Optimization of Assembly Sequence Planning of Turbine Low-pressure Rotor Blades Based on the Improved Simulated Annealing Algorithm

Liu Jun-kong¹,a, LI Li-li¹,b*
¹State Key Laboratory of Mechanical Manufacturing Systems Engineering, Xi’an Jiaotong University, Xi’an, Shanxi, China
aemail: i1196689756@stu.xjtu.edu.cn, bemail: lilili199013@stu.xjtu.edu.cn

Abstract: In view of the NP-hard characteristics of assembly sequence planning problem and the low efficiency of solving the relatively optimal assembly sequence, this paper adopts meta-heuristic algorithms to solve the rotor blades assembly sequence optimization problem. Taking solution accuracy, solution efficiency, and solution robustness as assessment criteria, the effectiveness of solving the rotor blades assembly sequence with several meta-heuristic algorithms is compared and analyzed. The comparison results show that the simulated annealing algorithm has the best solution accuracy, efficiency, and robustness for the assembly sequence optimization problem of rotor blades. In order to solve some problems in the solving process of simulated annealing, one improvement is added into it, by adding the reheating process to the SA, the probability that the SA algorithm accepts inferior solutions is increased, and the ability of SA jumping out of the local optimal solution is increased, and the global search capability of the SA algorithm is further enhanced. Finally, the effectiveness of the improved simulated annealing algorithm is verified in this paper by the assembly of steam turbine rotor blades.

1. Introduction
In order to ensure the static balance quality of the rotor, the assembly sequence planning of the rotor blades must be carried out before assembly. The assembly sequence planning problem has NP-hard characteristics. The complexity of searching for the optimal sequence increases with the size of the possible assembly sequence space to 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 computerized assembly sequence planning research [1]. At present, scholars have realized the solving of assembly sequence planning problem by different optimization algorithms, such as: Ant colony optimization algorithm (ACO) [2], genetic algorithm (GA) [3,4], Immune algorithm (IA) [5], neural networks (NN) [6], genetic simulated annealing (GSA) [2], scatter search algorithm (SSA) [7], and other heuristic methods [8,9,10]. At present, many researchers have made remarkable achievements in solving ASP optimization problems, but there are still some problems that need to be solved urgently. One of the main problems is that it is difficult to obtain a relatively optimal assembly sequence in a short time. This problem urges researchers to improve the efficiency of solving ASP problem under the premise of ensuring the accuracy and robustness by introducing various algorithms and improvements.

The above research results provide a reference for solving the optimization problem of rotor blade assembly sequence. The rotor is the core component of the steam turbine, and its balance quality is the main criterion of the rotating blades assembly quality [11]. A good assembly sequence of blades can not
only reduce the residual imbalance of the rotor and ensure its static balance, but also reduce the difficulty of its dynamic balance experiment and shorten the assembly cycle of the entire rotor.

In summary, a reasonable assembly sequence of blades is a key link in the assembly quality control of steam turbine rotor. In this paper, the static balance of the rotor is taken as the optimization goal, and the solution accuracy, solution efficiency and robustness of the algorithm are used as evaluation indicators to select an algorithm that is more suitable for solving the assembly sequence planning problem of rotor blades, and improve the selected algorithm to further improve the accuracy and robust stability of the algorithm. Finally, the effectiveness of the method is verified by the measured data of rotating blades of steam turbine factory.

2. Materials and Methods

2.1. The mathematical model of static balance of turbine rotor blades

According to the principle of static balance, the optimization goal of the rotor blades assembly sequence is to make the x and y components of the mass and or gravitational moments of all blades infinitely approach zero or reach the minimum [12]. The mathematical model of the short blades and the long blades are shown as follows.

