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Product Volume Forecasting Model Based on Integrated Learning and EOQ

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Abstract. With the rapid development of China's e-commerce industry, how to effectively manage commodity inventory costs has become one of the core issues to be solved. This paper presents a comprehensive solution to this challenge. First, through the analysis and processing of sales data, the combined model of ARMI-LSTM-XGBOOST is used to predict the sales volume of 1996 commodities during the period from May 16 to June 2, 2023, providing basic data for inventory management. Secondly, the optimal stock strategy (s, S) for each day of the period from May 16 to May 30, 2023 is determined by combining the joint order point method and the regular order method. Finally, the model of commodity replenishment cost is established and solved by genetic ant colony algorithm, and the optimal replenishment plan to meet the inventory demand at the lowest cost is obtained. Taking a product (PRODUCT_994-East China) as an example, the lowest cost of replenishment was determined to be 964 yuan. The results of this study provide important guidance for e-commerce enterprises, which can help them manage inventory more effectively, reduce costs, and improve competitiveness.

Keywords: ARIMA-LSTM-XGBoost combination model, Joint order point method and periodic order method, "modern" EOQ model, Dynamic Adjustment inventory strategy (s,S), Genetic ant colony algorithm.

1 Introduction

With the rapid development of the Internet, as an emerging business model of e-commerce, online shopping attracts a large number of young and middle-aged people with its advantages of high efficiency and low costs, so that people's demand for online shopping continues to grow, making e-commerce get the opportunity for rapid development in China, and catalyzing its status as an important part of China's economy today. Up to now, the total scale of China's e-commerce market has reached 10 trillion

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yuan. At the same time, the scale of China's e-commerce market will continue to maintain stable growth, the addition of emerging e-commerce platforms not only transforms the original e-commerce demand market, but also simultaneously impacts consumers' preferences for certain products and the inventory management strategies driven by e-commerce orders. In such a complex and changeable e-commerce market, e-commerce companies need to consider the supply and demand relationship that may change at any time, and formulate effective method models. This is to accurately predict the demand for consumer goods, so as to prepare the corresponding goods in advance, reduce storage costs and improve the service level of e-commerce, and achieve the lowest cost of merchants and the highest quality of service.

How to accurately predict commodity sales, formulate effective inventory strategies and reduce commodity replenishment costs are of great significance for e-commerce enterprises, which can not only help merchants prepare goods in advance and reduce inventory costs, but also improve service levels, thereby achieve the goal of cost minimization and service maximization.

In order to solve the above problems, many scholars have carried out extensive research: Brown[1] proposed the high-order exponential smoothing prediction method and discussed its application in nonlinear prediction; Kenneth[2] conducted an in-depth research on the ARIMA model considering multi-level demand in the supply chain environment, and predicted the inventory and order volume of commodities. Issam[3] et al. used the relevant parameters of ARIMA model to construct nonlinear objective functions and analyzed the methods that can reduce the distortion of supply chain demand information. Peter[4] combined ARIMA model and MLP network based on the idea of combination forecasting, and the results showed that the combined prediction model had better effect than the single prediction. Tseng et al. [5] proposed a FSARIMA model combining ARIMA model with fuzzy regression, which showed good predictive performance in predicting two seasonal time series data. Egrioglu et al. [6] proposed an intuitive time series fuzzy inference system (I-TSFIS), and verified its good prediction ability by using ten time series data sets. Huard[7] et al. built a combined model for e-commerce sales forecast based on exponential smoothing and Holt linear trend method, and proved the effectiveness of the model on the sales data set. Ji S[8] incorporated the sales characteristics into the C-XGBoost model as an influential factor in the prediction, and finally obtained the forecast results by assigning weights, which was superior to the single-stage forecasting method in the sales prediction of cross-border e-commerce. Guo[9] et al. used genetic algorithm to search for optimal diffusion of generalized regression neural networks and apply it to GRNN for prediction. Chan[10] et al. established a production inventory path distribution model to minimize the total cost of the system, maximize the average food quality, minimize carbon emission and minimize the delivery time, and solved it by GLNPSO algorithm. Yantong[11] et al. studied the integrated planning of intelligent logistics system and designed a two-stage iterative heuristic method combined with fuzzy logic method. Chen[12] et al. established a supply chain logistics collaborative optimization model under the circumstances of joint replenishment and channel coordination. Shah[13] et al. studied the minimum-maximum inventory strategy between customers and their upstream suppliers based on the implementation of VM-managed inventory in the centralized distribution center. Eppen[14] et al. analyzed the centralized control system that adopts (T,S) inventory strategy with fixed lead time under the distribution model of single distribution center and multiple points of sale. Fr[15] et al. analyzed the single-distribution center multi-point of sale system under the (R, nQ) inventory strategy; Francis[16] et al solved the optimal allocation strategy problem of a production inventory system by using dynamic programming method. Jeong[17] et al. proposed a general linear causal prediction model applicable to SCM, and constructed a linear regression combined prediction model based on GGA genetic algorithm.

