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Multi-objective Optimization Study for Enterprise Supply and Transit Problems

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Abstract: *This paper focuses on the ordering and transportation of raw materials for companies. This paper establishes a logistic regression equation to fit the relationship between supply quantity and order quantity based on the supply characteristic index system. In this paper, a multi-objective BP neural network model is established to solve the supply solution with the lowest purchase and storage cost, the highest supplier reliability score, as the objective function. A gray prediction model is built based on the past loss rate data of the forwarder to obtain a prediction formula to predict the loss rate. Finally, a linear programming model is built to solve for the optimal operation solution to meet the demand based on the predicted loss rate.*

Keywords: *Logistic Regression; BP Neural Network Model; Gray Prediction*

1. Introduction

Only when the production enterprises of raw materials sell their products in time and realize their values can they create conditions for the reproduction and expansion of raw materials [1]; likewise, only when the production enterprises buy raw materials in time and in quality and quantity according to the needs of production can they successfully carry out production. The rational use of raw materials will reduce costs, improve efficiency, and save energy. In this paper, a mathematical model is developed to calculate the minimum number of suppliers that an enterprise should choose to supply raw materials to meet its production needs. The most economical raw material ordering scheme is developed for the suppliers, and the least costly transportation scheme is developed based on the raw material ordering scheme, and the implementation effect of the ordering scheme and transportation scheme is analyzed.

2. Establishment of model

2.1. Single objective programming model

The order demand directly determines the supply relationship. In order to meet the order demand of the enterprise, the supplier may dispatch the supply to meet the order quantity. Define a fluctuation factor for fluctuations in the number of orders:

$$H_j = \sum_{i=1}^{T_d-1} (D_{i+1} - D_i)^2 \tag{1}$$

According to the supply relationship of the data processing, there are 7 factors x1, x2, x3, x4, x5, x6, x7 (guarantee rate, satisfaction rate, stability, contribution, supply, loss factor, and fluctuation factor), which will affect the relationship between the order quantity and the supply quantity.

The linear correlation coefficient model for the indicators in the regression equation was simulated by the major indicators as:

$$\begin{gathered}\ln\frac{p_i}{1-p_i} = \mu_0 + \mu_1 x_1 + \mu_2 x_2 + \mu_3 x_3 + \mu_4 x_4 + \mu_5 x_5 + \mu_6 x_6 + \mu_7 x_7 \\ p_i = \frac{1}{1-e^{-(\mu_0+\mu_1 x_1+\mu_2 x_2+\mu_3 x_3+\mu_4 x_4+\mu_5 x_5+\mu_6 x_6+\mu_7 x_7)}}\end{gathered} \tag{2}$$

The constant term u_0 is the natural logarithm of the ratio of supply to firm demand when the supplier supply is less than the firm demand [2]. The partial regression coefficient uj (j=1,2, ..., m) represents the average change in logit(p) for each unit change in the jth independent variable with other independent variables fixed.

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The values of the seven dependent factors can be obtained as x1 = 0.8419, x2 = 0. 4155, x3 = 0.5132, x4 =0.3290, x5 = 0.2164, x6 = 0. 4611, x7 = 0.4427.

With the production needs of the enterprise as the target, based on the procurement cost of raw material category A is 20% higher than raw material category C, and raw material category B is 10% higher than raw material category C, so as to establish the single-objective demand planning model.

$$minz = k\left(1.2Q_{Aj} + 1.1Q_{Bj} + Q_{Cj}\right)$$
$$\text{s.t.}\begin{cases} Q_{Aj} - \bar{Q}_{Aj} > 0 \leftrightarrow 1 \\ p_i < \frac{\sum_{i=1}^{n}\left(Q_{Aj} - \bar{Q}_{Aj}\right)}{24} < 1 \\ Q_{Aj} + Q_{Bj} + Q_{Cj} \geq 56400 \end{cases} \tag{3}$$

2.2. BP Neural Network Enterprise Ordering Model

With economy and reliability as the target variables, we combine the features of BP neural network with adaptive learning and multi-objective iteration to build an enterprise ordering model [3].

