Research on Automatic Pricing and Replenishment Decision of Vegetable Commodities Based on Machine Learning

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Abstract. In order to enhance the sales profit of fresh food supermarkets, a universal replenishment and pricing strategy applicable to vegetable commodities is proposed. First, multiple machine learning techniques are applied to deeply explore the potential relationship between the sales volumes of different vegetable commodities, and the intrinsic connection between the sales volumes of these commodities is revealed through data analysis and modeling. Second, considering the additional costs associated with the loss of vegetables during transportation and storage, a comprehensive analysis was conducted by combining multiple constraints such as sales, demand and order quantity. Based on these factors, an optimization model with the objective of maximizing the operating profit of the supermarket is constructed. In order to verify the effectiveness of the model, data simulation experiments were conducted on the model. The experimental results show that the model performs well in improving the revenue of fresh food supermarkets, which can significantly improve the sales profit of vegetable goods, reduce losses, and optimize the replenishment and pricing strategy. This strategy has strong practicality and promotion value, and provides scientific decision support for the operation and management of fresh food supermarkets.

Keywords: Machine learning, Association rules, Commodity sales decision, Dynamic programming optimization

1 Introduction

In fresh produce supermarkets, the shelf life of vegetable products is generally short due to their natural attributes. As sales time increases, the appearance of vegetables gradually deteriorates, with color fading, texture softening, and nutritional value declining. If most types of vegetables are not sold by the end of the day, they cannot be sold the next day. Therefore, to ensure the freshness and quality of vegetables, supermarkets typically restock daily.

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Supermarkets formulate their restocking strategies based on historical sales data and demand conditions. By analyzing sales data over a period, supermarkets can understand the sales volume and trends for each type of vegetable. Based on this data, they can predict future sales demand and adjust the restocking quantity for each variety.

Supermarkets sell a wide variety of vegetables from different places of origin. The purchase transaction time for vegetables is usually between 3:00 AM and 4:00 AM. Merchants must make restocking decisions for each vegetable category for the day without knowing the specific items and purchase prices. Vegetable pricing generally follows a "cost-plus pricing" method, and supermarkets usually offer discounts on damaged or deteriorated products. Market demand analysis is crucial for restocking and pricing decisions. The sales volume of vegetable products often has a certain relationship with time. The supply of vegetable varieties is more abundant from April to October, making a reasonable sales mix extremely important due to the limited sales space in supermarkets.In fresh produce supermarkets, vegetables typically have a short shelf life due to their inherent properties. As time passes, the quality of vegetables deteriorates—they lose their vibrant color, become softer, and their nutritional value diminishes. If most vegetables are not sold by the end of the day, they cannot be sold the next day. To ensure freshness and quality, supermarkets generally restock their vegetable supply daily.

2 Exploration and Derivation of the Relationship between Vegetable Replenishment and Pricing

2.1 Correlation and Difference Testing between Different Categories of Vegetables

This study analyzes the sales volumes of different categories of vegetables to develop optimized restocking and pricing strategies. Firstly, a correlation analysis was conducted on the sales volume data of six pre-processed vegetable categories. The correlation coefficients between each product were calculated using Kendall's tau-b test, and the results were visualized using a heatmap as an illustration:

Heatmap of Correlations Among Vegetable Categories from the data in the Fig.1, it can be seen that the correlation coefficients between the sales volumes of various vegetable categories are all greater than 0.2, mostly within the medium range. This indicates a positive correlation between different vegetable categories, with a relatively high correlation strength.

Differences among various vegetable categories and individual items were then examined. Initially, a Pearson chi-square test was used, but due to over 20% of expected counts being less than 5, the hypothesis was unreliable. Therefore, the Friedman test[1], a non-parametric statistical method, was employed to compare differences among multiple paired samples. The calculation formula for the Friedman test coefficient$E$is as formula 1:

$$E = \frac{12-n}{(K(K+1))} \times \left[\sum R^2 - \frac{(K(K+1))^2}{4}\right] \tag{1}$$