Ng[18] et al. used multiple regression analysis model and time series model respectively, as well as a comprehensive model combining the two, when predicting the bid price index. Zhu[19] et al. studied the problem of minimizing the cost of associated control constrained by storage capacity, and established a control mechanism for the continuous increase of products under the maximum storage capacity. Choi[20] et al. built the average downside risk and mean-variance newsboy model based on the endogeneity of random demand and price. Wang[21] et al regard customer perceived value as a uniform distribution function of customer cycle time, which reflects the randomness of demand. Huang[22] et al. established a braided inventory model in which product price is affected by inventory level and demand rate is affected by price difference under the condition of stock shortage. Haji[23] et al. considered the time-varying holding cost,and built a deteriorating item EPO model under inflation where demand is affected by price and advertising promotion. Blanchini[24] et al discussed the cost control of multi-level inventory under uncertain demand. Salameh[25] et al. considered the EOQ model with certain defective products in primary inventory. Wahab[26] et al. considered the impact of defective products and environment on the basis of EOQ model of secondary supply chain. A Y Q[27] et al. constructed a demand function under the combined influence of price, quality and inventory, and studied the optimal pricing and ordering of fresh agricultural products. Cai[28] et al. studied the coordination problem of the three-level supply chain composed of manufacturers, distributors and third-party logistics, and proposed that combined incentive contracts make the main body of the supply chain share the risks in transportation and sales.

Based on previous studies, this paper uses mathematical modeling methods, combined with actual data and algorithm programs, puts forward corresponding models and algorithms, and verifies their effectiveness and feasibility through empirical analysis. The research results of this paper will provide effective reference and guidance for e-commerce enterprises, so as to promote the development and progress of e-commerce industry.

2 The Presented ARMI-LSTM-XGBoost Model for Predicting the Sales Volume

In order to achieve demand management and optimization in the supply chain of e-commerce[29-31], it is first necessary to predict the demand of 1,996 commodities of various merchants in various warehouses during 05/16/2023 to 05/30/2023 based on the historical shipment data. By analyzing the data, it is found that the total demand for goods in December 2022 and January 2023 fluctuates greatly due to the "Double 12" activities and the Spring Festival holiday. Due to the sudden increase in the quantity of goods during some large-scale promotions and the irregularity of the demand for goods brought by holidays, it is difficult to accurately forecast the demand. Therefore, this paper will only refer to the demand for goods from February 2023 to May 2023. Forecast the demand of 1996 products from 05/16/2023 to 05/30/2023.

Firstly, it is divided into training set and test set according to the ratio of 8:2, that is, 02/01/2023 to 04/24/2023 is the training set, and 04/25/2023 to 05/15/2023 is the test set. In order to make the prediction more accurate, the training set is put into the LSTM model, ARIMA model and XGBoost regression model respectively to obtain the predicted value of the product demand from 04/25/2023 to 05/15/2023 in 1996. The predicted value and test set were then used to evaluate the performance of the model with the evaluation index 1-wmape.

Next, the relative error reciprocal method is used to determine the weights of the three models LSTM, ARIMA and XGBoost, and then the model fusion method is adopted to build the fusion model combining the advantages of the three models to get the final prediction result.

This paper uses the above model and method to predict the demand of 1996 kinds of goods in each warehouse of various merchants during 05/16/2023 to 05/30/2023. Next, the product (PRODUCT_994 -East China) will be taken as an example, and the experimental results are obtained through the above analysis method: the weights of ARIMA, LSTM and XGBoost are 0.26, 0.43 and 0.31, respectively. Based on this, the ARMI-LSTM-XGBoost combined model[32] was obtained, which was used to predict the demand of product (PRODUCT_994-East China) from 04/25/2023 to 05/15/2023, and finally the predicted value was obtained: [8 4 3 7 8 4 15 10 8 10 5 5 4 8 9 7 7 11 7 9 8 8].

In order to better judge the performance of the model, this paper will use the 1-wmape index given in the title to evaluate the accuracy of three single models and one combined model. The formula for indicator 1-wmape is as follows:

$$1 - wmape = 1 - \frac{\sum |y_i - \widehat{y}_i|}{\sum y_i}.$$

Finally, the prediction accuracy of ARIMA, LSTM, XGBoost and combined models was obtained, and the specific results were shown in Table 1 below.

Table 1. Prediction accuracy of ARIMA, LSTM, XGBoost and combined models

Learning device	Training set accuracy	Testing set accuracy
ARIMA	0.712	0.642
LSTM	0.827	0.782
XGBoost	0.776	0.712
ARIMA-LSTM-XGBoost combination model	0.864	0.804

In addition, in order to better observe the prediction effect of each model, Figure 1 will visually compare the prediction results of the four models with the real values.

By comparing the prediction effect of each model in Table 1 and Figure 1, it is found that the prediction effect of the combined model of ARMI-LSTM-XGBoost is much better than that of the other three single learner models. Therefore, the team finally chose to use the combined model of ARIMA-LSTM-XGBoost to predict the demand of 1996 commodities from 05/16/2023 to 05/30/2023.

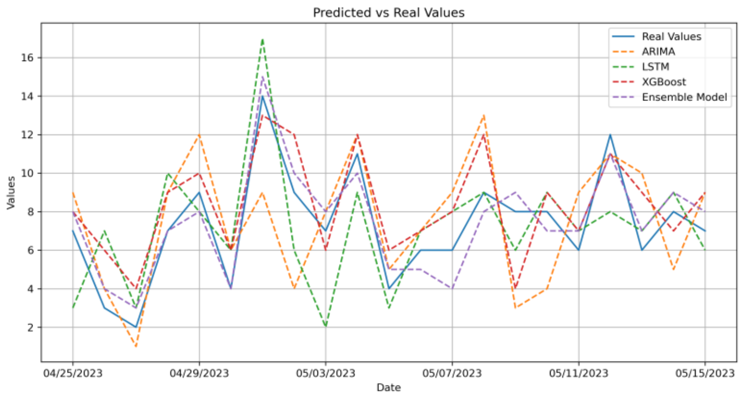

Fig. 1. Comparison of the predicted and true values of the four models

3 The Strategy of the Initial Inventory (s, S)

In order to formulate the replenishment plan for each commodity, this paper uses the joint order point method and the regular order method to determine the initial inventory strategy (s, S) and the daily replenishment total of each commodity during 05/16/2023 to 05/30/2023.