The short blade has a short steam path, and the inertia moment caused by the mass of the rotating blades is basically on the outer circle of the rotor impeller. The imbalance of the steam path section has only a little effect on the whole imbalance. Therefore, when planning the assembly sequence of the short steam path blades, it is based on the blades' weight, not weight moment, as long as the weight of the short blades are evenly distributed within 360 degrees, the balance quality of the short blades can be guaranteed.

\[
m_x = \sum_{i=1}^{n} m_i \cos \theta_i \tag{1}
\]

\[
m_y = \sum_{i=1}^{n} m_i \sin \theta_i \tag{2}
\]

\[
m_{left} = \sqrt{m_x^2 + m_y^2} \tag{3}
\]

\[
\beta = \arctan \frac{m_y}{m_x} \tag{4}
\]

\(m_x, m_y\) are the sum of the masses of all blades in the x and y directions respectively; \(m_i\) is the mass of the No. \(i\) blade; \(\theta_i\) is the angle between the radial line of the No. \(i\) blade and the x-axis; \(m_{left}\) is the remaining unbalanced weight (unit: g); \(\beta\) is the angle of the remaining unbalance.

When planning the assembly sequence of long blades based on gravitational moment of the blades, the calculation methods of the residual unbalanced gravitational moment of long blades are the same as equations (1) ~ (4), but \(m_x, m_y, m_i, m_{left}\) are replaced by \(M_x, M_y, M_i, M_{left}\).

\(M_x, M_y\) are the sum of the masses of all blades in the x and y directions respectively; \(M_i\) is the gravitational moment of the No. \(i\) blade; \(\theta_i\) is the angle between the gravitational moment vector of the No. \(i\) blade and the x-axis; \(M_{left}\) is the remaining unbalanced gravitational moment (unit: g.m), \(\alpha\) is the angle of the remaining unbalance.

This paper uses the measured weight (unit: g) and the measured gravitational moment (unit: g.m) of the blades obtained from the enterprise, take the minimizing residual imbalance as the optimization goal, and uses intelligent sorting algorithms to optimize the assembly sequence of the rotor blades according to certain optimization rules. Equation (3) is used as the objective function of the optimization algorithm in this paper to plan the assembly sequence of blades. Solving the ASP problem...
of rotor blades using simulated annealing algorithm

2.1.1. Simulated annealing algorithm
The simulated annealing algorithm is a general and effective approximation algorithm, which is suitable for solving large-scale combinatorial optimization problems. It is based on the Metropolis criteria. It can not only accept optimized solutions with good performance, but also accept deteriorating solutions with worse performance with a certain probability, which prompts 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 or near-optimal solution [13].

2.1.2. Case verification and result analysis
Now use the measured weight data of forward 4th stage rotor blades to carry out an example analysis. The weighing data of the fourth stage rotating blades is shown in Table 1. The blade assembly sequence planned by SA algorithm is shown in Table 2, and the remaining unbalance moment of the sorting result is 0.0088 g m. The convergence diagram of the simulated annealing algorithm and the assembly sequence diagram of blades are shown in Figure 1.

Table 1 Weighing data of the fourth stage rotating blades

| blade weighing number | design weight (kg) | measured weight (kg) | measured gravitational moment (g m) |
|-----------------------|--------------------|----------------------|-------------------------------------|
| 001                   | 48.100             | 48.512               | 58137.215                           |
| 002                   | 48.100             | 48.829               | 58519.691                           |
| 003                   | 48.100             | 48.394               | 57959.086                           |
| 004                   | 48.100             | 48.473               | 58104.137                           |
| 005                   | 48.100             | 48.747               | 58490.207                           |

...  ...

Table 2 Sorting results of rotor blades

| assembly sequence | blade weighing number | assembly sequence | blade weighing number | assembly sequence | blade weighing number | assembly sequence | blade weighing number |
|-------------------|-----------------------|-------------------|-----------------------|-------------------|-----------------------|-------------------|-----------------------|
| 1                 | 55                    | 21                | 2                     | 41                | 16                    | 61                | 58                    |
| 2                 | 11                    | 22                | 50                    | 42                | 33                    | 62                | 17                    |
| 3                 | 37                    | 23                | 9                     | 43                | 6                     | 63                | 70                    |
3. Results & Discussion

3.1. Comparison of solution accuracy and solution time of different algorithms

Based on the measured data of 3 groups of blades, the optimization effect of each algorithm is shown in Table 3, and the remaining imbalance is the best value after running each algorithm for 10 times. It can be seen from Table 3 that for the three groups of data, the results obtained by simulated annealing are significantly better than the greedy algorithm. This is because the greedy algorithm only accepts solutions that are better than itself, while simulated annealing not only accepts better solutions than itself, it also accepts the inferior solution probabilistically. The advantage of simulated annealing makes up for the shortcomings of the greedy algorithm, so the solution accuracy obtained by simulated annealing is obviously better than that of the greedy algorithm. The genetic algorithm is second to the simulated annealing algorithm in terms of solving accuracy. The comparison results of the Table 3 show that the simulated annealing algorithm has the highest solution accuracy.