For Class A, B, and C materials ordered, we build a scoring-based reliability provisioning model to achieve the lowest storage and procurement costs and the highest reliability scores from our suppliers.

$$\begin{cases} P_{min} = C_{min} + B_{min} \\ G_{max} = \sum_{i=1;j=1;m=1} A_i + B_j + C_m \end{cases} \tag{4}$$

$$\frac{\sum_{i=1}^{n_1} A_i}{0.6} + \frac{\sum_{j=1}^{n_2} B_j}{0.66} + \frac{\sum_{m=1}^{n_3} C_m}{0.72} \geq 56400 \tag{5}$$

The price of material class A is higher, but the volume consumed for capacity is smaller, and the price of material class C is lower, but the volume required for manufacturing capacity is larger, so we need to build an optimization model for material purchase. The objective function equation for purchase and storage costs is:

$$P_{min} = 1.2P \cdot \sum_{i=1}^{n_1} A_i + 1.1P \cdot \sum_{j=1}^{n_2} B_j + P \cdot \sum_{m=1}^{n_3} C_m + P' \cdot \sum_{i=1}^{n_1} A_i + P' \cdot \sum_{j=1}^{n_2} B_j + P' \cdot \sum_{m=1}^{n_3} C_m \tag{6}$$

The objective function for the reliability score of the supply is:

$$G_{\min} = \sum_{i=1}^{n_1} G_i A_i + \sum_{j=1}^{n_2} G_j B_j + \sum_{m=1}^{n_3} G_m C_m \tag{7}$$

The purchase function P and the reliability scoring function G are established as metric variables of different dimensions, and it is necessary to combine the two objective functions into one dimension, so a neural network model with multiple objective dimensions is established. The advantage of BP neural networks is that they can learn adaptively and assign weights to the inputs of different dimensions in order to output a target value.

The neural network mainly adjusts the value of the network according to the weight and threshold value. We use neural networks to find optimal results.

$$\begin{cases} F = minf(\psi) \\ f(\psi) = \frac{-1}{m}\sum_{i=1}^{m} \sum_{k}^{K} \left[y_k^{(i)} \log h_\psi\left(x^{(i)}\right)_k + \left(1 - y_k^{(i)}\right)\log\left(1 - h_\psi\left(x^{(i)}\right)_k\right)\right] \end{cases} \tag{8}$$

First regularize the function such that m= 1,

$$f(\psi) = \sum_{k=1}^{K} \left[y_k \log h_\psi\left(x^{(i)}\right)_k + \left(1 - y_k^{(i)}\right)\log\left(1 - h_\psi\left(x^{(i)}\right)_k\right)\right] \tag{9}$$

Based on the nodes and weights of the previous layer, using the chain rule through the association between ϖ and Z, the partial derivative for finding f (ϖ) is obtained.

$$\frac{\partial f(\psi)}{\partial \psi_{i,j}^{(l)}} = \left(\frac{\partial f(\psi)}{\partial z_i^{(l+1)}}\right) a_j^{(l)} \tag{10}$$

Substituting the objective function equation as:

$$\begin{cases} P_{min} = 1.2P \cdot \sum_{i=1}^{n_1} A_i + 1.1P \cdot \sum_{j=1}^{n_2} B_j + P \cdot \sum_{m=1}^{n_3} C_m + P' \cdot \sum_{i=1}^{n_1} A_i + P' \cdot \sum_{j=1}^{n_2} B_j + P' \cdot \sum_{m=1}^{n_3} C_m \\ G_{max} = \sum_{i=1}^{n_1} G_i A_i + \sum_{j=1}^{n_2} G_j B_j + \sum_{m=1}^{n_3} G_m C_m \end{cases} \tag{11}$$

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2.3. Gray predictive loss rate model

The gray correlation prediction algorithm predicts systems containing known information as well as unknown or non-deterministic information [4], treating the known information as a white box system and the unknown information as a black box system, and predicting the time-dependent gray information. It is better to predict the loss rate with both known information such as loss rate fluctuation and loss rate, and unknown information such as the influence of environmental factors that are difficult to measure.

Suppose the original time series of the loss rate of the transporter is:

$$L^{(0)} = \left\{L^{(0)}(1), L^{(0)}(2) \ldots . L^{(0)}(240)\right\} \tag{12}$$

An accumulation of the last 240 weeks time series for each supplier has.

$$L^{(1)} = \sum_{i=1}^{k} L^{(0)}(i), k = 1,2 \ldots . .240 \tag{13}$$

Let $L^{(1)}$ satisfy the first-order ordinary differential equation.

$$\frac{dL^{(1)}}{dt} + aL^{(1)} = \mu \tag{14}$$

The solution of this ordinary differential equation by successive differentiation method equation is:

$$L^{(1)}(t) = \left[x^{(1)}(t_0) - \frac{\mu}{\alpha}\right] e^{-\alpha(t-t_0)} + \frac{\mu}{\alpha} \tag{15}$$

