

Retraction

Retracted: Research on Distribution and Inventory Cooperation of Agricultural Means Supply Chain

Discrete Dynamics in Nature and Society

Received 10 October 2023; Accepted 10 October 2023; Published 11 October 2023

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Zhu, J. Wang, and L. Liu, "Research on Distribution and Inventory Cooperation of Agricultural Means Supply Chain," *Discrete Dynamics in Nature and Society*, vol. 2021, Article ID 4428725, 12 pages, 2021.

Research Article

Research on Distribution and Inventory Cooperation of Agricultural Means Supply Chain

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Received 26 July 2021; Accepted 3 September 2021; Published 20 September 2021

Academic Editor: Ahmed Farouk

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This paper constructed a biobjective model based on the total cost and time satisfaction to provide a desirable solution to the distribution and inventory cooperation of agricultural means supply chain. The model simulated how the distribution center and retailers collaborate to meet the needs of the order customer in the random lead time and out-of-stock loss costs. By the features of the model, the biobjective genetic algorithm was improved based on elitism selection, aiming to improve the quality of noninferior solution in biobjective model. Finally, the influence degree of the lead time of delivery, unit inventory cost, and unit transport cost on the total cost of the system was quantified through the analysis of examples and sensitivity of model parameters. This research has provided valuable new insights into the distribution and inventory coordination of supply chain.

1. Introduction

Grain is a strategic material essential to the survival and development of our society. Agricultural production materials like pesticides and fertilizers not only guarantee the sustainable development of agriculture but also maintain the stability of the rural market and boost farmers' income. In a large agricultural country like China, it is critical to ensure the production and supply of agricultural means. In particular, the efficiency and cost of agricultural means supply directly determine whether the agricultural production system could operate highly efficiently. To gain a competitive edge, agricultural means producers and circulators should establish a synergistic and win-win supply chain system.

Currently, logistics cost takes up a growing portion of the circulation cost of agricultural means. Many agricultural means enterprises are facing more and more severe problems in logistics operation and management. However, most enterprises only resort to the internal management of a single logistics function, failing to address logistics management from the perspective of supply chain. Agricultural means enterprises need to further explore how to solve the following problems in the circulation and supply

chain of agricultural means: inventory risk sharing, collaborative replenishment, and timely, accurate, and efficient distribution to multiple customers on varied levels. Therefore, it is of great significance to study the collaboration between upstream and downstream enterprises on agricultural means supply chain based on supply chain coordination theory.

Supply chain cooperation is the collaborative decision-making process for raw material supply, goods production, product distribution, and retail among material suppliers, manufacturers, distributors, and retailers. As lots of independent enterprises are included in a supply chain, the imbalance between supply and demand can become a serious problem, if the decisions of each entity are made independently without necessary cooperation and information sharing; therefore, inventory-distribution coordination plays a significant role in conducting efficient operation of the whole supply chain for agricultural means.

So far, researches on collaborative distribution of supply chain have been mainly based on deterministic demand and stochastic demand. For example, Cohen and Moon [1] established a multiperiod mixed-integer programming model, stating that plant load involved the distribution of raw materials, product manufacturing, and product

shipments; Arntzen et al. [2] defined a multiperiod based mixed-integer model for the supply-production-distribution plan of DEC Company; and Pilz-Glombik and Glombik [3] established a multiperiod hybrid programming model based on calculation by computer to make decisions on order, production, and transportation.

However, the collaborative planning model has not been widely applied due to the great constraints of demand environment hypothesis. As a result, more scholars begin to explore the collaborative planning of supply chain in stochastic demand environment. For example, Lee and Sook [4] established a multiperiod linear programming model and studied the production-distribution coordination of the supply chain through simulation of random factors such as machine capacity and transport capacity with optimization methods; Torabi and Hassini [5] established a multiobjective mathematical programming model with probability constraints based on a fuzzy solution algorithm to study the supply and demand planning of the supply chain composed of multiple suppliers, a single manufacturer, and multidistribution centers, while Tian et al. [6] constructed a multiperiod bilevel stochastic programming model, proposing a simulation-optimization solution to deal with compensation problems. Maihimi et al. [7] formulated an inventory control model for both retailer and manufacturer and thus determined the pricing, replenishment cycle, and number of shipments in a manufacturer-retailer supply chain of deteriorating items. Drawing on the optimal design of distribution network and inventory control, Yan [8] constructed a dual-objective inventory joint control model for multilevel distribution network supply chain, which fully considers the interaction and mutual influence between the joints.

2. A Bilevel Inventory-Distribution Coordination Model

Inventory-distribution coordination in the supply chain for agricultural means involves the collaborative decision-making to control the production, supply, and sales of products among producers, distributors, and retailers. To minimize the total cost of the system with the highest time satisfaction of customers and maintain a balance between supply and demand, the volume and time period of shipments, inventory, and freight should be defined at first, and a wide range of complex relations among raw material suppliers and other enterprises are posing a great challenge to solve in a single model.

2.1. Basic Factors of the Model. It has always been a hot and difficult issue to achieve a high-efficient distribution system. With the rapid development of information technology and an increasing boom in collaborative distribution, supply chain management concepts have witnessed in-depth practices; for example, the strategies of collaborative distribution, inventory, and replenishment have been sought after by many enterprises with bold practices, as this is an effective way in reducing the cost of the logistics distribution chain [7].

In general, supply chain coordination is mainly affected by such factors as supply chain partnership, information sharing, win-win benefit, and resource sharing, whose differences will directly lead to the variance in distribution cost, reaction time, and shortage cost in the whole supply chain. Based on this, a reasonable coordination model is established in this section to study the inventory-distribution coordination.

In reality, the bilevel distribution system is commonly applied, which is composed of distributors, retailers, and customers (see Figure 1). Although there have been researches done on this field, lots of parameters were simplified. For example, the distribution centers were assumed to have no inventory; optimization of the cost is simply studied without considering factors such as time efficiency. Besides, it is difficult to consider both time efficiency and cost during optimization, and there has never been a biobjective optimization problem-solving algorithm composed of cost and time satisfaction. In view of this, a biobjective inventory-distribution coordination model based on cost and time satisfaction was constructed to study the optimization coordination of the supply chain for agricultural means.

2.2. Description of Distribution Process and Symbols Used.

Without loss of generality, the downstream of the supply chain is a multilayer network of producers, distributors, and retailers. As shown in Figure 1, each distributor divides its administrative region into multiple markets and sets up multiple regional distribution centers. Each distribution center is responsible for storage, distribution, and delivery. The development of e-commerce and popularization of communication network further expand the distribution channels of agricultural means. Many distributors and retailers are exploring the hybrid sales mode of online sales and offline sales. Considering the large differences between online and offline sales in cost and transaction method, this paper divides the end customers into ordering customers (the customers placing orders via the Internet or communication tools; they generally require home delivery service) and real-time customers (the customers who walk away after buying goods and require no delivery service). Each distribution center radiates several retail stores (franchised stores and chain stores) and some ordering customers in the downstream. The stores can meet the needs of both real-time customers and ordering customers. Figure 2 shows the process of purchase, distribution, and delivery of agricultural means of the supply chain.

