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Pricing and Replenishment Strategies for Vegetable Commodities Based on Time Series Models

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Abstract: *This paper presents a proposed pricing and replenishment strategy for vegetable commodities in fresh food supermarkets. The aim is to address the challenges faced by these supermarkets in making decisions regarding pricing and replenishment. The strategy is based on a time series model, which involves statistical analysis of sales volume using the average trend rejection method and Spearman coefficient. This analysis provides a descriptive statistical understanding of past sales volume patterns. A time series model is then established based on these statistical laws to predict the sales volume for the next three days. The relationship between sales volume and pricing is determined using K-mean clustering and regression fitting. Subsequently, a single-objective optimization model is formulated based on this relationship and solved using the simulated annealing algorithm to obtain the optimal pricing and replenishment strategy for the commodities. Experimental tests are conducted to validate the model, and the results demonstrate that the proposed model successfully identifies the seasonal distribution of sales volume for vegetable commodities, indicating the presence of an off-peak season. Additionally, the model reveals that while there is no significant correlation between different vegetable categories, there is a strong correlation between certain individual products within the same category. The model accurately predicts sales for the next three days and provides pricing and replenishment quantities for the commodities through the single-objective optimization model. Furthermore, the model enables the estimation of the superstore's profit based on the determined pricing and replenishment quantities. This study holds practical significance for fresh food supermarkets in terms of pricing and replenishment of vegetable commodities, as well as for maximizing the revenue of superstores.*

Keywords: *Moving average method, Spearman coefficient, Time series model, Regression fitting*

1. Introduction

In practical situations, the freshness of vegetable commodities tends to deteriorate[1-3] over time, leading to changes in their desirability for customers. The willingness of customers to purchase these commodities is often influenced by both their freshness and price[4-7]. Consequently, it is necessary to adjust the pricing of vegetables as their freshness changes in order to maintain customer interest and prevent stagnation of goods. Determining the appropriate pricing and stocking quantities on a daily basis presents a challenging problem. Various factors impact the pricing and replenishment quantities of commodities. For instance, research by Yang Shuai et al.[8] suggests that allocating shelf space primarily to seasonal commodities and slightly reducing their prices can maximize profits for superstores. Additionally, Li Yali et al.[9-10] found that preservation technology and pricing have a reciprocal relationship, as pricing that is too high or excessive inventory can negatively impact product demand and sales, while pricing that is too low or insufficient inventory can reduce retailer profits and result in missed sales opportunities. Inventory levels[11-13] also play a significant role in determining pricing and replenishment quantities. Higher inventory levels necessitate clearing stock by lowering prices and reducing stock quantities, while lower inventory levels allow for increased stock quantities. However, none of the aforementioned strategies consider the influence of past replenishment quantities on same-day replenishment quantities, nor the relationship between replenishment quantities and pricing. This paper proposes a pricing and replenishment strategy for vegetable items based on time series modeling. The time series model predicts the sales volume for the day, and to minimize losses, the replenishment quantity for the day is set equal to the predicted sales volume. Simultaneously, the pricing for the day is determined based on the relationship between pricing and replenishment quantities.

2. Seasonal distribution pattern of vegetable categories

2.1 Seasonal indices for vegetable categories

As depicted in Fig 1, the sales volume of each vegetable category exhibits notable fluctuations, with a more pronounced cyclical pattern observed across all categories. This study posits that this pattern is strongly correlated with quarterly changes.

