# Research on Enterprise Raw material ordering and Transportation process based on Multi-objective programming and Machine Learning algorithm

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**Abstract.** This paper analyzes the various production factors that affect the building materials enterprises, including the production cost of the enterprise itself and the degree affected by suppliers and transporters. Then, according to the relevant data, the objective function of minimum production cost is established, and under the premise of ensuring production, a mathematical model is established with the influence degree of each related enterprise as the constraint. In this paper, the model is solved to help enterprises make a reasonable production and management plan. First of all, the random forest algorithm is used as a machine learning method to analyze the characteristics of the given supplier. Then we evaluate the importance of each supplier to the production of the enterprise, and then rank it according to the level of influence, and select the top 20 suppliers. Then three goals are selected based on the multi-objective programming algorithm. First, the cost of production is the lowest, that is, the total cost of purchasing all kinds of materials is the least. Second, the loss is the lowest in the process of material transportation. In this paper, the materials collected are divided into three kinds of ABC, thus it is concluded that increasing the purchase of A material and reducing the purchase of C material. Therefore, a multi-objective programming model is established to solve the ordering and transshipment scheme. Finally, the neural network algorithm is used to evaluate the supplier's supply volume and transshipment loss in the next 24 weeks. The main goal is to maximize the production capacity of the enterprise, without considering the material procurement cost and the purchase demand of An and C materials, but still keep the minimum material transfer loss. In this paper, the weight analysis and multi-objective programming algorithm around the ordering and transportation process based on the principle of production enterprises can effectively provide reliable reference analysis for this process that needs to be optimized.

**Keywords:** Ordering and transportation, Machine learning, Random forest importance index, Multi-objective programming model.

## 1. Introduction

In recent years, with the promotion of national urbanization, the development space of building materials enterprises is growing. The competition among enterprises is very fierce. If enterprises want to gain a firm foothold, they must start from the internal production, operation and management. The production, operation and management of building materials enterprises are related to the development of enterprises, so it is necessary to formulate a management plan with strong economy and high feasibility. In order to ensure the demand of normal production, building materials production enterprises should make raw material ordering and transfer plan in advance and guarantee the inventory of raw materials for two weeks.

The procurement cost of raw materials has a direct impact on the production efficiency of the whole enterprise, smart enterprises should determine in advance the appropriate suppliers to provide themselves with the scheduled volume. When the supplier cannot supply the goods strictly according to the order quantity, the enterprise will buy all the goods no matter how much it is supplied. In the process of transportation, the loss rate of raw materials varies among different transporters, which is also an important factor for enterprises to consider when choosing transporters. Therefore, the production, operation and management of building materials enterprises is very important to the development of enterprises, and the formulation of a reasonable and feasible production management plan is very important to promote the development of enterprises.

Enterprises in the procurement of raw materials, and storage and distribution, the formulation of the plan needs to be considered in the long run, and can effectively reduce production costs and improve the economic benefits of enterprises. Cooperation with more reliable suppliers should be increased as much as possible, while reducing the loss of materials during transportation. The materials stored in the warehouse should guarantee the production needs for at least two weeks, and when the actual supply quantity provided by the supplier does not match the quantity of materials ordered by the enterprise, the production enterprise should buy it at the same time regardless of the amount of materials. In this paper, through the machine learning method [1], through the data building model for the research and analysis of the problem.

## 2. Supplier importance Evaluation Model based on Random Forest algorithm

Random forest algorithm[2] can integrate many different learning ideas into one algorithm, and its basic unit is decision tree, which is essentially an integrated learning method in machine learning.

### 2.1. Importance multiplier index

Importance multiplier index:

$$a_s = k_s \bullet n_s \bullet \sum_{t=1}^{T} g_s^t \bullet \sum_{t=1}^{T} r_s^t \tag{1}$$

Including price weighting factor, number of orders, total supply, total completion rate. Then the supply quantity characteristics of each supplier, the order times of each supplier, the total quantity of supply, the completion rate of each supplier and so on are calculated. The ranking of the top 20 enterprises is calculated according to the supplier importance multiplier index, and the visualization is carried out.

