

# Research on Material Ordering and Transportation Issues Based on RBF Neural Network and 0-1 Planning Model

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**Abstract:** To select the best 50 from 402 suppliers, this article mainly establishes a principal component comprehensive evaluation model to formulate the five most important supplier service indicators. To reflect the impact of timeliness on the modeling results, time weights are introduced for dynamic weighing. The RBF neural network model is used to predict the supply and order situation in the next 24 weeks. According to its time-weighted average supply capacity, two forecast corrections are made to make the forecast results more reliable. Establish a 0-1 planning model to decide on the most economical ordering plan and the transfer plan with the least loss.

**Keywords:** PCA, RBF neural network, 0-1 planning

## 1. Introduction

In the production and operation process of a production enterprise, the procurement and transportation of raw materials play an important role in the normal operation of the enterprise and the efficiency of production.

First of all, according to the supplier's historical supply data, five evaluation indicators are determined to establish a set of an evaluation systems. Quantitative assessment is carried out through these five indicators.

Then, we use the RBF neural network prediction model to train the original 240 weeks of data to predict the supply and subscription situation in the next 24 weeks. A planning model can be established to solve the problem, and the most economical ordering plan and the transportation plan with the least loss can be decided.

## 2. Model establishment and solution

### 2.1. Principal component comprehensive evaluation model

Through the application of principal component analysis (PCA), comprehensive indexes that replace the original more information with fewer comprehensive indexes are established.

We have established five comprehensive indicators, which are the cumulative supply volume (supplier's supply capacity), cumulative order volume (acceptance of this supplier), cumulative supply and order satisfaction rate (satisfying order requirements), the weighted sum of cumulative weekly volume (supplier's production stability), and the number of large quantities of supply.

The numbers 1 to 5 indicate the above 5 indicators in sequence. Principal component analysis results are listed in Table 1.

Table 1: Principal component analysis results

Num.	Characteristic root	Contribution rate (%)	Cumulative contribution rate (%)
1	2.434382514	48.68765027	48.68765027
2	1.320536606	26.41073212	75.0983824
3	0.972958599	19.45917199	94.55755438
4	0.16969122	3.393824392	97.95137878
5	0.102431061	2.048621223	100

It can be seen from Table 1 that the cumulative contribution rate of the first three characteristic roots has reached more than 94%, and the principal component analysis has a very good effect.

Therefore, the first three feature vectors are selected, and the contribution rate of the principal component is used as the weight, and the comprehensive evaluation model of the principal component is constructed as follows.

$$Z = 0.4869y_1 + 0.2641y_2 + 0.1946y_3 \quad (1)$$

The comprehensive evaluation value is calculated, and the top 50 suppliers with the highest evaluation value are selected from the 405 suppliers.

## 2.2. The prediction of supply and subscription relationship based on RBF neural network

It is necessary to predict the supply and subscription relationship in the next 24 weeks based on the supply and subscription data of the first 240 weeks. This article chooses to use the RBF neural network prediction model.

We can train the 31st from the first 30 data every week, then use the 2nd to 31st data to train the 32nd, and so on, predicting the last 240th data. That is, input 30 training samples to output 1 training result. For the number of neurons in the hidden layer, the RBF network will automatically determine the appropriate value based on the data during the training process. The number of training sample groups is 210. The larger the number of training, the more consistent the predicted results will be with the actual situation. The maximum number of training cycles is 10,000 cycles, and the number of training steps is 50 cycles per cycle. The training error target is 0.001. On this, the RBF neuron prediction model is established.

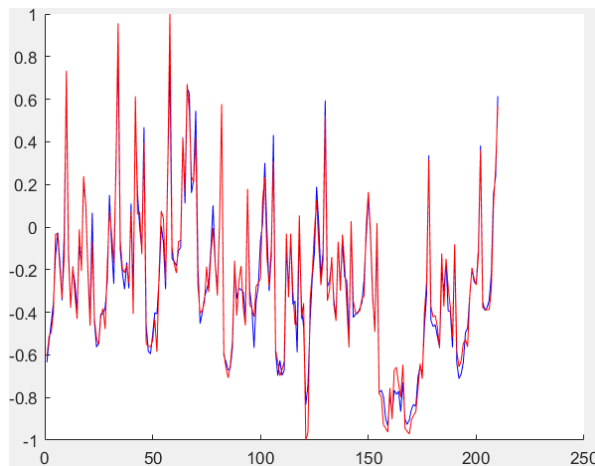


Figure 1: The match between the forecast data and the sample data

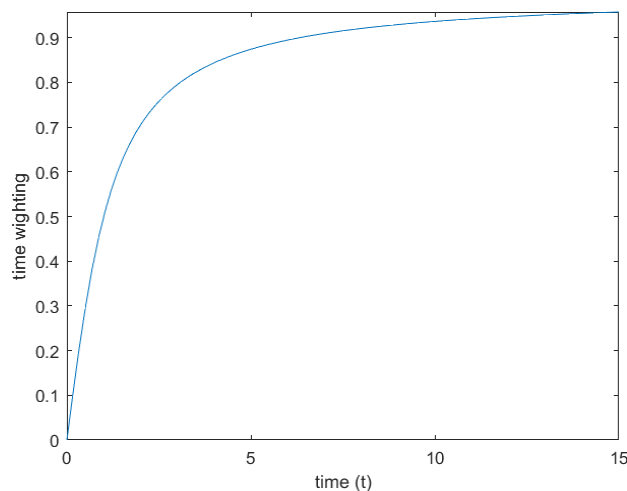


Figure 2: Time weight change trend chart

The model can be used to predict the supply situation in the next 24 weeks. This predicted value may not fully show its supply capacity, but it meets the supply characteristics of the previous 24 weeks.

