

Retraction

Retracted: Research on Optimizing Selection and Optimizing Matching Technologies of Aeroengine Fan Rotor Blades

Shock and Vibration

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Li, K. Chen, J. Gao, Z. Gao, and J. Liu, "Research on Optimizing Selection and Optimizing Matching Technologies of Aeroengine Fan Rotor Blades," *Shock and Vibration*, vol. 2021, Article ID 5595535, 17 pages, 2021.

Research Article

Research on Optimizing Selection and Optimizing Matching Technologies of Aeroengine Fan Rotor Blades

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Aiming at the problem of low resources utilization of rotating blades in the selection process of aeroengine fan rotor blades, this paper takes the first-order bending dispersion, first-order torque dispersion, and gravitational moment difference of rotor blades as the selection criteria and takes the minimum remaining blades as the optimization goal. An intelligent selection algorithm of blades based on the collocation degree of blades is proposed and achieves the efficient selection and full utilization of rotating blades. Aiming at the problem of multiple installations and multiple adjustments and low assembly success rate of fan rotor blades, this paper takes the gravity moment difference of the two blades at the diagonal position of 180° as the constraint and takes the minimum residual unbalance as the optimization objective, adopts the improved simulated annealing algorithm to optimize the assembly sequence of rotating blades, and greatly reduces the residual unbalance of blades, which is beneficial to reduce the number of assembly adjustments of blades. The optimizing selection and optimizing matching methods of rotating blades realize the full utilization and efficient assembly of blades and lays a foundation for the reliability and robustness of the assembly quality and service performance of blades.

1. Introduction

In order to improve the balance quality of the aeroengine fan rotor, rotating blades need to be selected and matched according to the natural frequency and the gravitational moment before installation. The selection matching work before assembly of rotor blades mainly includes two parts: ① select rotating blades from the blade database according to the natural frequency dispersion and the gravity moment difference. The goal of selecting blades is to realize the efficient selection and full utilization of rotor blades; ② when the selection of the blade is completed, the assembly sequence of rotating blades must be planned with the goal of the smallest remaining unbalance according to the gravitational moment of rotating blades. The selection-matching work of rotor blades of the aeroengine fan directly determines the balance quality of the product and affects the service performance of the product. Efficient rotating blades selection-matching technology can improve the resources utilization rate of rotating blades and the reliability of the

balance quality, increase the success rate of rotating blades assembly, and reduce the number of installation and adjustment of rotating blades.

The constraint of rotor blade optimization-selection is not to exceed the given natural frequency dispersion and gravitational moment difference. The optimization goal is to minimize the number of remaining blades in the candidate library. Therefore, the optimization-selection process of rotating blades is actually an optimization process with constraints. There are not many researches on the optimization-selection of rotating blades, but the problem of rotor blade optimization-selection is essentially an engineering optimization problem. Practical engineering optimization problems often have many characteristics such as complexity, nonlinearity, constraints, and difficulty in modeling. Traditional optimization methods (such as simplex method, Newton method, etc.) need to traverse the entire search space and cannot complete the search in a short time, and it is easy to produce “combination explosion” of searching [1]. Therefore, seeking efficient optimization methods has

become one of the main research contents to solve engineering optimization problems. A lot of progress has been made in the research of optimization methods for optimization problems. It mainly includes genetic algorithm that imitates the biological evolution mechanism of nature [2], differential evolution algorithm that optimizes the search through cooperation and competition between individuals in a group [3], immunity algorithm that simulates the learning and cognitive function of biological immunity system [4], ant colony algorithm that simulates the collective path-finding behavior of ants [5], particle swarm algorithm that simulates the swarm behavior of birds and fish groups [6], simulated annealing algorithm [7] derived from the annealing process of solid matter, tabu search algorithm that simulates the memory process of human intelligence [8], neural network algorithm that simulates the behavioral characteristics of animal neural network [9], etc. [10]. These algorithms are developed by simulating or revealing certain natural phenomena, processes, or intelligent behaviors of biological groups. These optimization algorithms have the advantages of being simple, versatile, and convenient for parallel processing [11] and provide reference for the solution of the optimization-selection of rotating blades.

The assembly sequence planning of rotating blades is a nonnegligible part of the selection-matching work of rotating blades and directly determines the static balance quality of the rotor. However, the assembly sequence planning problem has NP-hard characteristics. In order to search for all feasible assembly sequence schemes and find the optimal assembly sequence, the complexity of searching for the optimal sequence will increase toward the direction of exhaustive search, and it is difficult to obtain a relatively optimal assembly sequence in a short time; this challenge has become one of the important driving forces to encourage the research of computerized assembly sequence planning [12]. In order to solve the ASP (Assembly Sequence Planning) problem, researchers used a variety of optimization algorithms to optimize the ASP problem, such as Ant colony optimization algorithm (ACO) [13], genetic algorithm (GA) [14, 15], immune algorithm (IA) [16], neural networks (NN) [17], scatter search algorithm (SSA) [18], and other heuristic methods [19–21]. At present, researchers have made remarkable progress in solving ASP optimization problems, but there are still some problems that need to be solved urgently. One of the most important problems is that it is difficult to obtain a relatively optimal assembly sequence in a short time. This problem has prompted researchers to introduce or improve various algorithms to improve the solving accuracy, robustness, and efficiency of the ASP problem.

The above research results provide a reference for the optimization-selection and optimization-matching of rotor blades. The rotor blade is the core component of the aeroengine fan rotor, and its balance quality is the main criterion for the assembly quality of rotating blades [22]. The “selection” and “matching” of rotating blades before assembly directly determine the “installation” and “adjustment” during the assembly process of rotor blades, as well as the balance quality and service performance of the rotor after

the assembly is completed. Therefore, in order to achieve the optimizing selection and optimizing matching of aeroengine fan rotor blades, this paper proposes an intelligent selection algorithm based on the collocation degree of blades to realize efficient selection and full utilization of rotor blades. The improved simulated annealing algorithm is used to optimize the assembly sequence of rotor blades, so that the residual unbalance of rotor blades can be as small as possible, and the success rate of one-time assembly of the rotor blades can be improved, and the number of installation and adjustment of rotor blades can be reduced. Finally, ensure that the goals of optimizing selection and optimizing matching of rotor blades before assembly, optimized assembly sequence and less adjustment during assembly, and reliable and stable balance quality after assembly are achieved.

2. Analysis of the Problem of Selection-Matching of Rotor Blades of the Aeroengine Fan

In order to ensure the robustness and reliability of the balance quality and service performance of the aeroengine fan rotor, the company currently guarantees it mainly from the following two aspects:

- (1) “Selection” and “matching” before assembly of aeroengine fan rotor blades. Aeroengines are mass-produced, and the blade database often contains hundreds of thousands of blades. If the blades are not selected, and the blades required by the fan rotor will be taken out randomly from the blade database, the first-order bending dispersion, first-order torque dispersion, and gravitational moment difference of the blades will lose control, which will not only be difficult to guarantee the remaining unbalance of rotating blades but also increase the difficulty of dynamic balancing of rotor blades. Therefore, before assembling rotating blades, blades must be selected according to certain selection criteria. The more the number of blades selected from the blade database, the remaining blades in the blade database will be fewer, and the utilization rate of blade resources will be higher. The blade selection is based on the dispersion of the first-order bending and the first-order torque, and the gravitational moment difference of the largest blade and the smallest blade of the rotor. The purpose is to ensure that the selected blades are as uniform as possible, and the characteristic gap between each other cannot be too big, laying the foundation for subsequent blade assembly sequence planning and the assurance of balance quality. “Matching” is to plan the assembly sequence of rotating blades and make the remaining unbalance of the rotor as small as possible. However, the remaining unbalance of rotating blades achieved by the current assembly sequence planning technology of the enterprise is generally too large, which causes rotor to be out of tolerance due to the assembly process error.

- (2) “Installation” and “adjustment” in the assembly process of aeroengine fan rotors. “Installation” is to complete the actual assembly of rotating blades according to the assembly sequence planned before assembly. “Adjustment” means that in the process of assembly, once the static unbalance of the rotor occurs, the assembly of rotating blades can reach the static balance quality by adjusting installation position and angle of the blades. At present, the success rate of one-time assembly of fan rotor blades in enterprises is not high, and the problem of multiple installations and multiple adjustments is obvious. One of the reasons is that although the residual unbalance obtained by the enterprise is within the design range, it is generally too large, which results in excessive residual unbalance due to assembly process errors. In order to compensate the excessive residual unbalance, the adjustment of rotating blades has to be carried out.

