Pricing and Replenishment Decision System Based on LSTM

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Abstract. Fresh supermarket vegetables have a very short shelf life, and the quality of vegetables will also be affected by the storage time. If most of the goods are not sold on that day, they will not be sold on the next day. From the demand side, the sales volume of vegetables is related to the supply side of vegetables from April to October. At the same time, the sales space of the supermarket is limited, which makes a reasonable sales portfolio extremely important. The commercial overpricing replenishment decision system based on LSTM analyzes the relationship between daily sales volume and cost-plus pricing for each vegetable category and single product over three years. It predicts the sales volume and wholesale price of each category for the next week, determining replenishment volume and pricing strategy based on forecasted sales volume and average loss rate. The system considers limited sales space and uses the entropy method to calculate weights for key indicators like total profit. It employs the TOPSIS method to sort items, considering forecasted wholesale prices, to select items for pricing decisions. The system aims to maximize total profit while ensuring the supermarket meets minimum display conditions. By assisting supermarkets in formulating more reasonable pricing strategies, it aims to reduce overstock, backlog, or stock shortages, ultimately improving sales volume and operational efficiency.

Keywords: Optimal Decision, LSTM neural network, Entropy weight method- TOPSIS, Regression Analysis, Target Planning.

1. Introduction

Fresh vegetables in supermarkets perish quickly and deteriorate with time. Unsold items often carry over to the next day. Vegetable sales from April to October are tied to supply. Purchasing typically occurs between 3:00-4:00 am, so the supermarket must necessitate same-day replenishment decisions based on specific product details and prices. Meanwhile, limited shelf space underscores the importance of a strategic sales approach [1]. The Overpricing Replenishment Decision System (ORDS) uses a Long Short-Term Memory (LSTM) network to better understand long-term relationships and handle multiple inputs in the vegetable category. Our data set is the sales data from a supermarket in Beijing from July 1, 2020, to June 30, 2023. It includes the commodity information of the 6 vegetable categories distributed by the supermarket, the sales flow details the related data of each commodity's wholesale price, and the recent loss rate data of each commodity. The innovation point of this paper is to propose a replenishment pricing system combining the LSTM model and entropy right-TOPSIS method according to the particularity of supermarket vegetable commodity procurement. The traditional supply and demand model cannot solve problems such as short shelf life, early purchase time, and sales affected by season and weather, while this system uses LSTM to predict weekly sales and wholesale prices for various vegetable categories, determining optimal replenishment quantities and pricing strategies. Additionally, the entropy-weighted TOPSIS method is used to identify daily replenishment priorities based on profit and other metrics and to forecast individual product replenishment quantities and prices. By the way, ORDS considers the sales and wholesale price of each vegetable item to forecast future sales volume and wholesale prices. It also takes into account the loss rate of each vegetable to determine the appropriate replenishment quantity and pricing. This helps to avoid inventory backlog or shortages and enables businesses to implement more reasonable pricing strategies, leading to improved commodity sales and more management efficiency [2-3].

The Economic Order Quantity (EOQ) model is a classical inventory management tool used to determine the optimal order quantity that minimizes the total cost of inventory. The traditional EOQ model assumes that the demand is stable and independent, regardless of the sales time variation and seasonal factors. However, the sales volume of vegetable commodities is usually affected by the season, weather, and other factors, leading to the temporal variation of the demand, which is inconsistent with the assumptions of the EOQ model. In addition, there are many categories of vegetables. The EOQ model assumes that only a single type of goods needs to be replenished, without considering the sales mix of multiple commodities [4]. In fact, in supermarkets, there is a sales combination effect between different vegetable categories, while the EOQ model cannot consider this complex situation. Compared with the EOQ model, ORDS not only considers the economy of order volume but also considers the sales volume and loss rate, to make more comprehensive replenishment and pricing decisions.

