DISRUPTION MANAGEMENT OF MULTI-OBJECTIVE FLEXIBLE JOB SHOP SCHEDULING PROBLEM

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***ABSTRACT**: In view of the problem for adjusting the initial scheduling scheme caused by disruptive events in the production process, this paper aims to study the disruption management of multi-objective flexible job shop scheduling problem (FJSSP). To this end, based on the prospect theory, a disruption management model considering the three behavioural subjects' (customers, enterprise managers and workshop workers) perception of disturbance, and an improved lexicographic multi-objective programming method was proposed to better solve the multi-objective FJSSP problem based on disruption management. In addition, it puts forward an improved quantum genetic algorithm (QGA) for adaptively adjusting the rotation angle, using the randomness and stability tendency of the cloud model. Finally, numerical experiments showed that this algorithm has good performance for solving disruption management problems.*

***KEYWORDS**: flexible job shop scheduling problem; disruption management; prospect theory; quantum genetic algorithm*

1 INTRODUCTION

Disruption management is a management model for solving uncertain disruptive events. This model not only considers the solution to uncertain disruptive problems, but also gives a re-scheduling scheme as close as possible to the original scheduling (Rock, 1984). The foreign scholar Clausen first proposed the concept of disruption management, with the basic goal of minimizing the system disturbance, and pointed out that as an application field of operations research the disruption management has a huge development potential (Clausen et al., 2001). Under the influence of uncertain disruptive events, how to establish a disruption management model and make a reasonable adjustment of the original scheduling scheme have become a research hotspot in recent years. Liu et al. (2014) constructed a disruption management model for the interference caused by workpiece priority changes in the single-machine scheduling problem related to installation time and order; Wang et al. (2015), in view of the disruptive problems of unplanned new workpieces in the permutation flow shop, established a disruption management model both considering the initial cost objective and the behavioural operation-based disturbance target; Liu et al. (2016) constructed a dual-objectiv rescheduling disruption model for the disturbance caused by the arrival of new workpieces in the permutation flow shop environment; Ding et al. (2016) proposed a method for generating disruption adjustment schemes with less disturbance to the system; Bo et al. (2018) constructed a disruption management scheduling model considering both initial scheduling targets and disturbance repair targets for the mixed wait-free pipeline problems under machine and workpiece disturbance. All scholars above have made meaningful studies on the problem of shop scheduling, but it is still one of the main problems in the field for how to perform the disruption management of multi-objective problems when considering human behaviour and perception factors (Li et al., 2018; Wang, 2017).

In this paper, based on the prospect theory, the impact of loss and benefit on the behavioural subjects was taken into full consideration and the decision behaviour of humans was modelled, to establish a disruption management model considering both the original multi-objective and the disturbance target. On this basis, a solution method based on QGA was proposed.

2 MULTI-OBJECTIVE FLEXIBLE JOB SHOP SCHEDULING MODEL

The FJSSP can be described as: n workpieces in the workshop need to be machined on m machines, where n workpieces are denoted by $J = \{J_1, J_2, \ldots, J_n\}$, and m machines are by $M = \{M_1, M_2, \ldots, M_m\}$; each workpiece contains $n_i (1,, i,, n)$ operations that needs to be processed; the order of the processes is predetermined, and the order of operations for each workpiece is different; each machine can process multiple processes of different workpieces. The jth operation of the workpiece $J_i(1 \leqslant j \leqslant n_i)$ is expressed as O_{ij}, which can be machined on any of its optional machine sets $M_{ij}(M_{ij} \subseteq M)$. Due to the different machine performance, the processing time on different machines by O_{ij} also varies.

Besides, the following constraints must be met during processing:

(1) Each machine can only process one workpiece at a time;

(2) Each workpiece can only be machined by one machine at the same time;

(3) Once each process begins, it cannot be interrupted;

(4) The processing order of different workpieces is randomly listed;

(5) The start time of each process for each workpiece must be after the end of the previous process;

(6) All workpieces and machines are scheduled from time 0.

In this study, the completion time, the total energy consumption, and the total load of the machine were taken as three original scheduling objectives:

(1) The completion time is the time for all the workpieces processed, denoted by T .