3. Ideas of Optimizing Selection and Optimizing Matching of Rotating Blades

Efficient selection and full utilization of blades are the two most critical goals for blade selection. The company initially relied on manual selection, which was inefficient and relied on workers' experience. Moreover, manual selection of rotating blades could only ensure that 37%–46% of rotating blades were picked out, and more than half of the rotating blades were left in the blade database and were imported into the next batch of new blades. The accumulation of the remaining rotating blades over time has eventually led to more and more blades becoming “nail households” in the blade database, causing idle and waste of blade resources. Later, the company introduced new technologies to select rotor blades, which greatly improved the efficiency of blade selection. However, the current blade selection technology of the enterprise can only achieve a utilization rate of 65%–74% of blade resources, and about 30% of remaining blades still are like “snowballs”; batches of backlogs of rotating blades are accumulated in the blade database, causing idle and waste of blade resources. Therefore, based on the actual engineering needs of the enterprise, this article proposes an intelligent and efficient blade selection algorithm.

After the blade selection is completed, the assembly sequence of selected blades must be planned. Although the remaining unbalance of rotor blades obtained by the

company's current assembly sequence planning technology does not exceed the design value, the overall remaining unbalance is generally too large. In actual assembly, the static balance of the rotor is difficult to meet the tolerance because of assembly errors, which leads to the problem of multiple installation and multiple adjustment in the process of assembly of rotor blades. Therefore, this paper adopts the improved simulated annealing algorithm to provide optimized assembly sequence for the rotating blades.

Aiming at the problem of low resource utilization of rotating blades in the selection process of blades, this paper proposes an intelligent optimization algorithm for selecting rotating blades based on the collocation degree. Aiming at the problem that the assembly sequence currently planned by the enterprise is prone to static unbalance because of assembly process errors, resulting in multiple installations and multiple adjustments of rotating blades, this paper adopts the improved simulated annealing algorithm to plan the assembly sequence of rotating blades. The framework of optimizing selection and optimizing matching of rotating blades is shown in Figure 1; b1, b2, . . . , b302 represent blade1, blade2, . . . , blade302.

4. Solution and Analysis of the Optimizing Selection Problem of Aeroengine Fan Rotor Blades

4.1. *The Establishment and Solution of the Intelligent Optimization Algorithm for Selecting Rotating Blades Based on the Collocation Degree of Rotating Blades.* The aeroengine fan rotor has three-stage blades; the research in this paper takes the selection of the first-stage blades as an example. The first-stage blade database with related data of a total of 302 blades obtained from the enterprise is shown in Table 1. A rotor requires 28 first-stage blades; there are 302 blades in the first-stage blade database in this article, and a maximum of 280 blades are picked out and assembled to form 10 rotors. The rules of selecting blades are shown in Table 2, and the calculation methods of dispersion and gravitational moment difference are shown in formulas (1)–(3). The goal of selecting blades is that the fewer remaining blades, the better, and the more fan rotors that can be assembled with the selected blades, the better. The calculation method of remaining blades is shown in equation (4); N represents the number of rotors assembled by selected blades.

$$\text{the first - order bending dispersion} = \frac{\max(\text{the first - order bending}) - \min(\text{the first - order bending})}{\min(\text{the first - order bending})} \leq 0.06, \quad (1)$$

$$\text{the first - order torque dispersion} = \frac{\max(\text{the first - order torque}) - \min(\text{the first - order torque})}{\min(\text{the first - order torque})} \leq 0.08, \quad (2)$$

$$\text{gravitational moment difference} = \max(\text{gravitational moment}) - \min(\text{gravitational moment}) \leq 6000, \quad (3)$$

$$\text{the remaining blades} = 302 - 28 * N. \quad (4)$$

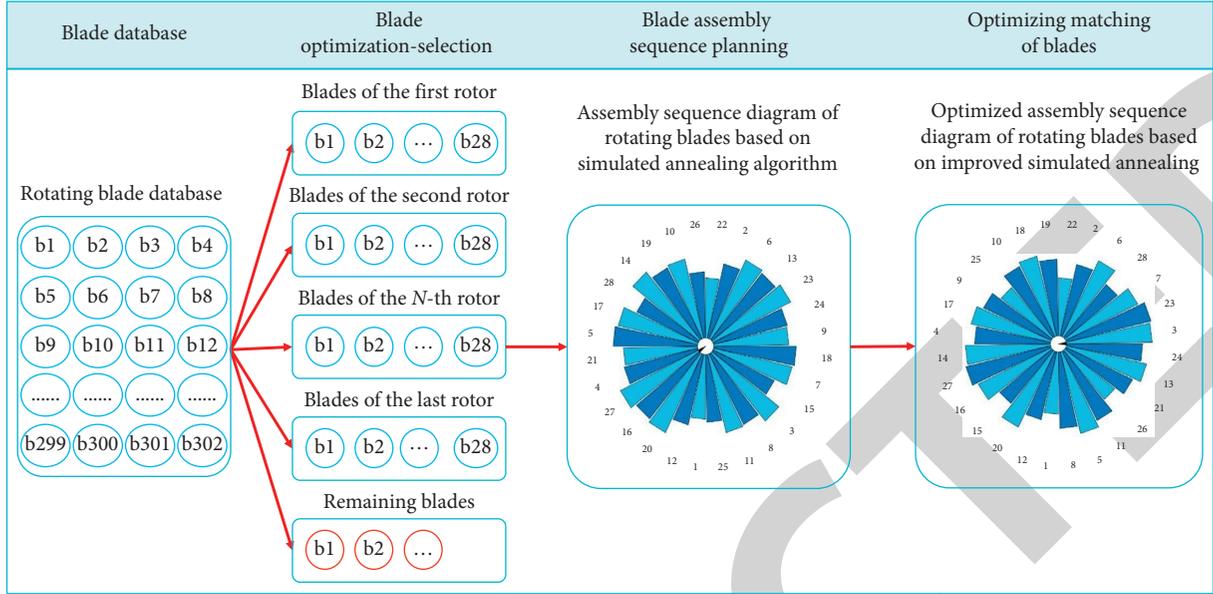


FIGURE 1: The framework of optimizing selection and optimizing matching of rotating blades.

TABLE 1: The rotating blade database of the first-stage fan rotor.

No.	First-order bending	First-order torque	Gravitational moment (g^*mm)	No.	First-order bending	First-order torque	Gravitational moment (g^*mm)
1	127	616	276180	11	122	670	275320
2	128	603	275040	12	133	655	273820
3	130	613	276560	13	127	665	270440
4	129	624	281520	14	137	644	278460
5	136	616	275280	15	125	680	276120
6	129	624	280900	16	136	679	273660
7	124	661	272900
8	121	666	275820	300	134	670	276340
9	121	688	278380	301	136	656	276000
10	125	652	272860	302	128	664	277020

TABLE 2: The selection rules of the first-stage rotor blades.

The number of blades of the first-stage rotor	The first-order bending dispersion	The first-order torque dispersion	Gravitational moment difference
28 blades/group	≤ 0.06	≤ 0.08	$6000g^*mm$

The collocation of rotating blades: if the first-order bending dispersion, the first-order torque dispersion, and the gravitational moment difference of two rotating blades meet in formulas (1)–(3), we call these two blades collocation. The number of collocations of a rotating blade: there are 302 blades in the blade database in this article, and each blade can form 301 pairs of blades with the rest. Take No.i blade as an example, if among the 301 pairs of blades, there are n_i pairs of blades satisfying formulas (1)–(3), we call the number of collocation of the No.i blade as n_i . By analogy, these 302 blades, each of which has its own number of collocation, are recorded as $n_1, n_2, n_3, \dots, n_i, \dots, n_{302}$. Before calculating the collocation degree of each blade, we must first calculate the number of collocation of each blade: $n_1, n_2, n_3, \dots, n_i, \dots, n_{302}$. Then, we must calculate the collocation degree of each blade according to the number of

collocation of each blade: $P_1 = n_1 / \sum_{a=1}^{302} n_a, P_2 = n_2 / \sum_{a=1}^{302} n_a, P_3 = n_3 / \sum_{a=1}^{302} n_a, \dots, P_i = n_i / \sum_{a=1}^{302} n_a, \dots, P_{302} = n_{302} / \sum_{a=1}^{302} n_a$. The collocation degree of each blade is the probability of each blade being selected, which reflects the ability of a blade matching other blades; the more the number of blades that can be matched with the blade, the higher the collocation degree of the blade. Otherwise, the fewer the number of blades that can be matched with the blade, the lower the collocation degree of the blade. In the blade selection process, the blade with the higher collocation degree has a greater probability of being selected, and the blade with the lower collocation degree may become the final remaining blade.

