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Ordering transit strategy based on time series forecasting and multi-objective planning

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Abstract: In order to reduce over-dependence on a single supplier, manufacturers often choose multiple suppliers to supply the same raw material and will commission forwarders to transport the goods, increasing the complexity of the supply chain system. This paper therefore focuses on establishing a time series forecasting and multi-objective planning model to provide a collaborative decision for ordering forwarding solutions to improve the production efficiency and stability of the enterprise. We first calculated the minimum number of suppliers to meet the production demand and used the ARIMA time series forecasting model to obtain the weekly supply quantities for the next 24 weeks using the weekly supply quantities of each supplier for the past 5 years as input to the model. In addition, based on the supplier supply capacity values from problem 1, we set the supplier selection priority, and based on this, we set up a multi-objective planning model for an enterprise's ordering and forwarding solution with the objective of minimizing the weekly ordering cost of raw materials and minimizing the loss in the forwarding process, and finally obtained the minimum number of suppliers to meet the production demand as 28, and gave the best weekly ordering and forwarding solution for the next 24 weeks.

1. Overview of relevant theories

In a progressively more competitive market environment, the cost of raw material procurement has a direct impact on the production efficiency of enterprises, leading to an increasing interdependence between manufacturers and suppliers. In order to reduce the over-dependence on a single supplier, many companies choose to supply from multiple sources. This reduces the incidence of stock-outs and allows suppliers to compete with each other on price and quality to ensure normal production and efficiency [1]. In addition, many manufacturers commission third party logistics companies to transport their goods, increasing the complexity of the supply chain system. Therefore, it is necessary to arrange the ordering of transport plans separately in order to promote synergy between the different members of the supply chain, thus improving the supply chain performance of the company and optimizing the stability and efficiency of production.

This paper needs to distil the supply characteristics based on the transaction data between the company and the supplier given in the topic, and identify the main factors affecting the effectiveness of the synergy from the loss rate data of the forwarder, etc. Provide decisions for the synergistic ordering of transport solutions for the enterprise based on different production requirements [2].

In the actual ordering of raw materials, companies tend to choose suppliers with higher supply capacity, and choose suppliers with higher supply capacity to meet capacity demand faster. In order to rationalize the ordering plan for the next 24 weeks, a time series model is used to predict the average of the next 24 weeks using the company's supply data for the past five years as input to the model. Based on the supplier supply capacity values in problem 1, the supplier selection priority is set and the predicted average supply quantity is used as the future supply quantity for each supplier, and the suppliers are selected in turn until the capacity demand is reached. Based on this, a multi-objective planning model is developed and solved to minimize the consumption of raw materials ordered each week and minimize losses during shipment to find the ordering and transit solutions.

2. Time series forecasting and multi-objective planning based model

2.1 Supplier delivery capability evaluation model

In order to avoid the influence of subjectivity on the quantitative results and to reflect the different quantitative differences of indicators of the same degree of importance and the qualitative changes of indicators of different degrees of importance, a normal weighting function is introduced at [3]. After determining the weights, a dynamic weighting summation is used to obtain the supply capacity of each supplier. In this way, the importance of each supplier to the production of the enterprise is quantified, and a production guarantee strategy model is established to select the 50 most important suppliers to the enterprise, so as to ensure the normal operation and efficiency of the enterprise's production.

For narrative purposes, the average annual number of transactions, the average annual volume of transactions and the average annual quasi-quantity delivery capacity are used as the first category of secondary indicators, and the average annual rate of change in the number of transactions, the average annual rate of change in the volume of transactions and the average annual rate of change in the quasi-quantity delivery capacity are used as the second category, respectively. The higher the weight of the indicator, the more important the supplier is to the business. That is, when the importance assessment level is higher, the importance to the enterprise tends to be extreme; when the assessment level is lower, the curve will tend to flatten out. From this, introducing the partial large *S* distribution, we can derive the weighting function:

$$\lambda_z(X_z') = \begin{cases} 2 - e^{-X_z X_z'}, X_z \geq 0 \\ e^{-X_z X_z'}, X_z < 0 \end{cases} \tag{1}$$

Where X_z is the *zth* indicator of the first category of the secondary indicator and Xz' is the *zth* indicator of the second category of the secondary indicator. In addition, the indicator weights need to satisfy both.

