Rnn-Ade-Based Multi-Product Replenishment-Pricing Modeling Study

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Abstract. Unscientific replenishment-pricing strategies can greatly reduce the sales profit of supermarkets, and choosing an appropriate decision model is crucial for supermarket operations. Therefore, this paper proposes a multi-product replenishment pricing model based on RNN-ADE, which fully utilizes the details of historical sales transactions with the help of recurrent neural networks to make the model results more credible, and also improves the DE algorithm to give the algorithm adaptability, so that the model has excellent global optimal solution search capability while having excellent solution efficiency. Then the model is tested practically based on the historical transaction flow detail data and historical product wholesale price of x superstore, and the replenishment and product pricing strategy for 2023-07-01 is formulated, the profit is predicted to be $741.44, and the sensitivity test is carried out. The results show that the model can effectively help supermarkets make more accurate and efficient replenishment and pricing decisions in a complex market environment.

Keywords: RNN, Adaptive DE algorithm, Replenishment-Pricing Model.

1. Introduction

In fresh food superstores, the freshness period of general vegetable commodities is relatively short, and the quality deteriorates with the increase of sales time, and most of the varieties, if not sold on the same day, cannot be re-sold on the next day. Therefore, supermarkets usually restock daily based on historical sales and demand for each product. Unscientific replenishment and pricing strategies will likely lead to a sharp increase in the cost of the superstore, which in turn will lead to a decrease in sales margins. This poses new challenges to pricing and replenishment strategies [1].

Optimization of merchandise replenishment and pricing strategies has long been a challenge in the retail industry. To solve this problem, different scholars have proposed diverse strategies. For example, Yuan Li [2] focuses on developing replenishment models based on market demand and cost analysis. Their study shows that these models work effectively under specific conditions but may fall short in considering the effects of historical sales data on future demand forecasts.

At the same time, more and more research has begun to emphasize the role of historical data in prediction. In particular, the RNN (Recurrent Neural Network) model has received widespread attention in this regard. Take the work of H. Hewamalage, C. Bergmeir [3] and Serrano W [4] as examples, they successfully predicted the sales and price trends of specific commodities by using RNN models, demonstrating the excellent performance of RNN in processing time series data, especially in the prediction of commodity sales.

Intelligent evolutionary algorithms have shown their effectiveness in dealing with the complexity of multi-commodity replenishment and pricing problems, especially their NP-hard properties. For example, Shen Y [5] and Parmentier A [6] successfully solved the optimization problem of inventory management and pricing using heuristic algorithms. These studies provide new ideas and methods for finding efficient solutions in complex systems.

In addition, the DE (differential evolution) algorithm, with the advantages of easy coding and high solution efficiency, is an efficient global optimization algorithm [7], suitable for quickly finding the optimal pricing and replenishment strategies. However, the traditional DE algorithm slows down the convergence in the late iterations, while it is easy to fall into the local optimal solution situation [8]. Therefore, this paper improves the standard DE algorithm by focusing on adjusting the form of the

crossover and variation operators during evolution so that they change with the number of iterations. This change is intended to ensure that the crossover and variation operators have large values at the beginning of the evolution to maintain the diversity of the population. As the number of iterations is gradually increased, these values are reduced to induce the population to retain good chromosomes in the later stages of evolution, mitigating the disadvantage of the algorithm falling into local optimal solutions. Improving the efficiency and accuracy of the algorithm [9].

In summary, this paper presents an innovative RNN-ADE-based multi-product replenishment-pricing model for supermarkets based on their historical sales flow detail data from the problem of multi-product replenishment and pricing strategy. This model aims to help retailers make more accurate and efficient decisions in the complex market environment and improve the operating profit of hypermarkets.