At present, the company's blade selection technology can only achieve a utilization rate of 65%–74% of blade resources, and there will still be about 30% remaining rotating

blades, which are backlogged in the blade database. These remaining blades will be like “snowballs,” creating a backlog, batch by batch, in the blade database, causing idle and waste of blade resources. Based on the actual engineering needs of the enterprise, this paper establishes an intelligent algorithm for selecting blades, takes the fewest remaining blades (which means that the most fan rotors can be assembled by the selected blades) as the optimization goal, and takes the efficiency of blade selection into account. In order to realize the intelligent selection of rotating blades, there are two ideas for programming the optimization algorithm of selecting blades, as shown in Figure 2. Idea one is based on the random selection method to select rotating blades. Each blade in the blade database has the same probability of being selected. For each new blade selected, the constraint conditions must be calculated and verified. If it is satisfied, the new blade will be picked out successfully; otherwise, randomly select a blade from the candidate library again until the constraint conditions are met. The disadvantage of this method is that it is not sure how many times the No. N blade is selected before it can be successfully selected, causing the selection of rotating blades to be random and unstable. The second idea selects rotor blades based on the collocation degree of rotating blades. Each blade has a different probability of being picked out, blades with a higher collocation degree are more likely to be picked out first, and those blades with a lower collocation degree are more likely to become final remaining blades. All the blades in the blade database will be combined into pairs to form many pairs of blades in idea 2, and these blades’ collocation degree will be calculated before being selected. If the pair of blades meets the constraint conditions, the pair of blades can be matched and recorded as “1”; otherwise, it is recorded as “0”. The collocation matrix formed by these pairs of blades is a symmetric matrix, as shown in Figure 2(c), and the diagonal “1” is not considered because the blade cannot form a pair with itself in actual application. Every time a new blade is selected, there is no need to repeat the calculation in idea 2; it is only necessary to determine whether all the pairs of blades composed by the new blade and the selected blades are matched. If they are all matched, the new blade is successfully picked out; for example, when selecting the No. 4 blade of the rotor, if all the three pairs of blades 4–3, 4–2, 4–1 meet the constraint conditions, which means all the three pairs of blades are matched, then the No. 4 blade is successfully picked out. The advantage of the second idea is that it can complete the calculation of the collocation degree matrix of blades before selecting blades, and when selecting the blades, it is only necessary to judge whether the pairs of blades formed by the new blade and the selected blades are all matched; there is no repeated calculation, idea 2 has a certain selection law, and the probability of each blade being selected is different. Compared with the first idea, the blade selection method based on the second idea is more reliable and robust.

Compile two optimization algorithms of selecting rotating blades according to idea 1 and idea 2, respectively, and run the two algorithms multiple times and compare the solution results (as shown in Figure 3). The optimization

algorithm based on the collocation degree of rotating blades can pick out more blades and cost less time than the optimization algorithm of selecting blades based on idea 1; the solution effects of the later optimization algorithm of selecting blades are unstable, especially the solution time, which is very volatile, and the robustness is obviously inferior to the optimization algorithm based on the collocation degree of blades. Therefore, this paper adopts the optimization algorithm based on the collocation degree of rotating blades to select rotating blades.

The flowchart of the optimization algorithm of selecting rotating blades based on the collocation degree of blades is shown in Figure 4. The specific process of the optimization algorithm is shown as follows:

Step (1): combine 302 blades in pairs to form $302 \times 301 \div 2 = 45451$ pairs of blades, and judge whether the first-order bending dispersion, first-order torque dispersion, and gravitational moment difference of these 45451 pairs of blades meet the blade selection rules; if the selection rules are met, the pair of blades is marked as “1”; otherwise, it is recorded as “0”. The collocation matrix formed by these pairs of blades is a symmetric matrix, as shown in of Figure 2(c); the diagonal “1” is not considered because the blade cannot form a pair with itself in actual application.

Step (2): establish a candidate library and a finished product library of rotating blades. The candidate library stores 302 blades waiting to be selected, and the finished product library stores blades that meet selection rules and have been picked out. For example, if you can pick out rotating blades needed by 5 rotors from 302 blades, the finished product library will store these rotating blades needed by 5 rotors.

Step (3): among the 302 blades in the blade database, each blade can form 301 pairs of blades with the remaining blades. Take the No. i blade as an example, assume that the No. i blade and the remaining blades are composed of 301 pairs of blades, There are n_i pairs of blades marked as 1, the No. i blade is marked as n_i , which means that it can combine with the other blades into n_i pairs of blades marked as 1, and its number of collocations is n_i . By analogy, count the number of collocations of each rotating blade and record them as $n_1, n_2, n_3, \dots, n_i, \dots, n_{302}$, then the probability of the No. i is $P_i = n_i / \sum_{a=1}^{302} n_a$; by analogy, get the probability of each blade, respectively, recorded as $P_1, P_2, P_3, \dots, P_i, \dots, P_{302}$. The probability of each blade obtained in this step is the collocation degree of each blade, reflecting the ability of a blade to combine with other blades to form pairs of blades that meets selection rules.

Step (4): use the roulette method to select the first blade of the first rotor according to the collocation degree (probability) of each blade calculated in step (3). Then, continue to use the roulette method to select the second blade of the rotor, check whether the pair of blades formed by the second blade and the first blade is marked as 1 in step (1). If it is marked as 1, the second

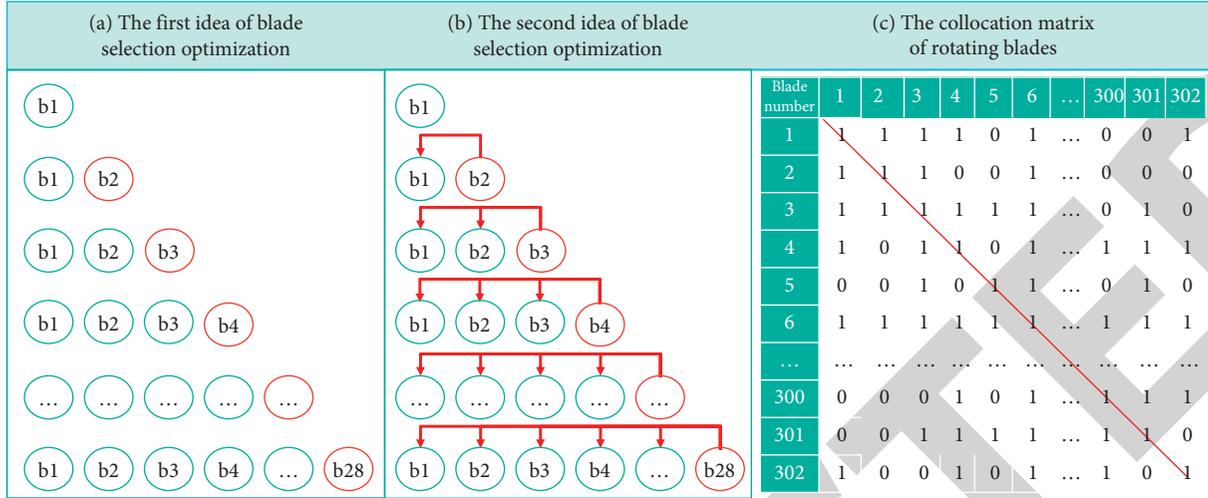


FIGURE 2: Two ideas of establishing blade optimization-selection algorithm and the collocation matrix of blades.

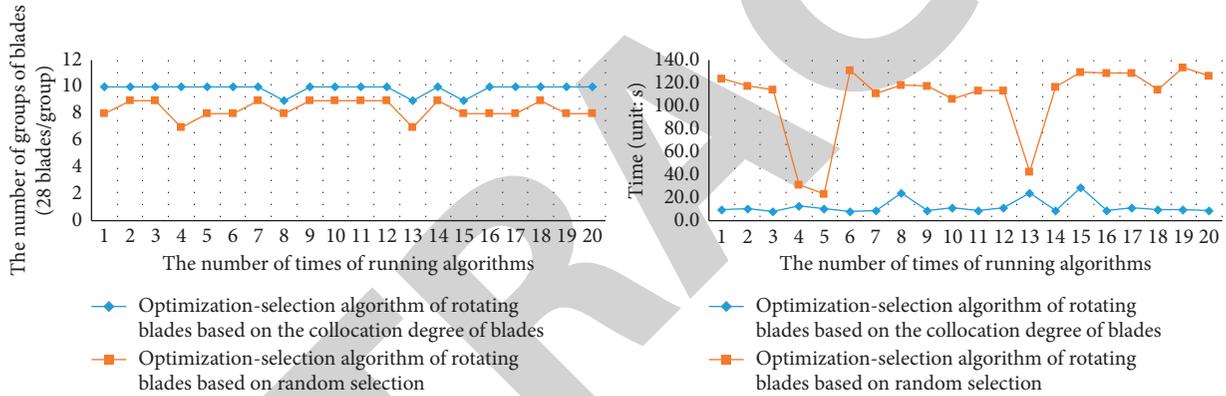


FIGURE 3: Comparison of the solution effects of the two algorithms based on two ideas.

blade is picked out successfully, and then pick out the third blade in the same way, check whether the two pairs of blades (No. 3 blade and No. 2 blade, No. 3 blade and No. 1 blade) formed by the third blade and the first two selected blades are all marked as 1. If yes, the selection of the third blade is finished; otherwise, use the roulette method, and according to the probability of each blade, reselect the third blade. That is to say, when selecting the No. N blade, check whether the $n - 1$ pairs of blades formed by it and the $n - 1$ selected blades before are all marked as 1 in step (1). If they are all marked as 1, the No. N blade is picked out successfully; otherwise, reselect the No. N blade, and so on, until all the blades of the first rotor are picked out successfully. Then, continue to select blades of the second rotor. When selecting blades, every time a blade is picked out, the blade will be put into the finished product library in time. When 28 blades of a rotor are picked out from the candidate library, the collocation degree of the remaining blades in the candidate library must be recalculated. Then, use the same method of selecting blades to pick out blades of the next rotor.

