

Research Article

Supply Chain Optimization Strategy Research Based on Deep Learning Algorithm

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The ordering and transportation of raw materials are a key process for enterprises to produce and receive receivables, and it is necessary to conduct a targeted study of this process. In order to solve this problem, this paper first collects relevant data and information on the ordering quantity of each enterprise, the inventory of various types of raw materials, the supply quantity of suppliers, the transshipment capacity, and the loss of transporters. After a comprehensive evaluation of enterprises, suppliers, and transporters, we propose a reasonable ordering, supply, and transshipment decision scheme. Specifically, we first use principal component analysis to screen out several important suppliers. Second, we screen out 26 stable suppliers based on the regularity of supply using LSTM and ARIMA models, respectively, and then based on the transportation cost and loss cost minimization objectives, further refine the ordering and forwarding scheme. Finally, we realign our ordering and forwarding schemes according to the transportation cost and warehousing cost minimization objectives. The experimental evaluation structure shows that our model yields the most economical ordering and shipping scheme each week. Moreover, after replacing the objective function, our model can still improve the single-week capacity by 0.79% as well, demonstrating strong robustness and generalization ability.

1. Introduction

At the present stage of rapid development of production enterprises, the scale of enterprises' production has gradually expanded. In this process, the costs consumed by production enterprises have increased significantly, and with it, the potential economic pressure has increased. Therefore, the cost control work of production enterprises is very critical for the economic benefits of enterprises [1]. In particular, for the production of construction and decorative panels, the accounting and control of costs can guarantee the reproduction of the enterprise and the compensation of value from the sales revenue, trying to use the minimum amount of money to obtain the maximum profit [2]. Among them, the cost of purchasing raw materials, transportation, and storage costs can directly affect the production efficiency of the producer. However, the ordering risk of production

enterprises is brought about by the possible default of raw material suppliers, such as after the material procurement contract is signed, the supplier does not deliver the goods on schedule or the supply quantity is much smaller than the order quantity [3]. That may lead to the failure of production enterprises to meet the raw material needs of normal production and bring great economic losses to the enterprises. At the same time, there are also transportation risks in the actual transfer process, because there will be certain losses in the actual transfer process of raw materials, and the number of raw materials received in the enterprise warehouse may be less than the number of raw materials ordered, and enterprises should also take into account the transportation risks in the actual decision of raw materials transportation. Based on the above information, how to quantify the raw material ordering and transportation risks of manufacturing enterprises and how to help them develop the most economical

raw material ordering and transportation plans taking into account the risks is becoming an issue of increasing interest.

To address the problem, researchers have proposed various solutions from different perspectives. For example, Wu [4] et al. developed a bi-objective stochastic programming model to solve the problem of production and ordering decisions in supply chains under uncertain environments using computer simulation. Gan and Xu [5], on the contrary, considered the relationship between retailers and suppliers, while building two types of models with and without delayed demand information. Xu [6] introduced a delayed supply scenario and proposed an optimal ordering model using the CvaR criterion. Yang et al. [7] analyzed systems with multiple correlations and developed a multivariate degradation model using Gamma process and Copula function to derive the optimal ordering strategy. Huang et al. [8] extended the ordering problem for a single system to multiple stages and multiple systems of the ordering problem, which minimizes the total cost of the entire multistage production system. Zhang and Yuan [9] proposed a multiobjective weighted gray target decision model to identify 11 decision objectives in a supply chain system by a hierarchical analysis method and achieved the selection of optimal countermeasures based on the comparison of the integrated effect measure values. Cai et al. [10] proposed a generalized gray target decision model based on improved principal component weights of moderating variables for the limitation that the current gray target does not fully consider the coexistence of multiple uncertainty factors of the decision object. Zheng and [11] constructed a novel assignment model by combining AHM subjective weights and CRITIC objective weights to address the shortcomings of the traditional single assignment method.

In this paper, we focus on four aspects to complete the establishment of the model for raw material production and ordering. First (1) we establish a mathematical model reflecting the importance of guaranteeing the production of enterprise, and from this model, the most important 50 suppliers are selected as the key research objects. Then (2) we set the optimization goal as selecting the least number of suppliers and used LSTM and ARIMA models to forecast their raw material supply for the next 24 weeks and selected the least number of suppliers that could meet the production requirements. Second, we introduced a 0–1 programming model for the selection between transporters and suppliers to make the least loss, and we determined the transshipment scheme. In addition (3), we add a new optimization objective to the model of the first two steps: to make the transshipment loss rate of the forwarder minimum, and by constructing the transshipment loss rate minimum objective function, we complete the model for determining the ordering scheme and the transshipment scheme. Finally, (4) we propose an objective of maximizing the weekly capacity of an enterprise. Based on the model of the three steps above, we determine a new objective function: minimizing the amount of loss and determining the constraints of the objective function to develop a new transshipment scheme for the enterprise. In general, our contribution points in this paper are as follows:

- (1) Principal component analysis assigns objective weights to indicators, unlike hierarchical analysis, with a strict mathematical theoretical basis, ensuring the accuracy and objectivity of the enterprise's production guarantee model and improving the credibility of the supplier's importance score.
- (2) ARIMA algorithm is a kind of model that captures the time structure in time series data. However, it is difficult to model the nonlinear relationship between variables by using the ARIMA model alone. LSTM can model complex multivariate sequences without specifying any time window. Therefore, the combination of ARIMA time series analysis with LSTM neural network suppliers with high supply volatility and suppliers with smoother supply are considered. The accuracy of the model in predicting the future supply of different suppliers is ensured.
- (3) Using reasonable assumptions, the optimization model reduces the large-scale linear programming problem to a 0–1 programming problem, which is easy to calculate and understand.