The approximate white differential equation can be obtained by applying a continuous differential treatment to time t as:

$$\frac{dL^{(1)}}{dt} + \alpha L^{(1)} = \mu \tag{16}$$

The parameter vector is solved according to the existing loss rate using the least squares method as:

$$\hat{a} = (B^T B)^{-1} B^T T \tag{17}$$

The whitening prediction equation of the gray model can be obtained as:

$$\hat{L}(\mathrm{t}) = \left(L^0(1) - \frac{\mu}{\alpha}\right) e^{-\alpha t} + \frac{\mu}{\alpha} \tag{18}$$

3. Solution of model

Since different initial time series of transporters lead to different prediction results, bringing in the initial time series of the ith supplier and choosing 24 weeks as a measure in the time dimension, we can find the average of the attrition rate of the i-th supplier as:

$$\bar{L}_i = \frac{\sum_{t=1}^{24} \hat{L}(t)}{24} \tag{19}$$

Because the maximum limit for each transporter is 6000, the total amount of transportation is set to Z from the ordering scheme above, we must select the shippers in the order of selecting the elements from the first to the last element of the vector A. Let the m-th element in the selection have the following constraint.

$$\begin{cases} 6000m \leq Z \\ 6000(m+1) > Z \end{cases} \tag{20}$$

At this point, the optimal shipping solution is obtained. That is, for the first element to the mth element of the vector A, the supplier chooses the maximum limit of $6000m^3$, while for the (m + 1)th elements of the vector A, the supplier chooses the maximum limit of $Z - 6000m^3$ for shipment. The partial sequencing scheme and the minimum loss rate scheme are shown in Table 1 and Table 2.

This paper consists of a multi-objective dimensional BP neural network model enterprise ordering model. At least 45 suppliers are required to supply raw materials, and the allocation of different vendors within each week's suppliers is achieved based on their ratings and past historical data, resulting in a robust supply solution that can maintain the manufacturers' production requirements within a certain range.

The transshipment scheme is based on the developed procurement scheme, and the transshipment risk of the transshipment vendor is used as the basis to decide the transshipment vendor. Based on the

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gray prediction loss model established by the transshipment, the loss rate of the vendor is ranked using mathematical analysis, and the optimal transshipment scheme with small risk degree and strong robustness is selected.

Table 1: Data table for ordering program results

Suppliers ID	***Week1***	***Week2***	***Week3***	***Week4***	***Week5***	***Week6***	***Week7***	***Week8***	***Week9***	***Week10***
S055	55	812	56	51	74	59	56	69	71	53
S080	55	21	89	17	104	24	82	27	162	23
S108	556	7871	832	636	761	707	615	636	736	730
S131	2	539	657	628	620	663	426	661	699	751
S151	146	553	643	610	721	663	628	612	720	617
S194	242	349	304	369	435	427	404	431	427	402
S229	2006	1138	993	1027	1155	1175	1299	1786	1781	1570
S247	215	182	205	194	247	230	199	206	241	226
S268	509	516	522	521	569	574	433	481	498	514
S275	395	525	577	546	643	651	487	618	697	583

Table 2: Data sheet of the minimum loss transfer scheme

Supplier ID	***Week1***	***Week2***	***Week3***	***Week4***	***Week5***	***Week6***	***Week7***	***Week8***	***Week9***	***Week10***
Transit	T6	T6	T6	T3	T7	T2	T3	T6	T6	T4
S055	55	812	56	51	74	59	56	69	71	53
S080	55	21	89	17	104	24	82	27	162	23
S108	556	7871	832	636	761	707	615	636	736	730
S131	2	539	657	628	620	663	426	661	699	751
S151	146	553	643	610	721	663	628	612	720	617
S194	242	349	304	369	435	427	404	431	427	402
S229	2006	1138	993	1027	1155	1175	1299	1786	1781	1570
S247	215	182	205	194	247	230	199	206	241	226
S268	509	516	522	521	569	574	433	481	498	514
S275	395	525	577	546	643	651	487	618	697	583

4. Conclusion

In this paper, the logistic regression model is used to predict the quantitative indexes of the enterprise stability model and determine the optimal transportation solution. Dynamic planning and BP neural network are used instead of nonlinear planning, while ensuring the efficiency and accuracy of the calculation process. It can be obtained that at least 45 suppliers are needed to provide raw materials, and the composed supply scheme is robust and can maintain the requirements of manufacturers' production within a certain range.

However, when considering the minimum transit loss rate, the data given is too little to take into account the transportation environment and material consumption, and the results from the gray prediction model may have errors with the real value.

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