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Construction and analysis of optimal decision-making model for vegetable sales based on entropy weight-TOPSIS algorithm and gray prediction

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Abstract: *Vegetable commodities have a short freshness period and need to be replenished every day, to develop the optimal pricing and replenishment strategy, this paper develops the optimal pricing and replenishment strategy by comprehensively applying the entropy-weight-TOPSIS algorithm, gray prediction, and nonlinear programming. Through the entropy weight-TOPSIS algorithm, the single product was evaluated by multiple indicators, and the top 27 vegetable products were selected for subsequent research. The average selling price, cost, and total sales volume of each type of vegetables were obtained through gray prediction. The penalty function model of sales volume and average selling price was established based on regression analysis, and the fitting effect was good. Finally, the optimal decision-making model was established through nonlinear programming, with maximizing profit as the objective function, and combined with the fluctuation constraints of the selling price, the optimal solutions of the maximum profit value of 520.897 and the selling unit price were successfully solved. Meanwhile, the replenishment decision under the optimal selling unit price is proposed by combining the penalty function model and the attrition rate.*

Keywords: *Nonlinear Programming, Gray Prediction, Entropy Weight-TOPSIS*

1. Introduction

With the development of the fresh food market entering the stage of rigid demand, fresh food superstores have become the main way of fresh food sales in China [1]. However, we need to maintain a rational orientation in establishing the optimal store revenue model. The traditional static pricing strategy is not applicable to fresh food retailers because consumers are affected by time and context when purchasing fresh products [2]. In addition, vegetables have a short shelf life and need to be replenished on a daily basis, and superstores usually conduct the purchase transactions in the early morning hours. However, without knowing exactly the specific individual items and the inbound prices, supermarkets need to make replenishment decisions for each vegetable category on the same day. In order to rationalize the pricing, supermarkets usually adopt the "cost plus pricing" method [3]. Supermarkets usually adopt discounts to sell goods that are damaged or in poor condition. In order to reduce wastage and maximize profits, fresh food retailers need to adopt flexible pricing and marketing strategies and replenishment decisions in order to meet the inherent requirements of the fresh food industry [4].

Based on this background, this paper will focus on how to develop optimal pricing and replenishment strategies. Zeng Minmin (2021) studied the dynamic pricing strategy based on the time context of A fresh community supermarket, the study based on the time context factors, the use of dynamic pricing theoretical tools, through the A fresh community supermarket field visits, questionnaires, statistical analysis of data and other methods, the study put forward the dynamic pricing strategy of the community supermarket, in order to improve the sales of the A fresh community supermarket, as well as the profitability of the supermarket [5]. Chen Jun, Kang Sha (2021) studied the joint decision making of pricing and inventory replenishment of agricultural products for dual-channel sales, which takes the maximization of cycle profit as the goal, adopts the theory of deteriorating inventory, constructs the joint decision making model of retailer's dual-channel pricing and inventory replenishment whose demand depends on the price and the inventory level, and analyzes the nature of the existential nature of optimal solution [6]. Mao Lisha (2022) studied the pricing strategy and production and marketing model of vegetable wholesale market under the perspective of supply chain, which used ARIMA model to make intelligent prediction on the price trend of vegetables, and integrated pull supply chain ideas to analyze how vegetables are scientifically priced in terms of macro-strategy with consumer demand as the core [7].

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In this paper, the solution is based on the entropy weight-TOPSIS algorithm and gray prediction model, firstly, the vegetable items with daily average sales volume less than the minimum display volume in the available varieties from June 24-30, 2023 are excluded, and then, the entropy weight-TOPSIS method based on the entropy weight method is established to screen the vegetable items with high profitability, and then, the K-Means clustering model is established to divide the screened items into three categories, and the regression analysis is established based on the negative direction relationship between sales volume and cost-plus pricing, and the penalty function corresponding to each cluster is developed. Then, the K-Means clustering model of each item is established to divide the screened items into three categories, and regression analysis is established based on the negative direction relationship between sales volume and cost-plus pricing, and the corresponding penalty function of each cluster is formulated. Then, the predicted value of selling price and the predicted value of cost on July 1 are obtained based on the grey correlation prediction, and finally, the optimal decision-making model of nonlinear programming is established to solve for the maximal benefit of the superstore and the corresponding replenishment plan and cost-plus pricing on July 1, and then the optimal decision-making model of non-linear programming is established.The data for this article was obtained from the following web site:http://www.mcm.edu.cn

2. Modeling and Solving

2.1 The establishment of the screening model based on last week's data vegetable single sellable varieties

This question needs to give the replenishment quantity and pricing strategy of individual items on July 1 based on the sellable varieties on June 24-30, 2023, as shown in Table .1.

