Research on Vegetable Pricing and Replenishment Strategy Based on TOPSIS Method and Simulated Annealing Algorithm

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Abstract. By mining the relationship between categories and individual products, this paper puts forward enterprise replenishment and pricing strategies under different conditions. First of all, from the 49 kinds of vegetables sold, the TOPSIS method based on entropy weight is used to select the top 20 important items by taking the market demand and excess income as the first-level index, and taking the historical sales rate, average daily sales volume, variance of sales volume, vegetable loss rate and unit profit as the second-level index. Then, based on the concept of complementary and alternative goods, through the Spearman correlation coefficient, and using the weighted correlation coefficient method, select the top 9 items, such as ginger, garlic, millet pepper combination and so on. Using these selected items, taking the profit maximization of fresh merchants as the objective function and the demand of each category as constraints, a 0-1 integer nonlinear programming model is established. Then, the simulated annealing algorithm is used to simulate the planning for 1000000 times, and the pricing strategy and supply plan of the enterprise on July 1st are obtained, and the maximum profit on that day is 2098.17 yuan.

Keywords: Vegetables, Pricing replenishment, Spearman, Simulated annealing algorithm.

1. Introduction

1.1. Background of the question.

In the supermarket of fresh food merchants, most vegetables have a short shelf life, and such goods cannot be sold unless they are sold on the same day. Accordingly, Shang Chao replenishment is often based on historical sales and demand. Shang Chao restocking should make daily replenishment decision in the case of uncertain unit product and purchase price[1-4]. The "cost plus pricing" method is used for vegetable pricing, and Shang Chao will sell bad goods at a discount. Market demand analysis is very important for replenishment and pricing decisions. From both sides of supply and demand, there are many kinds of vegetables from April to October, and Shang Chao needs to match the sales mix reasonably in the limited space[5-9].

1.2. Questions raised.

At present, there are the types and numbers of items contained in the six categories of Shang Chao, the sales details from July 2020 to June 2023, the wholesale prices and the latest loss rate of each item from July 2020 to June 2023. It is proposed to solve the following problems: The venues of vegetable merchants are limited, and a replenishment plan accurate to a single product is needed, requiring that the number of products available for sale is 27-33, and the order quantity per item is greater than or equal to 2.5 kg. Through the varieties that can be sold from June 24 to 30, 2023, the replenishment and pricing schemes for each item in the following day are given, which can maximize the profit of Shang Chao while meeting the market demand as much as possible[10,11].

2. Research methods.

First of all, this paper selects the single products that have been sold from June 24 to June 30, and selects some vegetable items which are of great importance to fresh and fresh merchants according to the market demand index and super income index by using the TOPSIS method based on entropy weight, and then considers the items which may be suitable for bundling sale according to the Spearman correlation coefficient, and selects the rest of them.

Using the selected items, the objective function is established with the maximum profit of fresh merchants, and the demand of each category is taken as the constraint condition, the 0-1 integer nonlinear programming model is established, and then the 0-1 integer nonlinear programming model is solved by simulated annealing algorithm. the pricing strategy and supply plan of the enterprise on July 1 are obtained.

3. Establishment and solution of the model.

3.1. Analysis and processing of data.

Because Shang Chao takes into account the limitations of sales space, the types of sales items are between 27 and 33 per day, and it is necessary to specify replenishment and pricing strategies according to the available varieties and their data characteristics from June 23 to June 30. Therefore, this paper first selects the items with sales records between June 23 and June 30 to screen them.

After data processing, it was found that a total of 49 items had been sold between June 23 and June 30, so only the data of these 49 items were analyzed.

Selection of salable varieties based on TOPSIS method and spearman correlation coefficient based on Entropy weight.

Due to the need to formulate replenishment plans and pricing strategies for the future day, we first need to screen out the types of purchase items in the next day. For the 49 items and data selected, this paper uses the TOPSIS method based on entropy weight to screen out some items, and then uses the Spearman correlation coefficient between different items to pick out the goods with strong correlation with the previously selected items, that is, the goods that are suitable for binding sales.