(2) The energy consumption of the machine is its power consumption. Its model is expressed as:

$$W = \sum_{i=1}^{m} (P_1^i t_1^i + P_2^i t_2^i) \quad (1)$$

where, P_1^i and t_1^i are the operating power and working time of machine i; P_2^i and t_2^i are the standby power and idle time of machine i, respectively.

(3) The total load of the machine represents the proportion of its working time in the total processing time, denoted by F . The machine load model is expressed as:

$$F = \sum_{i=1}^{m} t_1^i \Big/ mT \quad (2)$$

where m is the number of machines, and t_1^i is the working time of the machine.

3 DISRUPTION MODEL OF MULTI-OBJECTIVE FLEXIBLE JOB SHOP SCHEDULING BASED ON PROSPECT THEORY

3.1 Problem definition

The purpose of disruption management is to quickly generate an effective adjustment scheme when the system is disturbed, and minimize the negative impact of the disruption on the system. The prospect theory is a decision model for describing the user's sensitivity to results under uncertain conditions (Tversky and Kahnerman, 1992). Based on the prospect theory, it is possible to measure the three behavioural subjects' perception of the disturbance (the customer, enterprise manager, and workshop worker). The disruption management problems in this paper are defined as follows:

(1) The initial scheduling scheme is known;

(2) The moment at which the disruption occurs is defined to be 0;

(3) Rescheduling is only performed for the process that has not started processing at time 0.

3.2 Disruption measurement method based on prospect theory

3.2.1 Analysis of disruption

The production scheduling problem is a typical "human-machine" system. After the disruptive event occurs, it is necessary to focus on the influence of disruption on the behavioural subjects. This paper analyses the impact of disruption from the perspective of customers, managers and workers.

The customer is the final delivery target of the products produced on the shop floor. Once the products cannot be delivered on time due to certain disruption, it will inevitably affect the customer's original scheme, and produce a negative impact on it, thus increasing the customer's dissatisfaction. Therefore, the customer is most concerned about the timely delivery of the produces after the disruption occurs.

Business managers are leaders in the entire production process. When the production process is disturbed, the original processing scheme often needs to be adjusted or even re-scheduled. In this process, due to the change of the processing scheme, the processing time adds, the processing personnel change, and the workpieces need rework, which will increase the operating cost of the enterprise and cause the manager's dissatisfaction. Therefore, the main concern of enterprise managers after disruption occurs is the impact of disruption on operating costs.

Workshop workers are the executors of the production plan. The disruptive event affects the work of the workers most directly. Changes in processing schemes caused by disruption can result in additional workload on the workers. When the workload exceeds the range that workers can afford, it could cause the worker's dissatisfaction. Therefore, the workers are most concerned about the changes of the processing scheme.

Disruption management needs to consider the multi-objective characteristics of the original scheduling objective while considering the above three behavioural subjects. The original scheduling objectives in this paper are: the shortest total time, the lowest total energy consumption, and the smallest total machine load. According to the measurement standard of disruption management, both the original objective and the disturbance target should be considered so that the impact of the disruption on the entire production system can be reasonably reflected.

3.2.2 Construction of disruption measurement function

Prospect theory is a theoretical model that describes people's decision-making behaviour under uncertain conditions. It embodies the characteristics of loss aversion and marginal utility during the decision-making. According to this theory, it is necessary to select a reference point as a point with zero value and then judge whether the decision is profitable or losing relative to the reference point. Therefore, the current state was selected as the reference point, and the value function model can be expressed as:

$$V^i(x) = \begin{cases} x^{\alpha^i} & x \geq 0 \\ -\lambda^i(-x)^{\beta^i} & x \geq 0 \end{cases} \quad i = 1, 2, \cdots, n \qquad (3)$$

Among them, α^i and β^i determine the degree of the subjects' preference to risk behaviour in the face of gains and losses, and λ^i determines the degree of their sensitivity to the loss in making decisions.