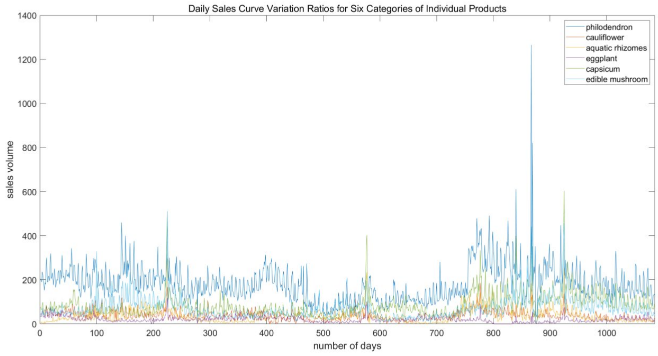

Figure 1: Changes in sales of the six vegetable categories

An evaluation metric is developed to examine the influence of each quarter on sales volume, while the average trend elimination method is employed to separate seasonal factors from a composite series characterized by substantial long-term trend fluctuations.

1) Calculate the moving average

$$F_t = \frac{A_t + A_{t-1} + A_{t-2} + \cdots + A_{t-k+1}}{k} \tag{1}$$

where F_t is the predicted value for the next point in time, and k is the number of periods for the moving average, and A_t is the actual value for the first period, and A_{t-1} denotes the second period, and so on.

2) Obtain the centered moving average(CMA)

$$CMA_t = \frac{(F_t + F_{t+1})}{2} \tag{2}$$

To determine the quarterly ratio σ_t, which represents the sales to CMA, the actual value of the sample should be divided by the corresponding CMA. This calculation will yield the quarterly ratio for each sample.

$$\sigma_t = \frac{A_t}{CMA_t} \tag{3}$$

3) To obtain the quarterly index S, it is necessary to compute the average of the sales ratios across multiple years and subsequently divide this value by the sum of the averages of the sales ratios.

$$S = \frac{\frac{\sigma_t + \sigma_{t+1}}{2}}{\sum \frac{\sigma_t + \sigma_{t+1}}{2}} \tag{4}$$

2.2 Results of solving for quarterly indices

The quarterly indices for each category are obtained as shown in Table 1.

Table 1: Quarterly indices for each vegetable category

Vegetable category	First quarter	Second quarter	Third quarter	Fourth quarter
Philodendron	0.9168	0.8367	1.3104	0.9361
Cauliflower	0.9925	0.8270	1.2424	0.9381
Aquati crhizomes	1.2779	0.2761	1.1864	1.2596
Eggplant	0.9706	1.3857	1.1627	0.4810
Capsicum	1.2793	0.8379	1.0158	0.8669
Edible mushroom	1.2012	0.5733	0.8891	1.3365

According to Table 1, it can be seen that the peak season for foliage is in the third quarter, cauliflower

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is in the third quarter, aquatic roots and tubers are sold in large quantities in the first, third and fourth quarters, eggplants are in the second and third quarters, chili peppers are in the first and third quarters, and edible mushrooms are in the first and fourth quarters.

3. Interrelationship of sales by vegetable category

3.1 Spearman's coefficient of correlation for each vegetable category

This paper employs Spearman's coefficient of correlation to examine the correlation between the sales of various categories in relation to their phase relationship. The mathematical expression for Spearman's coefficient of correlation is presented in equation (5).

$$R = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{5}$$

Where R is the Spearman's coefficient, x_i is the first taken value of the first variable, $\bar{x}$ is the average taken value of the first variable, y_i is the first taken value of the second variable, and $\bar{y}$ is the average taken value of the second variable.

3.2 Results of solving for Spearman's coefficients

The correlation coefficients for each category of vegetables are visually represented in a three-color ordinal diagram, as depicted in Fig 2. In this diagram, the color green signifies a positive correlation, while the color orange signifies a negative correlation. Furthermore, the intensity of the color corresponds to the strength of the correlation.

	philodendron	cauliflower	aquati crhizomes	eggplant	capsicum	edible mushroom
philodendron	1.00	0.63	0.44	0.25	0.59	0.60
cauliflower	0.63	1.00	0.40	0.19	0.43	0.46
aquati crhizomes	0.44	0.40	1.00	−0.21	0.33	0.60
eggplant	0.25	0.19	−0.21	1.00	0.10	−0.11
capsicum	0.59	0.43	0.33	0.10	1.00	0.54
edible mushroom	0.60	0.46	0.60	−0.11	0.54	1.00

Figure 2: Spearman's coefficient of correlation color scale for vegetable category

Based on the data presented in Fig 2, it can be observed that there are relatively higher correlation coefficients between leafy flowers and cauliflower, as well as between aquatic roots and edible mushrooms. This suggests a potential association, indicating that customers may tend to purchase cauliflower alongside leafy flowers, and edible mushrooms alongside aquatic roots and mushrooms.