Step (5): when the blade selection process reaches a certain degree, the process of blade selection in step (4) will encounter a “bottleneck”, which means it is no longer possible to pick out new blades by the method of selecting blades in step (4). At this time, it is assumed that blades of n rotors have been picked out and put into the finished product library, which are, respectively, recorded as T_1, T_2, \dots, T_n . Randomly select a blade from the blades of No. T_n Rotor, and record it as No. M blade, and use the roulette method to select a blade from the candidate library; check whether the blade can replace the No. M blade of No. T_n rotor of the finished product library. If it can, replace the No. M blade with the blade of the candidate library and put it in the finished product library. At the same time, put the No. M blade into the candidate library; otherwise, continue to select the blade that can replace the No. M blade from the candidate library. After completing the replacement of the No. M blade, proceed to step (4) to select blades of the next rotor.

Step (6): when the process of blade selection encounters the “bottleneck” again, and the new blade cannot be

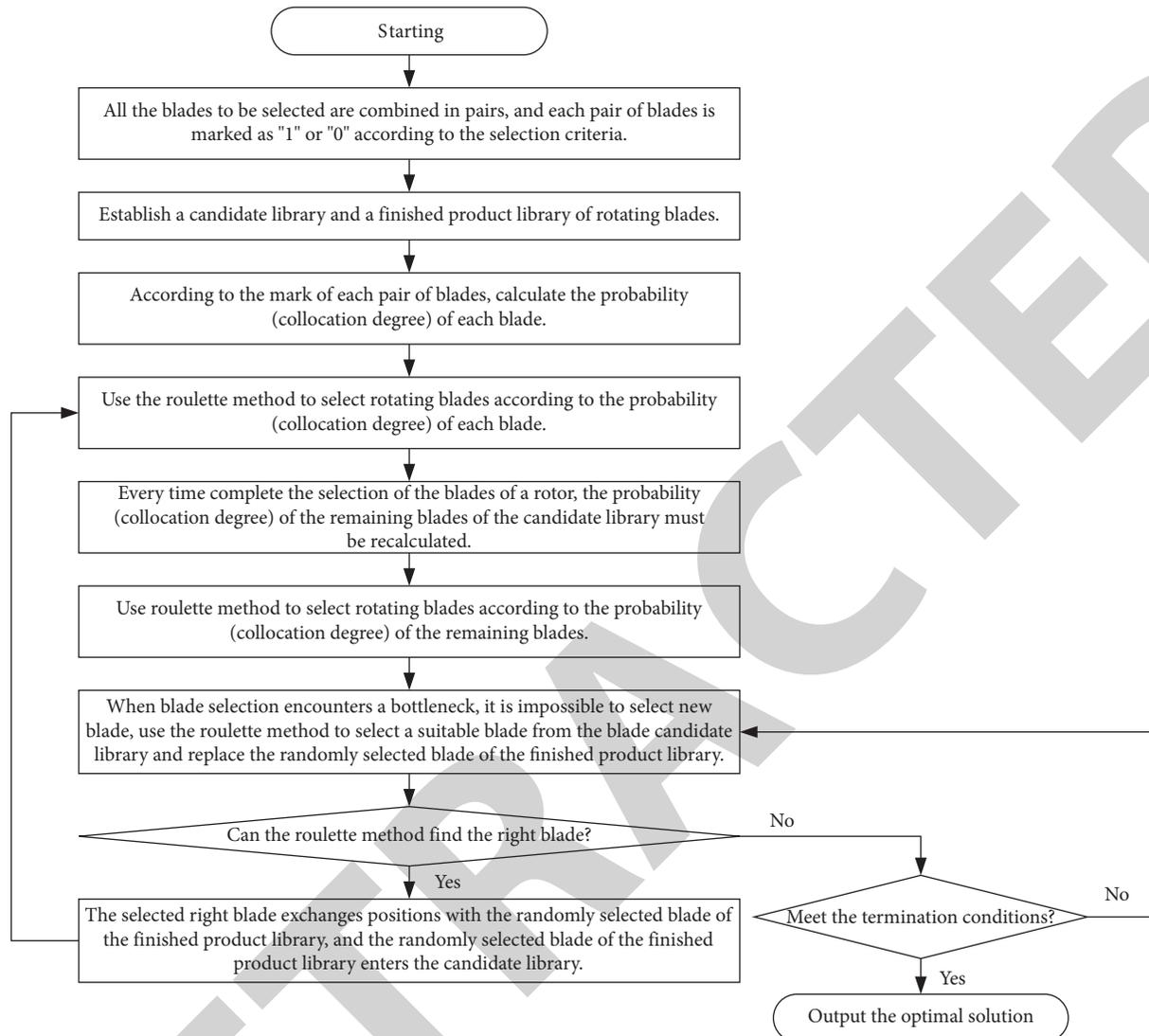


FIGURE 4: The flowchart of the optimization algorithm of selecting rotating blades based on the collocation degree of blades.

picked out according to the method of selecting blades in step (4), the algorithm goes to step (5), and step (5) is used to solve the problem of the “bottleneck”.

Step (7): the number of selected blades and the corresponding blade information are output. The number of rotors that assembled by the selected blades and the corresponding blades of each rotor are output.

The optimization algorithm of selecting rotor blades based on the collocation degree of rotating blades can pick out 10 groups of blades that meet the selection rules; these 10 groups of rotor blades correspond to 10 rotors, and the assembly of these 10 rotors can be completed by these 10 groups of rotor blades. The optimization-selection results are shown in Table 3. There are a total of 302 blades in the rotating blade database of the first-stage rotor; 28 blades are a group of rotor blades corresponding to a rotor, and 302 blades can select 10 groups of rotor blades at most and can assemble 10 rotors. The optimization algorithm picked out 280 blades, and the remaining blades are the fewest, which is

22 blades; blade utilization has reached the theoretical maximum: $280/302 * 100\%$. The distributions of the number of collocations of all the blades before selection and the remaining blades after selection are counted, respectively, as shown in Figure 5; the number of blade collocations refer to the number of pairs that each blade can match with in the remaining 301 blades, as can be known from Figure 5. The number of collocations of most remaining blades is relatively low; only a few remaining blades have a slightly higher number of collocations. Therefore, Figure 5 further explains that blades with a higher collocation degree are more likely to be picked out, while blades with a lower collocation degree tend to become the remaining blades. The higher the number of collocations of the blade, the higher the collocation degree of the blade.

The optimization algorithm of selecting rotor blades based on the collocation degree of rotating blades can pick out 10 groups of blades that meet the selection rules; in order to verify the 10 groups of blades corresponding to 10 rotors, the dispersion and gravitational moment

TABLE 3: Ten groups of rotating blades (280 blades) selected from the blade database.

