Research on Pricing and Replenishment Strategies of Supermarkets Based on PSO-LSTM- Transformer Models

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Abstract. The supermarket's role in ensuring market supply and enhancing livelihoods prompted the implementation of a new PSO-LSTM-Transformer hybrid model in this study. This amalgamation combines Particle Swarm Optimization (PSO), Long Short-Term Memory (LSTM), and Transformer to forecast commodity prices and inventory needs. By combining these methods, the research aimed to satisfy market requirements while maximizing grocery store profits and improving market operations sustainability.Particle Swarm Optimization (PSO) enhances prediction accuracy by effectively exploring the vast solution space for optimal solutions. Long Short-Term Memory (LSTM), which is known for capturing long-term data dependencies, enhances the comprehension and forecasting of market trends. Furthermore, the Transformer model enhances the forecasting process by capturing intricate patterns and relationships in market data through its attention mechanism.The research concludes that the PSO-LSTM-Transformer model effectively predicts commodity pricing and replenishment needs, thereby aiding supermarkets in making informed decisions to balance market demands and optimize revenue. The findings of the study contribute to the promotion of forecasting methods within the supermarket sector, facilitating efficient management of the market and sustainable economic growth.

Keywords: LSTM Algorithm, Transformer Algorithm, PSO-LSTM-transformer Algorithm, Replenishment Strategy.

1. Introduction

In the competitive retail industry, superstores encounter distinctive management obstacles while handling produce [1][2]. Vegetables possess a short shelf-life and undergo quality deterioration over time. Therefore, superstores need to precisely make replenishment decisions supported by restricted data, counting demand and sales history within the 3:00-4:00 a.m. stocking interval each day [3][4]. By doing so, they can ensure that the merchandise they display on their shelves remains fresh and visually appealing [5]. However, hypermarkets often lack precise information about individual item prices and stocking costs before making stocking decisions [6][7]. Supermarkets, on the other hand, typically employ a "cost-plus pricing" [8] approach to establish product prices while maintaining the flexibility to adjust prices to boost the sale of items that are prone to wear and tear or deterioration in quality.

This thesis aimed to help supermarkets address the challenges of managing produce merchandise, improving operational efficiency, and meeting customer demands. The market demands, encompassing sales trends, seasonal fluctuations, and shifts in consumer demand, were evaluated for improved precision of replenishment decisions by integrating machine learning models. Concurrently, consideration was given to seasonal vegetable supply factors and the implementation of sales strategies to overcome space constraints. The goal was to offer proficient management techniques that would foster market competitiveness while providing top-notch vegetable products and promoting the sustainable operation of supermarkets.

2. The basic funamental of PSO-LSTM-Transformer neural network

2.1. Long Short-Term Memory Network (LSTM)

LSTM tackles the issue of vanishing gradients by incorporating "gates" that act as a mechanism to control information flow. A singular LSTM cell houses three gates -- an input gate, a forgetting gate, and an output gate -- in addition to a cell state. These gates empower the LSTM cell to regulate what information enters its cell state, what data to discard, and when to present the contents of the cell state. By learning, these gates enable the network to automatically determine and retain the most critical data [9].

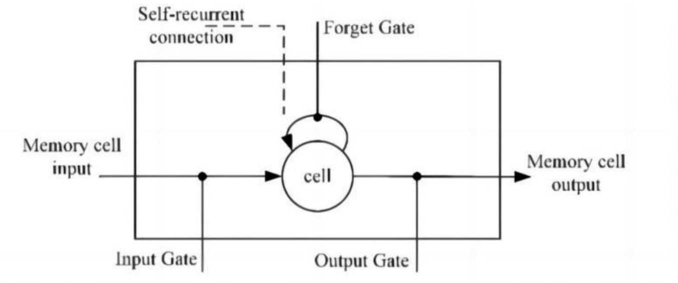


Figure 1 LSTM Algorithm

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

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

$$o_t = sigmoid(W_o \cdot [h_{t-1}, x_t] + b_o \tag{3}$$

$$\widetilde{c_t} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{4}$$

$$c_t = f_t \times c_{t-1} + i_t * \widetilde{c_t} \tag{5}$$

$$h_t = o_t \times \tanh(c_t) \tag{6}$$

Core Components:

Input gate decides what information to add to the cell state.

The forget gate decides what information should be removed from the cell state.