3.1 The Establishment of Inventory Replenishment Model

Order point method refers to when the inventory of a certain item drops to a predetermined point, the order plan is issued and the inventory is replenished. This method needs to check the inventory regularly and grasp the inventory in real time.

The regular order method is a kind of inventory management measure that replenishes inventory by ordering according to a clear order cycle in advance. Merchants set an order cycle in advance according to their previous experience and planning indicators, and place an order every time they arrive at an order cycle. The order quantity varies each time, and the order interval can be expressed by the order cycle, which remains unchanged in the regular order method.

The application of order point method can understand the inventory situation in time and avoid stock shortage, but because of the need to regularly check each variety and order separately, the ordering cost and transportation cost are increased. Most businesses generally use regular ordering, a variety of consumables together to order, reduce order processing costs and transportation costs, and this way does not require frequent inventory inventory, and because of the frequent inventory inventory, can not grasp the inventory changes in real time, if there is an emergency, a large number of needs, it is easy to cause out-of-stock phenomenon. The inventory replenishment model discussed in this study combines the order-point method and the periodic order method, reducing the out-of-stock rate through the use of order-point ordering and reducing operational costs through regular ordering. When the inventory level is less than or equal to the ordering point or reaches the order cycle, the ordering plan is issued, and the order quantity is the difference between the maximum inventory and the inventory inventory.

Order Point Method.

Confirm order point.

The order point indicates that the goods should be ordered when the inventory has fallen to this point, which is also the minimum inventory point. The order point is defined on the basis of safety stock, and its calculation formula is shown below.

$$Order\ Point = Q_L + Q_{ss}.$$

Where, Q_L is the expected demand within 3 days of the lead time, Q_{ss} is the safety stock under the order point.

Safety stock is an additional stock held in inventory management, which is set to deal with sudden demand or the corresponding high cost of stock shortage. Due to the random transformation of demand and the unstable change of lead time, the demand in the replenishment period will cause the shortage caused by the disturbance of the uniform demand point in the replenishment period. Safety stock is the buffer stock planned to prevent this uncertainty factor, and can be used as a buffer. Whether the establishment of safety inventory is appropriate has a great impact on reducing the shortage rate of materials. The formula for calculating safe inventory in this paper is shown as follows.

$$Q_{ss} = K \times \sigma \times \sqrt{l}.$$

Determine order quantity and maximum inventory.

Where, Q_{ss} is the safety inventory, K is the safety factor, σ is the standard deviation of the demand, $\sqrt{L}$ represents the order lead time, and the time interval from placing the order to receiving the goods.

The quantity of goods ordered should be sufficient to satisfy the demand for goods during the ordering cycle. In this study, the order quantity is calculated as the following formula:

Order quantity = Maximum inventory - Inventory at the time of inventory.

Order not arrived + Customer delayed purchase

Under normal circumstances, the general merchant does not order and the customer delays the purchase phenomenon, the order quantity of goods is generally calculated as the following formula:

Order quantity = Maximum inventory - Inventory at time of count

Thinking about the quantity of goods ordered becomes thinking about the maximum stock of goods. The maximum inventory of goods should satisfy the needs during the order cycle (T) and the order lead time (L). Similar to the way order points are determined, the maximum inventory is the sum of the expected or average amount of demand during the life of the goods and the quantity of a safety stock. The maximum inventory is calculated by the following formula:

$$Q_{max} = E(Q_{T+L}) + Q_s.$$

The determination method of the safe stock here is similar to that of the previous determination of the safe stock when ordering points are obtained. The safe stock under the maximum stock is determined according to the distribution of the shortage rate and residual. When the lead time is a fixed constant and the residual meets the normal distribution, the safe stock should satisfy the needs during the order cycle (T) and the order lead time (L). The safe inventory is calculated by the following formula:

$$Q_s = K \times \sigma \times \sqrt{L + T}.$$

After the maximum inventory is clear, you can specify the order quantity, that is: Order quantity = Maximum inventory - Inventory at the time of inventory.

Classification of Goods.

There are many kinds of e-commerce commodities, and their urgency of demand and harm caused by out-of-stock are different, and the out-of-stock rate is also different. For such phenomena, in the process of this study, the commodities are first classified. Used to measure the ability of goods inventory to meet customer needs is the inventory service level, the specific formula is shown below:

$$\text{Service level} = \frac{\text{The number of items satisfied}}{\text{Total number of actual demand}} \times 100\%.$$

However, the determination of inventory service level is more of a non-objective and simple discriminating method, usually without rigorous scientific verification. The sum of service level and out of stock level is 100%, so the service level is determined at the same time, the out of stock level is basically determined. First, the goods are classified, and then the safety inventory under various categories is determined, and the safety inventory of various categories of goods is calculated according to the difference in the urgency of their needs and the difference in the stock shortage rate. According to the emergency situation of commodity application, the service level can be divided into three grades: 0.60 ~ 0.80, 0.81 ~ 0.90 and 0.91 ~ 0.99. The corresponding relationship between service level and safety factor is shown in Table 2.

