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Research on E-commerce Supply Chain Inventory Optimization and Multi-Objective Planning with Database Technical Support

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ABSTRACT
This paper first describes the basic theoretical knowledge of supply chain inventory control and analyzes the existing supply chain inventory control strategies. For the relationship between safety stock and customer service level and inventory cost, the safety stock factor is used as a decision variable, and a supply chain multilevel inventory control model is established under (t,s,S) inventory replenishment strategy. Secondly, the selection operator, crossover operator and mutation operator of the traditional genetic algorithm are adaptively improved, and an improved multi-objective adaptive genetic algorithm is proposed, and this algorithm is used to solve the inventory optimization with the two objectives of supply chain inventory cost and customer service level. The simulation results of the algorithm show that the improved genetic algorithm has better convergence and the obtained Pareto optimal solution set is closer to the real optimal frontier. When the IGD value is minimized and kept constant, the convergence speed of this paper's algorithm (34 times) is 38.18% lower than that of the traditional genetic algorithm (55 times), and the model converges faster while its Pareto solution set is more uniformly distributed. Example results also show that using the model in this paper can reduce the inventory of each node in the supply chain system and reduce the transportation cost.

Keywords: Supply Chain Inventory Control, Inventory Replenishment Strategy, Multilevel Inventory Control Model, Selection Operator, Multi-Objective Adaptive Genetic Algorithm

1. Introduction

With the development of economic globalization, e-commerce has become an important part of economic development in China and the world. The sales of e-commerce companies show a rapid growth trend in the competitive market environment, but the changing forms of online channel

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activities, the variety of products and the short lead time of the activities make it difficult to make decisions about the order quantity and the ordering cycle, and the inventory management of e-commerce companies becomes more and more important [1-4]. The empirical purchasing model often used by traditional companies is not applicable in e-commerce companies, which is prone to problems such as inventory redundancy and capital deposition, leading to cost waste and increased operational risk [5-6]. In today's competitive e-commerce market, it is crucial to accurately manage and reduce inventory pressure. In this context, supply chain platforms, business-to-business platforms and user-direct manufacturing platforms in e-commerce have also received increasing attention one after another [7-8]. In the supply chain platform, each enterprise carries out transaction accounting in the supply chain and realizes the interactive operation of capital flow, information flow and physical flow among enterprises [9-11]. Blockchain, as a decentralized-style database technology, enables nodes in the system to realize de-trusted peer-to-peer transactions in a distributed environment through the use of data encryption, timestamps, distributed consensus, and incentive mechanisms, thus solving the problems of trust and insecure data storage that exist in centralized systems [12-15]. Combined with the blockchain's bookkeeping and storage mode, it assigns ordering stores to ordering customers and provides view information such as logistics and inventory for store regions, etc., which provides technical support for inventory management with diverse transaction types and complex data structures [16-19]. In the management mechanism of the supply chain, the requirements of the enterprises to jointly respond to the changing form of the external market, the relevant departments how to increase the supply chain control has been an important part of enhancing the competitiveness of modern enterprises.

This paper first introduces the inventory control related theories and common control models, with e-commerce supply chain inventory as the object of study, analyzes in detail the supply chain multilevel inventory control operation process and control objectives. Taking cost, customer service level as the optimization goal, considering production, transportation, inventory and cost factors, the safety inventory control model of supply chain multilevel inventory control is established. The use of genetic algorithm is determined in conjunction with the dual-channel supply chain. Collaborative operators are introduced to perform the operations of annexation, division, and cooperation by judging the state of the optimal solution set, corresponding to the competition and cooperation existing in the supply chain, simulating the annexation or cooperation behaviors, obtaining a more excellent solution set, and verifying the feasibility of the model.

2. Multi-objective supply chain inventory control model construction

2.1. Overview of theories related to inventory control

2.1.1. Basic concepts of inventory control. Inventory control [20], also known as inventory management, is to achieve the financial and operational objectives of the enterprise, through the optimization of the supply chain management process and the entire demand, and to set up the appropriate ERP control strategy, and at the same time, with the help of information processing means and tools, in order to reduce the level of inventory, to reduce the risk of backlog obsolescence and depreciation. Enterprises need to consider market demand, inventory costs and inventory optimization goals when making inventory control decisions.

1) Market demand. The purpose of holding inventory is to better meet market demand and alleviate supply disruption caused by demand uncertainty. Most of the current literature on supply chain inventory strategy is centered on the demand model, which shows that demand analysis is very important for the development of reasonable inventory control.

2) Cost. Cost is an important factor for enterprises to consider when making inventory control decisions, and the level of cost also determines the advantages and disadvantages of the entire inventory system. Inventory decisions have a direct impact on the enterprise's procurement costs, inventory holding costs, out-of-stock costs, etc. Decision makers need to adopt appropriate inventory strategies according to the characteristics of the product, so that the total cost is minimized. For goods with high fixed procurement costs, the replenishment cycle should be increased appropriately to reduce the number of purchases; for goods with high inventory holding costs, the decision maker needs to strictly control the maximum inventory level and improve the turnover rate of the goods; for expensive goods with high stock-out costs, the decision maker can replenish them in time through continuous inspection.

3) Inventory optimization objectives. Inventory optimization of supply chain mainly includes three aspects, namely, cost optimization, time optimization and customer satisfaction optimization. The inventory control objective based on cost optimization is to minimize the total cost or maximize the total profit of the supply chain, which is the more commonly used optimization method at present. Time-based optimization takes time minimization as the goal, and optimizes inventory turnover, order lead time, order effect time, etc., which is mainly applied to the research of agile supply chain. Optimization based on customer satisfaction is to formulate the inventory strategy that is most conducive to the customer experience from the customer's point of view, to minimize the loss of customers, in order to improve the supply chain's ability to attract customers.

2.1.2. Inventory control strategies

1) Continuous checking inventory control strategy. Continuous checking inventory control strategy, i.e., continuously focusing on the inventory level and replenishing whenever the inventory level is below the replenishment point, mainly includes (Q, r) strategy, (r, S) strategy and (S-1, S) strategy.

The (Q, r) strategy is also known as quantitative inventory control strategy. The inventory manager keeps a constant eye on the inventory level and issues an order whenever the inventory level is below the ordering point r. The order quantity is a fixed value Q. The (Q, r) strategy is also known as the quantitative inventory control strategy.

The (Q, r) inventory strategy is suitable for goods with high sales volume, high cost of stock-outs, and unstable demand.

The (r, S) strategy also follows the inventory continuity checking principle, where the inventory decision maker places an order whenever the inventory level of the good falls below the ordering point r, ensuring that the replenished good is stocked up to the maximum inventory level S. The quantity ordered each time this strategy is used is variable and is determined by the actual inventory level at the time of ordering and the maximum inventory level.

In the (S-1, S) strategy, S is the maximum inventory level. This strategy sends out replenishment requests whenever a demand occurs, and is applicable to goods that are valuable and have a low demand.

2) Cycle checking inventory control strategy. Cycle checking inventory control strategy refers to the replenishment strategy of checking inventory and issuing orders every time after a fixed cycle, which is applicable to goods with more types, high demand and high fixed ordering cost.

