A study on vegetable stocking-pricing decision-making in supermarkets based on regression analysis and planning models

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Abstract. Vegetable products in the superstore require high freshness and must meet market demand while maximizing profit. This study proposes a pricing strategy based on the proportion of sales for each product category. Using data from the previous four weeks, a relationship model is developed. Additionally, a BP neural network regression is used to analyze the relationship between vegetable sales and cost-plus pricing. A planning model is then established to determine the replenishment quantity and daily maximum profit, with the objective of maximizing profitability. Adjustments to the replenishment program and pricing strategy are made to accommodate changes in sales conditions. By extracting sellable goods data and using prediction results, the planning model is further refined by setting constraints such as ordering limits, historical pricing records, and quantity limits. This model enables the determination of replenishment quantities and pricing strategies for each individual product, ultimately maximizing profit for the superstore.

Keywords: BP Neural Network Regression, Replenishment Decision, Planning Model.

1. Introduction

Nowadays, the trend of consumers selecting and purchasing fresh food from fresh food supermarkets has gained significant popularity. Fresh food items have a limited shelf life, and their quality deteriorates as time passes. In most cases, if fresh food items are not sold on the same day, they cannot be sold the next day. Therefore, it becomes essential for fresh food supermarkets to develop effective replenishment and pricing strategies based on daily historical sales data.

The pricing of vegetables in supermarkets typically follows the widely used "cost-plus pricing" method. This method involves calculating the cost of the product and adding a markup to determine the selling price. Supermarkets also employ strategies such as offering discounts on vegetables that have declined in quality. These measures are implemented to maximize profits and minimize losses [1-2].

In this study, a novel approach is proposed to determine the optimal total amount of daily replenishment and pricing strategy in order to maximize the revenue of the superstore. The planning model developed in this research takes into consideration various factors, including historical sales data, cost-plus pricing, and the perishability of fresh food. By analyzing these factors, the model provides valuable insights into the appropriate replenishment quantities and pricing strategies under different conditions.

The innovation of this study lies in the comprehensive planning model that integrates multiple variables and considerations to optimize the replenishment and pricing decisions. By utilizing this model, fresh food supermarkets can make informed decisions that not only maximize revenue but also ensure the freshness and quality of the products offered to consumers. This research contributes to the improvement of operational efficiency and profitability in the fresh food supermarket industry [3].

2. Modelling and solving

2.1. Vegetable sales forecasting based on RBFNN

RBFNN is a three-layer feed-forward neural network that can globally approximate any nonlinear relationship with arbitrary accuracy. It has the advantages of fast learning convergence, no local minima problem, and strong generalisation ability, and is widely used in the fields of nonlinear function approximation, pattern recognition, system control, and prediction.The RBFNN structure consists of an input layer, a hidden layer, and an output layer[4].The RBFNN input layer transmits the signals, while the radial basis function maps the input layer to the hidden layer, and a simple linear weighting is used between the hidden layer and the output layer. The performance of the RBFNN is a function of its extended Spread; the larger the Spread, the smoother the function fit is, but the larger the approximation error, thus requiring more hidden layer neurons.The smaller the Spread, the more accurate the function approximation is, and the smoothing of the approximation process decreases, which reduces the performance of the network[5].

The RBFNN mapping relation from input to output can be determined.

$$\phi_k(\|x-c_k\|)=\exp\left(-\frac{\|x-c_k\|^2}{2\sigma_k^2}\right)$$
$$y=\sum_{i=1}^{m} w_i\phi_k(\|x-c_k\|)+b \tag{1}$$

where x and y are the input and output of the RBFNN, respectively, σ_k is the width of the kth neuron, c_k is the centre of the radial basis function unit, ϕ_k is the radial basis function of the kth hidden node, b is the bias term, w_i is the weight of the connection from the hidden to the output layer the connection weights, and m is the total number of hidden nodes[6-7]. The iterative process and evaluation results are shown in Fig. 1 and Table 1, respectively.