Table 2. Relationship between service level and safety factor

Service level	0.65	0.70	0.75	0.80	0.83	0.86	0.89	0.93	0.96	0.99
Safety factor value	0.71	0.83	0.88	0.92	0.95	0.98	1.02	1.05	1.10	1.20

Time Order Method.

This is a "modern" version of the EOQ model. In the operation process of e-commerce goods, it is observed that the purchase price, sales price and sales quantity of a product are very stable, but the supplier does not provide free delivery service, and each delivery requires the merchant to pay a fixed delivery fee. In order to reduce the number of deliveries and save the total delivery fee, the supermarket can buy more goods each time, but this will occupy a lot of capital and storage space, resulting in a rise in capital costs and storage costs. Therefore, it is necessary to decide the best purchase cycle, that is, how long to enter once and how many goods each time.

Such problems are common in reality. Assuming that no shortage is allowed, and the sales price and sales quantity are given, the sales revenue of the merchant is fixed, so it is only necessary to consider meeting the market demand with the minimum cost. In this article, the following assumptions, parameters, and variables are typically introduced when modeling such problems:

1) The demand rate of the product (sales per unit time) is a constant, denoted as D;

2) The purchase price of the product (price of a single piece) is a constant, denoted as C;

3) The delivery fee for each purchase is a constant (independent of the purchase quantity) denoted as S;

4) The holding cost per unit time of each commodity (capital cost and storage cost, etc.) is a constant, denoted as H;

5) The quantity of each purchase (decision variable) is a constant, denoted as Q;

6) The purchase cycle (that is, how often to buy goods) is a constant, denoted as T, obviously T=Q/D.

It can be seen in Figure 2, because the demand rate of the product is constant, the average storage

volume (inventory) of the product is Q/2, so the total cost in a purchase cycle can be obtained:

$$F(Q) = S + CQ + HT(Q/2) = S + CQ + HQ^2.$$

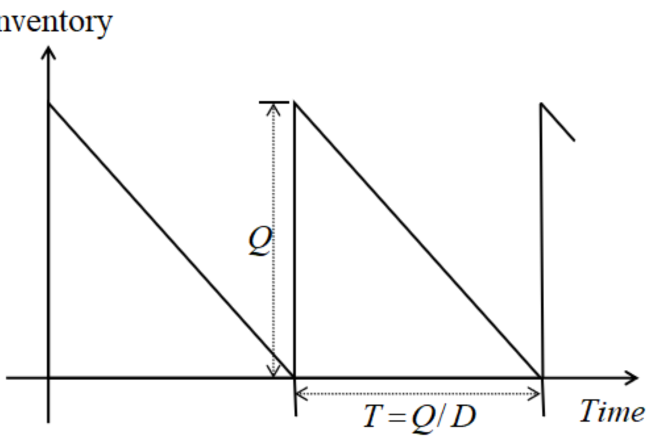

Fig. 2. Changes in inventory over time

Therefore, in order to meet the product demand, the average cost per unit of time needs to be paid by the merchant:

$$G(Q) = F(Q)/T = SD/Q + CD + HQ/2.$$

It is easy to know that Q in $G(Q)$ is a convex function, and the minimum order quantity $Q^* = \sqrt{2SD/H}$ is the corresponding purchase cycle Q^*, which is usually called economic order quantity (EOQ), and the above model is called the EOQ model. Since expressions are in the form of square roots, they are sometimes called "square root formulas".

3.2 The Solution of Inventory Replenishment Model

Bring the demand of the product (PRODUCT_994-East China) from 04/16/2023 to 06/02/2023 into the order point method and the regular order method to obtain the order cycle of the product for 8 days, and then obtain the initial inventory strategy (s, S) and the daily replenishment amount of the product for each day from 05/16/2023 to 05/30/2023. The specific results are shown in Table 3.

Table 3. Product (product_994- East China) inventory replenishment result

Date	Initial inventory strategy(s,S)	Inventory at the beginning of the day	Ending stock	Forecast demand	Sup-plynum
05/16	(32,79)	5	0	7	79
05/17	(30,82)	0	0	9	0
05/18	(26,75)	0	0	7	0
05/19	(29,80)	0	79	7	0
05/20	(30,79)	79	70	9	0
05/21	(28,77)	70	66	4	0
05/22	(31,79)	66	57	9	0

Date	Initial inventory strategy(s,S)	Inventory at the beginning of the day	Ending stock	Forecast demand	Sup-plynum
05/23	(33,83)	57	50	7	0
05/24	(34,84)	50	39	11	0
05/25	(33,75)	39	35	4	0
05/26	(36,82)	35	29	6	53
05/27	(37,91)	29	20	9	0
05/28	(34,87)	20	12	8	0
05/29	(32,88)	12	59	6	0
05/30	(33,82)	59	47	12	0

ps: where in each day, the beginning of the day inventory + replenishment - forecast demand = the end of the day inventory. The ending inventory of the current day is the beginning inventory of the next day.

4 Cost of Replenishment of Goods

Get goods every day during 05/16/2023 to 05/30/2023 initial (s, S) inventory strategy and replenishment amount, then the goods during 05/16/2023 to 05/30/2023, the minimum cost as the objective function, through continuous to adjust inventory strategy (s, S) {e.g. (0.9s,S),(s,0.9S), etc.}, and finally an optimal inventory strategy (s, S) is obtained, which minimizes the cost of the goods in that half month.

In order to better solve the minimum cost of goods, this problem is transformed into the minimum value of the sum of ordering cost, holding cost (related to inventory turnover days) and out-of-stock cost (related to service level) of each commodity in this half month.

