An improved genetic algorithm for low carbon dynamic scheduling in a discrete manufacturing workshop

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Abstract. Due to energy consumption activities, manufacturing enterprises produce many carbon dioxide emissions in the production process, which exacerbates global climate deterioration. The production scheduling optimization method is an effective way to reduce carbon emissions and relieve environmental pressure. The paper proposed a low-carbon dynamic scheduling optimization method to solve machine failure interference and to minimize the total cost of production and carbon emissions in the discrete manufacturing workshop. The rolling window mechanism driven by abnormal events and rescheduling strategy are used to update the original schedule in real-time when the machine fails. In the carbon emission measurement method, the machine's carbon emission parameters in different states are considered. The traditional genetic algorithm is improved in the initial population strategy and crossover operator. The experimental results show that the proposed low-carbon dynamic scheduling method based on the improved genetic algorithm can effectively reduce carbon emissions under the premise of ensuring the completion of production tasks as soon as possible.

1. Introduction

More and more attention has been paid to global warming and climate change. Global warming is caused by the increase in greenhouse gas emissions. The carbon dioxide emission from manufacturing enterprises' production process is the primary source of carbon emissions in China, affecting the country's sustainable development \cite{1}. With the research on global climate issues and the promulgation of energy conservation and emission reduction policies, the low-carbon production model has gradually become a manufacturing model promoted by the state and society. Manufacturing enterprises must seek practical ways to reduce energy consumption and carbon emissions in the production process to build a low-carbon production and manufacturing system \cite{2}.

Most of the similar manufacturing processes in automotive, aviation, electronic, mechanical manufacturing, and other discrete manufacturing industries can be described as flexible job shop scheduling problem (FJSP). The main characteristics of FJSP are that the process route of each job is not entirely the same, and there may be multiple candidate machines in each process, and the processing time of the workpiece in each machine is not the same. The machine may also run in different states, such as no-load, processing, stop, and fault. Due to machines' different energy consumption under no-load and processing conditions, the carbon emissions under different scheduling schemes are also different \cite{3}. Therefore, we need a suitable scheduling optimization method to select the appropriate processing machine for the workpiece and arrange the appropriate processing sequence to ensure the efficient completion of the production task and effectively control the carbon emissions in the production process.
There are more and more researches on low-carbon scheduling problems. Most of the literature considered the efficiency-related indicators and some energy-saving and emission reduction optimization indicators. Due to the great difficulty of solving the scheduling problem, genetic algorithm, particle swarm optimization algorithm, teaching optimization algorithm, and other intelligent optimization algorithms are widely used in scheduling problems. Seng et al. [4] proposed an improved multi-objective genetic algorithm (NSGA II) to minimize the completion time and carbon emissions, which solved the flexible job-shop scheduling problem. Zhang and Chiong [5] proposed a multi-objective genetic algorithm with a dual-domain search pattern for job shop scheduling problem, considering the total carbon emissions and the total weighted delay time. Aiming at the flexible job shop scheduling problem, Lei [6] proposed a new teaching optimization algorithm aiming at the total carbon emissions and average delay time.

The above literature mainly assumed the static scheduling environment. However, some interference events will inevitably occur in a workshop production, such as machine failure, new order insertion. If we do not make full use of the real-time production data, combined with green production indicators to guide the scheduling decision, carbon emissions will be significantly increased. The wide application of the Internet of things makes it possible to obtain real-time data in the production process and to make scheduling decision-making with real-time data support. For example, Cai et al. [7] proposed a dynamic green scheduling optimization method based on the real-time manufacturing resources situation, considering the situation of downtime in the production process. Wang et al. [8] proposed an implementation scheduling method based on multi-cycle production planning (MPPRS) for FSJP to realize low-carbon scheduling optimization. In order to obtain a feasible solution, a method based on game theory is designed.

In this paper, a low-carbon dynamic scheduling method considering machine failure is proposed using a rolling window mechanism and a rescheduling strategy to minimize the total cost of production and carbon emissions. To establish a more practical mathematical model of low-carbon scheduling, we considered machines' carbon emission parameters in different states, such as processing and idling. Aiming at the low search efficiency of traditional genetic algorithm, we propose an improved genetic algorithm by improving the initial population strategy and new individual updating method. The example shows that the low-carbon dynamic scheduling method based on the improved genetic algorithm can effectively reduce carbon emissions under the premise of ensuring the completion time.