The remainder of the article is organized as follows. Section 2 describes the specific implementation of the model, Section 3 presents the experimental results and discussion of the model, and Section 4 is the conclusion.

2. Model Frame

For Aspect 1, we can know the order quantity and supply data of 402 raw material suppliers of this enterprise in the past 5 years from Annex 1 [13]. Based on this, we quantify and analyze the supply characteristics of 402 suppliers in Annex 1: data preprocessing is carried out for 402 enterprises, and considering the existence of supply risks of suppliers, we summarize six supply characteristics indicators of 402 suppliers from three perspectives of suppliers' supply capacity, supply stability, and reputation. Then, considering the importance of suppliers to enterprise production guarantee, we need to consider both the supply quantity and the possible risk at the same time, so with the supply characteristics indicators, we have built, after data reprocessing, we establish the enterprise production assurance model based on principal component analysis to reflect the importance of different suppliers to guarantee enterprise production. The model is built and solved by Python software and Matlab software. Finally, we quantify the importance of suppliers based on the enterprise production assurance model and identify the top 50 suppliers.

For Aspect 2, according to Annex 1 [13] and Aspect 1, we select the most important 50 suppliers, which are the result of Aspect 1, as the research objects of Aspect 2. First, our optimization objective is to select the least suppliers. We forecast the supplier's raw material supply for the next 24 weeks, predict the supply quantity of more volatile suppliers with the ARIMA time series model, predict the supply quantity of less-volatile suppliers with LSTM neural network, and determine the least supplier according to the supply quantity forecast value. The weekly capacity of the

enterprise is fixed at $28,200 \text{ m}^3$, so our next optimization goal is to minimize the total cost. We assume that the enterprise's order quantity is equal to the forecasted supplier's supply quantity, so we only have to consider which suppliers to order from. Therefore, we simplify this optimization model to a 0–1 programming problem that can be solved using Matlab software. Finally, our optimization objective is the transshipment solution with the lowest loss, and we first predicted the loss rate for the next 24 weeks for the eight transshipment suppliers using an LSTM neural network. Based on the predicted values, we also simplify the problem to a 0–1 programming problem, which can be solved using Matlab software, and then determine the transshipment solution.

Aspect 3 is a 0–1 planning problem similar to Aspect 2. The first optimization objective of this problem is to minimize the transshipment and storage costs. We take the 50 most important suppliers identified in Aspect 1 as the objects of study, construct the objective function for minimizing the transshipment and storage costs based on the predicted values of the next 24 weeks' supply of the 50 suppliers in Aspect 2, and use Matlab software to calculate the optimal solution of the objective function and a new raw material ordering scheme for the enterprise for the next 24 weeks is formulated. The further optimization objective is to minimize the transshipment loss rate of forwarders. The further optimization objective is to minimize the transshipment loss rate of the forwarders. Based on the already predicted loss rate for the next 24 weeks of the eight forwarders, we construct the objective function of minimizing the transshipment loss rate, and we develop a transshipment plan for the company with the lowest transshipment loss rate of the forwarders based on the new raw material ordering plan for the next 24 weeks when the transshipment and storage costs are the lowest. Finally, we compare the calculation results of the ordering and purchasing scenarios in Aspect 2 and Aspect 3 to analyze the effectiveness of the ordering and transshipment scenarios.

For Aspect 4, our optimization objective is to maximize the weekly production capacity of the enterprise, and we construct a capacity optimization model using the 50 most important suppliers identified in Aspect 1 as the research objects. With the help of MATLAB, we calculate the optimal solution of the objective function and the weekly capacity increase of the enterprise and develop an ordering scheme for raw materials for the enterprise for the next 24 weeks. The ordering scheme ensures both the importance of suppliers to the enterprise and the low loss of raw materials to a large extent. Our further optimization objective is the minimization of wastage. We construct an objective function for minimizing consumption based on the predicted values of the loss rates of the eight forwarders in Aspect 2 and the enterprise's raw material ordering scheme developed in the first optimization problem of Aspect 4 and determine the constraints of this function. With the constraints satisfied, we developed the transshipment scheme for the enterprise with the least amount of transportation losses based on the raw material ordering scheme that maximizes capacity.

2.1. Enterprise Production Assurance Model

2.1.1. Data Preprocessing Module. To avoid undue influence of invalid supplies on the quantitative analysis of supply characteristics, we screen and record the invalid supplies provided by suppliers to guarantee the accuracy of the next index construction. As shown in Equation (1), we define the sum of the weekly supply ratio with time assignment.

$$S = \sum_{i=1}^{240} w_i \cdot \frac{N_i}{N}. \quad (1)$$

Among them $w_i = 1 + i/120$. In addition, as shown in Equation (2), we define the total volume of raw materials supplied to the firm by the supplier in 240 weeks:

$$N = \sum_{i=1}^{240} N_i. \quad (2)$$

Besides, we define the regularity of the supply quantity and the regularity of the supply time as shown in Equations (3) and (4):

$$J = \frac{1}{1 + D(N^*)}, \quad (3)$$

$$T = \frac{1}{1 + D(\Delta T^*)}, \quad (4)$$

where N^* indicates the valid supply quantity of the supplier, ΔT^* indicates the time difference between two valid supplies from the supplier in order to reflect the reputation of the supplier and the ability to complete the order task, we define the supply rate indicator Q . In the completion of the cooperation between the suppliers and the enterprise, we define the number of supplies K , respectively:

$$\frac{1}{1 + \sum_{i=1}^{240} l_i |N_i - R_i| / R_i}, \text{ where } l_i = \begin{cases} 0.2 & \text{if } N_i \geq R_i, \\ 0.8 & \text{if } N_i < R_i. \end{cases} \quad (5)$$

