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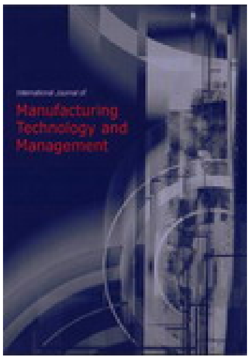


**International Journal of Manufacturing Technology and Management**

ISSN online: 1741-5195 - ISSN print: 1368-2148
https://www.inderscience.com/ijmtm

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**DOI:** 10.1504/IJMTM.2023.10056616

**Article History:**

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| Received: | 29 December 2022 |
| Last revised: | 14 February 2023 |
| Accepted: | 21 March 2023 |
| Published online: | 28 January 2025 |

# Multi-product supply chain scheduling method based on hybrid genetic algorithm

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**Abstract:** In order to solve the shortcomings of traditional methods such as high Hamming loss value and low demand supply rate, a multi-product supply chain scheduling method based on hybrid genetic algorithm was designed. First, build supply time series, and sort the priority of supply chain scheduling according to the priority attribute values of backup plans in each link of the supply chain closed-loop model. Then, taking the shortest scheduling time as the objective function and the location constraints of the revolving warehouse as the constraints, the scheduling results are obtained by combining the genetic algorithm. In order to avoid the genetic algorithm falling into the local optimum, the simulated annealing algorithm is introduced to solve the global optimal solution of the objective function to achieve the coordinated scheduling of the supply chain. The experimental results show that this method can achieve multi-product supply chain scheduling more reasonably and effectively.

**Keywords:** genetic algorithm; simulated annealing algorithm; multi-product supply chain; supply chain scheduling; dispatch time; positioning of turnover warehouse.

**Reference** to this paper should be made as follows: Yang, L. (2025) 'Multi-product supply chain scheduling method based on hybrid genetic algorithm', *Int. J. Manufacturing Technology and Management*, Vol. 39, Nos. 1/2, pp.122–136.

**Biographical notes:** Lingmin Yang received her PhD in Traffic and Transportation Engineering from Wuhan University of Technology in 2019. She is currently a Lecturer in the College of Management, Hubei University of Education. Her research interests include transportation planning and management, traffic behaviour and intelligent transportation.

## 1 Introduction

With the development of logistics technology, a certain scale of product supply chain has been formed in many fields. There is a complex network structure in the multi-product supply chain, and it is often difficult to meet the needs of customers by relying on a single supplier. The key point in the supply chain is the coordination and collaboration between the various links, and the reasonable distribution of product orders in the supply chain to achieve the smooth operation of the supply chain (Zhang et al., 2021). The multi-product supply chain is centred on the production link, turnover warehouse and customer, and needs to supply or receive goods at each supply node in the supply process. If problems occur in one of the links in this process, it is difficult for the entire supply chain to achieve coordination (Cai, 2019). At the same time, the lack of timely and accurate product orders, delivery time and other information will lead to a certain degree of blindness in the subsequent links, increasing the uncertainty of the supply chain, which will have a certain impact on the supply chain regulation (Tang et al., 2019).

According to Li et al. (2019), the problem between 'scale effect' and 'customer demand' should be solved by optimising the scheduling of the supply chain. Therefore, the method is based on fuzzy mathematics and quantifies the multi-stage fuzzy scale effect. In the process of processing, the minimum cost, maximum customer satisfaction and supply chain coordination are taken as the objectives to complete the optimal scheduling of the supply chain. The experimental results show that this method can effectively reduce the production cost of products through supply chain scheduling, but there is a problem that the priority of supply chain scheduling is not reasonable. Zhang and Zhang (2019) designed a joint scheduling process integrating raw material purchase, continuous production and efficient distribution based on continuous production environment and minimum scheduling time. For this process, the two-dimensional matrix is used to record the optimal weight of supply chain transportation and material combination, and the continuity of the production process is ensured by decoding in stages. Then, the artificial bee colony algorithm is used to schedule the transportation vehicles to achieve the joint optimal scheduling of the supply chain. The experimental results show that this method can effectively divide the supply chain scheduling carriers and reduce the scheduling time of each stage, but its Hamming loss value is high, and the scheduling effect needs to be further improved. The research in Bo et al. (2021) is mainly aimed at two-stage manufacturing supply chain, reducing the manufacturing cost and time conflict cost of suppliers as much as possible, taking the delivery time of goods as a constraint condition, designing a coordination scheduling model according to the revenue sharing contract, and using adaptive genetic algorithm to solve the optimal value of the model, so as to avoid the interruption of goods processing orders as much as possible. The experimental results show that this method can avoid the interruption of commodity processing orders, but the product supply rate on demand is low.