First, each distributor decides its order quantity according to the predicted demand, the demand of each retail store, and the orders placed by customers. The lead time of the orders is assumed to be L . Besides, the distributor sends all the above information to the head office, which will summarize the information and make unified purchases from producers.

Second, the producer directly distributes goods to regional distribution centers according to the orders received.

Third, once receiving the goods, regional distribution centers determine their distribution plan based on inventory level and demands of retail stores.

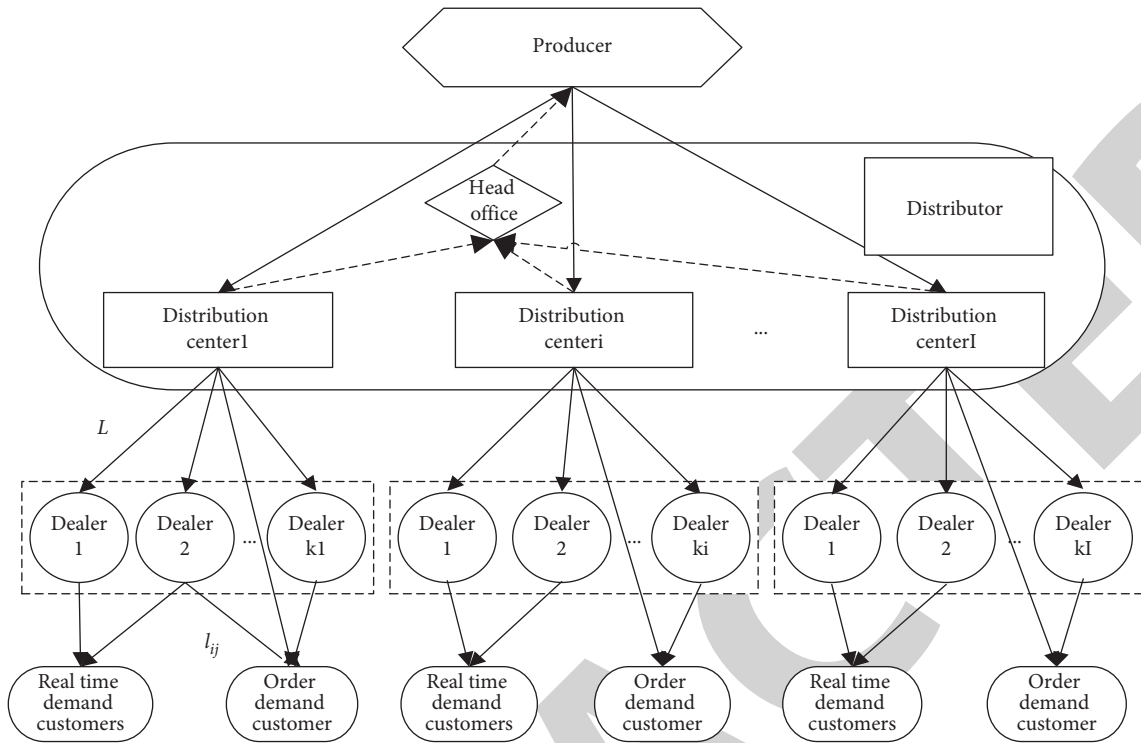


FIGURE 1: Structure of the bilevel distribution system.

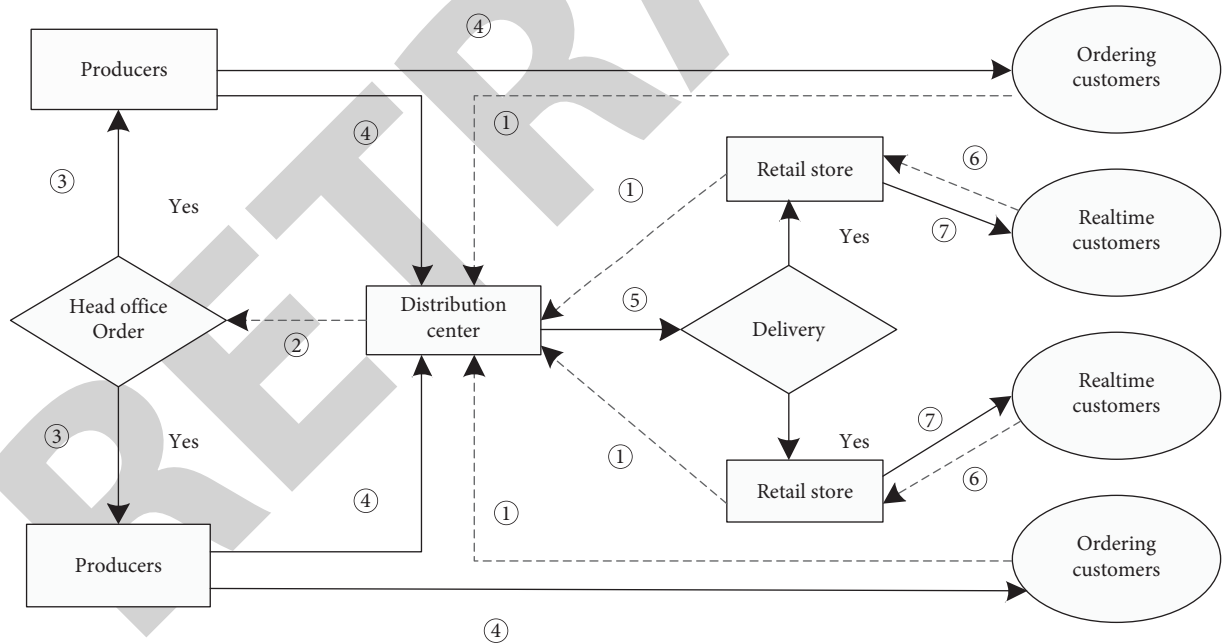


FIGURE 2: Purchase, distribution, and delivery of agricultural means.

Fourth, real-time customers and ordering customers generate random demand.

Fifth, the demand of real-time customers is satisfied in real time, while that of ordering customers is satisfied by one of the retailers and supported by delivery service.

Sixth, the total cost of the whole system is evaluated (including the operating cost of distributors, inventor cost of

distribution centers, transport cost from each producer to every distribution center, transport cost from each distribution center to every retailer, and shortage cost of each retailer), and the time satisfaction of ordering customers is assessed.