2. Description of low carbon FJSP scheduling problem

The following variables and parameters are defined to describe the low-carbon scheduling problem.

- $n$: the number of workpieces; $m$: the number of machines; $h_i$: the number of operations of workpiece $J_i$, $i = 1, 2, 3, ..., n$; $i$: the serial number of the workpiece, $i = 1, 2, 3, ..., n$; $j$: the process number, $j = 1, 2, 3, ..., n$; $k$: the serial number of the machine, $k = 1, 2, 3, ..., m$; $O_{ijk}$ indicates that the process $O_{ij}$ is processed on machine $M_k$; $t_{ijk}$ is the processing time of process $O_{ij}$ on machine $M_k$; $s_{ij}$ and $c_{ij}$ denote the start time and completion time of process $O_{ij}$; $C_{max}$ is the total completion time of all jobs in the planning period; $x_{ijk} = 1$ indicates that the process $O_{ij}$ is processed on the machine $M_k$, otherwise $x_{ijk} = 0$; $L_{ijk} = 1$ indicates that process $O_{ij}$ is processed on machine $M_k$ before operation $O_{ijy}$, otherwise $L_{ijk} = 0$; $e_{ijk}$ is the unit time carbon emission of process $O_{ij}$ during machine $M_k$ processing; $E_k$ is the carbon emission of machine $M_k$ processing, $E_k = \sum (x_{ijk} \cdot t_{ijk} \cdot e_{ijk})$; $t_{k0}$ is the idle time of the machine $M_k$, $t_{k0} = C_{max} - \sum (x_{ijk} \cdot t_{ijk})$; $h_i$; $e_{k0}$ is the carbon emission per unit time when the machine $M_k$ is empty; $E_{k0}$ denotes the carbon emission of the machine $M_k$, $E_{k0} = t_{k0} \cdot e_{k0}$; $a_i$ is the processing cost per unit time, $a_i = 10$ yuan/min in this paper; $a_2$ represents the unit carbon emission cost, $a_2 = 2.5$ yuan / kg.

Low carbon FJSP can be described as follows: $n$ jobs are processed on $m$ machines, each job contains one or more operations, and each operation can be processed by any machine in its candidate machine set. The appropriate processing machine for each workpiece process and the processing
sequence of the process need to be determined to achieve high efficiency and low emission. The low carbon FJSP problem has the following assumptions:

a) Processing is non-preemptive. That is, all processes are not allowed to be interrupted in the process.

b) There is no processing sequence constraint between different jobs, and there is a processing sequence constraint between different processes of the same workpiece.

c) A machine can only process a specific operation of a workpiece at the same time.

d) The machine may break down due to failure, and the machine's maintenance time is known.

e) The same machine's carbon emissions are different when they are in different states or when processing different workpieces.

f) When the machine breakdown, the workpiece being processed can continue to be processed after the machine is restored or transferred to another candidate machine to start processing again.

To achieve the goal of pursuing high efficiency of production and emission reduction, we considered the optimization objective of minimizing the total cost of production and carbon emissions in the paper. The mathematical model is established as follows.

\[
\begin{align*}
\text{Min } F &= a_1^* C_{\text{max}} + a_2^* (\text{sum}(E_{k0} | k = 1, 2, 3, \ldots, m) + \text{sum}(E_{k1} | k = 1, 2, 3, \ldots, m)) \\
\text{s.t. } & c_{ij} <= s_{ij} + 1; i = 1, 2, 3, \ldots, n; j = 1, 2, 3, \ldots, h_i - 1 \quad (1) \\
& \text{sum}(x_{ijk} = 1 | k = 1, 2, 3, \ldots, m); i = 1, 2, 3, \ldots, n; j = 1, 2, 3, \ldots, h_i \quad (2) \\
& \text{if } L_{ijk} = 1, \text{ then } c_{ij} <= s_{xy}; i = 1, 2, 3, \ldots, n; j = 1, 2, 3, \ldots, h_i \quad (3)
\end{align*}
\]

The constraint condition (1) represents the sequence constraint of the same work piece; the constraint condition (2) represents the machining machine constraint; and the constraint condition (3) represents the resource constraint.