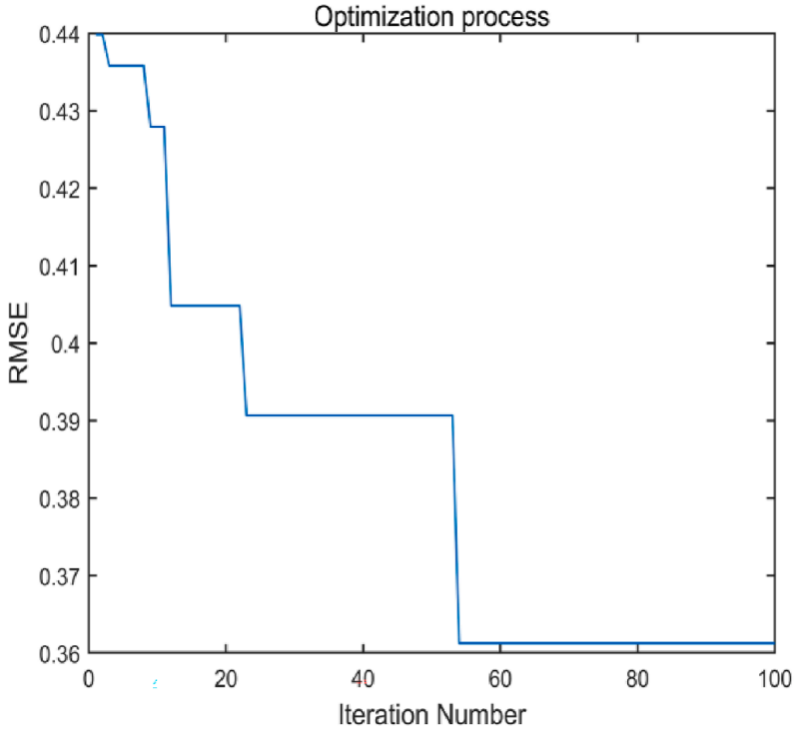


Figure 1. Iterative process

Table 1. Evaluation results

Assessment of indicators	value
MAE	0.242
RMSE	0.360
MAPE	0.087
TIC	0.051

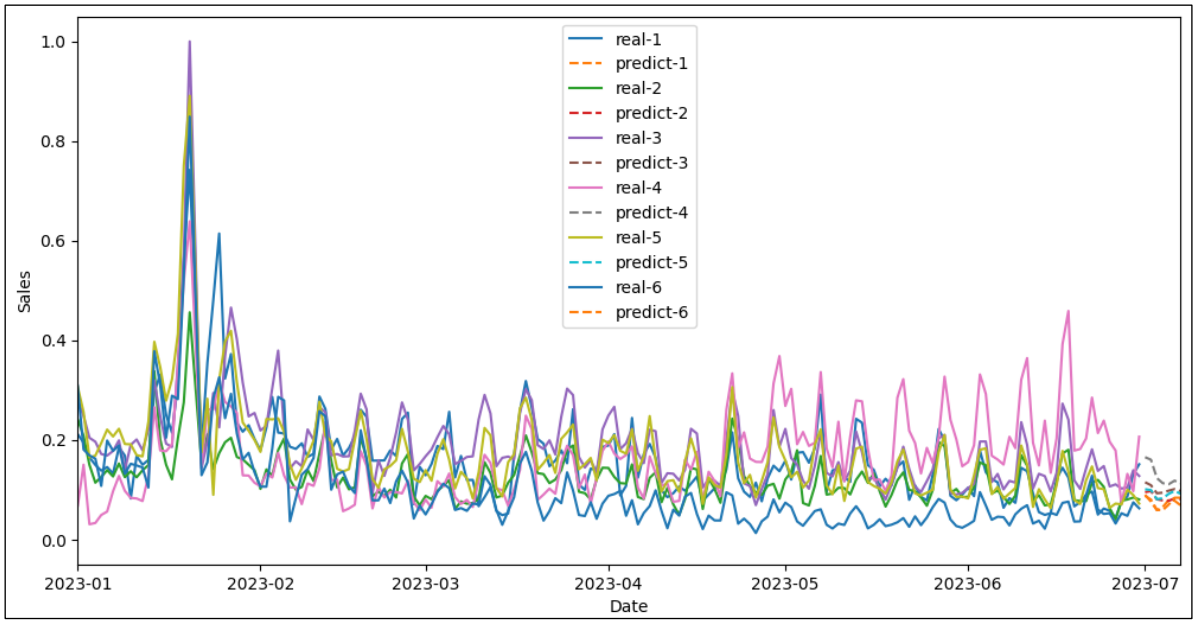


Figure 2. Time-series data on sales of vegetable categories

Figure 2 shows a schematic of the time series data for sales in the vegetable category.