To study the inventory-distribution coordination, the following assumptions were made:

- (i) The supply capacity of manufacturers was assumed to be adequate, as it is found that there is an oversupply in the entire agricultural market
- (ii) The unit operating cost, unit product transport cost, and unit inventory cost of distributors were assumed to be relatively stable in the planning period
- (iii) The needs of the same area were assumed to be satisfied by only one distribution center
- (iv) The market demands of real-time customers and ordering customers are stochastic and obey independent normal distribution

It is shown in Figure 1 that the distribution centers operate independently, with strictly zoning supply. Therefore, the distribution coordination data of the entire system can be obtained based on the inventory and distribution needs of only one distribution center selected. Please refer to Table 1 for symbolic representation and meanings of parameters in the model.

2.3. Establishing a Biobjective Inventory-Distribution Coordination Model. Since seasonal characteristics are obvious in the supply chain for agricultural means, attention should be paid to both total cost of the system and the time efficiency of product supply. In view of this, a biobjective constraint planning model with cost and time as decision-making objectives was established in this section to achieve customer satisfaction with lower cost and shorter time.

2.3.1. Objective Function of the Predicted Total Cost. To predict the total cost, the associated costs of distributors and retailers are mainly considered in this section. After analysis, it is found that the predicted total cost consists of fixed cost CG , inventory cost CS , transport cost CC , operating cost CO , and shortage cost CB .

Whether they are open to online customer orders, the fixed cost of distribution centers and retailers can be defined as

$$CG = \sum_{i=0}^K (x_i \cdot c g_i). \quad (1)$$

It is assumed that distribution centers can directly meet the needs of ordering customers. Referring to the methods of Wang and Wu [9] and Wu et al. [10], the initial inventory after allocation to distribution centers can be described by

$$r_0 = \sum_{j=1}^M (\mu_j, y_{0j}) + \frac{Q - \sum_{i=0}^K [\mu_i + \sum_{j=1}^M (\mu_j, y_{0j})]}{\sum_{i=0}^K \sqrt{\sigma_i^2 + \sum_{j=1}^M (\sigma_j^2, y_{ij})}} \sqrt{\sum_{j=1}^M (\sigma_j^2, y_{0j})}. \quad (2)$$

Supposing that D is the total demand of ordering customers for the distribution center $L + 1$ and its demand meets $N(\mu_j, \sigma_j^2)$ distribution, the total demand D would meet the linear combination of normal random variables. Then, the mean and standard deviation of the total demand of ordering customers of a distribution center can be calculated by

$$\mu_0 = \sum_{j=1}^M (\mu_j, y_{0j}), \sigma_0 = \sqrt{\sum_{j=1}^M (\sigma_j^2, y_{0j})}. \quad (3)$$

Therefore, predicted inventory cost and shortage cost of distribution centers meeting the needs of ordering customers at the end of period L can be expressed as $CS_0 + CB_0 = \int_0^{r_0} h_0 (r_0 - x) dG_0(x) + \int_{r_0}^{\infty} s_0 (x - r_0) dG_0(x)$, where $G_0(\cdot)$ is the cumulative distribution function of demand D of ordering customers.

Then,

$$CS_0 + CB_0 = [h_0 \lambda_0 + (h_0 + s_0) R(\lambda_0)] \sqrt{\sum_{j=1}^M (\sigma_j, y_{0j})}, \quad (4)$$

where $G_0(\cdot)$ represents linear loss function of unit normal right tail and λ_0 refers to the ratio of ending inventory of distribution centers to the standard deviation of inventory, with the following value:

$$\lambda_0 = \frac{Q - \sum_{i=0}^K \mu_i + \sum_{j=1}^M (\mu_j, y_{ij})}{\sum_{i=0}^K \sqrt{\sigma_i^2 + \sum_{j=1}^M (\sigma_j^2, y_{ij})}}, R(\lambda_0) = \int_{\lambda_0}^{\infty} \frac{x - \lambda_0}{\sqrt{2\pi}} e^{-x^2/2} dx. \quad (5)$$

Similarly, predicted inventory cost and shortage cost of retailers are

$$CS_i + CB_i = \sqrt{L+1} \sum_{i=1}^K \left[[h_i \lambda + (h_i + s_i) R(\lambda)] \sqrt{\sigma_i^2 + \sum_{j=1}^M (\sigma_j^2, y_{ij})} \right]. \quad (6)$$

According to the results of Eppen and Schrage [11], the total predicted inventory cost and shortage cost of distribution centers and retailers are

$$CS + CB = L \sum_{i=1}^K \left[h_i \left[\mu_i + \sum_{j=1}^M (\mu_j, y_{ij}) \right] \right] + [h_0 \lambda_0 + (h_0 + s_0) R(\lambda_0)] \sqrt{\sum_{j=1}^M (\sigma_j, y_{0j})} + \sqrt{L+1} \sum_{i=1}^K \left[[h_i \lambda + (h_i + s_i) R(\lambda)] \sqrt{\sigma_i^2 + \sum_{j=1}^M (\sigma_j^2, y_{ij})} \right], \quad (7)$$

where λ is the ratio of retailers' ending inventory to standard deviation of inventory expressed as follows:

TABLE 1: Description of symbols applied in the biobjective distribution network model.

System parameter	Description
i, j	When $i = 0$, i represents distribution center; when $i \in [1, K]$, it means the retailer, while $j \in [1, M]$ refers to the number of ordering customers.
μ_i, σ_i	Retailer i meets the mean and standard deviation of real-time requirements.
μ_j, σ_j	The mean and standard deviation of demand from ordering customer j .
p_i	The demands on unit operating cost of distribution center and retailer i are met.
s_i	Unit cost from shortage of goods in retailers or distribution centers.
cg_i	Fixed cost to meet the needs of ordering customers (i.e., the fee to purchase communication devices and distribution vehicles).
cr_i	Unit distribution cost from a distribution center to retailer i .
cu_{ij}	Delivery cost of a distribution center and a retailer i to meet the demand of ordering customer j .
h_i	Unit inventory cost of distribution center and retailer i .
L	The lead time for retailer replenishment.
l_{ij}	The lead time of retailers and distributors in meeting needs of ordering customers.
wp_i	Inventory capability of distribution center and retailer i .
Decision variable	Description
Q	Quantity of orders from manufacturers to distribution centers.
x_i	Whether distribution center or retailer i is open to customer orders ($x_i = 1$ means “open,” while $x_i = 0$ means “close”).
y_{ij}	Whether distribution center or retailer i meets the needs of customer j ($y_{ij} = 1$ means “meet” and $y_{ij} = 0$ means “not meet”).