For the calculation results of 402 supplier supply characteristics indicators, as shown in Figure 1, we found a large number of companies with extremely small supplies. In order to protect the importance of enterprise products and to avoid the situation that enterprises with very small supply achieve a high ranking in the results of the subsequent principal component analysis (other indicators score very high, such as enterprises with small weekly supply like 1 m^3 but extremely stable supply), we reprocessed the data and filtered out 176 suppliers with supply above 100 m^3 in 5 years. In all subsequent steps, we considered only these 176 suppliers for analysis and modeling treatment.

2.1.2. Principal Component Analysis Module. For the six quantitative indicators of supply characteristics that have been constructed, each indicator has a certain importance to the production of the enterprise, in addition, the indicators are also related to each other, that is, the constructed indicators are more and more complex. In this case, principal

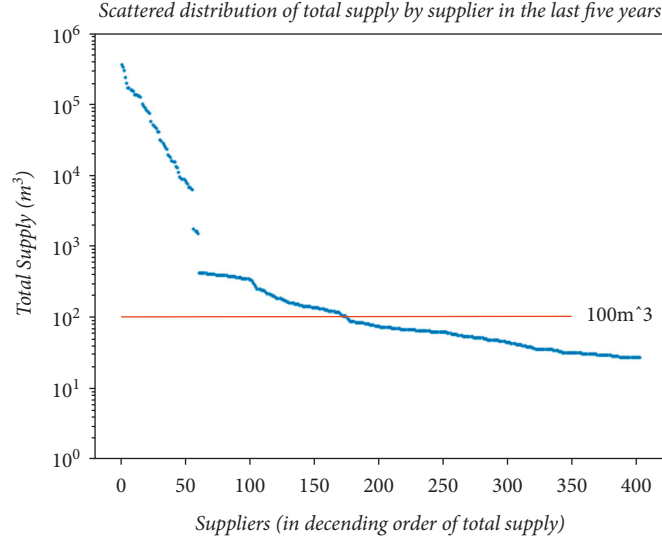


FIGURE 1: The calculation results of 402 supplier supply characteristics indicators. 100 m^3 is what we consider a high supply standard, marked with a red horizontal line.

component analysis can be used to synthesize indicators and reduce the dimensionality of the indicators.

The main purpose of principal component analysis is to use fewer variables to explain most of the variables in the original data, which are generally to reduce the dimensionality of the original variables into fewer new variables, that is, principal components, and evaluate the original data with new comprehensive indicators. We convert the original six indicators into new evaluation indicators and evaluate the importance of suppliers comprehensively. The specific process is as follows:

- (1) Normalize original data.
- (2) Calculate coefficient matrix.
- (3) Calculate the eigenvalues and eigenvectors of the coefficient matrix as

$$\begin{aligned} y_1 &= u_{11}S + u_{12}R + u_{13}J + u_{14}T + u_{15}Q + u_{16}K \\ y_2 &= u_{21}S + u_{22}R + u_{23}J + u_{24}T + u_{25}Q + u_{26}K \\ &\vdots \\ y_6 &= u_{61}S + u_{62}R + u_{63}J + u_{64}T + u_{65}Q + u_{66}K \end{aligned} \quad (6)$$

- (4) Calculate the information contribution and cumulative contribution of the eigenvalues λ_i as

$$\begin{aligned} b_i &= \frac{\lambda_i}{\sum_{k=1}^6 \lambda_k}, i = 1, 2, \dots, 6, \\ c_i &= \sum_{k=1}^i b_k, i = 1, 2, \dots, 6. \end{aligned} \quad (7)$$

- (5) The p principal components that make the cumulative contribution exactly exceed 85% are selected, and the composite score is calculated as

$$l_p = \sum_{i=1}^p b_i y_i. \quad (8)$$

- (6) The composite score is normalized to restrict its value range to $[0, 1]$ as

$$M = \frac{l_p - \min(l_p)}{\max(l_p) - \min(l_p)}. \quad (9)$$

Combined with the above definition of quantitative indicators of supplier supply characteristics, it can be seen that the higher the value of these seven indicators of suppliers, the higher the final composite score, the better the enterprise's production can be guaranteed, and the more important the suppliers are to the enterprise. Therefore, the normalized composite score M is the importance score, and the importance of the supplier to guarantee the production of the enterprise can be quantified.

2.2. Minimum Loss Strategy Model. In order to achieve the optimization goal of selecting the smallest number of suppliers, first of all, we forecast the supply quantity of the next 24 weeks for the 50 most important suppliers, which are ranked from highest to lowest based on the importance of ensuring the production of enterprises. As the volatility of different suppliers over time varies, we adopt two prediction methods to predict the supplier's supply: for suppliers with large fluctuations and obvious periodicity, we adopt ARIMA time series model to predict the supplier's supply in the next 24 weeks; for suppliers with small fluctuations or more chaotic supply, we adopt LSTM neural network to predict the supplier's supply quantity in the next 24 weeks.

2.2.1. ARIMA Time Series. Real-life time series are often trending and volatile. For forecasting data with trend or volatility, we use the ARIMA time series model.