4. Pricing and stocking strategies for the vegetable category

4.1 Relationship between sales volume and selling price based on regression fitting

Figure 3: Distribution of 50 clustering centers after clustering

Using factor analysis to select the important single product of each vegetable category, and get the contribution of each single product, using the contribution of the weighted calculation of the daily sales and selling price of each type of single product, and then K-mean clustering, the establishment of 50 clustering centers, to get the total sales volume and selling price of leafy and flowery vegetables as shown in Fig 3 corresponds to the relationship between the total sales volume and selling price, according to the graphical analysis shows that the total sales volume and selling price present a certain correlation

The curve fitting analysis was conducted using SPSS software, and the resulting plot is presented in Fig 4. Upon comparison of the different fitting functions, it was determined that the power function exhibited the most optimal fit. Consequently, the power function was selected as the fitting model for this research study.

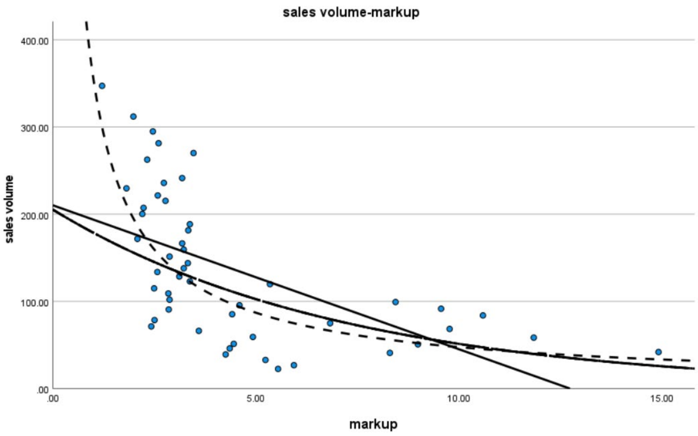

Figure 4: Comparison of each fitted curve

The correlation between each vegetable category and its corresponding selling price has been determined and modeled as a fitting function.

$$W_{ij} = a_j\left(P_{ij} - C_{ij}\right)^{b_j} \tag{6}$$

Where W_{ij} is the total sales volume of goods of category j in day i, P_{ij} is the selling price of goods of category j in day i, C_{ij} is the unit cost of goods of category j in day i, a_j is the coefficient and b_j is power of the function of sales volume and selling price of goods of category j.

The solution yields the coefficients and powers for each vegetable category, as presented in Table 2.

Table 2: Coefficients and powers for each vegetable category

Vegetable category	a	b
Philodendron	484.3	-0.7851
Cauliflower	111	-0.7574
Aquati crhizomes	21.65	-0.4268
Eggplant	101.5	-0.8499
Capsicum	194.7	-0.6264
Edible mushroom	61.94	-0.5126

4.2 Time series modeling for sales forecasting

Based on the weighted historical sales of each vegetable category, a time series model was developed for forecasting:

$$(1 - \sum_{i=1}^{p} \alpha_i L^i)(1 - L)^d y_t = \alpha_0 + \left(1 + \sum_{i=1}^{q} \beta_i L^i\right)\varepsilon_t \tag{7}$$

$$L^i y_t = y_{t-i} \tag{8}$$

Where p is the autoregressive order, α is autoregressive rate, L is the lag operator, d is the difference order, y_t is the value y of the moment t , α_0 is the constant, q is the moving average order, β is the moving average coefficient and ε_t is the white noise series.