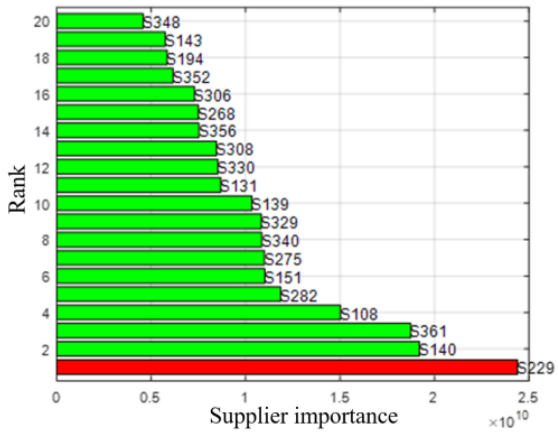



**Figure 1.** Importance multiplier Index Top 20 Vendor Visualization Chart

### 2.2. Importance log index

Importance log index: Price weighting factor, number of orders, total supply, total completion rate. Calculate the supply quantity characteristics of each supplier, the order times of each supplier, the total quantity of supply, the completion rate of each supplier, etc.

$$l_s = k_s \bullet n_s \bullet \sum_{t=1}^{T} r_s^t \bullet \log(\sum_{t=1}^{T} g_s^t) \tag{2}$$

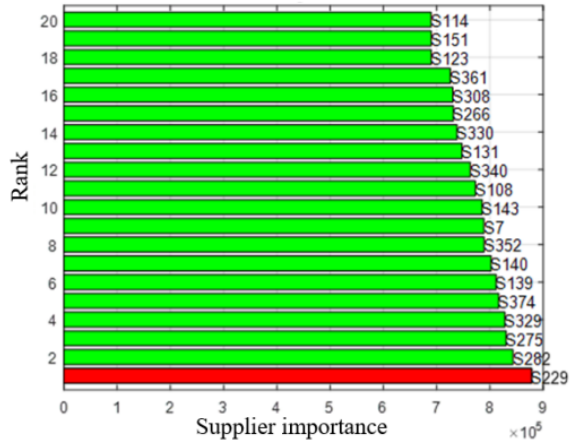



**Figure 2.** Importance log Index Top 20 Vendor Visualization Chart

### 2.3. Importance random forest index

Importance random forest index: represents the random forest evaluation process $f_s = \Lambda(s,t)$.

The weekly completion rate of each supplier forms a feature sequence, and the total weekly completion rate is used as label data. The random forest decision tree model is established, and the contribution degree of each supplier to the total completion rate is calculated by the algorithm, which can be understood as the degree of importance.

Steps to solve the importance of stochastic forest model:

(A) Establish the time series variables of weekly order completion rate, and establish a set of feature tags of the relationship between suppliers and manufacturers. In this paper, the total weekly order completion rate is used as the label.

(B) Generate a decision tree.

(C) Calculate the contribution of suppliers to the total weekly completion rate.

(D) Draw the top important suppliers.

The random forest decision tree structure diagram is solved according to the characteristic data of the completion rate time series.

