WEP Warwick Evans Publishing

International Journal of Global Economics and Management

ISSN: 3005-9690 (Print), ISSN: 3005-8090 (Online) | Volume 2, Number 3, Year 2024
DOI: https://doi.org/10.62051/IJGEM.v2n3.01
Journal homepage: https://wepub.org/index.php/IJGEM/index

Automated pricing and replenishment strategies for vegetable products based on SVR and simulated annealing

Wanting Wang, Yudie Luo, Xuming Yang

Jiangsu University, Jiangsu, China

ABSTRACT

In fresh supermarkets, the shelf life of general vegetable products is relatively short, and the quality deteriorates with the increase of sales time, and most varieties cannot be sold the next day if they are not sold on the same day. However, due to the fact that the vegetables sold by fresh supermarkets often have a wide variety and different origins, merchants need to make replenishment decisions for each vegetable category on the same day without accurately judging the specific single product and purchase price, and the reliability of market demand analysis is very important for supermarkets to make correct replenishment and pricing decisions. Based on the relevant data of sales details and wholesale prices of six vegetable commodities operated by a supermarket from 2020 to 2023, this paper uses Fourier series and Gaussian function to predict the sales volume of vegetable single products, clarifies the relationship between supermarket revenue and the pricing and replenishment quantity of vegetable products based on multiple linear regression theory, and establishes a pricing strategy model based on simulated annealing algorithm and SVR. On the premise of trying to meet the market's demand for various categories of vegetable products, the supermarket will make the maximum profit, so as to help the supermarket further formulate the pricing and replenishment plan of a single product.

KEYWORDS

Apriori algorithm; Entropy weight; Topsis method; Fresh supermarket; Pricing and replenishment

1. INTRODUCTION

In recent years, with the improvement of consumption level and the enhancement of health awareness, the important position of fresh products in the national economy has become increasingly prominent. According to Frost & Sullivan data, China's total retail sales of fresh food increased from 3.67 trillion yuan in 2017 to 6.1 trillion yuan in 2022, with an average annual compound growth rate of 10.7%, and is expected to grow to 6.62 trillion yuan in 2023. At the same time, fresh products have a short life cycle, are perishable and perishable, and are perishable, so it is important for merchants to develop a reasonable pricing and ordering strategy to increase profits [1].

In this paper, we review the relevant research on the pricing and replenishment strategies of fresh products at home and abroad, in which Chen Jun et al [2]. Constructed a joint decision-making model of dual-channel pricing and inventory replenishment for retailers whose demand depends on price and inventory levels, and found that lower freshness and spoilage costs, higher sales prices, and larger online market share are the basic conditions for retailers to obtain higher profits. Cui Ligang et al [3]. Introduced the investment parameters of preservation technology, constructed a joint replenishment and pricing model of fresh products based on preservation technology investment, and found that reasonable investment in preservation technology is conducive to reducing product deterioration losses and enabling enterprises to obtain higher profits. Most of the existing studies focus on the improvement of exogenous factors to improve the profits of supermarkets, but there is a lack of research on how to choose among many vegetable products and suppliers. The main innovations and contributions of this paper are as follows: 1) The Fourier series and Gaussian function are used to predict the sales volume of vegetable single products, which is more accurate than the general linear regression method. 2) Establish a support vector machine regression model, and propose a method to determine the optimal cost-pricing ratio by maximizing the width of the interval band and minimizing the total loss optimization model. 3) When fitting the relationship between sales volume and cost-pricing ratio, the simulated annealing algorithm is used, and a certain deterioration solution is allowed to be accepted according to the Metropolis criterion to avoid falling into the local optimal solution.

2. PROBLEM ANALYSIS

Based on the multiple linear regression theory, this paper comprehensively considers the profit margin and loss rate to establish a pricing strategy model. From the perspective of market demand, there is a certain correlation between the sales volume of vegetable products and time, so this paper uses Fourier series and Gaussian function to predict the sales volume of vegetable products. From the perspective of merchant supply, there are more vegetable varieties from April to October, so this paper selects the relevant data of a supermarket from July 1, 2020 to June 30, 2023 for analysis, and gives the single product replenishment volume and pricing strategy in early July according to the saleable varieties at the end of June; In this article, the total number of saleable items is controlled at 27-33, and the order quantity of each item meets the minimum display quantity of 2.5 kg.