4.1 The Establishment of Commodity Replenishment Cost Model

In inventory management and replenishment planning, the main costs include four aspects.

(1)Ordering Costs.

Order cost refers to various fixed and variable costs generated by enterprises for ordering, including order processing cost, order processing cost and scheduling cost. These costs vary with the quantity and frequency of orders and affect inventory management decisions of enterprises. The order cost formula in this paper is defined as follows:

$$\text{Ordering cost}(p_d) = \text{The cost of an order}(p_d) \times \text{Order times}(n).$$

Among them, this paper assumes that the cost of an order is p_d , and the order times is n. After the inventory strategy (s, S) is determined by solving the inventory replenishment model, the order times (n) of the goods during the period from 05/16/2023 to 05/30/2023 are also determined, so a variable value p_d can be obtained finally.

(2)Holding Costs.

Carrying cost refers to the various expenses incurred by merchants to maintain and manage inventory, including capital costs, storage costs, insurance costs, wear and obsolescence costs, and theft and scrap losses. High carrying costs encourage merchants to reduce inventory levels to reduce capital tie up and risk, but too low inventory can lead to undersupply or missed sales opportunities. The cost of carrying formula in this paper is defined as follows:

$$\begin{aligned}\text{Carrying cost}(P_c)\\ &= \text{Daily carrying cost per piece} \times \text{Average daily inventory}\\ &\times \text{Holding days.}\end{aligned}$$

Among them, this paper sets the daily holding cost of each piece of goods as 0.01 per piece of goods price (p), that is, 0.01p; After the inventory strategy (s, S) is determined by the inventory replenishment model, the daily average inventory of the goods from 05/16/2023 to 05/30/2023 is also determined. The number of days held is the period of half a month, that is, 15 days. So you end up with P_c.

(3)Shortage Costs.

Out-of-stock cost refers to various losses and expenses incurred by merchants due to insufficient inventory and inability to meet market demand. When a business cannot supply the required product or service in a timely manner, it may face problems such as reduced sales, lost customers, and damaged reputation, which are manifestations of out-of-stock costs.

Since the sum of service level and out of stock level is 100%, so the service level is determined at the same time, the out of stock level is basically determined. The service level formula for this article is defined as follows.

$$\text{Service level} = \frac{\text{The number of items satisfied}}{\text{Total number of actual demand}} \times 100\%.$$

The Shortage Costs formula in this paper is defined as follows:

$$\text{Shortage Costs } P_q = \text{ Out of stock } \times \text{ Profit per item.}$$

Where, the quantity out of stock is the number of unmet items, and the profit of each item is set as 20% of the price (P), that is, 0.2P. After the inventory strategy (s, S) is determined by solving the inventory replenishment model, the stock shortage P_q of the goods during the period of 05/16/2023 to 05/30/2023 is also determined, so it can finally be obtained.

(4)Objective Function - Cost.

In this problem, an initial inventory strategy (s, S) is obtained through the inventory replenishment model, and then the cost P is taken as the objective function. Based on the initial inventory strategy (s, S), an optimal inventory strategy (s, S) is found by constantly adjusting the daily s and S, so as to minimize the cost of goods from 05/16/2023 to 05/30/2023. The specific cost P is calculated as follows:

$$\text{Cost of replenishment of goods } P = \text{Ordering cost } P_d + \text{Carrying cost } P_c + \text{Shortage Cost } P_q.$$

The daily inventory strategy (s, S) adjustment range is: (0.7s, 0.7S), (0.7s, 0.8S), (0.7s, 0.9S), (0.7s, 0.9S), (0.8s, 0.8s), (0.8S, 0.8s), (0.8s, 0.9s), (0.8S, 0.9s), (0.9s, 0.7S), (0.9s, 0.8s), (0.9s, 0.8s), (0.9s, 0.8s), (0.9s, 0.8s), (0.9s, 0.8s), 0.9S), (0.9s, S), (s, 0.7S), (s, 0.8S), (s, 0.9S), (s, S), a total of 16 inventory strategies (s, S).

4.2 Genetic Ant Colony Hybrid Algorithm

Since there are 16 inventory strategies (s, S) per day, there will be approximately one combination between 05/16/2023 and 05/30/2023. In order to solve the minimum value of commodity replenishment cost more efficiently, this paper will use genetic ant colony hybrid algorithm to solve the problem.

The Basic Idea of Genetic Ant Colony Hybrid Algorithm.

Through the study of references, it is found that genetic algorithm[9] and ant colony algorithm[33] each have certain advantages in solving the inventory optimization cost minimization problem, but there are also corresponding defects. For example, in the initial stage of seeking the optimal solution, the genetic algorithm has a high search efficiency and is suitable for a large range of searches. However, in the second half of the search for the optimal solution, the genetic algorithm does not make full use of the feedback information, and this deficiency will appear, and consume a lot of time in ineffective iteration. The outstanding parallel computing ability and overall optimization ability are the biggest advantages of ant colony algorithm, but the disadvantage is that in the initial stage of the algorithm, the shortage of pheromones will lead to the slow search for the optimal solution, so the running time of the algorithm is relatively long.

According to the characteristics of commodity replenishment, this paper further combines genetic algorithm and ant colony algorithm on the basis of previous studies, so as to give full play to their respective advantages. In particular, the advantages of genetic algorithm can be fully utilized to achieve higher search efficiency during the operation of the algorithm. In other words, it has the characteristics of efficient search in the initial stage, and then can generate the necessary pheromones for the use of the ant colony algorithm, and then use the ant colony algorithm to obtain the global optimal solution, making full use of the overall optimization ability of the ant colony algorithm and the outstanding parallel computing ability.