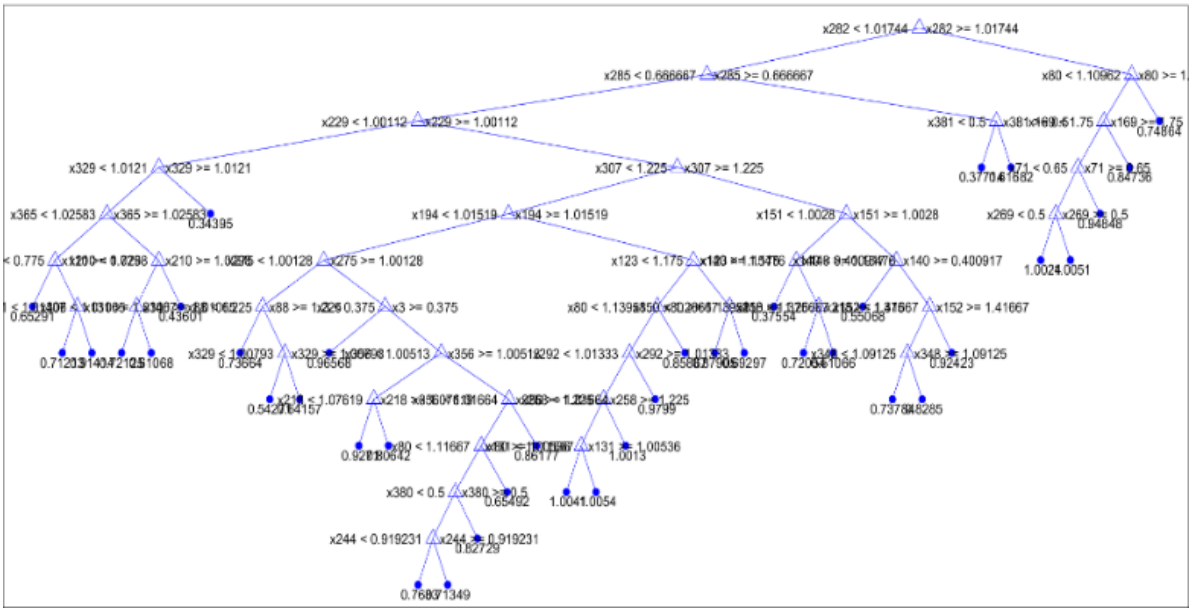


**Figure 3.** Structure diagram of random forest decision tree

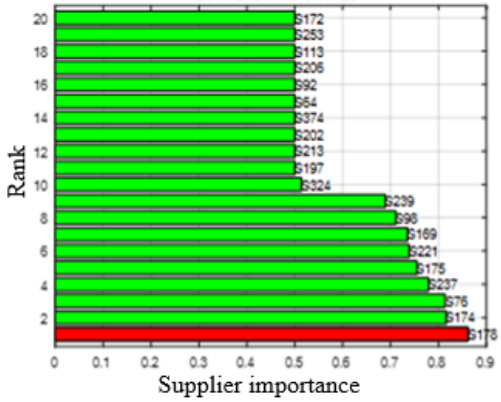



**Figure 4.** Visualization figure of the top 20 suppliers in the importance random forest index

**Table 1.** Top 20 suppliers under different sorting rules

| Importance serial number | Sorting rules | | |
|---|---|---|---|
| | Importance multiplier index | Importance log index | Importance random forest index |
| 1 | S229 | S229 | S178 |
| 2 | S140 | S282 | S174 |
| 3 | S361 | S275 | S076 |
| 4 | S108 | S329 | S237 |
| 5 | S282 | S374 | S175 |
| 6 | S151 | S139 | S221 |
| 7 | S275 | S140 | S169 |
| 8 | S340 | S352 | S098 |
| 9 | S329 | S007 | S239 |
| 10 | S139 | S143 | S324 |
| 11 | S131 | S108 | S197 |
| 12 | S330 | S340 | S213 |
| 13 | S308 | S131 | S202 |
| 14 | S356 | S330 | S374 |
| 15 | S268 | S266 | S064 |
| 16 | S306 | S308 | S092 |
| 17 | S352 | S361 | S206 |
| 18 | S194 | S123 | S113 |
| 19 | S143 | S151 | S253 |
| 20 | S348 | S114 | S172 |

## 3. Weight importance result

Under the three importance index indexes, the top 20 suppliers are obtained respectively. In order to make comprehensive use of the three evaluation results and effectively avoid the error of a certain index, this paper considers using the following calculation method to calculate the comprehensive importance value of the top 20 important suppliers.

The importance order of each supplier under each index is O, which represents the ranking of the s supplier under the u index. The smaller the ranking value is, the stronger the importance is.

Calculate the ranking value of comprehensive importance for each supplier:

$$o_s = \frac{1}{3}\sum_{u=1}^{3} o_{s,u} \tag{3}$$

**Table 2.** Comprehensive importance order

| Ranking | ID | Comprehensive score | Ranking | ID | Comprehensive score |
|---|---|---|---|---|---|
| 1 | S229 | 18.66667 | 11 | S374 | 24.33333 |
| 2 | S140 | 18.66667 | 12 | S131 | 24.66667 |
| 3 | S361 | 19.66667 | 13 | S330 | 26.33333 |
| 4 | S108 | 20.33333 | 14 | S356 | 26.33333 |
| 5 | S282 | 21 | 15 | S268 | 26.33333 |
| 6 | S139 | 21 | 16 | S308 | 27 |
| 7 | S275 | 22.33333 | 17 | S306 | 27.33333 |
| 8 | S340 | 22.33333 | 18 | S352 | 29 |
| 9 | S151 | 22.66667 | 19 | S194 | 29 |
| 10 | S329 | 23.33333 | 20 | S143 | 30.33333 |

## 4. Raw materials Purchasing and Transportation Model based on Multi-objective programming[3]

Two objectives are determined here: first, the production cost is the lowest, that is, the sum of the procurement costs of all raw materials is the lowest; the second transshipment loss rate is the lowest; and the two objectives need to be met at the same time, which constitutes a multi-objective programming model. In addition, there are also requirements for the purchase of A and C materials, and the purchase opportunities of A and C materials can be restricted by setting a reasonable purchase cost factor.

