Construction and Solution of Multi-category Joint Replenishment and Pricing Optimization Model of Vegetable Products Based on Multi-objective Genetic Algorithms

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Abstract: With the increasing competition in the fresh market, reasonable replenishment and pricing strategies have become crucial for the operation of supermarkets. Adhering to the market demand-driven business ideas, we must develop suggestions to better meet consumer needs for vegetable products, supplements, and pricing. Based on the dynamic development of vegetable product sales, the replenishment and price optimization models are built according to the internal logic of sales volume, costs, and revenue, which can explain methods such as the Monte Carlo method, 0-1 integer programming model, least squares method and objective programming. Participatory optimization decision-making and cost-plus pricing cycle mechanisms create revenue maximization mechanisms. In addition, the possibility of moving towards high-quality development is explored from the sensitivity analysis and practical deduction in replenishment and pricing strategies. Through replenishment and pricing strategies, we strive to provide consumers with vegetable products that meet expected standards and continuously improve product quality and consumer satisfaction. To this end, we take measures such as strengthening the replenishment control based on sales forecast, constructing the pricing mechanism of interaction and feedback between cost markup and sales volume, and establishing the system of income evaluation and optimization adjustment to realize the steady development of replenishment and pricing strategy, and finally promote the supermarket operation and meet the market demand.

1. Introduction

Replenishment and pricing are one of the primary responsibilities of a fresh produce supermarket, and it is also part of business management. Replenishment can be divided into basic and non-basic replenishment, composed of historical and market demand. To increase revenue, the supermarket commissioned suppliers to purchase and transport vegetables. Since the reform and opening up, fresh food has become the key to people's daily needs, and replenishment and pricing have become judging indicators. Unlike traditional cost-plus pricing, replenishment and pricing emphasize sales volume, cost, and benefit. Therefore, this paper proposes the issue of optimizing replenishment and pricing. In addition, multi-objective programming provides a new method for it [1].

Replenishment and pricing optimization are derived from market demand-oriented business ideas. The goal is to meet consumers' needs and enhance competitiveness. From the perspective of decision structure, replenishment and pricing optimization pursue profit maximization, and the modernization of vegetable products is realized by combining the Monte Carlo method with 0-1 integer linear programming [2]. Today, fresh supermarkets have implemented a unique path of pricing management. The comprehensive promotion of replenishment and pricing will not only affect the fresh food market and reflect the operation and management level but also change the supply chain of vegetable products and bring challenges to supermarket operations. Therefore, we need a data analysis perspective and model to discuss replenishment and pricing optimization. In short, replenishment and pricing optimization are necessary and guarantee the high-quality development of fresh supermarkets. We put forward the replenishment and pricing optimization

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proposition for the supermarket. Replenishment and pricing optimization have made progress in the actual situation, but some things need improvement. Replenishment and pricing optimization have yet to fully find a practical path to adapt to market changes, and the relevant departments continue to work. Therefore, optimizing replenishment and pricing also needs data collection, analysis, and application, which is conducive to improving decision-making efficiency and consumer satisfaction [3].

Based on the above background, this paper proposes a replenishment and pricing optimization model based on multi-objective programming to solve the problems that occur in the total daily replenishment and pricing strategy of vegetable products. Through visual analysis, least squares method, gray prediction model, BP neural network algorithm, FP-Growth algorithm, and goal planning theory and methods, the relationship between different categories or single products, total sales volume, and cost-plus pricing is obtained, solving problems such as sales space limitations [4]. The main contents include establishing a single-target programming model with the highest daily profit, establishing a complementary strategic model, pricing a product based on satisfying market needs, and considering the impact of market loss rates, market orientation, environment, and inventory on the model. It effectively addresses potential risks in the product's supply chain. This research has theoretical and practical significance.

