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Research on Flexible Production Plant Scheduling Problem Based on Improved Sparrow Algorithm

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Abstract. The flexible job shop scheduling problem (FJSP) is an important scheduling problem in the manufacturing industry, which involves how to reasonably allocate and arrange the workpieces to be processed to minimise the total production time or maximise the production efficiency in a flexible job shop with multiple processes and irregular working hours. Aiming at the multi-objective flexible job shop scheduling problem, this paper establishes a flexible production shop scheduling problem model with the optimisation objectives of minimising the maximum completion time, minimising the total cost and minimising the total energy consumption of machining, and combines the sparrow algorithm with the Levy flight strategy to optimise it. Firstly, the initial solution quality and population diversity of the algorithm are improved by using the golden sine strategy; secondly, the global and local search ability of the sparrow algorithm is improved by incorporating the Levy flight strategy; finally, the effectiveness of the model and the algorithm is verified by several multi-objective function tests.

Keywords: Multi-objective optimisation; Sparrow search algorithm; Levy flight strategy

1 INTRODUCTION

With the rapid development of Internet technology and the transformation and upgrading of the manufacturing industry, intelligent manufacturing[1] and flexible production workshops, as an important part of modern manufacturing, are increasingly becoming a key driving force for the development of the industry. In flexible manufacturing systems, there is usually a high degree of flexibility and variability between equipment and processes, so an effective scheduling method is needed to optimise the production process in order to maximise productivity and resource utilisation, and the Flexible Job Shop Scheduling Problem[2] (FJSP) has arisen. Key concepts in management are widely used in flexible job shop scheduling. For example, Zhou et al[3] proposed an adaptive grey wolf fast optimization algorithm (SS-GWO) to solve the problem of dynamically adapting to the basic parameters during the computation process of intelligent algorithms; Meng et al[4] established 13 models designed according to three different modelling ideas and solved four different energy-saving scheduling problems; and Liu, Hui, et al[5] investigated the shop floor green scheduling problem under the

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complex synergy of multi-person and multi-machine collaboration, and analysed the impact of assigning equipment with different numbers of workers on the machining lead time in production. In summary, this paper establishes a flexible job shop scheduling problem model, takes the maximum completion time, total processing cost and total machine energy consumption as the optimisation objectives, adopts a sparrow algorithm incorporating Levy's flight strategy to optimise the problem, and verifies the effectiveness of the model and algorithm.

2 PROBLEM DESCRIPTION AND MODELLING

2.1 Problem Description

Flexible job shops need to schedule production based on order and machine information, and each job involves multiple operations, each operation can be processed on multiple machines, and the processing time varies with the machine type, which is a typical NP problem. The production floor scheduling problem in this paper is described as follows. For a production problem with K machines processing N workpieces, denote the machines as {M1,M2,···,MK } and the workpieces as {T1,T2,···TI }. The number of processes for each workpiece is determined and known, denote the number of processes for workpiece Ti as Ji, and the jth process for workpiece Ti as Oij. The set of optional machines for process Oij is denoted as Mij. The symbols and meanings of the parameters used are as follows: i: Workpiece number, $i = 1,2,3,\cdots,n$; j: Workpiece process number, $j = 1,2,\cdots,j_i$; k: Machine number, $k = 1,2,3,\cdots,m$; O_{ij}: The jth process of workpiece i; $O_{i'j'}$: Previous operation of the machine for processing process O_{ij}; t_{Sij}: Start time of the j th process of workpiece i; t_{Tij}: Completion time of the jth process of workpiece i; t_{Sijk}: Start time of the jth process of workpiece i on machine k; t_{Pijk}: Machining time on machine k for the jth process of workpiece i; t_{Tijk}: Completion time of the jth process of workpiece i on machine k; t_i: Completion time of workpiece i; t: Completion time of all workpieces; E: Energy consumption of all completed workpieces; C_{ijk}: Processing cost of the j th process of workpiece i on machine k; x_{ijk}: The j th process of workpiece i is processed on machine k.

