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Research on Optimization of Demand Forecasting-Based Inventory Control Systems

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Abstract: With the upgrading of production and operation methods of fresh agricultural products in China, people's requirements for the timeliness and quality of fresh products are increasing. However, currently, China's fresh supply chain faces serious premium issues, high logistics and storage costs, and great losses and high costs at the retail end, which are not conducive to the healthy development of the market. Too small inventory can affect customers' choices, while too large inventory can increase corporate costs. To ensure fresh agricultural products appear on consumers' tables in higher quality, this paper, against this background, analyzes the profile and inventory management status of P Supermarket, and through the analysis and forecasting of historical sales data, finds problems such as unreasonable inventory control and low accuracy of customer demand forecasting. This paper focuses on using a scientific demand forecasting optimization research model to analyze and solve the problems existing in P Supermarket. It also uses Matlab for inventory optimization control, applies the particle swarm algorithm for 500 iterations to obtain the optimal inventory level and determine the optimal order quantity.

Keywords: Demand forecasting; Inventory control; Fresh agricultural products.

1. Introduction

1.1. Research Background

In recent years, the rapid development of the Internet, the Internet of Things, and the emergence of express delivery services have greatly changed our way of life. Compared with offline physical stores, online malls and supermarkets have vigorously promoted contactless delivery, effectively resolving people's travel difficulties. With the continuous improvement of people's living standards, the demand for the quality of fresh agricultural products, especially fruits, vegetables, meats, and aquatic products, has increased. Traditional supermarkets mainly adopted the "agency model" [1], which involves multiple layers of turnover through intermediaries and wholesalers before selling to consumers. This supply chain model is more complex, not only increasing product costs but also making it difficult to guarantee the quality and freshness of perishable agricultural products due to their easy-to-spoil nature. In contrast, fresh supermarkets using the "direct procurement model" offer better product freshness and timeliness [2]. With the improvement of consumers' living standards, their requirements for the quality of fresh agricultural products have gradually increased. Meanwhile, the rapid development of Internet technology has made the purchase of fresh agricultural products no longer limited to traditional offline wholesale markets or supermarkets. The "14th Five-Year Plan" for Cold Chain Logistics Development issued by the General Office of the State Council in 2021 pointed out that China's cold chain logistics capacity and market size are increasingly occupying a larger proportion of the existing logistics market. The national strategy of promoting the O2O model has also achieved diversification in the purchase and sales channels of fresh agricultural products [3]. How to deliver fresh products to consumers more efficiently, address the pain points of fresh supermarkets, and reduce the high inventory costs due to the characteristics of fresh products have become the top priority for fresh product-selling supermarkets and enterprises.

1.2. Research Significance

Fresh agricultural products are characterized by high water content, short shelf life, and perishability. Many supermarkets, in pursuit of high-profit markets, often neglect inventory management and turnover rates. Given the high requirements for transportation time, temperature, and other objective conditions, failure to adjust procurement and sales strategies in line with market conditions can lead to inventory accumulation or product spoilage, increasing costs and reducing profits. Fresh foods are the main commodities in cold-chain logistics and are closely related to people's daily lives [4]. With the continuous development and strengthening of industrial, agricultural, production equipment, and service industries, the demand standards for cold-chain logistics have been raised. People now have higher expectations when purchasing food and hope to wait less for fresher fruits and more natural milk from farther places. Thus, researching and developing the fresh-product supermarket industry chain has become an imperative. The unique properties of fresh products, such as perishability, seasonality, and climate sensitivity, make their demand highly unstable. Demand forecasting is crucial for business process management, marking the start of all planning and execution processes. In fresh-product supermarkets, inaccurate demand forecasting can cause problems like over-inventory (leading to waste) and stock-outs, negatively impacting economic benefits and customer experience. Therefore, precise demand forecasting is essential for inventory management, procurement planning, and formulating scientific marketing strategies to boost sales and market share. Considering the development needs of cold-chain logistics in recent years, studying inventory control and optimization in fresh-product supermarkets is of great significance and necessity.

2. Research status of fresh food industry

2.1. Domestic Research Status

Characterized by cold chain transportation and cold storage, the fresh-product supply chain is unique. Even within a single supermarket, different fruits have different transport requirements. This increases the difficulty of long-distance and long-term transportation, shortens the shelf life of fresh fruits, and significantly raises inventory costs. Cold chain logistics is crucial for food, medicine, and cosmetics. In recent years, the Chinese government has increased investment and introduced policies to boost the cold chain logistics industry. However, as a late-comer, China's cold chain logistics still faces challenges [5].