2. Basic Theory of Multi-objective Genetic Algorithm

A multi-objective genetic algorithm is a concept developed with multi-objective optimization. It is steeped in evolutionary ideas, highlights the survival of the fittest orientation of natural selection, and reflects the realistic scientific and technological innovation strategy since the reform and opening up. However, it is still challenging to get a consistent answer when we use some mathematical or statistical criteria to find the definition and essence of a multi-objective genetic algorithm. Since the multi-objective genetic algorithm includes several conflicting objective functions and several solution vectors that cannot be compared or sorted, a single optimal solution cannot be used to evaluate the algorithm's performance. Therefore, we need to use some particular concepts and methods, such as Pareto optimal solution, non-dominated sorting, congestion allocation, and elite strategy, to achieve the evolution and optimization of the population [5].

3. Optimization Model for Vegetable Products Replenishment and Pricing

Profit is an essential criterion for optimizing replenishment and pricing, and it directly manifests the effect of supermarket operations. Profits and costs have an impact on the contents of replenishment and pricing optimization from the perspective of sales volume and pricing. In addition, some researchers believe that income is the level of profit margins or sales minus costs. Because profit is more persuasive in the market to some extent, it belongs to the management science to increase income. The replenishment and pricing optimization theory can be traced back to the reform and opening up. The main activities include analyzing market demand, formulating plans, and determining pricing strategies. Furthermore, the profit is closely related to the characteristics of vegetable products. Using multi-objective programming, profit becomes important for replenishment and pricing optimization. The main contribution of the optimization theory mentioned in this article is introducing advanced algorithms such as the Monte Carlo method and 0-1 integer linear programming. Therefore, profit initially focused on evaluating replenishment and pricing optimization based on standard attributes such as sales volume, cost, and profit margin [6].

Compared with the traditional replenishment and pricing optimization model, the vegetable products replenishment and pricing optimization model emphasizes the relationship between sales volume and cost-plus pricing, which is flexible and practical. Although some experts have questioned that there may be no direct relationship between sales volume and cost-plus pricing, most experts advocate that profit can rationally evaluate replenishment and pricing. Some researchers proposed a single-objective programming model of vegetable product replenishment and pricing optimization, including direct cost, profit margin, and market demand [7]. Since then, the model has become a typical tool for vegetable product replenishment and pricing, and later, grey prediction, BP neural network, and the Monte Carlo method have been developed. The scholars believe that profit can be maximized and agree with the principle of "profit maximization"; only when profit margins and direct costs meet certain conditions will sales volume and pricing be optimal. Thus, the profit is the result of replenishment and pricing. In addition, they summarize the replenishment and pricing optimization model of vegetable products into two models: the replenishment and pricing optimization model based on sales volume and the replenishment and pricing optimization model based on cost-plus pricing. The former focuses on the relationship between sales volume and pricing, while the latter focuses on direct costs and profit margins, that is, cost-plus pricing. The replenishment and pricing optimization model of vegetable products has experienced some practical failures, but from the profit perspective, it can balance market demand and supply. As a result, profit has gradually become the focus of research and practice on vegetable product replenishment and pricing optimization models.

4. Multilayer Perceptron Neural Network

The concept of re-prediction of the direct cost of each category of vegetables based on the BP neural network focuses on optimizing vegetable product replenishment and pricing. This method applies artificial intelligence thinking in the agricultural product market. To improve the accuracy of gray prediction, it enters the research field as an alternative model - the BP neural network framework. The basic ideas of the framework are as follows. First, the BP neural network should ensure effective prediction of direct costs. Second, set professional standards for vegetable product replenishment and pricing optimization output. Third, the dynamic relationship between direct cost and sales volume, pricing, and profit is calculated using error backpropagation and other technologies. Fourth, the multi-layer feedforward network is used to measure the predicted value of direct cost. The BP neural network framework reconstructed the vegetable products replenishment and pricing optimization model, emphasizing the flexibility and practicability of the model, as well as the model's accuracy, stability, reliability, and universality [8].