The main idea is that the Box-Jenkins method, that is, the difference method [12], is used to eliminate its trend and volatility, so that the transformed series is a smooth series, the ARMA series is forecasted, and finally the forecast results

are reduced to obtain the forecasted data with partial suppliers satisfying the trend and volatility. The introduction of the backward shift operator is more convenient for describing the difference operation, and the operator B is defined as

$$BX_t = X_{t-1}, B^k X_t = X_{t-k}. \quad (10)$$

The operator polynomial $\varphi(B)$ is as follows:

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \dots - \varphi_p B^p. \quad (11)$$

Then, we get the d -order difference as

$$\nabla^d X_t = (1 - B)X_t \quad (12)$$

Let $\{X_t, t = 0, \pm 1, \pm 2, \dots\}$ be a nonsmooth series. If there exists a positive integer d , such that $\nabla^d X_t = W_t$, and $\{W_t, t = 0, \pm 1, \pm 2, \dots\}$ is the ARMA (p, q) sequence, then we call $\{X_t\}$ is ARIMA (p, d, q) sequence.

2.2.2. LSTM Neural Network. Long short-term memory (LSTM) is a special kind of RNN, which is mainly designed to solve the gradient disappearance and gradient explosion problems during the training of long sequences. Simply speaking, it means that LSTM [14] can have better performance in longer sequences compared to normal RNN. LSTM is suitable for processing and predicting important events with very long intervals and delays in time sequences. By observing the data, we found that some suppliers' data in the last five years are relatively lack of regularity, and there are more delays and noises between effective supplies, which are difficult to predict using ARIMA. At this time, we put the data into the classical LSTM network, and for each supplier, the first 216 weeks of data are used as the training set, and the remaining 24 weeks are used as the test set, and the learning rate is appropriately increased to reduce the noise. We finally use the training model to predict the next 24 weeks, in which the average accuracy of the validation set is 92.38%, and we can find that the prediction results are reasonable through observation [15–17].

2.2.3. Constraints and Implementation. We use the data of the loss rate of 8 raw material forwarders for the last 5 years in Annex II [13], and with the exclusion of 0 (the value "0" means that the corresponding weekly supplier has no supply, so it is not considered), we calculate the average value of the loss rate of 8 forwarders for the last 5 years and consider it as the predicted value of the loss rate of 50 suppliers in the next 24 weeks of forwarding $h = 0.013338$. We assume that the current enterprise warehouse stores the amount of raw material inventory to meet two weeks of production demand. In order to achieve the optimization goal of selecting the least number of suppliers, we need to satisfy the following two conditions when selecting suppliers.

Condition 1. Under the premise that the enterprise's weekly production capacity is 28,200 cubic meters [13], the weekly supply of these suppliers in the next 24 weeks can guarantee

that the weekly stock of raw materials in the enterprise's warehouse is greater than or equal to zero, thus guaranteeing the enterprise's normal production.

Condition 2. Under the premise that the weekly production capacity of the enterprise is 28,200 cubic meters, the stock of raw materials in the enterprise's warehouse at the end of the last delivery of the next 24 weeks will meet the enterprise's production demand for two weeks and guarantee the normal production, and also guarantee the assumption that "the company's warehouse has two weeks' worth of raw materials in stock at the time of the 24-week raw material ordering and transfer plan" is valid.

In order to satisfy Condition 2, first, we convert the forecasted supply quantity of each of the 50 suppliers for the next 24 weeks into the forecasted production capacity conversion value, without considering the loss of transportation. Combined with the information of the topic [13], 1 m^3 product needs to consume 0.6 m^3 raw materials of class A, or 0.66 m^3 raw materials of class B, or 0.72 m^3 raw materials of class C. We convert the weekly production capacity of the enterprise into the ideal production capacity before transportation loss $L(10^4 \text{ m}^3)$, so as to facilitate the calculation of the production capacity conversion prediction of raw materials: $L = 24 \times 2.82 / (1 - h)$. Then, we calculate the sum of the forecasted production capacity conversion of raw materials provided by 50 suppliers in the next 24 weeks, and sort the 50 enterprises according to the sum of the forecasted capacity conversion in the next 24 weeks from the highest to the lowest, starting from the sum of the forecasted maximum capacity conversion and accumulating them one by one until the result of accumulation is greater than or equal to the sum of the ideal capacity of the enterprises in the next 24 weeks. At this point, the number of suppliers that have participated in the accumulation calculation is the minimum number of suppliers satisfying Condition 2.

On the basis of Condition 2, we construct a new variable G to satisfy Condition 1, which is defined as the amount of new inventory (there is a possibility that the forecast value of weekly supply is less than the ideal weekly production capacity of the enterprise). We assume that the enterprise warehouse currently stocks raw materials to meet the two-week production demand, so we can set the weekly production end inventory of the enterprise warehouse equal to the sum of the original inventory (the warehouse's initial stock of raw materials to meet the two-week production demand) and the new inventory, and in order to satisfy condition one, we need to ensure that the weekly production end inventory of the enterprise warehouse should be greater than or equal to 0, and the constraints are that the number of suppliers to satisfy Condition 1 should be equal to the minimum number of suppliers determined in Condition 2. If not, then the minimum number of suppliers to satisfy condition two should be added to one until condition one is satisfied, at which time the number of suppliers is the minimum number of suppliers we seek to satisfy the production demand. Through the calculation, we found that the number of 26 suppliers calculated by satisfying Condition 2,

exactly satisfies Condition 1, so we finally concluded that the minimum number of suppliers should be 26.