$$\begin{cases} \lambda_z(X_z') \in [0,1] \\ \sum_{z=1}^{Z} \lambda_z(X_z') = 1 \end{cases} \tag{2}$$

where Z denotes the total number of indicators in the second category. According to the conditions to be satisfied by the indicator weights, it is necessary to first normalize the weighting function $\lambda_z(X_z')$ is normalized, i.e., the normalized indicator weights $W_z(X_z')$

$$W_z(X_z') = \frac{\lambda_z(X_z')}{\sum_{z=1}^{Z}\lambda_z(X_z')} \tag{3}$$

The higher the score, the more important the supplier is to the production of the enterprise. The higher the score, the greater the impact of the supplier on the production of the enterprise. The importance score of supplier S_i with number i for the enterprise is as follows.

$$Score_i = \sum_{z=1}^{Z} X_z \cdot \lambda_z(X_z') \tag{4}$$

Using the Matlab software to program the solution, the supply capacity value of each supplier can be obtained, with higher scores representing higher importance to the production of the enterprise, as shown in Figure 1 Distribution of supply capacity scores by supplierFigure 1 below.

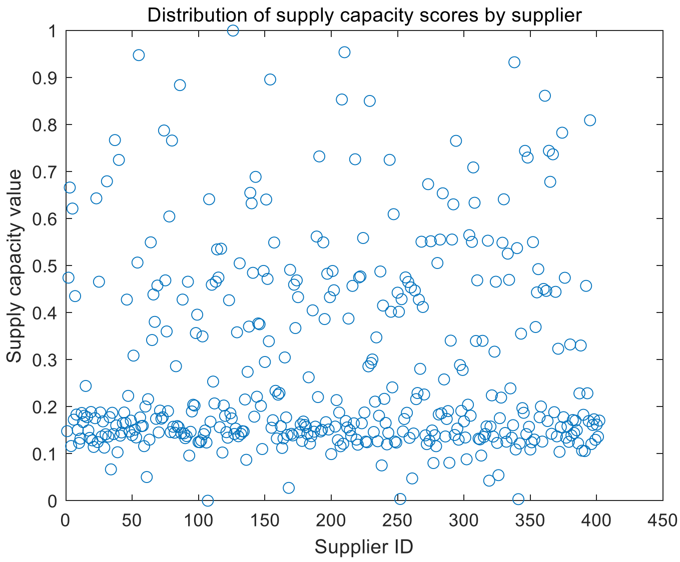

Figure 1 Distribution of supply capacity scores by supplier

According to the above chart, the supplier numbers with importance scores close to 1 are S055, S126, S210, S361, etc. An analysis of the importance scores for each supplier shows that suppliers can be classified into 4 categories according to their score distribution. The higher the supplier importance score, the better the supplier is able to meet the production needs of the company and the more important it is for the company to ensure production. most of the suppliers are at level 3, which means that they are generally important to the production of the company, and a small number are at level 4, which means that they are slightly important to the company. The 50 most important suppliers to the company are all at level 1.

2.2 Supplier selection to meet production needs

When ordering raw materials, companies prefer to cooperate with suppliers of higher importance. As a result, the supplier selection strategy gives priority to selecting suppliers in order of their importance ratings. In order to better arrange the next 24 weeks of ordering transit program, the time series model is used to predict the average value of each supplier's supply in the next 24 weeks, and this supply is selected in order of ranking until the capacity demand of the enterprise is satisfied, and the supplier is initially determined, and then a multi-objective planning model is established, and the minimum number of suppliers can be obtained by analyzing the model results.

2.3 Supplier selection based on time series forecasting models

Firstly, using a time series model, the company's supply data for the last five years was used as input to the model to predict the average of the next 24 weeks of supply. The raw materials supplied by the different suppliers are divided into three categories, A, B and C. Each category of raw materials can be used individually in the production of the product, and the capacity is set at 28,200 cubic meters per week. Suppose that γ suppliers are selected for supply and the weekly supply quantity of supplier S_i is q_i, then the total supply quantity S_a is, when the total supply quantity S_a reaches the weekly capacity requirement of the enterprise, the minimum number of suppliers to meet the production demand of the enterprise can be solved. Using the software Matlab programming, the number of suppliers and the total supply quantity are plotted as shown in Figure 2 below.

