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Research and Analysis of Vegetable Pricing Strategy Model Based on Single Objective Optimization Algorithm

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Abstract: For vegetable sellers, appropriate purchasing and pricing strategies can generate greater profits. This paper explores the periodicity of sales volume for different categories of vegetables using wavelet analysis, and analyzes the differences between different categories through t-tests. Specifically. (1) representative daily average sales volumes of individual products are selected for Spearman correlation analysis, revealing weak correlations among different products within the same category, but strong correlations among certain products from different categories; (2) the relationship between sales volume and selling price, cost price data for each category is analyzed, revealing an exponential relationship between sales volume and selling price/cost price. Based on the principle of market lag, a single-objective optimization model is established to maximize profits; (3) the model is solved using differential evolution algorithm to obtain the optimal pricing and purchasing quantities for each category of vegetables. After implementing the strategies, the benefits have increased by approximately 167% (aquatic root and stem vegetables), 55% (flower and leaf vegetables), 21% (flower vegetables), 81% (eggplants), 40% (peppers), and 38% (edible fungi) over the past 30 days. Significant profit growth is observed in all categories, indicating the rationality of decision-making.

1. Introduction

With the continuous improvement of people's living standards, there has been a significant shift in the daily needs of citizens. An increasing number of individuals are now pursuing a higher quality of life and opting to shop at supermarkets or specialized vegetable stores. In recent years, the prominence of vegetable products in supermarkets has been on the rise, leading to the emergence of supermarkets and stores that have garnered a wide customer base. The way in which fresh produce is sourced and priced has become a matter of great interest to business owners, as they seek to formulate effective strategies that can attract more customers and maximize profits.

Yang et al. [1] discussed the problem of maximizing total profits over a given time period for online retail enterprises, focusing on green delivery technology investment, dynamic pricing, and replenishment strategies for perishable and out-of-stock products. By applying the Pontryagin maximum principle, they obtained optimal strategies for green delivery technology investment, dynamic pricing, and replenishment for perishable products. Chen et al. [2] aimed to maximize periodic profits and utilized the perishable inventory theory to develop a joint decision-making model for pricing and inventory replenishment in a dual-channel retail setting where demand depends on price and inventory level. They devised heuristic algorithms to optimize pricing and inventory for fresh agricultural products. Li et al. [3] investigated the joint decision-making problem of ordering and pricing for time-varying deterioration rate products. They developed a mathematical model that integrated considerations of demand, price, inventory level, and deterioration handling costs. The objective was to maximize the average system profit while accounting for stockouts and delayed replenishments. An algorithm was proposed to find the optimum solution, and sensitivity analysis of various parameters was conducted through numerical simulations. Wang et al. [4] studied the inventory replenishment and pricing strategy for cold chain products characterized by Weibull survival-death characteristics. Considering the stochastic demand, price influence, three-parameter Weibull distribution for deterioration rate, and fixed lead time, they formulated an inventory model under (r, Q) policy with the objective of profit maximization. The model was approximately solved using a direct approach, leading to optimal replenishment and pricing strategies. Zhang et al. [5] primarily investigated the ordering and pricing strategies when demand rate was exponentially related to selling price and deterioration rate followed a three-parameter Weibull distribution. They incorporated the cost associated with product deterioration and introduced price discounts, constructing an inventory model. Direct approach and Taylor expansion were used for approximate solution, and sensitivity analysis of discount rate and deterioration rate was conducted to provide rational management recommendations. Tang et al. [6] studied the joint pricing and ordering decision problem faced by retailers under two different preservation methods. They considered three scenarios: no inventory constraint, single inventory constraint, and dual inventory constraints, and examined the influences of market capacity, perishability rate, demand substitution rate, and maximum order quantity on decision-making. Fan et al. [7] considered the impact of consumer strategic behavior on pricing and inventory decisions for fresh agricultural products at retailers. They employed the newsboy model to address the discrete issue of product value decay and constructed single-stage and two-stage pricing and inventory decision models to analyze the effects of product residual value rate on consumer behavior, optimal pricing, optimal inventory levels, and retailer profits.

Building upon the previous studies, this paper proposes a vegetable pricing prediction model aimed at providing effective guidance for business decision-making. Specifically, this paper will combine historical sales data, procurement costs, and spoilage rates to predict the total daily replenishment amount and pricing strategy for each vegetable category in the coming week by establishing a mathematical model.