2. Modeling and theoretical foundations

2.1. Multi-product replenishment-pricing model for superstores

In this part, a multi-product replenishment-pricing decision model will be constructed with the objective of maximizing the profit of the superstore, and the following are the steps of model construction:

Step1: decision variables

The profit of the superstore is closely related to the pricing strategy of the vegetable category, the replenishment strategy, and the wholesale price of raw materials, so let P_i, Q_i , Wp_i , S_i represent the pricing, replenishment quantity, wholesale price, and sales volume of the ith commodity, respectively, serving as decision variables.

Step2: Objective function

The objective of this model is to calculate the maximum profit Z , so the objective function is as follows:

$$max\ Z = \sum_{i=1}^{n} S_i \cdot P_i - Q_i \cdot Wp_i \tag{1}$$

where n is the number of goods sold.

Step3: Constraints

(1) Constraint on the relationship between vegetable sales and pricing

For vegetable products, there is often a certain functional relationship between sales volume and pricing among different products. Zhang [9] depicts the relationship between vegetable sales volume and pricing with a linear relationship, and Cephas Naanwaab [10] analyzes the relationship between sales volume and unit price with a demand curve model. Kumari P [11] and Yan L [12] used RNN to forecast the prices of bananas and oil, respectively. The expressions are as follows:

- Linear modeling: $g(x) = ax + b$
- Demand modeling: $h(x) = ae^{bx}$

This model takes into account the fact that sales and pricing of vegetables tend to vary across categories and cannot be generalized. Therefore, two function fitting models are synthesized to fit the relationship between sales volume and pricing for each vegetable category, and for the ith type of vegetable product, the fitting function between sales volume and pricing is chosen based on the function with the smaller RMSE (Root Mean Square Error) as the final fitting result, and the expression is as follows:

$$S(x_i) = \begin{cases} g(x_i), RMSE_g < RMSE_h \\ h(x_i), RMSE_h < RMSE_g \end{cases} \tag{2}$$

(2) Constraint on costs

The cost of the ith type of vegetable product is determined by its wholesale price and purchase quantity, with the formula as follows:

$$C_i = Q_i \cdot Wp_i \tag{3}$$

(3) Constraint on replenishment quantity

The purchase quantity of the ith type of vegetable product is determined by the loss rate and sales volume, with the formula is shown below:

$$Q_i = \frac{S_i}{1 - q_i} \tag{4}$$

of which q_i is the wastage rate of vegetable category.

(4) Constraint on Loss Ratio

For the ith type of vegetable product, the loss rate q_i is determined by historical purchase volume and historical sales volume with the following expression.

$$q_i = \frac{1}{n}\sum_{t=1}^{n} 1 - \frac{S_i}{Q_i} \tag{5}$$

(5) Constraint on Historical pricing

Under normal circumstances, vegetables, as a daily necessity, have a relatively stable demand for the product during adjacent days. Consider that there is a functional relationship between sales volume and pricing. This model assumes that product pricing during the adjacent day period will be around a small percentage of price fluctuation θ up and down. In addition, vegetable pricing is a cyclical time series data set with a period. Based on this, the model proposes that for the ith vegetable product, the actual pricing for the next day P_i for the ith vegetable product, there is a certain price fluctuation ratio between the actual price on the next day and the predicted price on the next day based on the historical pricing data. P_i' There is a certain price fluctuation ratio between the actual pricing of the next day and the predicted pricing of the next day θ The price fluctuation index in this model is the price fluctuation index in this model is preset to be 0.2. θ in this model is preset to be 0.2. The pricing constraint expression is as follows:

$$(1 - \theta)P_i' < P_i < (1 + \theta)P_i' \tag{6}$$

2.2. Future pricing prediction for Vegetable Category Based on RNN Modeling

The historical selling price and wholesale price of vegetables are a set of regular time-series data [13]. The RNN recurrent neural network has strong model fitting ability as well as good prediction performance for time series data [2]. Therefore, in order to satisfy the historical pricing constraints of commodity sales, an RNN recurrent neural network is constructed to predict the pricing and wholesale price of vegetable commodities on the coming day. The modeling principle of the RNN is as follows:

As shown in Figure 1, at moment t, the RNN receives the inputs x_t, and combined with the hidden layer state at time $t-1$, denoted as h_{t-1}, generates the output h_t and the new hidden state h_t. This structure allows the network to retain memory and take contextual information into account when processing sequential data. The following is the specific computational procedure of the RNN model:

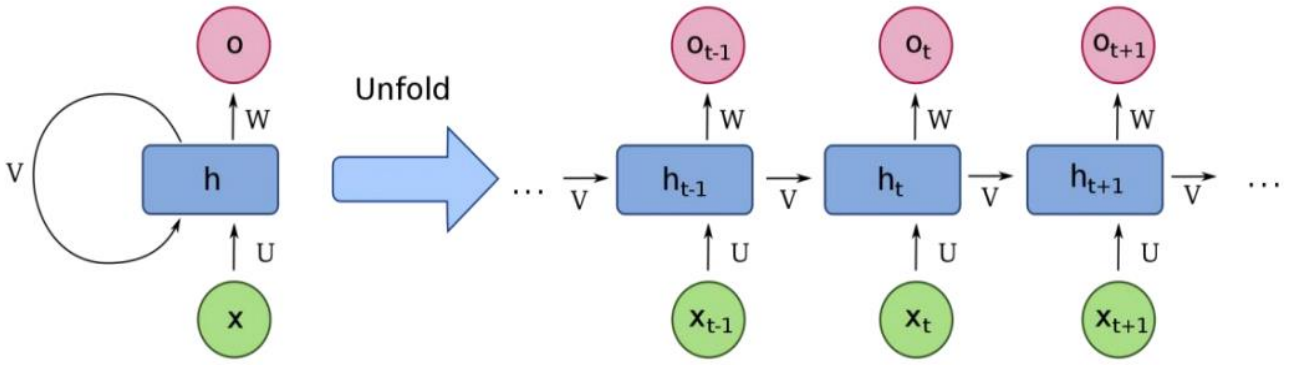


Figure 1. RNN network structure

2.2.1 Forward propagation

(1) The computation process between the input layer and the implicit layer is as follows:

$$a_t = U \cdot x_t + V \cdot h_{t-1} + b \tag{7}$$

$$h_t = \sigma(a_t) \tag{8}$$

Where U is the weight matrix from the input layer to the hidden layer, and V is the weight matrix from the hidden state at the previous time step to the hidden state at the current time step, and b is the bias, and σ is the activation function.

(2) The computation process between the implicit layer and the output layer is as follows:

$$z_t = W \cdot h_t + c \tag{9}$$

$$o_t = \sigma(z_t) \tag{10}$$

Where W is the weight matrix from the hidden to the output layer, and c is the bias, and o_t is the final output.

(3) The backpropagation calculation procedure is as follows:

This model defines the output layer activation function as a softmax function and the hidden layer activation function as ReLU function. According to the RNN forward propagation, the gradient descent method is utilized to calculate the RNN model parameters U, W, V, b, c gradient. The loss function is the MSE function. Each position of the sequence has a loss, defining the loss L to be the sum of losses at each moment, and its expression is as follows:

$$L = \sum_{t=1}^{\tau} L_t \tag{11}$$

τ is the total time step of the sequence. Next, a pair of V, the c find the gradient:

$$\frac{\partial L}{\partial c} = \sum_{t=1}^{\tau} \frac{\partial L_t}{\partial c} = \sum_{t=1}^{\tau} \frac{\partial L_t}{\partial o_t} \frac{\partial o_t}{\partial c} = \sum_{t=1}^{\tau} (\hat{y}_t - y_t) \tag{12}$$

$$\frac{\partial L}{\partial V} = \sum_{t=1}^{\tau} \frac{\partial L_t}{\partial V} = \sum_{t=1}^{\tau} \frac{\partial L_t}{\partial o_t} \frac{\partial o_t}{\partial V} = \sum_{t=1}^{\tau} (\hat{y}_t - y_t) h_t \tag{13}$$