Under the (t, Q) replenishment strategy, the manager initiates an order for a fixed quantity Q every fixed period t. This strategy is suitable for situations where demand is relatively stable.

The basic idea of the (t, S) strategy is to check inventory and place an order to replenish the inventory level to the maximum inventory level S every after a replenishment cycle t. This strategy does not need to set an ordering point, does not need to check the inventory balance at any time, and only needs to order according to a fixed cycle, which is suitable for lower-value and lower-demand supplies.

The (t, r, S) strategy is a combination of the (t, Q) strategy and the (t, S) strategy, where after a fixed checking cycle t, if the inventory level is below the order point r, an order request is issued to bring the inventory up to the maximum inventory level S. This strategy is suitable for materials of average value on which the consumer is less dependent.

2.1.3. Common inventory control models. In the study of the actual inventory problem, it is necessary to abstract the actual scene into a mathematical model according to the replenishment strategy, so that scholars can choose the appropriate method to quantitatively analyze it and provide theoretical guidance for the actual inventory control. According to the different replenishment strategies, the common inventory control models include the following models.

Model 1: Do not allow stock-outs, instantaneous arrivals

This model is the most common model in inventory control, belonging to the deterministic inventory model, from which the economic order lot model is developed. The conditions set by the model is not allowed to run out of stock, so there is no need to consider the cost of stock-outs, the development of ordering plans will be more convenient.

Model 2: No stock-outs allowed, gradual and uniform arrival of goods

This model also assumes that stock-outs are not allowed, but the arrival method is different from Model 1, which is gradual and even. In reality, due to production capacity and transport capacity and other aspects of the limitations of the enterprise orders will not be idealized immediately to all, but gradually delivered. During the period of replenishment, the maximum level of inventory in this model is usually lower than the fixed order quantity Q because some of the goods that have been stocked have already been consumed.

Model 3: Allow out-of-stocks, instantaneous arrivals, and out-of-stocks to be replenished

This model allows firms to run out of stock. When the firm's inventory gradually drops to zero, the firm does not replenish immediately, but instead issues an order when the out-of-stock level reaches the maximum out-of-stock level B, and the product arrives instantaneously so that the inventory level reaches the maximum raw level S. The firm's inventory is allowed to fall below the fixed order quantity Q.

2.2. Multi-level inventory control targeting and provisioning

2.2.1. Multi-level inventory control targeting

1) Supply chain inventory cost. For a supply chain multilevel inventory [21] system, its total inventory cost is the sum of the costs associated with the operation of the inventory system paid outside the system. In this paper, production and transportation costs are also taken into account in supply chain inventory costs. Specifically, it includes “inventory holding cost Ch, transaction ordering cost Co, out-of-stock cost Cs, transportation cost Ct” 4 kinds of costs.

2) Customer service level. In this paper, supply chain inventory cost is considered as an objective, and customer service level is defined as the probability that customers can obtain demand directly without waiting for replenishment. The expression is as follows:

$$S = 1 - \frac{1}{KDP}\sum_{k=1}^{K}\sum_{d=1}^{D}\sum_{p=1}^{P}\frac{Hq_{dk}^{p}}{\bar{Q}_{dck}^{p}} \tag{1}$$

Eq:

K - Total number of cycles:

D - Total number of distributors;

P - Number of types of products;

Hq_{dk}^{p} - Out-of-stock quantity of distributor d :

$\bar{Q}_{dck}^{p}$ - the amount of customer demand for distributor d .

2.2.2. Supply chain inventory costs and safety stocks

1) Supply chain inventory cost. In this paper, supply chain inventory cost is considered as one of the optimization objectives, using a centralized inventory control method with a (t,s,S) replenishment strategy at each inventory node [22].

2) Safety stock. Safety stock mainly solves the problems of customer demand uncertainty, delivery delays and fluctuations in demand during the lead time. In order to ensure that there is no shortage of stock, companies often add additional safety stock on the basis of the average demand in the lead time, and there is also literature to cope with it by setting up a safety lead time, but the inventory fluctuation brought by setting up a safety lead time is much larger than that brought by setting up a safety stock.

Define safety stock as SS and its expression is shown below:

$$SS = k\delta \tag{2}$$

Eq:

k - Safety stock factor;

δ - standard deviation of order lead time demand. In this paper, the safety stock factor k is used as a decision variable, and when k increases, the inventory level improves, the chance of out-of-stock becomes smaller, and the level of customer service improves, but there is a possibility that the total inventory cost increases. The order point method based on safety stock is more widely used in existing inventory replenishment strategies. After determining the safety stock at each node of the supply chain, the order point at each node can be determined accordingly s:

$$s = X + SS \tag{3}$$

where: X - Average value of ordering lead time requirements.

2.3. Establishment of inventory control model based on multi-objective supply chain

2.3.1. Production analysis and production control. This paper assumes a certain value of production per unit of time for the manufacturer of the core business, so the total production is related to the production time, which is considered in this paper as normal working hours and overtime working hours. Their actual working time range can be determined by the following formula:

$$t_{mo}^{p} + \sigma_{mk}^{p} \Delta t_{m}^{p} \geq t_{mk}^{p} \geq 0 \tag{4}$$

$$\sum_{t=0}^{T} \sigma_{mk}^{p} (t_{mk}^{p} - t_{mo}^{p}) \leq T_{m}^{p} \tag{5}$$

where: t_{mk}^{p} -Actual production time in ordering cycle k ; t_{mo}^{p} -Average production time under normal conditions; σ_{mk}^{p} -Overtime control switch T_{m}^{p} -Working time limit in an ordering cycle. Eq. (4) is the actual production time limit and Eq. (5) is the total overtime time limit in cycle T .

2.3.2. Transportation analysis. Carrying capacity and unit commodity transportation costs can be determined by the following formula:

$$Y_{smk} = \sum_{P'} Y_{smk}^{p'} \tag{6}$$

$$Y_{mdk}=\sum_{P}Y_{mdk}^{p} \tag{7}$$

$$f_{*k}=\alpha(\omega Y_{*k})^{\beta} \quad *\in\{sm,md\} \tag{8}$$

where: Y_{*k} - total shipments; f_{*k} - unit transportation costs of raw materials p' and finished goods p for the k rd ordering cycle; in this paper, $\omega=1,\alpha=0.5,\beta=-0.5$ is taken.

2.3.3. Inventory analysis. Supplier, manufacturer, and distributor level inventory levels can be determined by the following formula:

$$EI_{sk}^{p'}=I_{s,k-1}^{p'}+Y_{smk}^{p'} \tag{9}$$

$$EI_{mk}^{p'}=I_{mk-1}^{p'}+\sum_{P}t_{mk}^{p}V_{m}^{p}\gamma_{p}^{p'} \tag{10}$$

$$EI_{mk}^{p}=I_{m,k-1}^{p}+\sum_{d}Y_{mdk}^{p} \tag{11}$$

$$EI_{dk}^{p}=I_{d,k-1}^{p}+\bar{Q}_{dck}^{p} \tag{12}$$

where: $I_{s,k-1}^{p'},I_{m,k-1}^{p'},I_{m,k-1}^{p'},I_{d,k-1}^{p}$ - inventory at the end of the previous week at each node; $Y_{smk}^{p'},Y_{mdk}^{p}$ - quantity of finished goods; $\bar{Q}_{dk}^{p}$ - customer demand; V_{m}^{p} - production capacity; $\gamma_{p}^{p'}$ - matching coefficient.