3.1.1 Entropy weight TOPSIS method.

(1) selection of characteristic index variables and construction of index evaluation system.

This paper focuses on how to extract 49 kinds of single vegetables from June 24 to June 30 and their data to measure the dependence of Shang Chao on this single vegetable in the next day, that is, the importance of this item to Shang Chao.

Shang Chao often makes daily replenishment plans according to the historical sales and demand of goods, and one of the research objectives is to maximize the revenue of Shang Chao. Therefore, in this paper, the selection of the importance of individual items is mainly from the two angles of demand indicators and income indicators.

For the demand index, this paper selects the historical sales rate, the average daily sales volume and the variance of sales volume to quantify; for the income index, this paper selects the unit profit rate and vegetable loss rate to quantify.

The following is a specific description of each indicator:

Historical sales rate (LSX):

$$LSX_m = \sum_{q}^{7} r_{m,q} (m = 1, 2, \cdots, 49) \tag{1}$$

Where LSX_m indicates that the mth single product of 49 single varieties has been purchased by consumers for a few days from June 24 to June 30, and $r_{m,q}$ indicates whether the mth single product has been purchased on the first day or not, and if the single product has been purchased on the same day, $r_{m,q}$ takes the value of 1, or else it is 0. This indicator can reflect the demand for a certain single product in the past 7 days, and the greater the value of the indicator, the higher the demand of the single product, the more effective the indicator is, and the higher the demand is. The larger the value of this indicator, the higher the demand for the product, and it can be used as a benefit indicator.

Average daily sales volume ($\overline{XSL}$):

$$\overline{XSL_{m,q}} = \frac{\sum_{q=1}^{7} XSL_{m,q}}{7} (m = 1, 2, \cdots, 7) \tag{2}$$

Where $\overline{XSL_{m,q}}$ denotes the average daily sales volume of the mth individual product within the period from June 24 to June 30, and $XSL_{m,q}$ denotes the sales volume of the mth individual product within the qth day, the sales volume is subject to the direct effect of the demand volume, and this indicator, as one of the most intuitive indicators reflecting the demand, can reflect the magnitude of the demand for a certain individual product in the past 7 days, and its can be used as a benefit type indicator.

Variance of sales volume ($Var(XSL)$):

$$Var(XSL_{m,q}) = \frac{\sum_{q=1}^{7} (XSL_{m,q} - \overline{XSL_{m,q}})^2}{7} (m = 1, 2, \cdots, 49) \tag{3}$$

$Var(XSL_{m,q})$ indicates the variance of the sales volume of the mth type of single product from June 24th to June 30th, so this indicator can reflect the fluctuation of the sales volume of the single product in these 7 days, the greater the fluctuation of the single product, then it means that the demand for this single product fluctuates every day, and it is very likely that it is not a necessity of daily-use vegetables, and therefore it can be used as a cost-based indicator.

Vegetable wastage rate (β_m): this indicator indicates the recent wastage rate of the mth type of single product, vegetable wastage rate includes the transportation loss of vegetables and unsold vegetables, the higher the wastage rate, the higher the risk of purchasing the single product, the higher the cost, which affects the revenue, which can be used as a cost-based indicator.

Profit per unit (LR)

$$LR_m = price_m - cost_m \tag{4}$$

Where LR_m denotes the unit profit of the mth kind of single product, $price_m$ denotes the selling price of the mth kind of single product, and $cos\,t_m$ denotes the cost price of the mth kind of single product, i.e. wholesale price. The unit profit of a single product can be used as an important indicator to measure the profitability of a single product, and it can be used as a benefit indicator.

(2) Entropy weighting method to calculate weights

This paper adopts entropy weighting method to give weight to the five single product indicators, the core idea is to standardize the indicators in the measurement of the basis, based on the degree of variation in the data of each indicator to get the weight of the information reflected in the degree of variability, compared with the hierarchical analysis, fuzzy comprehensive evaluation and other methods of the subjective assignment method, entropy weighting method greatly reduces the interference of the subjective human factors in the assignment of indicators and focuses on the characteristics of the data itself. Characteristics.