### 4.1. Definition

Purchase cost factor: for An and C raw materials, the purchase cost is different with different materials. The purchase cost factor is used to express the purchase cost coefficient of the two materials. The higher the value is, the higher the purchase cost is. The range of m value is {1 ~ 2}, in which Bamboo 1, that is, the purchase intention of material C is set as the benchmark.

In the establishment of the model, the cost increase caused by the purchase cost factor of An and C will become a part of the purchase cost.

### 4.2. Decision variables

$y_s^t$: Supplier s supply quantity in week t, $s \in \{1,2,...,50\}$, $t \in \{1,2,...,24\}$;

$z_{h,s}^t$: Transshipment volume of transporter h to suppliers in week t, $h \in \{1,2,...,8\}$, $t \in \{1,2,...,24\}$, $s \in \{1,2,...,402\}$.

### 4.3. Objective function

(1) The goal is to minimize the cost of materials:

$$\min F_1 = \sum_{s=1}^{s\in A}\sum_{t=1}^{24} y_s^t \bullet k_s + \sum_{s=1}^{s\in B}\sum_{t=1}^{24} y_s^t \bullet k_s + \sum_{s=1}^{s\in C}\sum_{t=1}^{24} y_s^t \bullet k_s \tag{4}$$

(2) The goal is to maximize the total purchase intention of materials s and C

$$\min F_2 = \sum_{s=1}^{s\in A}\sum_{t=1}^{24} y_s^t \bullet \beta_1 + \sum_{s=1}^{s\in C}\sum_{t=1}^{24} y_s^t \bullet \beta_2 \tag{5}$$

(3) The goal is to minimize the transfer loss

$$\min F_3 = \sum_{t=1}^{24}\sum_{s=1}^{402}\sum_{h=1}^{8} z_{h,s}^t \bullet q_h \tag{6}$$

### 4.4. Constraint condition

(1) Production demand of not less than two weeks (mainly reflected in the need to ship materials with twice the capacity in the first week):

$$\begin{cases} \frac{Y_A}{0.6}+\frac{Y_B}{0.66}+\frac{Y_C}{0.72} \geq 3\bullet 2.82\bullet 10^4 \\ Y_A=\sum_s^{s\in A} y_s^1 \\ Y_B=\sum_s^{s\in B} y_s^1 \\ Y_C=\sum_s^{s\in C} y_s^1 \end{cases} \tag{7}$$

(2) Meet the demand of weekly production (after the second week):

$$\begin{cases} \frac{Y_A}{0.6}+\frac{Y_B}{0.66}+\frac{Y_C}{0.72} \geq 2.82\bullet 10^4 \\ Y_A=\sum_s^{s\in A} y_s^t \\ Y_B=\sum_s^{s\in B} y_s^t \\ Y_C=\sum_s^{s\in C} y_s^t \end{cases} \quad t\in\{2,3,...,24\} \tag{8}$$

(3) The order quantity is not larger than the supply quantity:

$$\sum_{t=1}^{24} y_s^t \leq g_s^t \tag{9}$$

(4) Weekly restrictions on transshipment capacity:

$$\sum_{s=1}^{S} z_{h,s}^t \leq 6\bullet 10^3 \tag{10}$$

(5) The raw materials of a supplier should be transported by a transporter as far as possible:

$$\sum_{h=1}^{8} e_{h,s}^t \leq 1 \tag{11}$$

(6) Variable non-negative constraint:

$$\begin{cases} y_s^t \geq 0,\ \ z_{h,s}^t \geq 0 \\ s\in\{1,2,...,402\},\ \ t\in\{1,2,...,24\}, h\in\{1,2,...,8\} \end{cases} \tag{12}$$

## 5. Prediction of supply volume and transshipment loss rate based on neural network[4]

Due to the enhancement of the production capacity of production enterprises, the increase in weekly production capacity in the future will greatly affect the weekly supply. Therefore, it is necessary to extract the historical data of nearly five years to predict the weekly supply volume of 402 suppliers in the next 24 weeks[5].

### 5.1. Supply forecast

The input characteristic matrix of the neural network prediction model is constructed, and the historical data is constructed by the way of data sliding. A total of 6 samples are used for neural network model training, and then the combined sequence of 7, 8, 9 and 10 cycles is used as the input feature to predict the weekly supply volume of the 11th cycle in the future, that is, the next 1 to 24 weeks. Then 402 suppliers are forecasted respectively.