3. Improved genetic algorithm

3.1. Procedure of ICA

The procedure of ICA is described as follows:

Step1: set parameters; Step2: initialization population; Step 3: evaluate the fitness of the individual population; Step 4: if the number of iterations reaches \(N_{\text{gen}}\), the algorithm ends, and the final result is output; otherwise, it is transferred to step 5; Step 5: using roulette selection method to select \(p_{\text{size}}\) chromosomes for crossover operation; Step 6: select the parent individuals according to the cross probability \(p_c\), and conduct crossover operation to get the offspring to enter the temporary population; Step 7: select the parent individuals from the temporary population according to the mutation probability \(p_m\), and randomly select a mutation operator to mutate to obtain new individuals; Step 8: select excellent individuals from the temporary population and original population obtained by crossover and mutation operation to form a new population, and then transfer to step 3.

3.2. Encoding and decoding scheme

Coding and decoding refer to the conversion between individuals in the population and scheduling schemes and is the first problem to solve the problem by using swarm intelligence optimization algorithm [9]. Effective coding and decoding can improve the efficiency of the algorithm. Considering the influence of machine selection and process sequencing on the optimization goal of low-carbon FJSP, we adopted equal length double chain coding. That is, two segments of chromosomes represent the machine code and process code, respectively. For example, the machine code is = \{2,1,3,4,2,5,3,1\}, and the operation code is = \{1,3,1,3,2,1,3,2\}. In decoding, the workpiece's processing machine is determined according to the machine code, and then the processing sequence of different workpieces on the same machine is determined according to the operation code. The above chromosome was decoded into three workpieces with eight operations, and the processing sequence was \(O_{112}, O_{312}, O_{123}, O_{224}, O_{212}, O_{133}, O_{333}, O_{221}\). It can be seen that the processing sequence of workpiece on machine \(M_1\) are \(O_{312}\) and \(O_{221}\), on machine \(M_2\) are \(O_{112}\) and \(O_{212}\), on machine \(M_3\) are \(O_{123}\) and \(O_{333}\), on machine \(M_4\) is only \(O_{324}\), and on machine \(M_5\) is only \(O_{133}\).
3.3. Initialization method
The initial population is generated by the tent chaotic sequence method \[7\]. The initialization steps of each individual are as follows:

Step 1: each gene bit randomly generates a chaotic number of \((0,1)\) interval and carries out five trial calculations to obtain the available initial chaotic number.

Step 2: each gene's initial chaotic number is obtained from the initial chaotic number using formula (4).

\[ x_{k+1,i} = \begin{cases} 2x_{k,i} & \text{if } x_{k,i} \leq 0.5 \\ 2(1-x_{k,i}) & \text{if } 0.5 < x_{k,i} \leq 1 \end{cases} \]  

(4)

Step 3: get the value of each gene from each gene's initial chaotic number using formula (5).

\[ x_{k,i} = x_{k,i} \times (x_{\text{max},i} - x_{\text{min},i}) + x_{\text{min},i} \]  

(5)

Step 4: the gene value of each locus is discretized into an integer. For the process code, according to the gene value of each gene bit, the corresponding process number on the sequence edge sorted from small to large. For machine codes, rounding converts decimal numbers to integers.