Firstly, compared to developed countries, China's cold chain logistics has an average inventory cost and damage rate nearly double, indicating huge room for improvement, especially in technology [6]. The existing biological cold chain transport technology is not perfect, with limited infrastructure. Some areas lack advanced cold chain equipment, making it hard to separately control the transport conditions for different fresh products. As a result, products cannot maintain freshness sufficiently during the same transport, losing nutrients and water quickly or spoiling. Geographical, climatic, and economic-technological imbalances also widen the development gap between eastern and western China. In remote rural areas, the introduction of biological cold chain technology is difficult [7]. Additionally, the management and operation levels of some small logistics companies need to be enhanced. The lack of professional personnel leads to improper use of specialized equipment, which does not fully utilize its potential. These issues threaten the freshness of fresh products and cause severe losses [8]. On the other hand, China's underdeveloped processing technology for fresh agricultural products is another reason for serious inventory and damage problems in supermarkets. This technology is still in the early stages of development, leading to processing losses and a high damage rate from fresh agricultural products to shelf-ready products. This affects costs and causes significant losses to supermarkets.

2.2. International Research Status

In developed countries, advanced biological cold chain technology is widely used in rural ranches and urban areas, effectively preserving fresh products. With a long-standing cold chain logistics history, these countries are more technically and managerially mature than China [9]. Their cold chain logistics use advanced equipment like refrigerated vehicles and cold stores, featuring superior cooling and precise temperature control. This ensures products stay fresh during transport. Some countries also invest heavily in developing new technologies and equipment. Additionally, their logistics distribution networks are well-developed, with standardized transport routes and schedules from production to sales, ensuring fast and efficient delivery and reducing product damage.

Bassey et al. [10] (2022) proposed a novel two-echelon location-inventory system model incorporating response time constraints. The system employs an (S-1, S) inventory control policy, comprising a finite set of customers, a limited number of service facilities, and a single manufacturing plant. The study's primary theoretical contribution lies in its integration of lateral transshipment mechanisms into a two-echelon location-inventory framework with stringent response time requirements. This advancement aligns with the evolving logistics paradigms identified by Nayeon Kim et al. [11] (2023), who demonstrated that the proliferation of e-retail and omnichannel home delivery services has substantially elevated customer expectations regarding fulfillment responsiveness. Stringent service-level agreements (e.g., X-hour delivery guarantees) necessitate the physical proximity of inventory to demand points, requiring both extensive inventory networks and intelligent stock deployment strategies. These studies have established robust theoretical frameworks that continue to inform contemporary inventory optimization practices.

Not only do logistics enterprises in developed countries have highly efficient management and operation systems, but they also employ advanced logistics management systems and technologies, which significantly enhance transportation efficiency and safety. In addition, information technology is widely used in cold chain transportation. Technologies such as sensors, GPS positioning, and the Internet of Things are used to monitor temperature, humidity, and transportation time in real-time, ensuring product quality and safety. These data also enable more precise supply chain management and product traceability for logistics enterprises and manufacturers.

2.3. Current Status of Supermarket Fresh Food Inventory

Supermarkets hold large inventory units and bear high inventory costs, especially for fruits and vegetables, as their freshness is crucial to consumers and vital for supermarkets' competitiveness. These products have high consumption frequency and stable demand, making them essential daily purchases. With rising health awareness, demand for fresh, healthy produce is increasing, solidifying their position as key strategic commodities in supermarkets [12]. The quality and freshness of fresh products greatly influence customer satisfaction. Consumers often equate the quality of fresh products with the supermarket's reliability. High-quality fresh products enhance a supermarket's image and customer loyalty. Moreover, fruits and vegetables, despite their low unit price, are significant profit contributors. Their high consumption frequency attracts customers to buy other items, boosting overall sales and profit [13].

However, P Supermarket's current inventory issues stem from reliance on manual management experience for procurement lists, ordering, and determining purchase volumes. This approach often leads to the bullwhip effect and subjective, potentially misguided decisions. The inventory control methods and order patterns can cause significant product losses, high inventory costs, and low profit per unit. To attract customers, the supermarket may excessively pursue safety stock and economies of scale, neglecting the perishability and freshness of fresh products, as well as inventory costs. To prevent stock-outs and sales losses, the supermarket frequently offers irregular discounts on fruits and vegetables. This can damage profitability if inventory levels far exceed sales volumes, leading to product write-offs and reduced profits.

3. Data Acquisition and Analysis

This study focuses on P Supermarket and examines consumer demand for fresh produce. Through on-site investigations of fresh-product and general supermarkets around campuses, we selected four representative fruits from P Supermarket. Mangoes, which are tropical and subtropical fruits sensitive to low temperatures and unsuitable for traditional refrigerated transport; Grapes, temperate fruits with distinct seasonality, thin skins, and susceptibility to bruising; Watermelons, which have the most pronounced seasonality among the four, with large, brittle volumes and high transport and storage requirements; Apples, the most common fruit with a relatively long shelf life and stable sales throughout the year, though their sales fluctuate slightly during holidays due to gift box promotions. Using these four fruits as examples, we analyzed the status of fresh- product inventory management at P Supermarket. By considering regional factors, local economic conditions, and relevant literature, we identified issues and shortcomings in the supermarket's fresh-produce management. We then selected a practical demand-forecasting method, simulated optimal ordering frequencies and inventory-cost scenarios based on actual sales data, and provided scientific recommendations for improving procurement, transportation, and inventory control of fresh products at P Supermarket.