Considering that the disruption may bring additional benefits to the behavioural subjects, they have a certain degree of tolerance to the disruption, that is, when the loss is much smaller than the benefit, it won't cause their dissatisfaction. Therefore, the value Q_i indicating the tolerance of the subject to the disruption can be given as:

$$Q_i = \begin{cases} \gamma G_i & G_i > 0 \\ 0 & G_i \leq 0 \end{cases} \qquad (4)$$

where, G_i is the benefit brought by the disruption to the behaviour subject, and γ is the degree of tolerance to the loss. When the disruption brings benefits to the subjects, they shall have a certain degree of tolerance and thus the value Q_i is influenced. Taking the new order as an example, the customer had more profits of the new workpiece due to this disruption, and the relevant value Q_i was greater than zero; while for the worker, the new order didn't bring new incomes, and then the corresponding value Q_i was equal to zero. .

Combined with the prospect theory, the dissatisfaction membership function of x_i can be expressed as:

$$\mu_i(x_i) = \begin{cases} 1 & x_i \geq R_i \\ \lambda_i(x_i - O_i - Q_i)^{\beta_i} & O_i + Q_i \leq x_i < R_i \\ 0 & 0 \leq x_i < O_i + Q_i \end{cases} \quad i = 1, 2, \cdots, n$$

(5)

where in, $R_i = O_i + Q_i + (1/\lambda_i)^{\beta_i^{-1}}$, λ_i is the loss aversion coefficient of the behaviour subject i, and O_i is the reference point of the dissatisfaction membership function $\mu_i(x_i)$ for the subject (Figure 1).

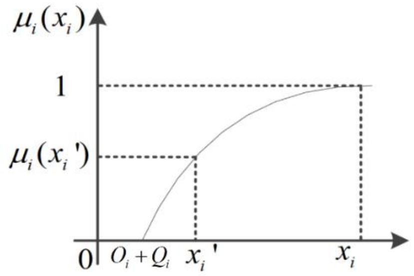

Fig. 1 Dissatisfaction function of behavior subjects

According to the analysis of disturbances in Section 3.2.1, the dissatisfaction of customers, managers and workers were measured:

(1) The customer's concern is the timely deliver, so the total delay time t was used to measure their dissatisfaction.

$$\mu_1(t) = \begin{cases} 1 & t_1 \geq R_1 \\ \lambda_1(t - t_0 - Q_1)^{\beta_1} & t_0 + Q_1 \leq t_1 < R_1 \\ 0 & t_1 \end{cases} \qquad (6)$$

In the formula above, the reference point of the customer's dissatisfaction function was determined by the completion time t_0 of the initial scheme and the benefit Q_1 generated by the disruption. And $R_1 = t_0 + Q_1 + \left(\frac{1}{\lambda_1}\right)^{\frac{1}{\beta_1}}$

(2) The enterprise manager focuses on the operating cost of the enterprise. Therefore, the total operating time of the plant equipment was used to measure the operating cost of the enterprise, and the changes of the operating cost f was observed to measure their dissatisfaction.

$$\mu_2(f) = \begin{cases} 1 & f \geq R_2 \\ \lambda_2(f - f_0 - Q_2)^{\beta_2} & f_0 + Q_2 \leq f < R_2 \\ 0 & 0 \leq f < f_0 \end{cases} \qquad (7)$$

The reference point of enterprise manager's dissatisfaction function was determined by the initial operating cost f_0 and the benefit Q_2 generated by the disruption. And $R_2 = f_0 + Q_2 + \left(\frac{1}{\lambda_2}\right)^{\frac{1}{\beta_2}}$.

(3) Workshop workers are concerned with the changes in subsequent processing schemes, so their dissatisfaction was measured by the changes c of the processing machines.

$$\mu_3(c) = \begin{cases} 1 & c \geq R_3 \\ \lambda_3 (c - Q_3)^{\beta_3} & Q_3 \leq c < R_3 \\ 0 & 0 \leq f < Q_3 \end{cases} \quad (8)$$

In the formula, the number of changes of the initial processing machine is zero under no disturbance. Thus, the reference point of the dissatisfaction function for the worker was determined by the number of changes Q_3 in the processing machines. And $R_3 = Q_3 + \left(\frac{1}{\lambda_3}\right)^{\frac{1}{\beta_3}}$.

