experiment of CAGA-Based Fixed Tenon Slot Constrained Rotor Imbalance Control Method

To verify the effectiveness of the CAGA-based fixed tenon slot constrained rotor imbalance control algorithm, this section optimizes the blade installation sequence using three different assembly methods: random assembly, a blade array arrangement algorithm based on the traditional genetic algorithm, and the CAGA-based fixed tenon slot constrained rotor imbalance control algorithm. The rotor imbalance results of these three assembly methods are compared.

The input is the sequence numbers of the rotor blades, while the outputs of the three assembly methods include the rotor blade sequence numbers, the overall rotor imbalance, and the phase. The two qualified blade sets obtained in the previous section are assembled with the rotor discs according to the installation sequences output by the three assembly methods. The assembled rotor is then measured using a vertical balancing machine, as shown in Fig. 13. The measurement results are listed in Table 9.

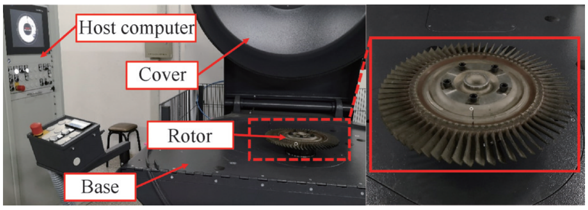


Fig.13 Experimental photograph of turbine rotor imbalance measurement using a vertical balancing machine

Table 9 Rotor imbalance measurement results under different assembly methods (g·mm @°)

Arrangement method	Random assembly	Traditional genetic algorithm	CAGA algorithm
Set 1	58 @130	46 @308	7 @9
Set 2	94 @286	72 @144	10 @37

From the experimental results, it can be seen that when the blades in Set 1 were assembled with the rotor disc using the random assembly method, the overall rotor imbalance reached 58 g·mm, which significantly exceeded the acceptable range, making the assembly unqualified. When using the blade array arrangement sequence optimized by the traditional genetic algorithm, the resulting rotor imbalance was 46 g·mm, which was lower than that of the random assembly method but still did not meet the assembly requirements. However, when using the CAGA-optimized blade array arrangement, the rotor imbalance was reduced to 7 g·mm, representing an 87.9% reduction compared to random assembly and an 84.8% reduction compared to the traditional genetic algorithm. Similarly, the assembly results of Set 2 showed that the imbalance after CAGA optimization (10 g·mm) was 86.1% lower than the imbalance after traditional genetic algorithm optimization (72 g·mm) and improved by 89.4% compared to random assembly. These results indicate that the CAGA-based blade array arrangement method can significantly reduce the overall rotor imbalance after assembly, meeting the assembly requirements.

The following validation examines situations where blade errors occur during actual manufacturing and processing, causing certain blades to be unfit for assembly with the rotor disc. In such cases, blade replacement is necessary to ensure that the optimized assembly maintains the imbalance within the acceptable standard. This evaluates the effectiveness of the CAGA-based fixed tenon slot constrained rotor imbalance control algorithm under fixed tenon slot constraints. The algorithm's input is the sequence numbers of the rotor blades, and the fitness function is the overall rotor imbalance after assembly. By progressively increasing the number of fixed tenon slots, the impact of different constraints on the optimization effectiveness of the algorithm was validated. The optimized installation sequences were assembled with the rotor disc, and the rotor imbalance was measured using a vertical balancing machine. The results are shown in Table 10.

Table 10 Rotor imbalance measurement results under different fixed tenon slot constraints

Fixed tenon slot number	Overall rotor imbalance(g·mm)
4	8
4、16	9
4、16、25	8
4、16、25、38	7

As shown in Table 10, with an increase in the number of fixed tenon slots, the overall rotor imbalance fluctuated but remained within the assembly requirement of less than 10 g·mm. Specifically, when the number of fixed tenon slots increased from 1 to 4, the rotor imbalance values were 8 g·mm, 9 g·mm, 8 g·mm, and 7 g·mm, respectively, all meeting the technical requirements. This proves the effectiveness of the fixed tenon slot constrained blade array arrangement algorithm in optimizing rotor imbalance, making it suitable for addressing real-world assembly challenges and guiding blade arrangement optimization.

5 Conclusion

This study proposes an intelligent co-optimization-driven method for blade selection and imbalance control in the rotor of an aircraft engine with a disk-blade separation structure, offering an innovative solution to the rotor imbalance problem after assembly. By applying the intelligent co-optimization-driven theoretical framework, this study employs a two-stage collaborative optimization strategy to achieve efficient and precise assembly of rotor blades in the disk-blade separation structure. This significantly improves blade utilization, assembly efficiency, and qualification rates, thereby enhancing the operational performance and service life of the aircraft engine. The main conclusions of this study are as follows:

1. A two-stage collaborative optimization strategy is proposed: This strategy first eliminates the inherent mass moment differences between blades, addressing the bottleneck problem in traditional multi-set blade selection methods. It then optimizes rotor assembly by compensating for residual imbalance, providing a novel solution for rotor assembly optimization in aircraft engines and significantly improving assembly efficiency and precision.

2. A multi-set blade selection method based on the DRWS algorithm is proposed: This method effectively addresses the issue of local optima in traditional roulette selection algorithms. By optimizing the selection process, it enhances blade selection efficiency and significantly reduces blade resource waste. Experimental results show that the DRWS algorithm successfully selects two sets of blades meeting mass moment standards from a candidate pool of 145 blades. Each selected set meets the predefined criteria for mass moment range and dispersion, greatly improving selection efficiency.

3. A fixed-tenon-slot-constrained rotor imbalance control method based on the CAGA is proposed: By incorporating an elitism strategy and adaptive crossover and mutation probabilities, this method addresses the blade arrangement optimization problem under fixed-tenon-slot constraints in actual assembly. Experimental results demonstrate that the CAGA optimization algorithm reduces rotor imbalance from 58 g·mm and 94 g·mm (random assembly) to 7 g·mm and 10 g·mm, achieving optimization improvements of 87.9% and 89.4%, respectively. Compared with the traditional genetic algorithm, the CAGA algorithm effectively optimizes rotor imbalance even under fixed-tenon-slot constraints, ensuring stable and reliable optimization results.

Overall, the optimization methods proposed in this study provide an efficient and feasible solution for aircraft engine rotor blade assembly, demonstrating significant engineering application value. By enabling precise blade selection and imbalance control, these methods significantly improve assembly accuracy, reduce vibrations, and extend the service life of aircraft engines, laying the foundation for efficient engine operation. Experimental validation further confirms the effectiveness and feasibility of the proposed methods in practical applications, providing essential theoretical support and technical assurance for optimizing aircraft engine assembly.

Author Contribution:

Chunyu Shao: Conceptualization, Methodology, Writing-original draft. Haixu Yu: Validation. Like Zhang: Formal analysis. Quanyi Ge: Software. Bobo Fang: Investigation. Ruirui Li: Writing-review & editing. Chuanzhi Sun: Visualization. Yongmeng Liu: Supervision, Project administration. Jiubin Tan: Supervision.

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Data Availability:

The authors declare that the main data supporting the findings of this study are available within the paper and its Supplementary Information files.

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The authors declare no competing interests.

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