$$\lambda = \frac{Q - \sum_{i=1}^K [(L+1) [\mu_i + \sum_{j=1}^M (\mu_j y_{ij})]]}{\sqrt{(L+1) [\sum_{i=1}^K \sigma_i^2 \sum_{j=1}^M (\sigma_j^2 y_{ij})]}} \quad R(\lambda) = \int_{\lambda}^{\infty} \frac{x - \lambda}{\sqrt{2\pi}} e^{-x^2/2} dx. \quad (8)$$

Operating cost of the system mainly includes that of the distribution center and retailers to meet the demands of ordering customers, with expression as

$$CO = \sum_{i=0}^K \sum_{j=1}^M (p_i \cdot \mu_j \cdot y_{ij}). \quad (10)$$

Transport cost in the model consists of two aspects: the transport cost from distribution center to retailer and the delivery cost from distribution centers and retailers to ordering customers, which is expressed as follows:

$$CC = \sum_{i=1}^K \left[cr_i \left[\mu_i + \sum_{j=1}^M (\mu_j y_{ij}) \right] \right] + \sum_{i=0}^K \sum_{j=1}^M (cu_{ij} \cdot \mu_j \cdot y_{ij}). \quad (9)$$

Then, the predicted total cost of the system in a single period of time is

$$\begin{aligned} TC &= CG + CS + CB + CC + CO \\ &= \sum_{i=0}^K (x_i \cdot cg_i) + L \sum_{i=1}^K \left[h_i \left[\mu_i + \sum_{j=1}^M (\mu_j y_{ij}) \right] \right] + [h_0 \lambda_0 + (h_0 + s_0) R(\lambda_0)] \sqrt{\sum_{j=1}^M (\sigma_j y_{0j})} \\ &\quad + \sqrt{L+1} \sum_{i=1}^K \left[[h_i \lambda + (h_i + s_i) R(\lambda)] \sqrt{\sigma_i^2 + \sum_{j=1}^M (\sigma_j^2 y_{ij})} \right] + \sum_{i=1}^K \left[cr_i \left[\mu_i + \sum_{j=1}^M (\mu_j y_{ij}) \right] \right] \\ &\quad + \sum_{i=0}^K \sum_{j=1}^M (cu_{ij} \cdot \mu_j \cdot y_{ij}) + \sum_{i=0}^K \sum_{j=1}^M (p_i \cdot \mu_j \cdot y_{ij}). \end{aligned} \quad (11)$$

2.3.2. *Objective Function of Time Satisfaction.* To reflect users' satisfaction of time with respect to the response time of the upstream firms, the cosine-distribution time satisfaction function is selected in this section [10]. In the whole system, time satisfaction mainly refers to the satisfaction of

ordering customers on the delivery time of products from the upstream distribution center or retailers.

It is assumed that UL_j is the longest waiting time acceptable by the ordering customer j when he/she feels very satisfied; UU_j is the minimum waiting time acceptable by the

order customer j when he/she feels very dissatisfied. Then, time satisfaction function on the needs of ordering customer j is

$$ts_{ij} = \begin{cases} 1, & l_{ij} \leq UL_j, \\ \frac{1}{2} + \frac{1}{2} \cos \left[\frac{\pi}{UU_j - UL_j} \left(l_{ij} - \frac{UU_j + UL_j}{2} \right) + \frac{\pi}{2} \right], & UL_j < l_{ij} < UU_j, \\ 0, & l_{ij} > UU_j. \end{cases} \quad (12)$$

Therefore, the predicted time satisfaction level of the system is

$$TS = \sum_{i=0}^K \sum_{j=1}^M (ts_{ij} \cdot y_{ij}). \quad (13)$$

2.3.3. Coordination Model of Distribution and Inventory. The model is a biobjective nonlinear integer programming model to achieve maximum time satisfaction of the system at the minimum total cost, which is expressed as

$$(P1) \begin{array}{l} \text{MinTC} \\ \text{MaxTS} \end{array} \quad s.t. \quad \mu_i + \sum_{j=1}^M (\mu_j y_{ij}) + \gamma_i \sqrt{\sigma_i^2 + \sum_{j=1}^M (\sigma_j^2 y_{ij})} \leq wp_i, \quad i = 0, 1, \dots, K, \quad (14)$$

$$\sum_{i=0}^K y_{ij} = 1, \quad j = 1, 2, \dots, M, \quad j = 1, 2, \dots, M, \quad (15)$$

$$y_{ij} \leq x_i \quad i = 0, 1, \dots, K; \quad j = 1, 2, \dots, M, \quad (16)$$

$$Q \geq 0, \quad (17)$$

$$x_i \in \{0, 1\}, \quad i = 0, 1, \dots, K, \quad (18)$$

$$y_{ij} \in \{0, 1\}, \quad i = 0, 1, \dots, K; \quad j = 1, 2, \dots, M. \quad (19)$$

Constraint (12) in the model is on inventory capability of distribution centers and retailers, where $\gamma_i = \varphi^{-1}(s_i/s_i + h_i)$ (Eppen and Schrage [11]) is the safety factor. Constraint (13) ensures that the needs of the same ordering customer can only be met by one facility. Constraint (14) means that the distribution center and the retailer i can be assigned to meet the needs of ordering customer only when they are open. Constraint (15) defines that the order quantity of the distribution center is nonnegative, while Constraints (16) and (17) define the variables to be 0-1.

3. Genetic Algorithm Chosen for Multiobjective Optimization

3.1. Multiobjective Optimization Algorithm. Real-world problems are very complicated. Multiple objectives need to

be achieved under various influencing factors. Therefore, the single-objective model is often too limited to solve enterprise problems. As research problems get more and more complex, multiobjective optimization gradually catches the attention of many scholars. To better fit the reality, multiobjective optimization model came into being:

$$\begin{array}{l} \min \quad [f_1(x), f_2(x), \dots, f_n(x)], \\ s.t. \quad \begin{cases} lb \leq x \leq ub, \\ A * x \leq a, \\ Aeq * x = beq, \end{cases} \end{array} \quad (20)$$

where $f_i(x)$ is the objective function; the constraints are the upper and lower bounds of variable x , linear inequality, and linear equality, respectively.

In the above objective function, the objectives tend to conflict with each other. In other words, the value of an objective increases at the cost of another or several other objectives. The inconsistency between the multiple objectives makes it hard to find a globally optimal solution. Even if all objectives are optimized, many noninferior solutions will appear, forming a set of compromises, that is, conflicting solutions [10]. Among them, one or more noninferior optimal solutions exist: one or more objectives can neither be further optimized nor be worsened relative to the other objectives.

There is no widely recognized algorithm to solve multiobjective planning models. In general, the goal is to find a noninferior solution that best satisfies demand. Three methods are available for real-world optimization problems.