However, in practical application, it is found that the above traditional methods have poor rationality in ranking the supply chain scheduling priorities, resulting in high Hamming loss value, and there is also great room for improving the on-demand supply rate of products. In order to solve the shortcomings of traditional methods, this study designed a multi-product supply chain scheduling method based on hybrid genetic algorithm. The technical route of this method is as follows:

1 Build a dynamic closed-loop multi-product supply chain model, and divide the supply chain into three parts: supply point (raw material supplier, manufacturing support enterprise, and production workshop), logistics and transportation (including turnover warehouse) and demand point (customer).

2 Build a supply time series for different supply links, including the time spent in the raw material supply link, the time spent in the product production link, and the time spent in the product transportation and distribution link.

3 Based on the product supply time series, product resource quantity, etc., the priority of supply chain scheduling is sorted according to the priority attribute value of each link backup plan in the supply chain closed-loop model.

4 Set the shortest scheduling time as the objective function, and then describe the supply cost of each turnover warehouse as an increasing convex function of the product supply, and design the constraint conditions for the location of the turnover warehouse.

5 Combining the objective function of the shortest scheduling time and the positioning constraints of the turnover warehouse, the multi-product supply chain scheduling problem is described as the problem of reasonably arranging the transportation of products from the supply point to the turnover warehouse, and the transportation of products from each turnover warehouse to each demand point. Combining the genetic algorithm's genetic, crossover, and mutation process, the preliminary scheduling results are obtained by finding the best supply and demand scheme, and the coordinated scheduling of the supply chain is realised.

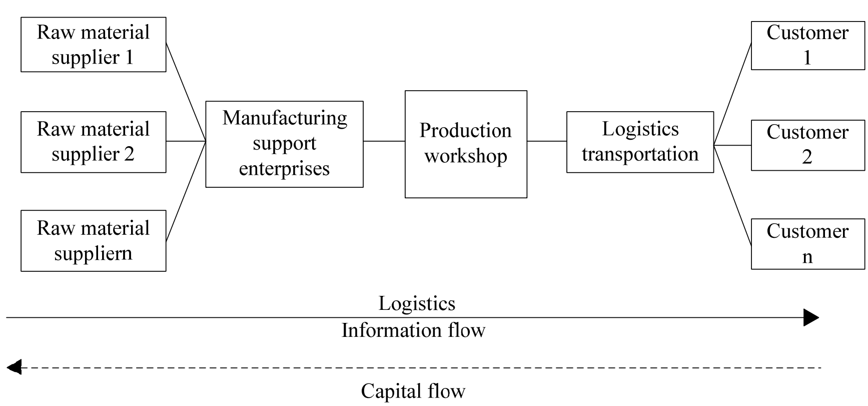
## 2 Multi-product supply chain closed-loop model and product supply time series analysis

### *2.1 Construction of closed-loop model of multi-product supply chain*

Due to the large randomness of the supply chain, each link in the supply chain will directly affect the efficiency and stability of the multi-product supply chain. Therefore, a multi-product supply chain closed-loop model is constructed, which is conducive to orderly connecting all links and reducing the negative impact of the randomness of different links on the supply chain scheduling.

According to the basic supply chain structure, this research has designed a dynamic closed-loop multi-product supply chain model considering product resource constraints, as shown in Figure 1.

**Figure 1** Dynamic closed-loop multi-product supply chain model



In Figure 1, there are three phases: supply point (raw material supplier, manufacturing support enterprise, and production workshop), logistics transportation (including turnover warehouse), and demand point (customer). After orderly connecting each phase, a dynamic supply chain model is established and used as the carrier of multi-product supply chain scheduling.

In the dynamic closed-loop multi-product supply chain model, each link will directly affect the efficiency and stability of the multi-product supply chain. Therefore, considering the complexity of the product supply process, the following assumptions are made:

1 In the process of product supply, the raw material inspection and testing conducted at the raw material supplier shall not be included in the total supply time;

2 Considering the goal of low carbon and environmental protection, compared with the external resources involved in the supply chain, the manufacturing link gives priority to the use of recycled materials for remanufacturing.