Based on the context, this study selects Fresh P Supermarket as its focal subject. By leveraging data on order quantities, pre-order inventory levels, average inventory levels, and sales volumes for four key products: watermelons, grapes, mangoes, and apples. This study delves into the inventory control challenges of fresh produce within P Supermarket's warehouse management system. Currently, P Supermarket encounters issues such as low inventory turnover rates and stockpiling in certain out-of-season fruits and vegetables, leading to significant spoilage and losses. Internal audits have revealed that these challenges primarily arise from inaccurate demand forecasting and an absence of a robust ordering strategy. To address these concerns, this study advocates for the implementation of demand forecasting to regulate ordering periods and quantities, with dynamic adjustments in response to market volatility. In this study, fresh produce inventory control is defined as the management of inventory levels through strategic business approaches such as order batching and ordering cycles, aiming to oversee the stock quantities on supermarket shelves and in warehouses. Consequently, this study meticulously analyzes the components of inventory costs, enhances inventory management through demand forecasting, and optimizes inventory control to identify more beneficial management models for the development of fresh produce in P Supermarket. By refining ordering cycles and managing stock-out periods, this study aims to bolster P Supermarket's competitiveness and customer satisfaction. Furthermore, these strategies can enhance the product quality and operational profits of P Supermarket's fresh produce business, providing actionable recommendations for optimizing inventory management and elevating overall performance.

4. Demand Forecasting Methodologies and Data Processing

Demand forecasting, which predicts future product or service requirements over a specific period, is a cornerstone of supply chain and warehouse management. Accurate demand forecasting enables businesses to optimize supply chains and warehouse operations, reduce costs, enhance efficiency, and improve customer satisfaction, thereby strengthening their competitive edge [14]. This paper introduces three key forecasting methodologies employed subsequently: qualitative forecasting, grey forecasting and exponential smoothing analysis.

4.1. Qualitative Forecasting

Based on the context, this study selects Fresh P Supermarket as its focal subject. Qualitative forecasting is a predictive method based on non-quantitative information, such as expert experience, professional knowledge, historical data, and industry trends. Unlike quantitative forecasting, it doesn't involve specific numerical predictions. Instead, it analyzes and judges non-quantitative information to predict future trends, changes, and impacts. It is often used in situations requiring consideration of non-economic factors like cultural, political, and social elements.

In complex policy environments, relying solely on historical data for quantitative forecasting may not accurately reflect market conditions. Therefore, during the initial stages of qualitative forecasting, it's crucial to conduct objective, comprehensive, and accurate analysis and judgment of non-quantitative information. Due to the subjective nature of qualitative forecasting, it's advisable to combine it with scientific and reasonable methods for comprehensive predictive analysis, enhancing the accuracy and credibility of forecasts. In summary, qualitative forecasting, as a supplement to quantitative forecasting, can enhance the accuracy and reliability of predictions to a certain extent and holds significant practical and research value.

4.2. Quantitative Forecasting

Quantitative forecasting is a predictive technique that combines formula algorithms and diverse mathematical models to analyze relevant historical data and influencing factors, thereby generating precise data for future demand or development. It employs mathematical methods to predict and analyze the development and changes of things, uncovering the intrinsic relationships among related variables. This approach ultimately aims to reveal the development trends and variations of specific subjects, offering a robust predictive tool for decision-making.

4.2.1. Grey Forecasting

Grey forecasting is a method for predicting grey systems. A grey system lies between white and black systems. White systems have completely known internal information, while black systems are opaque, with no data accessible from the outside. Grey systems have only partially known information, with strong uncertainties in the relationships among factors within the system [15]. Due to these characteristics, grey forecasting is suitable for short-term and medium-term predictions when sample data is limited or of poor quality. It works by analyzing the correlation of development trends among system factors, generating data sequences with strong regularity, and establishing differential equation models to predict future trends [16].

In the face of the diversity and complexity of logistics processes, grey forecasting emerges as a powerful tool when precise data acquisition and processing are challenging. This method, grounded in grey system theory, is designed to handle such uncertainties. Grey systems occupy the middle ground between white systems, where all information is known, and black systems, where no information is accessible. In grey systems, only partial information is known, and the rest is unknown or hard to obtain, with relationships among factors shrouded in uncertainty. Grey forecasting shines in scenarios with limited or low-quality sample data, making it ideal for short term and medium term logistics demand predictions. It works by processing data to eliminate uncertainties and noise, enhancing prediction accuracy. The process involves cumulative data generation to uncover patterns, building differential equation models, and forecasting future trends. This allows businesses to predict future inventory demands and optimize warehouse stock levels.