2.2. Price setting for vegetable category based on cost-plus pricing strategy

In order to develop a more reasonable pricing strategy, this paper adopts a cost-plus pricing strategy, which takes into account the cost of each category, the average wastage rate and the predicted sales volume to develop an appropriate selling price[8]. The relationship between cost and sales volume for each category is shown in Figure 3.

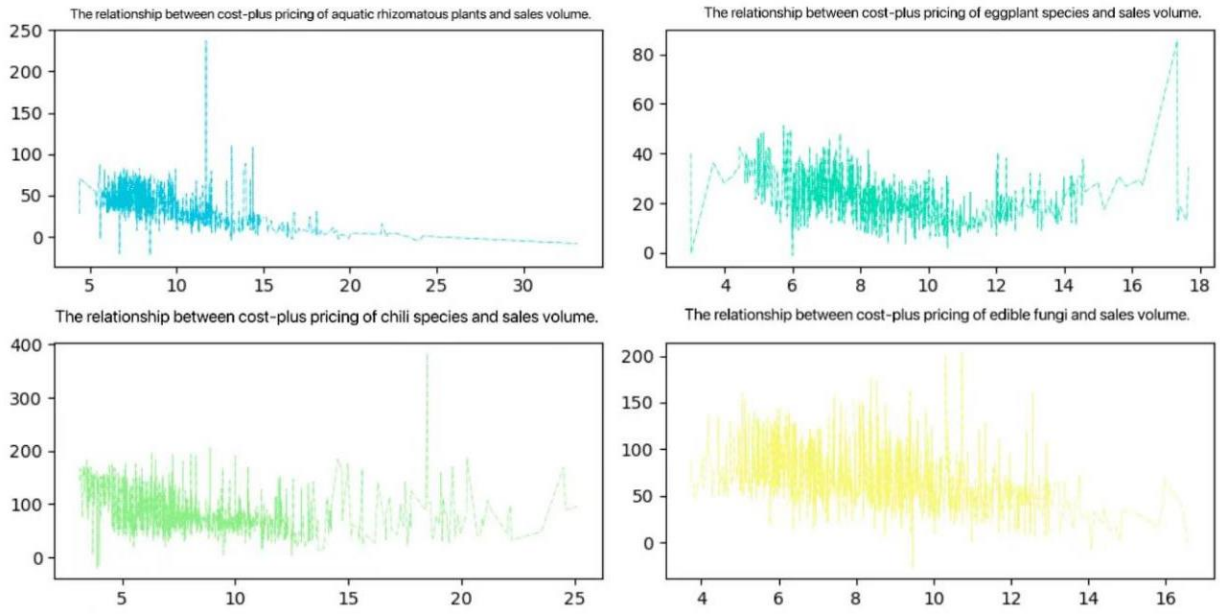


Figure 3. Relationship between cost and sales volume by category

The steps are as follows:

Step1: Calculate the cost of each vegetable item:

Cost = wholesale price * (1 + wastage rate)

Step2: Determination of mark-up rates based on forecasted sales volumes:

(1) If the projected daily sales volume of this category of vegetables is less than 20kg, the mark-up rate is 150 per cent.

(2) If the forecasted daily sales volume of this category of vegetables is more than 20kg and less than 50kg, the mark-up rate is 130%.

(3) If the predicted daily sales volume of the vegetable category is greater than 50kg, the mark-up rate is 120%.