1) Indicator data normalization and normalization

In this paper, there are 5 evaluation indexes for 49 vegetable products to be evaluated, firstly, the data in each evaluation index are normalized and normalized, and a non-negative normalization matrix Z is constructed from the processed data.

$$z_{ij}=\frac{x_{ij}-min_j(x_{ij})}{max_j(x_{ij})-min_j(x_{ij})} \tag{5}$$

$$Z=\begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{m1} & \cdots & z_{mn} \end{bmatrix} \tag{6}$$

In the formula: for the vegetable single product (i=1,2,⋯,m); j is the evaluation index of the importance of the single product (j=1,2,⋯,n); x_{ij} is the initial value of the evaluation index; $max\ _j(x_{ij})$ is the maximum value of x_{ij} in the jth evaluation index; $min_j(x_{ij})$ is the minimum value; z_{ij} is the normalized value, where m=49, n=5; z_ij is the normalized value, where m=49, n=5; z_ij is the normalized value, where m=49, n=5; z_ij is the normalized value, where m=49, n=5; z_ij is the normalized value, where m=49, n=5.) is the minimum value; z_ij is the value after normalization, where m=49, n=5.

2) Entropy weight method to calculate the weight

For the ith element of the jth vegetable single product importance evaluation index, normalization is carried out under the same vegetable single product importance evaluation index, and the normalized matrix Z is recorded as the probability matrix P in entropy calculation, in which the formula for each element p_{ij} is as follows.

$$p_{ij}=\frac{z_{ij}}{\sum_{i=1}^{m} z_{ij}} \tag{7}$$

The information entropy e_j and information utility d_j of each vegetable individual evaluation index can then be calculated using the element p_{ij} in matrix P.

$$e_j=-\frac{1}{lnn}\sum_{i=1}^{m} p_{ij}ln(p_{ij}) \tag{8}$$

$$d_j=1-e_j \tag{9}$$

Finally, the information utility e_j is normalized to obtain the weights w_j and weight matrix W for each vegetable item importance evaluation index.

$$w_j=\frac{d_j}{\sum_{j=1}^{n} d_j} \tag{10}$$

$$W=\begin{bmatrix} w_1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & w_n \end{bmatrix} \tag{11}$$

The information entropy of each evaluation index calculated by entropy weighting method, the weights are shown in Table 1 below:

Table 1. Table of entropy weights

	The information entropy value e	Information utility value d	Weight %
unit profit	0.945	0.055	24.967
Average daily sales volume	0.877	0.123	55.462
Historical sales rate	0.977	0.023	10.26
Sales volume variance	0.994	0.006	2.508
Vegetable wastage rate	0.985	0.015	6.803

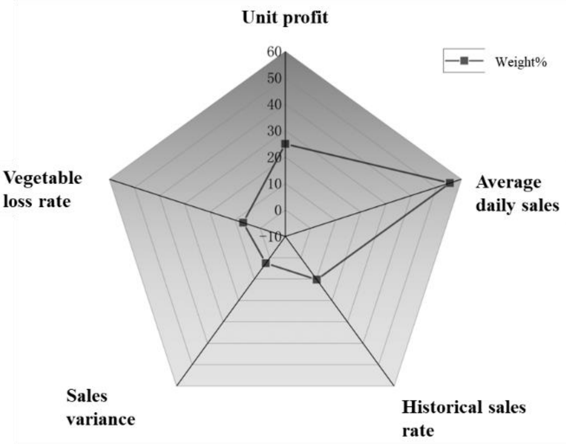

Figure 1. Radar chart of indicator weights

Although the entropy weight method is based on the degree of difference in the data to derive the indicator weights, but the weight distribution can be seen by the weight distribution of unit profit and average daily sales accounted for most of the weight, and the weight distribution of the indicators is relatively gentle, there is no case of a certain indicator is too large or small, in line with the common sense of the evaluation of the superstore's priority order commodities, so that the indicator weights derived through the entropy weight method is more reasonable (Figure 1).