2.3.4. Cost analysis

1) Cost of production: Cost of production includes the cost of production of finished goods during normal working hours and the additional cost of production for overtime. To wit:

$$C_{m}=\sum_{k}g(\sum_{p}(t_{mk}^{p}f_{mp}^{p}+\sigma_{mk}^{p}(t_{mk}^{p}-t_{mo}^{p})\Delta f_{mp}^{p})g) \tag{13}$$

where: f_{mp}^{p} - production cost per unit of time; Δf_{mp}^{p} - additional production cost per unit of time.

2) Inventory holding cost: Inventory holding cost C_h is proportional to the level inventory at each node and can be determined by the following equation:

$$C_{h}=\sum_{k}\left(\sum_{p'}EI_{sk}^{p'}f_{ss}^{p'}+\sum_{p'}EI_{mk}^{p'}f_{ms}^{p'}+\sum_{p}EI_{mk}^{p}f_{ms}^{p}+\sum_{d}\sum_{p}EI_{dk}^{p}f_{ds}^{p}\right) \tag{14}$$

where: $f_{ss}^{p'},f_{ms}^{p'},f_{ms}^{p},f_{ds}^{p}$ - Finished product storage cost; $EI_{sk}^{p'},EI_{mk}^{p'},EI_{mk}^{p'},EI_{dk}^{p}$ - Inventory volume.

3) Transportation costs: ignoring the impact of transportation time on the cost of transportation, and only consider the impact of the volume of shipments and the cost of transportation per unit of finished goods on the cost of transportation C_t, the cost of transportation is determined by the following formula:

$$C_{t}=\sum_{k}g\left(\sum_{s}Y_{smk}f_{smk}+\sum_{d}Y_{mdk}f_{mdk}g\right) \tag{15}$$

where: Y_{smk} -volume of semi-finished products; Y_{mdk} -volume of finished products; f_{smk},f_{mdk} -finished product transportation costs.

4) Ordering costs: ordering costs C_o include the purchase costs incurred in purchasing raw materials and the fixed transaction costs incurred per order. Then:

$$C_o = \sum_k g(\sum_s \sum_{p'} Q_{sk}^{p'} f_o^{p'} + \sum_s \mu_{sk} f_{so}^{p'} + \sum_m \mu_{mk} f_{mo}^{p'} + \sum_d \mu_{dk} f_{do}^{p} g) \tag{16}$$

where: $Q_{xx}^{p'}$ -order quantity; $f_o^{p'}$ -purchase cost; $\mu_{sk}, \mu_{mk}, \mu_{dk}$ -order switch; $f_{so}^{p'}, f_{mo}^{p'}, f_{do}^{p}$ -fixed transaction cost.

5) Out-of-stock cost: by the definition of in-chain cost, the out-of-stock cost C_s in this paper only considers the distributor's out-of-stock cost:

$$C_s = \sum_k g\left(\sum_d \sum_p D_{dk}^p f_{dd}^p\right) \tag{17}$$

where: D_{dk}^p - Out-of-stock quantity; f_{dd}^p - Out-of-stock cost.

2.3.5. Determination of optimization objectives. In this paper, total inventory cost and customer service level are taken as supply chain inventory optimization objectives, and the optimization direction of each objective needs to be determined.

As one of the supply chain inventory control objectives, the total cost of supply chain inventory C_{total}, its expression is:

$$C_{total} = C_m + C_h + C_t + C_o + C_s \tag{18}$$

where: C_m - production costs; C_h - inventory holding costs; C_i - transportation costs; C_o - goods ordering costs; C_s - out-of-stock costs.

Optimization Objective:

$$Min(C_{total}) \tag{19}$$

Customer service level has been defined in various ways in the existing literature, and in this paper, the ratio of distributor's out-of-stock to customer's actual demand throughout an operating time of the system is used as a criterion for evaluating the customer service level Sat:

$$Sat = 1 - \frac{1}{KDP} \sum_{k=1}^{K} \sum_{d=1}^{D} \sum_{p=1}^{P} \frac{D_{dk}^p}{\bar{Q}_{dck}^p} \tag{20}$$

where: K - the total number of operating cycles of the system; D - the total number of distributors; P - the number of product categories; D_{dk}^p - the number of out-of-stocks of distributors; $\bar{Q}_{dck}^p$ - the actual demand of customers.

Optimization Objective:

$$Max(Sat) \tag{21}$$

2.3.6. Constraints and logistics operation process control. The constraint problem of critical replenishment point s and maximum replenishment level S for each inventory node: its critical replenishment point s and maximum replenishment level S should take values within a certain range, guaranteed:

$$s < S \tag{22}$$

There is also a production control constraint for the manufacturer, i.e., the actual production time needs to satisfy the following equation:

$$t^p_{mk} = \min\left\{\max\left\{\frac{\overline{Q_{yc}}}{V^p_m}, \frac{Q^p_m}{V^p_m}\right\}, t^p_{mo} + \Delta t^p_{mo}, t^p_{mo} + T^p_m \sigma^p_{mk}\right\} \tag{23}$$

where: $\overline{Q_{ye}}$ - forecast demand; Q^p_m - total order lot size.

2.3.7. Logistics and information flow analysis

1) Each parameter of distributor logistics and information flow is expressed as follows:

$$TY^p_{mdk} = \sum_{(k-1)T<t<kT} TY^p_{mdt} \tag{24}$$

$$TY^p_{dck} = \begin{cases} 0 & I^p_{d,k-1} + TY^p_{mdk} < D^p_{d,k-1} \\ D^p_{d,k-1} & D^p_{d,k-1} \le I^p_{d,k-1} + TY^p_{mdk} \le D^p_{d,k-1} + \overline{Q^p_{dck}} \\ D^p_{d,k-1} + \overline{Q^p_{dck}} & I^p_{d,k-1} + TY^p_{mdk} \ge D^p_{d,k-1} + \overline{Q^p_{dck}} \end{cases} \tag{25}$$

$$D^p_{d,k} = \begin{cases} 0 & I^p_{d,k-1} + TY^p_{mdk} > D^p_{d,k-1} + \overline{Q^p_{dck}} \\ \overline{Q^p_{dck}} & D^p_{d,k-1} \le I^p_{d,k-1} + TY^p_{mdk} \le D^p_{d,k-1} + \overline{Q^p_{dck}} \\ D^p_{d,k-1} + \overline{Q^p_{dck}} & I^p_{d,k-1} + TY^p_{mdk} < D^p_{d,k-1} \end{cases} \tag{26}$$

$$I^p_{d,k} = I^p_{d,k-1} + TY^p_{mdk} - \overline{Q^p_{dck}} - D^p_{d,k-1} \tag{27}$$

$$Q^p_{mdk} = \mu^p_{dk}(S^p_d - I^p_{d,k}) \tag{28}$$

$$\mu^m_{dk} = \begin{cases} 1 & I^p_{d,k} \le s^p_{d,k} \\ 0 & I^p_{d,k} > s^p_{d,k} \end{cases} \tag{29}$$

$$s^p_{d,k} = X^p_{d,k} + k^p_{d,k}\delta^p_{d,k} \tag{30}$$

where: TY^p_{mdk} -Arrivals; TY^p_{dck} -Shipments; $D^p_{d,k}$ -Shortages; $I^p_{d,k}$ -Inventory; Q^p_{mdk} -Orders; μ^p_{dk} - Ordering switches; $s^p_{d,k}$ -Ordering points; $X^p_{d,k}$ -Average demand; $\delta^p_{d,k}$ -Standard deviation; $k^p_{d,k}$ - Safety stock factor.