In the process of supply chain scheduling, there is no competition between different links (Xie et al., 2020). Therefore, it is also necessary to maximise the profit between each link as much as possible. At any moment, the resource allocation function of the multi-product supply chain is:

$$f = \frac{\frac{n_c - n_t}{m_t^r}\left(m_t^1 - m_t^2\right)}{c} \tag{1}$$

where, $m_t^1$ represents the quantity of raw materials required by the workshop at time $t$, and $m_t^2$ represents the quantity of raw materials that can be recycled by the workshop at time $t$, $n_t$ represents to the production volume of the workshop, $n_c$ represents to the purchase volume of customers, $m_t^r$ represents to the remaining raw material quantity at time $t$, and $c$ represents to the product inventory cost.

Due to the randomness of the multi-product supply chain, the fuzzy information entropy of the resource allocation function designed above is calculated as follows:

$$s_f = f \times p_\varepsilon \times \gamma \tag{2}$$

where $\varepsilon$ represents the set of random fuzzy information in the multi-product supply process, $p_\varepsilon$ represents the probability of fuzzy information entropy in the set, and $\gamma$ represents the fitness of resource allocation in each link of the supply chain (Liu and Yao, 2020; Qi et al., 2019).

## *2.2 Construction of product supply time series*

Based on the dynamic closed-loop multi-product supply chain model built in Section 2.1, the supply time series is built for different supply links.

Sequence 1 Time $t_1$ spent in the raw material supply phase is also the time required to transport the raw materials from the supplier to the production workshop. The calculation process is as follows:

$$t_1 \geq t_{mov}^1 + t_{write}^1 \tag{3}$$

where $t_{mov}^1$ represents the transportation time of the raw materials of the product, and $t_{write}^1$ represents the waiting time of the raw materials of the product in the loading area.

Sequence 2 Time $t_2$ spent in product production. This time indicator is also the time required for product processing. The calculation process is as follows:

$$t_2 \geq \sum_{i=1}^{n_t} t_{ij} \tag{4}$$

where $t_{ij}$ represents the processing time of the $i^{\text{th}}$ product in the $j^{\text{th}}$ operation.

Sequence 3 Time $t_3$ spent in product transportation and distribution. This time indicator is also the time required to complete the transportation and distribution of manufactured products to customers. The calculation process is as follows:

$$t_3 \geq t_{mov}^3 + t_{write}^3 \tag{5}$$

where $t_{mov}^3$ represents the time required to transport the finished products to the unloading area of the logistics centre, and $t_{write}^3$ represents the time required for all processing procedures to complete the products waiting for transportation and distribution.

To sum up, the established product supply time series is $t = \{t_1, t_2, t_3\}$.

## 3 Multi-product supply chain scheduling

### *3.1 Prioritisation of multi-product supply chain*

The scheduling problem of multi-product supply chain should be sorted according to the priority of the plan to help determine the best scheduling scheme. Conventional priority ranking adopts priority weight ranking method, which is measured by subjective evaluation method and relatively objective AHP method (Su et al., 2022). This method has a high degree of randomness and subjective colour. Through in-depth analysis of the data, the information obtained is quite different from the actual situation (Wang et al., 2021). To solve this problem, this study uses the principles of informatics to rank the backup plans in each link of the supply chain closed-loop model according to the priority attribute values of the backup plans in each link of the supply chain closed-loop model, taking the above product supply time series, product resource quantity, etc. as indicators.

Suppose that the observation value $g_j$ of the scheduling priority attribute $p_j$ contains $l$ categories, then the measure $c_j$ of $p_j$ is:

$$c_j = \{c_{j1}, c_{j2}, \cdots, c_{lj}\} \tag{6}$$

If the scheduling priority ranking is considered as a sample selection process, the weight information of $p_j$ to make sample $g_j$ in $l$ categories is $1 / l$. It can be seen that attribute $p_j$ does not play a decisive role in the priority ranking of sample $g_j$. On the contrary, if there is only one 1 in $c_j$ and the rest is 0, the entropy value of the scheduling task is 0, indicating that attribute $p_j$ is important. Thereby:

$$z_j = 1 + \frac{1}{\log l} \sum_1^l c_j \tag{7}$$

It can be seen that when $0 < z_j < 1$, the entropy value of the scheduling task is the minimum. When $z_j = 1$, the weight value of attribute $p_j$ makes the entropy value of sample $g_j$ in the first class 1 and the entropy value in other classes 0, which shows that $p_j$ has a great influence on the scheduling priority; When $z_j = 0$, attribute $p_j$ divides sample $g_j$ into weight sorting. At this time, the more concentrated the value of $c_j$ is, the greater the effect of attribute $p_j$ on the priority sorting of $g_j$, so the priority sorting weight of multi-product supply chain scheduling is:

$$\omega_j = \left( c_j \times \frac{1}{l} \right)^T \tag{8}$$

where $T$ represents transposition.