The Augmented Dickey-Fuller (ADF) test was conducted on the sales data of the class, revealing that the data exhibits smoothness and can be effectively predicted using time series analysis. Upon comparing the goodness of fit between the exponential smoothing model and the Autoregressive Integrated Moving

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Average (ARIMA) model, it was determined that the ARIMA model outperforms the former. Consequently, the ARIMA model was selected for forecasting purposes, and the resulting time series residual plot is depicted in Fig 5.

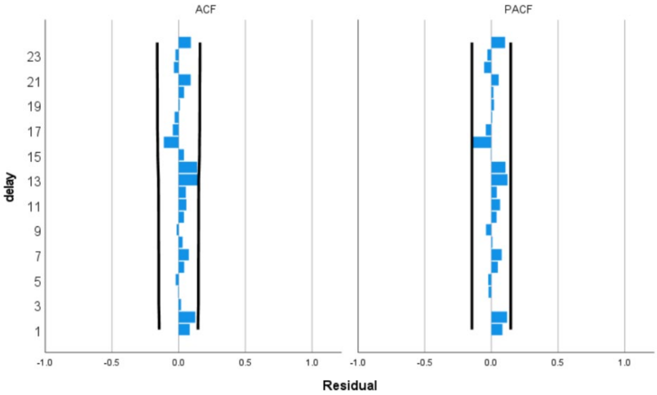

Figure 5: Residual plots of the time series

Based on the analysis of the residual autocorrelation function (ACF) and residual partial autocorrelation function (PACF) depicted in the figure, it is evident that the p-value for the autoregressive (AR) component is 1 and the q-value for the moving average (MA) component is 14 in the ARIMA model. Additionally, based on the previous augmented Dickey-Fuller (ADF) test, it can be concluded that the differencing parameter (d) is 0. Consequently, the appropriate model for predicting the sales of the class is ARIMA (1,0,14). The ARIMA model was tested to obtain a trend comparison graph as shown in Fig 6:

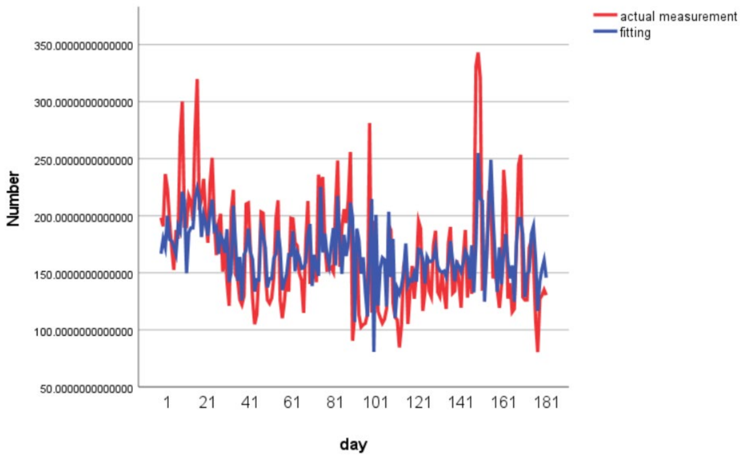

Figure 6: Comparison of projected and actual trends

Based on the graphical representation, it is evident that the time-series plots of the real data and the predicted data exhibit a considerable degree of overlap after eliminating the peaks. This observation suggests that the ARIMA(1,0,14) model outperforms other models. Furthermore, the R-squared value of 0.773 indicates a higher level of goodness-of-fit for the aforementioned model.

Accordingly, the class sales forecasts for July 1-7, 2023 were obtained as shown in Table 3.

