Research on Automatic Replenishment and Pricing Strategy of Vegetables Based on Dynamic planning of targets

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Abstract. As the national living standard continue to improve, the demand for goods across all categories in shopping malls is increasing, particularly for vegetable products, which are considered to be necessities of life. After preprocessing the data in the *Vegetable Industry Data In-depth Research and Analysis and Development Strategic Planning Report*, this study establishes a linear regression model by Pearson correlation coefficient method. Additionally, it transforms the replenishment and pricing strategy problem into a backpack problem under dynamic programming by using time series analysis and Holt-Winter smoothing index method. It is found that the backpack problem under dynamic programming can model the automatic replenishment of vegetables, and predict the replenishment volume of each category and single product to gram units through the sales volume of each category and each single product, which is convenient for vegetable merchants to efficiently price and purchase the corresponding vegetable categories and quantities reasonably.

Keywords. Auto-replenishment; Cost-plus pricing; Dynamic planning of targets; Linear regression models

1 Introduction

With the continuous improvement of national living standards, people are increasingly concerned about their diet, which has led to a growing interest in vegetable products. However, in the fresh produce market, the shelf life of vegetable products is generally shorter than that of other products. Thus, it's difficult to resell vegetables the next day if they're not sold out the first day, making "replenishment" a critical consideration for produce. What's more, significant fluctuations in vegetable prices can lead to "spider shocks" in the market, which not only harm farmers but also dissipate social welfare [1]. Therefore, how to better supply and price vegetable products has always been a topic of great interest.

Vegetable products do not spoil immediately upon delivery, but they deteriorate in a short time as conditions change. These types of goods that have deteriorated over a certain period are called "non-immediate deterioration" [2]. BANERJEE and AGRAWAL took a single non-

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immediate spoilage product as the research object, the ordering decision related to the demand for the product and the price and freshness is assumed [3]. Wu and YANGR looked at the replenishment, pricing, and collaborative decision-making of the optimal selling price and the optimal replenishment cycle for individual non-immediate spoiled goods [4]. Chen Huafei and Lu Yin used the TPLSP method to analyze the factors affecting the price of vegetables [5]. Cui et al. proposed an adaptive differential evolution algorithm to construct a joint replenishment model to minimize the total cost [2]. Zhao Yu used the kernel density estimation method to fit the marginal distribution of vegetable yield fluctuation and price fluctuation and estimated the joint distribution function of yield and price fluctuation with the help of the semiparametric Copula method [1]. The above studies focus on the strategy of a single variety or individual replenishment in the joint decision-making of inventory and pricing of non-immediate spoiled products, and the automatic replenishment and pricing strategy of vegetable commodities has not captured enough attention.

To sum up, this paper starts with the automatic replenishment and pricing strategy of vegetable commodities [7], establishes a linear regression model through the Pearson correlation coefficient [6], uses time series analysis [8], and the Holt-Winter smoothing index method [9], to transform the pricing and replenishment problem of vegetable commodities into a backpack problem under the dynamic programming model [10], and uses Python tools to solve the corresponding model to form the "automatic replenishment" method and cost-plus pricing strategy [11] .

2 Subjects and Methods of the Study

2.1 Subject

At present, the average wholesale price of the vegetable market is used as the price index of insurance design in the pilot area of vegetable insurance. The price in the circulation link, nonetheless, includes profits, transportation costs, and the loss of fresh vegetables, which cannot accurately reflect the cost of vegetable planting [1]. The price used in this study is the transaction price of the field, and the data covers six types of vegetable commodities, namely mosaic leaf, peppers, and edible fungi. The impact of price variation is excluded, and the nominal vegetable price is deflated by the consumer price index to obtain the actual price data.