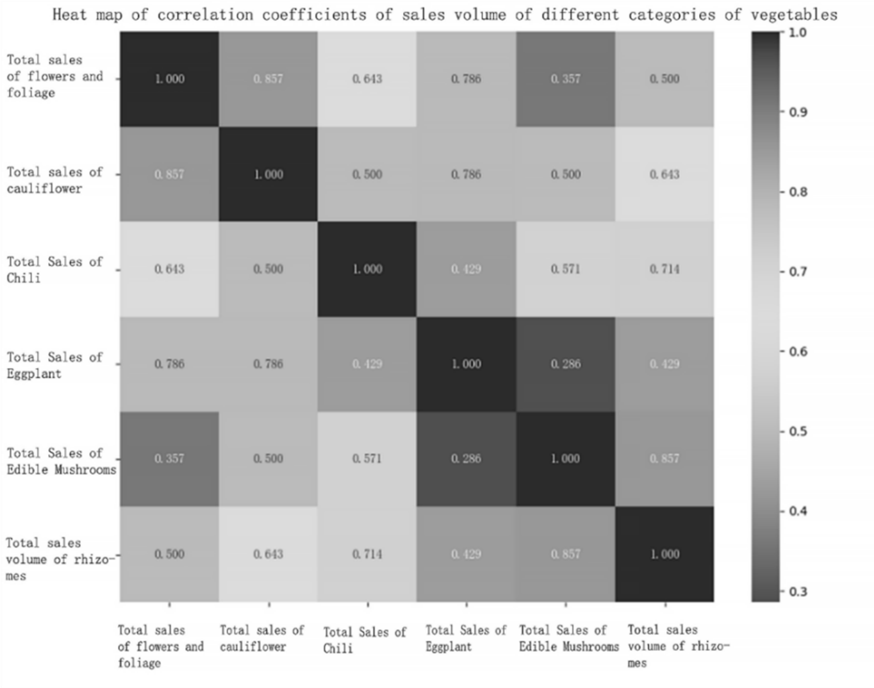

Fig. 1. Heatmap of Correlations Among Vegetable Categories

In the formula, n represents the sample size, K denotes the number of groups, and R signifies the rank sum of each group. After deriving the coefficient E for the Friedman test for multiple paired samples, Sales data of different vegetable categories were substituted into the formula for calculation. The results are displayed as table 1:

Table 1. Multiple Paired Sample Friedman Test Results

Variable name	Standard deviation	P	Cohen's f
Mosaic sales	10380.855		
Cauliflower sales	2288.432		
Pepper sales	4930.495		
Solanum sales	1498.012	0.000001	1.552
Edible mushroom sales	2440.007		
roots and stems sales	2551.477		

The p-value of 0.000001 indicates significant differences in sales volumes among the six vegetable categories. With a Cohen's f value of 1.552, there is substantial overall variability. Therefore, sales volumes among different vegetable categories show significant differences and high correlation.

2.2 Distribution Patterns of Sales Volumes Across Different Vegetable Categories

The distribution of merchandise sales volume is usually represented by statistical models such as normal, exponential, and Poisson distributions. In order to determine the sales volume distribution model suitable for different vegetable categories, it is necessary to carry out a one-sample Kolmogorov-Sminov test for vegetable sales volume. This test by comparing the observed data distribution and the theoretical distribution of the cumulative distribution function (CDF) difference, to determine whether they are significantly different, the distribution function for the one-sample Kolmogorov-Smirnov test[2] is represented as formula 2:

$$\begin{cases} K = sup|B(t)|, t \in [0,1] \\ B(t) = [W(t)|W(1) = 0], t \in [0,1] \\ W(t) \sim N(0, \sigma^2 t), t \geq 0 \\ P(K \leq x) = 1 - 2\sum_{i=1}^{+\infty}(-1)^{i-1}e^{-2i^2x^2} \end{cases} \tag{2}$$

Analysis of the Kolmogorov-Smirnov test results reveals that the sales volumes of cauliflower, pepper, edible fungi, and root vegetables conform to the normal distribution model at a 95% confidence level. Although the normal distribution significance for leafy vegetables and eggplants is higher than the minimum significance threshold $\rho = 0.05$, it is notably lower compared to the other four categories. Therefore, further validation is needed to confirm the confidence in their normal and other distribution models. To explore the optimal distribution model, use the P-P plots shown in Fig.2 to visualize the fit for normal and exponential distributions:

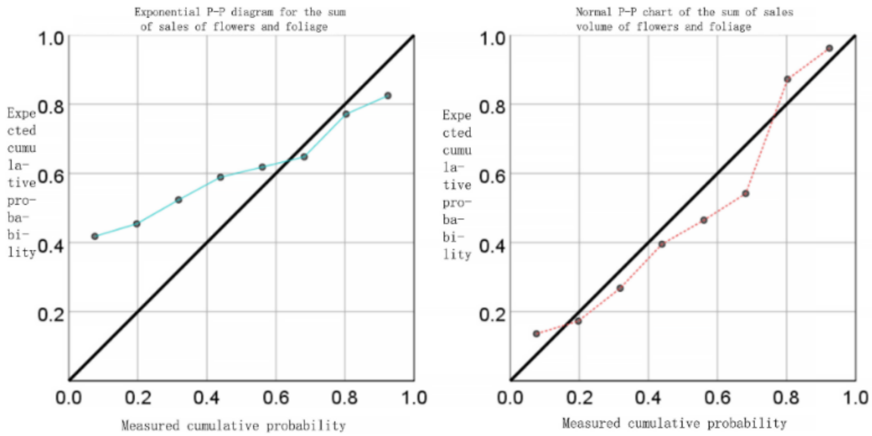

Fig. 2. P-P Plots of Total Sales Volume for Leafy Vegetables under Normal and Exponential Distributions

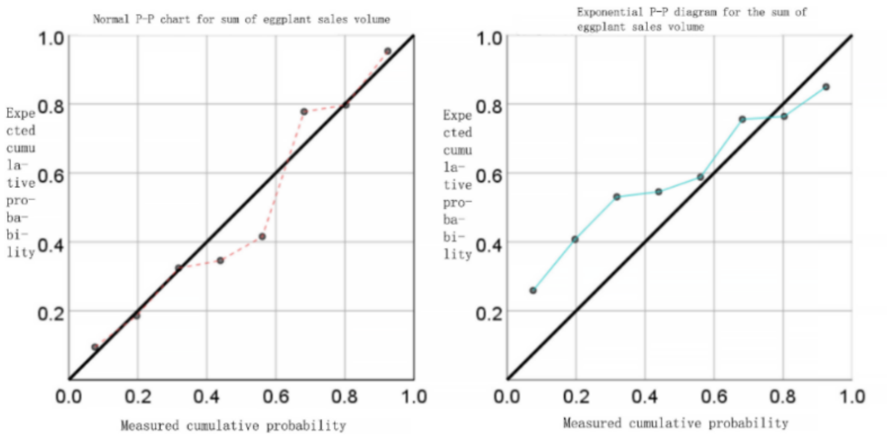

Fig. 3. P-P Plots of Normal and Exponential Distributions for Total Sales Volume of Eggplants

If the empirical data aligns with the theoretical distribution, then the empirical data points will approximate the diagonal line in the P-P plot. From the P-P plots shown in Fig.3 of the total sales volume of leafy and solanaceous vegetables under normal and exponential distributions, it is evident that the empirical cumulative probabilities in the normal distribution plot are closer to the reference diagonal. Therefore, the best fit distribution for the sales volume of leafy and solanaceous vegetables is the normal distribution. Considering the Kolmogorov-Smirnov test results and the P-P plot as validation, It is concluded that the sales volumes of various types of vegetables follow a normal distribution.

2.3 Exploring the Relationship Between Vegetable Categories and Individual Product Sales Volumes

The FP-Growth[3] algorithm optimizes the Apriori algorithm by using iterative database traversal. It involves two main passes over the dataset. In the first pass, it counts occurrences of each item in the vegetable itemsets and filters out those that do not meet the minimum support threshold, resulting in frequent itemsets. In the second pass, it traverses the dataset again, sorts the items in each itemset by their support in descending order, and inserts them into an FP-tree. This recursive process continues until the tree cannot be further expanded.