3.3 Lexicographic multi-objective programming method

In order to better adapt to the needs of multi-objective disruption management, an improved lexicographic multi-objective programming method was adopted to expand the target priority order to the priority order of the target set. In this method, each priority may contain multiple targets of the same priority, and combined with the mining method of large item-sets in the Apriori algorithm, the non-inferiority in line with the priority order was obtained by calculating the support number of each solution. The constructed multi-objective solution model is as follows:

$$\min \; L = P_1 : \{A_1, \;\; \mu_1\} \; P_2 : \{A_2, \;\; \mu_2\} \; P_3 : \{A_3, \;\; \mu_3\}$$
$$P_1 \; ? \; P_2 \; ? \; P_3$$

A_1, A_2, A_3 are the original scheduling target of the multi-objectiveFJSSP, μ_1, μ_2, μ_3 are the disturbance target after the disruption, and P_1, P_2, P_3 are the priority of the different target sets, indicating that the priority order in which the target is considered, and the decision maker can adjust the priority of each target. Setting the priority in a collective manner is more in line with the reality, which is conducive to dealing with targets with fuzzy importance.

In this model, the first-level goal is reducing customer dissatisfaction with overdue work and realizing early completion; the second-level goal is reducing the dissatisfaction of enterprise managers on processing costs and decreasing energy consumption; the third-level goal is reducing workers' dissatisfaction about the changes in processing machines and lowering machine load.

4 QUANTUM GENETIC ALGORITHM OF ADAPTIVE ROTATION ANGLE

4.1 Quantum coding

In quantum computing, qubits are the most basic unit for describing the state of a quantum line. It is characterized by being able to be superimposed on two quantum states at the same time, e.g.:

$$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \quad (9)$$

where, α and β are both complex numbers, called the probability amplitude of the quantum state; when the quantum bit was measured, $|\psi\rangle$ collapsed to $|0\rangle$ at the probability $|\alpha|^2$, and to $|1\rangle$ at the probability $|\beta|^2$; α and β satisfy the normalization condition:

$$|\alpha|^2 + |\beta|^2 = 1 \quad (10)$$

When the qubit is in the superposition state, it will be between the $|0\rangle$ and $|1\rangle$state at the same time, and only collapse to one of the states immediately when it is measured. Therefore, the quantum coding of the shop scheduling problem can be expressed as:

$$p_i = \begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_L \\ \beta_1 & \beta_2 & \cdots & \beta_L \end{bmatrix} \quad (11)$$

In the formula, p_i is a quantum chromosome, and α and β satisfy the normalization condition $|\alpha|^2 + |\beta|^2 = 1$. Thus, after being measured, it collapses into a pair of binary strings of length L consisting of 0 and 1.

In this paper, a two-layer coding method combining process coding and machine coding was adopted. The length of the real number code depends on the total number of steps. In the initialization phase, the qubit encoding of all individuals in the population was initialized to $(\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}})$, indicating that the probability of all possible outcomes measured for each chromosome is equal. This also reflects the global convergence of the QGA.

4.2 Genetic manipulation

4.2.1 Quantum crossover

This paper uses a crossover mode that draws on quantum coherence properties, i.e., full interference crossover. This crossover is characterized by the fact that all chromosomes are involved in the crossover.

In Figure 2, a 5×5 population was taken as an example, in which each uppercase letter represents a new chromosome after the crossover operation, and the numbers in parentheses represent the corresponding gene. The genes were rearranged in a diagonal line to form a new chromosome. This crossover-operation draws on the coherent nature of quantum and makes full use of the chromosomal information of the whole population, which can effectively overcome the premature phenomenon in the later period of evolution.