Table 1: Selected individual products screened

serial number	Vegetable singles
1	Shanghai Youth
2	Yunnan oilseed rape (portion)
3	Yunnan lettuce
4	Yunnan lettuce (portion)
5	Lotus root(1)
...	...

2.2 Establishment of evaluation model based on TOPSIS vegetable single product

On the basis of Table.1, this paper selects the entropy weight-TOPSIS algorithm for comprehensive evaluation of vegetable single products and selects the following indicators:

(1) Average selling price

The average selling price represents the profitability of a single vegetable item; the higher the average selling price, the higher the profit earned for a given cost and volume.

(2) Total sales

Sales volume can most intuitively reflect the market demand for individual vegetable products, which is a key factor affecting the automatic pricing and replenishment decisions for vegetable products. At the same time, since the market can produce oversupply and stagnation, replenishment decisions for vegetable products need to be adjusted at any time according to sales volume.

(3) Number of transactions

The number of transactions represents the degree of customer demand for a vegetable item. The higher the number of transactions, the more popular the vegetable item is in the market, and the more likely it is that more profit will be made from the sale of that type of vegetable item.

(4) Attrition rate:

Fresh vegetables supply chain is difficult to control the quality, the logistics link cold chain transportation is not perfect, the supply and marketing process will produce loss [8], the excessive amount of loss will increase the procurement cost, and at the same time affects the relationship between the replenishment volume of the superstore and the sales volume.

(5) Average wholesale price:

The average wholesale price reflects the wholesale cost of individual vegetable items; the lower the average wholesale price, the lower the cost, the lower the probability of a loss, so the average can be used as a factor in risk judgments.

2.2.1 Entropy weighting method to calculate weights

In this paper, average selling price, total sales volume, and number of transactions are selected as positive indicators, and attrition rate and average wholesale price are used as negative indicators, and entropy weighting method is used to solve their weighting ratios, and the theory is as follows:

Determine the weight of the ith sample value under the jth indicator, which is defined as$p_{ij} = y_{ij}\left(\sum y_{ij}\right)^{-1}$, calculate all the information entropy in turn

$$e_j = -\frac{\sum p_{ij}\, ln(p_{ij})}{ln(12)} \tag{1}$$

information utility value

$$u_j = 1 - e_j \tag{2}$$

Calculation of weighting factors

$$w_j = \frac{u_j}{\sum u_j} \tag{3}$$

For the five types of indicators selected in this paper, the weights of the information entropy values calculated by SPSS are shown in the table.2.

Table 2: Weights of information entropy values

entropy weighting (physics)			
term (in a mathematical formula)	The information entropy value e	Information utility value d	Weight (%)
Number of transactions	0.946	0.054	19.237
Average selling price	0.895	0.105	37.529
Sales volume (kg)	0.92	0.08	28.624
Loss rate (%)	0.98	0.02	7.154
Average wholesale	0.979	0.021	7.455

The TOPSIS solution process is shown in the table.3.

Table 3: TOPSIS solution flow

TOPSIS algorithm solution flow
Step1 Prepare the data and perform homotrending with the quantile problem. **Step2** Use entropy weighting method to determine the weight of each indicator **Step3** Find the optimal and worst matrix vectors and determine the optimal and worst solutions **Step4** Calculate the distance D+ or D- between each evaluation object and the positive ideal solution, and determine its proximity to the optimal solution and the worst solution. **Step5** Calculate the closeness of each evaluation object to the optimal solution, and combine the distance value to calculate the composite degree score C value, and rank the conclusion. **Output:**TOPSITS evaluation results by supplier

Through the TOPSIS algorithm, this paper gives the top 27 vegetable singles in the score ranking, due to space limitation, this paper only shows the top 10 vegetable singles in the comprehensive score, as shown in Table 4.