The cell state maintains long-term dependent information about data sequences that protects model learning.

The output gate regulates the information flow from the cell state to the output. Determining the output information from current input and cell state is a task performed.

By LSTM, a robust neural network architecture suited for analyzing data sequences with long-term dependencies.

2.2. PSO-LSTM- Transformer Modeling

Suppose a search space exists in a D-dimensional area and is populated with N particles. Each particle, represented by a D-dimensional vector, is denoted as i and has a position of Xi=(xi1,xi2,...,xiD), where i is equal to 1, 2, ..., N. The particle's "best" position is marked as pbest=(pi1,pi2,...piD), where i is equal to 1, 2, ..., N. Each position represents a plausible solution to the requirement. Each particle's position represents a potential solution to the requirement. These solutions can be substituted into the objective function to calculate the particle's fitness value, which measures its level of "goodness." The optimal position found by the entire population is referred to as gbest=(g1,g2,...gD). Abbreviations will be explained when first used. We will utilize a passive tone and focus on clear, objective language without biased or figurative expressions. The text will be structured in a logical flow with causal connections between statements. Furthermore, common academic sections will be included, and regular author and institution formatting will be maintained. The language will be formal, precise, and grammatically correct, with consistent citation and footnote style. These solutions can be substituted into the objective function to calculate the particle's fitness value, which measures its level of "goodness." The optimal position found by the entire population is referred to as gbest=(g1,g2,...gD). Usually, the range of positional change in the d-th dimension (1≤d≤D) is confined to [Xmin,d, Xmax,d], while the velocity change range is restricted to [-Vmax,d, Vmax,d]. If Vid or Xid surpasses the boundary value during an iteration, then the velocity or position of that dimension is restrained to the maximum velocity or boundary position of that dimension.

The PSO algorithm sets a penalty function method. If a solution does not meet the constraints, a penalty term is applied to the fitness value. The total penalty, P(x), is the sum of the individual constraint penalty terms [10].

$$P(x)=\sum_{i=1}^{l} e_i\ (x)+\sum_{j=1}^{m} e_j\ (x)=\sum_{i=1}^{l} max(0,-g_i(x))+\sum_{j=1}^{m} max(0,\left|h_j(x)\right|-\varepsilon) \tag{7}$$

$$L_j=\frac{\sum_{i=1}^{N} e_j(x_i)}{\sum_{i=1}^{m}\sum_{i=1}^{N} e_j(x_i)},j=1,\dots.M \tag{8}$$

Lj denotes the degree of violation of each constraint and m is the number of constraints.

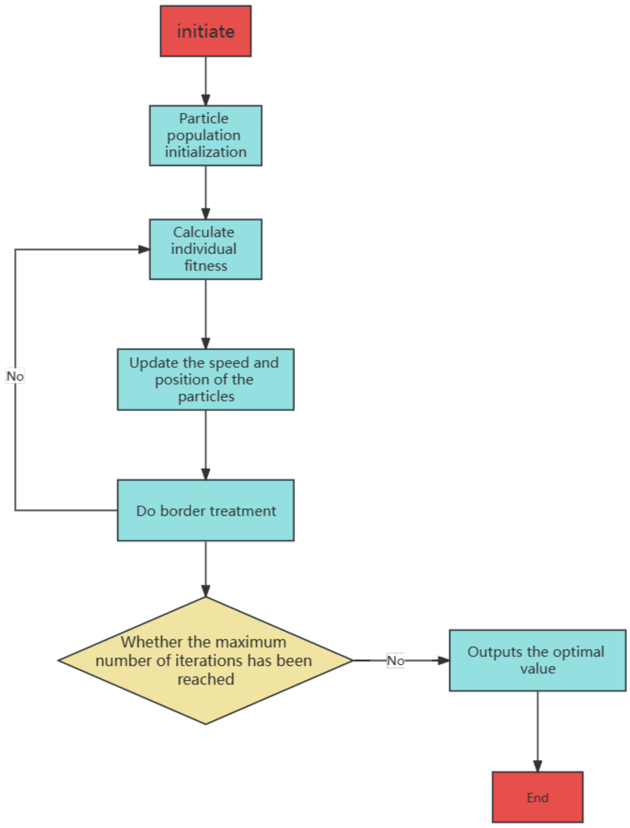


Figure 2 PSO Algorithm

The approach shares a striking resemblance to the interior point method of linear programming, as both employ a supplementary penalty function to continuously drive the model towards optimization within the feasible domain during iterative computation. Meanwhile, the particle swarm algorithm updates Pbest and Gbest at each iteration step. Although the constrained problem can be converted to an unconstrained problem for iterative solution, there may be a solution xi that does not satisfy the constraints. Therefore, rules must be compiled to compare the advantages and disadvantages of the two particles. The following rules apply:

(1)If both xi and xj of two particles are feasible, the particle with the lowest value is selected as superior by comparing the fitness functions f(xi) and f(xj) of xi and xj.