Our next optimization goal is to make the raw material ordering and transportation cost the lowest, so as to develop the most economical raw material ordering scheme for each week of the next 24 weeks. Combined with the question [13], we can see that the capacity of the enterprise is fixed at 28,200 per week, so we can transform the problem of developing the most economical raw material ordering scheme per week for the next 24 weeks into the optimization problem of minimizing the procurement cost. In this problem, the procurement cost of the enterprise includes the purchase cost of raw materials, transportation cost, and storage cost. We assume that the order quantity of the enterprise is equal to the forecasted value of the supplier's supply. Combined with the question [13], the actual unit purchase price of raw materials of categories A and B is 20% and 10% higher than that of raw materials of category C, respectively. The unit costs of transportation and storage of the three types of raw materials are the same. Based on this, we construct the objective function for cost minimization:

$$\min \sum_{i=1}^{50} \sum_{j=1}^{24} d_{ij} Y_{ij} \cdot (\beta_i P_c + P_x + P_y), \quad (13)$$

$$\left\{ \begin{array}{l} \sum_{i=1}^{50} \sum_{j=1}^{24} d_{ij} Y_{ij} \cdot \frac{1}{\alpha_i} \cdot (1-h) \geq 28200 \times 24 \\ \sum_{i=1}^{50} \sum_{j=1}^k d_{ij} Y_{ij} \cdot \frac{1}{\alpha_i} \cdot (1-h) \geq 28200 \cdot (k-2), k=1, 2, \dots, 23 \\ \sum_{i=1}^{50} d_{ij} \leq d, j=1, 2, \dots, 24. \end{array} \right. \quad (15)$$

Our further optimization goal is the least lossy forwarding solution. We first used LSTM neural network to predict the loss rate of 8 forwarders for the next 24 weeks, in the prediction should be eliminated loss rate of 0 data (the value "0" means no delivery, so should be removed). In the previous optimization problem, we developed the most economical raw material ordering plan for the company for each week of the next 24 weeks, and if the company is known to order from n suppliers, each ordering $c_1, c_2, \dots, c_n \text{ m}^3$, the predicted attrition rate is k_1, k_2, \dots, k_8 . Based on this we constructed the objective function for loss minimization (for one week for example, just repeat the calculation 24 times):

$$\min (c_1, c_2, \dots, c_n) U(k_1, k_2, \dots, k_8)^T. \quad (16)$$

The constraints are as follows:

$$\begin{aligned} m_{ij} &= 0 \text{ or } 1, \\ \sum_{j=1}^8 m_{ij} &= 1, i=1, \dots, n, \\ \sum_{j=1}^n m_{ij} \cdot c_i &\leq 6000, j=1, \dots, 8. \end{aligned} \quad (17)$$

where

$$\beta_i = \begin{cases} 1.2, & \text{The raw material type of the } i\text{-th supplier is A;} \\ 1.1, & \text{The raw material type of the } i\text{-th supplier is B;} \\ 1, & \text{The raw material type of the } i\text{-th supplier is C.} \end{cases}$$

Combined with the relevant literature and the actual situation in the manufacturers of construction and decorative panels, the logistics and transportation costs of raw materials procurement costs account for 10% of the procurement costs [5]. Therefore, we believe that the unit price of C raw materials, the unit cost of three types of raw materials transportation, and the unit cost ratio of three types of raw materials storage in this problem is 8:1:1. We then further simplify the objective function to obtain the new objective function as

$$\min \sum_{i=1}^{50} \sum_{j=1}^{24} d_{ij} Y_{ij} \cdot \left(\beta_i + \frac{1}{4} \right) P_c. \quad (14)$$

The constraints are as follows:

2.3. Minimum Transshipment and Storage Cost Decision Model. The unit costs of transporting and storing the three types of raw materials are the same, and in 2.2 Minimum Loss Strategy Model, we determine the proportional relationship between the unit costs of transporting and storing the three types of raw materials and the purchase unit price of the raw materials of Category C, that is, the unit costs of transporting and storing the three types of raw materials are $(1/8)P_c$. We first select the 176 suppliers ranked from the highest to the lowest importance of guaranteeing the production of the enterprise in Aspect 1 as the research objects here. Then the LSTM neural network is used to predict the supply quantity of these 176 suppliers for the next 24 weeks. Based on this, we construct the objective function for minimizing the transshipment and storage costs as follows:

$$\min \frac{1}{4} \cdot \sum_{i=1}^{176} \sum_{j=1}^{24} d_{ij} Y_{ij} P_c. \quad (18)$$

The constraints are as follows:

$$\left\{ \sum_{i=1}^{176} \sum_{j=1}^{24} d_{ij} Y_{ij} \cdot \frac{1}{\alpha_i} \cdot (1-h) \geq 28200 \times 24 \sum_{i=1}^{176} \sum_{j=1}^k d_{ij} Y_{ij} \cdot \frac{1}{\alpha_i} \cdot (1-h) \geq 28200 \cdot (k-2), k = 1, 2, \dots, 23. \right. \quad (19)$$

Under the premise of satisfying the constraints, we solve the optimal solution of the objective function by calculation, that is, the value of the minimum cost of transshipment and storage is $1.0986 \times 10^5 P_c$. Based on the calculation of the most economical raw material ordering solution for the next 24 weeks in 2.2, the cost of transshipment and storage is $1.1046 \times 10^5 P_c$. By comparing the values of forwarding and storage costs in 2.1 and 2.2, we find that the forwarding and storage costs remain almost unchanged. This shows that the most economical raw material ordering plan for the next 24 weeks specified in 2.2 is reasonable, and the control of each cost constituting the procurement cost is more accurate, which not only makes the overall cost most economical but also ensures that the cost of transportation and storage is almost the most economical. On the other hand, it also shows that the production guarantee model we constructed in 2.1 is in line with the actual situation, more robust and objective, and also shows that the supplier's supply characteristics are considered in the quantitative analysis of the 402 suppliers are more comprehensive and reliable.