In backpropagation, the sequence$t$ gradient loss at a position consists of two parts: the output at the current position and the sequence index. For W at the sequence position t the gradient of the sequence is:

$$\delta_t = \frac{\partial L_t}{\partial o_t}\frac{\partial o_t}{\partial h_t} + \frac{\partial L}{\partial h_{t+1}}\frac{\partial h_{t+1}}{\partial h_t} = V^T(\hat{y}_t - y_t) + W^T\delta_{t+1}diag\left(1 - {h_{t+1}}^2\right) \tag{14}$$

It can be based on δ_{t+1} recursively δ_t. For δ_τ since there is no other sequence indexed after then, the

$$\delta_\tau = \frac{\partial L}{\partial o_\tau}\frac{\partial o_\tau}{\partial h_t} = V^T(\hat{y}_\tau - y_\tau) \tag{15}$$

And then to W, U, b find the gradient:

$$\frac{\partial L}{\partial W} = \sum_{t=1}^{\tau}\frac{\partial L_t}{\partial h_t}\frac{\partial h_t}{\partial W} = \sum_{t=1}^{\tau} diag\left(1 - {h_t}^2\right)\delta_t(h_{t-1})^T \tag{16}$$

$$\frac{\partial L}{\partial U} = \sum_{t=1}^{\tau}\frac{\partial L_t}{\partial h_t}\frac{\partial h_t}{\partial U} = \sum_{t=1}^{\tau} diag\left(1 - {h_t}^2\right)\delta_t {x_t}^T \tag{17}$$

$$\frac{\partial L}{\partial b} = \sum_{t=1}^{\tau}\frac{\partial L_t}{\partial h_t}\frac{\partial h_t}{\partial b} = \sum_{t=1}^{\tau} diag\left(1 - {h_t}^2\right)\delta_t \tag{18}$$

2.3. Modeling the ADE solving algorithm.

In this model, for the DE algorithm in the late iteration, the convergence speed will become slower, and at the same time, it is easy to fall into the local optimal solution, the improved ADE (Adaptive Differential Evolution) algorithm is proposed, the variational operator and the crossover operator will be adaptive to the changes in the number of iterations, to improve the model's solving efficiency and accuracy.

(1) Chromosome coding

Coding the chromosomes, the n indicates the number of vegetable commodities. The length of each chromosome is n, and each gene is the price of the ith commodity.

(2) Initialization of stocks

Set the chromosome size to N_p, the chromosome length is N_d, the differential evolution operator is Cr_{min}, Cr_{max}, F_{min}, F_{max}. A random assignment is used to generate the initial population, but each gene needs to satisfy the constraints of Eqs. (5).

(3) Mutation

The Gth generation chromosome was selected for mutation and three different chromosomes were randomly selected r_1, r_2, r_3. The formula for the mutation operator F is given below:

$$F = F_{min} + (F_{max} - F_{min})e^{\left(1 - \frac{G_{max}}{G_{max} - G + 1}\right)} \tag{19}$$

$$V_i(G+1) = X_{r_1}(G) + F\left[X_{r_2}(G) - X_{r_3}(G)\right] \tag{20}$$

Among them: F_{min} and F_{max} are the minimum and maximum values of the mutation operator, respectively; G_{max} is the maximum number of iterations and G is the number of current iterations; V_i is the chromosome after mutation, and X_{r_i} is the number of the first r_1 individual on the chromosome.