In this study, preprocessed data was input into the GM (1, 1) prediction model. The model used the purchase quantity of a single apple as the independent variable and inventory levels as the dependent variable, with simulations run using the prediction model in SPSS software. The results showed that the R^2 and adjusted R^2 values were negative, indicating a poor fit and unsatisfactory prediction accuracy for inventory demand analysis of individual products. This suggests that the grey forecasting method is not suitable for such cases and has significant deviations, especially for non-linear data with large fluctuations.

4.2.2. Exponential Smoothing Analysis

Exponential smoothing analysis is a time-series forecasting method mainly used for short term and medium term predictions. It smooths historical data and uses the smoothed values to forecast future data trends. Its key feature is the ability to quickly reflect changes in time-series data, offering high accuracy and practicality. The core idea is to use past data to predict future data. After preprocessing the time-series data, the prediction formula is: $St=a\times Yt+(1-a)\times St-1$. The smoothing coefficient α is crucial as it controls the influence of past data on the forecast. A larger α means greater influence from past data and a slower change trend in the forecast values [17]. When applying this method, selecting an appropriate smoothing coefficient is essential for optimizing the forecasting results.

This paper compares the forecasting accuracy of three different smoothing coefficients. Given the non-linear sales data of fresh products and their seasonal fluctuations, the smoothing coefficient α is set to 0.8, which yields the most accurate results. Details are shown in Table 1.

Table 1. Comparison and Forecasting Results of Smoothing Coefficients

Assuming the smoothing index α=0.3, a single exponential smoothing method is used to predict the supermarket sales volume						If α=0.8				If α=0.5			
Number	Actual value: Yt	α*Yt	(1-α) *St-1	Predicted value: Yt+1	Out of stock	α*Yt	(1-α) *St-1	Predicted value: Yt+1	Out of stock	α*Yt	(1-α)* St-1	Predicted value: Yt+1	Out of stock
1	117	35	82	117	0	94	23	117	0	59	59	117	0
2	236	71	82	153	-83	189	23	212	-24	118	59	177	-60
3	413	124	107	231	-182	330	42	373	-40	207	88	295	-118
4	698	209	162	371	-327	558	75	633	-65	349	147	496	-202
5	736	221	260	480	-256	589	127	715	-21	368	248	616	-120
6	777	233	336	569	-208	622	143	765	-12	389	308	697	-80
7	765	230	399	628	-137	612	153	765	0	383	348	731	-34
8	668	200	440	640	-28	534	153	687	19	334	365	699	31
9	485	146	448	594	109	388	137	525	40	243	350	592	107
10	243	73	415	488	245	194	105	299	56	122	296	418	175
Sum total					-867				-46				-301

In fresh-product supermarkets, stock-outs not only mean profit losses but also erode consumer trust and negatively impact branding. Hence, when selecting the smoothing coefficient, the priority is to minimize stock-out levels. The chosen coefficient should yield the most accurate predictions with the least stock-outs, ensuring efficient inventory management and maintaining consumer confidence.

After determining the smoothing index, we forecasted the monthly sales data for four representative fresh fruits at P Supermarket. This demand forecasting helps determine optimal order quantities, reduce inventory levels, and achieve inventory control and optimization, as shown in Table 2.

In Table 2, the sales (demand) data for watermelons are in the upper - left corner (Nos. 1-10), those for grapes in the lower-left corner (No. 11-20), those for mangoes in the upper-right corner (No. 21-30), and those for apples in the lower-right corner (No. 31-40).

SPSS statistical analysis software was leveraged as an auxiliary tool to conduct time-series analysis using the exponential smoothing model. This makes it a reliable tool for predicting demand and determining order quantities in fresh-product supermarkets. By doing so, it helps reduce inventory levels and lower inventory costs. Therefore, in the subsequent sections on optimized control, the demand-forecasting values obtained through exponential smoothing analysis will be used to calculate the optimal order quantities.

Fresh-product sales are influenced by seasonality and consumer behavior, making demand forecasting challenging. Data-driven methods like grey forecasting and exponential smoothing are commonly used. However, grey forecasting is better for small datasets, while exponential smoothing suits nonlinear time-series data. Despite their advantages, these methods have limitations such as low precision with large datasets and the inherent uncertainty of forecasting. Therefore, selecting the right method is crucial for minimizing errors. The forecasting method provided in this study is a relatively optimal solution. With algorithm evolution, more sophisticated comprehensive forecasting methods await further research.