On the other hand, Markov chain models are useful for predicting future states based on the current state, without needing historical data. However, the predictions of Markov chains are based only on the current state, sensitive to the initial state, and do not consider historical state effects. Therefore, it may not capture long-term dependencies, and different initial state choices may also lead to completely different prediction results. Moreover, to apply the Markov chain, it is required to meet the Markov conditions, meaning that the daily sales situation is only related to the previous day, which is not in line with the actual situation of supermarket vegetable goods sales [5]. Compared with the Markov chain prediction model, ORDS uses the LSTM model to predict the sales volume and wholesale price, and can more accurately predict the sales volume and wholesale price of each category in the next week, without requiring the data to meet the Markov conditions.

Similarly, the ARIMA model is widely used for forecasting stable or approximately stable time series data. While it is powerful for certain applications, it may perform poorly when dealing with non-linear and non-stationary data and requires data preprocessing to achieve good results, making it less suitable for the scenario of supermarket replenishment pricing. Furthermore, the ARIMA model may be limited by the number of lag terms when dealing with long-term dependencies, making it difficult to capture all the patterns and trends in the data. Compared with the ARIMA model, the LSTM-based system is highly adaptable and suitable for non-stationary data, which is more flexible in dealing with different types of data and problems [6].

2. The Fundamentals and Principles of Overpricing Replenishment Decision System

2.1. Cost-plus Pricing

The cost-plus pricing method is the method to set the product price according to the unit cost of the product plus a certain proportion of the profit, that is, the method to increase a part of the profit in the product cost. It is set as the daily selling price, the daily unit cost, the daily average cost of a category, the number of items sold daily, the average selling price of a daily category, and defined as the total daily sales of a category. The cost plus pricing is set as, and the cost plus ratio is β, which is the daily profit of one category.

2.2. Structure of the Long Short-Term Memory Model

Long Short-Term Memory (LSTM) networks are a commonly used architecture of Recurrent Neural Networks (RNNs), particularly suited for handling and predicting time series data. Compared to standard RNNs, LSTMs have enhanced memory capabilities, allowing them to better manage long sequences of data and avoid the issues of gradient vanishing and gradient explosion commonly encountered in traditional RNNs [7]. An LSTM network consists of three types of gates: the input gate, the forget gate, and the output gate. The input gate controls the input data flow, the forget gate manages the information to be discarded, and the output gate regulates the output of the cell. These gates collectively determine how information is retained or ignored, thereby improving the network's ability to capture long-term dependencies within the sequence. The network structure is shown in Figure 1.

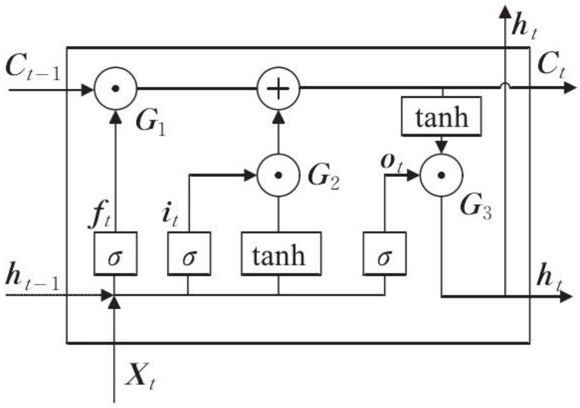

Figure 1. Neural network structure

The general model of the LSTM consists of three basic elements, which are:

(1) Forget gate: decide which information to discard from the cell state. By entering the input x_t at the current moment and the hidden state h_{t-1} at the previous moment, through a sigmoid function, we output a value between 0 and 1, representing the proportion of information to be retained, where W_f is the forgetting gate weight matrix, and b_f is the forgetting gate bias vector. The calculation formula is as follows:

$$f_t = \sigma[W_f(h_{t-1}, x_t) + b_f] \tag{1}$$

(2) Input gate: Determine which new information to add to the cell state. The updated candidate values are first determined by a sigmoid function, and then a candidate value vector is created through a tanh function representing the new information to add. Similarly, W_i, W_c represents the input gate weight matrix and the candidate value weight matrix, b_i, b_c means the input gate bias vector and candidate value bias vector, C_t is the candidate value, representing the new information to be added to the cell state, the candidate value weight matrix, and the candidate value bias vector. Finally, the output of the forgetting gate is multiplied by the candidate values to obtain the cell state to be updated. The calculation formula is as follows:

$$\mathrm{i_t} = \sigma(\mathrm{W_i} \cdot [h_{\mathrm{t-1}}, \mathrm{x_t}] + \mathrm{b_i}) \tag{2}$$

$$\tilde{\mathrm{C}}_\mathrm{t} = \tanh(\mathrm{W_C} \cdot [h_{\mathrm{t-1}}, \mathrm{x_t}] + \mathrm{b_C}) \tag{3}$$

$$\mathrm{C_t} = \mathrm{f_t} \cdot \mathrm{C_{t-1}} + \mathrm{i_t} \cdot \tilde{C}_\mathrm{t} \tag{4}$$

(3) Output gate: It determines the final hidden state h_t. The part of the cell state to be output is first determined by a sigmoid function, and then a vector containing the current cell state is obtained by a tanh function. W_o is the output gate weight matrix, while b_o stands for the output gate bias vector. Finally, it is multiplied by the output of the output gate to obtain the final hidden state. The calculation formula is as follows:

$$\mathrm{o_t} = \sigma(\mathrm{W_o} \cdot [h_{\mathrm{t-1}}, \mathrm{x_t}] + \mathrm{b_o}) \tag{5}$$

$$h_\mathrm{t} = \mathrm{o_t} \cdot \tanh(\mathrm{C_t}) \tag{6}$$

Compared with the standard RNN, LSTM has stronger memory ability and can handle the long sequence data better, avoiding the problem of gradient disappearance and gradient explosion in the conventional RNN, so it is suitable for various time-series prediction and processing tasks [8].

2.3. TOPSIS comprehensive evaluation method combined with Entropy right

According to the definition and principle of information entropy, when the system may be in several different states and the probability of each state is p_i (i=1, 2, ..., m), and the entropy of the system can be defined as:

$$e = -\frac{1}{\ln m}\sum_{i=1}^{m} p_i \ln p_i \tag{7}$$

As an objective weight setting method, the entropy weight method calculates the entropy right of each index according to the information entropy of each index, to get the more objective index weight. The TOPSIS method is a comprehensive evaluation scheme, whose core idea is to find the optimal scheme and the worst scheme in the limited scheme, and then calculate the distance between the evaluation object and the optimal scheme and the worst scheme respectively, and take this as a basis to evaluate the quality of the sample [9]. Here are the evaluation steps:

(1) There are n evaluation objects and m evaluation index variables, and the value of the j index variables of the i (i=1, 2, ..., n; j=1, 2, ..., m) evaluation object is to construct the data matrix A.

Using the original data matrix A, that is, the proportion of the j index variable of the i evaluation object:

$$\text{Per}_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{jj}} \tag{8}$$

(2) Use Equation (4) to calculate the entropy value of item j index, which is e_j;

(3) The coefficient of variation of the jth index was calculated, which is g_j

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

(4) The weight of item j index, w_j, is calculated:

$$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \tag{10}$$

(5) Calculate the comprehensive evaluation value of the i th evaluation object, which is v_i:

$$v_i = \sum_{j=1}^{m} w_j \text{Per}_{ij} \tag{11}$$

Then, find out the optimal values and the worst values of each index, and establish the optimal value vector z + and the worst value vector z –.

$$\mathrm{z}^{+} = \max_{n_j}\left(\mathrm{z}_1^{+}, \mathrm{z}_2^{+}, \cdots, \mathrm{z}_\mathrm{p}^{+}\right) \tag{12}$$

$$z^{-} = \min_{n_j}\left(z_1^{-}, z_2^{-}, \cdots, z_p^{-}\right) \tag{13}$$

After that, calculate the distance between the individual evaluation object and the best value and the worst value [10]. The distance defined from the optimal solution is D_i^+, the distance from the worst solution is D_i^-, and the score of the first scheme is recorded as R_i:

$$D_i^+ = \sqrt{\sum_j \left(z_{ij} - z_j^+\right)^2}, D_i^- = \sqrt{\sum_j \left(z_{ij} - z_j^-\right)^2} \tag{14}$$

$$R_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{15}$$

3. Results

3.1. The establishment of ORDS

Firstly, the process begins with data preprocessing and modeling. Historical sales data is utilized to train an LSTM model, which then predicts the sales volume and wholesale price for each product category in the coming week. Following this, the replenishment volume for each category is determined based on the predicted sales volume and the category's average loss rate. Next, the pricing strategy is formulated according to the relationship between sales volume and cost-plus pricing. This strategic approach ensures that pricing is aligned with market dynamics and cost considerations. In the supermarket environment, the forecasted sales data is used to allocate sales space for vegetable goods and to set minimum display quantities on shelves. The entropy power-TOPSIS method is employed to identify which items should be replenished for the next day, guided by each item's profit index. The LSTM model's forecasts for item replenishment and pricing are integral to this process. Finally, an optimization model is established with item pricing as the decision variable, aiming to maximize the supermarket's total profit. This model is solved to derive the optimal replenishment and pricing strategy for future days, thereby enhancing revenue generation, ensuring efficient inventory management, and enabling strategic pricing decisions. For the sake of brevity and aesthetic appeal of the article, only some important results are presented here.

3.2. Forecast the daily replenishment and pricing in the coming week

3.2.1 Explore the relationship between the total sales volume and the pricing of each category

MATLAB is used to draw the daily sales, daily sales revenue, and daily profit of each category over time in the first three years. Since the sales volume of the category is 0, the price is not 0, which will cause great interference with the regression. Therefore, the daily sales volume of the category is removed before drawing the scatter map. And it is clear to see that the total category sales have a linear relationship with cost-plus pricing.

3.2.2 LSTM neural network training

The sales flow details and wholesale price of each commodity from July 1, 2020, to June 30, 2023, are selected as the original data. 80% of the data from the three years of data were randomly selected as the training set, and the remaining 20% as the test set. In terms of parameter selection, 1000 rounds of training were conducted, the maximum training period was 300, the gradient threshold was set to 1 to prevent gradient explosion, and the initial learning rate was set to 0.01. After 50 rounds of training, the learning rate was reduced by multiplying the factor of 0.5. The above parameters were preliminarily adjusted according to the experimental effect. To address the severe deviation from actual edible fungus predictions, the training set was adjusted using data from 600 to 1095. Here is a single example of an LSTM model predicting the wholesale price for cauliflower for the upcoming week, as shown in Figure 2, the blue line represents the actual sales, and the orange line represents the predicted sales. Overall, the forecast data can basically follow the trend of the actual data change. On the timeline axis, the two curves show similar trends, especially in the later stages, indicating that the LSTM model performs better in capturing the overall trend.

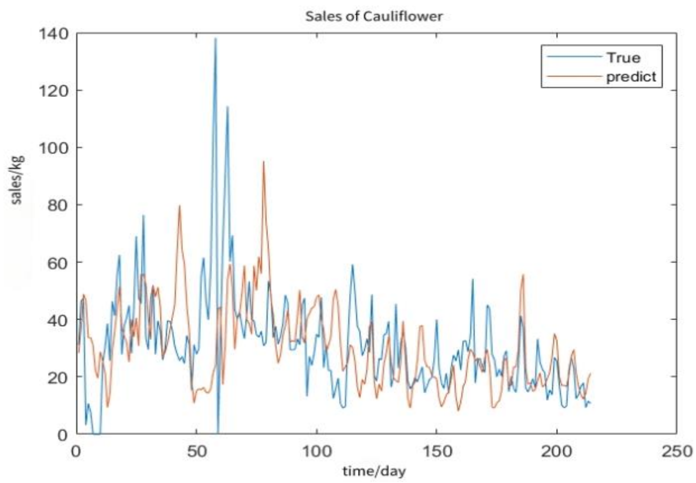

Figure 2. The Prediction of Next Week's sales of Cauliflower

3.2.3 According to the forecast results of each category of replenishment and pricing

First, the weight of the loss rate of each item is set as the ratio of daily item sales to daily category sales. The daily loss rate of a single item is l_i, the daily average loss rate of a category is L_j, and the daily replenishment amount of a category is S_j.