## 3.2 Construction of multi-product supply chain scheduling objective function

In combination with Figure 1, the quantity of products supplied to the warehouse centre and customers in the logistics transportation link should be less than the production capacity of the production workshop. The efficiency of product supply seriously affects the demand, circulation and production costs of the supply chain. Therefore, before scheduling, the objective function should be set with the shortest scheduling time as the objective.

Analyse the characteristics of demand point, supply point and turnover warehouse in the supply chain, so that the shortest transportation time target of the logistics route formed by the supply point and demand point is divided into two parts: one is the transportation time from the workshop to the turnover warehouse, and the other is the transportation time from the turnover warehouse to the customer. The sum of the two should be less than or equal to the limit of the warehouse demand point on the product distribution time (Song et al., 2021; Lian et al., 2022). On this basis, the objective function is designed from the perspective of time constraints, assuming that the product material turnover warehouse is $I = \{I_1, I_2, \cdots, I_M\}$, the demand point is $J = \{J_1, J_2, \cdots, J_N\}$, and the supply point is $K = \{K_1, K_2, \cdots, K_L\}$. In addition, set $n_{IJ}$ as the transportation volume from the turnover warehouse to the demand point, $n_{KI}$ as the transportation volume from the supply point to the turnover warehouse, $p_{IJ}$ as the transportation unit price from the turnover warehouse centre to the demand point, $p_{KI}$ as the transportation unit price from the supply point to the turnover warehouse centre, $t_{IJ}$ as the transportation time from the warehouse supply point to the demand point, and $t_{Jk}$ as the transportation time from the demand point to the warehouse supply point; $h$ is the maximum number of available turnover warehouses, and the objective function of the shortest scheduling time is as follows:

$$\min t = \sum_{I=1}^{M} \sum_{J=1}^{N} p_{IJ} n_{IJ} + \sum_{I=1}^{M} t_K + \sum_{K=1}^{L} \sum_{I=1}^{M} p_{KI} n_{KI} \tag{9}$$

where $t_K$ represents the limit of supply point on delivery time. If $n_J$ is the demand quantity at the demand point and $n_K$ is the supply quantity at the supply point, equation (9) satisfies the following relationship:

$$\begin{cases} \sum_{I=1}^{M} n_{IJ} \geq n_J \\ \sum_{I=1}^{M} n_{KI} \leq n_K \\ t_{IJ} + t_{Jk} \leq t_K \end{cases} \tag{10}$$

If formula (1) in formula (10) is satisfied, it indicates that the revolving warehouse can meet the requirements of the warehouse at the demand point. If formula (2) in formula (10) is satisfied, it indicates that the quantity of goods transported from the supply point to the turnover warehouse is less than the production capacity of the production workshop. If formula (3) in formula (10) is satisfied, it means that the sum of the time from the supply point to the turnover warehouse is less than or equal to the supply time limit of the product at the demand point.

### 3.3 *Implementation of multi-product supply chain scheduling based on genetic annealing algorithm*

On the basis of sorting the priority of multi-product supply chain scheduling and establishing the objective function of the shortest scheduling time, genetic annealing algorithm is used to achieve supply chain scheduling. Genetic annealing algorithm is the combination of genetic algorithm and annealing algorithm. It is a hybrid genetic algorithm with the comprehensive characteristics of the two methods (Yue and Shang, 2019). In the process of applying the genetic annealing algorithm to the multi-product supply chain scheduling, the real number is selected as the chromosome code, and the multi-product supply chain scheduling problem is described as the problem of reasonably arranging the supply point to transport the product $n_{KI}$ to the turnover warehouse, and each turnover warehouse to transport the product $n_{IJ}$ to each demand point. The optimal scheduling result is obtained by obtaining the optimal supply and demand scheme.