Table 2. Sales Data Forecast for Watermelon, Grapes, Mangoes, and Apples

Number	Actual value: Yt	α*Yt	(1-α)* St-1	Predicted value: Yt+1	Number	Actual value: Yt	α*Yt	(1-α)* St-1	Predicted value: Yt+1
1	117	94	23	117	21	411	329	82	411
2	236	189	23	212	22	421	337	82	419
3	413	330	42	373	23	466	373	84	457
4	698	558	75	633	24	522	418	91	509
5	736	589	127	715	25	560	448	102	550
6	777	622	143	765	26	534	427	110	537
7	765	612	153	765	27	663	530	107	638
8	668	534	153	687	28	588	470	128	598
9	485	388	137	525	29	531	425	120	544
10	243	194	105	299	30	422	338	109	446
11	380	304	76	380	31	731	585	146	731
12	495	396	76	472	32	642	514	146	660
13	619	495	94	590	33	669	535	132	667
14	705	564	118	682	34	449	359	133	493
15	673	538	136	675	35	467	374	99	472
16	972	778	135	913	36	405	324	94	418
17	678	542	183	725	37	361	289	84	372
18	592	474	145	619	38	541	433	74	507
19	442	354	124	477	39	376	301	101	402
20	409	327	95	423	40	763	610	80	691

5. Inventory Control Optimization

5.1. Inventory Cost

This study establishes an inventory model for P Supermarket that allows stock-outs. Given the non-linear daily sales and continuous yet uneven demand, the total inventory cost within a cycle (from the last replenishment to the current one) is the sum of four specific costs:

$$\begin{aligned}&\text{Inventory Procurement Cost :}\\&\text{Fruit wholesale price cost per unit multiplied by the wholesale quantity of fruit} = \mathrm{a} \cdot \mathrm{X}\end{aligned} \tag{1}$$

$$\text{Inventory reorder cost : Reorder cost unit price multiplied by reorder quantity} = \mathrm{r} \cdot \mathrm{E} \tag{2}$$

$$\begin{aligned}&\text{Inventory carrying cost :}\\&\text{Operating cost of keeping fruit in cold storage for a certain period of time} = \mathrm{X} \cdot \frac{\mathrm{b}+\mathrm{y}}{2} + I \cdot b\end{aligned} \tag{3}$$

$$\text{Cost of out of stock : The average out-of-stock cost over a period of time} = \mathrm{c} \cdot \mathrm{E} \tag{4}$$

By summing these four cost components, the total cost expression for a single inventory cycle is obtained:

$$TC = a \cdot X + r \cdot E + X \cdot \frac{b+y}{2} + I \cdot b + c \cdot E \tag{5}$$

The total cost expression for a single inventory cycle is derived by summing four cost components: a is the unit purchase price; X is the wholesale quantity; r is the unit replenishment cost after stock-out; E is the replenishment quantity; b is the unit storage cost; y is the unit cost for storing fruit; I is the inventory quantity; c is the unit shortage cost. This study calculates the inventory-holding, procurement, reordering, and stock-out costs for P Supermarket. It analyzes inventory-cost variations across different scenarios and optimizes fresh-product inventory through a single-objective model for four typical fruits. Using Matlab, the model determines the optimal inventory levels and order quantities for each product across multiple warehouses, minimizing inventory costs while meeting practical-demand constraints.

5.2. P Supermarket Inventory Cost Analysis

This study uses 10 actual sales data points for four fruits at P Fresh Supermarket as the demand quantity. P Supermarket's current order quantity is determined by rounding up monthly sales estimates to ensure a safety stock, denoted as X. Other relevant data are presented in Tables 3, 4, and 5.

Table 3. Monthly Sales Volume of Four Fruits

Species	March	April	May	June	July	August	September	October	November	December
Watermelon	117	236	413	698	736	777	765	668	485	243
Grapes	380	495	619	705	673	972	678	592	442	409
Mango	411	421	466	522	560	534	663	588	531	422
Apple	731	642	669	449	467	405	361	541	376	763

Table 4. Monthly Ordering Volume of Four Fruits

Species	March	April	May	June	July	August	September	October	November	December
Watermelon	200	250	430	720	800	800	800	700	500	200
Grapes	400	520	640	730	700	990	700	630	500	430
Mango	440	440	500	550	600	550	700	600	550	490
Apple	800	700	700	500	500	440	400	570	400	800

Table 5. Additional Cost Data for Four Products

Species	Purchase Cost: a (RMB)	Shrinkage Cost: y (RMB)	Finished Goods Inventory Carrying Cost per Unit: b (RMB)	Stock -out Cost per Unit: c (RMB)	Reordering Cost per Unit: r (RMB)	Volume per Unit: u (dm^3)
Watermelon	2	46	1. 1	3	2	4
Grapes	9	22	1.9	4	9	1.3
Mango	11	49	2. 1	6	11	1
Apple	4	17	0.7	1	4	0.5

In fresh-product management, over-ordering due to subjective experience can lead to spoilage and waste, inflating costs and damage rates. To address this, P Supermarket's inventory data was analyzed to quantify losses and remaining stock, as detailed in Table 6.