The structure of the constructed BP neural network is shown in figure below. The number of input layers is 96, the hidden layers of the two layers are 24 and 20 respectively, and the 24 layers of the output layer correspond to 24 output values.

Forecast all suppliers, and select the forecast results of suppliers 1, 2, 20, 40, 200, 400 for visualization

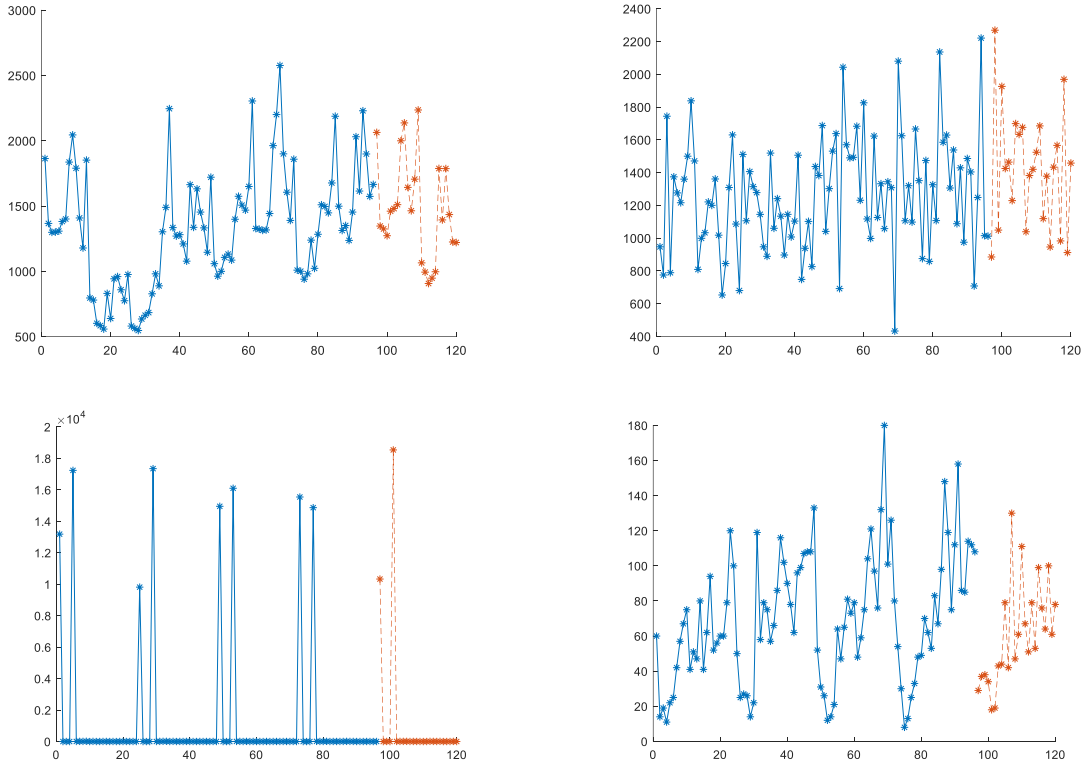


**Figure 5.** Forecast chart of suppliers 1, 2, 20 and 40

### 5.2. Prediction of transshipment loss rate

The forecasting principle is the same as the supply volume forecasting principle, and the forecast results are as follows.