2. Analysis of Vegetable Sales Volume Patterns

2.1 Analysis of Distribution Patterns for Different Vegetable Categories

To analyze the distribution patterns of different vegetable categories, this study calculates the daily total sales volume for each individual item within each category based on preprocessed data. The effective data quantities vary across different categories, with 1085 valid data entries for Leafy Vegetables and 1050 valid data entries for Solanaceous Vegetables. Therefore, the average daily sales volume for each category is calculated on a monthly basis. This average sales volume reflects the sales level of various vegetable categories in that particular month. The variations in sales volume for different vegetable categories over time are illustrated in Figure 1.

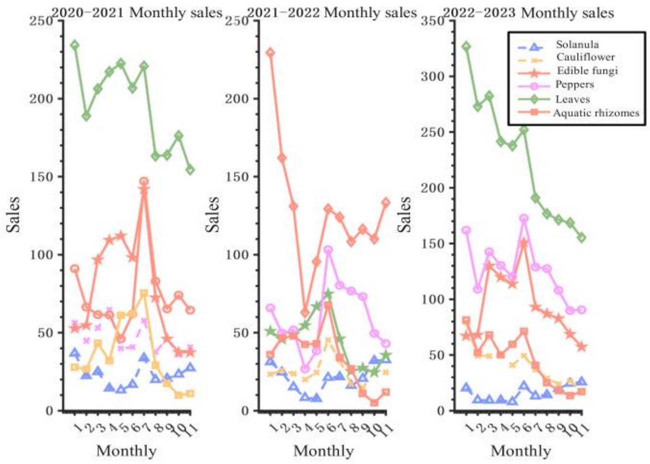


Figure 1: Monthly Sales Volume Fluctuation of Vegetable Categories

Figure 1 illustrates the monthly variation in average sales volume for different categories from July 2020 to June 2021, July 2021 to June 2022, and July 2022 to June 2023. It can be visually observed that there are significant differences in sales volume among different categories. The sales volume of each category exhibits a periodic distribution trend, and the periodic changes vary greatly among different categories. For example, there is an opposite trend in sales volume between Edible Fungi and Root Vegetables during the period from July to January.

Using the SPPPRO software, the distribution characteristics of sales volume for different vegetable categories were analyzed, and the normality of sales volume distribution for each category was tested. Table 1 presents the descriptive statistics and normality test results for the quantitative variables of Solanaceous Vegetables, Cauliflower Vegetables, Edible Fungi, Chili Peppers, Leafy Vegetables, and Aquatic Root Vegetables sales volume.

Table 1: Sales Volume Characteristics by Vegetable Category

Vegetable Category	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Shapiro-Wilk Test**
Solanaceous	20.942	8.833	0.482	-0.019	0.964(0.289)
Cauliflower	38.591	14.767	0.44	0.096	0.957(0.178)
Edible Fungi	70.681	33.771	0.75	-0.263	0.932(0.029**)
Chili Peppers	85.007	36.544	0.759	-0.182	0.937(0.041**)
Leafy	183.181	56.877	0.258	0.073	0.99(0.983)
Aquatic Root	37.624	21.73	0.311	-1.049	0.947（0.084*）

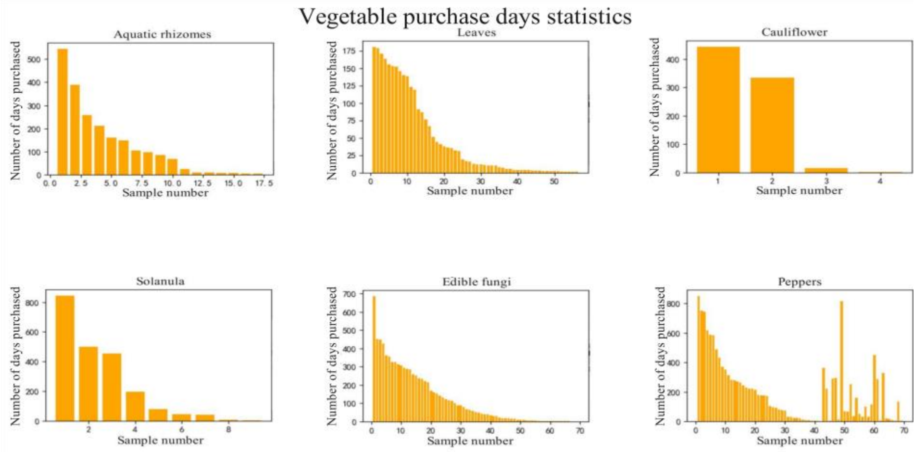
Note: ***,**,* represent the significance levels of 1%, 5%, and 10% respectively