Table 6. Inventory Balance Quantities

Species	Incoming Quantity	Outgoing Quantity	Balance Quantity	Shrinkage Quantity
Watermelon	720	689	31	19
Grapes	730	705	25	37
Mango	550	522	28	29
Apple	500	449	51	33

P Supermarket, a small-scale supermarket, has room for improvement in fresh-product management. Its operating gross profit margin for fresh fruits and vegetables is only 7% - 9%, compared to 20% at Walmart. This indicates higher shrinkage costs and lower profits than industry peers. The sales volumes of the four products are used as demand-forecasting benchmarks. Analysis shows that while inventory turnover rates meet sales demands, the supermarket's inventory costs are high due to storage and shrinkage costs. The incomplete cold chain also boosts procurement and sales costs. To maintain sufficient stock and display quantities, the supermarket keeps high safety stock, further increasing inventory costs. To address these issues, subsequent sections employ demand forecasting and the particle swarm optimization algorithm.

5.3. Particle Swarm Optimization Algorithm

The Particle Swarm Optimization (PSO) algorithm [18] is inspired by the social behavior of bird foraging. It creates a population of particles with variable positions and velocities within a defined search space. Each particle represents a potential solution to the problem, with its velocity allowing it to explore the feasible region. Particles adjust their trajectories based on their own and their neighbors' "flying experiences" or "results". Mathematically, let $X_i = (x_{i1}, x_{i2}, \cdots, x_{in})$ d enote the current position of particle i, $V_i = (v_{i1}, v_{i2}, \cdots, v_{in})$ denote the current flight velocity of particle i, and $P_i = (p_{i1}, p_{i2}, \cdots, p_{in})$ denote the optimal position encountered by particle i . This study employs the Particle Swarm Optimization (PSO) algorithm to optimize inventory management and determine the optimal stock levels. Consider a population $P = \{p_1, p_2, \cdots, p_N\}$ consisting of N particles, where P_i denotes the i-th particle. Let the number of particles in the population be S, and the best position encountered by all particles in the population $P_g(t)$ is referred to as the global best position, so $P_g(t) \in \{P_0(t), P_1(t), \cdots, P_g(t) | f(P_g(t))\} = \min\{f(P_0(t)), f(P_1(t)), \cdots, f(P_s(t))\}$. In the context of particle swarm optimization (PSO), c_1, c_2 are acceleration constants, typically set within the range of 0 to 2. The parameter w, referred to as the inertia weight, determines the extent to which a particle retains its previous velocity; r_1, r_2 are two independent random functions with ranges [0, 1] uniformly distributed. In order to limit particle overflight 0 in the search space, v_{ij} is usually limited to a certain range, that is, $v_{ij} \in [-v_{\max}, v_{\max}]$. First, the random solutions of the total objective function TC (x) are initialized, all of which belong to the range of real numbers [19]. Then M iterations are carried out, and each particle is taken as a new solution in the multidimensional space position after M iterations. The smaller the value, the better the position and the better the solution. The formula for particle velocity V_i^m and position X_i^m updates is as follows:

$$V_i^m = w \cdot v_i^{m-1} + c_1 \cdot r_1 \cdot (pbest_i^m - x_i^m) + c_2 \cdot r_2 \cdot (pbest_i^m - x_i^m) \quad (6)$$

$$X_i^m = x_i^{m-1} + v_i^{m-1} \quad (7)$$

Pbestmi and Gbestmi are respectively the optimal position of each particle extremum and the optimal position of the entire particle swarm extremum in the process of M iterations. Gbestmi is the optimal solution in particle swarm optimization [20]. The part before the first plus sign in the formula (average out-of-stock cost=c×E) is a memory term to represent the influence of the last speed and direction. The part before the second plus sign is the self-cognition term, which refers to a vector moved from the current point to its own best advantage, derived from the particle's own experience. The part after the second plus sign is the group cognition term, which refers to a vector that moves from the current point to the best of the group, derived from the experience between the particles. In this study, the parameters of the particle swarm optimization (PSO) algorithm are set as follows: c_1=2; c_2=2; w=1; M=500; N=150. First, the particle velocity and position are initialized, the particle fitness value is calculated, the individual extreme value and the total extreme value are labeled, then the particle velocity and position are updated, the fitness value is calculated, and finally the individual extreme value and the group extreme value are updated. If the constraints and the final objective function are not met, the particle velocity and position are updated, and the following steps are repeated until the optimal value is obtained [21]. Through the exponential smoothing forecast above, the monthly demand forecast of each fruit is obtained. Then Matlab software is used to build a model, change the initial order quantity and demand value, and optimize the inventory cost by using PSO algorithm simulation.

