Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 6, No. 2, 2023

Production Scheduling Optimization of An Aviation Bearing Manufacturing Enterprise Based on Teaching-Learning-based Optimization

-- Subtitle Is Not Required, Please Write It Here If Your Article Has One

Yifan Liang[1, *]

[1]Mechanical major, Tongji University, Shanghai, China

[*]Corresponding author: Yifan Liang (Email: 1095470313@qq.com)

Abstract: This article is based on an aviation bearing manufacturing and wind power bearing manufacturing enterprise production scheduling for its key process optimization, in Qingdao, Shandong. The production scheduling is aimed at the shortest delivery time, and the production scheduling assessment indicator is the on-time delivery rate of orders. This article, based on the production process and production mode characteristics of the enterprise, improves the convergence ability of the Teaching-learning-based optimization (TLBO) in the early stage and the detail search ability in the later stage by optimizing the static teaching factor function and algorithm retrieval method of the classic algorithm. By combining Levy flight to further enhance the algorithm's global search ability and reduce the probability of falling into local optima. The theoretical reliability of the algorithm was verified by comparing the calculation result of the MK calculation example with other algorithms. The reliability of the algorithm in actual production was verified through the long-term order execution data and order delivery rate of the enterprise.

Keywords: Levy algorithm, Manufacturing execution system, MES implement, Production management, Production scheduling algorithm optimization, Teaching-learning-based algorithm(TLBO).

1. Introduction

Modern manufacturing enterprises are no longer able to rely on traditional management methods to ensure complex information processing in the manufacturing process, such as meeting customer product expectations, quality, product types, and delivery services. The measurement of whether a manufacturing enterprise has achieved excellence in manufacturing is mainly based on the ability to obtain the required information at the "right time", "right quantity", and "right place", as well as the ability to process and apply information. In the current industry background, the production mode of enterprises is increasingly tending towards multiple varieties and small batches to meet the customized production needs. The production mode of multiple varieties and small batches means more products, while processing different types of products means requiring different molds and materials. When different materials are applied to production, it is necessary to consider how to reduce the time to change line and mold through production scheduling. Therefore, optimizing production scheduling algorithms has always been an important part of production management.

At present, some scholars have optimized production scheduling problems through TLBO. Su improved the quality of teaching search and reduced the maximum completion time by establishing collaborative TLBO, multi class TLBO, and introducing teaching reward and punishment mechanisms for assembly flow shop scheduling and distributed hybrid flow shop scheduling problem [1]. Cao improved search ability and algorithm robustness, during the teaching stage, by optimizing discrete TLBO for the distributed prefabricated component flow shop scheduling problem [2]. Zhang improved TLBO by using permutation mutation for initial population and combining continuous algorithms with discrete strategies, for permutation flow shop scheduling problems, giving attention to both of quality and diversity [3].

Although present production scheduling algorithms have been proven to be reliable through methods such as adaptive parameters, adjusting trust weights, K-means clustering, and testing with relevant functions, the above research has not optimized the search method [4-6]. This article designs an improved TLBO by setting piecewise TF parameter and combing Levy flight, which improves the search ability.

2. Model Solving Based on Improved TLBO

2.1. Classic TLBO model

The inspiration of the classic TLBO comes from classroom teaching, which simulates the behavior of teaching students and learning from others to search. It is a population based heuristic random swarm intelligence algorithm. The algorithm process mainly consists of two stages: teaching(first) and learning(second), and the algorithm has the advantages of fewer parameters and fast convergence.

In the first stage, individuals improve their fitness level through the difference between the optimal solution of the population and the average level of the population, and the mathematical expression is shown in equation 1.

$$x_new = x_i + \text{rand} * (\text{x}_t - \text{TF} * \text{x}_m) \quad (1)$$

In above equation 1 x_{new} is the new individual which calculated from the original population. Rand is a random vector with each element within the range of [0,1]. x_t is the

current optimal value. x_m is the current average value. TF is teaching parameter, which is a random value within the range of [1,2]. Priority should be given to using small fitness values during the first stage, and after completing the calculations, the second stage should be entered.

In the second stage, the mathematical expression is shown in equation 2.

$$x_{new} = \begin{cases} x_i + \text{rand} * (x_i - x_j) & , if\ f(x_i) < f(x_j) \\ x_i + \text{rand} * (x_j - x_i) & , if\ f(x_i) \geq f(x_j) \end{cases} \quad (2)$$

x_j is a different individual which is picked randomly. $f(x_j)$ is the calculation result of this individual.