#### 3.3.1 *Design the location constraints of the revolving warehouse*

Suppose $G_I$ is the supply capacity of each supply point, $D_K$ is the demand quantity at the demand point, $U$ is the unit circulation cost of the turnover warehouse, $S$ is the supply capacity of the supply point, and $W$ is the capacity of the turnover warehouse, $\gamma \in [0, 1]$ is an empirical parameter, and $P$ is the fixed investment of turnover warehouse; $B$ is a Boolean value. When the corresponding turnover warehouse is selected, it is marked as 1, and when it is not selected, it is marked as 0 (Sun et al., 2021; Wang et al., 2019; Cai et al., 2019).

Regardless of the impact of different products on supply costs and the situation of demand exceeding supply, in order to meet the actual demand of the multi-product supply chain, the following constraints are made:

$$\sum_{I=1}^{M} G_I \geq \sum_{K=1}^{L} D_K \tag{11}$$

Since the supply cost is proportional to the product supply, the supply cost of each turnover warehouse can be described as an increasing convex function of the product supply, as shown below:

$$F_{IJ} + U \times n_{KJ} \times \gamma \tag{12}$$

Since the unit transportation cost between the product supply point and each turnover warehouse, and between each turnover warehouse and each demand point is a known quantity, the positioning constraints of the turnover warehouse can be designed as follows:

$$F\left(B, n_{IJ}, n_{KJ}\right) = \frac{\gamma \times W}{p \times G_I} \sum_{I=1}^{M} \sum_{J=1}^{N} B \times U \times n_{IJ} + \sum_{J=1}^{N} \sum_{K=1}^{L} D_K \times n_{KJ} \tag{13}$$

It meets the following requirements:

$$\begin{cases} \text{s.t.} \sum_{K=1}^{L} D_K S \\ \text{s.t.} \sum_{K=1}^{L} D_K \leq W \\ B = 0 \rightarrow \sum_{J=1}^{N} n_{KJ} = \sum_{I=1}^{M} n_{IJ} = 0 \\ \sum_{I=1}^{M} W_{IK} = \sum_{K=1}^{L} D_k \end{cases} \tag{14}$$

In formula (14), formula (1) indicates that the output of each supply point does not exceed its supply capacity. Formula (2) indicates that there is no product stranded in each turnover warehouse, and there is no shortage of supply, and the product supply cannot exceed the capacity of the turnover warehouse. Formula (3) indicates that the unselected turnover warehouse capacity is 0. Equation (4) shows that the total output of all supply points is equal to the total input of all demand points.

### *3.3.2 Realisation of multi-product supply chain scheduling*

Multi-product supply chain scheduling problem is a kind of combinatorial optimisation problem. Therefore, this research combines the shortest scheduling time objective function in Subsection 3.2 and the revolving warehouse location constraint in Subsection 3.3.1, and uses genetic annealing algorithm to complete the iterative scheduling of multi-product supply chain.

In order to make the genetic annealing algorithm better adapt to the multi-link process of multi-product supply chain scheduling, this paper has improved and optimised it. In order to maintain the elite strategy, individual dislocation and the highest degree of intersection, the curve type speed adaptive operator is selected to ensure that excellent individuals are not injured by the outside world. When the individual physical capacity is close to the maximum, select the individual method of elite retention strategy and roulette synthesis, and the individual will not be damaged in the process of crossover and mutation. At the same time, in order to avoid the algorithm falling into local optimum, it is solved by the subsequent adaptive crossover mutation and annealing operation. The algorithm follows the following principles:

1 Initial population: The initial population with random cost is usually used. This method can also determine the initial population through approximate interval estimation, and reduce the cost of the algorithm. The initial population size is usually 40–200.

2 Variation probability: when the variation probability is too small to ensure the diversity of the population, there will be some genes that cannot be inherited to the next generation and cannot be repaired. However, if the mutation probability is too large, the diversity of the population will be guaranteed, but the high-order model will be destroyed. Therefore, it is appropriate to select 0.001~0.2 as the variation probability.

3 Crossing probability: add a new population through this step. When the solution of the problem is close to the optimal solution, the mutation algorithm is used to speed up the solution and obtain the optimal solution. In the case that the population of the algorithm is relatively discrete, in order to prevent distortion of the optimal solution due to mutation, in this case, it is necessary to select a smaller crossover probability. On the contrary, when the population of the algorithm is relatively concentrated, it is necessary to select a larger crossover probability to prevent early convergence. Generally, 0.4~0.99 can be obtained.

4 Evolution algebra: The number of iterations depends on the complexity of the algorithm. With the growth of chromosome length, the diversity of the population will increase. At this time, the number of evolution generations cannot be too small, or the algorithm will not converge and lead to premature linearity. As the number of evolutionary generations increases, time and system resources are wasted. Generally, 100~3,000 evolutionary generations are taken. In this study, the evolutionary algebra is set to 500.