1	A(1)	E(2)	D(3)	C(4)	B(5)
2	B(1)	B(2)	E(3)	D(4)	C(5)
3	C(1)	C(2)	A(3)	E(4)	D(5)
4	D(1)	D(2)	B(3)	A(4)	E(5)
5	E(1)	A(2)	C(3)	B(4)	A(5)

Fig. 2 Quantum full interference cross

4.2.2 Quantum mutation

Quantum NOT gates are commonly used to achieve transitions between a single quantum ground state and an excited state.

$$N = |0\rangle\langle 1| + |1\rangle\langle 0| = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (12)$$

For a single qubit, a quantum non-gate can be implemented $N|1\rangle = |0\rangle$, $N|0\rangle = |1\rangle$.

In order to increase the diversity of the population, the quantum non-gate was used for the mutation operation with certain probability.

4.2.3 Catastrophe strategy

In order to prevent the algorithm from falling into the local optimal solution, the population catastrophe strategy is adopted when the optimal solution is still not updated after a certain number of iterations. It's found through experiments that the individual optimal solutions of quantum chromosomes often appeared in the evolution process and did not coincide with the optimal solution of the population. Therefore, the optimal real number coding and the corresponding quantum chromosome were first preserved, and then all chromosomes of the population were replaced by the optimum in their individual history to form a new population for continuous evolution.

4.3 Cloud model adaptive adjustment of quantum rotation angle

The quantum rotation gate is the core of the QGA. Its main function is to shift the probability amplitude of each gene position in the chromosome to the optimal solution with a certain rotation angle, so as to achieve the optimal solution at a greater probability. Traditional quantum genetic algorithms mostly use fixed rotation angles, and their size is often given empirically.

In this paper, the normal cloud model was used to dynamically adjust the quantum rotation angle. The cloud model is a model of uncertainty conversion between qualitative concepts and quantitative representations, with both randomness and ambiguity. The normal cloud model is a stochastic set of random numbers with stable tendency that follow a normal distribution. It's characterized by expectation E_x, entropy E_n and super entropy H_e. The model is expressed as follows:

$$\begin{aligned} & E_x = \overline{f} \\ & E_n = (f_{\max} - \overline{f}) / c_1 \\ & H_e = E_n / c_2 \\ & E_n' = RANDN(En, He) \\ & \Delta\theta = \begin{cases} k_1 e^{\frac{-(f'-E_x)^2}{2(E_n')^2}} & f' \geq \overline{f} \\ k_2 & f' < \overline{f} \end{cases} \end{aligned} \quad (13)$$

where, c_1 and c_2 are the control parameters; k_1 and k_2 are constants representing the maximum value of the rotation angle; $\overline{f}$ is the average fitness of the population; f_{max} is the optimal individual fitness. Figure 3 shows the resulting probability distribution.

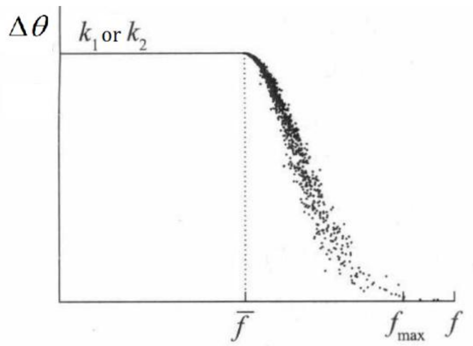

Fig. 3 Distribution route in process segment

The principle of adaptive rotation angle can be described as: for the individuals above the average fitness of the population, as the fitness increases, the amplitude of the rotation angle gradually decreases, so as to protect the high quality individuals from being destroyed; for the individuals below the average fitness of the population, the maximum angular amplitude of rotation is used, making their quantum bits more susceptible to "disturbance", thereby increasing population diversity and preventing local optimality.

4.4 Algorithm steps

Step 1: Initialize the population and obtain the quantum-coded population $Q(t)$;

Step 2: Perform a measurement on $Q(t)$ to obtain a binary coded population $B(t)$;

Step 3: Convert $B(t)$ to decimal code $P(t)$, and segment the process codes and machine codes;

Step 4: Decode the process code and machine code into an effective schedule, and evaluate the fitness of each individual;

Step 5: Record the global optimal individual and record the historically optimal individual of each chromosome;

Step 6: Update $Q(t)$ with quantum rotation gates, and perform quantum crossover and mutation operations to obtain next generation populations $Q(t+1)$;

Step 7: Determine whether the maximum number of iterations is reached. If not, return to Step 2;

Step 8: If the optimal individual is not updated for a long time, adopt a population catastrophe strategy, and replace the population individual with its historically optimal individual, to form a new population. Then, return to Step 2;

Step 9: Output the optimal solution.