Step3: Calculate the selling price of each vegetable category:

Selling price = cost * mark-up

The calculated pricing and stocking levels for each category of vegetables are shown in table 2 and table 3 below:

Table 2. Pricing table (two decimal places for display)

	1 July	2 July	3 July	4 July	5 July	6 July	7 July
Foliage	5.55	5.48	5.79	5.51	5.50	5.31	5.87
Cauliflower	15.20	15.08	15.20	15.20	9.53	9.81	14.87
Aquatic Roots	11.84	11.25	12.58	12.43	17.88	17.05	13.18
Eggplant	5.63	5.52	5.78	6.02	9.55	9.33	6.07
Chilli	7.30	7.20	7.51	7.72	7.83	7.27	7.97
Wild Mushrooms	6.40	6.84	6.65	6.49	3.30	3.70	6.20

Table 3. Table of incoming shipments (two decimal places are reserved for display)

	1 July	2 July	3 July	4 July	5 July	6 July	7 July
Foliage	184.82	182.98	184.86	183.93	214.64	200.82	187.38
Cauliflower	25.68	26.79	26.00	26.73	40.66	38.28	26.84
Aquatic Roots	38.78	37.29	37.32	35.79	24.51	22.08	37.92
Eggplant	25.62	26.20	27.64	25.99	24.07	24.16	26.74
Chilli	108.36	105.03	106.14	105.09	138.00	132.31	105.96
Wild Mushrooms	99.58	94.35	92.97	92.82	106.52	98.10	96.42

The profitability results are shown in Table 4.

Table 4. Profit for the day (total)

	1 July	2 July	3 July	4 July	5 July	6 July	7 July
sum of money earned	1201.90	1139.06	1246.00	1186.24	1205.64	1011.02	1356.72

3. Modelling and solving the replenishment decision model under consideration of constraints

3.1. PSO Particle Swarm Algorithm Modelling Principles

Particle Swarm Optimization (PSO) algorithm is a population intelligence algorithm that searches for the global optimal solution by designing a massless particle that mimics the biological behaviour of a flock of birds and using cooperative competition among the population.The PSO algorithm is a particle learns the historical optimal solution (Pbest) and the global optimal solution (Gbest) to achieve the optimal search[9-10]. Velocity and position updates are the core of the PSO algorithm and the principle expressions and updates are as follows:

$$V_{i+1,d} = \omega \cdot V_{i,d} + c_1 \cdot r_1 \cdot (Pbest_{i,d} - X_{i,d}) + c_2 \cdot r_2 \cdot (Gbest_{i,d} - X_{i,d}) \quad (2)$$

where V=[Vi,1,Vi,2,...,Vi,D] is the velocity of particle i, and X=[Xi,1,Xi,2,...,Xi,D] is the position of particle i. D is the dimension of the particle. $\omega \geq 0$ is the factor that maintains the original velocity, which is known as the inertia weight, and ω enhances PSO's local searching ability when it is small , which can enhance the global search ability of PSO when large; c1 and c2 are learning factors which regulate the particle between Pbest and Gbest,and are usually set to c1=c2=2; r1 and r2 are random numbers between [0, 1]. pbest=[Pi,1,Pi,2,...,Pi,D] is the individual optimum. Gbest=[Gi,1,Gi,2,...,Gi,D] is population optimal. The locally optimal stochastic component of the cognitive component is computed from the vector difference between the locally optimal solutions found so far and the randomly chosen solutions, while the globally optimal stochastic component of the social component is computed from the vector difference between the globally optimal solutions found so far and the randomly chosen solutions, and is used to approximate the ith solution (i.e., the randomly chosen solution) towards the best solution found so far Mobile. the PSO algorithm uses Pbest and Gbest bootstrapping.