Table 3 Comparison of solution accuracy of different algorithms

| Algorithm name              | The first group of blades | The second group of blades | The third group of blades |
|-----------------------------|---------------------------|---------------------------|--------------------------|
| Greedy Algorithm            | 8.792299e-05 g           | 0.046145 g·m             | 0.157198 g·m             |
| Genetic algorithm           | 1.173570e-05 g           | 0.019587 g·m             | 0.048161 g·m             |
| Simulated annealing algorithm | 7.374770e-05 g           | 0.009415 g·m             | 0.006956 g·m             |
| Maximum remaining unbalance allowed by design | 0.50000g | 1.815197 g·m | 5.813057 g·m |

Note: the first group of blades are short blades, and the other two groups of blades are long blades.

The rotor in this article has four-stage blades. The first-stage blades are short blades, and the remaining three stages of blades are long blades. In order to test the adaptability and generalization of each algorithm, this paper compares the solving results of algorithms based on the measured data of short blades and long blades.

Table 4 Comparison of solution time of different algorithms of the above three groups of blades

| Algorithm name     | Running time (unit: s) | Solving accuracy level |
|--------------------|------------------------|------------------------|
| Greedy Algorithm   | 0.4185 s               | $10^{-1}$              |
| Genetic algorithm  | 17.0358 s              | $10^{-1}$              |
| Simulated annealing| 0.3427 s               | $10^{-1}$              |
In order to compare the efficiency of optimization algorithms, this paper uses the gravitational moment data of the fourth-stage blades as an example to compare the solution time of algorithms, and the comparison results is shown in Table 4. According to Table 4, the solution efficiency of simulated annealing is the best. Therefore, according to Table 3 and Table 4, the solution accuracy and efficiency of simulated annealing are both optimal.

3.2. Comparison of the robustness of different algorithms
Robustness is an important indicator that cannot be ignored when choosing algorithms. This paper uses the value of the standard deviation (mse) to quantify the robust stability of algorithms.

![Comparison of the results of each algorithm running 20 times](image)

Figure 2 Comparison of the results of each algorithm running 20 times
Taking the gravitational moment data of the fourth-stage blades as an example, the comparison results of the robust stability of different algorithms are shown in Figure 2 and Table 5.

In summary, SA's solution accuracy, solution efficiency and robust stability are all optimal. Compared with the other two algorithms, the simulated annealing algorithm is most suitable for solving the assembly sequence optimization problem of steam turbine rotor blades.

| Algorithm                      | Mean square deviation of residual imbalance (mse) |
|-------------------------------|-----------------------------------------------|
| Greedy algorithm              | 0.1748                                         |
| Genetic algorithm             | 0.1617                                         |
| Simulated annealing algorithm | 0.0445                                         |

Table 5 Comparison of robust stability of different algorithms

3.3. Improved simulated annealing with additions of taboo search and reheating process
It can be seen from formula (13) that when the temperature of the SA algorithm decreases to a certain level, the probability of the algorithm accepting inferior solutions will becomes very small, and the probability of the algorithm jumping out of the local optimal solution will also becomes very small, resulting in the algorithm cannot get the optimal solution that meets the specified accuracy. Therefore, this article improves the simulated annealing by introducing the idea of taboo search and increasing the reheating process. The process of improved simulated annealing algorithm is shown in Figure 4.
Figure 3 The convergence diagram of the improved simulated annealing algorithm

Figure 4 The flow chart of the improved simulated annealing algorithm

Table 6 Robustness comparison of the algorithm before and after the improvement

|                      | Standard SA | Improved SA | The improved percentage of robustness after SA being improved |
|----------------------|-------------|-------------|---------------------------------------------------------------|
| Mean square deviation of residual imbalance | 0.0419      | 0.0256      | 38.9021%                                                      |
| Mean residual imbalance | 0.0727      | 0.0384      | 47.1802%                                                      |

Figure 3 is the convergence diagram of the improved SA algorithm. The comparison results of the robustness of algorithms are shown in Table 6. The robustness of the improved algorithm is increased by 38.9021%. Therefore, the improvement for SA effectively improves its robust stability and solution accuracy.