Table 3: Class Sales Forecast for July 1-7, 2023

Dates	7/1	7/2	7/3	7/4	7/5	7/6	7/7
Philodendron	132.5	126.53	126.65	139.84	148.07	140.83	142.86
Cauliflower	23.7	21.93	21.09	22.03	22.84	23.7	24.86
Aquati crhizomes	21.43	19.99	20.95	20.62	20.99	20.97	21.16
Eggplant	23.47	22.72	20.27	21.1	20.67	22.77	22.59
Capsicum	79.59	80.16	80.47	82.15	81.78	84.41	86.31
Edible mushroom	43.14	46.19	49.56	53.95	53.38	52.73	50.84

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4.3 Single-objective optimization modeling

With profit maximization as the objective function, it can be derived:

$$\alpha_{ij} = P_{ij}W_{ij} - C_{ij}Q_{ij}, i = 1 \dots 7, j = 1 \dots 6 \tag{9}$$

Where α_{ij} is the profit of the jth category of goods in the ith day, then P、W、C and Q represents the selling price, sales volume, unit cost and incoming quantity, respectively, and the subscript indicates the same α_{ij}.

The decision variables are given as stocking quantity Q_{ij} and vegetable pricing P_{ij}.

Considering the aforementioned limitations:

$$P_{ij} \geq C_{ij} \tag{10}$$

$$W_{ij} \leq Q_{ij} \tag{11}$$

Simultaneously, there exists a distinct functional correlation between the overall sales volume and the selling price:

$$W_{ij} = a_j\left(P_{ij} - c_{ij}\right)^{b_j}, i = 1 \dots 7, j = 1 \dots 6 \tag{12}$$

The unit cost is related to the attrition rate and the wholesale price, where l is the attrition rate and c is the wholesale price:

$$C_{ij} = (1 + l)c_{ij} \tag{13}$$

The selling price is obtained using the cost-plus pricing method, where r_{ij} is the markup rate and p'_{ij} is the average selling price of the commodity.

$$P_{ij} = C_{ij}\left(1 + r_{ij}\right) \tag{14}$$

$$r_{ij} = \frac{p'_{ij} - c_{ij}}{c_{ij}} \tag{15}$$

In conclusion, a mathematical model is derived for the purpose of optimizing profit over a 7-day period, with a focus on a single objective.

$$\max\left(\sum_{i=1}^{7}\sum_{j=1}^{6}\alpha_{ij}\right)$$

$$s.t.\begin{cases} P_{ij} \geq C_{ij} \\ W_{ij} \leq Q_{ij} \end{cases} \tag{16}$$

4.4 Solving the model

Solving yields the daily intake and pricing of each vegetable as shown in Table 4.

Table 4: Daily intake and pricing of various types of vegetables

Vegetable category	**7.1**	**7.2**	**7.3**	**7.4**	**7.5**	**7.6**	**7.7**
stock intake(1)	132.5	126.53	126.65	139.84	148.07	140.83	142.86
stock intake(1)	8.52	8.84	8.83	8.17	7.83	8.13	8.04
stock intake(2)	23.7	21.93	21.09	22.03	22.84	23.7	24.86
stock intake(2)	11.12	11.95	12.4	11.9	11.51	11.12	10.66
stock intake(3)	21.43	19.99	20.95	20.62	20.99	20.97	21.16
stock intake(3)	3.43	3.61	3.49	3.53	3.48	3.49	3.46
stock intake(4)	23.47	22.72	20.27	21.1	20.67	22.77	22.59
stock intake(4)	11.23	11.45	12.28	11.98	12.13	11.43	11.49
stock intake(5)	79.59	80.16	80.47	82.15	81.78	84.41	86.31
stock intake(5)	8.73	8.68	8.66	8.52	8.55	8.36	8.22
stock intake(6)	43.14	46.19	49.56	53.95	53.38	52.73	50.84
stock intake(6)	5.8	5.55	5.32	5.09	5.11	5.15	5.25

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5. Conclusions

This study centers on the anticipation of vegetable demand by employing a time series model. Additionally, it utilizes a regression model and a single-objective optimization model to establish the most advantageous daily stocking quantity and pricing strategy, with the aim of maximizing the profit of the superstore.