2) Each parameter of the manufacturer's finished goods logistics and information flow is expressed as follows:

$$TY^p_{mmk} = t^p_{mk} V^p_m \tag{31}$$

$$TY^p_{mdk} = \begin{cases} 0 & I^p_{m,k-1} + TY^p_{mnk} < D^p_{m,k-1} D^p_{m,k-1} \\ D^p_{m,k-1} & D^p_{m,k-1} \le I^p_{m,k-1} + TY^p_{mnk} \le D^p_{m,k-1} + \sum_d Q^p_{m,d} \\ D^p_{m,k-1} + \sum_d Q^p_{mdk} & I^p_{m,k-1} + TY^p_{mnk} \ge D^p_{m,k-1} + \sum_d Q^p_{mak} \end{cases} \tag{32}$$

$$D_{m,k}^{p}=\begin{cases}0 & I_{m,k-1}^{p}+TY_{mnk}^{p}>D_{m,k-1}^{p}+\sum_{d}Q_{mdk}^{p}\\ \sum_{d}Q_{mdk}^{p} & D_{m,k-1}^{p}\le I_{m,k-1}^{p}+TY_{mdk}^{p}\le D_{m,k-1}^{p}+\sum_{d}Q_{mdk}^{p}\\ D_{m,k-1}^{p}+\sum_{d}Q_{mdk}^{p} & I_{m,k-1}^{p}+TY_{mdk}^{p}<D_{m,k-1}^{p}\end{cases} \tag{33}$$

$$I_{m,k}^{p}=I_{m,k-1}^{p}+TY_{mdk}^{p}-\sum_{d}Q_{mdk}^{p}-D_{m,k-1}^{p} \tag{34}$$

$$Q_{mmk}^{p}=\mu_{mk}^{p}(S_{m}^{p}-I_{m,k}^{p}) \tag{35}$$

$$\mu_{mk}^{p}=\begin{cases}1 & I_{m,k}^{p}\le s_{m,k}^{p}\\ 0 & I_{m,k}^{p}>s_{m,k}^{p}\end{cases} \tag{36}$$

$$s_{m,k}^{p}=X_{m,k}^{p}+k_{m,k}^{p}\delta_{m,k}^{p} \tag{37}$$

where: TY_{mmk}^{p} -Arrivals, TY_{mdk}^{p} -Shipments, $D_{m,k}^{p}$ -Shortages, $I_{m,k}^{p}$ -Inventory, Q_{mmk}^{p} -Ordering. μ_{mk}^{p} -Ordering switch, $s_{m,k}^{p}$ -Ordering point, $X_{m,k}^{p}$ -Average demand, $\delta_{m,k}^{p}$ -Standard deviation, $k_{m,k}^{p}$ -Safety stock factor.

3) Each parameter of the manufacturer's raw material or semi-finished goods logistics and information flow is represented as follows:

$$TY_{smk}^{p'}=\sum_{(k-1)T<t<kT}TY_{smt}^{p'} \tag{38}$$

$$TY_{mmk}^{p'}=\min\left\{I_{m,k-1}^{p'}+TY_{smk}^{p'}-D_{m,k-1}^{m'},TY_{mk}^{p}\gamma_{p}^{p'}\right\}+D_{m,k-1}^{m'} \tag{39}$$

$$D_{m,k}^{p'}=-\min\left\{0,I_{m,k}^{p'}\right\} \tag{40}$$

$$Q_{smk}^{p'}=\mu_{mk}^{p'}(S_{m}^{p'}-I_{m,k}^{p'}) \tag{41}$$

$$\mu_{mk}^{p'}=\begin{cases}1 & I_{m,k}^{p'}\le s_{m,k}^{p'}\\ 0 & I_{m,k}^{p'}>s_{m,k}^{p'}\end{cases} \tag{42}$$

$$s_{m,k}^{p'}=X_{m,k}^{p'}+k_{m,k}^{p'}\delta_{m,k}^{p'} \tag{43}$$

where: $TY_{smk}^{p'}$ -Arrivals; $TY_{mmk}^{p'}$ -Shipments; $D_{m,k}^{p'}$ -Shortages; $I_{m,k}^{p'}$ -Inventory; $Q_{smk}^{p'}$ -Orders; $\mu_{mk}^{p'}$ -Ordering switches; $s_{m,k}^{p'}$ -Ordering points; $X_{m,k}^{p'}$ -Average demand; $\delta_{m,k}^{p'}$ -Standard deviation; $k_{m,k}^{p'}$ -Safety stock factor.

4) Each parameter of supplier logistics and information flow is expressed as follows:

$$TY_{ssk}^{p'}=\sum_{(k-1)T<t<kT}TY_{sst}^{p'} \tag{44}$$

$$TY_{smk}^{p'}=\begin{cases}0 & I_{m,k-1}^{p'}+TY_{mmk}^{p'}<D_{m,k-1}^{p'}\\ D_{s,k-1}^{p'} & D_{s,k-1}^{p'}\le I_{s,k-1}^{p'}+TY_{ssk}^{p'}\le D_{s,k-1}^{p'}+\overline{Q_{smk}^{p'}}\\ D_{s,k-1}^{p'}+\overline{Q_{smk}^{p'}} & I_{s,k-1}^{p'}+TY_{ssk}^{p'}\ge D_{s,k-1}^{p'}+\overline{Q_{smk}^{p'}}\end{cases} \tag{45}$$

$$D_{s,k}^{p'} = \begin{cases} 0 & I_{s,k-1}^{p'} + TY_{ssk}^{p'} > D_{s,k-1}^{p'} + \overline{Q_{smk}^{p'}} \\ \overline{Q_{smk}^{p'}} & D_{s,k-1}^{p'} \le I_{s,k-1}^{p'} + TY_{smk}^{p'} \le D_{s,k-1}^{p'} + \overline{Q_{smk}^{p'}} \\ D_{m,k-1}^{p'} + \overline{Q_{smk}^{p'}} & I_{s,k-1}^{p'} + TY_{smk}^{p'} < D_{s,k-1}^{p'} \end{cases} \tag{46}$$

$$I_{s,k}^{p'} = I_{s,k-1}^{p'} + TY_{smk}^{p'} - Q_{smk}^{p'} - D_{s,k-1}^{p'} \tag{47}$$

$$Q_{sk}^{p'} = \mu_{sk}^{p'} (S_s^{p'} - I_{s,k}^{p'}) \tag{48}$$

$$\mu_{sk}^{p'} = \begin{cases} 1 & I_{s,k}^{p'} \le s_{s,k}^{p'} \\ 0 & I_{s,k}^{p'} > s_{s,k}^{p'} \end{cases} \tag{49}$$

$$s_{s,k}^{p'} = X_{s,k}^{p'} + k_{s,k}^{p'} \delta_{s,k}^{p'} \tag{50}$$

where: $TY_{ssk}^{p'}$ -Arrivals; $TY_{smk}^{p'}$ -Shipments; $D_{s,k}^{p'}$ -Shortages; $I_{s,k}^{p'}$ -Inventory; $Q_{sk}^{p'}$ -Orders; $\mu_{sk}^{p'}$ -Ordering switches; $s_{s,k}^{p'}$ -Ordering points; $X_{s,k}^{p'}$ -Average demand; $\delta_{s,k}^{p'}$ -Standard deviation; $k_{s,k}^{p'}$ -Safety stock factor.