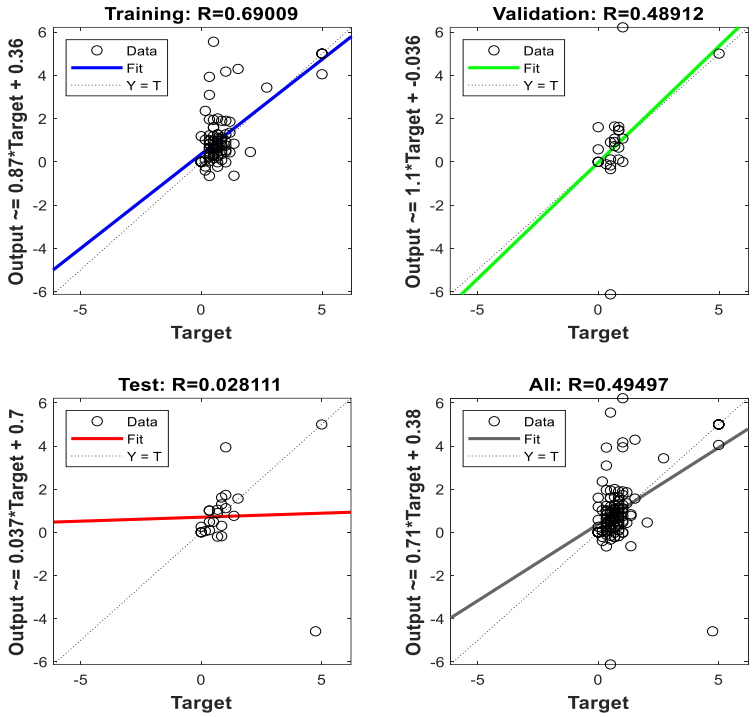



**Figure 6.** Forecasting results of the same forecasting principle as the supply volume forecasting principle

By selecting the eighth transporter's prediction result visualization, we can see that the prediction effect shows the periodic change trend of the loss rate, and more accurately realizes the prediction of the transshipment loss rate in the next 24 weeks.

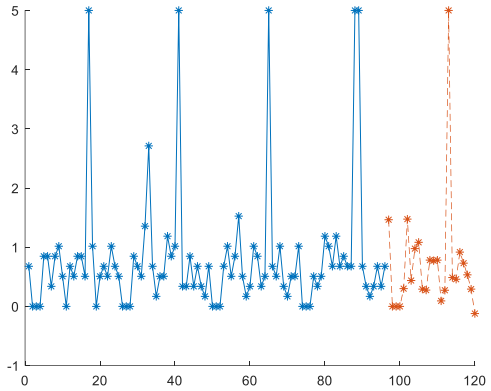


**Figure 7.** Forecast results of transshipment loss rate of the eighth transporter in the next 24 weeks

## 6. Conclusion

This paper optimizes and analyzes the various factors in the process of ordering and transportation of production materials, and then establishes the objective function of minimizing production cost according to the relevant data. Under the premise of ensuring production, we set up a mathematical model with the influence degree of each related enterprise as the constraint. In this paper, the model is solved to help enterprises make a reasonable production and management plan. Based on the machine learning method of random forest algorithm, we evaluate the characteristics of the given suppliers, get the importance of each supplier to the enterprise production, and then rank them according to the level of influence, and select the top 20 suppliers. Then, based on the multi-objective

programming algorithm, three objectives are selected and a multi-objective programming model is established to solve the ordering and transshipment plan. Finally, the neural network algorithm is used to evaluate the supplier's supply volume and transshipment loss in the next 24 weeks. The main goal is to maximize the production capacity of the enterprise, without considering the material procurement cost and the purchase demand of An and C materials, but still keep the minimum material transfer loss. In this paper, the weight analysis and multi-objective programming algorithm around the ordering and transportation process based on the principle of production enterprises can effectively provide reliable reference analysis for this process that needs to be optimized. This paper uses a variety of machine learning methods, such as random forest algorithm, BP neural network and so on, which make the data evaluation and prediction processing objective and accurate, and can effectively solve the problem of ordering and transportation.

## References

[1] Fang ran, Liu Yanhui, Huang Zhiquan. Summary of regional landslide risk assessment methods based on machine learning [J]. Chinese Journal of Geological Hazard and Prevention, 2021 focus 32 (04): 1-8.10.16031/j.cnki.issn.1003-8035.2021.04-01.

[2] Song Shufang, he went to foreign countries. Importance measurement index system based on random forest [J]. Journal of National University of Defense Science and Technology, 2021 Journal 43 (02): 25-32.

[3] Wang Shen, Lu Lianhong, Zhang Wei, Wang Siyi, Wu Jing, Fu Jiafeng, Luo Hong. Study on carbon neutralization path of low-cost carbon peak in China based on multi-objective model [J/OL]. Environmental Science Research: 1-15 [2021-07-05 09:25].

[4] Cui Yunhao, Zhu Jun, Meng Hao. Application of Neural Network in Agricultural Product sales Forecast [J]. Modern Agricultural Science and Technology, 2021 (17): 262,266.

[5] Zhang Yiting, Li Tianhong. Study on prediction of river water quality based on long-and short-term memory neural network [J/OL]. Environmental Science and Technology: 1-7 [2021-09-11]. Https://doi.org/10.19672/j.cnki.1003-6504.0018.21.338.