3. MODEL BUILDING AND SOLVING

2.1. Saleable single product screening model - entropy weight Topsis method

Compared with the analytic hierarchy process and the rank-and-sum ratio comprehensive evaluation method, the entropy-weighted Topsis method avoids the influence of subjective factors on the results, and the results are more objective and accurate. In this paper, the entropy weight Topsis method was used to screen 251 known vegetable items, and the optimal 27-33 vegetable items were obtained as saleable commodities by considering the factors such as sales volume and profit margin.

2.1.1. Model building

(1)Determination of evaluation indicators

The revenue of supermarkets is closely related to sales volume and profit margin, so this paper selects sales volume, profit margin and loss rate as the basic weight indicators. For the sales volume, considering that the sales volume presents a cyclical distribution, it is not rigorous to use only the three-year average sales volume, and the search calendar finds that July 1, 2022 is a Saturday, so the three indicators of the daily average sales volume on July 1 of each year, the daily average sales volume of each Saturday, and the daily average of the total sales volume for three years are further selected to measure the sales volume.

(2)Positive indicators

In order to unify the types of indicators, the loss rate of the above five indicators is a very small index, and it is necessary to carry out positive processing, that is, to convert this index into a very large index.

$$y_i = \max - x \tag{1}$$

(3)Normalization of forward matrices

Since the data given in the question are of different magnitudes and vary greatly, the data matrix obtained after positive processing of the data is standardized to eliminate the influence of different index dimensions.

Write the forward matrix as X

$$X=\begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{pmatrix} \tag{2}$$

The normalized matrix is noted G, and each element in G is processed by the forward matrix element G_{ij}.

$$G_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{3}$$

Finally, a standardized matrix composed of n evaluation objects and m evaluation indicators is formed.

$$G=\begin{pmatrix} g_{11} & g_{12} & \cdots & g_{1m} \\ g_{21} & g_{22} & \cdots & g_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ g_{n1} & g_{n2} & \cdots & g_{nm} \end{pmatrix} \tag{4}$$

Define the maximum value for each metric

$$\begin{aligned} Z^+ &= (Z_1^+, Z_2^+, \cdots, Z_m^+) \\ &= (\max\{z_{11}, z_{21}, \cdots, z_{n1}\}, \max\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots, \max\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) \end{aligned} \tag{5}$$

Define the minimum value for each metric

$$\begin{aligned} Z^- &= (Z_1^-, Z_2^-, \cdots, Z_m^-) \\ &= (\min\{z_{11}, z_{21}, \cdots, z_{n1}\}, \min\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots, \min\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) \end{aligned} \tag{6}$$

(4)Get information entropy

The entropy of the j-th first indicator e_j

$$e_j=-k\sum_{i=1}^{n} p_{ij}\times\ln(p_{ij}),(j=1,2,3,\cdots,m) \tag{7}$$

Usually taken $k=\frac{1}{\ln(n)},(0\leqslant e_j\leqslant 1)$

(5)Calculate the weights of evaluation indicators

The j-th index of the i-th evaluation object was vector normalized

$$u_{ij}=\frac{z_{ij}-z_{j,\min}}{z_{j,\max}-z_{j,\min}} \tag{8}$$

Get the normalization matrix

$$U=\begin{pmatrix} u_{11} & u_{12} & \cdots & u_{1m} \\ u_{21} & u_{22} & \cdots & u_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ u_{n1} & u_{n2} & \cdots & u_{nm} \end{pmatrix} \tag{9}$$

The weight of the j-th sample value in the i-th indicator p_{ij}

$$p_{ij}=\frac{u_{ij}}{\sum_{i=1}^{n}u_{ij}},(i=1,2,3,\cdots,m) \tag{10}$$

Weights are given to item j

$$w_j=\frac{d_j}{\sum_{j=1}^{m}d_j},(j=1,2,3,\cdots,m) \tag{11}$$

2.1.2. Model solving

Total sales, Saturday sales, 7.1 day sales, attrition rate, return rate, and profit margin are ω_1 ω_2 ω_3 ω_4 ω_5 ω_6 recorded as follows.