2.4. Improved genetic algorithm design based on cofactors

2.4.1. Genetic strategy improvement

1) Improvement of selection strategy. The improvement of selection strategy is mainly divided into two parts: first, retaining the optimal value of the individual of the parent generation at the stage of performing selection, and using the optimal value as a solution in the Pareto solution set [23]. Second, at the later stage of population evolution, the adaptation value of the excellent individual is preferentially weighted so that the excellent individual is more competitive than the average individual.

2) Crossover and variation improvement. The initial values of crossover and variation [24] need to be determined by repeated trials, which is a complicated process. Due to the complexity of the determination process, they are usually chosen as fixed values based on experience, which leads to a decrease in the solution rate when facing different optimization problems. An adaptive genetic algorithm (AGA) capable of optimizing the crossover probability P_c and the variance probability P_m is proposed and calculated as follows:

$$P_c = \begin{cases} P_{c1} - \dfrac{(P_{c1} - P_{c2})(f - f_{avg})}{f_{\max} - f_{avg}} & f \ge f_{avg} \\ P_{c1} & f < f_{avg} \end{cases} \tag{51}$$

$$P_m = \begin{cases} P_{m1} - \dfrac{(P_{m1} - P_{m2})(f - f_{avg})}{f_{\max} - f_{avg}} & f \ge f_{avg} \\ P_{m1} & f < f_{avg} \end{cases} \tag{52}$$

In the above equation, $f_{\max}$ is the maximum fitness; f_{ag} is the average fitness; f is the fitness of the excellent individuals to be crossed; P_{cl}, P_{c2} is the maximum and minimum crossover probability, respectively; and P_{cl}, P_{c2} is the variance probability of high frequency and low frequency, respectively.

2.4.2. Genetic Collaborative Algorithm Design. Refer to the cooperative operator of the co-evolutionary multiobjective algorithm to improve SGA.The co-evolutionary operator is introduced on the basis of SGA.The cooperative operators used in this paper are as follows:

1) Cooperative operator: Initially, two populations $p_t^a = (z_1^a, z_2^a, ..., z_M^a)$ and $p_t^b = (z_1^b, z_2^b, ..., z_x^b), [O_t^a, O_t^b]$ are set to be the Pareto optimal solution set of the population, and any individual $(x^a, x^a, \cdots, x^a)$ in p^a, and an individual $(r_1^b, r_2^b, \cdots, r_n^b)$ in O_i^b are randomly selected to produce a new individual $(z_1^a, z_2^a, \cdots, z_n^a)$ by pressing the following equation, thus forming a new population p_{t+1}^a. Then:

$$z_i^a = r_i^b + U(-1,1) \times (r_i^b - x_i^a)\, i = 1, 2, \cdots, n \tag{53}$$

Similarly, for any individual $(x_1^b, x_2^b, \cdots, x_n^b)$ within p_t^b in the initial population, a new individual $(z_1^b, z_2^b, \ldots, z_n^b)$ is produced by pressing the formula with any solution $(r_1^a, r_2^a, \ldots, r_n^a)$ in O_t^a, thus forming a new population p_{t+1}^b. Then:

$$z_i^b = r_i^a + U(-1,1) \times (r_i^a - x_i^b)\, i = 1, 2, \cdots, n \tag{54}$$

where: U (-1, 1) is uniformly distributed between (-1, 1).

2) The annexation operator. Suppose the initial populations $p_t^a = (z_1^a, z_2^a, ..., z_w^a)$ and $p_t^b = (z_1^b, z_2^b, ..., z_x^b)$, have Pareto optimal solutions O_i^a and O_t^b, if the following relationship exists:

$$\forall x \in O_t^a, \exists z \in O_t^b, x \prec z \tag{55}$$

At this point population b annexes population a and forms a new offspring population $p_{t+1}^b = (l_1, l_2, ..., l_{X+N})$, Eq. $l_i = z_i, i = 1, 2, \cdots N l_i (i = N+1, N+2, \cdots N+M)$ with the following equation arising:

$$l_{ij} = r_j + U(-1,1) \times (r_j - x_{i-N,j})\, j = 1, 2, \cdots, n \tag{56}$$

The Pareto solution set O_i^b of population b contains the solutions of O_i^a, that is, population b performs better than population a, when the probability of obtaining an excellent solution for population a is lower than that of population b. Eliminate population a and keep the excellent individuals of population a to simplify the computation.

3) Splitting operator. $p_i = (x_1, x_2, x_3, ..., x_m)$ was randomly divided into two subpopulations $p_{t+1}^a = (z^a 1, z_2^a, ..., z_{M/2}^a)$ and $p_{t+1}^b = (z_1^b, z_2^b, ..., z_{N/2}^b)$, and one subpopulation was subjected to the following mutation operation with all individuals of p_{t+1}^a:

$$z_i^a = \begin{cases} z_i^a & U(0,1) < 1/n \\ z_i^a + G(0, 1/\beta) & U(0,1) \geq 1/n \end{cases} \quad (i = 1, 2 \cdots n) \tag{57}$$

where G is the Gaussian distribution; β is the number of chromosome evolutionary generations.

2.4.3. Model solving steps for improved genetic algorithm. The improved algorithm is based on the original genetic algorithm, which is different from the original algorithm in that two different populations are initially set up, and the two populations iterate in parallel to derive the Pareto optimal solution set, and the optimal individual is obtained through the updating of the Pareto optimal solution set and the subsequent execution of the synergistic operator after entering the convergence region. The specific steps of the algorithm are as follows:

Step1: Set up two populations a and b with size N; O^a and O^b are the Pareto optimal solution sets for populations a and b, respectively; and $\bar{P}$ is the outset of the population with size $\bar{N}$. The direction of the arrow indicates the evolution of the parent to the child.

Step2: Initialize the population and parallelize the computation to get two optimal solution sets O^a and O^b, while making $\bar{P} \leftarrow \phi, t \leftarrow 0$.

Step3: Update the outer set $\bar{P}_t$ with O^a and O^b to obtain a new set $\bar{P}_{t+1}$.