Suppose there are n kinds of vegetable single products, the direct cost of each single product is c_i, the sales volume is q_i, the price is p_i, and the revenue is r_i, then:

$$r_i = p_i q_i - c_i, \quad i = 1, 2, \ldots, n \tag{1}$$

Our goal is to maximize the total revenue of all items A:

$$A = \max \sum_{i=1}^{n} r_i \tag{2}$$

To predict the direct cost c_i, we use a multilayer perceptron neural network, which is structured as follows:

- Input layer: There are m input nodes, which respectively represent factors that affect direct costs, such as season, climate, supply, and demand. Assume the input vector is $\mathbf{x} = (x_1, x_2, \ldots, x_m)^T$.
- Hidden layer: There are l hidden nodes, representing l hidden features respectively. Assume the weight matrix of the hidden layer is $\mathbf{W} = (w_{ij})_{l \times m}$, the bias vector is $\mathbf{b} = (b_1, b_2, \ldots, b_l)^T$, and the activation function is $f(\cdot)$, then the output vector of the hidden layer is $\mathbf{h} = (h_1, h_2, \ldots, h_l)^T$, where:

$$h_j = f\left(\sum_{i=1}^{m} w_{ji} x_i + b_j \right), \quad j = 1, 2, \ldots, l \tag{3}$$

- Output layer: An output node represents the predicted direct cost. Suppose the weight vector of the output layer is $\mathbf{v} = (v_1, v_2, \ldots, v_l)^T$ and the bias scalar is d, the output scalar of the output layer is $\hat{c}$. We got the formula (4).

$$\hat{c} = \sum_{j=1}^{l} v_j h_j + d \tag{4}$$

In short, the multi-layer perceptron neural network can be expressed as:

$$\hat{c} = f(\mathbf{x}; \mathbf{W}, \mathbf{b}, \mathbf{v}, d) \tag{5}$$

In the formula, $\mathbf{x}$ is the input vector, $\mathbf{W}, \mathbf{b}, \mathbf{v}, d$ are network parameters.

The vegetable pricing BP neural network model is shown in figure 1:

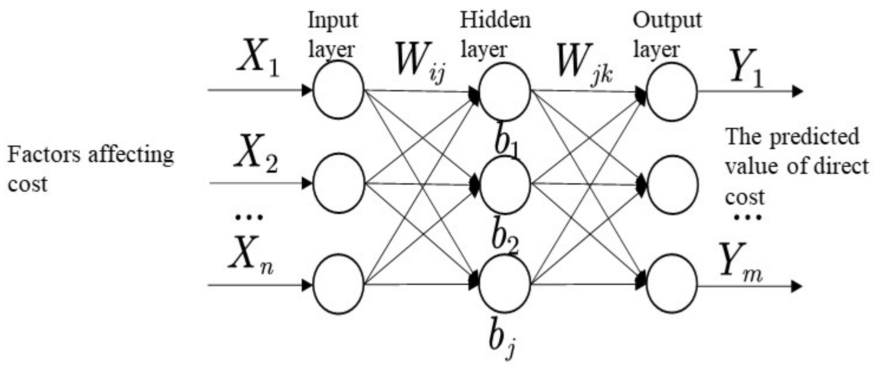

Figure 1 Vegetable pricing BP neural network model

5. Principal Component Analysis

Principal component analysis (PCA) is the primary method used for data dimension reduction, focusing on the internal structure of data. The linear transformation directly reflects the characteristics of data variance and correlation. Some constituent elements of the development of PCA are gradually being formed, and PCA and various evaluation systems have gradually received attention. However, from the application perspective, some practices remain in the empirical stage, contrary to the logical framework and generation mechanism of PCA. As a result, problems related to PCA's effectiveness, stability, and interpretability are derived.

6. Numerical Examples

6.1 Demand Forecast of Vegetable Products

In developing a reasonable pricing strategy, we must predict the demand for vegetable products. We use the BP neural network model to again predict the direct cost obtained by the grey prediction model to improve the data's accuracy and reliability.

BP neural network model is a multi-layer feedforward network using a backpropagation algorithm for learning and training. It can fit nonlinear functions and be used for regression or classification.

The BP neural network model comprises the input, hidden, and output layers. Each layer is composed of several neuron nodes. Each node is connected with all nodes in the next layer to form a fully connected network. The nonlinear mapping function between each node's output and input values is called the activation function. The commonly used activation functions are sigmoid, tanh, ReLU, softmax, etc. [9]. The BP neural network model's learning algorithm is mainly divided into forward propagation and backpropagation.