Table 1. Forward matrix

numbering	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6
5762	7.8593	10.5111	6.2170	10.7300	0.7435	0.7144
5779	19.3272	33.8159	32.9827	14.0000	0.7267	2.2658
5786	10.5594	21.2978	16.4873	15.6300	0.7044	0.8997
5793	3.4704	0.0000	4.1547	21.6600	0.7603	0.6160
5823	8.1804	10.4574	8.0960	14.8200	0.7658	2.2647
5908	6.2578	9.0657	11.6600	15.5500	0.7714	1.1034
5946	3.6930	4.5773	3.0540	21.6400	0.7658	0.9671
5960	39.4322	0.0000	12.3240	6.9800	0.7603	0.8468
…	…	…	…	…	…	…

Table 2. Standardization matrix

numbering	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6
5762	0.0543	0.0940	0.0644	0.0341	0.0635	0.0117
5779	0.1335	0.3024	0.3415	0.0445	0.0621	0.0371
5786	0.0730	0.1905	0.1707	0.0497	0.0602	0.0147
5793	0.0240	0.0000	0.0430	0.0689	0.0649	0.0101
5823	0.0565	0.0935	0.0838	0.0471	0.0654	0.0371
5908	0.0432	0.0811	0.1207	0.0494	0.0659	0.0181
5946	0.0255	0.0409	0.0316	0.0688	0.0654	0.0158
5960	0.2724	0.0000	0.1276	0.0222	0.0649	0.0139
…	…	…	…	…	…	…

The metric weights are shown below.

Table 3. Indicator weights

Total sales	Saturday sales	7.1th sales	Attrition rate	Return rate	Profit margin
0.1047	0.3734	0.3486	0.0081	0.0020	0.1632

The final score rankings are shown below.

Table 4. Entropy-weighted Topsis method score ranking

numbering	score	ranking
102900005115779	100.00	1
102900005116714	91.56	2
106949711300259	90.76	3
102900005117056	90.54	4
102900011016701	82.96	5
102900011030059	74.11	6
102900005115984	57.16	7
102900005115786	55.64	8
102900011030097	53.86	9
102900011035962	46.96	10
…	…	…

After screening from the categories of saleable commodities from June 24th to June 30th, 31 vegetable items were finally determined.

Table 5. List of items available for sale

Commodity number	102900005115762	102900005115779	102900005115786	102900005115823
Name	Amaranth	Yunnan lettuce	bamboo leaf cabbage	Shanghai green
commodity number	102900005115908	102900005115960	102900005115984	102900005116257
Name	Choy sum	Chinese cabbage	Yunnan oily wheat cabbage	purple eggplant
commodity number	102900005116509	102900005116714	102900005116899	102900005117056
Name	Green Eggplant	Broccoli	Lotus Root	Pickled Pepper
commodity number	102900005118831	102900005119975	102900011000328	102900011008164
Name	baby cabbage	sweet potato tips	screw peppers	milk cabbage
commodity number	102900011008522	102900011009970	102900011016701	102900011022764
Name	Sweet cabbage	green stalks	Wuhu green pepper	Long tomato
commodity number	102900011030059	102900011030097	102900011030110	102900011031100
Name	Yunnan lettuce (portions)	Yunnan oil wheat cabbage (portions)	Spinach (portions)	Millet pepper (portions)
commodity number	102900011032251	102900011033906	102900011033975	102900011034026
Name	Screw pepper (part)	Baokang alpine Chinese	Green eggplant (2)	Zhijiang green stalk scattered
commodity number	102900011034330	106949711300259	106971533450003	
Name	Bisporus mushroom (box)	Enoki mushroom (box)	Seafood mushroom (pack)	

2.2. Cost pricing model - multi-objective linear programming

2.2.1. Model establishment

A. Determine decision variables

In this paper, a cost-plus pricing model based on the profit margin of vegetable commodities is constructed, so the decision variable is the profit margin, which is denoted as.

B. Determine the optimization goal

This paper analyzes the relationship between the total sales volume of each vegetable category and the cost-plus pricing and maximizes the revenue of the supermarket, so the optimization goal is the maximum revenue, which is recorded as $\max W$.

C. Determine the constraints

The total sales volume of the i-th first vegetable category is Z_i, the cost of the i-th first vegetable category is C_i, and the cost-plus pricing of the first vegetable category is P_i.