No.	Blade no.	First-order bending	First-order torque	Gravitational moment ($g^* \text{ mm}$)	No.	Blade no.	First-order bending	First-order torque	Gravitational moment ($g^* \text{ mm}$)
1	222	134	674	281280
2	50	131	661	278100	254	194	129	662	280920
3	293	135	675	276160	255	287	136	662	279360
4	115	132	669	275700	256	252	135	658	281140
5	96	135	664	281080	257	298	132	695	277460
6	143	134	677	276440	258	57	135	676	278620
7	221	134	675	280220	259	214	129	663	281260
8	203	130	679	278560	260	177	136	678	280620
9	158	134	643	276460	261	167	133	670	278520
10	120	134	667	277300	262	189	130	661	277000
11	178	132	661	278760	263	201	134	675	281200
12	237	135	662	281120	264	140	135	679	278300
13	238	129	676	276840	265	186	129	674	276800
14	174	134	662	278820	266	233	134	676	281080
15	265	129	660	276520	267	225	134	676	280760
16	171	131	667	276080	268	157	130	662	276080
17	213	131	671	281600	269	296	129	644	279540
18	142	136	676	278640	270	147	134	663	277120
19	262	129	662	278140	271	51	131	661	278440
20	44	134	676	277056	272	85	132	661	278040
21	185	134	653	279280	273	289	132	690	277620
22	52	135	661	277100	274	279	130	677	275520
23	285	136	661	276600	275	183	129	663	277460
24	93	130	673	277700	276	235	133	662	275460
25	195	129	673	277360	277	263	136	673	277880
26	116	134	677	275980	278	256	132	645	275680
27	149	130	677	275760	279	133	134	679	276660
28	234	135	659	279840	280	137	131	673	278600

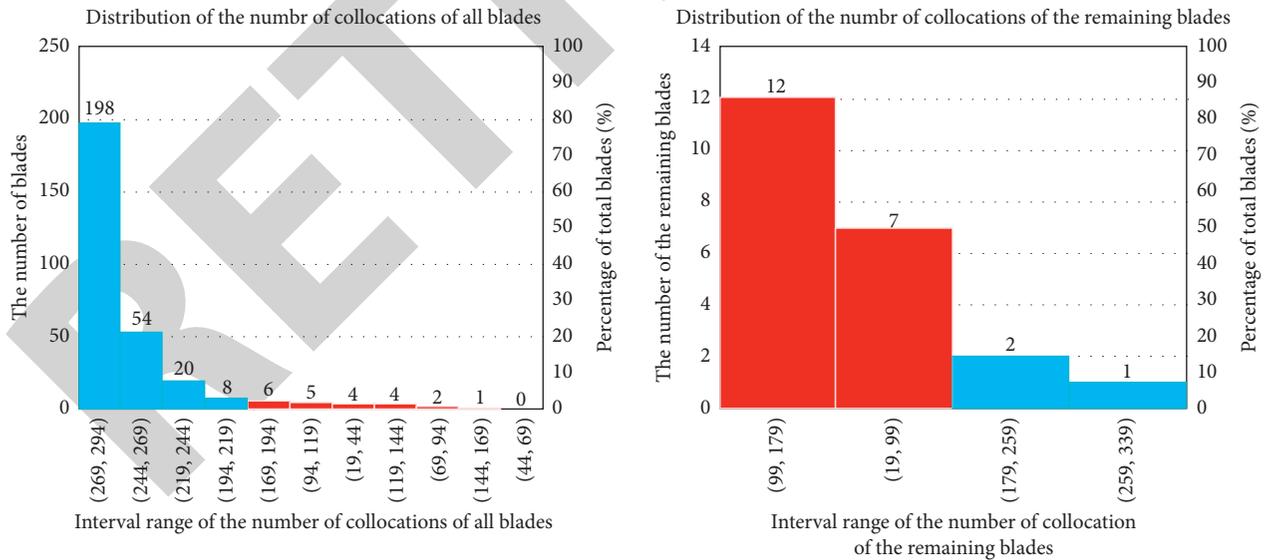


FIGURE 5: The distributions of the number of collocations of all the blades before selection and the remaining blades after selection.

difference of the selected 10 groups of blades are verified, respectively. The verification results are shown in Table 4. The verification results show that the dispersion and gravitational moment difference of the selected 10 groups of blades are within the specified range, which means that the selected 10 groups of blades by the intelligent

optimization algorithm based on the collocation degree of rotating blades meet the requirements of selecting blades. Therefore, the intelligent optimization algorithm has reached the optimal selection goal, and the number of the remaining blades has reached the fewest, and the blade resources are utilized to the greatest extent. The running

TABLE 4: Ten groups of rotating blades picked out by the algorithm based on the collocation degree of blades.

	First-order bending dispersion	First-order torque dispersion	Gravitational moment difference (g^*mm)
Design requirements (blade selection rules)	0.06	0.08	6000
The blade group of the first rotor	0.054	0.056	5900
The blade group of the second rotor	0.054	0.040	6000
The blade group of the third rotor	0.055	0.047	5780
The blade group of the fourth rotor	0.055	0.059	5640
The blade group of the fifth rotor	0.054	0.078	5400
The blade group of the sixth rotor	0.054	0.059	5980
The blade group of the seventh rotor	0.054	0.059	5820
The blade group of the eighth rotor	0.056	0.074	5940
The blade group of the ninth rotor	0.053	0.064	5980
The blade group of the tenth rotor	0.054	0.079	5800

time of the optimization algorithm of selecting blades and the robustness of the results are also two important indicators to measure the quality of the algorithm; therefore, run the optimization algorithm for 20 times, and the running time and optimization results of the optimization algorithm are counted. The statistical results are shown in Table 5. As can be seen from Table 5, the optimization results are very impressive; the minimum running time of the algorithm is 7.7 seconds, the maximum is 28.7 seconds, and the solution efficiency is very high. Therefore, compared with the 65%–74% blade utilization rate currently achieved in the enterprise, the optimization algorithm established in this paper can reach 83%–93% blade utilization rate. Moreover, the solution time of the optimization algorithm based on the collocation degree of blades is very short, which is very convenient for promotion and application in enterprises.

4.2. Comparison and Analysis of the Solution Effect of the Intelligent Optimization Algorithm Based on the Collocation Degree of Rotating Blades and Other Intelligent Optimization Algorithms. The basic idea of the greedy algorithm is to only make the best choice at the moment, the greedy algorithm does not consider the overall optimality, and the choice it makes is only a local optimal choice in a certain sense [23]. The solution of each step of the greedy algorithm is feasible and meets the corresponding constraints; the solution of each step is a local optimal solution and the best solution of all the current feasible solutions. The most obvious disadvantage of the greedy algorithm is that it cannot guarantee that the result obtained is the global optimal solution. However, the greedy algorithm usually does not take up too much time and manpower in the specific solution process. Starting from the purpose of business operation, although the greedy algorithm cannot obtain the global optimal solution, it can find a feasible solution close to the global optimal solution in a short time. Therefore, the solution is close to the global optimal solution sought by the greedy algorithm and can also be accepted by related companies.

The core idea of the simulated annealing algorithm (Simulated Annealing, SA) is derived from the principle of solid annealing. Because of the similarity between the

physical annealing process and the combinatorial optimization problem, it was introduced into the field of combinatorial optimization in 1983 [24]. The simulated annealing algorithm selects new solutions according to Metropolis criteria; it not only accepts optimized solutions with excellent performance but also accepts deteriorating solutions with poor performance as a certain probability, prompting the algorithm to jump out of the “trap” of local optimal solutions, thereby ensuring that it can search for the global optimal solution or near optimal solution [25].

In addition to the intelligent optimization algorithm of selecting blades proposed in this paper, this paper also uses the greedy algorithm and the simulated annealing algorithm for selecting blades. The comparison of the solution results and solution efficiency of the three algorithms are shown in Figures 6 and 7, respectively. The intelligent optimization algorithm of selecting blades based on the collocation degree of blades picks out 9 groups of blades (only 3 times), which can complete the assembly of 9 rotors, but the algorithm picked out 10 groups of blades in the remaining 17 times; therefore, the intelligent optimization algorithm based on the collocation degree of blades has the optimal optimization effect. The solution effect of the greedy algorithm is more stable than that of simulated annealing, but it can only select 9 groups of blades at most, which cannot reach the global optimal solution of 10 groups of blades. This is related to the inherent properties of the greedy algorithm; it cannot find the global optimal solution, but it can obtain a feasible solution close to the global optimal solution in a short time. As shown in Figure 7, the greedy algorithm has the most stable and shortest solution time. It can be seen from Figure 6 that simulated annealing can find the global optimal solution, but the solution result of simulated annealing is the most unstable; it can pick out 10 groups of blades at most, but the smallest is only 1 group of blades being selected. Because the simulated annealing algorithm is based on the Metropolis criterion to select new solutions, it can not only accept the optimized solution with good performance but also accept the deteriorating solution as a certain probability. The advantage of the Metropolis criterion is to promote the algorithm to jump out of the “trap” of the local optimal solution, so as to ensure that it can search for the global optimal solution. But, at the same time, precisely because of accepting the inferior solution as a certain probability during

TABLE 5: Statistic table of solution time and selection results of rotating blades optimization-selection algorithm based on the collocation degree of blades.