However, as the object of our study is selected from 176 suppliers ranked from high to low according to the

importance of the production of the enterprise in Section 2.1, we do not take into account that some of 176 suppliers were ranked low according to the importance they have in a greater risk of default, so that the importance of enterprise production safety is not guaranteed. We should select the 50 most important suppliers identified in question one based on the importance of the production of the enterprise from high to low. The 50 most important suppliers identified in Section 2.1 are the object of study here. These suppliers take into account the supplier's supply risk and supply capacity, and we should determine the ordering procurement program and the forwarding program with full consideration of the supplier's supply risk and supply capacity. We establish 50 most important suppliers as the target of problem three research objects of transshipment and storage cost minimization objective function as

$$\min \frac{1}{4} \cdot \sum_{i=1}^{50} \sum_{j=1}^{24} d_{ij} Y_{ij} P_c. \quad (20)$$

The constraints are as follows:

$$\left\{ \sum_{i=1}^{50} \sum_{j=1}^{24} d_{ij} Y_{ij} \cdot \frac{1}{\alpha_i} \cdot (1-h) \geq 28200 \times 24 \sum_{i=1}^{50} \sum_{j=1}^k d_{ij} Y_{ij} \cdot \frac{1}{\alpha_i} \cdot (1-h) \geq 28200 \cdot (k-2), k = 1, 2, \dots, 23. \right. \quad (21)$$

Our further optimization objective is to minimize the transit loss rate of forwarders, and we have predicted the loss rate of eight forwarders for the next 24 weeks in Section 2.2. Based on this, we construct the objective function for minimizing the transit loss rate:

$$\min \frac{(c_1, c_2, \dots, c_n) U(k_1, k_2, \dots, k_8)^T}{\sum_{i=1}^n c_i}. \quad (22)$$

The constraints are as follows:

$$\begin{aligned} m_{ij} &= 0 \text{ or } 1, \\ \sum_{j=1}^8 m_{ij} &= 1, i = 1, \dots, n, \\ \sum_{j=1}^n m_{ij} \cdot c_i &\leq 6000, j = 1, \dots, 8. \end{aligned} \quad (23)$$

2.4. Enterprise Limit Capacity Decision Model. Our optimization goal is to maximize the weekly capacity of the enterprise. We assume that the supply capacity of the

existing suppliers of raw materials and the transshipment capacity of the forwarders remain unchanged. In order to increase the weekly capacity of the enterprise, it is necessary to increase the supply of raw materials as well as the number of suppliers per week, which may lead to the importance of suppliers to ensure the production of the enterprise is not guaranteed. The suppliers may appear to be at greater supply risk, on the other hand, to improve the enterprise's weekly production capacity, forwarders in the case of unchanged forwarding capacity, trying to transport more raw materials, is likely to require more forwarders, which is likely to cause higher loss rate and loss volume. In order to avoid the above situation, we need to consider the supplier's supply risk and the transshipment loss of the forwarder while pursuing the maximum capacity and consider the importance of the supplier to the enterprise. Based on this, we construct an objective function for capacity maximization as

$$\max \sum_{i=1}^{50} \sum_{j=1}^{24} (1-h) d_{ij} Y_{ij} \cdot \frac{1}{\alpha_i}. \quad (24)$$

The constraints are as follows:

$$\left\{ \sum_{i=1}^{50} \sum_{j=1}^k d_{ij} Y_{ij} \cdot \frac{1}{\alpha_i} \cdot (1-h) \geq 28200 \cdot (k-2), k=1, 2, \dots, 23, \frac{\sum_{i=1}^{50} \sum_{j=1}^{24} d_{ij} M_i}{\sum_{i=1}^{50} \sum_{j=1}^{24} d_{ij}} \geq 0.35 \frac{1}{1152000} \cdot \sum_{i=1}^{50} \sum_{j=1}^{24} d_{ij} Y_{ij} \leq 0.7. \quad (25) \right.$$

Our further optimization goal is to minimize the amount of loss volume, and we forecast the loss rate for the next 24 weeks for the eight forwarders in Section 2.2. At the same time, we develop a raw material ordering scheme for the firm above. Based on this, we constructed the same loss minimization objective function as in Section 2.2.

3. Experimental Results and Discussion

We set the parameters of LSTM as follows: hidden_size = 200, num_layers = 2, dropout = 0.2, lear_rate = 0.001. The parameters of ARIMA: p (autoregressive model order) = 5, q (moving average model order) = 1, d (differential order) = 0. The number of experiments was the same and was performed under the same experimental conditions. Personal PC (Intel(R) Core(TM) i5-8300H CPU @ 2.30 GHz 2.30 GHz), repeat the experiment 30 times and take the average value.