(1) Cost-plus pricing

$$P_i = C_i(1 + r_i) \tag{12}$$

(2) Total sales

$$Z_i = f(P_i) \quad (i = 1, 2, \cdots, 6) \tag{13}$$

(3) The total number of single items of vegetables that can be sold is a

(4) The replenishment amount of each vegetable item is m_i:

(5) Market demand for various vegetable commodities Q

(6) The total amount of orders for each category of vegetable products N_i

(7) The order quantity of each vegetable item $M_i = \frac{m_k}{(1-\beta)}$, β is the loss rate

(8) Revenue

$$W = \sum_{i=1}^{n} P_i \cdot Z_i \quad (i = 1, 2, \cdots, 6) \tag{14}$$

In summary, the cost-plus pricing model is:

$$\max W$$
$$s.t. \begin{cases} P_i = C_i \times (1 + r_i), \\ Z_i = f(P_i), \\ W = \sum_{i=1}^{a} P_i \cdot Z_i, \\ M_i = \frac{m_i}{(1-\beta)}, \\ 27 \leqslant a \leqslant 33, \\ M_i \geqslant 2.5, \\ N_i \geqslant Q_i, \end{cases} \tag{15}$$

2.3. Pricing strategy model - SVR model, simulated annealing algorithm

2.3.1. Model establishment

In the process of selling fresh vegetables, from the perspective of customers, there is a strong relationship between whether to buy vegetable products and the direct pricing of vegetable products. From a merchant's point of view, cost, pricing, and sales volume largely determine the final revenue. Therefore, this paper establishes a support vector regression machine model, and uses the simulated annealing algorithm to further explore the relationship between the cost-pricing ratio and the sales volume.

A. Support Vector Regression Machine Model (SVR) – Determine the optimal cost-pricing ratio

Support vector regression machines (SVRs) are used to solve linear and nonlinear regression problems. Based on the SVM linear binary classification, the insensitive loss function is introduced to solve the regression problem, which has a good effect in dealing with small-shot, nonlinear and high-dimensional problems[4]. Compared with the general linear regression method of finding the mean after gradient descent, the optimization method of maximizing the width of the spacer and minimizing the total loss of SVR has higher model adaptability. In addition, the SVR model has strong boundary characterization ability and prediction uncertainty measurement function, which can provide accuracy guarantee for the final determination of the cost-pricing ratio in this paper [5].

(1) The $\{(x_i,y_i),i=1,2,...,n\}$ set of data on the sales volume of a given vegetable single product and the cost-pricing ratio of a vegetable per product based on the simulated annealing algorithm, where x_i in the cost-pricing ratio of the i-th vegetable single product is used as the input of the training sample; y_i is the corresponding sales volume, which is used as the output value of the training sample; n is the sample size.

(2) Linear regression function:

$$g(x)=\omega^T\varphi(x)+b \tag{16}$$

In the formula, $\varphi(x)$ is a nonlinear mapping function, ω is a weight vector, and b is a bias.

The final objective function is as follows.

$$\begin{gathered}\min_{\omega,b,\epsilon}\frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{n}(\delta_i+\delta_i^*)\\ s.t.\begin{cases}y_i-\omega\cdot x_i-b\leqslant\delta_i\\ \omega\cdot x_i+b-y_i\leqslant\delta_i^*\\ \delta_i,\delta_i^*\geqslant 0\end{cases}\end{gathered} \tag{17}$$

B. Simulated annealing algorithm (SA) – fits the relationship between sales volume and cost-pricing ratio

The simulated annealing algorithm (SA) is an optimization algorithm derived from the principle of solid annealing, which starts from a high initial temperature, and as the temperature decreases, combined with the probability jump characteristics, the local optimal solution can be jumped out, and finally the global optimal solution can be reached [6]. In this paper, SA is used to fuse the influencing factors that affect the revenue of supermarkets, and pays attention to the correlation between different characteristics such as sales volume, cost per vegetable item, and loss rate in the whole input [7], and in the fitting process, the SA algorithm accepts a worse solution with a certain probability to avoid falling into the local optimal solution, and finally finds the global optimal solution [8].