Serial number	Number of groups of blades	Solution time (unit: s)	Serial number	Number of groups of blades	Solution time (unit: s)
1	10	9.6	11	10	8.2
2	10	10.0	12	10	11.1
3	10	7.7	13	9	23.7
4	10	12.3	14	10	8.6
5	10	10.5	15	9	28.7
6	10	7.9	16	10	8.9
7	10	8.5	17	10	11.1
8	9	23.8	18	10	9.0
9	10	8.7	19	10	9.5
10	10	11.2	20	10	8.7

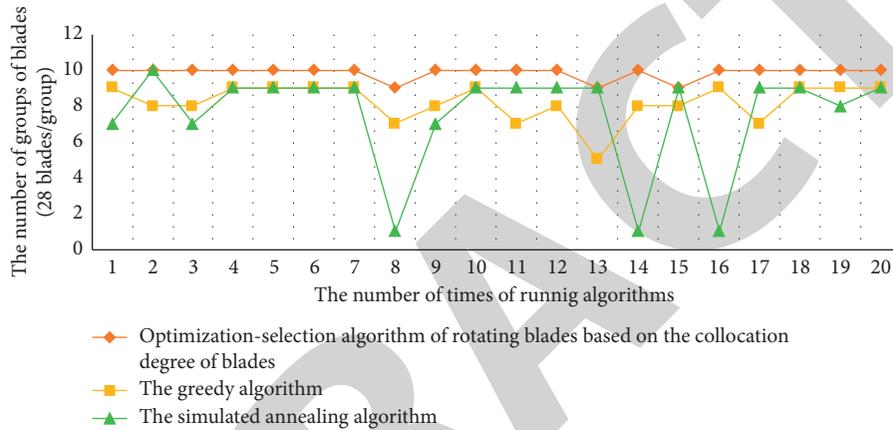


FIGURE 6: Comparison of solution results of the three algorithms.

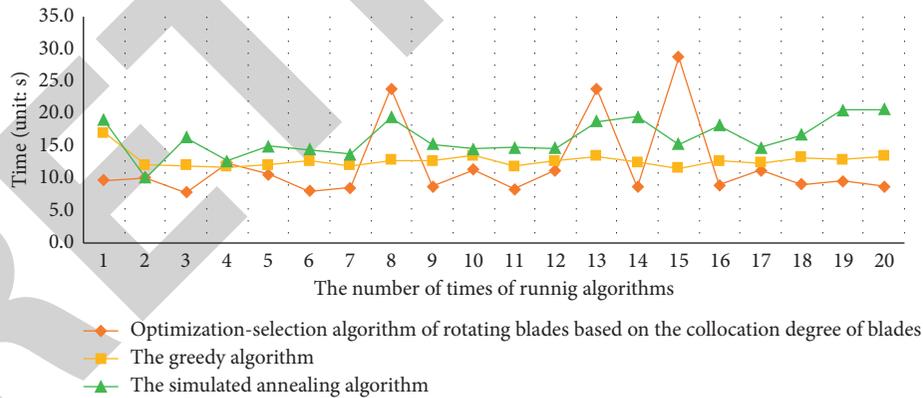


FIGURE 7: Comparison of solution time of the three algorithms.

the search process, the algorithm may miss the current encountered optimal solution, that is, the optimal solution may be discarded when the simulated annealing algorithm accepts the inferior solution probabilistically, resulting in the final result of simulated annealing algorithm, which is not always the optimal solution.

Step (4) of the intelligent optimization algorithm based on the collocation degree of blades ensures that the algorithm will not destroy the number of groups of blades that have been selected when the algorithm encounters the

“bottleneck”, which means that when blades are selected by the algorithm, the number of groups of blades already selected and put in the finished product library may increase or maintain the current number, but will not decrease, which is similar to the greedy algorithm; however, the greedy algorithm cannot find the global optimal solution. The simulated annealing algorithm can achieve the global optimal solution by the Metropolis criterion, but at the same time, when it accepts inferior solutions probabilistically, the number of groups of blades that have been

selected and put in the finished product library will decrease, which results in the final solution result of simulated annealing not always being the global optimal solution.

In terms of the solution time, the solution time of all the above three algorithms is not long, and the longest is no more than 30 seconds, which is acceptable in the actual application of enterprises. The termination conditions of the three algorithms set in this paper are: ① when picking out 10 groups of blades (280 blades), terminate the running of the algorithm; ② when the number of iterations is reached, the algorithm terminates. As can be known from Figure 6, when the intelligent optimization algorithm based on the collocation degree of blades picks out 9 groups of blades, the termination conditions of picking out 10 groups of blades is not met; therefore, the algorithm continues to select blades until the number of iterations is reached; as a result, it costs more time. In the other 17 times of running algorithm, when 10 groups of blades are selected, the algorithm will terminate, even if the number of iterations is not used up, so it costs less time. Since the greedy algorithm cannot find the global optimal solution, it terminates only when its number of iterations is used up every time, so the solution time of the greedy algorithm is more stable than the other two algorithms. The solution time of the optimization algorithm based on the collocation degree of blades is not as robust as the other two algorithms, but its solution results are significantly better than the greedy algorithm and the simulated annealing algorithm. In general, within the solution time range acceptable by the enterprise, the optimization algorithm based on the collocation degree of blades has the best solution effect, which can realize efficient selection and full utilization of rotating blades.

5. The Solution and Analysis of Optimizing Matching Problem of Rotor Blades of Aeroengine Fan

5.1. Assembly Sequence Planning of Fan Rotor Blades Based on Simulated Annealing Algorithm. “Optimizing matching” is to plan the assembly sequence of rotating blades and make the remaining unbalance of the rotor as small as possible. After the blade selection is completed, the assembly sequence of the selected rotor blades should be planned. The goal of the assembly sequence planning is to ensure that the remaining unbalance does not exceed the design value to ensure that the rotor static balance meets the design requirements after the rotor blades are assembled according to the planned assembly sequence. Although the remaining unbalance achieved by the current assembly sequence planning technology of the enterprise does not exceed the design value, it is generally too large, as shown in Table 6. Take the first-stage blades of the fan rotor as an example; Table 6 is the comparison result of the remaining unbalance obtained by the 6 kinds of blade sorting methods of the enterprise and design value.

For the n blades of the first-stage fan rotor, the calculation method of the remaining unbalance is shown in formulas (5)–(8).

$$M_x = \sum_{i=1}^n M_i \cos \theta_i, \quad (5)$$

$$M_y = \sum_{i=1}^n M_i \sin \theta_i, \quad (6)$$

$$M_{\text{left}} = \sqrt{M_x^2 + M_y^2}, \quad (7)$$

$$\alpha = \arctan \frac{M_y}{M_x}. \quad (8)$$

M_x and M_y are the components of the sum of gravitational moments in the x and y directions, respectively; M_i is the gravitational moment of the No. i blade; θ_i is the angle between the gravitational moment vector of the No. i blade and the x -axis; M_{left} is the residual unbalance; and α is the angle of the residual unbalance.

Although the current assembly sequence planning methods of the enterprise can make the remaining unbalance of the rotor blade within the design range, if the remaining unbalance is too large, the remaining unbalance of the rotor will exceed the design value due to errors during the assembly process. Therefore, this article takes the assembly sequence planning of the first-stage blades of the fan rotor as an example, takes the minimum residual unbalance as the goal, and takes the gravitational moment difference of the two blades at the diagonal position of 180° , which does not exceed $1500 \text{ g} \cdot \text{mm}$ as the constraint (the constraint is specified by the enterprise); the simulated annealing algorithm is used to plan the assembly sequence of the blades, and the obtained residual unbalance by simulated annealing can reach $0.52 \text{ g} \cdot \text{mm}$, and the corresponding assembly sequence is shown in Table 7. The running time of SA algorithm is 7.8 seconds. The residual unbalance comparison results of the current assembly sequence planning methods of the enterprise and the assembly sequence planning method based on SA are shown in Table 6. The results show that the assembly sequence planning method based on the simulated annealing algorithm has the advantages of high efficiency and high precision. The flow of the simulated annealing algorithm is shown in Figure 8. The assembly sequence diagram of blades obtained by simulated annealing is shown in Figure 9. The small arrow at the center of Figure 9 indicates the location of the heavy point of the blades. In order to better ensure the static balance of the rotor, when assembling the rotating blades, the location of the heavy point of the rotating blades should be assembled with the location of the light point of the rotor disk edge.

Figure 10 is a statistical chart of the solution accuracy and solution time of running the simulated annealing algorithm for multiple times. As can be seen from Figure 10, the residual unbalance obtained by the simulated annealing algorithm does not exceed $8 \text{ g} \cdot \text{mm}$, which is significantly better than the value of $32\text{--}83 \text{ g} \cdot \text{mm}$ (see Table 6)

TABLE 6: The comparison of the remaining unbalance obtained by 6 kinds of blade sorting methods of the enterprise and design value.