(4) Cross

A crossover operation was performed on chromosome generation G to select the target vector X_{ij}^G and the variant vector V_{ij}^{G+1} crossover is performed to produce the resultant vector u_{ij}^{G+1}, the crossover process is as follows:

$$Cr = Cr_{max} - \frac{G(Cr_{max} - Cr_{min})}{Gmax} \tag{21}$$

$$u_{ij}^{G+1} = \begin{cases} v_{ij}^{G+1}, rand(0-1) \le Cr \\ x_{ij}^{G}, else \end{cases} \tag{22}$$

Where $i = 1, 2, ..., N_p$, $j = 1, 2, ..., N_d$, and Cr_{min}, Cr_{max} are the minimum and maximum values of the crossover operator, respectively.

(5) Renewal of chromosomes

Calculate the fitness value of each chromosome, i.e., Equation 3-1, and compare the size of the fitness value of the target vector and the resultant vector. Select the chromosome with high fitness value for the next generation population. The selection process is as follows.

$$X_i^{G+1} = \begin{cases} u_i^{G+1}, fitness(u_i(G)) \le fitness(x_i(G)) \\ x_i^{G}, else \end{cases} \tag{23}$$

(6) Iteration

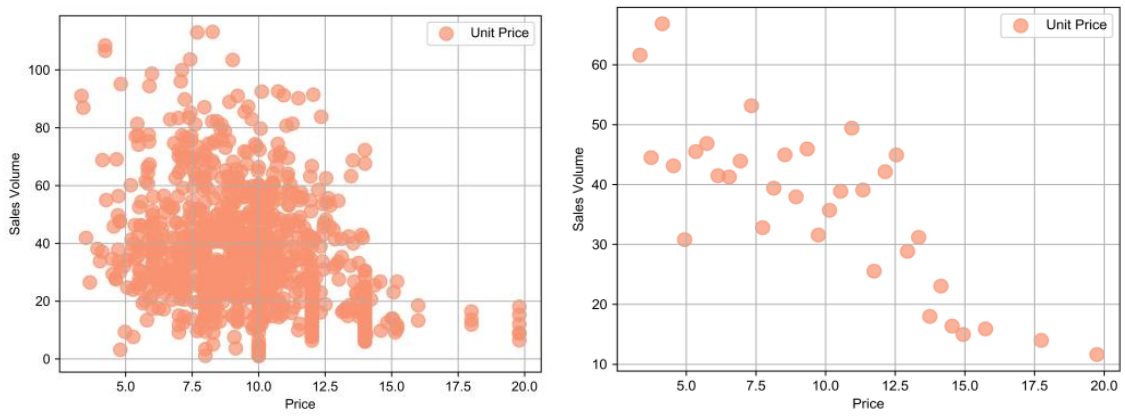
Repeat steps (3) to (5) until the maximum number of iterations is reached, the solution model stops running, and the best chromosome and the corresponding optimal solution are obtained.

3. Result

The data for this case was obtained from http://www.mcm.edu.cn. The data provided by the website of x superstore from July 1, 2020, to June 30, 2023, about the sales flow details and wholesale prices of each product. In the following sections, this paper will use the multi-product replenishment-pricing model to simulate the replenishment and pricing strategies for supermarket products on 7-1-2023.

3.1. Fitting the relationship between vegetable sales and ricing.

Start by plotting a scatterplot of prices and sales volumes. As can be seen from the scatter plot Figure 2 (a), there are certain noise points in the scatter distribution of price and sales volume of some vegetable categories, resulting in poor curve fitting. Therefore, this model optimizes the data distribution interval. First, the vegetable pricing interval is divided according to the step length d and then the sales volume corresponding to each unit price within the step range is summed and averaged, and the middle unit price within the step range is taken as the optimized unit price value, and the optimized scatter plot is shown in Figure 2 (b).



(a) Raw data (b) Processed data

Figure 2. Scatter plot of vegetable sales and pricing

From Fig. 2(b), it can be found that there is a strong functional relationship between the optimized price and sales volume, which can be fitted using the corresponding function.

The curves were fitted by MATLAB to obtain the functional relationship between sales volume and pricing for each vegetable category, and some of the fitted expressions are shown in Table.1.