3.1.1. Generation of the Noninferior Solution Set. Obtain lots of noninferior solutions through weighting, constraint method, and the hybrid method of weighting and constraint method, forming a set of noninferior solutions, and find the satisfactory solution in the set as the final solution.

3.1.2. Interaction Method. Gradually solve the final solution by analyzing the dialog between analyst and decision-maker, for example, Geoffrion's method for solving linearly constrained multiobjective optimization problem.

3.1.3. Weighting Method. Assign each objective a weight to create a set of weighted objectives, turning the multiobjective problem into a single-objective optimization problem.

So far, evolutionary algorithms such as genetic algorithm (GA), particle swarm optimization, ant colony algorithm, and immune optimization algorithm have been increasingly used to solve multiobjective optimization problems [12–15]. Among them, the genetic algorithm is undoubtedly one of the most widely used and the most successful methods.

3.2. GA Flow for the Hybrid Multiobjective Optimization Model. Since Professor Holland [16] proposed a genetic algorithm in 1975 for the first time, it has been widely applied in multiple fields such as industrial engineering, artificial intelligence, and automatic control, due to its high efficiency, practicability, and high robustness. Schaffer (1985) was the first to introduce GA to multiobjective optimization problem, creating the vector evaluated GA. The standard GA has been repeatedly improved in terms of encoding method, selection strategy, crossover operator, mutation operator, and parameter setting [6–8].

3.2.1. Encoding Methods for Multiobjective Algorithm. Apart from the 0-1 binary encoding, the improved encoding methods of GA include sequential encoding, real number encoding, and integer encoding. The sequential encoding uses nonrepetitive natural numbers from 1 to n . It is applicable to assignment problem, traveling salesman problem, and single-machine scheduling problem. Real number encoding represents different chromosomes with a set of real numbers. This method facilitates the search in a large space and suits the optimization of continuous problems. Similar to sequential encoding, integer encoding describes each chromosome as a set of natural numbers but allows different genes to be encoded by the same number. This approach fits in with time optimization problem and selection problem. These methods are often combined to solve multiobjective optimization problems.

3.2.2. Fitness Function Calibration. Facing multiobjective problems, the GA needs to solve a key problem called fitness assignment. Currently, fitness could be assigned by vector evaluation, objective planning, and Pareto-based methods. The weighting methods offer another way to solve the problem: multiple objectives are given reasonable weights by fixed weighting, random weighting, and adaptive weighting, such that the multiobjective problem can be transformed into a single-objective problem according to the set of weighted objectives. The key of weighting methods lies in selecting a reasonable weight assignment strategy.

3.2.3. Solving Mechanisms of Multiobjective GA. Different solving mechanisms are available for GA to handle multiobjective problems. The most common mechanisms include random-weight approach, strength Pareto evolutionary algorithm (SPEA), nondominated sorting GA (NSGA), and NSGA II [17, 18].

It is used in both multiobjective model and single-objective model to get an optimized Pareto solution. The basic GA optimization process mainly consists of generation of

initial population, coding method, fitness function, genetic operation, selection strategy, and stop criterion.

As the inventory-distribution coordination model of the supply chain for agricultural means is an issue of fixed multiobjective optimization, the genetic algorithm based on elite reorganization was applied in this paper. Please refer to Figure 3 for specific optimization steps of the algorithm.

Optimization of genetic algorithms is as follows:

- (a) Set initial parameters and population.

The algorithm parameters were set as follows: $NP = 300$, $P_c = 0.7$, $P_m = 0.3$, $NG = 2000$, and $\gamma = 0.1$, and the evolutionary algebra counter was set as $g = 0$. Besides, optimal individuals were selected and preserved by elite collection in a size of N , while NP individuals were randomly generated as the initial population $P(0)$.

- (b) Calculate the fitness of individuals in the population $P(t)$.

- (c) Select in accordance with the proportion of elite individuals preserved.

With the elite selection strategy, the optimal individuals were selected and gathered into the next generation according to their fitness values. Please refer to the following key step C for specific operations.

- (d) Implement crossover operation according to crossover probability.

For the selected individual pairs, some of their chromosomes were exchanged with a certain probability, resulting in new individuals for the next generation of groups. Please refer to the following key step D for description of specific crossover operation.

- (e) Conduct mutation operation according to mutation probability.

For the selected individuals, a few genes were changed with a certain probability, resulting in new individuals for the next generation of groups. Please refer to the following key step E for description of specific mutation operation.

- (f) Determine whether the stop criteria are met

If the maximum number of iterations was conducted, then the output would be accepted as an optimal solution and the algorithm ended; otherwise, the operation returned to the above step (c) for another selection operation.

3.3. Key Steps of Improved GA. According to the optimization flow of the improved GA, the distribution and inventory cooperation model of agricultural means supply chain can be solved in the following steps.

3.3.1. Transformation of Weight Coefficient, Namely, Transforming Multiobjective Problems, into Single-Objective Problems. In the objective function, the value of the total

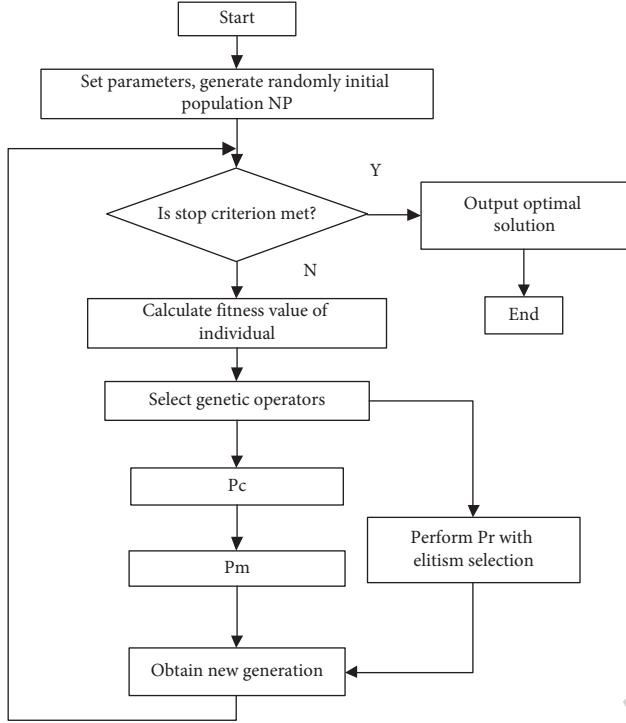


FIGURE 3: Optimization process of improved genetic algorithm.

cost TC has a negative relation with the goodness of a scheme, while that of time satisfaction TS has a positive relation with the optimization degree of scheme. To simplify the model, these two objectives were converted into one objective by the following method.

