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Rare Earth Price Fluctuation and Forecasting Methods under the COVID-19 Pandemic

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Abstract

As an important strategic resource, rare earth price has its fluctuation rules under the COVID-19 Pandemic and its price prediction are of great significance to the increase of mineral benefits in the future. A BP neural network (ACO-BP) combination model based on Ant Colony Optimization was constructed to predict the price of rare earth products in terms of the factors that affecting the price of rare earth resources. Principal component analysis is used to eliminate redundant information among influencing factors, which can reduce the input data dimension of BP neural network and improve the prediction accuracy. Then the Ant Colony algorithm is used to find the optimal neural network threshold to optimize the convergence rate of the model and reduce the prediction error. Taking dysprosium oxide price as sample, monthly data from January 2010 to March 2018 are selected to construct a multi-factor ACO-BP combination model for prediction. The results show that the ACO-BP combined model is superior to the traditional BP neural network model in simulation ability, error level and convergence accuracy, and can predict the dysprosium oxide price more accurately. This method may benefits for Rare Earth industry after the COVID-19 epidemic.

Keywords: *Rare earth resource, multi-factor ACO-BP combination forecasting, the COVID-19 Pandemic*

I. Introduction

The strategic status of rare earth resources has a profound impact on the world rare earth industry chain and trade pattern under the COVID-19 Pandemic. The heavy rare earths, with small reserves and low substitutability, mainly yttrium group rare earths which are widely used in advanced industries, have become veritable scarce goods in the rare earth industry. After breakthroughs in the industrialization of rare earth smelting and separation in the late 1980s, China became the largest producer of rare earths. Under continuous investment, the total production capacity of rare earth smelting and separation has reached 320,000 tons, far exceeding the annual global consumption demand by nearly three times. Under the influence of disordered competition caused by asymmetric supply and demand, the prices of rare earth products remain low, and a large number of rare earth resources are supplied to the global rare earth industry at the "cabbage price”. Since 2009, when the China government promulgated a series of industrial regulation policies, rare earth prices have changed from depressed state, and experienced a "roller coaster" boom collapsed. A sharp fluctuation in the price of rare earth industry severely disrupted the order and has caused great trouble to the price expectation of all the enterprises in the value chain. It also put forward new problems for rare earth industry managers, they have to focus on how to cover the rare earth production cost and environment cost, for promoting the sustainability and healthy quality of rare earth industry development.

In May 2011, the State Council of China issued several Opinions on Promoting The Sustainable and Healthy Development of the Rare Earth Industry. In July 2011, the first rare earth product purchase and storage was completed, and in September 2011, the ganzhou rare earth enterprise in Jiangxi province completely stopped production for rectification. It was at this stage that the price of rare earth products in China again showed a significant jump. Since 2012, the Ministry of Industry and Information Technology has issued a series of policies, including "Conditions for Access to the Rare Earth Industry" and "Interim Measures for the Administration of Rare

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Earth Enterprises' Access Announcement", for promoting the healthy development of the industry. Although policy introduced to stabilize prices has obtained certain result, but the project team by using the nonlinear method of MSVAR study found: The United States, Japan and Europe all have "low price reserve" and "high price wait" for rare earth products. Especially in the period of COVID-19 Pandemic, They adopt the corresponding management strategy of price fluctuations in the course of price stabilization and fluctuation. In fact, the United States, Japan and Europe have taken rare earth resources as their national strategic resources for many years. Their concern extent over the price of rare earth products can be clearly reflected from the WTO dispute in March 2012 to the official loss of China's rare earth WTO case in May 2015.Therefore, the price of rare earth products is an issue that industry participants cannot avoid under the COVID-19 Pandemic. In a certain sense, whoever can accurately predict the price of rare earth products may have an advantage in the game competition after the COVID-19 Pandemic.