Step4: $\bar{P}_t$ is divided into two parts $\bar{P}_t^a$ and $\bar{P}_t^b$, and the optimal individual retention policy is executed on both populations simultaneously, from the new sets $\bar{P}_t^{1a}$ and $\bar{P}_t^{1b}$ constituted under the retention policy. i.e:

$$a + \bar{P}_t^a \to \bar{P}_t^{1a}, b + \bar{P}_t^b \to \bar{P}_t^{1b} \tag{58}$$

Step5: Judge whether $\bar{P}_t^{1a}$ and $\bar{P}_t^{1b}$ satisfy the termination condition, if so, the algorithm terminates and outputs $\bar{P}_{t+1}$.

Step6: If it does not satisfy, expand $\bar{P}_t^{1a}$ and $\bar{P}_t^{1b}$ according to the mutation probability P_m, and join the co-evolution operator.

Step7: $\bar{P}_i^{1a}$ and $\bar{P}_i^{1b}$ are intersected to get $\bar{P}_{i+1}^{1a}$ and $\bar{P}_{i+1}^{1b}$. If $\bar{O}_{i+1}^{na}$ is contained by $\bar{O}_{i+1}^{nb}$, perform annexation operation of $\bar{P}_{i+1}^{1a}$ to $\bar{P}_{t+1}^{1b}$; otherwise perform cooperative operator operation to get $\bar{P}_{t+2}^{1a}$ and $\bar{P}_{t+2}^{1b}$.

Step8: Perform fitness evaluation, if the termination condition is satisfied, output $\bar{P}_{t+2}$; if not, return to Step2.

3. Multi-objective based e-commerce supply chain inventory optimization result analysis

3.1. *Comprehensive performance evaluation of the improved algorithm*

In order to verify the convergence of the improved multi-objective genetic algorithm based on cofactors designed in this paper as well as the good distribution and accuracy of the Pareto solution set. In this paper, a set of standard multi-objective test functions are selected to test the comprehensive performance of this paper's algorithm and compared with the algorithm before improvement. In this paper, three standardized test functions, DTLZ1, DTLZ2 and DTLZ3, are selected.All three functions are variable scale multi-objective test functions, which can be used to test the algorithm's comprehensive performance in different objective spaces. The test function calculation formula is as follows:

$$DTLZ1 = \begin{cases} f_1(x) = 0.5x_1x_2 \cdots x_{m-1}(1+g(x_m)) \\ f_2(x) = 0.5x_1x_2 \cdots (1-x_{m-1})(1+g(x_m)) \\ \cdots \\ f_{m-1}(x) = 0.5x_1(1-x_2)(1+g(x_m)) \\ f_m(x) = 0.5(1-x_1)(1+g(x_m)) \\ g(x_m) = 100(x_m + \sum_{x \in x_m} (x_i - 0.5)^2 - \cos(20\pi(x_i - 0.5)) \\ 0 \le x_i \le 1, i = 1, 2, \cdots, n \end{cases} \tag{59}$$

$$DTLZ2=\begin{cases} f_1(x)=\cos(x_1\pi/2)\cos(x_2\pi/2)\cdots\cos(x_{m-1}\pi/2)(1+g(x_m)) \\ f_2(x)=\cos(x_1\pi/2)\cos(x_2\pi/2)\cdots\sin(x_{m-1}\pi/2)(1+g(x_m)) \\ \cdots \\ f_{m+1}(x)=\cos(x_1\pi/2)\sin(x_2\pi/2)(1+g(x_m)) \\ f_m(x)=\sin(x_1\pi/2)(1+g(x_m)) \\ g(x_m)=\sum_{i\in N_n}(x_i-0.5)^2 \\ 0\le x_i\le 1, i=1,2,\cdots,n \end{cases} \tag{60}$$

$$DTLZ3=\begin{cases} f_1(x)=\cos(x_1\pi/2)\cos(x_2\pi/2)\cdots\cos(x_{m-1}\pi/2)(1+g(x_m)) \\ f_2(x)=\cos(x_1\pi/2)\cos(x_2\pi/2)\cdots\sin(x_{m-1}\pi/2)(1+g(x_m)) \\ \cdots \\ f_{m-1}(x)=\cos(x_1\pi/2)\sin(x_2\pi/2)(1+g(x_m)) \\ f_m(x)=\sin(x_1\pi/2)(1+g(x_m)) \\ g(x_m)=100(x_m+\sum_{x_i\in x_m}(x_i-0.5)^2-\cos(20\pi(x_i-0.5)) \\ 0\le x_i\le 1, i=1,2,\cdots,n \end{cases} \tag{61}$$

In evaluating the performance of the algorithm this paper selects the comprehensive evaluation index IGD for evaluation, which represents the inverse representation of the average distance from the Pareto optimal solution set to the optimal frontier surface, and is calculated as follows:

$$IGD=\frac{\sum_{j\in PF'} d_j'}{P} \tag{62}$$

where d_j' denotes the individual on the Pareto front surface j to the optimal solution set individual i minimum Euclidean distance. P denotes the number of individuals on the Pareto front surface. The inverse generation distance IGD reflects the accuracy of the Pareto solution set as well as the diversity of solutions, the smaller the value of IGD the better, the ideal value is zero.

In this paper, the comprehensive performance evaluation of the algorithm is carried out at the target dimension m=3, respectively, and the algorithm is implemented by using Python language for programming, and the test environment is 24G RAM Intel(R) Core(TM) i5-9400F CPU@2.9GHz.

In order to ensure the fairness of performance evaluation, the population size N is set to 200 under the same dimension, the maximum crossover probability is 1, the maximum variation probability is 0.7, the number of algorithm iterations is 350, the crossover and variation parameters are 25 and 15 respectively, and each algorithm is run 20 times.

3.1.1. Comprehensive algorithm performance evaluation. The results of the comprehensive performance evaluation of the algorithm are shown in Table 1. From the table, it can be seen that the improved multi-objective genetic algorithm based on synergistic factors has better convergence than the traditional genetic algorithm, and the Pareto optimal solution set obtained is closer to the real optimal frontier. And when the target dimension increases, the IGD value of the traditional genetic algorithm gradually increases, which indicates that the Pareto optimal solution of the traditional genetic algorithm has been far away from the real optimal frontier when facing the high dimensional target search space, mainly because the search space increases, and the algorithm is difficult to ensure the diversity and distribution of the population. And the improved multi-objective genetic algorithm with synergistic factors proposed in this paper ensures the diversity of the population. So this paper is better than the traditional genetic algorithm. In addition, from the standard deviation, it can be seen that the algorithm in this paper is also better than the traditional genetic algorithm in terms of stability. Comprehensive analysis reveals that the DTLZ2 standardized test function has better results in the comprehensive performance evaluation of the two algorithms, so in the following, this paper uses the DTLZ2 test function as the standard function to explore its performance.