Method 1 2-single beam h/l	Method 2 3-double beam h/l	Method 3 4-quadr beam h/l	Method 4 5-quadr beam h/l	Method 5 6-triple beam h/l	Method 6 7-sequence beam h/l	SA algorithm intelligent sorting	Design value (g*mm)
48	32	40	52	37	83	0.52	100

TABLE 7: The assembly sequence planned by simulated annealing algorithm (gravitational moment: g^*mm).

Assembly sequence	Blade number	Gravitational moment	Assembly sequence	Blade number	Gravitational moment	Assembly sequence	Blade number	Gravitational moment
1	22	272860	11	3	276260	21	21	274840
2	2	274780	12	8	275140	22	5	276100
3	6	276120	13	11	275300	23	17	275760
4	13	275840	14	25	273760	24	28	274120
5	23	276460	15	1	273380	25	14	276180
6	24	275080	16	12	274300	26	19	275180
7	9	274960	17	20	276120	27	10	275420
8	18	275880	18	16	275760	28	26	273580
9	7	275660	19	27	276460			
10	15	274100	20	4	275040			

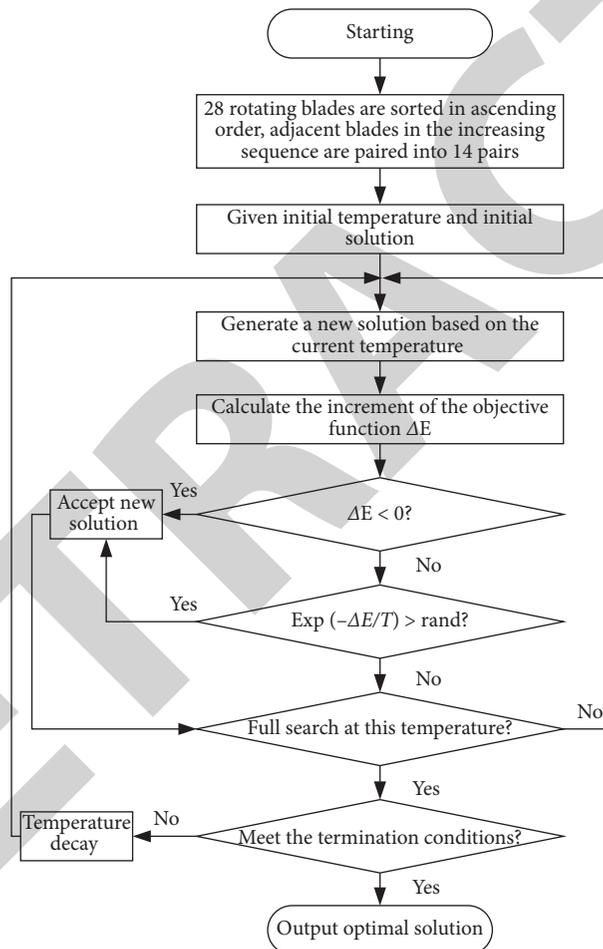


FIGURE 8: The flowchart of simulated annealing algorithm.

obtained by the enterprise, and is also far less than the design value of $100 g^*mm$ given by the design department. Besides, the running time of the simulated annealing algorithm is between 6 and 12 seconds, and its solution efficiency is very high. Therefore, compared with the current solution methods of the enterprise, the assembly sequence planning technology based on the simulated annealing algorithm not only provides the optimized assembly sequence for the enterprise but also its solution efficiency is very high.

5.2. Assembly Sequence Optimization of the Fan Rotor Blades Based on the Improved Simulated Annealing Algorithm. The simulated annealing (SA) algorithm realizes the global search by accepting inferior solutions probabilistically, so as to achieve the global optimization solution. However, at the same time, precisely because of accepting inferior solutions probabilistically in the search process, the algorithm may miss the current superior solution, and the current superior solution may be the optimal solution of the algorithm, which means the optimal solution may be discarded, and the

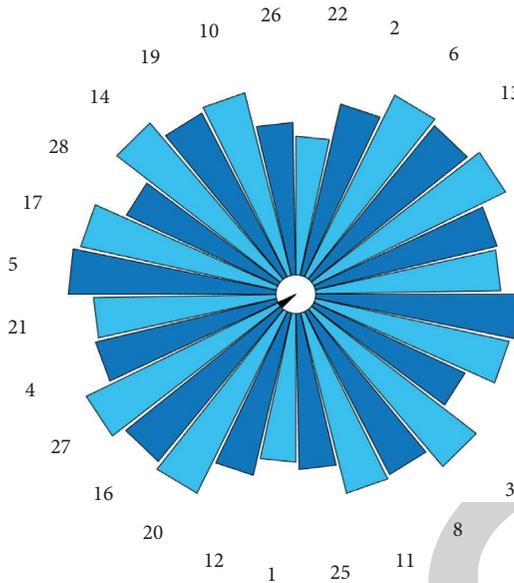


FIGURE 9: The assembly sequence diagram of blades.

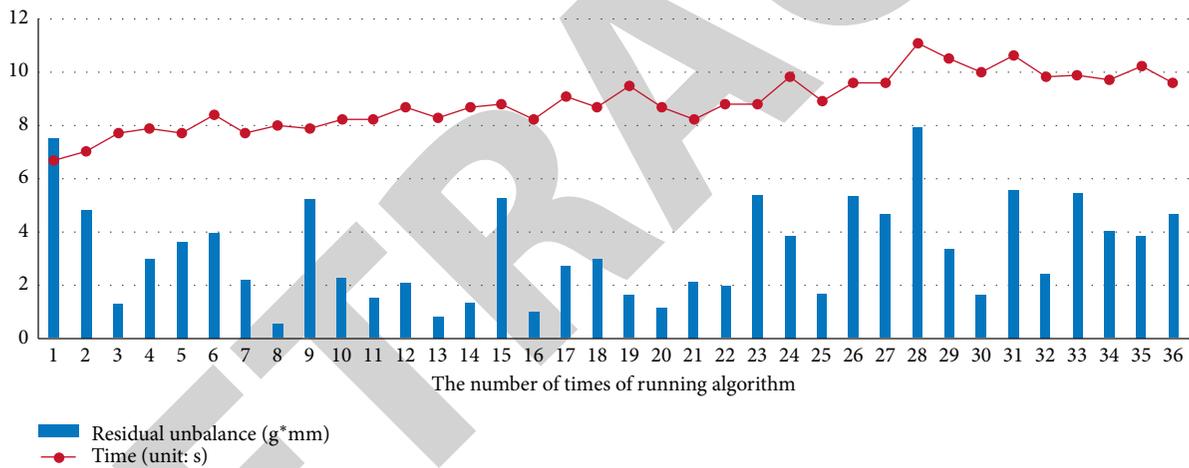


FIGURE 10: Statistical graph of the solution accuracy and solution time of the simulated annealing algorithm.

optimal solution finally output by the algorithm may not be the true optimal solution. $f = M_{left} = \sqrt{M_x^2 + M_y^2}$, when $\Delta E = f(\text{new}) - f(\text{old}) < 0$, $f(\text{new})$ is the superior solution, and the inferior solution $f(\text{old})$ will be discarded directly; when $\Delta E = f(\text{new}) - f(\text{old}) > 0$, $f(\text{new})$ is the inferior solution; at this time, turn to the link of accepting inferior solutions probabilistically; if the inferior $f(\text{new})$ is accepted, the superior solution $f(\text{old})$ will be discarded; otherwise, the inferior $f(\text{new})$ will be discarded. In every contest between the superior solution and the inferior solution, there is always a solution discarded; most of the time, the discarded solution is the inferior solution, but at the link of accepting the inferior solution probabilistically, the superior solution may also be discarded. Therefore, the link of accepting the inferior solution probabilistically may cause the algorithm to miss the optimal solution currently encountered. In order to avoid this situation, the SA algorithm is improved and optimized by adding a memory unit to the SA algorithm, and

put the discarded old solutions (old solutions include the superior solutions and the inferior solutions) into the memory unit. Finally, an optimal solution will be generated in the memory unit, denoted as MS. Compare the optimal solution MS and the optimal solution (denoted as SAS) obtained by SA algorithm without the memory unit; if $MS < SAS$, the optimal solution output by the improved simulated annealing algorithm is MS; otherwise, the output is SAS. The flowchart of the improved simulated annealing algorithm is shown in Figure 11.