2.2 Modelling

$$f_1 = \min(t) \tag{1}$$

$$f_3 = min\left[\sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{h}\left(t_{Pijk}x_{ijk}\right)\cdot\left(C_{ijk}x_{ijk}\right)\right] \tag{2}$$

$$f_3 = \min(E) \tag{3}$$

Where Eq. (1) represents the minimisation of the maximum completion time; Eq. (2) represents the minimisation of the total cost of the machine; and Eq. (3) the minimisation of the shop floor energy consumption. For the above objective function, the constraints of this paper are:

$$t_{Tij} \leq t_{Si(j+1)} \tag{4}$$

$$t_{Tijk} - t_{Sijk} = t_{Pijk} \tag{5}$$

$$x_{ijk} \begin{cases} 1 \text{ Process } O_{ij} \text{ is machined on machine } k \\ \qquad\qquad 0 \text{ If not} \end{cases} \tag{6}$$

Eq.(4) denotes the sequential order constraint of the machining process; Eq.(5)denotes that the process is not allowed to be interrupted after starting the machining; and Eq.(6)denotes the decision variable of whether or not the process O_{ij} is machined on k.

3 IMPROVED SPARROW ALGORITHM WITH MULTIOBJECTIVE OPTIMISATION

3.1 Sparrow Search Algorithm

Sparrow algorithm[6] is a new population intelligent optimisation algorithm. In the sparrow algorithm, the population consisting of n sparrows can be represented by equation (7):

$$X = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^d \\ \vdots & \vdots & \ddots & \vdots \\ x_n^1 & x_n^2 & \cdots & x_n^d \end{bmatrix} \tag{7}$$

In equation (7), d denotes the dimension of the optimisation problem vector and n is the number of sparrows in the population. Then the fitness of the sparrow population can be expressed in equation (8):

$$F_x = \begin{bmatrix} f(x_1^1 & x_1^2 & \cdots & x_1^d) \\ f(x_2^1 & x_2^2 & \cdots & x_2^d) \\ \vdots & \vdots & \ddots & \vdots \\ f(x_n^1 & x_n^2 & \cdots & x_n^d) \end{bmatrix} \tag{8}$$

3.2 Improvement Strategies

Join the Gold Sine Strategy and Fusion Levy Flight Strategy. The golden sine strategy[7], on the other hand, is an optimisation method based on the mathematical golden ratio, which uses the periodicity of the sine function and the golden ratio to generate a sequence of parameters. The specific formulas are as follows:

$$\mathrm{X}_t^{t+1} = \mathrm{X}_t^t \times |\sin(R_1)| - R_2 \times \sin(R_1) \times |c_1 \times P_i^t - c_2 \times X_i^t| \tag{9}$$

Levy flight strategy is a random walk strategy based on Levy distribution with long-tailed distribution, which helps to explore the search space extensively. The specific formula is as follows:

$$\nu_i(t+1) = \chi_i(t) + b \cdot D \cdot \chi_t(t) + \alpha \oplus \mathrm{Levy}(s, \beta) \tag{10}$$

Adaptive T-Distribution Variation Strategy and Non-Dominated Order. The t-distribution, also known as the student distribution, is perturbed to mutate the t-distribution with a certain probability during the follower phase of the sparrow algorithm. The specific formula is as follows:

$$X_{new}^{j} = X_{best}^{j} + t(C_{iter}) \cdot X_{best}^{j} \tag{11}$$

In the improved sparrow algorithm, a non-dominated ranking of the population is performed to determine the fitness size, and all individuals of the sparrow population are ranked to distinguish between discoverers and joiners. In Pareto sorting, the less number of times each individual is dominated indicates that the individual is superior. The flowchart of the improved multi-objective sparrow algorithm is shown in Fig. 1.