Table 1. The algorithm is comprehensive and can evaluate the results

Test function	Target dimension	Genetic algorithm		Improved genetic algorithm based on synergistic factors	
		Mean of IGD	IGD standard deviation	Mean of IGD	IGD standard deviation
DTLZ1	3	0.00503	0.0068	0.00011	0.0000
	4	0.01623	0.0107	0.00047	0.0002
	5	0.62952	0.0071	0.00933	0.0105
DTLZ2	3	0.00421	0.0025	0.00021	0.0000
	4	0.0067	0.0011	0.00045	0.0001
	5	0.0905	0.0493	0.0006	0.0002
DTLZ3	3	0.01923	0.0198	0.00052	0.0000
	4	0.04747	0.0336	0.00201	0.0004
	5	0.63063	0.0075	0.01997	0.0348

3.1.2. Algorithm convergence comparison. The results of the convergence comparison of the two algorithms are shown in Fig. 1. It can be seen that when trying to make the IGD infinitely close to zero, the traditional genetic algorithm needs 55 iterations, while the improved genetic algorithm only needs 34 iterations. It can be seen that the algorithm in this paper converges faster than the traditional genetic algorithm, which is also a proof that the strategy of introducing synergistic factors to improve the genetic algorithm in this paper is effective.

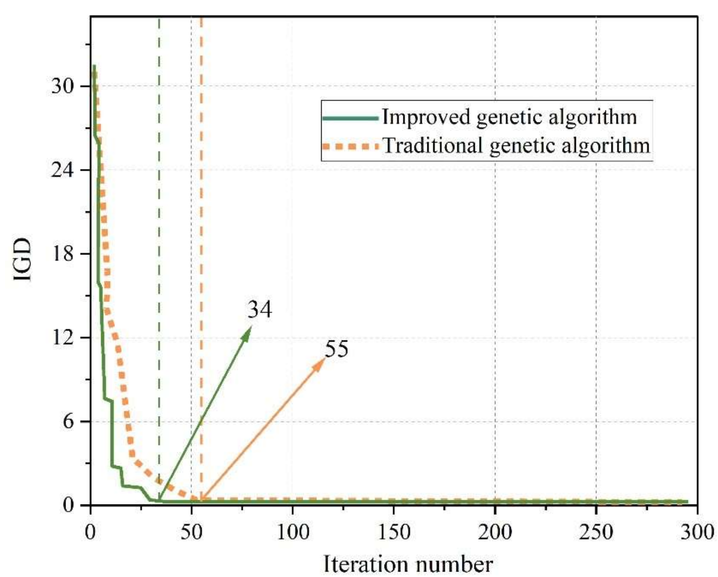
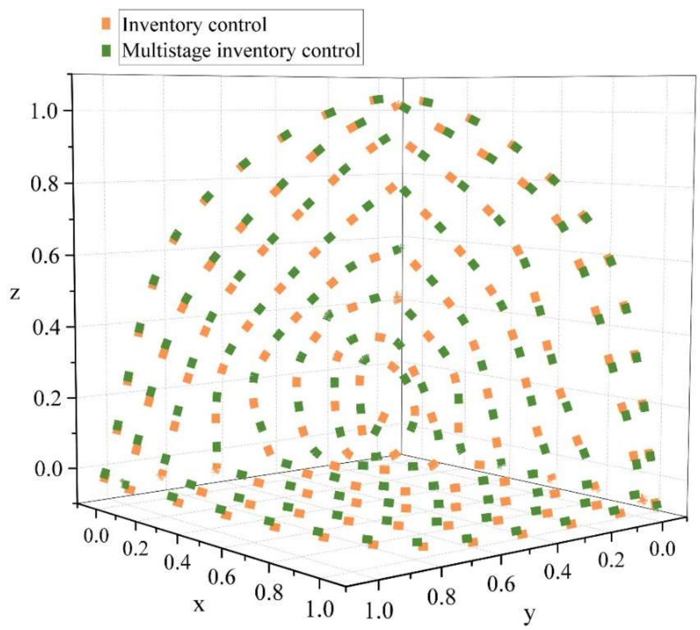
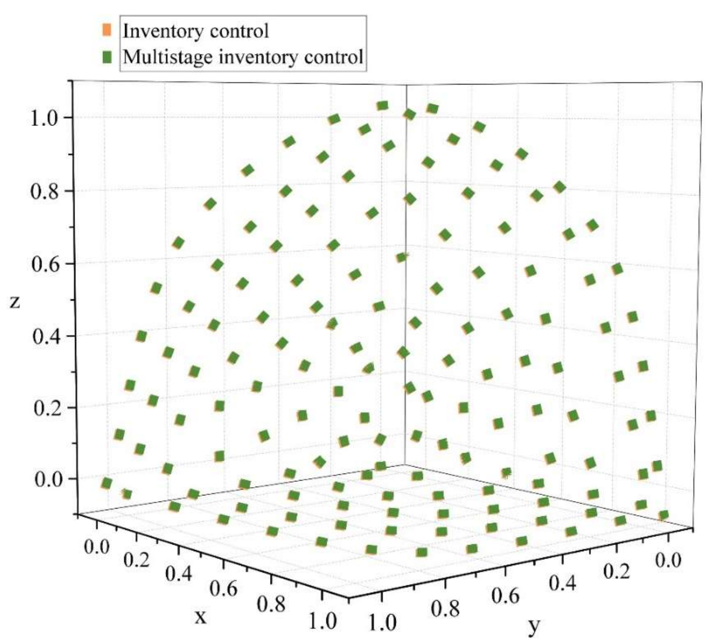


Fig. 1. The convergence of the two algorithms is the result of the convergence

3.1.3. Pareto optimal solution set for the model. Figure 2 shows the distribution of the Pareto optimal solutions of the two algorithms for the test function DTLZ2 when the objective dimension m=3. (a) and (b) refer to the set of Pareto optimal solutions of the model under the traditional genetic algorithm and the improved genetic algorithm, respectively. It can be seen that both the distribution and accuracy of the solutions, the improved genetic algorithm proposed in this paper is better than the traditional genetic algorithm, and the Pareto optimal solutions are closer to the real optimal frontier. When the algorithm is applied to supply chain management, each individual in the population represents the combination of nodes in the supply chain and the transportation route scheme, and this paper adopts the multi-objective supply chain inventory control method, so the supply chain has diversity, which can maximize the combination of nodes and the possibility of routes. In addition, the distribution of the solutions obtained from the solution model reflects the advantages and disadvantages of the Pareto solution set, the better the distribution, the better the solution obtained, and the management decision makers are more likely to make decisions according to the actual situation.



(a)Traditional genetic algorithm



(b)Improved genetic algorithm

Fig. 2. Pareto optimal solution set of DTLZ2 functions under different algorithms

3.2. Example analysis of multi-objective supply chain inventory control

Taking an e-commerce enterprise in Province Q as an example, the multilevel supply chain inventory and joint transportation optimization model is validated and analyzed. According to the characteristics of the materials delivered, the transportation modes used are road transportation, railroad transportation and waterway transportation combined transportation.

3.2.1. Case background. As a result of the research, the goods of X e-commerce company are mainly supplied through Distribution Center D in its region. Distribution Center D is a modern warehouse center responsible for handling, processing, processing, storage and transportation functions, providing goods to several e-commerce companies in the region. the main products of E-commerce enterprise X are supplied by 3 major producers, and the goods provided are centrally distributed by Distribution Center D. Distribution Center D is responsible for transshipment of goods mainly from production enterprise A, production enterprise B and production enterprise C. X e-commerce enterprise's sales ratio of goods A, B and C is 7:2:1, thus, forming a three-level supply chain system consisting of upstream by goods production enterprises A, B and C, midstream by Distribution Center D, and downstream by X e-commerce enterprise and other e-commerce enterprises.