The comparison results of the solution accuracy and the solution time of the traditional and improved SA algorithms are shown in Figure 12. The solution accuracy is significantly better than the SA algorithm without improvement, but the solution time is slightly slower than the traditional SA algorithm. Running the traditional and improved SA algorithms for 20 times, respectively, and the comparison results of the mean and standard deviation of the solution accuracy

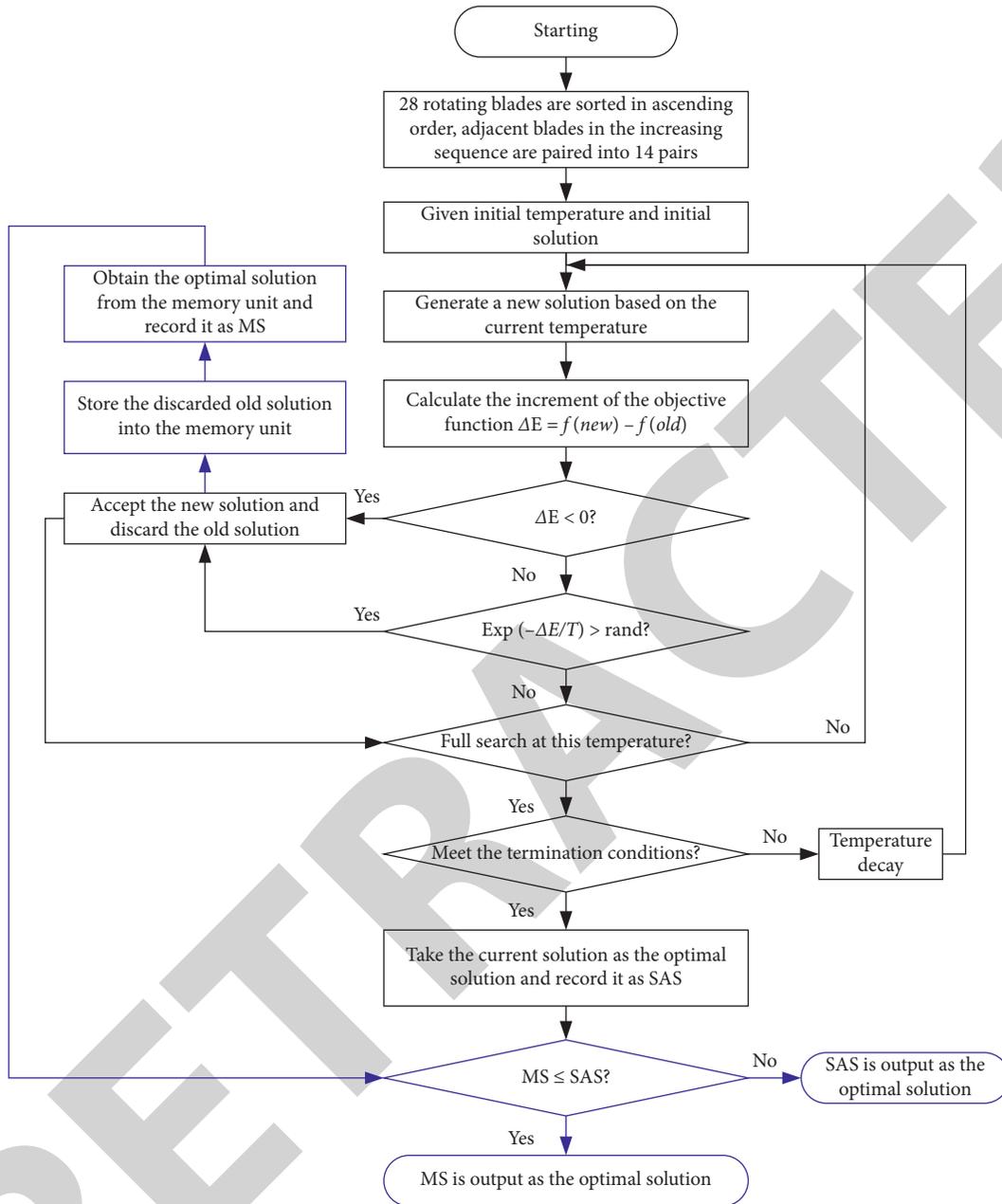


FIGURE 11: The flowchart of the improved simulated annealing algorithm.

and the solution time are shown in Table 8. The mean and standard deviation of the solution accuracy of the developed algorithm are significantly better than the traditional SA algorithm, but the solution time is a little slower than the traditional SA algorithm. Therefore, the improved simulated annealing algorithm can obtain better solution results, avoiding the situation wherein the algorithm misses the current optimal solution because of accepting the inferior solution probabilistically during the solution process.

Moreover, after the algorithm is improved, its average running time is increased only by 2 seconds. Therefore, after the algorithm is improved and optimized, the algorithm's solution accuracy and robustness are improved significantly. Besides, the algorithm's solution efficiency is still very high, which indicates that the improvement and optimization of the simulated annealing not only maintains its efficient solution efficiency but also significantly improves its solution accuracy and robustness.

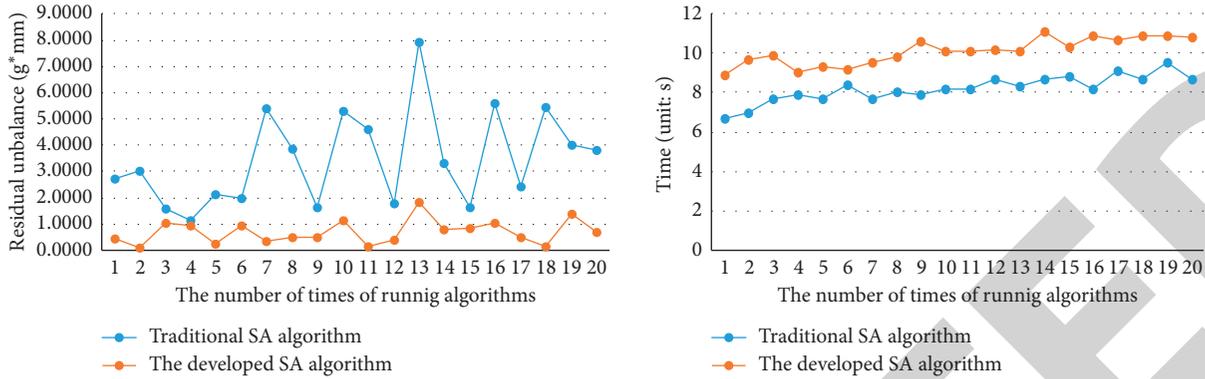


FIGURE 12: Comparison of solution accuracy and solution time of the traditional SA algorithm and improved SA algorithm.

TABLE 8: The comparison results of the solution effect of the traditional SA and improved SA.

	Solution accuracy of traditional SA	Solution accuracy of improved SA	Solution time of traditional SA	Solution time of improved SA
Mean	3.4682 g*mm	0.6950 g*mm	8.2 s	10.1 s
Standard deviation	1.7538	0.4412	0.6546	0.6641

6. Conclusions

- (1) This paper established the optimization algorithm of selecting blades based on the collocation degree of blades and realized efficient selection and full utilization of rotating blades before assembly. The blade resource utilization rate is increased from 65%–74% currently achieved by the enterprise to 83%–93% by the algorithm. The statistic results of the algorithm running 20 times show that the minimum solution time is 7.7 seconds, the maximum is 28.7 seconds, and the solution efficiency is very high. Moreover, the solution results of the optimization algorithm based on the collocation degree of blades are far ahead of the greedy algorithm and simulated annealing algorithm. Consequently, the algorithm of selecting blades based on the collocation degree of blades realizes the efficient selection and full utilization of blades.

The optimization algorithm of selecting rotating blades based on the collocation degree of blades has two highlights: ① the collocation degree of blades prompts the algorithm to select more blades faster, which ensures the efficient selection of blades; ② the “bottleneck” processing method of the algorithm determines that when the algorithm selects blades, it will not destroy the number of blades that have already been selected, which means the number of blades that have been picked out and put in the finished product library may increase, may maintain the current number, but not decrease, and this highlight ensures that the algorithm can make full use of blade resources.

- (2) This paper uses simulated annealing algorithm to plan the assembly sequence of blades, and the

residual unbalance obtained by SA algorithm can reach 0.52 g * mm, which is far less than the given design value of 100 g * mm, and 0.52 g * mm is also far smaller than the remaining unbalance (between 30 g * mm and 100 g * mm) achieved by the company’s current assembly sequence planning technology. Therefore, the assembly sequence planning method of blades based on simulated annealing algorithm greatly improves the static balance reliability of rotors.

The improved simulated annealing algorithm not only maintains the characteristic of efficient solution but also improves the solution accuracy and solution robustness significantly. Consequently, the improved simulated annealing algorithm provides optimized assembly sequence and efficient solution method for the assembly of rotor blades.

Data Availability

All the data and materials of the manuscript are available, and they are from the National Key Research and Development Program of China. The data can be provided in Supplementary Information files that are submitted along with the manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interests.

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Supplementary Materials

The data used to study the findings of this manuscript are provided as supplementary materials. (*Supplementary Materials*)

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