2.2. Optimize classic TLBO

The classic TLBO above has a simple process and involves fewer parameters, but the TF teaching factor cannot achieve adaptive control, which affects the solving iteration speed and accuracy [7-8]. In addition, this algorithm can be further optimized on the search path. Therefore, this article has made the following improvements on the classic teaching optimization algorithm.

This article further improves the adaptability of TF parameter, as shown in equation 3.

$$TF = \begin{cases} TF_{max} - 2\left(\frac{i}{i_{max}}\right)^2, & if\ i < \frac{i_{max}}{2} \\ TF_{min} + 2\left[\frac{i}{i_{max}} - 1\right]^2, & if\ i \geq \frac{i_{max}}{2} \end{cases} \quad (3)$$

The TF parameter is divided into two parts. The first part is the upper convex function, which aims to maintain a large TF value in the early stage and enable rapid convergence; The latter part is a lower concave function, which aims to reduce TF as much as possible for fine search.

(2) The TLBO is the global optimization algorithm, which searches for the global optimal solution in the entire solution space, but it has tendency to search towards the origin; When solving optimization problems far from the origin, this algorithm may lose its advantages [9-10]. Therefore, it is considered to combine the TLBO with Levy flight.

In the second stage, the mathematical expression is shown in equation 4, combined with Levy flight.

$$x_i(t+1) = \begin{cases} x_i(t) + \alpha_0 \frac{\mu}{|v|^{\frac{1}{\theta}}}(x_i(t) - x_b), if\ f(x_i) < f(x_b) \\ x_i(t) + \alpha_0 \frac{\mu}{|v|^{\frac{1}{\theta}}}(x_b - x_i(t)), if\ f(x_i) \geq f(x_b) \end{cases} \quad (4)$$

In summary, the iteration speed and search ability of the algorithm are dynamically adjusted by optimizing TF parameters and the search formula in the second stage of the algorithm, making the population more active.

2.3. Algorithm process based on improved TLBO

(1) Parameter initialization processing, such as individual quantity and decision variable dimension;

(2) Calculate the individual fitness value of the population, record the corresponding process code and machine code for this value;

(3) Set the individual with the smallest fitness as the optimal solution and calculate the average level of the individual;

(4) Find and calculate new individual fitness values based on the second-stage optimization search path, find and record the corresponding process code and equipment code;

(5) Determine whether the number of iterations has exceeded, and if so, output the result; If not exceeded, return to step (2).

After the above model process, the optimal value can be output.

3. Data Analysis and Research

To demonstrate the performance of this optimized TLBO, a comparison is made between Gao hybrid genetic algorithm and it. The evaluation index is based on the rate of iteration of the algorithm and the value of the optimal solution. The test example is based on the mk01-mk10 example.

Take the population of 100 and the number of iterations of 200. Use linear TF parameters and the piecewise TF parameters designed in this paper for the mk01 calculation example. The results are shown in the following figure 1.

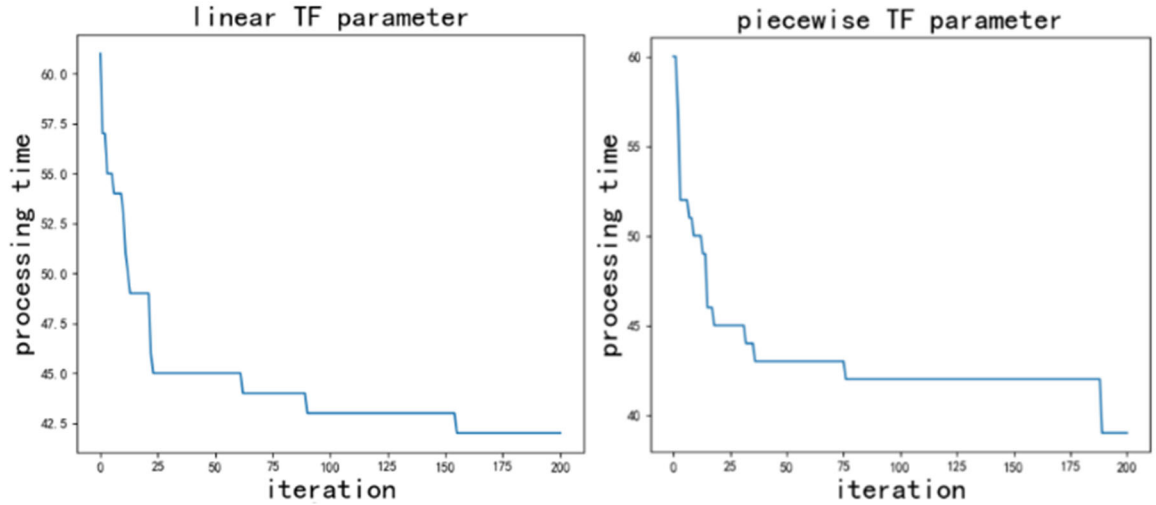

Figure 1. Mk01 example iteration result

Obviously, the piecewise TF parameter designed in this paper converges faster in the early stage of the algorithm, which converges to the lower optimal result 42 earlier compared to linear TF parameters; By optimizing the search path, compared to the original TLBO, the improved TLBO obtained an obvious better solution of 39. The improvement goal of fast iteration speed and strong search ability is achieved.