The Implementation Steps of Genetic Ant Colony Hybrid Algorithm.

The implementation steps of the genetic ant colony hybrid algorithm are as follows:

Step1 initializes the parameters of the genetic algorithm, generates the initial population, and sets the initial iteration number to 0;

Step2 Calculate the fitness function of all individuals;

Step3 Perform basic genetic operations on individuals and increase the number of iterations by 1;

Step4 Determine whether the termination conditions are met, if yes, continue to perform, otherwise jump to Step2;

Step5 Use genetic algorithm to find the approximate optimal solution and convert it into initial pheromone for the ant colony algorithm to use, and then build the bipartite graph model of the commodity restocking problem;

Step6 Before the ant colony algorithm runs, initialize the relevant parameters and set the number of iterations to gen=0;

Step7 Put m ants (in the vertex set on the left side of the bipartite graph), and establish a tabu table and a table that allows selection for each ant;

Step8 Ant k selects the transfer path according to the constraint conditions of commodity replenishment cost and transfer probability;

Step9 Record m paths and complete the iteration;

Step10 Calculate the length of m paths and record the current optimal path value.

Step11 Update the pheromone quantity on the top of the optimal path and volatilize the pheromones on the other sides;

Step12 determines whether the termination constraint conditions are met.

If yes, terminate the operation and find the value of the current optimal path; otherwise, gen=gen+1, and return to Step7 to continue the new iteration. The flow chart of the genetic ant colony hybrid algorithm to solve the problem of commodity replenishment cost is shown in Figure 3.

4.3 The Solution of Commodity Replenishment Cost

Since the initial inventory strategy (s, S) for each day of product (PRODUCT_994-East China) during 05/16/2023 to 05/30/2023 has been solved, the s and S in the initial inventory strategy (s, S) will be adjusted next to solve the inventory strategy (s, S) with the lowest replenishment cost of the product. Where the range of s is {0.7s,0.8s,0.9s, S}, and the range of S is {0.7S,0.8S,0.9S,S}, and they are combined, so there will be 16 inventory strategy combinations every day, that is, the question will be transformed into which inventory strategy (s, S) combination will be used every day. It can minimize the total replenishment cost of goods during 05/16/2023 to 05/30/2023.

The experimental scheduling system adopts the commonly used ant colony algorithm. On the basis of the research in this paper, the original algorithm is deleted and replaced by the genetic ant hybrid algorithm. Based on the above experimental data, several experiments were carried out in ant colony algorithm and genetic ant colony hybrid algorithm respectively. In this paper, the original ant colony algorithm system is referred to as system A, and the genetic ant colony hybrid algorithm is called system B, and the rationality and efficiency of the two algorithms to solve the problem of commodity replenishment are verified.

Algorithm Operation Time Comparison.

When the daily inventory strategy (s, S) units are 2, 3 and 4, the running time and fitness of system A and system B are compared and analyzed in detail. The comparison of algorithm operation time is shown in Table 4. The data in Table 4 shows that System A takes less time to operate than system B. When the scheduling unit is 1, system A is 45 and system B is 36. When the dispatching unit is 2, system A is 214 and system B is 165. When the scheduling unit is 3, the scheduling unit is 654 for system A and 597 for system B.

The length of an algorithm's ideal operation time is an important key performance index to measure the quality of the algorithm. The shorter the operation time, the smaller the possible loss and the more opportunities it brings. It can be seen from Table 4 that as the number of inventory strategy (s, S) units per day increases, the running time of the two algorithms will also increase. In the case of the same number of inventory strategy (s,S) units per day, the ant colony algorithm takes a longer time, while the genetic ant colony hybrid algorithm takes a shorter time.

Algorithm Fitness Comparison.

In genetic algorithm, fitness is the main index to describe the individual performance and driving force of genetic algorithm. From a biological point of view, normal conditions are equivalent to the "survival of the fittest" competition for biological sustainability, which is important in the genetic process. Establishing the mapping relationship between the target operation of optimization problem and individual adaptability is helpful to realize the objective role of optimization problem in group development. Therefore, we compared the adaptability of the two systems, and the results are shown in Table 5.

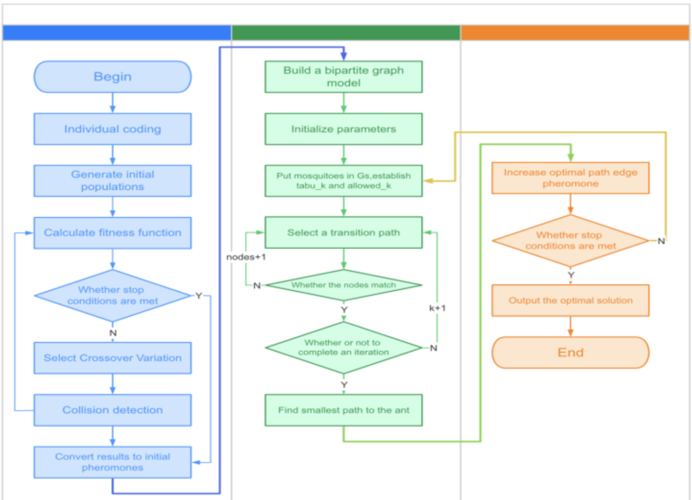

Fig. 3. Flow chart of the genetic ant colony hybrid algorithm to solve the problem of commodity replenishment cost