(1) Probability of acceptance

Suppose that a state is x_n, after becoming x_{n+1}, the corresponding function value is changed from F_n to F_{n+1}, and the acceptance probability E in the process of the change is defined as:

$$E=\begin{cases}1 & ,F(n+1)\geqslant F(n)\\ e^{-\frac{F(n+1)-F(n)}{T}} & ,F(n+1)\geqslant F(n)\end{cases} \tag{18}$$

(2) Algorithm initialization

Set the total sales revenue of the objective function as $G(x_0)$, the sales volume of each vegetable item T_0, the cost of each vegetable item C_i, and the loss rate of each product L_i, and build the model as follows.

$$G(x_i) = \sum_{i=1}^{n} (S_i \cdot (1 - L_i) \cdot C_i) \tag{19}$$

(3) The amount of change in the objective function

Define the subtraction of the value of the function ΔF in the two states to obtain the amount of change in the objective function. If $\Delta F < 0$, the value of the function in the new state is the new current value; If $\Delta F > 0$, the new state is accepted according to the probability of acceptance.

(4) Obtain the optimal solution

According to the flowchart algorithm, the algorithm is repeatedly iterated until the termination condition is satisfied, the optimal solution is output and the program is terminated.

2.3.2. Model solving

Table 6. Pricing strategies

The title of the product	Amaranth	Yunnan lettuce	bamboo leaf cabbage	Shanghai green	Choy sum
Sales	4.3403	9.1974	7.5709	5.0561	3.9906
Pricing	8.0979	13.3533	6.3778	8.0170	10.4770
Replenishment amount	5.3268	10.8524	8.7647	5.9088	4.6241
The title of the product	Chinese cabbage	Yunnan oily wheat cabbage	purple eggplant	Green Eggplant	Broccoli
Sales	13.1566	8.9522	9.7894	3.0076	19.8547
Pricing	2.3841	6.2255	13.5206	11.3798	18.3101
Replenishment amount	16.9260	10.2675	10.4220	3.1663	21.8808
The title of the product	Lotus Root	Pickled Pepper	baby cabbage	sweet potato tips	screw peppers
Sales	11.8532	14.7800	9.8065	4.9807	5.9142
Pricing	6.5419	17.5393	4.6569	9.3657	8.4484
Replenishment amount	12.5484	15.9062	10.0559	5.4386	6.5845
The title of the product	Sweet cabbage	green stalks	Wuhu green pepper	Long tomato	Yunnan lettuce (portions)
Sales	8.9252	13.8153	17.6092	3.9412	10.0019
Pricing	10.7404	9.1321	5.7788	9.9402	5.9115
Replenishment amount	9.8545	16.6569	18.6736	4.2334	11.0433
The title of the product	Enoki mushroom (box)	Seafood mushroom (pack)	Millet pepper (portions)	Screw pepper (part)	Baokang alpine Chinese cabbage
Sales	14.8447	8.6969	10.3420	11.5412	15.9905
Pricing	4.1130	3.6069	5.7676	4.3321	1.4704
Replenishment amount	14.9118	8.6969	11.4188	12.7428	17.6554

4. CONCLUSION

This article gives the replenishment volume and pricing strategy of the single product on July 1. In this paper, the entropy weight Topsis model was established to rank the calculated scores of 251 kinds of vegetable items, and 31 kinds of single products, such as amaranth, Yunnan lettuce, bamboo leaf cabbage, Chinese cabbage, sweet potato tip, and broccoli, were selected as saleable items, and the cost pricing model, sales volume prediction model, and pricing strategy model were established in the same problem as 2, and the pricing strategy and replenishment amount were solved based on simulated annealing algorithm, SVR, linear programming, etc., and the pricing strategy and replenishment amount were amaranth/8.09 yuan/5.33kg, Yunnan lettuce/13.35 yuan/10.85kg, Bamboo leaf cabbage / 6.38 yuan / 8.76kg, Shanghai green / 8.02 yuan / 5.91kg, cabbage sum / 10.47 yuan / 4.62kg, bisporus mushroom / 6.78 yuan / 12.27kg, etc.

The parameters and results of the model in this paper can be directly explained, and the impact of replenishment plans and pricing strategies on the revenue of supermarkets can be clearly understood. This helps decision-makers understand the results of the model and make adjustments and optimizations as needed. The scalability of the model in this paper is good, and it can be adjusted and optimized according to the actual situation in the future application process, while considering more factors and constraints. The model can also be flexibly customized according to the actual needs of supermarkets to meet the needs of different scenarios.

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