3.1. Results of the Enterprise Production Assurance Model.

According to the principle and steps of principal component analysis method, the article was calculated and solved using Matlab software. Principal component analysis was performed on three groups of six quantitative indicators, and the eigenvalues, contribution rates, and cumulative contribution rates of the correlation coefficient matrix are shown in Table 1:

The eigenvectors (principal component coefficients) corresponding to the above eigenvalues are shown in Table 2:

The principal components with a contribution of exactly more than 85%, that is, three principal components, are selected as follows:

$$\begin{aligned} y_1 &= 0.536S + 0.288N + 0.118J - 0.279T + 0.186Q - 0.709K, \\ y_2 &= 0.535S + 0.29N + 0.114J - 0.291T + 0.187Q + 0.705K, \\ y_3 &= -0.333S + 0.363N + 0.792J - 0.148T - 0.328Q + 0.001K. \end{aligned} \quad (26)$$

The importance score M and ranking results of each supplier are obtained by calculating and normalizing the composite scores of the three principal components with their respective contributions as weights. The following table shows only the 50 most important suppliers and their importance scores as shown in Table 3:

3.2. Results of the Minimum Loss Strategy Model

3.2.1. *Optimization Model 1.* By calculation, we arrive at the minimum number of suppliers satisfying Condition 2 as 26.

3.2.2. *Optimization Model 2.* We assume that the order quantity of the enterprise is equal to the predicted value of the supplier's supply, and the predicted value of the supply

quantity of 50 suppliers for the next 24 weeks is known. So, we do not need to consider the order quantity of the enterprise for each supplier when we develop the most economical raw material ordering scheme for each week of the next 24 weeks, but only whether the enterprise chooses to order from that supplier, and the variable of this optimization problem takes the value of "0" or "1," so the optimization problem with the lowest procurement cost is a 0–1 programming problem. We used Matlab's `intlinprog()` function to perform calculations to solve for the minimum value of the objective function and develop the most economical weekly raw material ordering plan for the enterprise for the next 24 weeks (some of the results are shown in Table 4).

3.2.3. *Optimization Model 3.* As we assume that the order quantity of the enterprise is equal to the supplier's supply quantity every week for the next 24 weeks, the supply quantity that the forwarder needs to transport from the supplier is determined. Therefore, we only need to consider whether the enterprise chooses the forwarder to dock with the supplier when considering the forwarding solution with the lowest loss, and the variable of this optimization problem takes the value of "0" or "1," reducing the problem to a 0–1 programming problem. With the constraints satisfied, we develop the least lossy forwarding solution for the company based on the most economical raw material ordering solution for each week of the next 24 weeks (some of the results are shown in Table 5).

3.3. Results of the Minimum Transshipment and Storage Cost Decision Model.

(1) Minimize Transshipment and Storage Costs

With the constraints satisfied, we computationally solve for the minimum value of the objective function and eventually develop a new raw material ordering plan for the enterprise for the next 24 weeks that satisfies the cost reduction requirement while taking into account the default risk and supply strength of the supplier (some of the results are shown in Tables 6 and 7.

(2) Minimize Transit Loss Rate

3.4. Results of the Enterprise Limit Capacity Decision Model.

(1) Maximize Production Capacity

Under the premise of satisfying the constraints, we solve the maximum value of the objective function with the help of Matlab by calculating the maximum value of the enterprise's weekly production capacity as 30604 m³, which is 2404 m³ higher than the enterprise's weekly production capacity in the past, and

TABLE 1: Result of three groups of six quantitative indicators.

No.	Eigenvalues	Contribution rate (%)	Cumulative contribution rate (9%)
2	2.7571	45.9521	45.9521
3	1.6756	27.9272	73.8792
4	0.6897	11.4944	85.3736
5	0.6293	10.488	95.8617
6	0.2482	4.136	99.9977
No.	0.0001	0.0023	100

TABLE 2: The eigenvectors corresponding to the eigenvalues.

No.	S	N	J	T	Q	K
1	0.536	0.288	0.118	-0.279	0.186	-0.709
2	0.535	0.29	0.114	-0.291	0.187	-.705
3	-0.333	0.363	0.792	-0.148	-0.328	0.001
4	-0.387	0.498	-0.041	0.243	0.736	0
5	0.381	-0.23	0.461	0.756	0.131	0.008
6	0.145	0.633	-0.362	0.429	-0.513	0.003

TABLE 3: The 50 most important suppliers and their importance ratings.

Supplier ID	S229	S361	S140	S108	S282	S275	S340	S329	S268	S306
Importance score	1	0.9292	0.7111	0.7	0.642	0.595	0.5916	0.5701	0.5057	0.4992
No.	1	2	3	4	5	6	7	8	9	10
Supplier ID	S151	S131	S356	S308	S194	S330	S139	S352	S374	S247
Importance score	0.4807	0.4794	0.4671	0.4337	0.4154	0.4147	0.3994	0.3722	0.3552	0.312
No.	11	12	13	14	15	16	17	18	19	20
Supplier ID	S284	S143	S365	S031	S348	S307	S395	S040	S364	S201
Importance score	0.3075	0.2964	0.267	0.249	0.2414	0.2337	0.2271	0.214	0.2129	0.2006
No.	21	22	23	24	25	26	27	28	29	30
Supplier ID	S367	S037	S080	S055	S346	S218	S294	S244	S126	S388
Importance score	0.1924	0.1772	0.1708	0.169	0.168	0.1667	0.1555	0.153	0.1405	0.1259
No.	31	32	33	34	35	36	37	38	39	S332
Supplier ID	S007	S338	S112	S147	S379	S003	S123	S005	S189	0.1021
Importance score	0.1254	0.121	0.1187	0.1169	0.1167	0.1104	0.1095	0.1069	0.1035	50
No.	41	42	43	44	45	46	47	48	49	S306

TABLE 4: The most economical weekly raw material ordering plan for the next 24 weeks.