Then L_j can be expressed as follows:

$$L_j = \frac{\sum_{i=1}^{K} l_i n_i}{N_j} \tag{16}$$

S_j can be expressed as:

$$S_j = \frac{N_j}{1-L_j} \tag{17}$$

Using the data from Forecasted Sales for Each Category for the Upcoming Week and applying Formula (17), the daily restocking quantities for each category for the upcoming week are calculated. The results are shown in Table 1 (all results are rounded to two decimal places). Days 1-7 correspond to July 1, 2023, to July 7, 2023 (the upcoming week), and this applies throughout.

Table 1. Forecast of the replenishment volume of each category in the coming week

Date Replenishment /kg Categories	Foliage	Cauliflower	WaterRoot	Eggplants	Peppers	Mushroom
1	215.35	24.18	17.82	59.28	128.42	159.65
2	168.93	22.45	18.60	48.61	66.07	114.04
3	182.17	19.61	15.56	28.37	37.46	62.99
4	190.20	15.80	14.71	28.67	62.02	60.51
5	186.65	14.27	21.58	19.48	51.34	51.23
6	202.19	15.98	25.42	18.45	64.17	56.40
7	251.47	20.48	27.16	38.10	92.39	99.22

Then use Formula (16) and combine the sales volume and pricing relationship of 3.2.1 to calculate the pricing of each category in the next week. The final results are shown in Table 2.

Table 2. Pricing forecast of each category in the coming week

Date Price/yuan Categories	Foliage	Cauliflower	WaterRoot	Eggplants	Peppers	Mushroom
1	5.42	13.55	12.11	7.60	5.15	4.78
2	5.30	13.55	15.26	7.43	5.00	6.06
3	5.31	13.44	16.00	7.37	4.93	6.06
4	5.49	13.51	17.49	7.30	5.10	5.94
5	5.63	13.73	17.38	7.48	5.14	5.87
6	5.87	13.95	16.28	7.83	5.10	5.55
7	5.93	13.95	15.72	8.15	5.41	6.88

The system predicts the sales volume and wholesale price of each category in the coming week using the LSTM model, which determines the replenishment volume of each category in the coming week according to the predicted sales volume and category average loss rate and determines the pricing strategy according to the relationship between sales volume and pricing strategy of each category in the coming week.

3.3. Forecast the next day of single product replenishment volume and pricing

The previous forecasts for weekly replenishment quantity and pricing can serve as the overall decision-making basis for replenishment and pricing in supermarkets. Now, to obtain a more precise daily replenishment pricing strategy, we can predict future daily needs based on sales data from the previous week.

3.3.1 Basic assumptions

Based on the actual situation, business super vegetable goods sales space is limited, every day to display on the shelf item quantity is limited, vegetable item each order also has the minimum order limit, assume constraints for item order minimum to meet 2.5kg, shelf minimum display 2.5kg, available item between 27~33.

3.3.2 Rank available items based on entropy-TOPSIS

By 3.3.1 hypothesis, the total number of super available items should be controlled in 27-33, to screen out the future day replenishment item, which should be based on the sales data of the previous week, considering the replenishment item factors, establish the item evaluation index system, selected indicators include: item total sales, item total profit, item preservation rate (preservation rate for loss rate positive results, preservation rate =1-loss rate), item daily sales of more than 2.5kg of days. The final index values of the available items from 24 to June 30 (the previous week) are shown in Table 3.

Table 3. Distribution of the weights of each indicator

The index value of the available single item corresponds to the weight from June 24 to June 30			
Total Sales	Total Profit	Preservation rate	Days that sales volume above 2.5kg
0.3541	0.3364	0.0719	0.2376

By calculating the relative closeness of each evaluation object to the ideal solution, that is, near the positive ideal solution and far from the negative ideal solution, we can try to choose the best solution. The top 33 places with high scores and negative correlation coefficients were obtained.