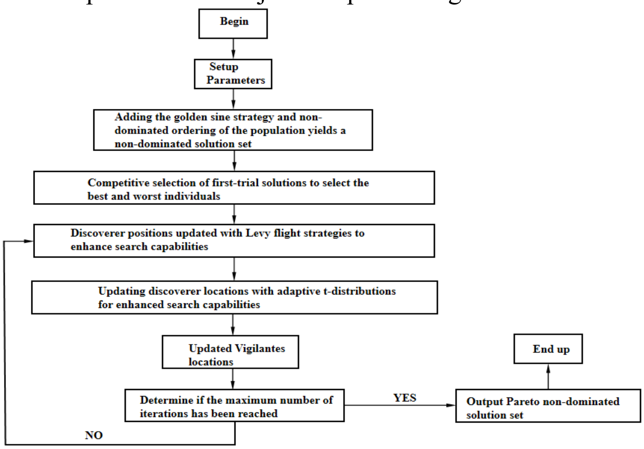

Fig. 1. Flowchart of the improved sparrow algorithm

4 SIMULATION EXPERIMENTS AND ANALYSES

4.1 Algorithm Comparison

In order to verify the performance of the algorithm (IMSSA), Multi-Objective Particle Swarm Algorithm (MOPSO), Multi-Objective Grey Wolf Algorithm (MOGWO), NSGA-II and SPEA2 are tested as comparison algorithms. Two evaluation indexes, inverse iteration distance (IGD) and spatial evaluation (SP), are taken to compare the performance of the algorithms. The test functions are selected as part of the ZDT series (bi-objective function) and DTLZ series (tri-objective function).The IGD is calculated as shown in equation (12):

$$IGD\ (P, P^*)\ = \frac{\sum_{x \in P^*} min\ dis(x, P)}{|P^*|} \tag{12}$$

P^* is the real Pareto Frontier; $P$is the set of optimal solutions obtained by the algorithm; $min\ dis(x, P)$ is the minimum Euclidean distance between the true Pareto solution x and the solution P obtained by the algorithm; $|P^*|$ is the number of solutions in the solution set P^*.The expression for SP is shown in equation (13) below:

$$SP = \sqrt{\frac{1}{|P| - 1} \sum_{i=1}^{|P|} (\bar{d} - d_i)^2} \tag{13}$$

In Eq. $d_i$denotes the minimum Euclidean distance from the ith solution to the other solutions in the solution set; $\bar{d}$ denotes the mean value of all d_i; $|P|$ denotes the number of P's in the solution set. Each test function is run 20 times with population size Pop=200 and maximum number of iterations M=150, and the mean (Mean) and standard deviation (Std) of IGD and SP for each algorithm on different test problems are obtained respectively. The test results are as follows.

Table 1. IGD test results

Test Functions	Norm	IMSSA	MOPSO	MOGWO	NSGA-II	SPEA2
ZDT1	Mean	**2.09E-03**	2.89E-03	1.03E-02	2.21E-03	2.57E-03
	Std	6.32E-05	3.81E-03	3.51E-02	1.44E-03	2.14E-02
ZDT2	Mean	**2.48E-03**	5.23E-02	6.83E-02	3.42E-03	1.25E-02
	Std	1.61E-04	5.81E-01	2.72E-03	1.70E-03	1.38E-01
ZDT3	Mean	2.49E-03	4.01E-02	4.12E-02	**1.83E-03**	3.11E-03
	Std	2.78E-02	1.16E-01	1.85E-03	3.56E-02	5.57E-02
ZDT4	Mean	2.31E-03	**1.58E-03**	5.26E-02	2.38E-03	6.47E-02
	Std	8.95E-05	1.85E-03	6.63E-01	9.69E-02	7.37E-03
ZDT6	Mean	**1.94E-03**	7.80E-03	6.34E-02	5.01E-02	2.78E-03
	Std	1.22E-04	1.01E-02	2.62E-02	4.35E-03	1.98E-02
DTLZ2	Mean	5.16E-02	1.61E-01	**1.10E-02**	6.99E-02	7.92E-02
	Std	2.26E-03	2.27E-02	5.36E-01	3.36E-02	2.14E-02
DTLZ5	Mean	**2.75E-03**	2.00E-02	1.62E-01	1.05E-02	4.86E-02
	Std	1.30E-04	6.35E-04	5.04E-01	6.21E-02	5.63E-03
DTLZ7	Mean	6.17E-02	6.78E-01	**1.68E-02**	1.20E-01	5.52E-01
	Std	3.23E-03	7.06E-03	4.50E-03	5.27E-02	4.12E-01