(3) Evaluation of vegetable single products by TOPSIS method

TOPSIS method, also known as Approximate Ideal Solution Sorting Method, is a comprehensive evaluation method, which obtains the relative order of merit of each evaluation object by calculating the Euclidean distance between the attribute indexes of the evaluation object and the optimal solution and the worst solution.

1) Constructing weighted normalization matrix

When using the TOPSIS method based on the entropy weight method, the data in the normalization matrix P obtained in the entropy weight method in the previous section should be weighted first to constitute a weighted normalization matrix:

$$A = W \cdot P = \begin{bmatrix} w_1 * p_{11} & w_2 * p_{21} & \cdots & w_n * p_{n1} \\ w_1 * p_{12} & w_2 * p_{22} & \cdots & w_n * p_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 * p_{1m} & w_2 * p_{2m} & \cdots & w_n * p_{nm} \end{bmatrix} \tag{12}$$

2) Determine positive and negative ideal solutions

For the vegetable single product importance indicators selected in this paper in accordance with its promotion or inhibition of the evaluation score, divided into benefit-type indicators and cost-type indicators, in which the benefit-type indicators means that the size of its value is positively proportional to the importance of the single product of fruits and vegetables, all other things being equal; the cost-type indicators means that the size of its value is inversely proportional to the importance of the single product of fruits and vegetables, all other things being equal. :

$$V^{+} = \{max_j V_{ij} | i = 1,2,.\cdots,m\}, \quad V^{-} = \{min_j V_{ij} | i = 1,2,\cdots,m\}(Benefit-based\ indicators) \tag{13}$$

$$V^{+} = \{min_j V_{ij} | i = 1,2,.\cdots,m\}, \quad V^{-} = \{max_j V_{ij} | i = 1,2,\cdots,m\}(Cost-based\ indicators) \tag{14}$$

3) Calculate the relative proximity of vegetable items to the ideal solution, and get the importance ranking of vegetable items.

Calculate the positive and negative ideal solution distance of each vegetable item, the positive ideal solution distance is d_i^{+}, the negative ideal solution distance is d_i^{-}, and calculate the relative proximity of each vegetable item to the ideal solution D_i:

$$d_i^{+} = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^{+})^2}, \quad d_i^{-} = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^{-})^2} \tag{15}$$

$$D_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}}(i = 1, 2, \cdots, m) \tag{16}$$

Where Di is the relative proximity of the evaluation object to the ideal solution, the larger Di indicates that the evaluation object is better, so the evaluation object can be ranked according to the size of Di, the ranking of the 49 vegetable items is shown in Figure. 2 below, and Table 2 only shows the importance of the top 10 vegetable items.

Table 2. Ranking of importance of individual vegetable items

Importance ranking	Vegetable singles
1	Yunnan lettuce (portion)
2	Peppers (portions)
3	Yunnan oilseed rape (portion)
4	Wuhu Green Pepper(1)
5	Golden Needle Mushroom(box)
6	broccoli
7	Brussels sprouts (Brassica oleracea var. botrytis)
8	Colorful Peppers(2)
9	Screw peppers (portions)
10	Honghu Lotus Roots