Table.1. Relationship between Sales Volume and Pricing

vegetable category	pacemaker	fit (math.)	R^2
broccoli	0.4	$y = -19.2619x + 284.9388$	0.82912
Yunnan lettuce	0.4	$y = -2.5882x + 62.0817$	0.64646
Lotus root	0.6	$y = 101.9195e^{-0.1193x}$	0.88491
Xixia Mushroom	0.5	$y = 34.1305e^{-0.0506x}$	0.7745
Yunnan oilseed rape	0.6	$y = -4.0267x + 99.6904$	0.77189

3.2. Vegetable category pricing and wholesale unit price prediction based on RNN modeling

Due to the large number of vegetable categories, this section solves for the projected wholesale price of broccoli on 7-1-2023 as an example. The model parameters are set as shown in Table.2.

Table.2. Table of model parameters

model parameter	set up	model parameter	set up
Number of input features	1	Time sliding window	7
Hidden_size	150	Training set ratio	0.7
Num_layers	2	Learning rate	0.001
Output_size	1	Loss function	MSe
Epoch	150	Optimize	adam

The model is trained and predicted with the help of python's pytorch library, and the model solution results in the prediction of the wholesale price of broccoli on 7-1-2023 at ¥7.498, and the prediction results are shown in Figure 3:

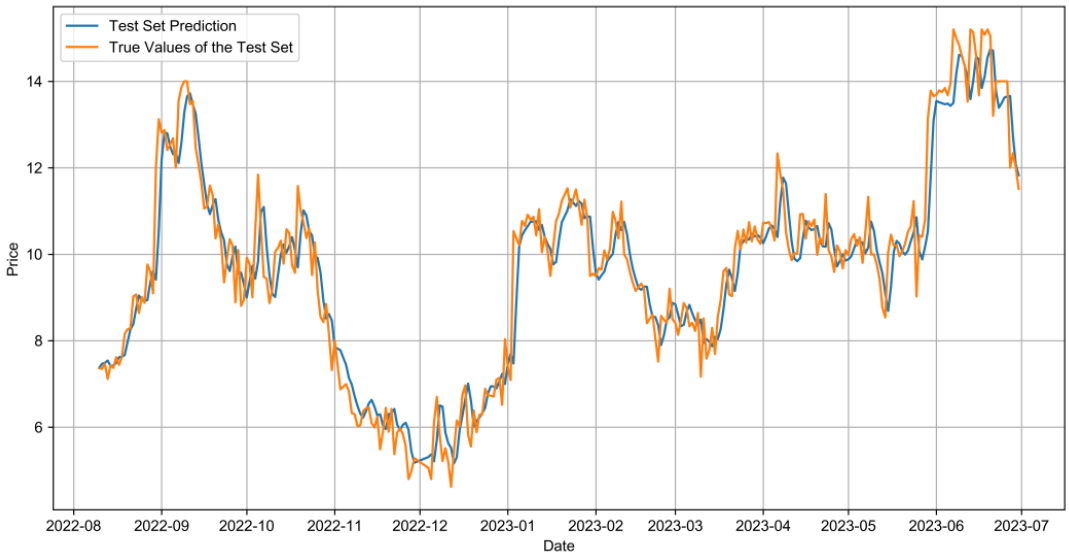


Figure 3. RNN prediction map of cauliflower class

From the figure, it can be found that the prediction curve of the RNN model on the test set has a high degree of fit to the real value, while the goodness of fit R^2=0.9316, $RMSE$=0.4934, so it can be concluded that the RNN model is excellent for predicting the wholesale price curve of vegetables.The forecast results for some vegetable categories are shown in Table.3.