As shown in Table 1, significant differences exist in the distribution of sales volume among different vegetable categories. Leafy Vegetables have the highest average sales volume, reaching 183.181 kg per day, while Solanaceous Vegetables have the lowest average sales volume at only 20.942 kg. The standard deviation reflects the degree of variation in sales volume distribution among different categories in different months. It is evident that the sales volume of Leafy Vegetables, Chili Peppers, and Edible Fungi exhibits greater fluctuations across different months compared to Aquatic Root Vegetables, Cauliflower Vegetables, and Solanaceous Vegetables.

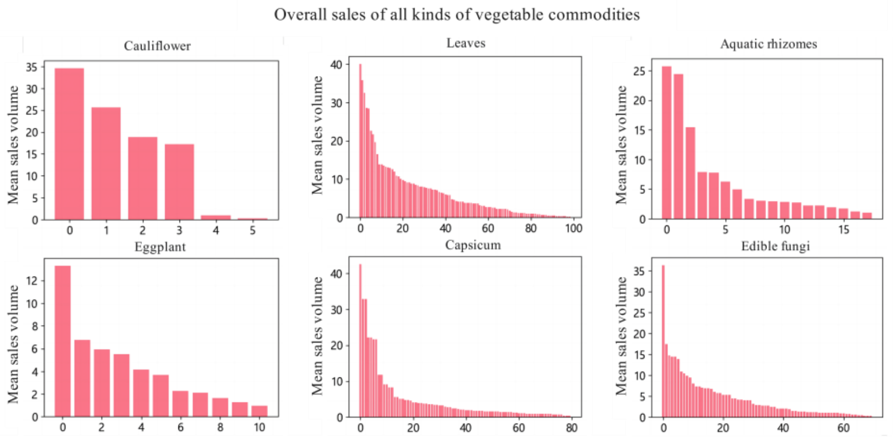
In order to further analyze the distribution of average sales volume for different vegetable categories, this study conducted descriptive analysis on the data for each category, and the results are shown in Table 1:

The Shapiro-Wilk test [8] was used to examine whether the distribution of daily average sales volume data for each vegetable category approximates a normal distribution. This method is suitable for testing small sample data (sample size ≤ 5000), and since there are 36 data points in this study, it is appropriate to use this test method. If the results show significance ($P < 0.05$), it indicates that the data does not follow a normal distribution. Therefore, the sales volume distribution of Edible Fungi, Chili Peppers, and Aquatic Root Vegetables conforms to a normal distribution, while the sales volume distribution of Solanaceous Vegetables, Cauliflower Vegetables, and Leafy Vegetables does not follow a normal distribution.

The sales duration of individual vegetable items corresponding to each vegetable category was analyzed, and the frequency distribution of the sales days for each vegetable item in each category was plotted as shown in Figure 2. It can be observed that there are significant differences in the sales frequency of individual vegetable items within the same vegetable category. Taking Solanaceous Vegetables as an example, the Purple Eggplant (2) has sales records for 1021 days, while the Round Eggplant (1) has sales records for only 3 days.



(a) Frequency distribution graphs of vegetable item sales by category



(b) Distribution graphs of average daily sales volume for each vegetable category

Figure 2: Histograms of distribution for different vegetable items

Figure 2 Distribution graphs of the average daily sales volume for individual vegetable items corresponding to each vegetable category. It can be observed that there are significant differences in sales volumes among individual vegetable items within the same vegetable category. Taking Cauliflower Vegetables as an example, Broccoli has an average daily sales volume of over 30kg, while Purple Cabbage (2) has an average daily sales volume of less than 1kg.

In this study, the top 3, 3, and 4 vegetable items with the highest average daily sales volume were selected for each vegetable category. For vegetable categories with a larger number of individual items, 5 vegetable items with the highest average daily sales volume were chosen as representative samples for further analysis.