ID	Week1	Week2	Week3	Week4	Week5	Week6
S031	224.7861124	219.9339613	218.6691386	220.7948613	225.5042335	226.2659145
S040				189.4309027	153.8503255	
S055			180.7915354		205.3131872	
S108	868.4871193	980.3835078	864.7714386	865.7480387	893.3451949	921.3481747
S131	500.4882488	1204.881336	1119.055435		343.7559422	1179.617532
S139	418.7508955	409.7234653	414.448815	412.4881102	399.8595033	403.3509507

TABLE 5: Transit solution with minimal losses.

ID	Week1								Week2							
	T1	T2	T3	T4	T5	T6	T7	T8	T1	T2	T3	T4	T5	T6	T7	T8
S031						224.7861124										219.9339613
S131						500.4882488				1204.881336						
S139						418.7508955										409.7234653
S140		709.364457								928.2626138						
S151						666.6758119										685.9420858
S194						514.5899899				507.4073697						

TABLE 6: New raw material ordering plan for the next 24 weeks (minimizing transit and storage costs).

ID	Week1	Week2	Week3	Week4	Week5	Week6
S005	0.343125623	0.10727673	0.48161928	0.358342855	0.520308055	0.423621757
S007	22.29428925	78.02782338	44.93821238	113.7216961		49.2882621
S031	224.7861124	219.9339613	218.6691386	220.7948613	225.5042335	226.2659145
S040	78.69181509	49.62994983	91.22393533	189.4309027	153.8503255	114.7042648
S055	130.909855	41.85683264	180.7915354	56.69825652	205.3131872	67.09127907
S108	868.4871193	980.3835078	864.7714386	865.7480387	893.3451949	921.3481747

TABLE 7: New raw material ordering program for the next 24 weeks (minimized transit loss rate 1).

ID	Week1								Week2							
	T1	T2	T3	T4	T5	T6	T7	T8	T1	T2	T3	T4	T5	T6	T7	T8
S005						172.2286113								2042.738341		
S007				174.7869902							11.14632725					
S031						669.8535279										1066.352584
S040						52.44189795										507.4073697
S055						6.903364812										458.9710913
S108						709.364457								928.2626138		

TABLE 8: New raw material ordering plan for the next 24 weeks (maximizing capacity).

ID	Week1	Week2	Week3	Week4	Week5	Week6
S003	76.10965461	85.28450339	120.698241	154.9712693	185.6960757	175.1030229
S007	22.29428925	78.02782338	44.93821238	113.7216961		49.2882621
S031	224.7861124	219.9339613	218.6691386	220.7948613	225.5042335	226.2659145
S037	44.56124038	42.80899222	89.39236798	45.6765207	33.94749456	71.08022821
S040	78.69181509	49.62994983	91.22393533	189.4309027	153.8503255	114.7042648
S055	130.909855	41.85683264	180.7915354	56.69825652	205.3131872	67.09127907

TABLE 9: New raw material forwarding plan for the next 24 weeks (minimized transit loss rate 2).

ID	Week1								Week2							
	T1	T2	T3	T4	T5	T6	T7	T8	T1	T2	T3	T4	T5	T6	T7	T8
S005			172.2286113								2042.738341					
S007				174.7869902										11.14632725		
S031						669.8535279								1066.352584		
S040						52.44189795					507.4073697					
S055				6.903364812							458.9710913					
S108						709.364457								928.2626138		

develop a raw material ordering plan for the enterprise for the next 24 weeks, which not only safeguards the importance of suppliers to the enterprise to a large extent but also guarantees both the importance of suppliers to the company and the low wastage of raw materials. Some of the results of the model are shown in Tables 8 and 9:

(2) Minimize Transit Loss Rate

4. Conclusion and Prospect

In this paper, we focus on the evaluation of suppliers based on the supply characteristics extracted by ordering quantity and develop the best ordering and forwarding solutions for companies in different situations and needs. Our model considers the stability of the model from several perspectives, such as the importance of the supplier, reliability, loss

reduction, total transportation capacity of the forwarder and other restrictions on the selection. Various objective functions such as minimizing total cost and total loss, minimizing transportation and storage costs, and increasing capacity are also established to obtain a continuously optimized supply chain model. The experimental results show that our ordering and forwarding plan can (1) reduce the inventory of multiple squeezes to below 1000m³; (2) reduce the total cost by 0.5%, while the total loss rate decreases from 0.48% in the second question to 0.437%, and the percentage of raw material A increases significantly and C decreases (we measure them through ablation experiments); (3) increase the single-week capacity by 0.79% compared with the existing optimal model. The experimental results validate the correctness of our proposed model and demonstrate the strong generalization ability of our model. Based on the excellent experimental results, the main reasons are because

- (1) The principal component analysis we used to guest-weight the indicators, which enhanced the objectivity of the model and led to an improvement in the generalization ability of the model
- (2) We effectively combined the ARIMA model and the LSTM model to ensure a high accuracy of the model for different suppliers, thus also improving the robustness of the model

In the future, we will focus on improving our model in the following two aspects: (1) for individual suppliers whose single-week forecast exceeds the transportation capacity of a single forwarder, our approach is to first treat it as the maximum, that is, .6000 m³/week, and the remaining is assigned to other spare forwarders with the lowest loss rate in that week using the greedy algorithm. You can try to defer it to the next week, or treat it as two suppliers and find the optimal solution together with other suppliers. (2) For the method of predicting the next 24 weeks of supply, when there is sufficient time, the training amount of the LSTM network can be increased to achieve a closer fit to the irregular fluctuations closer to reality.

Data Availability

The data used to support the results of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest between authors.

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