ISSN 2616-5775 Vol. 7, Issue 7: 65-72, DOI: 10.25236/AJCIS.2024.070709

Table 4: Vegetable items with top 27 scores (selected)

Vegetable singles	Composite score index	arrange in order
Yunnan lettuce (portion)	0.562375913	1
Xixia Mushroom(1)	0.558036246	2
broccoli	0.523410399	3
Wuhu Green Pepper(1)	0.49664035	4
Peppers (portions)	0.482947697	5
Yunnan oilseed rape (portion)	0.458344337	6
Honghu Lotus Roots	0.44718904	7
Brussels sprouts (Brassica oleracea var. botrytis)	0.431482281	8
Lotus root(1)	0.424719309	9
king cobra or chili (Naga jolokia)	0.408560832	10

2.3 Segmentation of Vegetable Singles Based on K-Means Model Clustering Results

Based on the clustering method given by the K-Means model for vegetable singles with the same sales pattern, this paper divides the screened 27 categories into 3 major categories, as shown in Table 5.

Table 5: Clustering of Vegetable Individual Products

clustering category	Specific dishes (some)	frequency	Percentage %
Clustering category-1	['Yunnan Lettuce (portion)', 'Millet Pepper (portion)', 'Yunnan Oleander (portion)', 'Bamboo Leaf Lettuce', 'Purple Eggplant (2)', 'Screw Pepper',......]	14	51.852
Clustering category-2	['Xixia Flower Mushroom(1)', 'Wild Powdered Lotus Root', 'Honghu Lotus Root Scallop', 'Red Pepper(2)', 'Agaricus bisporus mushroom(box)', 'Colorful Pepper(2)', 'Mullein Vegetable',......]	9	33.333
Clustering category-3	['Wuhu green pepper(1)', 'broccoli', 'enoki mushrooms(box)', 'net root(1)']	4	14.815
add up the total	-	27	100.0

Because of the similarity of the sales pattern of the same cluster, so here all the single product is divided into three categories to consider the whole, to make the average sales price of each cluster category and the total daily sales, through such data dimensionality reduction process, this paper will have similarity of the single product as a sales category, thus simplifying the subsequent planning equation.

2.4 Prediction of clustered individual items based on GM gray prediction

2.4.1 Pre-tests for gray sequence models

Before modeling, it is necessary to perform a rank-ratio test that

Let the initial non-negative data sequence be:

$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\right\} \tag{4}$$

The modeling can only be done if all$\sigma(k)$ all fall into the calculation range can be modeled. The formula for calculating and judging the grade ratio is:

$$\sigma(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)} \tag{5}$$

Taking cluster 1 cost of goods sold as an example, the test results are shown in the table.6:

From the analysis of Table 6, it can be obtained that all the rank ratio values of the original series are located in the interval (0.779, 1.284), indicating that the original series is suitable for constructing the gray prediction model. All other data in this paper satisfy the validation conditions.

ISSN 2616-5775 Vol. 7, Issue 7: 65-72, DOI: 10.25236/AJCIS.2024.070709

Table 6: Class ratio test results table

index entry	original value	sex ratio
2023-06-24	3.374	-
2023-06-25	3.425	0.985
2023-06-26	3.179	1.078
2023-06-27	3.504	0.907
2023-06-28	3.616	0.969
2023-06-29	3.663	0.987
2023-06-30	3.584	1.022

2.4.2 Sample Prediction Based on Gray Sequential Models

Due to the small amount of sample data, this paper uses gray prediction to predict the solution for each cluster. This paper predicts the average selling price, cost and total sales volume of the clusters for subsequent planning and solving. Here to figure 1 as an example to show. The gray predictive clustering 1 cost is shown in Figure 1 and the gray predictive clustering 1 selling price is shown in Figure 2.