Next, this study conducted Spearman correlation analysis [9] on the daily sales volume of these representative vegetable items. The heatmap of correlation coefficients is shown in Figure 3.

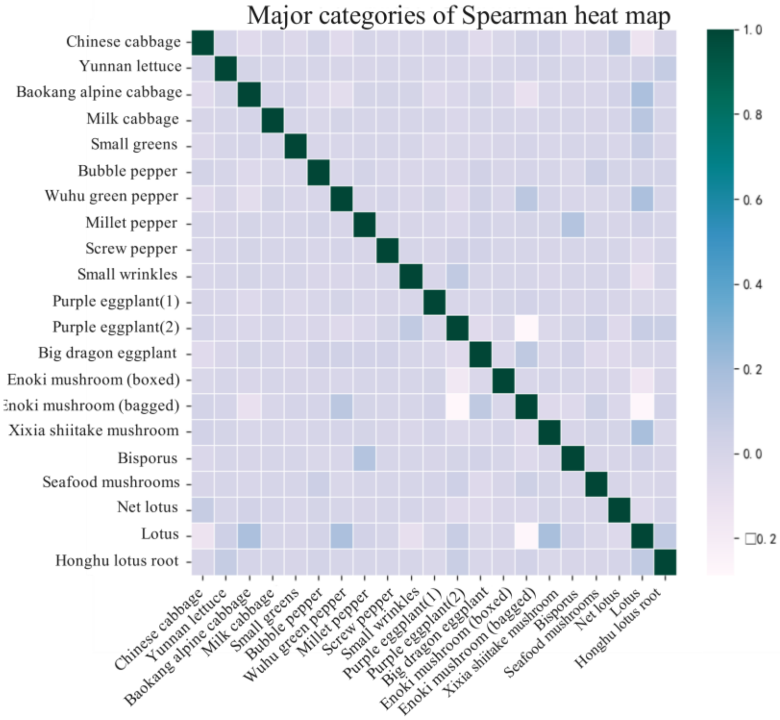


Figure 3: Heatmap of correlation coefficients for vegetable items

As shown in Figure 3, the values of correlation coefficients among individual vegetable items within the same category are close to 0, indicating that there are significant differences in the sales trends of different vegetable items within the same category. Based on this, it can be inferred that individual vegetable items within the same category are substitute products, and their sales volumes exhibit a trend of mutual substitution. For example, when customers buy more broccoli, they may reduce their purchases of purple cabbage.

However, there is a strong relationship between the sales trends of some vegetable items belonging to different categories, indicating that they may both be seasonal vegetables during a certain period. Figure 3 shows that there is a strong correlation between the sales volumes of millet pepper and shimeji mushroom, indicating that customers may tend to buy these two types of vegetable items together to make dishes.

2.2 Paired Sample T-Test

The paired sample mean T-test is applicable to quantitative data and can be used to test whether there is a significant difference in the unknown population means represented by two samples. In order to explore the differences in the monthly average daily sales volume distribution of different vegetable categories, this study conducted paired sample T-tests on the data of different vegetable categories.

The paired sample T-test can only be performed when the difference in the observed variables between the two paired groups is approximately normally distributed. Therefore, to explore the distribution of daily sales volume for different vegetable categories, the sales volume distribution for each vegetable category is shown in Figure 2.

Table 2: Results of paired sample T-test for vegetables.

Paired Variables	t	P	Cohen'sd
Solanaceous paired with cauliflower	-6.367	0.000***	1.061
Solanaceous paired with leafy	-16.88	0.000***	2.813
Solanaceous paired with chili peppers	-9.91	0.000***	1.652
Solanaceous paired with edible fungi	-7.889	0.000***	1.315
Solanaceous paired with aquatic root	-3.751	0.001***	0.625
Cauliflower paired with edible fungi	-6.454	0.000***	1.076
Cauliflower paired with chili peppers	-8.555	0.000***	1.426
Cauliflower paired with leafy	-18.516	0.000***	3.086
Cauliflower paired with aquatic root	0.301	0.765	0.05
Leafy vegetables paired with chili peppers	13.616	0.000***	2.269
Leafy vegetables paired with edible fungi	14.602	0.000***	2.937
Leafy paired with aquatic root	17.621	0.000***	2.937
Edible fungi paired with chili peppers	-2.811	0.000***	0.468
Edible fungi paired with aquatic root	7.967	0.000***	1.328
Aquatic root paired with chili peppers	-8.913	0.000***	1.485

Table 2 presents the results of paired sample t-tests for different vegetable categories, and differences between sales data of each category are evaluated based on t, P, and Cohen's d values. The larger the absolute value of the t-value, the more significant the difference. If the P-value is less than 0.05, it is considered that there is a significant difference between the data. The larger the Cohen's d value, the more significant the difference effect, indicating that the difference between the two groups of samples is larger.