It is supposed that $TC' = 10^a/TC$ and $TS' = TS$, where a is the difference between the magnitude of order by all individuals in the initial population and the magnitude of the two objectives.

Thus, the double objective function in the model was transformed into a single-objective function:

$$\begin{cases} \text{Max}F = \text{Max}(l_1 * TC' + l_2 * TS') \\ l_1 + l_2 = 1 \end{cases}, \quad (21)$$

where l_1 and l_2 are weights of cost index and time satisfaction index, which can be determined based on the firm's emphasis degree and preferences in practice. Please refer to Section 3.1 for relevant description and comparison.

3.3.2. Encoding Method. In the model, hybrid coding method was adopted due to different value scope of different variables, where binary coding method was applied for the unknown quantities x_i, y_{ij} in a variable to be either 0 or 1; real number coding was used for real variables such as unknown quantity Q and other parameters; and variables y_{ij}, l_{ij} of 11×50 matrixes were transformed into 1×550 one-dimensional matrixes. In addition, since the randomly generated variables x_i, y_{ij} could hardly satisfy Constraints (13) and (14), a set of x_i values were randomly generated at

the time of initial population generation and then a group of y_{ij} were randomly generated according to the generated x_i and constraints.

3.3.3. Selection Operation. To select the elite individuals and preserve them to form a stable next generation, an elite preservation strategy was adopted, where optimal individuals were selected from the old population after crossover mutation operation was implemented, and the worst individuals of the new population were replaced with the same number of elite individuals.

3.3.4. Crossover Operation. For random crossover operation, the single-point crossing was applied in this section, where tangent points for two individuals from the population were randomly selected based on crossover probability. During the operation, a rejection policy was used in case of illegal encoding of individuals, and the binary coding method was adopted for unknown quantities x_i, y_{ij} with variables to be either 0 or 1. If the randomly selected tangent points were in position of x_i, y_{ij} , the right substring would be directly interchanged in cross operation. In terms of real number coding, the real cross method is used as follows:

$$\begin{aligned} a'_{kj} &= a_{kj}\beta + a_{lj}(1 - \beta), \\ a'_{lj} &= a_{kj}(1 - \beta) + a_{lj}\beta, \end{aligned} \quad (22)$$

where a_{kj} and a_{lj} are the positions of the k -th and l -th chromosomes at j and β is the random number in interval $[0, 1]$.

3.3.5. Mutation Operation. To find the optimal solution for mutation operation, a local search was applied, and an improved place value mutation was used in this section as the mutation strategy. Since binary encoding was used for variables x_i, y_{ij} , their place value could only be 0 or 1, and for other variables using real number encoding, their place values could be changed within a certain range. In this section, as the chromosome is composed of seven variables, thus different positions of seven variables were randomly selected for mutation operation, and the mutation step size of each position was randomly generated. However, the range of mutation step size gradually reduced with the increasing number of iterations, thus ensuring a better local search. Mutation operation for real numbers was performed as follows:

$$\begin{aligned} z'_k &= z_k + \delta * f(g), \\ f(g) &= r(1 - g/G), \end{aligned} \quad (23)$$

where z'_k is the place value of a gene after mutation; z_k is the place value of a gene in chromosome before mutation; δ means the mutation step randomly generated in the range of $[-1, 1]$; r refers to the random number in interval $[0, 1]$; g represents the number of iterations; and G is the preset maximum number of iterations.

4. Case Study and Model Analysis

First, the validity of the model and algorithm was analyzed with test data; then, the model was applied to study the circulation of agricultural means in HN agricultural means company, and the influence of key parameters on inventory-distribution coordination decisions was evaluated in this section.

4.1. Analysis of Model Validity. To analyze the effectiveness of the model, experiments were conducted by comparing performance between single-objective model and biobjective model. In total, six tests were conducted, where the demand point number of retailers and the number of ordering customers were set as $1^\#(5,10)$, $2^\#(5,20)$, $3^\#(10,30)$, $4^\#(10,50)$, $5^\#(20,50)$, and $6^\#(20,80)$.

Parameters in the case study were set as follows: $\mu_i = U[20, 50]$ tons, $\sigma_i = 1.44$, $\mu_j = U[1, 3]$ tons, $\sigma_j = 0.28$, $p_i = 2$ yuan/ton, $s_0 = 10$ yuan/ton, $s_i = U[10, 50]$ yuan/ton, $cg_i = 50$ yuan/ton, $cr_i = 30$ yuan/ton, $cu_{ij} = U[8, 12]$ yuan/ton, $h_0 = 5$ yuan/ton, $h_i = 2$ yuan/ton, $wp_0 = 2000$ tons, $wp_i = 50$ tons, $\gamma_i = 0.2$, $L = 5$ d, $l_{ij} = U[1, 3]$ d, $UL_j = 1$ d, and $UU_j = 3$ d.

The algorithm parameters were configured as follows: $NP = 300$, $P_c = 0.7$, $P_m = 0.3$, $NG = 2,000$, and $\gamma = 0.1$.

The biobjective nonlinear integer programming model with capacity constraints as shown in Model P1 could be decomposed into submodel P11 for minimum cost and submodel P12 for maximum time satisfaction, which were expressed as follows:

$$(P11) \text{MinTC} \\ \text{s.t. (9), (12)–(13), (15).}$$

$$(P12) \text{MaxTS} \\ \text{s.t. (10)–(13), (15).}$$

In addition, to find out the impact of different weight combinations of cost and time satisfaction on the results, a comparison of the results between $(l_1 = 0.3, l_2 = 0.7)$ and $(l_1 = 0.5, l_2 = 0.5)$ was made based on the preference value acquired from leaders in HN agricultural company.

During the comparison, the improved genetic algorithm based on elite reorganization was applied to figure out results (see Tables 2 and 3).

The following three points are indicated in Table 2:

- (i) In the first four cases, the minimum total cost got from the single-objective model and the biobjective model has no big difference. However, the time satisfaction got from biobjective model is twice more than that from single-objective model. In the last two cases, as there is an exponential increase of retailers and ordering customers, the growth rate of total cost reaches over 5 times, while that of time satisfaction maintains twice, indicating that the time satisfaction objective of customers should be dynamically developed according to the scale of retailers and the number of ordering customers in the supply chain.

- (ii) When maximum time satisfaction of customers is considered to be the only objective, the growth rate of customer satisfaction is about 1%, while the total cost grows more than 10 times, which is far away from an optimal cost objective for enterprises and is not feasible.

- (iii) Results from the first four cases show that the cost and time satisfaction of biobjective models are close to optimal values. However, in the last two cases, the time satisfaction is close to optimal value, while the cost is far from the optimal value, as the weight of cost set in the algorithm is not big enough, and the weight of time satisfaction is relatively too high.