The maximum supply capacities of production enterprises A, B and C are 1.8 million tons, 1.5 million tons and 1.2 million tons, respectively. The fixed costs of transporting commodities by rail, waterway and road are RMB 3,200, RMB 3,000 and RMB 5,000, respectively; Distribution Center D orders commodities from Supply Enterprises A, B, and C respectively, which need to be transported by rail and waterway; and E-commerce Enterprise X orders commodities from Distribution Center D by road. The maximum inventory capacity of the distribution center is 1.4 million tons; the maximum inventory capacity of e-commerce enterprise X is 400,000 tons. Distribution Center D's monthly demand for goods A, B, and C (in tons) is shown in Figure 3.

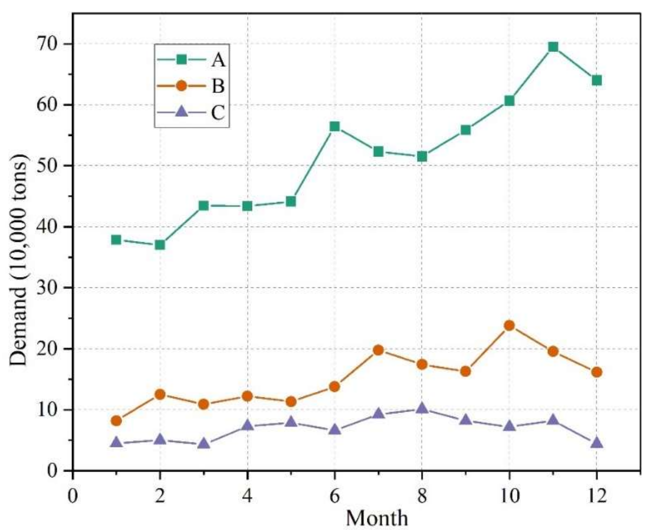


Fig. 3. Demand for monthly goods in the distribution center (10,000 tons)

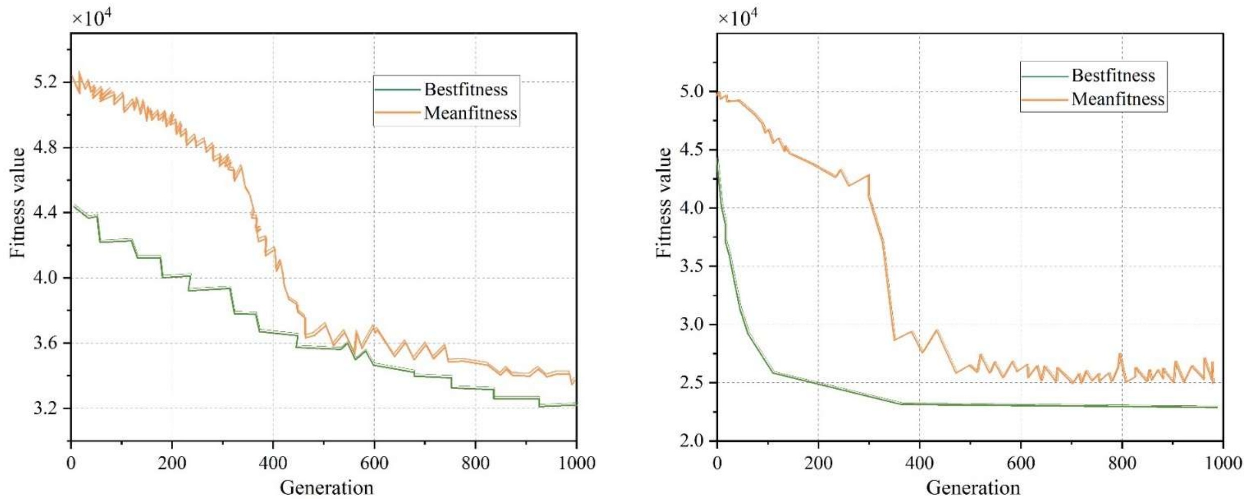
3.2.2. Model calculations. The objective function is solved by applying basic genetic algorithm and improved genetic algorithm respectively. The population size NN=200, crossover probability 0.88, variation probability 0.01, and the number of iterations 250 are taken.

The results of basic genetic algorithm and improved genetic algorithm for the objective function are shown in Table 2. As can be seen from the results, the optimal ordering strategy of the improved genetic algorithm ordering quantity in June 2022 is: distribution center D orders 700,408,900 tons, 312,078,000 tons, 216,522,000 tons and 392,720,000 tons of goods from goods producers A, B, C and D, respectively. This is a reduction of 505.54 million tons, 274.41 million tons and 64.496 million tons, respectively, over the traditional genetic algorithm. By substituting the order quantity of each commodity of distribution center D and the commodity order quantity of retail enterprise X into the objective function DTLZ2 respectively, we can get the minimum total cost of the system of this three-level supply chain is 98,341,418,000 Yuan.

Table 2. Two algorithms calculate the target function

Decision variable	Basic genetic algorithm order quantity (10,000 tons)	Improved genetic algorithm order (10,000 tons)
Q_A	75.4643	70.4089
Q_B	33.9519	31.2078
Q_C	28.1018	21.6522
Q_{MN}	43.2782	39.272

Fig. 4 shows the relationship between the fitness and the number of iterations under different algorithms, (a) and (b) represent the basic genetic algorithm and the improved genetic algorithm, respectively. The results show that compared with the basic genetic algorithm, the improved genetic algorithm is regionally stable in terms of both the best fitness and the average fitness when it is iterated about 375 times. While the basic genetic algorithm barely shifted to the stable state when iteration was close to about 450 times. In contrast, the method in this paper has excellent robustness.



(a)Basic genetic algorithm (b)Improved genetic algorithm

Fig. 4. The relationship between fitness and iteration times in different algorithms

4. Conclusion

This paper constructs a multi-objective inventory control model based on e-commerce supply chain on the basis of multi-objective supply chain inventory control, solves the Pareto optimal solution set of the model after optimizing the genetic algorithm by selecting the strategy and synergistic algorithm, etc., and examines the application effect of the model.

1) The simulation results of the arithmetic example show that the improved multi-objective adaptive genetic algorithm based on synergistic factors has better convergence, and the obtained Pareto optimal solution set is closer to the real optimal frontier. In addition, when the algorithm in this paper iterates 34 times, its IGD is the smallest, and it no longer changes with the increase of the number of iterations, which is faster than the traditional algorithm's convergence, and the algorithm model Pareto solution set has better distribution.

2) The use of multilevel supply chain inventory and transportation joint optimization model can not only maximize the realization of the optimal total cost of the supply chain system as a whole, but also optimize the inventory and transportation costs of each node enterprise in the supply chain system. And the inventory strategy solved by the joint optimization model of inventory and multimodal transportation can effectively reduce 27,441-6,449,660,000 tons of commodity inventory and save

inventory holding costs. The example analysis verifies the feasibility of the joint optimization model of inventory and transportation for multilevel should chain and its practicality.

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