As shown in the table, there is no significant difference in the distribution of sales data between only two pairs of different vegetable categories, which are Solanaceous paired with aquatic root vegetables, and cauliflower paired with aquatic root vegetables. Among them, the sales distribution difference between Solanaceous and aquatic root vegetables is the least significant, with a t-value of only 0.31, a P-value exceeding the significance level threshold, and a very small Cohen's d value of only 0.05.

2.3 Periodicity Analysis

2.3.1 Wavelet Analysis Model

Wavelet analysis is a tool used for decomposition and analysis of time series data. It provides information about the signal at different scales and helps reveal the periodicity and trends in the data [10]. The formula for the wavelet analysis model is shown in equation (1):

$$\begin{cases} cA_N, cD_N = W'(Q)(\hat{Q}_{self}^{(i)}, w(Q)) \\ cA_{\frac{N}{2}}, cD_{\frac{N}{2}} = W'(Q)(cA_N, w(Q)) \\ \cdots \\ cA_1, cD_1 = W'(Q)(cA_2, w(Q)) \end{cases} \tag{1}$$

Where $Q_{self}^{(i)}$ represents the input data. $w(Q)$ is the wavelet basis function, $W'(Q)$ is the function for performing wavelet decomposition at level i, cA_i represents the approximation coefficients at level i,, cD_i represents the detail coefficients at level i.

The standard deviation of the approximate component (cA_i) for each month is calculated and recorded as the periodic level T. The formula is shown in (2):

$$T = \frac{1}{N}\sum_{i=1}^{N}\sigma_i \tag{2}$$

Where cA_i represents the standard deviation of the approximation coefficients at level i,and T is the periodic fluctuation of the index, σ_i is the standard deviation of the approximate component of the first data column.

2.3.2 Calculation Steps

Step 1: Take the average daily sales $\widehat{Q}_{self}^{(i)}$ volume starting from July 2020 as the input signal.

Step 2: Perform multi-level discrete wavelet decomposition to determine the number of levels by calculating the maximum level of wavelet transformation.

Step 3: Use $w(Q)$ and $W'(Q)$ to obtain coefficients at different scales. In this study, only the approximation coefficients at the first level cA are used.

2.3.3 Calculation Results

As shown in Table 3, there are significant differences in the periodic length of sales distribution for different vegetable categories. Among them, leafy vegetables exhibit the strongest periodicity in sales variation, while Solanaceous vegetables have the weakest periodicity but still show a significant level of periodicity.

Table 3: Table of periodic horizontal coefficients of different types of dishes

Vegetable Category	Solanaceous	Cauliflower	Edible Fungi	Chili Peppers	Leafy	Aquatic Root
periodic horizontal coefficients	7.84	11.34	25.93	24.24	40.11	20.41

3. Decision Model Formulation and Result Analysis

The main reason for the decision to reduce prices is that the quantity of vegetables purchased exceeds the customer demand. To stimulate customers to purchase these "slow-moving" vegetables, supermarkets engage in price reduction to minimize cost losses. Therefore, this article suggests that when setting a reasonable inventory level, the purchased vegetables should be sold out.

3.1 Fitting of Total Sales Volume and Cost Markup Pricing

Based on actual sales data of vegetables in supermarkets, this study conducted a fitting analysis on the relationship between vegetable sales volume and selling price. As shown in Figure 4, the distribution of sales prices and sales volumes approximates a power function relationship resembling the P-Q curve of a unitary elastic commodity. From the customer's perspective, an increase in the price of goods will lower their desire to purchase, resulting in a decrease in sales volume. From the retailer's perspective, when the sales volume is high, retailers tend to prefer a "small profit but quick turnover" sales strategy [11]. By lowering the selling price, the sales volume can reach a higher level, and eventually, the selling price will tend to converge toward the cost price.