3.3.3 Establish the regression and optimization model of single product sales volume-pricing

First, calculate the linear regression function $y = ax + b$ for the pricing of the sales volume of the top 33 items selected by the entropy weight method and TOPSIS. As a result, 33 sets of a and b are obtained. Then, use the LSTM model to predict the wholesale prices of individual items for the next day. Use sales data of each item from the past three years as the dataset, randomly selecting 80% for training and 20% for prediction, with parameters chosen as in section 3.2.2. The predicted results are plotted using MATLAB, as shown in Figure 3 [11]. According to the following figure, the 20th item stands out with a price close to 25 yuan, significantly higher than other items, Besides, items numbered 4, 12, 16, 25, and 32 also have relatively higher prices, each exceeding 5 yuan. Compared to data from previous years, this predicted result is consistent and rational.

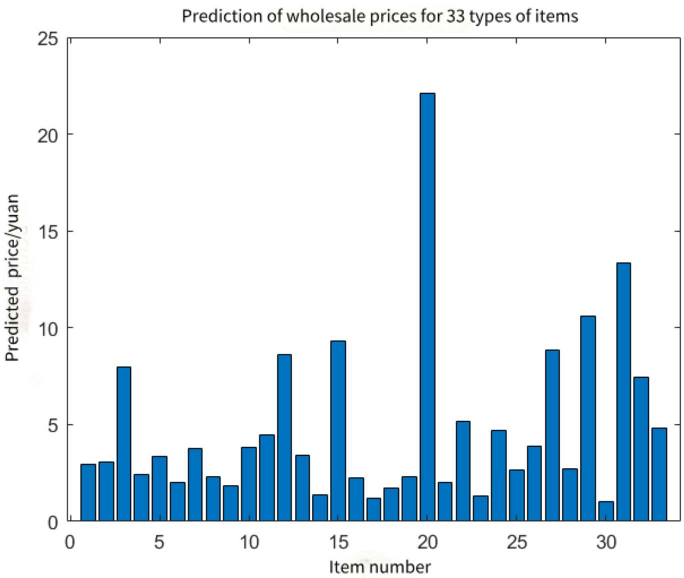

Figure 3. Prediction of Wholesale Prices for 33 Types of Items

To meet the market demand for each category of vegetable commodities, the LSTM model was used to predict the demand for the six categories. The prediction results are shown in Figure 4. It's clear to see that foliage has the highest predicted demand at nearly 190kg, peppers have a substantial predicted demand of around 110kg while mushrooms show significant demand at approximately 130kg. Cauliflower and water root show much lower predicted demands, slightly above 20kg and around 10kg. Based on historical sales data, the forecast is very reasonable.

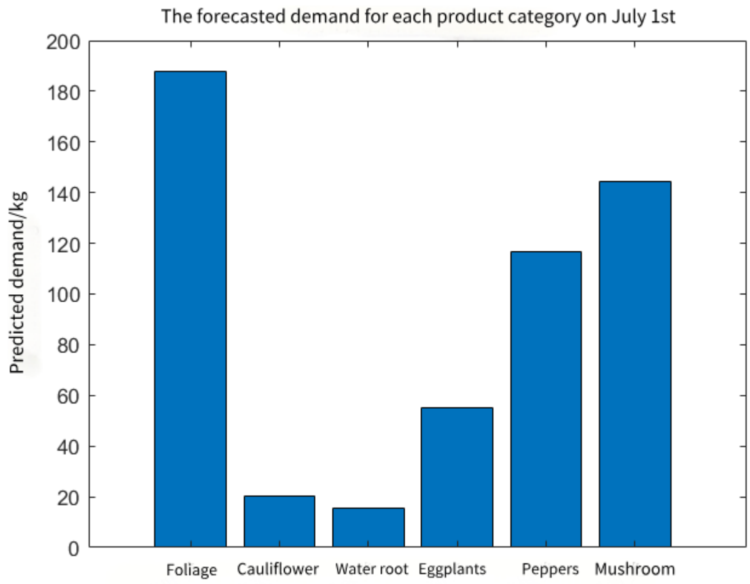

Figure 4. The Forecasted Demand for Each Product Category on July 1st

Finally, the MATLAB-yalmip optimization toolbox is used to establish a planning model with the pricing of each item as the decision variable and the total profit maximization of the supermarket as the target function. Constraints include:

(1) The minimum display volume is 2.5kg

(2) The ratio of the selling price of a single item to the forecast wholesale price (i. e., the cost-plus coefficient) is in line with the market law, somewhere between [1.3, 2.0]

(3) The predicted sales volume of each category reaches 0.7 times the demand

During the process of solving this model, the variables are set as the pricing of 33 types of items. The sales volumes of these items are obtained using the linear regression function mentioned earlier, multiplied by a set of correction coefficients σ, as expressed in Equation 18:

$$\sigma = 4\left(1.6 - \frac{p_i}{prdt_i}\right)^3 + 1 \tag{18}$$

Where the $prdt_i$ represents the wholesale price of a single product predicted for the LSTM model. After solving, there are 4 kinds of single products with a display volume of less than 2.5kg, so only the remaining 29 kinds are retained. Therefore, under the assumption that the minimum display amount of the shelf is 2.5kg and the number of optional items is controlled between 27 and 33, the final maximum daily total profit of the supermarket is 978.05 yuan.

It can be concluded that in business super according to the forecast sales to determine the vegetable goods sales space and the item shelf minimum display, the system will be based on each item profit index based on entropy power-TOPSIS method to determine the future day should replenishment item, based on the LSTM model forecast item replenishment and item pricing, established with item pricing decision variable, super total profit maximization as the target function planning model, solve the future of the day business super best item replenishment and pricing strategy, make the business super maximum revenue.

4. Conclusion

According to the characteristics of vegetable products with short shelf life, early purchase time, and sales affected by season and weather, a replenishment pricing system is constructed considering practical factors such as commodity loss, limited sales space, and limiting the minimum display amount of shelves. The system uses the historical sales data to predict the sales volume and wholesale price of each category in the coming week based on the LSTM model, determines the replenishment volume of each category in the coming week according to the predicted sales volume and category average loss rate; determines the pricing strategy according to the relationship between sales volume and cost-plus pricing, to provide the replenishment volume and pricing strategy of each category in the coming week. In business super according to the forecast sales to determine the vegetable goods sales space and the item shelf minimum display, the system will be based on each item profit index based on entropy power-TOPSIS method to determine the future day should replenishment item, based on the LSTM model forecast item replenishment and item pricing, established with item pricing decision variable, super total profit maximization as the target function planning model, solve the future of the day business super best item replenishment and pricing strategy, make the business super maximum revenue.

The proposed replenishment and pricing system for supermarket vegetables is highly feasible due to its comprehensive and practical approach. The system utilizes LSTM models to predict weekly sales and wholesale prices, ensuring accurate replenishment quantities that minimize waste and maintain freshness. By incorporating historical sales data and adjusting for seasonality and weather impacts, the model improves forecast accuracy and better manages inventory. Practical considerations such as product loss, limited sales space, and minimum shelf display requirements are factored in, making the model realistic and applicable. The pricing strategy is based on the relationship between sales and cost markup, providing effective weekly procurement and pricing strategies. Furthermore, the use of entropy-weighted TOPSIS for daily replenishment decisions ensures optimal choices by evaluating product profitability and other relevant metrics. Overall, the model's integration of advanced predictive analytics and real-world constraints demonstrates its high feasibility for effective vegetable procurement and pricing in supermarkets. In future research, the Support Vector Regression (SVR) algorithm could be employed for regression analysis, utilizing different kernel functions that may better reflect the relationship between sales volume and cost-plus pricing than linear regression. Additionally, when solving the optimization model, intelligent optimization algorithms such as simulated annealing, genetic algorithms, and particle swarm optimization should be considered. These heuristic algorithms can be used to find relatively optimal solutions, thereby avoiding the subjectivity caused by artificially adding constraints.

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