(1) As shown in Table 3, the biobjective model achieved near-optimal cost and satisfaction. Overall, the biobjective model outperformed the single-objective (cost) model and the single-objective (satisfaction) model. Hence, the model boasts a good optimization effect and optimizes cost and service at the same time. (2) Comparing Tables 2 and 3, it can be inferred that the cost was greatly reduced, but the satisfaction did not change much, after the weight adjustment of the total cost and satisfaction. For enterprises, it is important to set a reasonable customer satisfaction level. Blind pursuit of high satisfaction is difficult and costly. Hence, it is suitable to choose $l_1 = 0.5$ and $l_2 = 0.5$ for our algorithm.

4.2. Analysis of Algorithm Parameters. This section discussed the influence of crossover and mutation probabilities on the optimization results of the genetic algorithm during the operation process of the model applied in HN agricultural company. During the experiment, the algorithm was run 10 times with $K = 10$ and $M = 50$, while it was set that $P_m = 0.1$ and $P_c = 0.5–0.95$. It is shown in Table 4 that the results are more stable when $P_c = 0.7$.

As shown in Table 4, the result was relatively stable and better than the other cases, when $P_c = 0.7$. Hence, the crossover probability of our model algorithm was set to $P_c = 0.7$.

The mutation probability was determined similarly. The algorithm was run 10 times with $P_c = 0.7$ and $P_m = 0.05–0.5$. From the results in Table 5, it can be learned that the result was relatively stable and better than the other cases when $P_m = 0.3$.

4.3. Sensitivity Analysis of Model Parameters. To analyze the sensitivity of the model to parameters, parameters were set as described in Section 4.1, while it was set that $K = 10$ and $M = 50$ in HN agricultural company. Through calculation, when the distribution center and 8 retailers try to satisfy the demand of ordering customers via online business, the overall optimized goal of the enterprise would be achieved with a total cost of 23547.79 and a time satisfaction of 49.99.

To provide a basis for decision-making in inventory-distribution coordination of the supply chain, the sensitivity of the two objectives to lead time, unit shortage cost, unit delivery cost, and unit inventory cost was analyzed in this section.

TABLE 2: Comparison test results between single-objective model and biobjective model weight $l1 = 0.3$ and $l2 = 0.7$.

Cases	Cost single-objective strategy		Time satisfaction single-objective strategy		Cost-satisfaction biobjective strategy	
	MinTC	TS	TC	MaxTS	MinTC	MaxTS
1 [#] (5,10)	9447.08	4.60	127179.80	10.00	13426.20	10.00
2 [#] (5,20)	11548.41	10.77	24208.69	20.00	12436.61	19.95
3 [#] (10,30)	21010.63	16.27	563344.20	29.94	21986.06	29.69
4 [#] (10,50)	24705.78	22.89	34887.38	49.52	25129.38	46.64
5 [#] (20,50)	43251.01	22.26	612484.00	49.55	233901.40	48.83
6 [#] (20,80)	45316.98	41.05	1712665.00	79.26	598927.30	78.81

TABLE 3: Comparison test results between single-objective model and biobjective model weight $l1 = 0.5$ and $l2 = 0.5$

Cases	Cost single-objective strategy		Satisfaction single-objective strategy		Cost-satisfaction biobjective strategy	
	MinTC	TS	TC	MaxTS	MinTC	MaxTS
1 [#] (5,10)	10103.94	4.89	19848.47	10.00	10381.34	10.00
2 [#] (5,20)	9921.19	10.25	35736.93	20.00	9929.83	19.96
3 [#] (10,30)	23257.04	14.70	51079.29	30.00	22538.73	29.46
4 [#] (10,50)	23432.89	26.04	137211.84	50.00	23547.79	49.99
5 [#] (20,50)	35925.72	24.80	1456692.70	50.00	37528.38	49.87
6 [#] (20,80)	37573.27	38.61	1276620.96	79.75	38303.77	77.59

TABLE 4: Operating results of different crossover probabilities $Pm = 0.1$, $NP = 300$, and $NG = 2000$.

Pc	0.5		0.6		0.7		0.8	
	MinTC	MaxTS	MinTC	MaxTS	MinTC	MaxTS	MinTC	MaxTS
1	23254.66	47.29	25162.28	48.03	25513.43	46.41	26577.18	44.74
2	24115.56	47.72	25619.86	47.36	24988.49	48.01	23852.03	47.38
3	24045.56	47.56	25224.95	43.79	23851.03	43.49	23629.89	48.87
4	24679.81	45.75	26549.88	47.00	24577.98	46.62	23703.07	42.99
5	23342.08	44.17	22844.47	47.96	27840.83	47.98	26419.13	44.96
6	22452.54	47.48	26734.91	46.44	24830.75	47.61	23378.51	41.78
7	23668.72	45.19	27732.37	47.08	24685.75	48.72	24271.42	46.54
8	26654.94	48.96	25966.77	47.59	26285.49	46.84	27110.31	47.04
9	27199.69	46.90	24389.74	45.92	24780.72	48.30	25476.45	48.27
10	25075.78	48.66	25782.69	48.09	24224.25	46.25	24201.99	44.17

TABLE 5: Operating results of different mutation probabilities $Pc = 0.7$, $NP = 300$, and $NG = 2000$.

Pm	0.1		0.2		0.3		0.4	
	MinTC	MaxTS	MinTC	MaxTS	MinTC	MaxTS	MinTC	MaxTS
1	26584.30	46.37	26504.48	49.04	28162.48	48.67	25631.94	48.03
2	25046.36	46.39	23944.01	47.92	21726.38	47.74	24360.25	49.17
3	26789.79	46.87	24252.18	48.26	25765.97	49.22	25789.74	49.16
4	24479.50	47.99	26126.76	48.07	26301.57	48.49	24222.86	47.94
5	24400.24	43.83	28352.62	48.73	26520.46	47.39	25841.34	47.95
6	25246.05	43.81	24540.42	48.92	24737.81	48.73	24316.85	48.74
7	26030.89	45.31	24599.67	48.11	24692.00	48.17	24346.52	48.69
8	25942.66	48.35	25333.58	48.73	25665.11	49.17	26709.93	46.83
9	26910.19	45.82	26299.00	45.86	23968.13	49.25	24219.77	47.86
10	24185.68	48.01	24419.92	45.22	24815.90	48.90	23851.46	49.08

Hence, $Pc = 0.7$ and $Pm = 0.3$ were selected as parameters of our algorithm.