2.2 Research Method

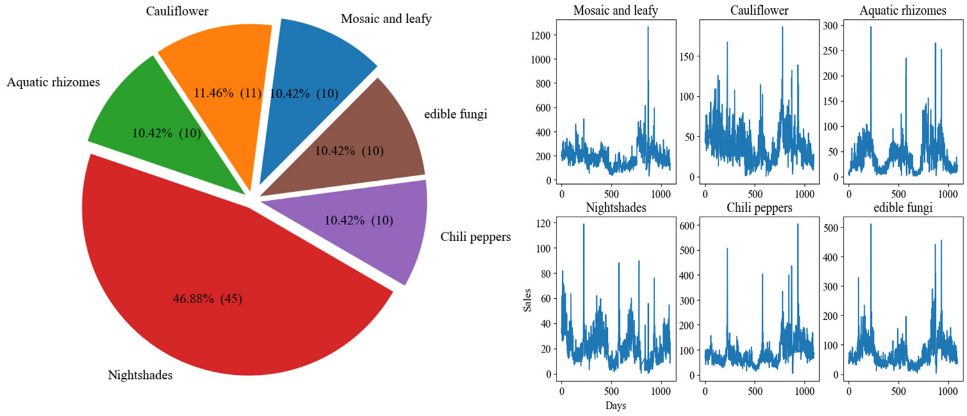
The trend of vegetable products over time was plotted by performing a missing value test on the obtained data. The correlation between the products of each category was observed, and the distribution relationship and correlation strength of the sales volume of each vegetable category and single product were studied more deeply by the Pearson correlation coefficient method. The linear regression model was established by analyzing the Pearson correlation coefficient, the cost-plus rate was obtained by solving the linear regression model, the pricing of various categories of vegetables was obtained by combining the cost-plus pricing method, and the corresponding pricing strategies were summarized by combining the market environment factors. By using the Holt-winter smoothing index method and time series analysis.

3 Model Establishment and Solution

3.1 Data Preprocessing

Data preprocessing is divided into three steps:data cleaning,data integration,data specification,Through the inspection and statistics of various missing data.In order to see the trend of each category over time more directly, the change in the sales volume of each vegetable category over time is plotted, the results of missing values of various vegetables are pinpointed in Figure and the results are addressed in **Figure 1**.

Figures 2. show the bar trend for each category from July 2020 to June 2023 based on the sales volume over time graphs.



(a) (b)

Fig. 1. Missing value and trend of sales volume by category

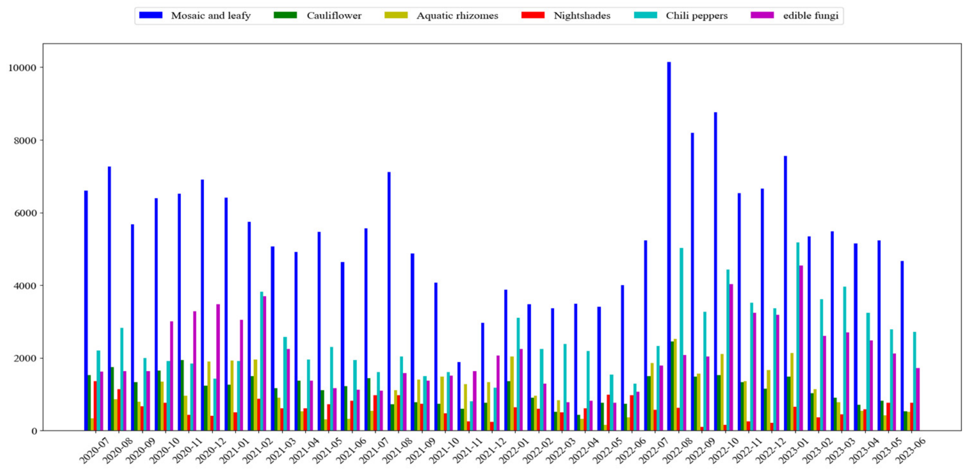


Fig. 2. Trend chart for each category over time

3.2 Establishment of the model

Through the observation and analysis of the above walking charts, it is observed that there is a correlation between the two adjacent categories. It was decided to use the Pearson correlation coefficient analysis to study the distribution relationship and correlation intensity of each vegetable category and single product sales volume in more depth. The Pearson model looks like this [6].

$$r = \frac{N\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{N\sum x_i^2 - (\sum x_i)^2}\sqrt{N\sum y_i^2 - (\sum y_i)^2}} \tag{1}$$

The cost-plus pricing method is a method of setting product prices based on the unit cost of the product plus a certain percentage of profits [11], and most enterprises determine the size of the added profits according to the cost-profit string.