Considering the timeliness of data, time weight is introduced. We use the time weighting function  $\rho(t) = \frac{2}{\pi} \arctan t$  for time weighting, and the function image is shown in Figure 2. We can weigh the average supply according to time. That is to show its recent supply capacity to revise it, and then make two forecast revisions.

Revision 1: Because some samples in the sample data are zero or close to zero, some of the predicted results will fluctuate around zero, and the supply quantity will be negative. Because the lower limit of supply is zero, this article will convert all negative values to zero when the forecast results appear negative.

Revision 2: The 24-week supply is time-weighted and the weighted average supply is obtained to ensure its timeliness and make it fully available. There is a gap between the predicted result and it. After the gap is averaged, it is added to the weekly forecast value.

**2.3. 0-1 planning model to seek the most economical purchase plan**

**2.3.1. Restrictions**

(1) Keep as much as possible the inventory of raw materials not less than two weeks of production needs.

$P_j$  is the inventory of week  $j$ .  $P_{sj}$  is the shipments of week  $j$ .  $X_{ij}$  is the forecasted 24 weeks supplier supply capacity. If  $Q_{ij}$  equals one, the supplier is chosen in week  $j$ ; else zero.  $1/K_{ij}$  indicates that different types of raw material suppliers are sorted by raw material types and the capacity per unit of raw material consumption.  $CN$  is a weekly production capacity of 28,200 m<sup>3</sup>.

$$P_j = P_{j-1} - CN + P_{sj} \geq 2CN$$

$$P_{sj} = \sum \frac{X_{ij} Q_{ij}}{K_{ij}} \leq 6000 \times 0.99 \times 8$$

$$K_{ij} = \begin{cases} 0.6, & i = 1, 2, \dots, 26, \\ 0.66, & i = 27, 28, \dots, 54, \\ 0.72, & i = 55, 56, \dots, 78 \end{cases}$$

(2) The transportation capacity of each forwarder is 6000 cubic meters per week.

$$Z_{kj} \leq 6000$$

(3) The raw materials supplied by a supplier every week should be transported by a forwarder as much as possible.

$$\sum_{k=1}^8 T_{ijk} = 1$$

Subscripts  $k$  indicates different carriers.

**2.3.2. Objective function: Lowest cost**

$$\min m = \sum_{i=1}^{78} \sum_{j=1}^{24} X_{ij} Q_{ij} b_{ij}$$

$$b_{ij} = \begin{cases} 1.2, & i = 1, 2, \dots, 26, \\ 1.1, & i = 27, 28, \dots, 54, \\ 1, & i = 55, 56, \dots, 78 \end{cases}$$

$b_{ij}$  indicates the purchase unit price corresponding to different suppliers.

**2.3.3. Results**

Draw a forecast trend chart for the supply of the supplier ranked first in the comprehensive index value in the next 24 weeks, as shown in Figure 3.

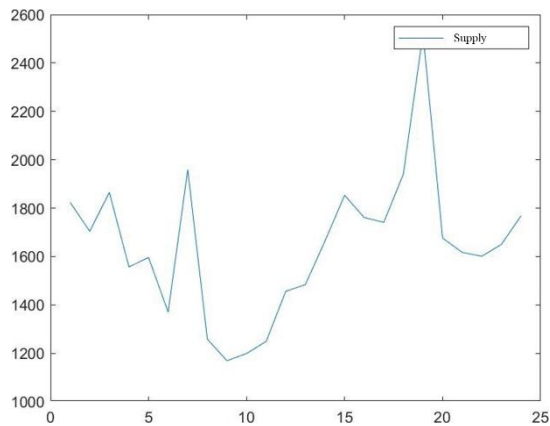


Figure 3: The company's order plan from this supplier in the next 24 weeks

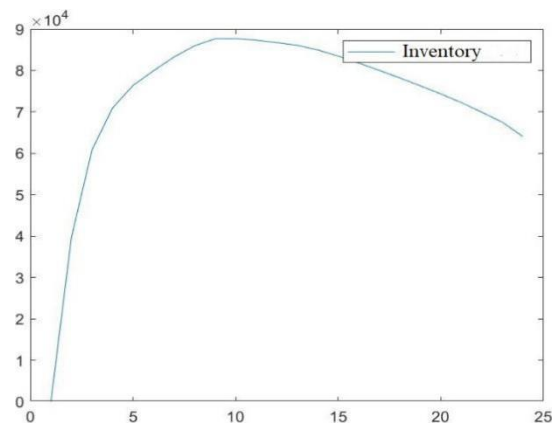


Figure 4: The company's inventory in the next 24 weeks

### 3. Evaluation and promotion of the model

The article fully takes into account the timeliness factor and does not treat the data at all moments equally, introduces the time weight, and adds this weight to the evaluation process based on time series data, making our evaluation effect more reasonable and scientific.

Through the RBF neural network prediction model, the future prediction results can be close to the true value, and the reliability of the prediction results is higher. However, the selection of the distribution factor of the RBF neural network model will have a certain impact on the training results of the neural network. The characteristics of convergence and the learning effect can be improved, and dynamic corrections can be added to make the results more reliable.

### References

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