Verify the algorithm solving ability for the mk01-mk10 problem. The results are shown in the table 1 as below.

Table 1. Mk example calculation results based on TLBO

Example	N*m	LB	UB	Gao hybrid genetic algorithm		TLBO with Levy flight		
				C_m	AV（C_m）	C_m	AV（C_m）	Cw
mk01	10×6	36	42	40	40	41	41.1	42
mk02	10×6	24	32	26	26	27	27	27
mk03	15×8	204	211	204	204	205	207.4	208
mk04	15×8	48	81	60	60	57	57.4	59
mk05	15×4	168	186	173	176.8	175	176.3	178
mk06	10×15	33	86	58	60.5	68	69.3	73
mk07	20×5	133	157	144	146.3	141	144.4	145
mk08	20×10	523	523	523	523	523	523	523
mk09	20×10	299	369	311	311	314	314	314
mk10	20×15	165	296	201	203.6	209	212.8	115

N is the order quantity. M is the machine quantity. LB is lower limit of Mk example optimal solution. UB is upper limit of Mk example optimal solution. Cm is calculated optimal value. AV(Cm） is average value of Cm. Cw is calculated worst value. From the table data, the algorithm proposed in this article is excellent in the Flexible Job-shop Scheduling Problem (FJSP), and clearly obtains better solutions in the mk04 and mk07 problems.

4. Conclusion

Based on FJSP, this article studies how to improve production scheduling by optimizing classic TLBO. This

article restores the classic TLBO and further improves the self-adaptability of TF parameters by designing TF function, enhancing the ability of the algorithm to quickly converge in the early stage and detailed search in the later stage. This article focuses on the problem of "origin preference" in the classic TLBO and improves the search ability of the algorithm in the second stage of Levy flight control. Through the application of Levy flight, the problem of origin preference has been obviously curbed, the tendency of the algorithm to stay at the current optimal solution has been reduced, and the ability of the algorithm to globally search for the optimal solution has been enhanced. By improving the classic TLBO through the above two methods, the algorithm quickly enters the optimal solution range in the early stage and combining Levy flight to further enhance the algorithm's global search ability and reduce the probability of falling into a local optimal solution.

References

[1] Su B. Research on Distributed Scheduling Problems Based on Teaching-Learning-Based Optimization Algorithm[D].Wuhan University of Technology,2021.

[2] Cao J S. Research on Distributed Precast Flow Shop Scheduling Based on Discrete Teaching-Learning based Optimization[J]. Computer Measurement & Control, (12),166-171+183.

[3] Zhang Q W. Teaching-Learning-Based Optimization Algorithm for Permutation Flowshop Scheduling[J]. Journal of System Simulation, 2022,34(05):1054-1063.

[4] Kang Y. A Hybrid Two-Stage Teaching-Learning-Based Optimization Algorithm for Feature Selection in Bioinformatics [J]. IEEE/ACM transactions on computational biology and bioinformatics,2022

[5] Wang J H. Energy-efficient scheduling for flexible job shop under multi-resource constraints using non-dominated sorting teaching-learning-based optimization algorithm[J]. Journal of Intelligent & Fuzzy Systems,2022,43(1).

[6] Wu D. An Improved Teaching-Learning-Based Optimization Algorithm with Reinforcement Learning Strategy for Solving Optimization Problems[J]. Computational Intelligence and Neuroscience, 2022,2022.

[7] Crawford Broderick. A Teaching-Learning-Based Optimization Algorithm for the Weighted Set-Covering Problem [J]. Tehnički vjesnik,2020,27(5).

[8] Wang C C. Solving discounted {0-1} knapsack problems by a discrete hybrid teaching-learning-based optimization algorithm [J]. Applied Intelligence,2020,50(6).

[9] Yang X N. Elite-guided multi-objective cuckoo search algorithm based on crossover operation and information enhancement[J]. Soft Computing,2022,27(8).

[10] Cheng J T. Parameter Control Based Cuckoo Search Algorithm for Numerical Optimization[J]. Neural Processing Letters, 2022, 54(4).