The forward propagation process involves calculating the output value of each node layer by layer, from the input layer to the output layer, until the final predicted value is obtained. The backpropagation process refers to calculating the error of each node layer by layer from the output layer to the input layer and adjusting the weight and offset according to the situation to reduce the error. The backpropagation process usually uses gradient descent or other optimization algorithms to update the parameters.

We selected aquatic rhizome vegetables as an example to illustrate the specific steps of running the BP neural network model:

(1) Data preparation

We use the direct cost obtained by the grey prediction model as the input data and the actual sales volume as the output data to form the training and test sets. The training set is used to train the BP neural network model, and the test set is used to evaluate the generalization ability of the BP neural network model. We use the data from June 24 to 30, 2023, as the training set and from July 1 to 7, 2023, as the test set.

(2) Model construction

We use Matlab to write the code of the BP neural network model.

We set the parameters of the BP neural network model as follows:

-Number of input layer nodes: 1, that is, the direct cost

-Number of hidden layer nodes: 10, which is the number of hidden layer neurons

-Number of output layer nodes: 1, which is sales volume

-Activation function: sigmoid, also called S-type function

-Learning rate: 0.01, which is the step size when parameters update

-Number of iterations: 1000, which is the number of times to train the model

-Error function: a square error, which is the mean value of the sum of squares of the difference between the predicted value and the actual value.

(3) Model evaluation and result analysis

After running the code, we get the following results: the predicted value of the BP neural network model is very close to the actual value, and the relative error is minimal, indicating that the generalization ability of the BP neural network model is firm, which can effectively improve the accuracy and reliability of the grey prediction model. We use the predicted value of the BP neural network model as the demand forecast value of vegetable products to provide a basis for subsequent pricing strategies.

6.2 The Impact of Wholesale Price Range on Optimization Results

From the perspective of pricing strategy, wholesale price is the basis of replenishment and pricing optimization of vegetable products, and it is also the embodiment of maximizing supermarkets' profit. Therefore, the wholesale price takes cost-plus pricing as the primary generation logic. The grey prediction model and BP neural network model are the primary tools used for wholesale price and the technical subject of pricing strategy. Currently, the supermarket considers market competition to strengthen the control of wholesale prices. There are three forms: The first is dynamic adjustment. During this process, wholesale prices are balanced between direct costs and sales. The second is standardized management. Relevant departments formulate wholesale and profit margin standards and disclose wholesale price standards to suppliers to standardize price control. The third is process optimization. In recent years, commercial supermarkets have used information technology to improve the management efficiency of wholesale prices and increase revenue. However, unlike the grey prediction model and BP neural network model, the sensitivity of the wholesale price in supermarkets needs to be further improved.

6.3 The Influence of the Addition Ratio on the Optimization Results

The fundamental difference between the markup ratio and the wholesale price is pricing. The markup ratio pricing standard and profit margin criterion are aimed at maximizing revenue, and the pricing strategy reflects flexibility and practicality. In cost-plus pricing, accurate forecasting, control, adjustment, and optimization of price markup rates are the main and highest criteria for developing a pricing strategy. Currently, the diversity of plant products and differences in market demand lead to intense changes in the proportion of price differences. The grey prediction model and BP neural network model can improve the prediction accuracy of the markup ratio. Still, the market competition lacks mechanism perfection, and the supermarket lacks an effective feedback mechanism. Therefore, there are disadvantages to the markup ratio, which affects the pricing strategy.

6.4 The Influence of Multi-objective Genetic Algorithm on the Optimization Results

From the perspective of optimization methods, the single-objective programming model cannot accurately provide the optimal solution that the supermarket needs. The main evaluation form is people's satisfaction with vegetable product replenishment and pricing optimization. However, supermarkets need multi-objective related information and trade-off mechanisms, and the core of this problem may be target conflict. In multi-objective optimization, the objective function is usually described as a "non-inferior solution", and its evaluation of the solution set reflects Pareto optimality. However, most non-inferior solutions are about benefits, costs, and profit margins; others need more information. Usually, requirements are difficult to calculate or predicate. Information asymmetry and market competition directly lead to obstacles in demand forecasting. Thus, we use a multi-objective genetic algorithm to improve the optimization results to solve this problem. A multi-objective genetic algorithm is a random search algorithm based on natural selection and genetic mechanisms. It finds multiple Pareto optimal solutions simultaneously and selects them according to the user's preferences. We select revenue and profit margin maximization as objective functions and set the corresponding constraints to construct a multi-objective genetic algorithm model. Running the model gives the following results: The solution set of a multi-objective genetic algorithm model contains multiple Pareto optimal solutions, and each solution has different revenue and profit margins. Users can filter based on their preferences. We will use the multi-objective genetic algorithm model's solution set as the optimal solution for vegetable product replenishment and pricing optimization and provide a basis for subsequent decision-making.