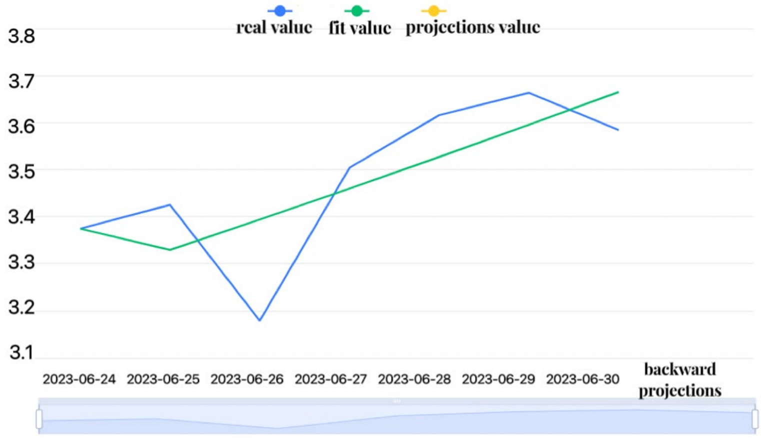

Figure 1: Gray prediction clustering 1 cost

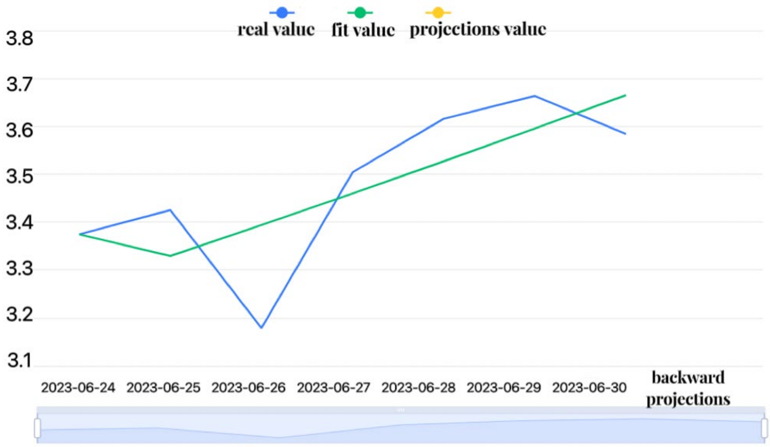

Figure 2: Gray prediction clustering 1 Selling price

The models were well fitted with mean errors of 2.488% and 1.787%, respectively.

The final prediction table for clusters 1, 2 and 3 is obtained as Table 7:

Table 7: Cluster prediction table

taxonomic category	Projected selling price	Cost projections
Cluster 1	5.359	3.736
Cluster 2	10.803	8.530
Cluster 3	6.480	4.969

ISSN 2616-5775 Vol. 7, Issue 7: 65-72, DOI: 10.25236/AJCIS.2024.070709

In this paper, the grey prediction is used to solve the predicted selling price and the predicted cost on July 1, so as to set the constraints in the subsequent optimization decision-making to achieve the optimal decision-making.

2.5 Modeling and solving based on regression analysis and nonlinear programming

2.5.1 Modeling of sales volume and average selling price penalty function based on regression analysis

According to the review of literature, the number of sales of a single product and the selling price has a certain negative correlation, this paper makes a regression analysis of the clustered categories of the above problem, and the correlation equations of the sales volume and the average selling price will be obtained as a penalty function, which is introduced into the subsequent planning model, and the fitting toolbox of MATLAB is used to fit it. Fig. 3 Fig. 4 Fig. 5 shows the fit to the clustering categories 1, 2 and 3 respectively.

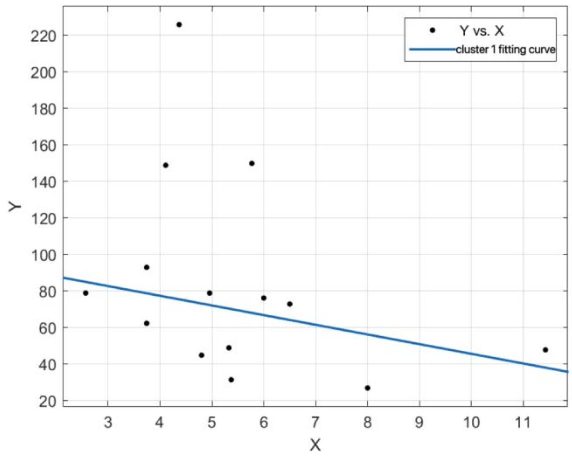

Figure 3: Fitted plot for clustering category 1

The clustered 1-fit equation is:

$$y = -5.298x + 98.7 \tag{6}$$

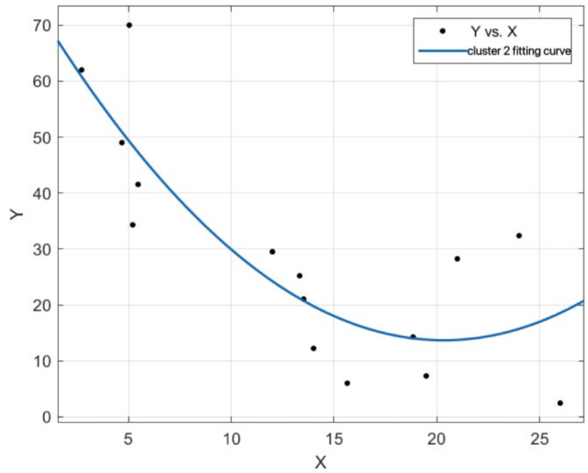

Figure 4: Fitted plot for clustering category 2

The clustered 2-fit equation is:

$$y = 0.1518x^2 - 6.174x + 76.45 \tag{7}$$

ISSN 2616-5775 Vol. 7, Issue 7: 65-72, DOI: 10.25236/AJCIS.2024.070709

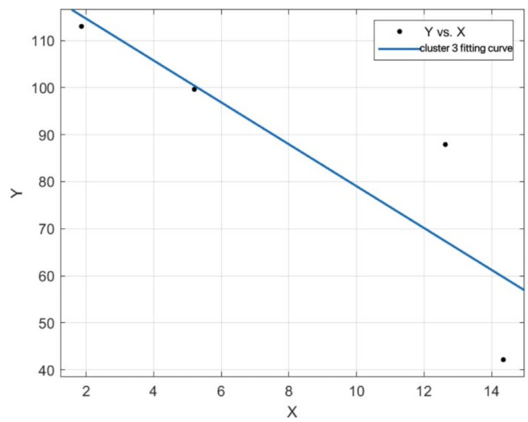

Figure 5: Fitted plot for clustering category 3

The clustered 3-fit equations are:

$$y = -4.45x + 123.5 \tag{8}$$

The R-square of the above curve fit is above 0.7, and the scatter plot shows that the fit is good, so the penalty function can be utilized for the next analysis and solution.

2.5.2 Optimal decision model solution based on nonlinear programming

In this paper, a nonlinear planning model is developed to solve for the maximum profit based on the predicted values of cost and unit sales price, as well as the sales volume and average selling price penalty functions that have already been solved above.

Let w be the profit, x be the unit sales price, y be the sales volume, and z be the cost, and establish the following objective function:

$$max(w) = \sum y_i x_i - z_i \tag{9}$$

In order to be realistic, this paper fluctuates the sales unit price within 20% of the predicted result, and the total sales volume of the three types of vegetables is set to be less than the predicted total sales volume, so as to prevent the emergence of extreme situations.

The following constraints are established in this paper:

$$\begin{cases} y1 + y2 + y3 < S \\ 0.8\gamma_i \leq x_i \leq 1.2\gamma_i \end{cases} \tag{10}$$

where γ is the predicted value of sales unit price solved by gray prediction, and S is the total sales volume after gray prediction.

After solving the problem it can be concluded that the optimal solution for the unit price of sales at the time of profit maximization as Table 8:

Table 8: Optimal solution for unit sales price

parameters	solution value
z (target value)	520.897
X1	6.431
X2	12.964
X3	7.776

After solving the optimal solution for the unit price of sales, the total amount of replenishment for each category can be derived from the penalty function model established above and the wastage rate as Table 9:

Table 9: Total replenishment by category

form	replenishment
Cluster 1	93.8134810710988
Cluster 2	24.62949
Cluster 3	71.8992767604137

In this paper, the problem is modeled as a linear programming problem by adding a penalty function, in which the variables include the replenishment quantity and selling price of each sellable item, and ultimately the individualized optimal pricing of different vegetable items is achieved by solving the selling unit price and replenishment quantity at the time of the maximum total revenue of the planned superstore [9].

3. Conclusion

According to the methods and results of the study, this paper formulates the optimal pricing and replenishment strategy by comprehensively using the entropy weight-TOPSIS algorithm, gray prediction and nonlinear planning in the case of vegetable commodities with short freshness period and the need for daily replenishment. In this paper, five indicators, namely, average selling price, total sales volume, number of transactions, wastage rate, and average wholesale price, were selected, and the multi-indicator comprehensive evaluation of single products was carried out through the entropy-weight-TOPSIS algorithm, which successfully screened out the top 27 vegetable single products for further research. Using the gray prediction method, the average selling price, cost, total sales volume and other data were solved, and the penalty function model of sales volume and average selling price was established based on the regression analysis, and R^2 was basically greater than 0.7, with good fitting effect.

Finally, the optimal decision-making model is established through nonlinear programming, with maximizing profit as the objective function and considering the fluctuation of selling price, combining with the established penalty function model and fluctuating the selling price in the range of 20% as the constraints, the maximum profit value of 520.897 and the optimal solution of the selling unit price are successfully solved. The replenishment decision in the case of optimal selling unit price is also proposed by combining the penalty function model and the wastage rate. These results show that the proposed method can effectively help vegetable merchandisers to make rational pricing and replenishment decisions in actual operations, thus improving profits and optimizing operational efficiency. Subsequent studies can extend the model of this paper, and more constraints can be added to the model established in this paper, such as capital limitation or inventory capacity limitation, in order to study situations closer to reality [10].

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