For data preprocessing, sales records within 1 second of each other are considered as one vegetable itemset, resulting in a total of 123,123 vegetable itemsets. With a minimum support threshold of 500, itemsets with fewer than 500 occurrences are filtered out to obtain the frequent itemsets. Based on these frequent itemsets, the FP-tree is constructed. During this process, the conditional pattern base for each item, which includes all itemsets ending with that specific vegetable item, is calculated. If N is the total number of distinct items in the vegetable itemsets, the conditional pattern base for the j -th vegetable item can be expressed as formula 3:

$$base(j) = \frac{\sum_{i=1}^{123123}\sum_{j=1}^{251} n_j}{\sum_{i=1}^{123123} N} \tag{3}$$

To construct an FP-tree and mine frequent patterns, each vegetable item is processed from the root node with a minimum confidence threshold of 0.9. Frequent vegetable items and their purchase combinations from 2020 to 2023, with a confidence level above 90%, are analyzed. Higher support indicates better sales performance.The FP-Growth[4] algorithm's primary functions are to mine association rules and improve decision-making efficiency:

1) Mining Association Rules: Analyzing frequent vegetable itemsets reveals hidden associations between different vegetable categories and items. For example, green and red peppers are often purchased together, indicating a strong culinary connection. This "bundle sales" strategy can help supermarkets better plan inventory and increase revenue.

2) Improving Decision-Making Efficiency: Extracting frequent itemsets reveals correlations between vegetable categories and individual items. Supermarkets can prioritize these combinations when determining daily restocking quantities, reducing workload and enhancing decision-making efficiency.

2.4 Prediction of Restocking Volume for Vegetable Categories

Due to the large and time-sensitive nature of sales data across various vegetable categories, the ARIMA[5] model is used for time series analysis to predict daily restocking quantities for the coming week. First, the ADF test[6] is conducted on the sales data for each vegetable category to ensure data stationarity. The results show that the p-values for 0, 1, and 2-order differences are all 0.000001, with regression coefficients less than 0, indicating stationarity. Similar results are found for other vegetable categories. After confirming data stationarity, residual autocorrelation tests are performed. If the correlation coefficients fall within the confidence interval, the AR model residuals are considered white noise, meeting the ARIMA model requirements. The residual autocorrelation test results for edible fungi meet these conditions. Similar results are obtained for the other vegetable categories:

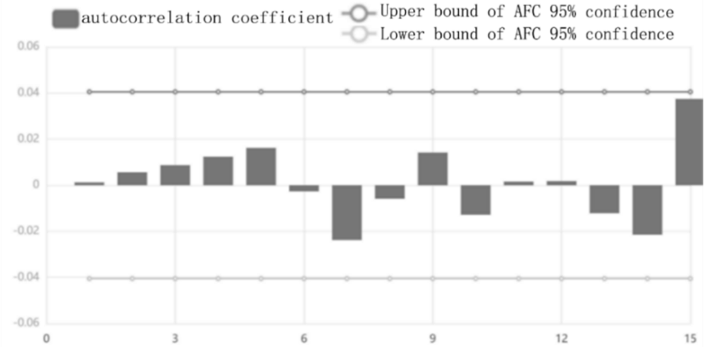

Fig. 4. Model Residual Autocorrelation Figure (ACF)

From the residual correlator in Fig.4, it is evident that the autocorrelation coefficients in the time series data of edible fungi fall within the 95% confidence interval, indicating that the edible fungi data represents a white noise sequence. Combining the results of the two tests, it can be concluded that the edible fungi data meets the requirements for time series analysis (ARIMA) models. The mathematical formula for the ARIMA[7] model can be expressed as formula 4:

$$J_t = \alpha_1 J_{t-1} + \alpha_2 J_{t-1} + \cdots + \alpha_p J_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q} \quad (4)$$

Applying the ARIMA[8] model principles, which include autoregressive, moving average, and differencing components, an ARIMA model is constructed for the edible mushroom data. Using the average daily sales quantity of 81 for edible mushrooms in mid-June 2023 as a time series indicator, the total sales quantity and the cost-plus pricing regression model derived earlier were combined to forecast the sales quantity for the next 567 steps (one week). The model's goodness-of-fit, R^2, was 0.875, indicating strong performance and suitability for time series forecasting. Thus, the predicted total daily replenishment of edible mushrooms for the upcoming week (July 1-7, 2023) is as table 2:

Table 2. Forecast results of daily replenishment of edible mushroom vegetables in the next week

Date	Daily replenishment (kg)
2023/7/1	55.05424918
2023/7/2	54.78667811
2023/7/3	54.4862248
2023/7/4	54.18714442
2023/7/5	53.89040327
2023/7/6	53.59543392
2023/7/7	53.30112205

2.5 Planning of Vegetable Category Pricing Model

Explanation of the Meaning of Cost Plus Pricing.
The cost-plus pricing method[9] is one of the most fundamental pricing strategies. It involves setting the sale price of a product by adding a fixed percentage markup to the total cost per unit. The formula for total cost-plus pricing is: Unit Product Price = Unit Product Total Cost × (1 + Target Profit Margin), where the target profit margin is calculated as (Total Revenue - Total Cost - Other Expenses) / Total Revenue.

In this study, only sales and procurement data are available, with no other data provided. Analysis shows that procurement quantity matches sales volume, this allows for the assumption that other costs are zero. Let the unit product price be P, unit product total cost be C, historical unit price be Z, and sales (procurement) volume be R. The target profit margin is denoted as μ. Thus, the mathematical formula for total cost-plus pricing can be expressed as formula 5:

$$P = C(1+\mu) = C\left[1 + \frac{(Z-C)R}{C\cdot R}\right] \tag{5}$$

Establishment of a Model for the Relationship between Total Sales and Cost Plus Pricing.
To derive the relationship between the total sales volume of cauliflower-type vegetables and cost-plus pricing, the same method can be applied to the other five vegetable categories. Each category shows a linear correlation between total sales volume and cost-plus pricing. By fitting the data, the relationship model for each category is obtained as formula 6:

$$T_i = \begin{cases} 8.726 \times 10^{-7} {P_1}^2 + 0.046P_1 + 2.209 \\ 7.243 \times 10^{-6} {P_2}^2 + 0.087P_2 - 0.124 \\ 5.855 \times 10^{-6} {P_3}^2 + 0.103P_3 + 2.027 \\ 2.231 \times 10^{-6} {P_4}^2 + 0.048P_4 + 0.635 \\ 1.522 \times 10^{-7} {P_5}^2 + 0.096P_5 - 16.688 \\ -4.592 \times 10^{-8} {P_6}^2 + 0.031P_6 + 0.036 \end{cases} ,i = 1,2..6 \tag{6}$$

In the formula, P_i represents the cost-plus pricing for the$i$ -th vegetable category, where $i = 1,2..6$ sequentially represents the cost-plus pricing for cauliflower-type vegetables, leafy vegetables, pepper-type vegetables, eggplant-type vegetables, edible fungi, and root-stem aquatic plants. T_i represents the total sales volume of the i -th vegetable category.

Marginal Cost Constraints for Various Categories of Vegetables.
In this study, marginal cost is the cost of selling each unit of vegetables, including the wholesale price and the rate of product spoilage. In the case of wholesale prices, pricing must exceed the wholesale cost C_s of each type of vegetable in order to avoid losses in vegetable sales. Assuming that the unit price is P, the relationship between the two can be expressed as formula 7:

$$P_d = (1+\delta)\,\mathrm{C}_s \qquad ,\delta \neq 0 \tag{7}$$

The target profit margin δ is determined by the percentage of profit derived from the product data. Utilizing a model that relates total sales volume to cost-plus pricing, the least squares algorithm is applied to find the optimal values of sales volume and cost-plus pricing. From this, total revenue and costs are calculated to further derive the target profit margin δ. The total replenishment quantity B_h can be expressed as formula 8:

$$\delta = \frac{B_h P - B_h C_s}{B_h P} \tag{8}$$

The wastage rate refers to the proportion of product loss due to spoilage, deterioration, or waste during storage, transportation, and sales. A higher wastage rate implies higher transportation costs. Supermarkets often discount damaged goods, but increasing restocking quantities to offset wastage is unreasonable as it raises costs. To mitigate profit loss from wastage, prices can be increased to cover additional costs. Adding 20% of the wastage cost to the base price suffices,formulated as formula 9:

$$P_d = (1+\delta)\,C_s + S_h \qquad ,\delta \neq 0 \tag{9}$$

The variable S_h is calculated by dividing the remaining stock by the loss cost. Let B_h be the total replenishment amount and γ the spoilage rate. The additional cost incurred due to vegetable spoilage is then compensated by:

$$S_h = \frac{B_h - B_h\gamma}{B_h C_s \gamma} \tag{10}$$

Analysis of Pricing Models for Various Categories of Vegetables.
Assuming that the daily replenishment is completely sold out, the obtained price is multiplied by the daily replenishment volume. Let P be the price and B_h be the replenishment volume. By integrating the mentioned factors, the aim is to maximize the total revenue of the vegetable seller and establish an optimization model:

$$s.t\begin{cases} MaxM_c = B_h P_d \\ \beta_1 = \frac{\sum(r_i-\bar{r})(u_i-\bar{u})}{\sum(r_i-\bar{r})^2} \\ \beta_0 = u - \beta_1\bar{r} \\ T_i = \lambda_i p^2 + \lambda_j p + \eta\ , i,j = 1,2..6 \\ \delta = \frac{B_h P - B_h C_s}{B_h P} \\ P_d = (1+\delta)\,C_s + S_h \qquad ,\delta \neq 0 \\ S_h = \frac{B_h - B_h\gamma}{B_h C_s \gamma} \end{cases} \tag{11}$$

Solving Pricing Models for Various Vegetable Categories

Step 1: Using the total sales volume and cost-plus pricing relationship model, the target profit margin can be determined by solving for the pricing and sales volume that maximize their product.

Step 2:Traverse the daily forecasted replenishment quantities to calculate their costs based on sales records and wholesale prices.

Step 3: To reduce profit loss from wastage, add 20% of the extra cost to the price.

Step 4: Repeat Step 2 and Step 3 to calculate daily pricing strategies for different replenishment quantities. Finally, determine the maximum profit for vegetable sellers based on the pricing and replenishment quantities.

The detailed results for edible mushroom vegetables are presented as table 3:

Table 3. Daily total replenishment results and pricing strategy for edible mushroom vegetables in the next week

Date	Pricing (¥/kg)	Revenue (¥)
2023/7/1	4.333914595	238.6004141

2023/7/2	4.277035637	234.3245747
2023/7/3	4.300618391	234.3244604
2023/7/4	4.324353114	234.3243467
2023/7/5	4.295846854	231.5049194
2023/7/6	4.319487506	231.5048072
2023/7/7	4.343336245	231.5046953

2.6 Analysis of Pricing Model for Marketable Vegetables

Vegetable Sales Margin Constraints.
In this study, the profit margin of vegetable sales[10] is calculated as (total revenue of vegetable products - total cost of vegetable products) / total revenue of vegetable products. The total cost of vegetable products can be determined by the product of the unit ordering cost of individual vegetable items and the ordering quantity of the vegetable items (including the loss rate). Let the ordering cost of vegetable products be a variable a_j and the loss rate of vegetable products be a variable ζ. Therefore, the formula for the total cost φ_j of vegetable products can be expressed as formula 12:

$$\varphi_j = X_j \cdot a_j(1+\zeta) \tag{12}$$

In terms of the total revenue of vegetable products, it can be determined by the product of the cost-plus pricing of each vegetable and its sales volume. Let the cost-plus pricing of vegetable products be a variable b_j, vegetable sales as a variable X_k. Therefore, the formula for the total revenue θ_j of vegetable products can be expressed as formula 13:

$$\theta_j = X_k \cdot b_j \tag{13}$$

For the profit margin of sellable vegetable products, let the profit margin of individual sellable vegetable items be a variable σ . To further clarify the constraints on the profit margin of individual products, a target profit margin T_{target} needs to be set based on actual conditions. It is required that the weighted profit margin of all individual products meets or exceeds this target value. Combining this with the profit margin calculation formula for vegetable products, the constraint calculation formula for the profit margin of individual sellable vegetable items can be expressed as formula 14:

$$\sum_{i=1}^{n} \sigma = \left(\theta_j - \varphi_j\right)/\theta_j \geq T_{target} \tag{14}$$