(2)If both particles xi and xj are infeasible, the particle that violates the constraints to a lesser extent is preferred by comparing the penalty terms P(xi) and P(xj).

(3) Select a feasible solution when particle xi is feasible but particle xj is not.

The particle swarm algorithm (PSO) offers several benefits, such as rapid convergence, minimal parameters, straightforward implementation, and a simple algorithm. It merges PSO with long and short-term memory network (LSTM) and self-attention mechanism (Transformer) to find the optimal solution through continuous iteration. This compensates for the weaknesses and limitations of LSTM in model fitting.

3. Results

Basic information about the vegetables is available, followed by data preprocessing. However, some data are missing. To deal with missing data, common approaches such as mean padding, model regression prediction, large-scale mapping, multiple interpolation, maximum likelihood estimation, and compression detection are frequently employed. We performed mean-padding and outlier detection using Python to carry out data cleaning. The text presents data containing all six categories with no outliers or missing values. The small amount of data that does not pass through the filtering and cleaning stages will be omitted.

The PSO-LSTM-Transformer model is built to harness the strengths of both models while minimizing the drawbacks of the LSTM model. The LSTM-Transformer model is developed in Python, and the pricing plan for July 1 relies on the flower varieties available between June 24-30, 2023. Additionally, historical sales pricing data and profit ranking are taken into account for the formulation of the pricing strategy, as demonstrated in Table 1.

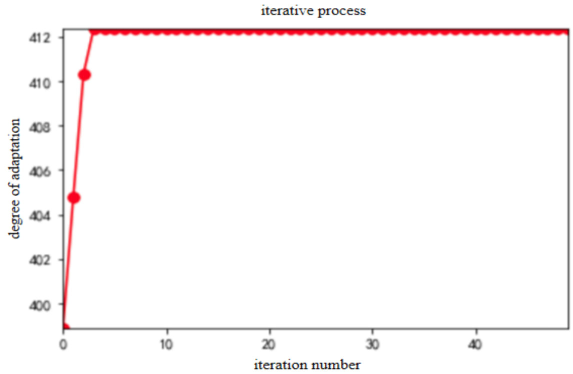
Table1 Predictive ricing

Vegetable Name	Forecast selling price (yuan/kg)	Vegetable Name	Forecast selling price (yuan/kg)
Millet pepper (portion)	5.72	Seafood mushroom (package)	2.75
Broccoli	13.99	Flammulina velutipes (box)	1.92
Xixia Mushroom (1)	23.34	Wild powder lotus root	25.97
Wuhu green pepper (1)	4.86	Green eggplant (1)	5.83
Purple eggplant (2)	5.91	Spinach	13.95
Screw pepper	9.74	Yunnan lettuce	7.12
Yunnan lettuce (portion)	4.04	Fresh Auricularia (parts)	22.22
Long line eggplant	12.47	Green red pepper combination (portion)	5.69
Zhijiang Qinggeng scattered flowers	13.65	Round eggplant (2)	7.12
Net lotus root (1)	11.59	Crab mushroom and white Hypsizygus marmoreus double (box)	4.85
Doll dishes	6.55	Outland chrysanthemum	13.18
Double spore mushroom (box)	4.89	Purple eggplant (1)	8.84
Screw pepper (portion)	4.72	White jade mushroom (bag)	3.95
Bamboo leafy vegetables	5.29	Muercai (portion)	3.67
Ginger garlic millet pepper combination (small)	4.50	Red lotus root belt	8.94
Milk cabbage	4.32	Chinese cabbage	6.11
Yunnan lettuce (portion)	4.35	Green pepper (portion)	4.88
Shanghai Qing	7.50	High melon (2)	15.01
Muercai	6.42	Cordyceps flower (portion)	3.51
Greengrocery (1)	5.41	Amaranth	3.76
Small wrinkled skin (part)	2.95	Spinach (portion)	4.66
Red pepper (2)	18.90	Rhombic horn	14.08
Sweet potato tip	6.42	Colorful peppers (2)	19.08
Yunnan lettuce	9.33		