This paper employs the average trend elimination method to analyze the seasonal pattern of vegetable categories by utilizing moving averages. The findings indicate that there are distinct peak and off-season periods in the sales distribution of various vegetables. For instance, flower and leafy vegetables are sold throughout the year, with the third quarter being the peak season. The Spearman coefficient is employed to examine the correlation of sales volume between different vegetables. The results suggest that the correlation between most vegetable categories is not statistically significant, except for leafy and cauliflower, as well as aquatic roots and edible mushrooms, which may exhibit some correlation. In terms of replenishment and pricing strategy for superstores, this study calculates the selling price and sales volume for each vegetable category based on factor analysis. K-means clustering is applied to sales volume and selling price, and a power function regression is fitted to describe the relationship between sales volume and selling price. Additionally, the paper predicts the sales volume for the period of July 1-7, 2023 using an ARIMA model, taking into account the influence of past values on the present. Furthermore, a single-objective optimization model is developed with profit maximization as the objective function, and it is solved to determine the quantity of each category of goods to be stocked daily and the pricing strategy.

References

[1] OU Yanfeng. Deterioration rate products with time-varying scheme design for perishable problem and cost sharing joint replenishment[D]. Southeast University, 2022.

[2] Latpate Raosaheb; Bhosale Maruti;Kurade Sandesh.Cold supply chain inventory models for agricultural products with multi-stage stochastic deterioration rates[J]. Journal of Management Analytics. Volume 10, Issue 3. 2023. PP 516-549.

[3] Pooja Soni;Rajender Kumar.A Deterministic Inventory Model with Time-varying Demand for Items with Static Deterioration Rate[J]. Journal of Research in Science and Engineering. Volume 4, Issue 8. 2022.

[4] ZHAO Haolu. Study on The Willingness and Influencing Factors of Community Group Purchase of Fresh Produce of Zhengzhou Residents [D]. Henan University of Technology ,2023.

[5] Steven, Haggblade. Food Policy for Developing Countries: The Role of Government in Global, National, and Local Food Systems[J]. Eur Rev Agric Econ, 2012.DOI:10.1093/erae/jbs023.

[6] CAO Yu, WU Kan,XIONG Shouyao. Research on Fresh-keeping Effort, Ordering and Pricing in Fresh Supply Chain [J]. Operations Research and Management, 2019, 10: 100 - 109.

[7] YANG Jingying. A Study on Consumers' Willingness to Buy Fresh Agricultural Products Online and Its Influencing Factors——A Case Study of Changchun City [D]. Jilin Agricultural University, 2023.

[8] YANG Shuai, HUANG Xiangmeng, WANG Junbin. Joint Pricing and Shelf Space Allocation Strategy for Perishable Food [J]. Chain management. 2022, 3(08).

[9] Li Yali. Joint Replenishment and Pricing Decision of Multi-item Considering Investment of Fresh Preservation Technology [D]. Chongqing Jiaotong University, 2022.

[10] CUI Ligang,LI Yali,LIU Jinxing, TIAN Yu. Joint Replenishment and Pricing Decision of Multi-item Considering the Investment of Fresh Preservation Technology [J]. Industrial Engineering and Management. 2023,28(03).

[11] XU Hao. Research on Supermarket Fresh Products Inventory Control Based on Demand Forecasting--Taking J Supermarket as an Example [D]. Henan University of Finance and Economics and Law, 2022.

[12] Liu Yuhong. Research on dynamic strategies and sales modes of e-commerce platforms under blockchain traceability [D]. Qingdao University, 2022.

[13] HUANG Lianruo, CEN Zhongdi. Study on Pricing and Inventory Decision of Fresh Agricultural Products Considering Dual Efforts [J]. Journal of Zhejiang Wanli University. 2023,36(05)