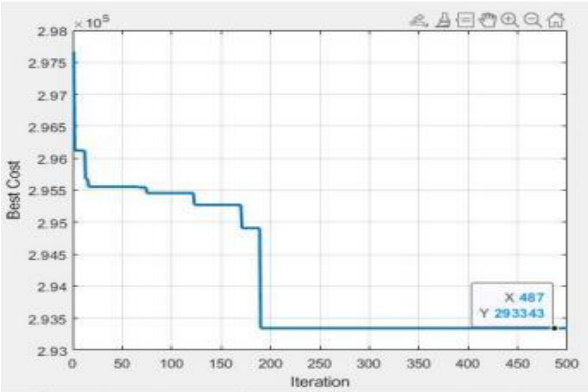

Figure 1. Simulation-derived Optimal Inventory Configuration

Based on the inventory cost calculation method and the computed unit holding and spoilage cost prices, the iterative results of inventory costs for P Supermarket, using its current ordering method and sales volume, are shown in Figures 1 and 2. The results demonstrate that the total inventory cost is TC = 293,343 RMB.

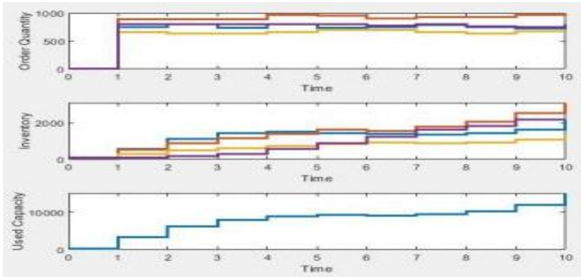

Figure 2. Simulation Results

The optimal inventory levels for the supermarket, derived from iterative optimization using the Matlab program, are presented in Figure 3. A comparison between the order quantities and demand volumes reveals a close alignment, with no stock-outs occurring across all 40 ordering and delivery cycles. The results demonstrate a high degree of consistency between the optimized inventory strategy and actual demand requirements.

BestSol.Sol.I

	1	2	3	4	5	6	7	8	9	10
1	567	1117	1430	1510	1452	1396	1380	1428	1652	2182
2	534	906	1160	1396	1645	1564	1789	2090	2556	3116
3	294	481	619	731	831	941	904	940	1065	1295
4	94	191	291	591	891	1232	1632	1831	2187	2187

Figure 3. Optimal Iteration of Inventory Levels for Four Types of Fruits

5.4. Results Optimization and Analysis

By comparing the order quantity and the demand, it is found that the two are close, but the order value tends to be stable, and the adjustment is weak according to the market situation, so the inventory in the later stage appears an increasing accumulation state [22]. Through the demand forecast, the relative forecast of sales volume makes the order quantity more match with the demand, to obtain the optimal result. Based on the method of demand forecasting, this paper determines the order quantity, changes the purchase quantity in the initial data in Matlab, simulates the optimal inventory cost through 500 iterations of particle swarm optimization algorithm, and obtains the optimal cost after multiple simulations. Change the demand as follows:

D=[117 236 413 698 736 777 765 668 485 243 % Watermelon

380 495 619 705 673 972 678 592 442 409 % Grapes

411 421 466 522 560 534 663 588 531 422 % Mango

731 642 669 449 467 405 361 541 376 763] % Apple

At the same time, the solution obtained by the particle swarm optimization algorithm is approximate, so there are differences in the results of each operation. After multiple simulations, the optimal value and the most qualified result are compared as the result. As can be seen from Figure 4-6, total inventory cost TC=271795.6 RMB.

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	1	2	3	4	5	6	7	8	9	10
1	605	1084	1415	1547	1597	1597	1597	1658	1844	2303
2	524	918	1179	1340	1494	1415	1561	1847	2283	2682
3	262	491	648	727	825	921	880	871	928	1102
4	66	85	149	324	512	759	1094	1318	1619	1644