Table 4. Comparison of operation time between the two algorithms

Daily inventory strategy (s,S) units	System A	System B
2	45	36
3	214	165
4	654	597

Table 5. Fitness comparison of the two algorithms

Daily inventory strategy (s,S) units	System A	System B
2	184	198
3	290	321
4	532	703

It can be seen from the data in the table that the adaptability of system B is better than that of system A. When the scheduling unit is 1, system A is 184 and system B is 198. When the scheduling unit is 2, system B is 31 higher than system A. If the scheduling unit is 3, system B is 71 times higher than system A. It can be seen that with the increase of course scheduling units, the fitness values of the two algorithms also increase. With the increase of the number of course scheduling units, the fitness values of the two algorithms tend to be stable. Therefore, it can be concluded that the fitness of genetic ant colony hybrid algorithm is better than that of single ant colony algorithm under the same number of arrangement units.

Finally, this paper will use the genetic ant colony hybrid algorithm to solve the minimum replenishment cost of this product during 05/16/2023 to 05/30/2023, and the solution results are shown in Table 6.

Table 6. Minimum replenishment cost of product (product_994- East China)

Date	Inventory strategy(s,S)	Opening inventory	Ending inventory	Quantity demanded	Supplynum	Cost	Total cost
5/16	(21,76)	5	0	7	76	84	
5/17	(24,70)	0	0	9	0	142	
5/18	(22,68)	0	0	7	0	112	
5/19	(21,62)	0	76	7	0	104	
5/20	(18,72)	76	67	9	0	76	
5/21	(19,70)	67	63	4	0	64	
5/22	(21,72)	63	54	9	0	52	
5/23	(23,67)	54	47	7	0	47	964
5/24	(25,63)	47	36	11	0	34	
5/25	(27,65)	36	32	4	0	27	
5/26	(21,60)	32	26	6	0	23	
5/27	(19,72)	26	17	9	0	21	
5/28	(18,69)	17	9	8	60	18	
5/29	(14,67)	9	3	6	0	15	
5/30	(19,71)	3	0	12	0	145	

Through the genetic ant colony algorithm, an optimal solution is obtained, which makes the target cost function reach the minimum value of 964 yuan. Therefore, the same operation method will be adopted next to solve the minimum cost of replenishment for 1996 kinds of commodities.

5 Conclusion

This study proposes a comprehensive solution to the inventory management challenges brought about by the rapid development of China's e-commerce industry. First of all, through in-depth analysis and processing of sales data, we use the combined model of ARIMA-LSTM-XGBoost to accurately forecast the sales volume of 1996 commodities during the period from May 16 to June 2, 2023, providing reliable basic data for subsequent inventory management. Secondly, we combined the joint order point method and the regular order method to determine the optimal inventory strategy (s, S) for each day of these items between May 16 and May 30, 2023. Through this step, we provide practical guidance to e-commerce enterprises to help them better manage warehouse inventory, reduce costs, and improve competitiveness. Finally, we set up commodity replenishment cost model, and solve it by genetic ant colony algorithm, and get the optimal replenishment plan to meet the inventory demand at the lowest cost. Taking a product (PRODUCT_994-East China) as an example, we verify the effectiveness of this method and determine that the lowest cost of replenishment is 964 yuan.

The method proposed in this study provides important decision support for e-commerce enterprises, which can significantly improve the efficiency of inventory management, reduce costs, and enhance competitiveness. In the future, we will continue to improve the model algorithm, explore more innovative methods, and make greater contributions to the sustainable development of the e-commerce industry.

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References

1. Brown R G. Forecasting and Prediction of Discrete Time Series[J]. Journal of the Royal Statistical Society, 1964, 127(2). DOI:10.2307/2344012.
2. G.Kenneth. An ARIMA supply chain model, Management Science, 2005, 51(2): 305-310.
3. Dhahri I, Chabchoub H. Nonlinear goal programming models quantifying the bullwhip effect in supply chain based on ARIMA parameters[J]. European Journal of Operational Research, 2007, 177(3): 1800-1810. DOI: 10.1016/j.ejor.2005.10.065.
4. Peter G, Zhang. Time series forecasting using a hybrid ARIMA and neural network model[J]. Neurocomputing, 2003. DOI: 10.1016/S0925-2312(01)00702-0.
5. Tseng FM, Tzeng G H. A fuzzy seasonal ARIMA model for forecasting[J]. Fuzzy Sets & Systems, 2002, 126(3): 367-376.
6. Egrioglu E, Bas E, Yolcu O C, et al. Intuitionistic time series fuzzy inference System[J]. Engineering Applications of Artificial Intelligence, 2019, 82: 175-183.
7. Huard M, Rémy Garnier, Stoltz G. Hierarchical robust aggregation of sales forecasts at aggregated levels in e-commerce, based on exponential smoothing and Holt's linear trend method[J]. Working Papers, 2020. DOI:10.48550/arXiv.2006.03373.
8. Ji S, Wang X, Zhao W, et al. An Application of a Three-Stage XGBoost-Based Model to Sales Forecasting of a Cross-Border E-Commerce Enterprise[J]. Mathematical Problems in Engineering, 2019. DOI:10.1155/2019/8503252.
9. Guo Z D, Fu J Y. Prediction method of railway freight volume based on genetic algorithm improved general regression neural net-work[J]. Journal of Intelligent Systems, 2018, 27(2): 291-302.
10. Chan F T S, Wang Z X, Goswami A, et al. Multi-objective particle swarm optimisation based integrated production inventory routing planning for efficient perishable food logistics operations[J]. 2024. DOI:info:doi/10.1080/00207543.2019.1701209.
11. Yantong L I, Chu F, Yang Z, et al. A Production Inventory Routing Planning for Perishable Food with Quality Consideration[C]. IFAC Symposium on Control in Transportation Systems, 2016.
12. Chen J M, Chen T H. Reply to "Comment on 'Optimizing supply chain collaboration based on joint replenishment and channel coordination'"[J]. Transportation Research Part E Logistics and Transportation Review, 2008, 44(5): 950-953. DOI:10.1016/j.tre.2007.05.001.
13. Shah J, Goh M. Setting Operating Policies for Supply Hubs[J]. Social Science Electronic Publishing. 2024, DOI:10.2139/ssrn.2157430.
14. Eppen G, Schrage L. Centralized ordering policies in a multi-warehouse system with lead times and random demand[J]. 1981.
15. Fr. C, Ys. Z. One-warehouse Multiretailer Systems with Centralized Stock Information[J]. Operations Research: The Journal of the Operations Research Society of America, 1997(2): 45.
16. Francis de Véricourt, Dallery K Y. Optimal Stock Allocation for a Capacitated Supply System[J].Management Science, 2002, 48(11): 1486-1501. DOI: 10. 1287/ mnsc. 48.11. 1486. 263.
17. Jeong B, Jung H S, Park N K. A computerized causal forecasting system using genetic algorithms in supply chain management[J]. Journal of Systems & Software, 2002, 60(3): 223-237. DOI:10.1016/S0164-1212(01)00094-2.
18. S. THOMAS N G, Cheung S O, Skitmore M, et al. An integrated regression analysis and time series model for construction tender price index forecasting[J]. Construction Management & Economics, 2004, 22(5): 483-493. DOI:10.1080/0144619042000202799.