Table 2. SP test results

TestFunctions	Norm	IMSSA	MOPSO	MOGWO	NSGA-II	SPEA2
ZDT1	Mean	**3.73E-03**	8.41E-03	6.63E-03	4.81E-03	9.41E-02
	Std	1.38E-04	4.48E-02	8.05E-02	3.87E-03	1.01E-03
ZDT2	Mean	3.39E-03	6.78E-03	1.50E-02	**1.14E-03**	7.12E-02
	Std	1.51E-04	4.98E-02	4.72E-02	3.83E-03	1.08E-01
ZDT3	Mean	**3.29E-03**	3.47E-02	4.25E-02	3.21E-03	2.31E-02
	Std	2.18E-04	2.41E-02	1.21E-02	1.45E-03	1.22E-01
ZDT4	Mean	**3.42E-03**	5.12E-03	4.33E-02	3.20E-02	5.81E-02
	Std	1.69E-04	9.52E-02	8.85E-01	8.92E-01	4.23E-02
ZDT6	Mean	1.23E-02	2.70E-03	2.16E-02	**2.52E-03**	3.00E-03
	Std	1.70E-02	1.42E-02	1.51E-01	7.04E-02	1.06E-01
DTLZ2	Mean	4.11E-02	5.47E-02	2.88E-02	**1.77E-02**	4.81E-02
	Std	1.29E-02	2.36E-02	5.26E-01	7.23E-03	5.87E-02
DTLZ5	Mean	**2.68E-03**	2.84E-03	3.32E-02	1.04E-02	1.17E-02
	Std	3.82E-04	2.56E-03	5.58E-02	3.24E-02	3.86E-02
DTLZ7	Mean	4.79E-02	**4.15E-02**	1.26E-01	6.79E-02	5.84E-02
	Std	5.11E-03	6.75E-02	4.52E-03	3.92E-02	4.92E-01

As can be seen from Tables 1 and 2, the IMSSA algorithm in this paper achieves four optimal IGD values[8] and four optimal SP values[9] on all the above eight test functions. Based on the above results, it can be seen that IMSSA shows good performance on the ZDT and DTLZ series of test functions, and the overall performance is better than other functions.

4.2 Algorithmic Test

The simulation analysis is carried out by MATLAB software to obtain the curve diagram of the proceeding process under each scheduling target, as shown in Fig. 2.

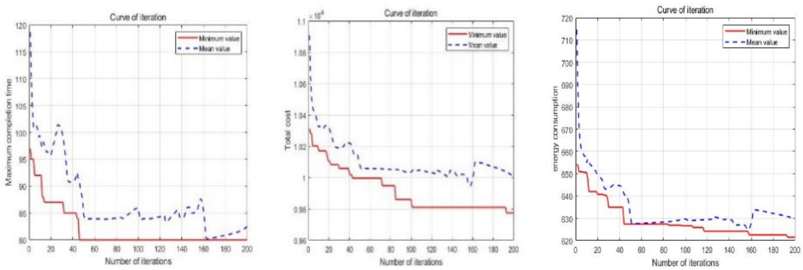

Fig. 2. Calculated example population evolution diagram

In Fig. 3, the horizontal coordinates are the machining time used in the machining process, the vertical coordinates are the different machine numbers, the colours marked for each workpiece are different, and the length of the rectangular graph indicates the time used for machining the process. Through continuous selection in the Pareto solution set, an improved optimal scheduling Gantt chart is finally produced as shown in

Fig. 3 below, in which the maximum completion time value is 80, the total energy consumption is 634.13, and the total cost is 10108.The optimal scheduling Gantt chart of the original Sparrow Algorithm before the improvement is 86, the maximum completion time, the total energy consumption is 645.15, and the total cost is 10397, the improved optimal scheduling Gantt chart has significant improvement in all three objectives optimisation. It can be seen that the improved sparrow algorithm is significantly better than the original sparrow algorithm for the optimisation of the three objective functions, and is a suitable algorithm for solving multi-objective FJSPs.