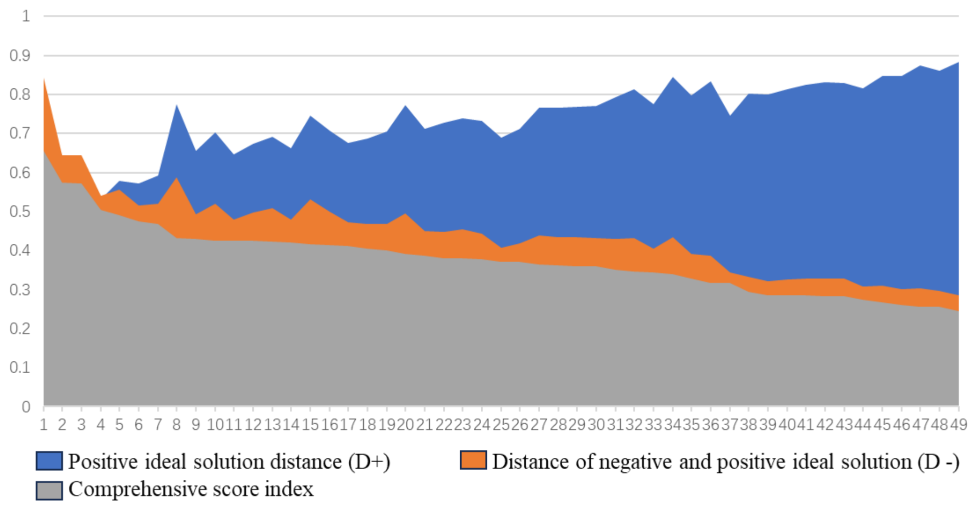

Figure 2. Positive and negative ideal solutions and composite score plot Score plot

3.1.2 Combined with Spearman correlation coefficient to determine the number of single product

Because in the index weight, the sales volume index weight accounts for a larger, so in the selection of higher scoring single product, because of its sales volume are larger, so we can not have to consider the higher scoring single product ordering volume of the minimum display volume, you can simplify the constraints.

As the middle part of the comprehensive score of each single product index distribution tends to flatten out, there is no significant difference, so we first obtain the score of the top 20 single product as a replenishment plan in the goods, and then the 20 after the order of the score of the goods to do the correlation coefficient of visualization, that is, the correlation coefficient of these single products and the first 20 single product analysis, selected with the first 20 single product positive correlation of single product as a subsequent selection of goods The correlation coefficient of these single products with the top 20 lists is analyzed, and the single products with larger positive correlation with the top 20 lists are selected as the subsequent selection of products, and the single products with larger negative correlation with the top 20 lists are excluded, so as to reduce the impact on the sales of the main commodities with higher scores, i.e., we select the single products that are in the relationship of the top 20 lists as the complementary commodities to each other, so as to increase the driving force of their sales, thus maximizing the profit of the superstore.

We find the correlation coefficients of the 20 list items and the top 20 list items one by one, and find the weighted total correlation coefficient, as shown in Figure 3 below:

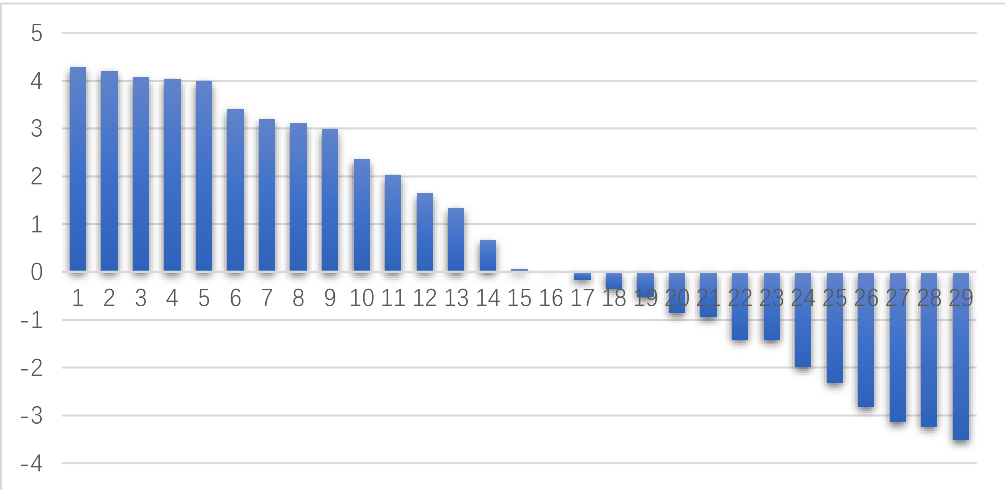

Figure 3. Weighted correlation coefficient diagram.

Get the bar chart as shown in the figure, because the topic requires the selection of 27 items, according to the bar chart gradient analysis, we can observe that there is an obvious cliff drop at 9-10 items, so it is more reasonable for us to choose 9 items. As shown in Table 3 below. To sum up, we have selected a total of 29 items as items in the replenishment plan.