19. Zhu, Chao, Weerasinghe, et al. Optimal inventory control with path-dependent cost criteria[J]. Stochastic Processes & Their Applications An Official Journal of the Bernoulli Society for Mathematical Statistics & Probability, 2016.
20. Choi T M, Chiu C H. Mean-downside-risk and mean-variance newsvendor models: Implications for sustainable fashion retailing[J]. International Journal of Production Economics, 2012, 135(2): 552-560. DOI:10.1016/j.ijpe.2010.10.004.
21. Wang X, Xie J, Fan Z P. B2C cross-border E-commerce logistics mode selection considering product returns[J]. International Journal of Production Research, 2020(1): 1-20. DOI: 10.1080/00207543.2020.1752949.
22. Huang Y F, Weng M W, Su R H, et al. An EPQ model for deteriorating items with allowable shortage and price difference-dependent demand[C]. 2017 8th International Conference on Awareness Science and Technology (iCAST). 2017. DOI: 10.1109/ICAwST.2017.8256527.
23. Haji A, Sabahno H, Haji R. Developing a partial backlogging deteriorating inventory model with selling price dependant demand rate and cycle length dependant selling price[C]. 2008 IEEE International Conference on Industrial Engineering and Engineering Management. 2024. DOI: 10.1109/IEEM.2008.4737859.
24. Blanchini F, Miani S, Rinaldi F. Guaranteed Cost Control for Multi-inventory Systems with Uncertain Demand [J]. IFAC Proceedings Volumes, 2002, 35(1): 13-18. DOI: 10.3182/20020721-6-es-1901. 00490.
25. Salameh M K, Jaber M Y. Economic production quantity model for items with imperfect quality[J]. International Journal of Production Economics, 2000, 64.
26. Wahab M I M, Mamun S M H, Ongkunaruk P. EOQ models for a coordinated two-level international supply chain considering imperfect items and environmental impact[J]. International Journal of Production Economics, 2011, 134(1):151-158. DOI:10.1016/ j. ijpe. 2011.06.008.
27. A Y Q, B J W, C C W. Joint pricing and inventory control for fresh produce and foods with quality and physical quantity deteriorating simultaneously - ScienceDirect[J]. International Journal of Production Economics, 2014, 152: 42-48.
28. Cai X, Chen J, Xiao Y, et al. Fresh-product supply chain management with logistics outsourcing[J]. Omega, 2013, 41(4): 752–765. DOI:10.1016/ j.omega.2012.09.004.
29. Blackburn J, Scudder G. Supply Chain Strategies for Perishable Products: The Case of Fresh Produce[J]. Production and Operations Management, 2009, 18(2): 129-137.DOI:10.1111/ j.1937-5956.2009.01016.x.
30. Junhai M, Qiuxiang L, Binshuo B. Study on Complex Advertising and Price Competition Dual-Channel Supply Chain Models Considering the Overconfidence Manufacturer[J]. Mathematical Problems in Engineering, 2016, 1-18. DOI:10.1155/2016/2027146.
31. Matsui K. When should a manufacturer set its direct price and wholesale price in dual-channel supply chains [J]. European Journal of Operational Research, 2016, 258(2). DOI: 10.1016/ j.ejor.2016.08.048.
32. Liu J, Yan J. Research on Maximum Temperature Prediction Based on ARIMA-LSTM-XGBoost Weighted Combination Model[J]. Journal of Circuits, Systems and Computers, 2024, 33(07). DOI: 10.1142/S0218126624501238.
33. Dorigo M, Gambardella L M. Ant colonies for the travelling salesman problem[J]. 1997. DOI: 10.1016/s0303-2647(97)01708-5.