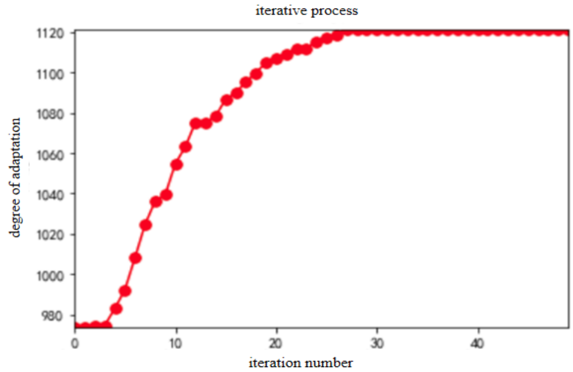
By applying PSO, each product is treated as a particle. The process begins with the initialization of the particle population, followed by the calculation of each individual's fitness level. The speed and position of each particle is then continuously updated. Since the order quantity of each product must meet the minimum display quantity of 2.5 kg, this leads to the establishment of boundary conditions. Hence, constraint optimization is performed, and the penalty function is increased to ensure that the model always seeks the best solution within the feasible domain during the iterative calculation. For each particle, its fitness value should be compared with that of the best position experienced, pbest. If the particle's fitness value is superior, it should be regarded as the current individual optimal position. The velocity and position of the particle can be optimized using velocity and position formulae to update the particle position. At present, the function's fitness is approximately 412 with no further changes after continued iterations, indicating that it has reached a local optimum. Therefore, the optimal fitness is 412.39, and the current optimal position is (15, 8, 8, 2.5,6).

Current optimal position:[15. 8. 8. 2.5 6.]

Current optimal adaptation:412.39

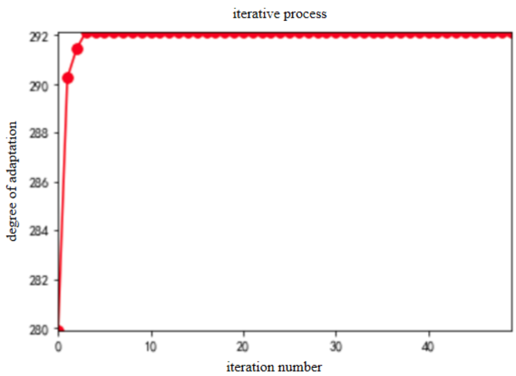


Current optimal adaptation:1121.5



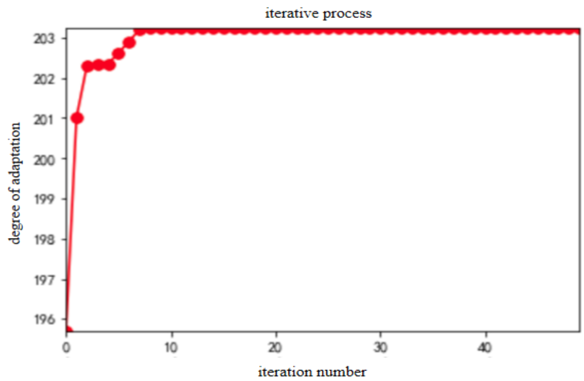
Current optimal position:[8.71234345 7.2446512 6.56587 8.3899055 7.5768984]

Current optimal adaptation:292.16



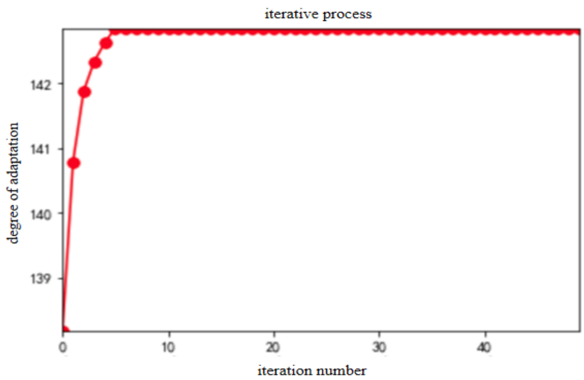
Current optimal position:[7.884 2.5 6.56587 5.78894 6.5768984]

Current optimal adaptation:203.25



Current optimal position:[4. 7. 26. 2.5 5.]