For a long time, the lacks of international pricing power of rare earth products get more attention. Industry managers also affect the return of rare earth prices from the following aspects: the crackdown on smuggling and rectification of the industry, the integration of China six groups, the control of mining license, the adjustment of export quota, the collection of resource tax, environmental protection requirements, the adjustment of purchase and storage, and the establishment and operation of spot exchanges. However, there is no futures exchange in the rare earth industry, which cannot effectively form the fair value and price reflecting the changes of long-term and short-term demand and supply, technological progress, industry expectations and demand management, investor expectations and so on. Rare earths, especially heavy rare earths, have its roles in trade frictions between China and the United States under the COVID-19 Pandemic .The accurate prediction of its price trend is undoubtedly an effective guarantee for the right to speak and the formulation of coping strategies in advance. Therefore, the scientific price prediction of rare earth is not only related to the formulation of national industrial policies, industry management and production decision of enterprises, but also is of great significance for the more scientific and intelligent use of rare earth resources and the eventual acquisition of international rare earth pricing power. At the same time, we focus on the quantitative mining of the factors affecting the price of heavy rare earth products, the price determination mechanism, combined with the method of data mining to carry out price prediction etc. That is also a useful supplement to the existing theory of rare earth product price decision which apply on the industry under the COVID-19 Pandemic in the future.

II. Literature Review

The academic research on rare earth prices mainly focuses on the loss of pricing power for China enterprise, factors affecting price fluctuations and pricing mechanism from the macro and qualitative perspectives. SONG, W. F. (2011)[1], Ding, K. (2014)[2], are the representatives. Fama, E. F. (2016) believed that the development of futures market to enhance international pricing power was a feasible method to finally obtain the pricing power of rare earth. In latest years, more and more experts have concerned the price fluctuations of rare earth products, price determinants, and lack of pricing power, price forecasting and other issues from a quantitative perspective [3]. Massari, S. et al.(2013) from the international price of the metal and rare earth products price interaction Angle [4]. Wübbeke, J. (2013) from the level of special rare earth international patent, distorted sustained growth rate of domestic low-end consumption of rare earths, the ratio of special rare earth consumption at the inlet and so on to explore the influence mechanism of rare earth price. As for the price prediction of rare earth products, more and more attention has been paid by academic circles. [5]. Lee, J. C. et al. (2018) used the full cost method to calculate the price of ionic rare earth and the cost and income of rare earth concentrate[6].Some scholars use ARIMA model to predict the price of rare earth oxides, such as García, M. V. R. (2018), Özdurak, C. et al. (2020) [7-8].

With the deepening of machine learning, artificial intelligence system and methods, combinatorial prediction method plays a significant role in improving the prediction accuracy. Issler, J. V. (2014) predicted methanol price by applying ARMA model combination GARCH model[9]. Neural network technology is a mathematical model that simulates the behavior characteristics of biological neural network and has distributed parallel processing capability. With simple structure and excellent simulation capability, it has remarkable effect in simulation and data prediction, and is more widely used in solving the problem of price prediction. However, the traditional BP neural network has the disadvantages of slow convergence, weak local minimum and weak generalization ability, and its model performance is relatively general. But the combination prediction method based on BP neural network has greatly improved the prediction effect. For example, Tang, L. (2020) predicted the international crude oil price with BP combinational empirical mode decomposition model [10].In the experimental process of data mining, the determination of parameters is often very sensitive to the prediction effect. How to optimize the parameters is the key to ensure the prediction effect of the model. In this article, ant colony optimization algorithm is used to calculate and seek the optimize parameters.

Different from the existing prediction methods, the principal component analysis method is first used to solve the problem of multicollinearity of influencing factors. Secondly, the influence factors are introduced into the prediction, and relevant parameters of BP neural network are optimized by ant colony algorithm to construct ACO-BP combined prediction model. Finally, monthly dysprosium oxide price data were used for simulation prediction to compare the effectiveness of the combined prediction method.

III. Selection Of Factors Influencing The Price Of Rare Earth Products-Dimensional Reduction Based On Principal Components

In the selection of influencing factors of rare earth price, the commodity and financial attributes of rare earth are taken into account, and many factors under the financial attributes of supply and demand are selected. Principal component analysis is used to reduce dimensions, and a variable with relatively large contribution rate is obtained as the input variable of ACO-BP model.