On this basis, the specific multi-product supply chain scheduling process is designed as follows:

Step 1 Initialise the parameters, and determine the shortest scheduling time objective function and turnover warehouse location constraints.

Step 2 Encode chromosomes. The spatial parameters (turnover warehouse, demand point, supply point) of the multi-product supply scheduling problem are converted into chromosomes, and according to certain rules, through the process of gene combination, this process is called the coding process.

Step 3 Generate the initial population. When initialising the population, set the screening conditions to make the initial population meet the screening conditions.

Step 4 Set fitness function. In this paper, the reciprocal of the shortest scheduling time objective function is taken as the fitness function, and the time window satisfaction is taken as the initial screening condition. If the reciprocal of the overall objective function is too small for observation and analysis, the fitness function can be set as:

$$F_q = \frac{\sigma}{\min t} \tag{15}$$

where $\sigma$ represents a constant greater than the overall objective function.

Step 5 Select. Suppose $q$ represents the chromosome of a product supply link, $S$ represents the number of scheduling population, and the fitness function $F_q$ is known, then the selection process is: First, set the fitness function $F_q$ in the chromosome $q$ objective function min $t$, and sum the fitness functions to get $\sum_{q=1}^{S} F_q$, then calculate the selection probability $p_{1q}$ and cumulative probability $p_{2q}$ of chromosome $q$, and calculate the number of times to select chromosomes by using the simulated gambling table operation method. $p_{1q}$ and p $p_{2q}$ are calculated as follows:

$$p_{1q} = \frac{F_q}{\sum_{q=1}^{S} F_q} \tag{16}$$

$$p_{2q} = \sum_{q=1}^{S} F_q \tag{17}$$

Step 6 Cross. In a random population, some genes of two different individuals are exchanged according to a certain crossing probability. According to the cross expansion of search scope, more groups are generated. Suppose the individuals at positions 3, 6, 8 and 9 are selected for crossing, which can be expressed as:

Parent chromosome 1: 1 2 <u>3</u> 4 5 <u>6</u> 7 <u>8 9</u>

Parent chromosome 2: 5 8 <u>9</u> 5 2 <u>5</u> 7 <u>9 0</u>

Then, children will retain these four positions, which is expressed as:

Offspring chromosome 1: * * 3 * * 6 * 8 9

Offspring chromosome 2: * * 9 * * 5 * 9 0

where * indicates the position where cross replacement is required. Since the coding heterogeneities need to be noted when crossing, the * position gene of the offspring chromosome 1 is extracted from the parent chromosome 2.

Step 7 Mutation. In the population, the real number mutation operation method of crossing before inversion is adopted to change the genes of some individuals.

Step 8 In order to speed up the efficiency of the genetic algorithm and avoid algorithm traps, the iteration is gradually cooled through the annealing process to maintain the lowest energy state, so as to select appropriate parameters to ensure the convergence of the genetic algorithm and remove the upper and lower speed limit.