Table 3. Correlation ranking table

Importance ranking	Vegetable singles
1	Combination of ginger, garlic and millet pepper (small portion)
2	Combination of green, red and Hangzhou pepper (part)
3	Scattered flowers from green stem of Zhijiang River
4	Green pepper (portion)
5	Spinach (portion)
6	Cordyceps sinensis flower (part)
7	Fresh fungus (portion)
8	Crab-flavored mushroom and white jade mushroom (box)
9	Purple eggplant (1)

3.2. Establishment of Integer nonlinear programming Model

3.2.1 decision variables.

$DJ_n{}^p$: indicates the pricing strategy of the nth item sold on July 1, where p indicates that the item belongs to the category, and its pricing strategy on that day will directly affect the profit of the merchant.

$BH_n{}^p$: represents the replenishment of the nth item sold on July 1, where p indicates that the item belongs to the category, $BH_n{}^p$ is an integer variable, and its specific value will directly affect the cost value of the daily category.

$r_{n,p}$: indicates whether the goods sold on July 1 belong to category p, which is a variable of 0-1. If it belongs to category p, then $r_{n,p}$ takes 1, and if it does not belong to category p, then $r_{n,p}$ takes 0.

3.2.2 objective function.

In order to maximize the revenue of the merchant, the following is to integrate the maximum revenue in the coming week and develop a dynamic programming model according to the wholesale prices of different categories every day. The final objective function is as follows:

$$Z_1 = \max \sum_{n=1}^{29} (DJ_n{}^p XL_n{}^p - BH_n{}^p PF_n (1+\beta_n)) \tag{17}$$

PF_n indicates the recent wholesale price of the nth item on July 1st, and β_n represents the wholesale price of the nth item.

3.2.3 constraints.

(1) Category replenishment constraints: the selected 29 items should meet the market demand as far as possible, so this paper restricts that replenishment should meet the daily demand of each category, that is, the following formula:

$$\sum_{n=1}^{29} r_{n,p} BH_n{}^p \geq XL^p (p = 1, 2, \cdots, 6) \tag{18}$$

Where XL^p represents the demand predicted by category p on July 1.

(2) Single item replenishment constraint: the minimum display quantity of each item in Shang Chao is 2.5kg, so the replenishment quantity of Shang Chao in replenishment should be greater than the minimum display quantity, otherwise it cannot be displayed on the same day, and most items can no longer be sold every other day, so the supply and sales volume of each category should meet:

$$GH_n{}^p \geq 2.5 (n = 1, 2, \cdots, 29)(p = 1, 2, \cdots, 6) \tag{19}$$

(3) Pricing constraints: the pricing of 29 items should obey the objective law of the pricing history of the item, and the pricing range of the nth item should be between the maximum and minimum historical pricing of the first category, for example, the historical pricing of the second category should be between DJ_{nmax} and DJ_{nmin}, so the pricing strategy of each category should meet:

$$DJ_{nmin} \leq DJ_n{}^p \leq DJ_{nmax} (n = 1, 2, \cdots, 29)(p = 1, 2, \cdots, 6) \tag{20}$$

(4) Sales volume constraints: this paper obtains the relationship between sales volume and pricing by fitting the relationship between pricing and sales volume of 29 kinds of products, so the daily sales volume and cost plus pricing should meet:

$$XL_n^p = f(DJ_n^p)(n = 1, 2, \cdots, 29)(p = 1, 2, \cdots 6) \tag{21}$$

Where $f_n(x)$ represents the correlation function between the pricing and sales volume of the nth item.