4. Conclusions
(1) Aiming at the problem of assembly sequence planning of steam turbine rotor blades, this paper takes the solution accuracy, efficiency, and robustness as the evaluation indexes of the algorithm, this
paper uses the measured data of the rotating blades to compare the solution effects of several commonly used algorithms. The results show that the simulated annealing is optimal, and it is most suitable for solving the assembly sequence planning problem of rotor blades.

(2) This paper increases the heating process at the right time of the solving process of simulated annealing algorithm, which increases the probability of the algorithm accepting inferior solutions, increases the possibility of the algorithm jumping out of the local optimal solution, and expands the search space of solution, strengthens the algorithm’s global search capability, increases the average solution accuracy of the SA algorithm by 47.1802% and its robustness by 38.9021%.

Acknowledgements
The authors gratefully acknowledge the financial supports by the National Key Research and Development Program of China under Grant No. 2019YFB1703800. The authors also sincerely thank the reviewers for their detailed recommendations and comments.

References
[1] Wang, H., Rong, Y., & Xiang, D. (2014) Mechanical assembly planning using ant colony optimization. Comput Aided Design, 47, 59-71.
[2] Shan, H., Zhou, S., & Sun, Z. (2009) Research on assembly sequence planning based on genetic simulated annealing algorithm and ant colony optimization algorithm. Assembly Autom, 29(3), 249-256.
[3] Chen, S., & Liu, Y. (2001) An adaptive genetic assembly-sequence planner. Int J Comput Integ M, 14(5), 489-500.
[4] Wang, D., Shao, X., Liu, H., & Xiaobo, G. E. (2017) Assembly sequence planning for panels of reflector antenna based on hybrid algorithm. Computer Integrated Manufacturing Systems, 23(6), 1243-1252.
[5] Zhang, H., Liu, H., & Li, L. (2014) Research on a kind of assembly sequence planning based on immune algorithm and particle swarm optimization algorithm. Int J Adv Manuf Tech, 71(5-8), 795-808.
[6] Chen, W. C., Tai, P. H., Deng, W. J., & Hsieh, L. F. (2008) A three-stage integrated approach for assembly sequence planning using neural networks. Expert Syst Appl, 34(3), 1777-1786.
[7] Martí, R., Laguna, M., & Glover, F. (2006) Principles of scatter search. Eur J Oper Res, 169(2), 359-372.
[8] Guo, J., Sun, Z., Tang, H., Yin, L., & Zhang, Z. (2015) Improved cat swarm optimization algorithm for assembly sequence planning. The Open automation and control systems journal, 7(1), 792-799.
[9] Li, X., Kai, Q., Bing, Z., Liang, G., & Su, J. (2016) Assembly sequence planning based on an improved harmony search algorithm. The International Journal of Advanced Manufacturing Technology, 84(9), 2367-2380.
[10] Ghandi, S., & Masehian, E. (2015). A breakout local search (BLS) method for solving the assembly sequence planning problem. Eng Appl Artif Intel, 39(mar.), 245-266.
[11] Kong, L. S., Yang, C. H., Wang, Y. L., & Gui, W.H. (2009) Intelligent optimization of raw material blending for alumina production with information uncertainty. Control theory and application, 26(9), 1051-1055.
[12] Yang, D., Xue, W., Jian, L., Co, D. T., & Ltd. (2014) Application of simulated annealing algorithm in optimization of rotor blade sorting. Dongfang Turbine.
[13] Kanagaraj, G., & Jawahar, N. (2017) A simulated annealing algorithm for optimal supplier selection using the reliability-based total cost of ownership model. International Journal of Procurement Management, 2(3), 244-266.