Table.3. Partial Forecast Results

● serial number	● Item Name	● wholesale prices (yuan/kg)	● unit price of goods sold (yuan/kg)
● 1	● broccoli	● 7.49813986	● 11.52909184
● 2	● Yunnan lettuce	● 3.1916635	● 4.381093502
● 3	● Lotus root	● 10.1684513	● 15.45092869
● 4	● Xixia Mushroom	● 14.9270668	● 22.82952118
● 5	● Yunnan oilseed rape	● 2.60962462	● 4.2741642

3.3. Solving optimization model based on ADE algorithm.

First, for the ADE algorithm, the initial parameter settings of the solution model are shown in Table.4 and five different sets of crossover and variational operators are used for the tests, with the variational operator as an example. F_{min} The range of the parameter test is from 0.1 to 0.5, and the adjustment step of each test is 0.1.

Table.4. Initial Parameter Settings

the calculus of variations (math.)	**intersection operator (math.)**	**population size**	**Number of iterations**	**Number of tests**
CF_{min}: [0.1: 0.1: 0.5]	CR_{min}: [0.1: 0.1: 0.5]	100	200	50
CF_{max}: [0.9: 0.1: 0.5]	CR_{max}: [0.9: 0.1: 0.5]			

After several trials, the profit reaches a maximum of ¥741.441 when the values of the crossover operator and the variational operator are in the range of 0.2-0.8 intervals. The solution iteration process is shown in Figure 4, and the model solution results are finally stabilized.

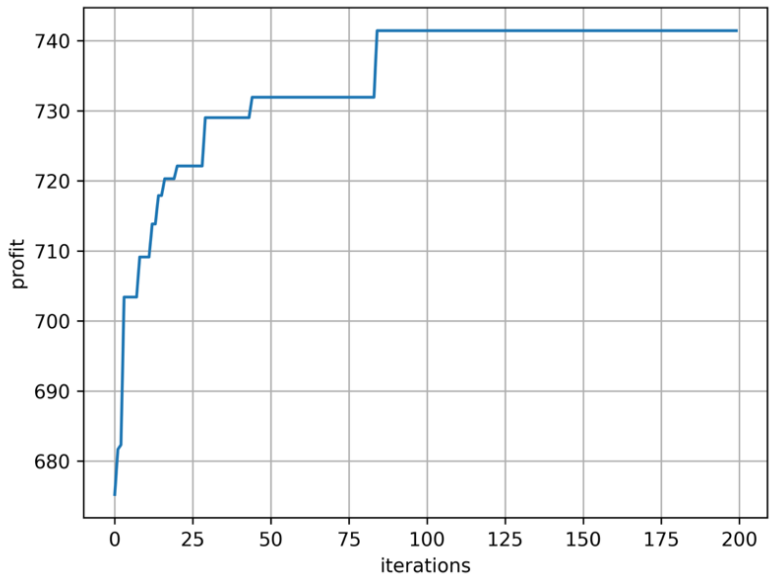


Figure 4. Iterative process of solving

The replenishment strategies and sales pricing strategies for some of the vegetable items are shown in Table.5.

Table.5. Partial Model Results

Item Name	quantity of imported goods (kg)	Selling unit price (yuan/kg)
broccoli	18.7938538	11.5290918
Lotus root	7.80349827	15.4509287
Xixia Mushroom	6.32106066	22.8295212
Yunnan lettuce	37.5919533	4.3810935
Yunnan oilseed rape	26.0507984	4.2741642
total profit	¥741.441	