(5) Restriction on the sales quantity of each category on the same day: the sales volume of each category shall meet the objective law of historical sales of each category, and the future sales volume

of the first item shall be between the maximum and the minimum of the historical sales volume of the first item. For example, the sales quantity of the first item on July 1st should be between XL_{nmin} and XL_{nmax}, so the sales volume of each category should meet:

$$XL_{nmin} \le XL_n^{\ p} \le XL_{nmax}(n=1,2,\cdots,29)(p=1,2,\cdots,6) \tag{22}$$

(6) Restriction on category sales quantity: the total category sales volume should meet the objective law of category historical sales, and the daily sales volume in the coming week should be between the maximum and minimum historical sales volume of each day in the previous three years, so the sales volume of each category should meet:

$$\min\sum_{n=1}^{29} r_n^p XL_n^p \le \sum_{n=1}^{29} r_n^p XL_n^p \le \max\sum_{n=1}^{29} r_n^p XL_n^{\ p}(p=1,2,\cdots,6) \tag{23}$$

3.2.4 Formula Integration

$$Z_1 = \max\sum_{n=1}^{29}(DJ_n^{\ p} XL_n^{\ p} - BH_n^{\ p} PF_n(1+\beta_n)) \tag{24}$$

$$s.t.\begin{cases} \sum_{n=1}^{29} r_{n,p} BH_n^{\ p} \ge XL^p(p=1,2,\cdots,6) \\ DJ_{nmin} \le DJ_n^{\ p} \le DJ_{nmax}(n=1,2,\cdots,29)(p=1,2,\cdots,6) \\ GH_n^{\ p} \ge 2.5(n=1,2,\cdots,29)(p=1,2,\cdots,6) \\ XL_n^p = f(DJ_n^p)(n=1,2,\cdots,29)(p=1,2,\cdots 6) \\ XL_{nmin} \le XL_n^{\ p} \le XL_{nmax}(n=1,2,\cdots,29)(p=1,2,\cdots,6) \\ \sum_{n=1}^{29} r_{n,p} BH_n^{\ p} \ge XL^p(p=1,2,\cdots,6) \\ r_n^p = 0 or 1(n=1,2,\cdots,29)(p=1,2,\cdots,6) \end{cases}$$

3.3. solution of optimization model.

(1) simulated annealing algorithm.

The intelligent algorithm of simulated annealing is selected to solve the planning model. Simulated annealing is an intelligent algorithm based on Monte Carlo model.

In this paper, the approximate maximum value is obtained by using Monte Carlo for 100000 simulations. the replenishment scheme and pricing strategy are shown in Table 4 below, showing only the replenishment and pricing strategies of the first 10 items.

Table 4. List of replenishment and pricing plans for individual items on July 1

Single product	Replenishment plan	Pricing scheme
Broccoli	18	15.73
Scattered flowers from green stem of Zhijiang River	11	3.08
Yunnan lettuce (part)	51	4.76
Yunnan rapeseed (portions)	20	11.62
Bamboo leaf vegetable	12	18.56
Baby vegetable	17	8.06
Amaranth	15	1.14
Spinach (portion)	16	2.28
Millet pepper (portion)	5	17.73

Through Table 4, combined with the predicted consumption plan, it is concluded that the maximum profit rate for the day is 2098.17 yuan. Through the data in Table 5, we can see that the supply volume of six categories meets the historical distribution law of each category, which can meet the prerequisite of market demand for all kinds of vegetable commodities.

Table 5. Distribution table of supply volume of individual categories

Category	Cauliflower	Mosaic class	Aquatic root	Eggplant	Edible fungi	Capsicum
Supply quantity	29	131	109	33	57	21

4. Conclusions

This paper excavates the relationship between categories and individual products, and formulates the enterprise replenishment plan and pricing strategy under different circumstances. First of all, 49 kinds of vegetable products are selected for sale, and the TOPSIS method based on entropy method is used to select the top 20 items as the first level index, historical sales rate, average daily sales volume, variance of sales volume, vegetable loss rate and unit profit as the second index. Then, based on the concept of complementary goods and alternative goods, according to the Spearman correlation coefficient, through the weighted correlation coefficient method to select the top 9 items, such as ginger, garlic, millet pepper combination and so on. Using the selected single product, the objective function is established with the maximum profit of fresh merchants, and the demand of each category is taken as the constraint condition, the 0-1 integer nonlinear programming model is established, and then the programming is simulated and solved for 1000000 times by simulated annealing algorithm. the pricing strategy and supply plan of the enterprise on July 1st are obtained, and the maximum profit on July 1st is 2098.17 yuan.

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