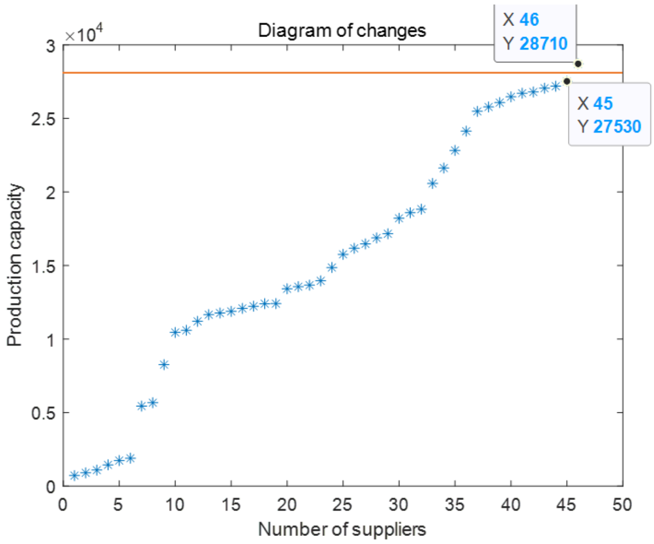

Figure 2 Diagram of changes in production capacity and number of suppliers

The above graph shows that when the number of suppliers is 45, the output reaches 27,530 m^3 and when the number of suppliers is 46, the output reaches 28,710 m^3, which is sufficient to meet the weekly production capacity, so at least 46 suppliers can be selected to meet the production needs of the company.

2.4 Supplier selection based on time series forecasting models

Raw materials for production are ordered from suppliers and transported via forwarders to the warehouse for storage. During the supply process, due to the specific nature of the raw materials, the quantity ordered does not correspond to the quantity supplied [4]. On the other hand, some of the raw materials are lost during the transit process. In the following, the ordering and transshipment options are arranged for the next 24 weeks for the company in terms of the most economical ordering and the least loss in transshipment, respectively. By looking at Annex II, the individual forwarders show different loss rates as the number of weeks varies. Over the next 24 weeks, the change in attrition rates cannot be measured directly. Therefore, a time series forecasting model was first used to predict the attrition rates for the next 24 weeks.

(1) ARIMA-based attrition rate time series prediction model

Time series data essentially reflects the trend of a random variable or variables over time, and time series forecasting methods are used to extract this pattern from the data and use it to make estimates of future data [5]. Analysis of Annex II shows that the attrition rate varies with the number of weeks, so an autoregressive integrated moving average model (ARIMA) can be used, where the algorithm takes a series of attrition rates over time and smooth the series by differencing it. A mathematical model is used to simulate the series and predict the attrition rates of different transshipment operators for the next 24 weeks, based on the known values of the time series [6].

The observations of the forwarder loss rate were obtained for graphical analysis, and the autocorrelation coefficient ACF and the partial autocorrelation coefficient PACF were obtained separately for the smooth time series below, as shown in Figure 3.

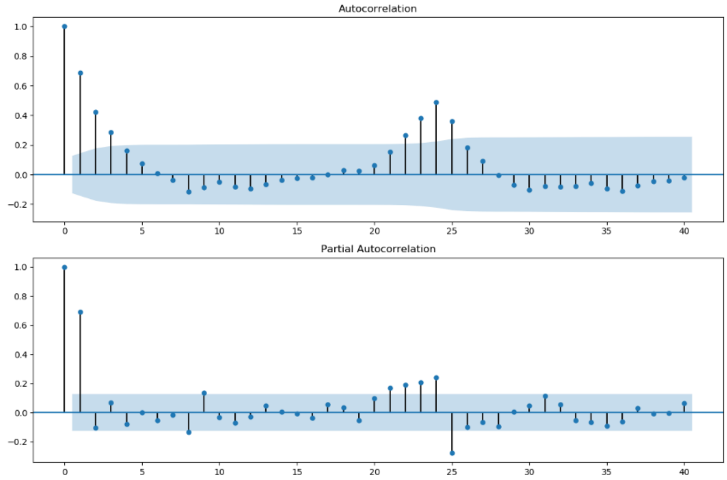

Figure 3 Diagram of ACF and PACF results

The above diagram allows us to observe that

a) Autocorrelation Chart showing lags of order 1 to 3 and orders 22 to 25 outside the confidence bounds.

b) The partial autocorrelation plot shows lags of order 1 and orders 21 to 25 are outside the confidence bounds. The series showed a tendency to be unstable, so the series was first subjected to a first-order difference change.