5 SIMULATION EXPERIMENT

5.1 Verification of algorithm performance

Simulation experiments were conducted to verify the feasibility and effectiveness of the improved algorithm by Matlab 2016a. The test was performed using the 8x8 scheduling problem, setting the population size to 60 and the number of iterations to 100. The improved chaos quantum genetic algorithm (CQGA) algorithm in this study was compared with GA, PSO and QGA, and the fitness changes are shown in Figure 4 below:

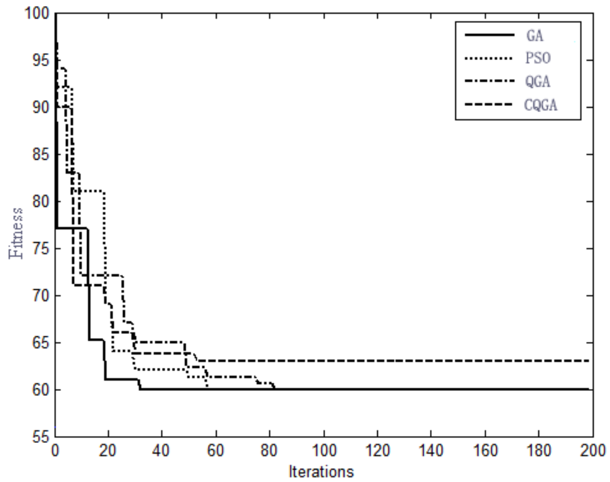

Fig. 4 Comparison of algorithm fitness changes

It can be seen from Figure 4 that the CQGA algorithm proposed in this paper effectively overcomes the problem that the standard QGA algorithm converges slowly on the FJSSP, easily falls into the local optimum problem, and its convergence speed is better than other algorithms, with a better global optimization ability.

5.2 Verification of disruption management method

It's assumed that the production workshop runs for 30, and the failure time is 8 when the failure of machine 7 interrupts the processing. The disruption management method was used to adjust the subsequent processing scheme. Figure 5 shows the initial scheduling. Figure 6 shows the adjustment scheme obtained by our method. Figure 7 and 8 show the adjustment schemes using the global rescheduling and right shift scheduling respectively. Table 1 compares the disturbance of each scheme to different behavioural subjects. Table 2 compares the performance of the original scheduling target.