The exact flow of the algorithm is shown in Figure 4 below:

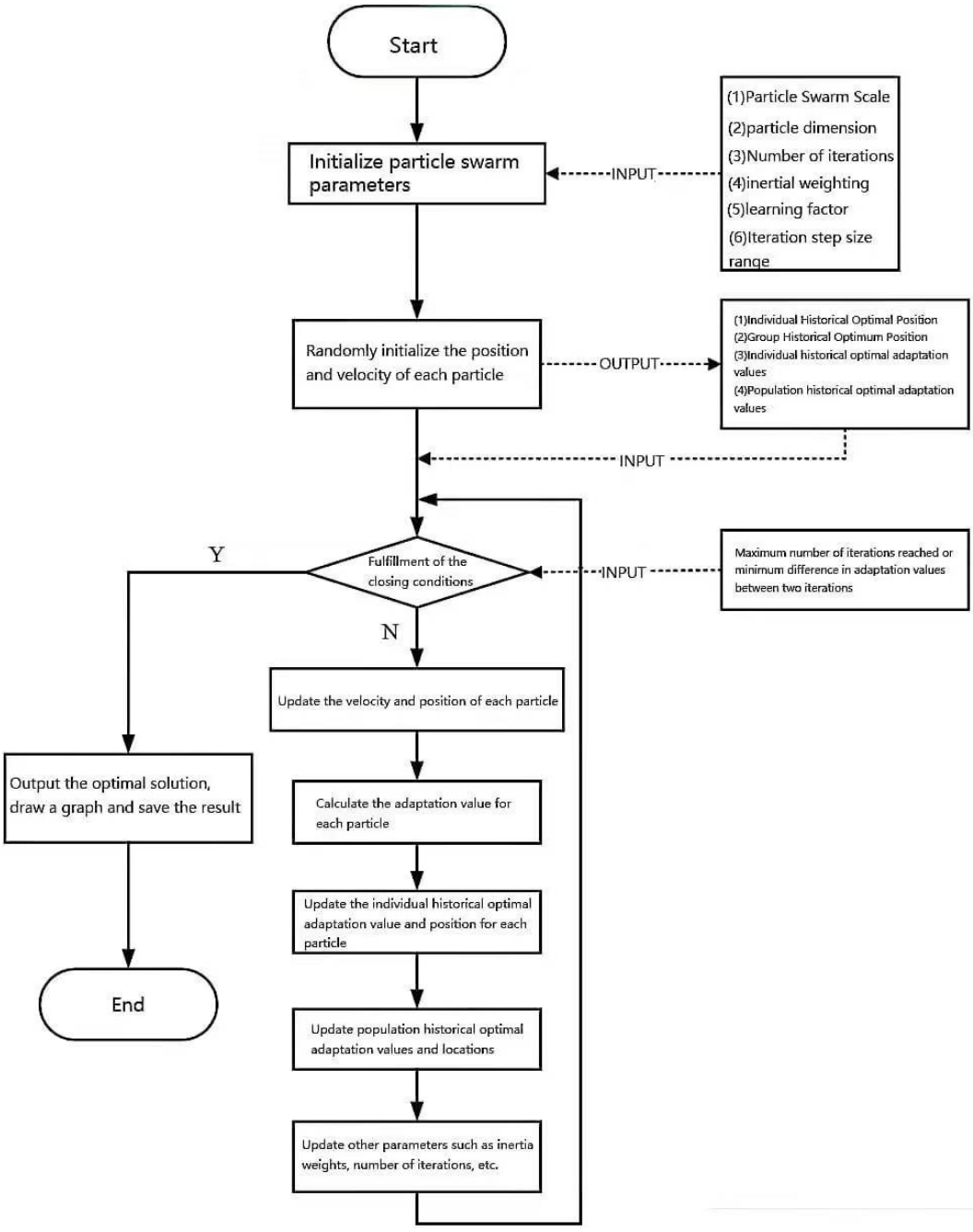


Figure 4. Flowchart of Particle Swarm Algorithm

3.2. Planning model solution and results

The data processed was first used to calculate the relationship between replenishment and pricing for each vegetable item, resulting in 251 linear regression models that served as constraints on the equation. For the 251 individual vegetable items, different combinations of vegetables need to be selected each day. Therefore, it is necessary to introduce the switching variables qi=0 or 1,i=1,2,3,...,251. qi is a 0-1 variable that takes the value of 1 to indicate that the vegetable item was sold on that day, and 0 to indicate that it was not sold on that day, i.e.:

$$q = \begin{cases} 0, unsold \\ 1, sold \end{cases} \tag{3}$$

For each individual item ordered to satisfy the minimum display quantity constraint, i.e., it can be expressed as the total amount of each individual item, ei, i=1,2,3,...,251 and needs to be greater than 2.5 kg, it can be expressed as:

$$e_i \geqslant 2.5, i = 1, 2, 3, \cdots 251 \tag{4}$$

For the calculation of profit, set wi as the profit margin. Thus, the pricing of each individual product can be expressed as:

$$y_i = (1 + w_i) c_i \tag{5}$$

where yi denotes the pricing of the ith individual item and ci denotes the cost price of the ith individual item. Therefore, the final total profit is expressed as:

$$W_{total} = \sum_{i=1}^{251} w_i x_i \tag{6}$$

In summary, the optimisation model is expressed as follows:

$$W_{total} = \sum_{i=1}^{251} w_i x_i$$

$$s.t. \begin{cases} y_i = (1 + w_i) c_i \\ y_i = k_i x_i + b_i \\ 27 \leqslant \sum_{i=1}^{251} q_i \leqslant 33 \\ e_i \geqslant 2.5 \\ q_i = 0 or 1 \\ c_i, x_i \geqslant 0 \\ w_i, y_i \in R \\ i = 1, 2, 3, \cdots 251 \end{cases} \tag{7}$$

Immediately after that the particle swarm optimisation algorithm is used to solve the problem and the results are shown in Table 5 below:

Table 5. Individual Replenishment - Pricing Methods

Single species category	Replenishment (kg)	Pricing (kg/$)
Small wrinkled skin (portions)	7.86	5.2
Amaranth	14.44	8
Yunnan lettuce (portion)	5.53	8
Field Chrysanthemum	5.51	10
Wuhu Green Pepper(1)	11.1	6.8
Yunnan Oil Wheat Vegetable(portion)	6.33	8.8
Seafood Mushroom(Packet)	11.65	5.2
Broccoli	6.55	6
Net Lotus Root(1)	36.83	5.8
Millet Pepper(portion)	22.66	4.5
Sweet Potato Tips	16.63	6.8
Zijiang Green Stem Scattered Flowers	14.35	15.2
Milk Cabbage	3.18	14
Chinese Cabbage	6.03	16
Baby Cabbage	2.8	16
Wood Ear Vegetable	4.91	26
Agaricus bisporus(box)	15.73	7.2
Honghu Lotus Root Scallop	6.23	16
Screw Pepper	8.60	12
Spinach	16.99	5.2
Crab Mushroom & White Jade Mushroom Duo (Box)	22.87	8.9
Horseradish	14.7	5.8
Colourful Peppers(2)	12.7	5.9
Red Lotus Root Scallops	7.67	4.8
Yunnan Oil Wheat Vegetable	5.13	24
White Jade Mushroom(bag)	2.7	3.8
Fresh Wood Ear(portion)	13.37	5.5
Purple Eggplant(1)	21.67	4
Wood Ear Vegetable(portion)	12.6	3

4. Conclusion

Vegetable items in superstores have high freshness requirements and need to maximise profits and determine appropriate replenishment totals and pricing strategies while meeting market demand. In this study, firstly, the pricing is added to the pricing based on the proportion of single-item sales, a relevant model is established, and the pricing strategy of each category is derived from the sales data of the previous four weeks as the object of study. Then, the relationship between vegetable sales and cost-plus pricing was analysed by BP neural network regression. Finally, a planning model was developed with maximum profit as the objective function and historical sales unit prices as the constraints to derive the replenishment volume and the maximum profit amount per day. The replenishment programme and pricing strategy were adjusted with changing sales conditions.

In further research, we extracted the data of saleable items and based on the prediction results, we set the ordering limit, historical pricing record, order ceiling and single-item quantity limit as constraints by using the profit amount of the superstore as the objective function, and built a planning model to determine the replenishment quantity and pricing strategy of individual items.

In summary, through this study, we have successfully determined the replenishment quantity and pricing strategy for vegetable items in superstores in order to achieve the goal of maximising profits while meeting market demand. These results provide useful guidance for supermarket operators to improve profitability while maintaining the freshness of goods.

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