After obtaining the transshipment loss rate observations, it was observed that most of the data were highly volatile and were a non-stationary time series. Therefore, the time series was differenced to the *dth* order to obtain a smooth series. From the experimental analysis, it can be seen that the mean and variance of the first-order differenced time series are already basically smooth, so the differencing factor d is set to 1.

The Bare Pool Information Criterion (AIC) is designed to increase the goodness of fit of the data, but try to avoid over-fitting. The Bayesian Information Criterion (BIC) avoids excessive model complexity due to high model accuracy. In order to obtain the best model, the integrated criterion for model selection, AIC+BIC, was used to find the p and q that minimize the value of the integrated criterion indicator. *p* and *q* were obtained after several attempts to program the software in Python to take the values 9 and 9. The following white noise tests were performed on the model residuals.

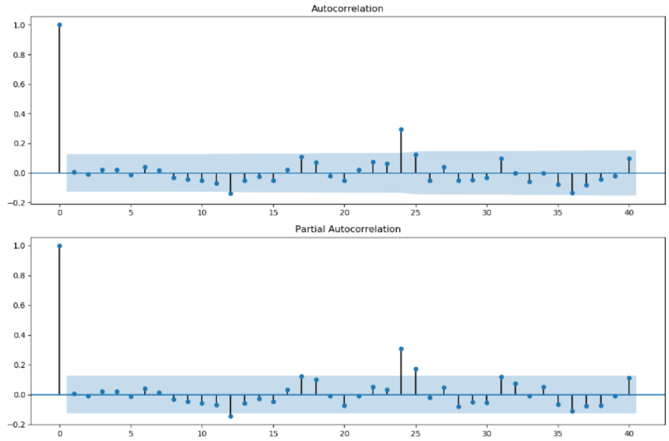

Figure 4 ACF and PACF plots of the residuals

Figure 4 above shows the ACF and PACF plots of the residuals. It can be seen that the series residuals are essentially white noise and the multi-parameter test indicates that the model is valid and can predict the attrition rates of the eight forwarders over the next 24 weeks, some of which are shown in Figure 5 below.

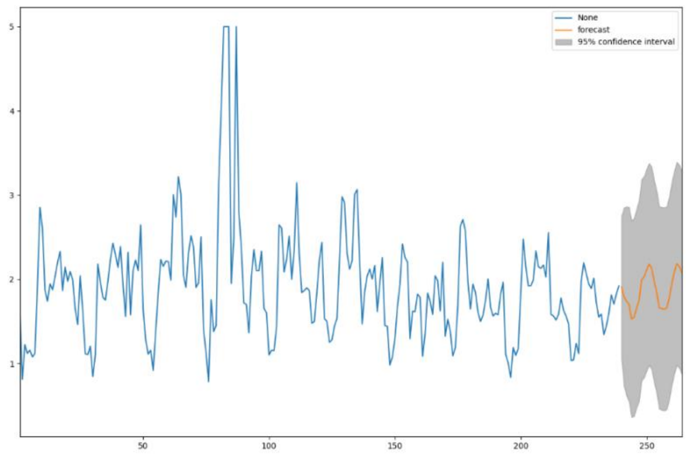

Figure 5 Diagram of the predicted volume of partial attrition rates

The graph above shows some of the attrition rate forecasts for the first forwarder and it can be observed that the forecasts meet the general trend of the data and are in line with the true picture.8 The specific attrition rate forecasts for the next 24 weeks for the forwarders can be found in the supporting material.

(2)Corporate Order Transit Decision Model

The loss rate for the predicted 24 weeks is obtained, a direct relationship between supply and receipt is established based on the loss rate, decision variables are set up by setting up relevant ordering schemes, forwarders and the actual receipt of raw materials, constraints are established based on the enterprise's capacity requirements, transport conditions and forwarders' transport capacity, etc., and a multi-objective planning model for ordering and forwarding is constructed with the minimum ordering cost and minimum forwarding consumption as the objective function. The model is used to optimize the costs and losses to arrive at the ordering and forwarding solution. In the following discussion, the optimization model for cost and loss is built with a time unit of one week.