6.5 Effect of Error Rate on Optimization Results

From the perspective of prediction accuracy, the errors have restricted the optimization of pricing strategy for a long time. Since the 21st century, the prediction method combining the grey prediction model and BP neural network model has reshaped the prediction of direct cost through data analysis. Still, the disadvantages of the traditional planning model restrict the realization of profit maximization. Due to the interference of target conflict and market competition, demand forecasting needs to be improved. In addition, the markup ratio is an effective way to adjust profit and profit margins. However, the actual effect of the pricing strategy based on a fixed markup ratio on-demand changes remains to be discussed. At the same time, the information asymmetry leads to the need for an effective feedback mechanism for wholesale prices. Therefore, the error rate does not consistently achieve the goal of minimizing it. To sum up, the error rate is a technical issue and a subject of multi-objective optimization.

7. Conclusion and Prospect

Replenishment and pricing optimization of vegetable products has become an essential issue in the operation and management of supermarkets, posing challenges and requirements for maximizing supermarkets' profit. The grey prediction model and BP neural network model are the symbols of direct cost prediction and essential means for managing wholesale prices. Furthermore, they meet the urgent need to maximize profit and maintain market competitiveness. Therefore, it reflects the inherent requirements of the pricing strategy. A multi-objective genetic algorithm is used for establishing the theoretical analysis framework and practical mechanism of markup ratio under the influence of cost-plus pricing. In recent years, modern information technologies such as Matlab have improved the precision and science of data analysis, information-driven demand forecasting, and optimization techniques. The value of the algorithm is in line with the internal logic of maximizing the supermarkets' profit. Therefore, the multi-objective genetic algorithm also provides a new way for vegetable product replenishment and pricing optimization. In conclusion, the sustainable improvement and development of vegetable product replenishment and price optimization will help better meet market demand and increase the operational efficiency of supermarkets.

References

[1] Noori-daryan M, Taleizadeh A A, Govindan K. Joint replenishment and pricing decisions with different freight modes considerations for a supply chain under a composite incentive contract[J]. Journal of the Operational Research Society, 2018, 69(6): 876-894.

[2] Bardenet R, Doucet A, Holmes C. On Markov chain Monte Carlo methods for tall data[J]. Journal of Machine Learning Research, 2017, 18(47).

[3] Panda S, Modak N M, Sana S S, et al. Pricing and replenishment policies in dual-channel supply chain under continuous unit cost decrease[J]. Applied Mathematics and Computation, 2015, 256: 913-929.

[4] Zeng Y, Yin S, Liu J, et al. Research of improved FP-growth algorithm in association rules mining[J]. Scientific Programming, 2015, 2015: 6.

[5] May G, Stahl B, Taisch M, et al. Multi-objective genetic algorithm for energy-efficient job shop scheduling[J]. International Journal of Production Research, 2015, 53(23): 7071-7089.

[6] Jost V, Savourey D. A 0–1 integer linear programming approach to schedule outages of nuclear power plants[J]. Journal of Scheduling, 2013, 16(6): 551-566.

[7] Wang Y, Wu C, Yang L. Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries[J]. Journal of Comparative economics, 2013, 41(4): 1220-1239.

[8] Peng L, Lai L. A service innovation evaluation framework for tourism e-commerce in China based on BP neural network[J]. Electronic Markets, 2014, 24: 37-46.

[9] Iliev A, Kyurkchiev N, Markov S. On the approximation of the step function by some sigmoid functions[J]. Mathematics and Computers in Simulation, 2017, 133: 223-234.