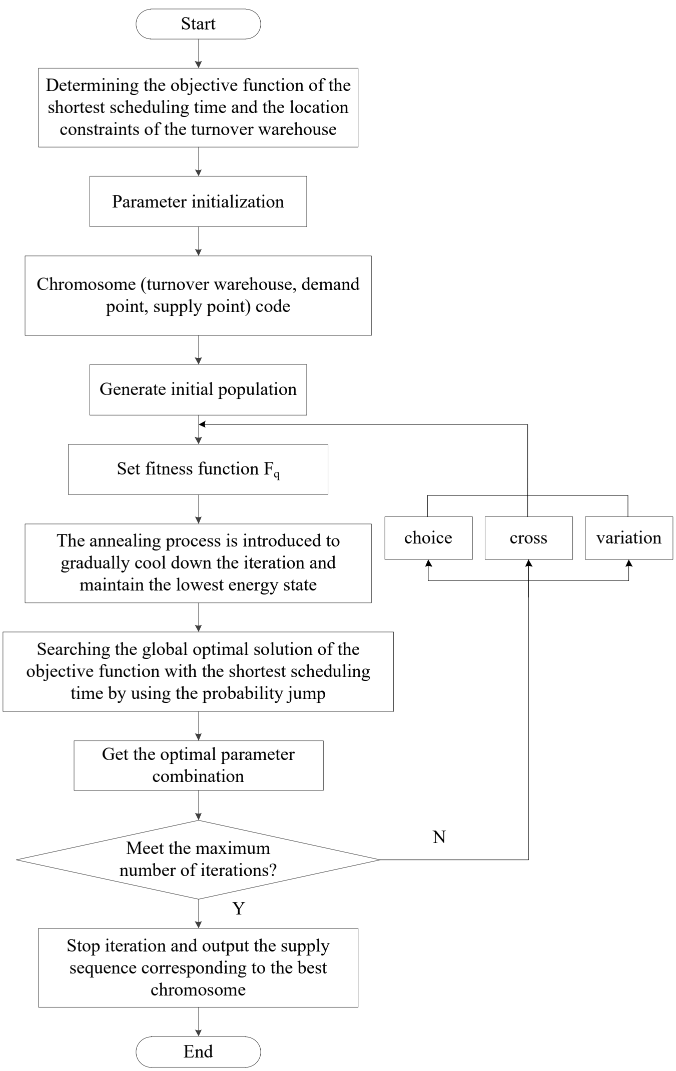
Simulated annealing algorithm takes a higher temperature as the starting point by simulating the process of metal heat treatment. With the temperature gradually decreasing, in the solution space, search the global optimal solution of the objective function with the shortest scheduling time by using the probability jump to get the best combination of the transportation volume from the revolving warehouse to the demand point, the transportation volume from the supply point to the revolving warehouse, the transportation time from the warehouse supply point to the demand point, the transportation time from the demand point to the warehouse supply point, and the maximum number of available revolving warehouses, as follows:

$$opt = \{n_{IJ}, n_{KI}, t_{IJ}, t_{Jk}, h\} \tag{18}$$

Step 9 Terminate. When the operation reaches a certain number of iterations, the shortest scheduling time objective function can be achieved. At this time, the supply sequence corresponding to the best chromosome is selected as the optimal solution output, which improves the industrial efficiency between supply points, turnover warehouses and demand points.

To sum up, the multi-product supply chain scheduling process is shown in Figure 2.

**Figure 2** Multi-product supply chain scheduling flow chart



To sum up, genetic annealing algorithm is used to schedule multi-product supply chain. Genetic algorithm has the characteristics of group search, which can effectively avoid searching for some unnecessary points, and is conducive to improving the efficiency of supply chain scheduling; Simulated annealing algorithm has the advantages of simple description, high efficiency and not easy to be constrained by conditions, which can further reduce the complexity of supply chain scheduling. Combining the two to schedule multi-product supply chain can improve the scheduling efficiency of multi-product supply chain and improve the work efficiency of supply chain.

## 4 Experiment and result analysis

In order to verify the effectiveness of the multi-product supply chain scheduling method based on hybrid genetic algorithm, the following test process is designed.

### *4.1 Experimental scheme design*

1 Experimental sample data: Set the experimental environment as follows: The data source is SCM supply chain management database. The database is a knowledge rule base with consistent data rule attributes, including eight storage categories and a total of 12,356.47 GB of data. The data confidence in the database is 1, and the minimum support is 0.005.

2 Experimental indicators

In the experiment, the application performance of different methods was verified with Hamming loss and product demand supply rate as indicators.

- In the field of machine learning, Hamming loss is a commonly used measure, which focuses on the wrongly classified sequence data, thus reflecting the rationality of supply chain scheduling priority from the side. The lower the Hamming loss is, the more reasonable the dispatching method is. The calculation formula is as follows:

$$\varphi = \frac{\sum_{1}^{N} \frac{|y-e|}{|A|}}{N} \tag{19}$$

where $y$ represents a binary vector, $N$ represents the total amount of scheduling, $A$ represents the set of scheduling priority sequences, and e represents the symmetric difference between two scheduling sequences.

- The application effect of different methods is analysed by using the product demand supply rate. The calculation process of this indicator is as follows:

$$\psi = \frac{D_1 - D_2}{D_3} \tag{20}$$

where $D_1$ represents the product quantity obtained at the demand point, $D_2$ represents the product quantity to be dispatched by the turnover warehouse, and $D_3$ represents the production quantity at the supply point.

3 Comparison method: To avoid the oneness of the experimental results, the method of Zhang and Zhang (2019) and method of Bo et al. (2021) are used as the comparison methods to complete the performance verification together with the method of this paper.