As a result, a multi-objective planning model for ordering transshipment is developed based on various constraints and objective functions as follows.

$$\min W = 1.2\sum_{o\in A_g} D_o + 1.1\sum_{p\in B_g} D_p + 1.2\sum_{q\in C_g} D_q \tag{5}$$

$$\min L = \sum_{j=1}^{8}\sum_{i=1}^{402} D_i S_{ij} loss_j \tag{6}$$

$$s.t. = \begin{cases} \sum_{j=1}^{8} S_{ij} = 1 \\ R_K = \sum_{i\in K_g}\sum_{j=1}^{8}(1-loss_j)D_i S_{ij} \\ \frac{R_A}{\mu_A} + \frac{R_B}{\mu_B} + \frac{R_C}{\mu_C} = 28200 + \Delta T \\ \sum_{i=1}^{402} D_i \cdot S_{ij} \le 6000 \end{cases} \tag{7}$$

Where, for the sake of intuition in the formula, R_K is a generic calculation for R_A, R_B and R_C, the set of suppliers producing each of the three raw materials.

3. Analysis of the effectiveness of the implementation of the order transfer program

3.1 Analysis of the effectiveness of the implementation of the subscription program

Overall ordering scheme analysis: Since the model is selected in order according to the supplier's supply capacity, the enterprise mainly concentrates on choosing suppliers with stronger supply capacity and the supply quantity is also concentrated in those suppliers. As the selected suppliers have stronger supply capacity, the ordering scheme is not only for the suppliers with higher supply capacity, but also for the suppliers with higher supply volume. The ordering scheme can be better implemented because of the strong supply capacity of the selected suppliers, i.e., the normal production of the enterprise can be better guaranteed.

Analysis of the ordering quantity of different raw materials: The ordering scheme is more concentrated in the suppliers of A class materials, which is due to the comprehensive consideration of the economy and the higher loss. The reason for considering the economy and the low loss is that ordering more A materials can not only meet the production capacity better, but also make the loss less. The higher order of Class A materials will not only better meet capacity but will also result in less waste. The small change in the total amount ordered in each week over the next 24 weeks is due to the model's ability to better the reason for the low variation in the ordering totals from week to week over the next 24 weeks is that the model is better able to focus on the optimal solution, allowing for a more similar ordering solution for different loss rates, thus achieving the target optimization. optimization.

3.2 Analysis of the effectiveness of the implementation of the transfer program

Transshipment efficiency: The model solves for the transshipment scheme that can be based on the loss rate of each transshipment provider for the week Rational selection of forwarders can better reduce the loss of raw materials. The analysis of the data related to the transshipment scheme shows that About 4~5 forwarders are commissioned every week, and almost every week at least 3 forwarders are close to or equal to the maximum weekly transport capacity. capacity. This means that the efficiency of each forwarder during the week is high. This is a good way for companies to save on raw material transfer costs.

Stability analysis of forwarders' demand: The results of the forwarding scheme show that the enterprise has a long-term relationship with the forwarder with the lower loss rate among the eight forwarders. Among the eight forwarders, the company has long term relationship with the forwarder with the smaller loss rate, which is in line with the realistic long-term partnership.

4. Conclusion

In the actual ordering of raw materials, enterprises tend to choose suppliers with higher supply capacity, and choose suppliers with higher supply capacity to meet the capacity demand faster. In order to reasonably arrange the ordering plan for the next 24 weeks, we first use the time series model, use the enterprise's supply data of the last five years as the model input, predict the average of the supply quantity of the next 24 weeks, set the priority of supplier selection, use the predicted average of the supply quantity as the future supply quantity of each supplier, and select suppliers in turn until the capacity demand is reached. On the basis of this, a multi-objective planning model is built and solved to find the ordering scheme and trans-shipment scheme with the objective of minimizing the consumption of raw materials ordered each week and minimizing the loss during shipment.

The data is pre-processed before building the model, making it more realistic and reliable. Six secondary indicators, namely average annual number of transactions, average annual rate of change in number of transactions, average annual volume of transactions, average annual rate of change in volume of transactions, average annual quasi-volume delivery capacity and average annual rate of change in quasi-volume delivery capacity, have been refined to influence supplier characteristics in a number of ways, and a reasonable order transit strategy has been given. The time series model ARIMA was used to scientifically predict unknown quantities such as supplier availability and forwarder attrition rates that fluctuate over time.

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