Model Development.
Based on the above derivation, the selection of vegetable items involves sales volume, order quantity, and the number of different items. After identifying the salable items, the daily replenishment quantity is predicted using the ARIMA time series model, and pricing is determined based on the cost-plus pricing principle. This process relies on the

previously established pricing model and constraints. Assuming the daily replenishment quantity of each salable item equals the daily sales volume, and setting the pricing ψ and daily replenishment quantity B_{dh} as variables, the goal is to maximize the supermarket's profit M_d under the new item replenishment plan. By integrating all constraints, the pricing model for salable items is obtained:

$$s.t.\begin{cases} Max\ M_d = B_{dh}\psi_d \\ f(M_j) \in (0,1) \\ \sum \omega_i \geq 1, i = 1,2..6 \\ \delta = \frac{B_{dh}P - B_{dh}\cdot X_j \cdot \alpha_j(1+\zeta)}{B_{dh}P\cdot X_j} \\ \psi_d = (1+\delta)\left[\alpha_j(1+\zeta)\right] + S_h \qquad ,\delta \neq 0 \\ S_h = \frac{B_{dh} - B_{dh}\cdot\zeta}{B_{dh}\cdot\alpha_j(1+\zeta)\cdot\zeta} \\ \qquad \sum_{i=1}^{n} \sigma = (\theta_j - \varphi_j)/\theta_j \geq T_{target} \end{cases} \tag{15}$$

Model Solution and Results.

Step 1: Based on the sales volume, selling price, and wholesale price of individual items, the target profit margin can be obtained by maximizing the linear relationship between the cost-plus pricing and the sales volume of vegetable items..

Step 2: The additional cost caused by the loss rate was calculated to minimize the loss due to wastage. A 20% compensation for the additional cost was added to the pricing strategy.

Step 3: The current profit was calculated based on the predicted replenishment quantity and the current pricing, and the results were recorded.

Step 4: The target profit margin was iteratively updated to calculate different pricing strategies, continuously considering the additional cost until the iteration was complete.

Step 5: From the recorded results, the pricing strategy that yielded the highest profit was selected, and the pricing and profit data were exported.

Partial results are shown in Table 4:

Table 4. Replenishment volume and pricing strategy for vegetables on July 1st

Item name	Daily replenishment (kg)	Sales unit price (¥/kg)	Revenue (¥)
Purple eggplant	10.46	5.45	57.11
Bamboo leaf	13.08	3.35	43.81
Romaine lettuce	8.55	13.11	112.14
Lettuce	33.82	4.00	135.29
Brassica chinensis	4.95	4.53	22.44

3 Evaluation and Promotion of the Model

The time series model established in this article is the ARIMA model, which is applicable to various types of time series data, thus enjoying wide applicability. The model in this article is based on historical data from the time series for modeling and prediction, thus enabling it to provide explanations for data changes. In terms of prediction accuracy, it is capable of capturing both long-term trends and short-term fluctuations in the data, thereby delivering accurate forecasting results for this article.

The replenishment forecasting and pricing optimization model for vegetable commodities mentioned in this article can be applied in multiple industries. The retail industry can utilize this model to predict the demand for various vegetables and develop replenishment strategies to ensure sufficient inventory while avoiding issues of overstocking or understocking. The catering industry, which requires a significant supply of vegetables, can leverage the replenishment forecasting model to accurately predict the demand for different vegetables, purchase the required vegetables in time, and ensure the quality and stability of dishes. Agricultural producers in the agricultural sector can formulate planting plans, adjust the quantity and timing of crop cultivation, and improve production efficiency based on market demand and sales trends using this model. The logistics and supply chain industry can utilize the replenishment forecasting model to plan the transportation and distribution of vegetable products. Accurate demand predictions can help optimize transportation routes and schedules, ensuring timely delivery of orders. In summary, the replenishment forecasting model for vegetable products plays a vital role in various industries. It enhances supply chain efficiency, reduces costs, optimizes inventory management, and meets consumer demand.

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