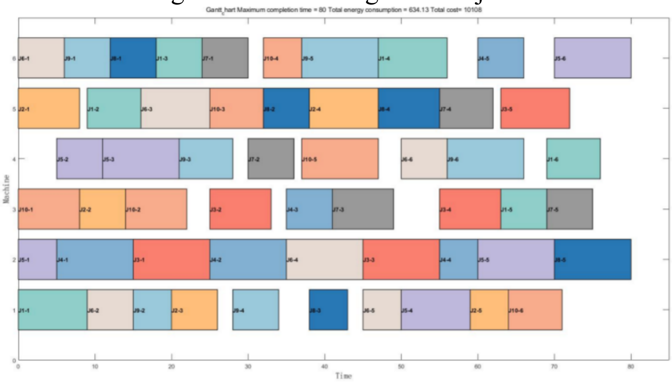

Fig. 3. Gantt chart of optimal scheduling for improved sparrow algorithm

5 CONCLUSION

In this study, a flexible scheduling optimisation method for production plants based on the improved sparrow algorithm is proposed, aiming at solving the scheduling problem in the manufacturing process to cope with the challenges of small-lot and diversified production. The initial solution quality and population diversity of the algorithm are improved by introducing the Levy flight strategy and employing the golden sine strategy, and the global and local search capabilities of the algorithm are strengthened. The experimental results verify the effectiveness of the method in minimising the maximum completion time, minimising the total machine cost, and minimising the total machine energy consumption, thus demonstrating its significant advantages in reducing the production cost and improving the productivity. Future research needs to further explore more algorithmic improvements and innovative strategies to adapt to the new challenges in production practice and promote the intelligent and efficient development of manufacturing.

REFERENCES

1. Ryalat, M., ElMoaqet, H., & AlFaouri, M. (2023). Design of a smart factory based on cyber-physical systems and Internet of Things towards Industry 4.0. Applied Sciences, 13(4), 2156.

2. Destouet, C., Tlahig, H., Bettayeb, B., & Mazari, B. (2023). Flexible job shop scheduling problem under Industry 5.0: A survey on human reintegration, environmental consideration and resilience improvement. Journal of Manufacturing Systems, 67, 155-173.
3. Zhou, K., Tan, C., Zhao, Y., Yu, J., Zhang, Z., & Wu, Y. (2024). Research on Solving Flexible Job Shop Scheduling Problem Based on Improved GWO Algorithm SS-GWO. Neural Processing Letters, 56(1), 26.
4. Meng, L., Duan, P., Gao, K., Zhang, B., Zou, W., Han, Y., & Zhang, C. (2024). MIP modeling of energy-conscious FJSP and its extended problems: From simplicity to complexity. Expert Systems with Applications, 241, 122594.
5. Liu, H., C. T. Xu, W. F. Chen & Z. R. Hu. (2024). Flexible job shop scheduling optimisation of aerospace parts for low carbon emission. Aviation Science and Technology (02), 47-57.
6. Xue, J., & Shen, B. (2020). A novel swarm intelligence optimization approach: sparrow search algorithm. Systems science & control engineering, 8(1), 22-34.
7. Li, M., Liu, Z., & Song, H. (2024). An improved algorithm optimization algorithm based on RungeKutta and golden sine strategy. Expert Systems with Applications, 247, 123262.
8. Wang, L., Ren, Y., Qiu, Q., et al. (2021). A review of research on performance evaluation indexes for multi-objective evolutionary algorithms. Journal of Computer Science, 44(8), 1590-1619.
9. Guo, J., Shi, Y.-Y., Zhang, D., et al. (2019). Hybrid flow shop robot scheduling based on SP-MCTS algorithm. Computer Integrated Manufacturing Systems, 25(9), 2208-2218.

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