Linear regression models are often used to linearly fit a set of data [7], so by establishing a linear regression equation, the approximate expression can be expressed as.

$$Y = \sum\nolimits_{i=1}^{P} \beta_i X_i + \beta_0 \tag{2}$$

(p is the total number of sample points, βi is the coefficient to be found, and β0 is the deviation). The ordinary formula for least squares to minimize bias is.

$$\beta^\wedge = min\sum_{i=1}^{p}(Y_i - \beta_0 - \sum_{i=1}^{p}\beta_i X_i)^2 \tag{3}$$

To eliminate the collinearity between the data, a penalty term $\lambda\sum_{i=1}^{p}\beta_j^{\,2}$ is added to obtain the ridge regression formula as follows.

$$\beta^\wedge = [min\sum_{i=1}^{p}\left(Y_i - \beta_0 - \sum_{i=1}^{p}\beta_i X_i\right)^2 + \lambda\sum\nolimits_{i=1}^{p}\beta_j^{\,2}] \tag{4}$$

The function is convex in nature, where when $\frac{\partial\beta^\wedge}{\partial\beta} = 0$, the function obtains a minimum value.

$$\beta_{min} = (X^T X + \lambda I)^{-1} X^T Y \tag{5}$$

The total sales volume and profit data of vegetable categories are substituted into the linear regression model established above, and the functional expressions between sales volume and profit in each category are obtained.

The cost price fluctuates every day and is subject to uncontrollable factors such as time and weather. To build a better model, we temporarily exclude external factors and focus only on solving the cost markup rate. This is accomplished through using the linear regression model based on the known sales volume and profit substitution, while satisfying the profit maximization. To improve the accuracy of the replenishment amounts of various items, the replenishment volume is roughly transformed into a typical backpack problem under dynamic programming by using the Holt-winter smoothing index method [12].

The dynamic programming model is modeled as follows.

$$max\ z = \sum_{i=1}^{n}\sum_{j=1}^{m}(x_{i,j} \times v_{i.j}) \tag{6}$$

$$s.t. \sum_{j=1}^{m}(x_{i,j} \times w_{i.j}) \leq b_i, j = 1,2, \dots, m \tag{7}$$

$$27 \leq \sum_{i=1}^{n}\sum_{j=1}^{m} x_{i,j} \leq 33 \tag{8}$$

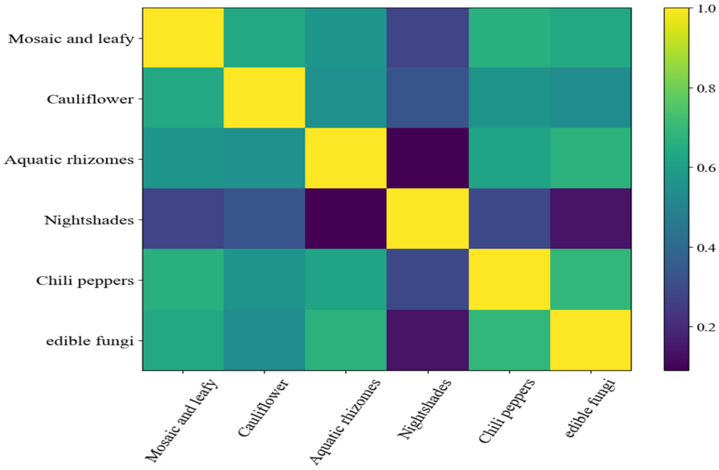


Fig.3. Heat map of Pearson correlation coefficient

3.3 Solving of the Model

The Pearson correlation coefficient is obtained by substituting the distribution relationship of each vegetable category, and single product sales volume over time into the established Pearson coefficient correlation model. Then the resulting Pearson correlation coefficient is plotted into a heat map, as depicted in **Figure 3.**

Pearson correlation analysis revealed that mosaic and leaf, cauliflower, aquatic rhizomes, chili peppers and edible fungi belong to a large category with moderate or higher degrees of correlation and similarity. The correlation between mosaic and cauliflower was the strongest, while the correlation between nightshades and edible fungi was the weakest.