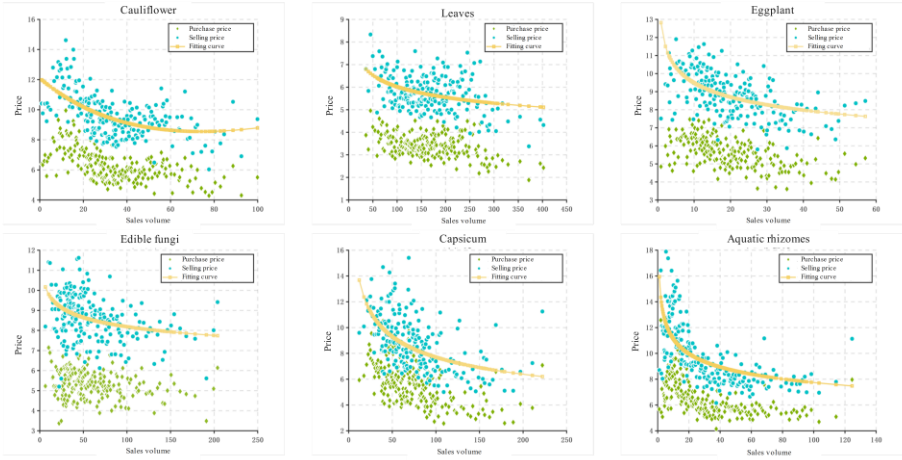


Figure 4: Sales volume and price fitting for different categories

3.2 Determination of Business Strategy

This article aims to maximize net profit and establishes the following single-variable, single-objective, multiple-constraint optimization model:

$$\max\ p_{ij}Q_{Sell}^{ij} - p_{Buy}^{ij}Q_{Buy}^{ij}$$
$$s.t\begin{cases} Q_{Sell}^{ij} = Q_{Buy}^{ij}(1-\overline{l}) \\ \dfrac{f(Q_{Sell}^{ij}) - p_{ij}}{p_{ij}} \le \lambda \\ h(p_{i-1j}) = Q_{Buy}^{ij} \\ p_{jpast}^{min}(1-\alpha_{down}) \le p_{ij} \le p_{jpast}^{max}(1+\alpha_{up}) \end{cases} \tag{3}$$

Differential Evolution (DE) algorithm is an efficient and robust evolutionary algorithm that can quickly converge to the global optimum [12]. In this study, the DE algorithm is employed to solve the established decision planning model and formulate pricing and procurement strategies based on the obtained results.

The standard DE algorithm starts by randomly generating an initial population. It then selects several individuals from the population and generates new offspring according to certain rules. The process continues by generating new individuals, retaining the fittest ones, and eliminating the weaker ones until the population reaches an optimal state [13]. The flowchart of the DE algorithm [14] is illustrated in Figure 5.

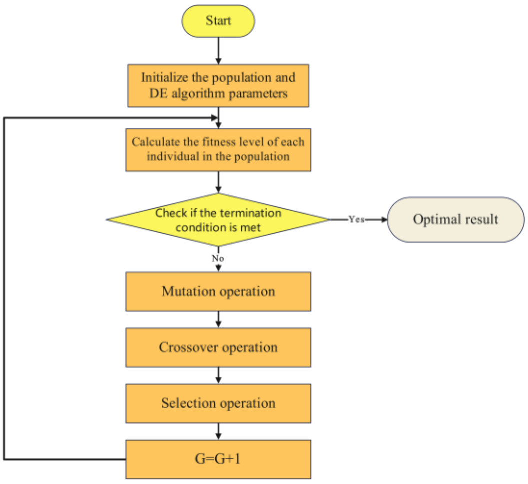


Figure 5: Flowchart of the Differential Evolution algorithm

4. Supermarket Procurement and Pricing Strategy

Using the DE algorithm, the optimal procurement quantities for different vegetable categories and their corresponding pricing strategies are determined to maximize the future seven-day revenue. The specific decisions regarding procurement quantities and pricing for each category are presented in Table 4 and Table 5.