3.4. Crossover operator
According to formula (6-7), the gene values of each gene locus of a new individual are generated from two individuals, and then converted into integers according to the above discretization method to form new individuals.

\[ x_{ij} = x_{p1,j} + r_a \times |x_{\text{max},j} - x_{p1,j}| + r_b \times |x_{\text{max},j} - x_{p2,j}| \]  

(6)

\[ x_{i+1,j} = x_{p2,j} + r_a \times |x_{\text{max},j} - x_{p1,j}| + r_b \times |x_{\text{max},j} - x_{p2,j}| \]  

(7)

Where \(x_{ij}\) are the gene values of the \(j\)-dimension of the new individual \(i\); \(x_{p1,j}\) and \(x_{p2,j}\) are the gene values of the \(j\)-dimension of the two parent individuals; \(|x_{\text{max},j} - x_{\text{p1,j}}|\) and \(|x_{\text{max},j} - x_{\text{p2,j}}|\) denote the difference between the gene values of the \(j\)-dimension of the two parent individuals and the \(j\)-dimension gene values of the optimal individuals in the population; \(r_a\) and \(r_b\) are \((0, 1)\). The scaling factor is \(r_a = 0.3, r_b = 0.5\).

3.5. Mutation operator
One of the three mutation operations, insert, exchange, and reverse sequence, is selected randomly for the process chain. For the equipment chain, one of the two operations is randomly selected from the machine's random replacement and the replacement of the shortest processing time machine.

4. Dynamic scheduling strategy
The rolling window mechanism driven by abnormal events and the rescheduling strategy used in reference \[10\] are used to update the original schedule in real-time when machine failure occurs.

5. Experiments
The instance from [11] is used, but only the processing time of the workpiece and the machine's average carbon emission when the machine is running at low speed, and the average carbon emission of the machine at no-load are considered.

In order to verify the effectiveness of the proposed low-carbon scheduling method based on improved GA (IGA), this method is compared with the GA based scheduling method used in reference [11]. For the convenience of distinguishing, the latter is recorded as a low-carbon scheduling method based on traditional GA (TGA). The main parameters of this method are: population size \(p_{\text{size}} = 50\), crossover probability \(p_c = 0.8\), mutation probability \(p_m = 0.1\), and maximum iteration number \(N_{\text{gen}} = 50\). The IGA and TGA run ten times, respectively. The results are summarized in Table 1. The results show that both IGA and TGA can obtain the optimal total cost. The Gantt chart corresponding to the optimal solution obtained by IGA is shown in Fig. 1. The total completion time is 40 minutes, the carbon emission is 279 kg, and the total cost is 1097.5 yuan. However, in 10 runs, the stability of IGA is better than TGA, and the average total cost is 8.95 yuan lower than that of TGA.
Table 1 performance comparison of IGA and TGA

| Comparison method | Optimal total cost (yuan) | Worst total cost (yuan) | Average total cost (yuan) | Standard deviation (yuan) |
|------------------|---------------------------|-------------------------|--------------------------|--------------------------|
| TGA              | 1097.5                    | 1123.25                 | 1112.58                  | 9.78                     |
| IGA              | 1097.5                    | 1118.5                  | 1103.63                  | 5.80                     |

Suppose that machine M1 breaks down at the 5th minute, and the estimated maintenance time is 10 minutes. If the right shift strategy is used for partial rescheduling, the new scheduling is shown in Fig. 2. The maximum completion time is 44 minutes, the carbon emission is 293.4 kg, and the total cost is 1173.5 yuan. The optimal rescheduling solution can be obtained by TGA and IGA, as shown in Fig. 3. The maximum completion time is 41 minutes, the carbon emission is 269.4 kg, and the total cost is 1083.5 yuan. It can be seen that the rescheduling method is better than the partial rescheduling method based on the right shift strategy. The maximum completion time is shortened by 3 minutes, the carbon emission is reduced by 24 kg, and the total cost is reduced by 90 yuan. The comparison results of partial rescheduling and complete rescheduling are shown in Table 2. The results of the TGA and IGA related to rescheduling are compared, as shown in Table 3. It can be seen that the stability of IGA is better than TGA, and the average total cost is reduced by 15.68 yuan.