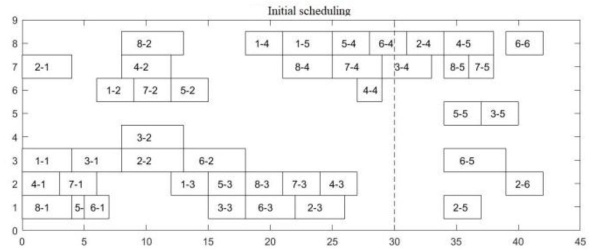

Fig. 5 Initial scheduling scheme

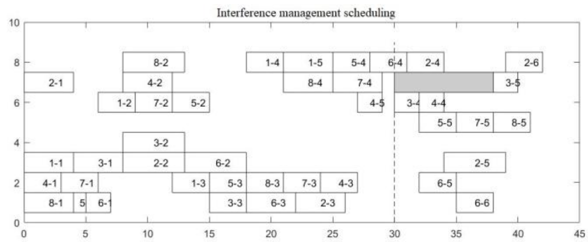

Fig. 6 Adjustment scheme using our disruption management method

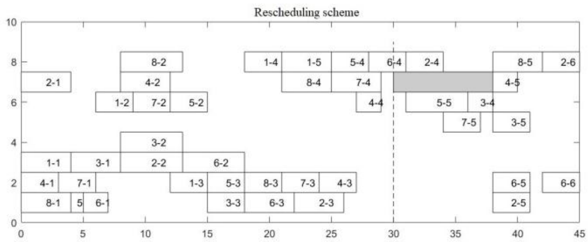

Fig. 7 Global rescheduling scheme

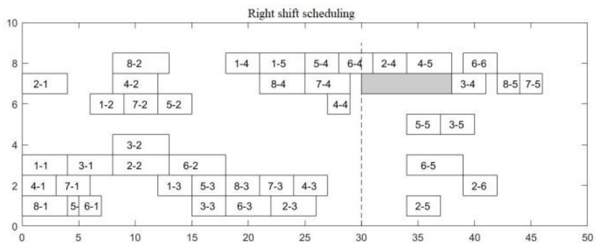

Fig. 8 Right-shift scheduling scheme

Table 1. Comparison of the disturbance to different behavioural subjects between different methods

Algorithm	Customer	Manager	Worker
Adjustment scheme	0	5	7
Global rescheduling	3	6	11
Right-shift scheduling	4	8	0

From Table 1, it can be concluded that the disruption management method of this paper is better than the other two methods in terms of the disturbance to the customers and managers; the right shift scheduling only shifts the original schedule, so it won't disturb the original work process of the workers, but the other two methods will cause disturbance to the workers.

Table 2. Comparison of the performance of original scheduling targets

Algorithm	Total time	Total energy consumption	Total load
Adjustment scheme	42	2042	44.1%
Global rescheduling	45	2074	43.9%
Right-shift scheduling	47	2040	43.8%

It can be seen from Table 2 above that the adjustment scheme obtained by our disruption management method is better than the other two methods in terms of total time; in terms of the total energy consumption it's superior to global rescheduling; in terms of total load, these three algorithms are basically equal.

In summary, our method can balance the original scheduling target and the disturbance target, effectively solve the multi-objective disruption management problems according to the target importance, and achieve more scientific results.

6 CONCLUSIONS

In this paper, combined with the prospect theory, the human decision-making behaviour was modelled, and the disruption management model considering both the original multi-objective and the disturbance target was established. The improved lexicographic programming method was used to take into account the initial multi-objective and the multiple disturbance targets. Meanwhile, an improved quantum genetic algorithm was proposed, which used a cloud model to adaptively adjust the size of the quantum rotation angle. Finally, the simulation experiment was carried out to verify the effectiveness and superiority of the disruption management method.

7 ACKNOWLEDGEMENT

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8 REFERENCES

►Bo, H.G., Zhang, X., Pan, Y.T. (2015). A Disruption Recovery Model for No-Wait Flow Shop with Outsourcing Option. Systems Engineering-Theory Methodology Application, 485-495.

►Clausen, J., Larsen, J., Larsen, A., Hansen, J. (2001). Disruption Management - Operations Research between planning and execution. Technical Report.

►Ding, D.L., Jiang, Y. (2016). A model of disruption management based on behavioral operation research in production scheduling. Systems Engineering-Theory & Practice, 664-673.

►Li, B., Guo, C., Ning, T. (2018). An improved bacterial foraging optimization for multi-objective flexible job-shop scheduling problem, Journal Européen des Systèmes Automatisés, 51(4-6), 323-332.

►Liu, F., Wang, J.J., Rao, W.Z., Yang, D.L. (2014). Research on Production Scheduling Disruption Management Related to Installation Time and Order. Chinese Journal of Management Science, 45-54.

►Liu, Y.J., Zhao, Q., Wang, J.J. (2016). Research on New Part Arrival Disruption Management in Replacement Flow Shop. Journal of Shijiazhuang Tiedao University, 86-92.

►Rock, H. (1984). The Three-Machine No-Wait Flow Shop is NP-Complete. Journal of the ACM, 31(2), 336-345.

►Tversky, A., Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty, 5(4), 297-323.

►Wang, H. (2017). Shortest route optimization of job-shop scheduling based on ant colony algorithm, Journal Européen des Systèmes Automatisés, 50(3), 323-334.

►Wang, J.J., Liu, Y.J., Liu, F. (2015). Management considering real-world behavioral participators in permutation flow shop. Systems Engineering-Theory & Practice, 3092-3106.