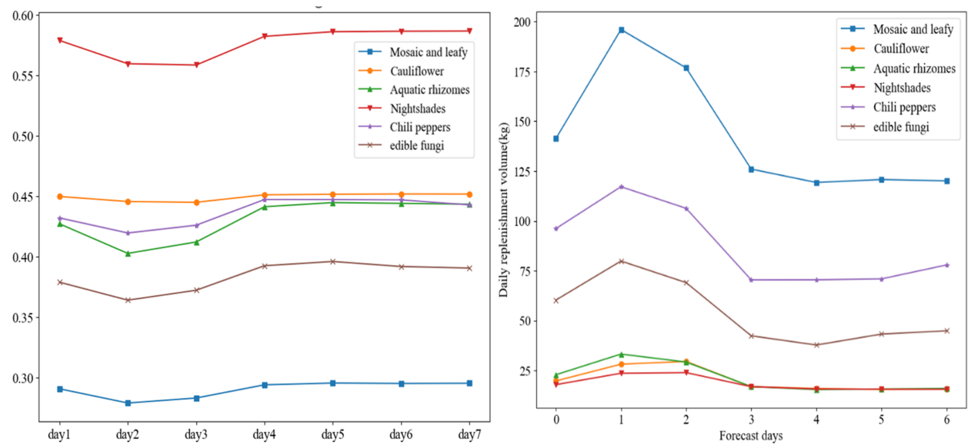
By converting cost-plus pricing into profit and substituting it into a linear regression model, the linear expressions between categories are shown in **Table 1.**

Table 1. Linear expressions and correlation coefficients between categories

Category Name	Linear expressions	Correlation Coefficient
Mosaic and leafy	Y=1.8928X+49.5433	0.628

Cauliflower	Y=3.0969X+1.3442	0.716
Aquatic rhizomes	Y=2.6088X+1.7604	0.727
Nightshades	Y=3.1241X-0.6745	0.562
Chili peppers	Y=3.7665X-59.9091	0.592
edible fungi	Y=2.5917X+26.0251	0.731

The cost markup rate of the corresponding product is obtained through the linear regression model described above and the pricing strategy of the corresponding product is obtained through calculation., the seven-day prediction data for each category can be seen in **Figure 4.**



(a) (b)

Fig.4. Rate by category and seven-day forecast daily replenishment

By observing the above bar charts, it is found that the overall trend of normal distribution in the predicted seven-day daily replenishment volume is high, first high and then low. Among them, the most predicted mosaic species were obtained, and the least were nightshades and aquatic rhizomes.

4 Analysis and Testing of the Model

In the stationarity test of time series [13], the ADF test is more accurate and important. The ADF test is done using the following model.

$$\Delta x_t = \delta x_{t-1} + \sum_{i=1}^{m} \beta_i \Delta x_{t-i} + \varepsilon_t \tag{9}$$

The results of the stationarity test are represented in **Table 2.**

Table 2. Stationarity test results

Category	ADF Statistic	p-Value	Lag 0rder	Number of Observations
Mosaic and leafy	-3.096	0.027	20	1073

Cauliflower	-3.082	0.028	20	1073
Aquatic rhizomes	-3.727	0.004	13	1080
Nightshades	-3.939	0.002	21	1072
Chili peppers	-3.118	0.025	20	1073
edible fungi	-2.834	0.054	20	1073

Through the analysis of the above test results, the p-value in the stationarity test of each category is significantly less than 0.05, indicating that the relevant model used is feasible and can help predict the corresponding results.It can be seen that the linear regression model and the dynamic target model adopted above possess a favorable overall prediction effect, which can be applied to automatic replenishment and pricing.

5.Conclusions of the study

By using the missing value test method to preprocess the data in the *Vegetable Industry Data In-depth Research and Analysis and Development Strategy Planning Report*, we studied the pricing and automatic replenishment of vegetable commodities. Furthermore, we established a linear regression model to obtain the pricing strategy of vegetable products based on the cost-plus rate. Finally, we pushed forward the stationarity test of the model, which contributed to the following conclusions.

1). The cost-plus ratio can be used as a paramount reference quantity for pricing. During the week, the cost-plus rate of each category fluctuates less, and the cost-plus rate of mosaic products is invariably lower than that of other categories, so the pricing of mosaic products should be lower in the pricing process.

2). It is found that this paper can use the corresponding model to predict the replenishment of vegetable products to gram units and finds that the replenishment of eggplant is invariably lower than that of other categories during the week, and should be reduced as much as possible in the replenishment process.

3). The backpack problem under dynamic programming can solve the replenishment of vegetable commodities extremely well.

Similarly, such models can also be applied to related fields, like the replenishment and pricing of bread in the market. But one inadequacy is that this paper excludes the environmental factors in the process of pricing and replenishment, there will be a certain deviation from the actual operating scenario.

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