Figure 4 shows the influence of the replenishment cycle L of retailers on total cost and customer satisfaction. The total cost increased with the replenishment cycle, for the

following reasons: With the extension of the replenishment cycle, distributors at all levels will increase inventory to safeguard supply and reduce the probability of shortage.

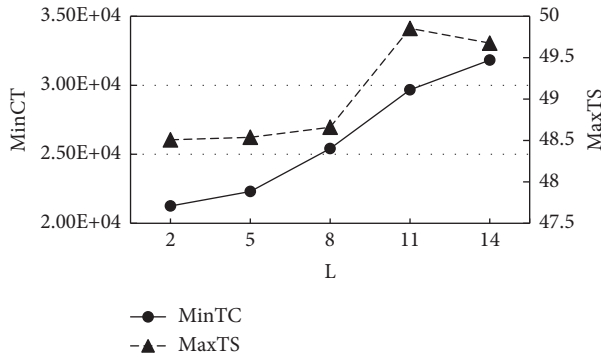


FIGURE 4: Sensitivity analysis of lead time.

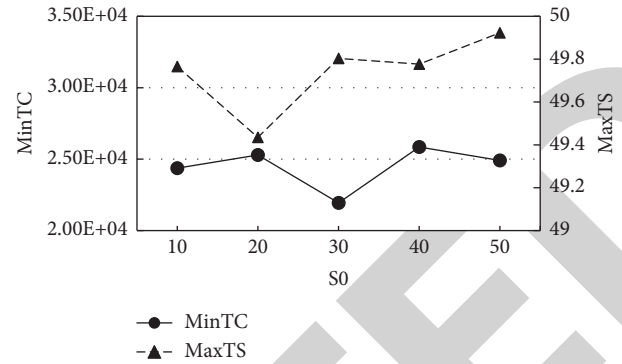


FIGURE 5: Sensitivity analysis of shortage cost.

That is why the inventory cost increases so markedly. Meanwhile, with the gradual extension of the replenishment cycle, customer satisfaction did not change significantly and dropped obviously only after L reached a large value. This is because the customer satisfaction model mainly deals with the delivery time l_{ij} to end customers and does not involve the satisfaction with the replenishment cycle L of retailers. However, when the replenishment cycle extends over a limit, chain reaction becomes inevitable. In this case, the retailers are forced to protect its own interests at the cost of delivery time to end customers. The customer satisfaction thereby nosedives.

As shown in Figure 5, the total cost was not sensitive to the shortage cost. The main reason lies in the collaborative operation between distributor and retailers. According to the inventory of each node, retailers with sufficient supply capacity are directed to meet the needs of online customers. This mechanism minimizes the occurrence of short supply and lowers the shortage cost, minimizing its impact on the total cost. This paper does not consider how the shortage cost S_i affects customers' time satisfaction because the two factors are not directly connected in our model.

As shown in Figure 6, the total cost increased apparently with the growth of unit delivery cost. This is in line with the actual operation. Transport and delivery costs are the main parts of agricultural means distribution cost. In recent years, transport infrastructure and logistics have been developing rapidly, weakening the functions of warehouses. This trend, coupled with the large capital occupation and low-profit margin of agricultural means, propels more retailers to cut down inventory and resort to the dynamic en route inventory to meet customer demand. For agricultural means supply chain, the key issues are to implement effective cooperation in delivery and optimize the delivery routes. This paper does not consider how the unit delivery cost C_{uij} affects customers' time satisfaction because the two factors are not directly connected in our model.

As unit inventory cost h_i is not directly related to customer time satisfaction, only its effect on the total cost of the model was analyzed in this section.

As is shown in Figure 7, the total cost is very sensitive to h_i and it increases rapidly with the rise of unit inventory cost. Therefore, distributors at all levels should cooperate to enhance ability in forecasting the market demands, to make

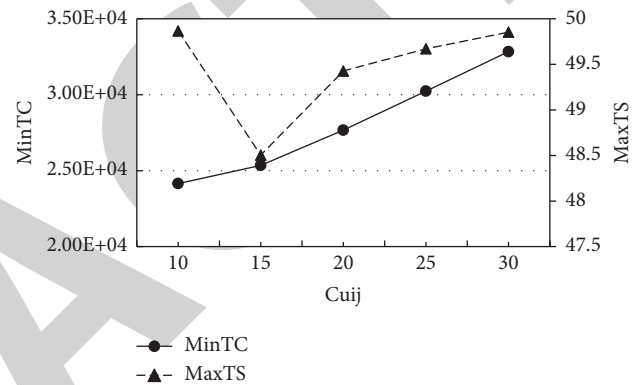


FIGURE 6: Sensitivity analysis of delivery cost.

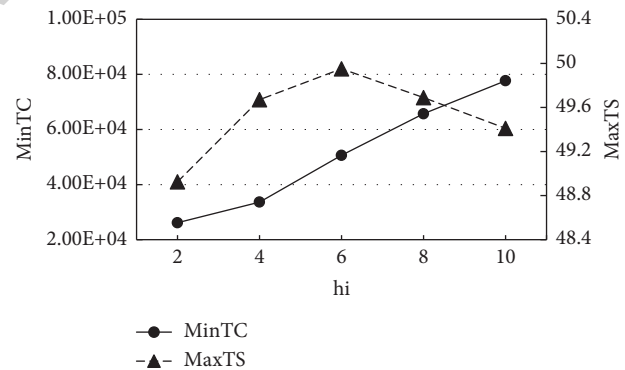


FIGURE 7: Sensitivity analysis of inventory cost.

scientific decisions of order in reducing inventory, and to improve management capability in reducing unit inventory cost.

5. Conclusions

This paper explores the distribution and inventory cooperation of agricultural means supply chain, constructs a distribution and inventory cooperation model, and optimizes the model with improved GA. Through calculation examples, the biobjective model was proved superior to single-objective models. Meanwhile, a sensitivity analysis

was performed on model parameters to visually quantify the degree of influence of replenishment cycle, unit inventory cost, and unit transport cost over total cost and total satisfaction, providing clear directions to enterprise decision-makers. First, enhance the inventory and delivery cooperation between distributors and retailers at all levels, aiming to shorten replenishment cycle and lower the cooperation cost of supply chain. Second, strengthen the management capability of enterprises, improve logistics efficiency, and reduce the operating and logistics costs per unit product. Third, improve the cooperative prediction ability of distributors and retailers at all levels and make scientific predictions to improve forecast accuracy, reduce inventory, and prevent shortage.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The work was supported by the project of Social Science Foundation of Hebei Province “Research on the Diagnosis and Modernization Collaborative Construction of the Industrial Chain and Supply Chain Network in Beijing-Tianjin-Hebei” (HB21YJ004) and “Strategy and Management Base of Mineral Resources in Hebei Province,” Hebei GEO University, China.

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