Current optimal adaptation:142.86



Current optimal position:[14.40532548 5.]

Current optimal adaptation:322.71

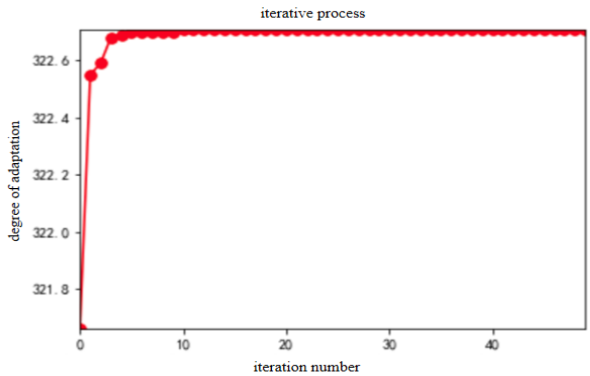


Figure 3 TSO Iteration Process Diagram

The quantity of each individual item's replenishment resulted from the effort to meet the market demand for vegetable commodities in every category. Based on the available data from June 24-30, 2023, it appears that sales of fresh rice dumpling leaves have experienced a surge, potentially influenced by various factors including weather and festivals. It has been determined that a festival, specifically the Dragon Boat Festival, occurred during this time frame, which may have impacted sales. Due to this information, the corresponding single item has been excluded. Table 2 displays the replenishment information for specific items.

Table 2 Replenishment of individual vegetable items

Vegetable Name	Replenishment (kg)	Vegetable Name	Replenishment (kg)
Purple eggplant (2)	15.0	Bamboo leafy vegetables	16.4
Long line eggplant	8.0	Shanghai cyan	7.0
Green eggplant (1)	6.0	Greengrocery (1)	2.5
Round eggplant (2)	2.5	Milk cabbage	9.4
Net lotus root (1)	7.9	Muercai	5.8
Wild powder lotus root	2.5	Yunnan lettuce	9.7
Rhombic horn	6.6	Amaranth	6.5
Red lotus root belt	6.6	Yellow cabbage	3.7
Yunnan lettuce (portion)	60.0	Broccoli	14.4
Yunnan Lettuce Meal	18.0	Zhijiang Qinggeng scattered flowers	5.0
Doll dishes	18.0	Xixia Mushroom (1)	4.0
Spinach (portion)	17.0	Twin mushrooms	7.0
Sweet potato tip	15.5	Flammulina velutipes (box)	26.0
Sea mushrooms	5.0	White jade mushroom	2.5
Millet pepper	8.7	Wuhu green pepper	7.2
Screw pepper	7.6	Colorful peppers (2)	8.4
Xiao Zou Pi	6.6		

4. Conclusions

To effectively address the challenge of automated pricing and replenishment decision-making for various vegetable categories in supermarkets, we utilized the innovative PSO-LSTM-Transformer (Particle Swarm Optimization Algorithm-Long Short-Term Memory Network) combination model. The model forecasted replenishment amounts through marketing data gathered from vegetable category products sold in a supermarket from 2020 to 2023. The main objective is to maximize supermarket revenue while meeting the market demand for every vegetable commodity group.

The Particle Swarm Optimization (PSO) algorithm incorporated within the integrated model significantly contributes to the precise forecast by effectively exploring the solution space for optimal results. Long Short-Term Memory (LSTM) networks improve the ability to capture and comprehend long-term patterns in the market data, thereby aiding in accurate trend prediction. The Transformer component, equipped with an attention mechanism, enhances the forecasting process by accurately identifying complex patterns and connections within market data.

Our study presents the PSO-LSTM-Transformer model as an effective means of predicting replenishment levels for vegetable categories. This model facilitates important decision-making related to pricing and restocking in supermarkets, providing useful insights for developing strategies for different commodity categories in the supermarket context.

Going forward, this research could be applied to a wider range of product categories within supermarkets and may even have implications beyond the retail industry. Implementing comparable predictive models and optimization algorithms can substantially enhance efficient decision-making in supply chain management, assisting in optimal resource allocation, waste reduction, and sustainable business practices across diverse industries. This avenue paves the way for future research and practical applications with broader implications beyond the supermarket sector.

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