Table 4: Procurement Quantities for Vegetable Categories

Date	Aquatic Root(kg)	Leafy (kg)	Cauliflower (kg)	Solanaceous (kg)	Chili Peppers (kg)	Edible Fungi(kg)
7.1	14.79	159.40	22.56	27.61	70.09	32.83
7.2	14.39	170.56	18.48	24.73	67.37	33.04
7.3	14.02	169.09	18.31	24.89	68.28	32.42
7.4	14.02	170.10	13.36	24.62	67.40	32.47
7.5	14.02	166.70	17.97	25.24	67.42	32.51
7.6	14.02	169.0	18.01	24.60	68.28	32.56
7.7	14.02	169.22	17.82	25.24	67.52	32.63

Table 5: Pricing Decisions for Different Vegetable Categories

Date	Aquatic Root(￥/kg)	Leafy (￥/kg)	Cauliflower(￥/kg)	Solanaceous (￥/kg)	Chili Peppers (￥/kg)	Edible Fungi (￥/kg)
7.1	18.84	6.124	14.654	10.390	8.214	7.341
7.2	22.08	6.033	14.779	10.265	7.529	8.521
7.3	22.08	6.124	14.968	10.478	8.197	8.435
7.4	22.08	5.821	15.021	9.986	8.182	8.356
7.5	22.08	6.031	14.989	10.499	7.528	8.258
7.6	22.08	6.045	15.123	9.988	8.106	8.125
7.7	22.08	6.113	15.065	10.024	8.022	8.057

Table 4 shows that there are fluctuations in the procurement quantities of different vegetable categories on different dates, and the fluctuations are relatively small, which is consistent with the actual changes in procurement quantities in supermarkets. Table 5 shows that there are also fluctuations in the prices of different vegetable categories on different dates, and the fluctuations are relatively small, which is in line with the principle that price changes should not be too large to attract customers and maximize revenue. Taking into account the decisions presented in Tables 4 and 5, when prices increase, procurement quantities decrease, and when prices decrease, procurement quantities increase. Procurement quantities are closely related to sales, and follow the general relationship between sales prices and procurement quantities [15].

Comparing the average revenue for the next seven days shown in Table 6 with that of the previous month, it is found that the optimized average revenue of aquatic root vegetables has increased by 167%, leafy vegetables have increased by 55%, cauliflower has increased by 21%, tomatoes have increased by 81%, peppers have increased by 40%, and edible fungi have increased by 38%. These results demonstrate the rationality and effectiveness of the single-objective planning model established in this study, which can significantly increase revenue and achieve the goal of maximizing profits.

Table 6: Seven-day forecast and comparison of vegetable income

Date	Aquatic Root(￥/kg)	Leafy (￥/kg)	Chili Peppers (￥/kg)	Edible Fungi (￥/kg)
7.1	72.904	322.387	279.111	103.363
7.2	110.390	331.893	226.621	145.896
7.3	108.081	342.900	272.239	143.337
7.4	107.574	299.123	268.394	137.616
7.5	105.902	324.756	228.543	133.825
7.6	104.723	332.732	267.784	129.320
7.7	103.850	344.143	259.983	126.552
Average Revenue for 7-Days	101.918	328.276	257.525	131.416
Last Month's Avg	38.160	211.359	184.332	95.566
Rev.Average Increase	167%	55%	40%	38%

5. Conclusions

(1) There are significant differences in the sales distribution of different vegetable categories. The sales of leafy vegetables, chili peppers, and edible fungi vary greatly across different months, indicating a higher susceptibility to seasonal factors.

(2) There are significant differences in the length of sales cycles among different vegetable categories. Among them, leafy vegetables exhibit the strongest cyclicality, while tomato vegetables exhibit the weakest cyclicality, although still displaying significant periodic patterns.

(3) There is no significant difference in the sales data distribution between the nightshade vegetables and aquatic root vegetables, as well as between the nightshade vegetables and brassica vegetables. However, significant differences exist among the sales data distributions of other vegetable categories.

(4) Different individual products within the same category exhibit significant variations in sales trends, indicating a fluctuating pattern in consumer preferences. There is a strong relationship between the sales of certain products belonging to different categories, suggesting that customers may prefer to purchase specific combinations of vegetables.

(5) This study provides a decision solution for the automatic pricing and replenishment of vegetable products, but it only considers the operational data of a few years for a subset of vegetable convenience stores. Further model expansion requires more in-depth investigations and research.

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