Figure 4. Optimal Iteration of Fruit Inventory Levels After Adjusting Demand

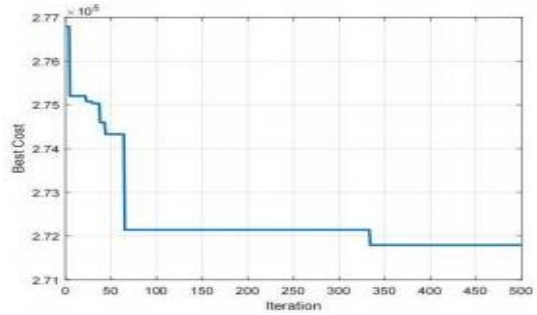

Figure 5. Optimized Simulation-derived Optimal Inventory Configuration

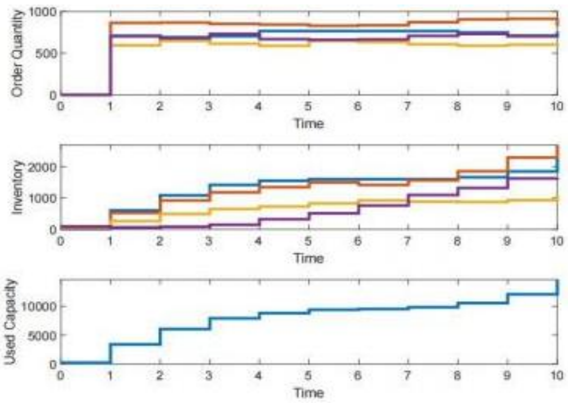

Figure 6. Optimized Simulation Results

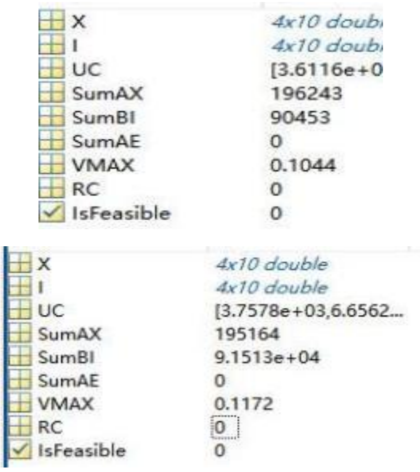

Figure 7. Comparison of Inventory Costs Before and After Optimization

As shown in Figure 7, a comparison of the costs before and after optimization reveals a reduction of 20,000 RMB, primarily attributed to decreases in ordering costs and inventory holding costs. Notably, despite the reduction in order quantities, no stockouts occurred, resulting in a stockout cost (AE) of zero. This demonstrates the rationality and effectiveness of the optimization approach. For P Fresh Supermarket, which operates on a smaller scale with relatively low profit margins, this optimization method significantly reduces inventory costs and aligns with the overall development goals of the enterprise. By employing a single-objective optimization model based on the particle swarm optimization (PSO) algorithm, P Supermarket can achieve an optimal solution that minimizes total inventory costs. This chapter presents the application of the PSO algorithm to optimize inventory management for P Supermarket, using demand forecasting data collected from the model established in the previous section. The optimization process focuses on minimizing the total inventory cost as the objective function.

Using Matlab, we calculated the optimal value and generated an optimization iteration graph for total inventory costs. By comparing inventory costs before and after optimization across different scenarios, it was found that the more uniform the distribution of order quantities around the demand forecast or mean demand, the greater the cost savings achieved. This underscores the importance of precise demand forecasting. Accurate forecasting reduces order quantities to levels that better match actual inventory requirements, thereby significantly lowering costs for supermarkets.

6. Summary and Prospect

6.1. Summary

This study identifies two main limitations in fresh produce demand forecasting. First, the dataset is limited, necessitating preprocessing. Future research should collect more extensive data to enhance forecasting precision and incorporate environmental and climatic factors for better accuracy. Second, the forecasting methods and models employed are relatively basic. Future studies could adopt more comprehensive approaches, such as multiple exponential analyses or neural network-based predictions, which offer more robust and persuasive results by integrating a wider range of influencing factors.

In addition, in this paper, the sales price and wholesale price are fixed and unchanged in data processing. However, in the actual sales situation in the market, the sales price and purchase price of fresh products change almost every day, and the market price will change with the change of the demand of the product in the market. The sale and purchase price of fresh food will directly affect the average cost and operation effect of the supermarket. Therefore, in the follow-up research, there are many aspects of this paper worthy of improvement and further study.

6.2. Prospect

With the improvement of people's health awareness of fresh food and the continuous increase of consumer demand, fresh supermarkets have developed rapidly in recent years. The fresh supermarket how to do inventory control, meet consumer demand, improve their own profitability and other issues have gradually become a hot topic in the industry. Through analysis, this paper concludes that inventory is the difficulty and pain point in the operation profit of fresh supermarket. Therefore, it is particularly important to reduce inventory cost in fresh supermarket through reasonable and scientific methods. Based on the analysis and prediction of the historical sales data, in practice, the fresh supermarket can make a reasonable purchase plan and optimize the inventory control according to different product types, seasonality, sales promotion and other factors. At the same time, fresh supermarkets can also adjust the sales price through demand forecasting, appropriately reduce the price at the low point of demand, and win by volume, to improve their competitiveness and profitability.

To sum up, fresh supermarket in the future development prospects is very broad, can continuously improve the quality of goods, service quality and supply chain management efficiency, as well as actively apply new technology and logistics distribution system, to achieve higher quality, higher efficiency and more green and sustainable development.

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