## *4.2 Results and analysis*

First, the Hamming loss of different dispatching methods is analysed, and the results are shown in Table 1.

**Table 1** Comparison of Hamming loss of different dispatching methods

| *Quantity of products to be dispatched/piece* | *Hamming loss* | | |
|---|---|---|---|
| | *Method of this paper* | *Method of Zhang and Zhang (2019)* | *Method of Bo et al. (2021)* |
| 5,000 | 0.15 | 0.33 | 0.26 |
| 10,000 | 0.12 | 0.42 | 0.33 |
| 15,000 | 0.09 | 0.35 | 0.24 |
| 20,000 | 0.17 | 0.36 | 0.26 |
| 25,000 | 0.06 | 0.36 | 0.32 |
| 30,000 | 0.05 | 0.35 | 0.31 |

Analysis of the data shown in Table 1 shows that the Hamming loss of method of this paper, method of Zhang and Zhang (2019) and method of Bo et al. (2021) shows a rising trend. In the experiment, with the increase of the quantity of products to be scheduled, the hamming loss of method of this paper varies from 0.05–0.17, the hamming loss of method of Zhang and Zhang (2019) varies from 0.33–0.42, and the hamming loss of method of Bo et al. (2021) varies from 0.24–0.33. In contrast, the Hamming loss value of method of this paper is smaller, which indicates that method of this paper is more reasonable in prioritising supply chain scheduling. This is because the method in this paper constructs a closed-loop model of the product supply chain before the supply chain scheduling. This model is conducive to orderly connecting all links, reducing the negative impact of the randomness of different links on the supply chain scheduling, thus improving the rationality of the supply chain scheduling priority.

**Table 2** Statistical table of demand supply rate of products by different methods

| *Quantity of products to be dispatched/piece* | *Demand supply rate of products / %* | | |
|---|---|---|---|
| | *Method of this paper* | *Method of Zhang and Zhang (2019)* | *Method of Bo et al. (2021)* |
| 5,000 | 92.54 | 81.37 | 80.81 |
| 10,000 | 92.63 | 85.33 | 78.88 |
| 15,000 | 95.49 | 82.30 | 77.85 |
| 20,000 | 97.36 | 79.42 | 79.72 |
| 25,000 | 94.70 | 85.45 | 81.74 |
| 30,000 | 92.14 | 88.30 | 81.21 |

The product demand supply rate of method of this paper, method of Zhang and Zhang (2019) and method of Bo et al. (2021) is compared and analysed. The results are shown in Table 2.

It can be seen from the results shown in Table 2 that the on-demand supply rate of products of method of this paper, method of Zhang and Zhang (2019) and method of Bo et al. (2021) shows a changing trend. In the experiment, with the increase of the quantity of products to be scheduled, the demand supply rate of method of this paper varies from 92.14% to 97.36%, the demand supply rate of method of Zhang and Zhang (2019) varies from 79.42% to 88.30%, and the demand supply rate of method of Bo et al. (2021) varies from 77.85% to 81.74%. In contrast, the product demand supply rate is higher, indicating that the method of this paper improves the efficiency of the multi-product supply chain. This is because this method uses genetic algorithm and simulated annealing algorithm to optimise the supply chain scheduling. Genetic algorithm can effectively avoid searching for some unnecessary points. Simulated annealing algorithm has the advantage of high efficiency, which is conducive to reducing the complexity of supply chain scheduling and improving scheduling efficiency.

## 5 Conclusions

In order to realise the reasonable scheduling of multi-product supply chain, a multi-product supply chain scheduling method based on hybrid genetic algorithm is proposed. The main innovations of this method are as follows:

1 On the basis of building a dynamic closed-loop multi-product supply chain model, a supply time series is built for different supply links, and the priority of supply chain scheduling is sorted according to the priority attribute value of the backup plan of each link in the supply chain closed-loop model.

2 The objective function is set with the shortest scheduling time as the goal, and the location constraint of the turnover warehouse is designed, and the preliminary scheduling results are obtained by combining the genetic algorithm. On this basis, simulated annealing algorithm is introduced to solve the problem of genetic algorithm falling into local optimisation through annealing operation, and supply chain collaborative scheduling is realised.

3 According to the experimental results, the Hamming loss of this method varies from 0.05 to 0.17, and the on-demand supply rate of products varies from 92.14% to 97.36%, which shows that this method is more reasonable for scheduling priority of supply chain and improves the efficiency of multi-product supply chain.

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