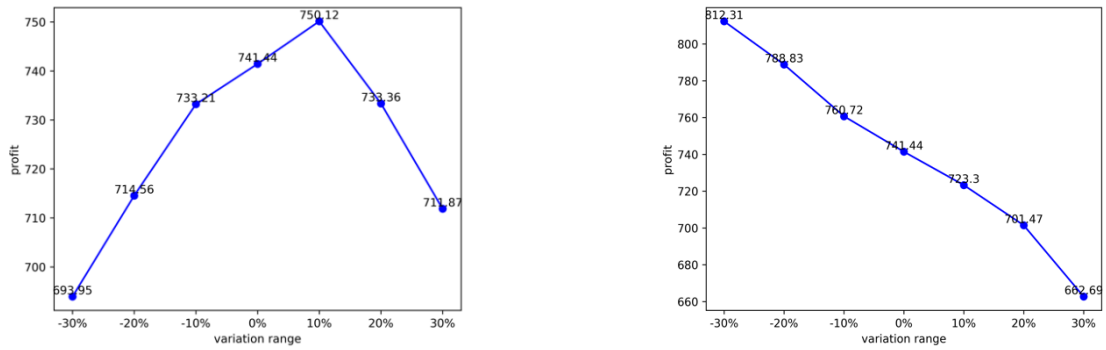
According to the results of the model, the manager can formulate the corresponding replenishment and pricing strategy, and it is expected that the profit of 741.44 yuan will be obtained.

3.4. Model sensitivity analysis

In this section, the important constraint parameters in the superstore profit optimization model: the price fluctuation index θ and merchandise wastage rate q are subject to sensitivity analysis. Keeping the other parameters unchanged, adjusting respectively θ with q, the variation range is [-30%, 10%, 30%], the lower limit is -30%, the upper limit is 30%, and the step size is 10%.

First, the sensitivity analysis of the price fluctuation index shows that the change in the product price fluctuation index has an impact on the total profit. As shown in Figure 5 (a), the total profit shows a tendency to increase and then decrease with the change in the product price index. The explanation for this trend lies in the fact that vegetables are regarded as a necessity and people buy approximately the same amount of them on a daily basis. Due to the relatively short shelf life of most vegetables, a downward adjustment in the price of the commodity does not stimulate the demand for consumption too much. When prices rise slightly, the change does not significantly affect people's purchasing demand, which drives profits up. However, when prices rise too much, people's buying demand may fall sharply, leading to a decrease in total profits.

Secondly, the sensitivity analysis of the vegetable wastage rate shows that the wastage rate of vegetables is negatively correlated with the total profit as shown in Figure 5 (b). Reducing the wastage rate of vegetables means that supermarkets can effectively manage their inventory, reduce waste, and reduce the amount of goods purchased, thus reducing the cost of goods sold, and thus promoting the total profit.



(a) θ Sensitivity analysis of (b) q Sensitivity analysis of

Figure 5. Sensitivity analysis

4. Conclusion and outlook

In order to solve the daily scientific replenishment and pricing needs of supermarkets, this paper takes the vegetable sales of supermarket X as the research object, collects the sales flow details and wholesale price data of each commodity from July 1, 2020, to June 30, 2023, and establishes a supermarket profit optimization model based on the RNN-ADE algorithm, which maximizes the profit of the supermarket through the objective function and constraints of the model. The RNN model makes full use of the historical sales data, which makes the decision-making results more credible; the improved ADE algorithm makes the model have excellent solution efficiency and improves the ability to search for the global optimal solution, so that the optimal replenishment and pricing strategies can be found in a short time. Thus, it can scientifically solve the problem of joint replenishment and pricing of multiple commodities in supermarkets and provide a reference basis for supermarket managers to formulate commodity replenishment and pricing strategies. This paper takes the replenishment and pricing strategy on July 1 as an example, solves the model, obtains the replenishment quantity of each product as well as the sales price, and the expected total profit of the commodity is 741.441 yuan.

Although the model is able to fully utilize historical data to formulate product replenishment and pricing strategies, there are still directions for improvement. Firstly, the model solution, due to the NP-hard nature of the problem, it is still difficult to find the optimal replenishment and pricing strategy, which can be improved by solving the problem repeatedly and taking the average. Secondly, the constraints of the model are not comprehensive enough, and other influencing factors can be included in the constraints, such as through customer research, collecting the user preference of each product and adding this as a constraint to the model, which is conducive to more accurate prediction and optimization.

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