Fig. 1 Gantt chart of optimal scheduling obtained by IGA

Fig. 2 new scheduling Gantt chart after moving the affected process to the right

Fig. 3 new scheduling Gantt chart obtained by IGA

6. Summary
To solve the high carbon emission of machines in the production process, we established an optimization scheduling model for discrete manufacturing environments with random machine failure. The model is solved by using an improved genetic algorithm. Green manufacturing with low consumption and emission reduction is achieved while ensuring high efficiency of production tasks. To respond to machine failures that may occur at any time in real-time, we used the rolling window...
mechanism driven by abnormal events and the entire rescheduling strategy to adjust the original scheduling. To describe the carbon emission in the production process as accurately as possible, we considered the carbon emission parameters of the machine in different states in the carbon emission measurement method. For the model solving algorithm, this paper improves the initialization population strategy and crossover operation. The experimental results show that the proposed low-carbon scheduling method based on improved GA can reduce the average total cost by 8.95 yuan compared with the traditional GA based low-carbon scheduling method in previous literature. When there is a machine failure, the average total cost of this method can be reduced by 15.68 yuan compared with the previous methods, verifying the effectiveness of the proposed method.

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Table 2 Comparison of partial and complete rescheduling results

| Comparison method          | Maximum completion time (min) | Optimal carbon emissions (kg) | Optimal total cost (yuan) |
|----------------------------|--------------------------------|-------------------------------|---------------------------|
| right shift strategy       | 44                             | 293.4                         | 1173.5                    |
| TGA rescheduling           | 41                             | 269.4                         | 1083.5                    |
| IGA rescheduling           | 41                             | 269.4                         | 1083.5                    |

Table 3 stability comparison of TGA and IGA

| Comparison method | Optimal total cost (yuan) | Worst total cost (yuan) | Average total cost (yuan) | Standard deviation (yuan) |
|-------------------|---------------------------|-------------------------|--------------------------|--------------------------|
| TGA rescheduling  | 1083.5                    | 1129                    | 1105.23                  | 18.60                    |
| IGA rescheduling  | 1083.5                    | 1127.5                  | 1089.55                  | 14.31                    |

References
[1] Mestl, 36H.E.S., Aunan, K., Fang, J. (2005) Cleaner production as climate investment: integrated assessment in Taiyuan City China. J. Clean. Prod., 13: 57-70.
[2] Wu, X. L., Cui, Q. (2018) Multi-objective flexible job shop scheduling problem with renewable. Comput. Integr. Manuf., 24: 2792-2807.
[3] Shi, J.L., Liu, F., Xu, D.J. (2009) Decision Model and Practical Method of Energy saving in NC Machine Tool. China Mechanical Engineering, 20: 1344-1346.
[4] Seng, D.W., Li, J.W., Fang, X.J., Zhang, X.F., Chen, J. (2018) Low-carbon flexible job-shop scheduling based on improved non-dominated sorting genetic algorithm-II. Int. J. Simul. Model., 17(4): 712-723.
[5] Zhang, R., Chiong, R. (2016) Solving the energy-efficient job shop scheduling problem: a multi-objective genetic algorithm with enhanced local search for minimizing the total weighted tardiness and total energy consumption. J. Clean. Prod., 112: 3361-3375.
[6] Lei, D.M. (2017) Novel teaching-learning-based optimization algorithm for low carbon scheduling of flexible job shop. Control and Decision, 32:1621-1627.
[7] Cai, Y.Y., Ji, W.X., Zhang, C.Y., Peng, W., Qiu, Y.T. (2019) Low-carbon Scheduling of Discrete Manufacturing Workshop Driven by Manufacturing Resources Real-time Status Monitoring. Mechanical Science and Technology for Aerospace Engineering, 39:2792-2807.
[8] Wang, J., Yang, J.H., Zhang, Y.F., Ren, S., Liu, Y. (2019) Infinitely repeated game based real-time scheduling for low-carbon flexible job shop considering multi-time periods. J. Clean. Prod., 247: 119093.
[9] Zhang, G.H., Gao, L., Shi, Y. (2011) An effective genetic algorithm for the flexible job-shop scheduling problem. Expert. Syst. Appl., 38: 3563-3573.
[10] Nie, L., Wang, X.G., Liu, K., Bai, Y.W. (2019) A rescheduling approach based on a genetic
algorithm for flexible scheduling problems subject to machine breakdown. J. Phys. Conf. Ser., 1453, 012018.

[11] Zhang, G.H., Dang, S.J. (2017) Research on low carbon flexible Job-Shop scheduling problem considering machine speed. Application research on Computers, 34: 1072-1075.