3.1 Factor selection and data source description

(1) Selection of supply and demand and financial factors

In terms of the supply of rare earth products, China's rare earth industrial chain has been suffering from severe overcapacity for latest years, resulting in low prices for a long time. In particular, breakthroughs were made in the industrialization of smelting and separation in the late 1980s, and large-scale and continuous production of rare earths was realized. In 1986, China became the largest producer of rare earths. Under continuous construction, the smelting and separation capacity has reached 320,000 tons, nearly three times the global annual consumer demand, and the actual market output is also much larger than the government's total production control. The jump in rare earth prices during the black war reflected the market's fear of supply reduction, but with the stabilization of market sentiment and the setting of the WTO standard price "ceiling", rare earth product prices returned to the state of non-jump volatility. According to the sampling of public data, the surplus value of rare-earth oxide production and inventory value plus sales volume is calculated, and it is found that the surplus is positive in recent years, which further reflects the oversupply situation of rare-earth oxide. As a result, we can see that rare earth products have buyer's market characteristics and that can be expected that the market characteristics will persist over a certain period of time. That is, demand is the main factor influencing the price fluctuation. Although the supply of rare earth has changed to some extent in the atmosphere of the trade war, with the progress of the trade war negotiation and the signing and confirmation of the terms, the external impact has gradually normalized, and the existing pattern of the rare earth market still affects the formation of the price. In addition, considering the difficulty in obtaining mining quantity, production quantity and inventory data of rare earth products by classification, this paper mainly considers demand and financial factors as the framework of price determination.

In the specific demand factors, this paper focuses on the domestic and foreign demand for rare earth products. As the domestic and foreign demands have independent and unrelated characteristics from the perspective of the current high and low level demands of product application, that is, the domestic market of rare earth and the main exporting countries and regions: The United States, Japan and Europe, their demands have independent characteristics. Therefore, in this paper, the demand for the influencing factors of the price of rare earth products is investigated from the regional markets in China, the United States, Japan and Europe, etc., and the downstream industry index is selected to reflect the strength of the demand, that is, the industry is thriving and the corresponding demand for rare earth products is strong. Therefore, it is reasonable to use the downstream industry index.

In general, from the perspective of commodity attributes, its price is determined by supply and demand, including production and consumption at home and abroad, such as domestic downstream product demand, foreign downstream industry index, foreign relevant country prosperity index, etc. In recent years, the financial attributes of rare earth products are increasingly prominent because of much attention has been paid to it. Relative to other commodities, rare earths spot market set up late, recognition and trading volumes are in their infancy, but its financial attribute namely investment and speculative still showed the direct indirect features: namely from the related factors influencing the capital market, commodity market and the impact of rare earth products price fluctuations in commodity. Therefore, indicators of financial attributes (hereinafter referred to as "financial factors") are selected to reflect relevant indicators of investment activities, such as stock index, oil index, gold index, metal index, etc.

(2) Explanations of other factors

Policies play a role in standardizing and guiding the direction of rare earth industry. On the industry policy, China has identified rare earths as strategic resources since 2010, domestic supply of rare earths policies have become the main factors influencing the supply and demand and the industry expectations, mainly including industry norms, development strategy, the establishment and abolition of import and export quotas tariff, total control plan for rare earth minerals and smelting separation, national reserves and commercial reserves, joint supervision and inspection of environmental protection, etc. Among them, the policy that brings about the change of supply and demand margin in 2018 mainly includes the promotion of the annual total quantity control plan and the joint supervision of eight ministries and commissions in the fourth quarter. The major influencing factors in 2019 May include joint supervision of 12 ministries and commissions, total quantity control plan, purchase and storage, etc. Thus, it can be seen that policy factors are mainly purchase and storage policies and anti-black policies based on industry norms. This research group's working paper proves that anti-black policies have no significant impact on prices through the event research method. In terms of the purchase and storage policy and its impact on prices, the state's purchase and storage information is secretly purchased and stored under the requirement of confidentiality, and the relevant data collection degree is not feasible. Simulation data cannot be applied to the objective data-based design framework in this paper unless a simulation method is used for exploration.

To face and solve the contradictions, this article believes that the focus of rare earth policy is on the impact on the supply side. Therefore, this paper turns the policy issue into a supply-demand relationship issue. From the perspective of policy evolution, the impact on the domestic rare earth industry chain may be as follows: (1) The normalization of "cracking down on criminals “and” purchasing and stockpiling "will bring about continuity.(2) Rare earth quota may continue to be increased in the future.(3)The marginal impact of the trade war on downstream exports is weakened;(4)The Rare Metal Management Ordinance may be introduced during the period of the fourteenth five year plan.(5) The varieties acquired and stored may be more targeted.

In conclusion, dysprosium oxide monthly prices from January 2010 to February 2018 were selected for modeling in this paper. Dysprosium oxide data from CBC China Rare Earth Network; Monthly adjustments were made using the Producer price index (PPI) based on January 2010;Glass, agricultural film, mobile phone production, auto production, purchasing managers index, dollar index are available in forward database. The global communications industry Index, the materials industry Index, the industrial industry Index, the electronic Information industry Index, and the utility industry index are derived from S&PDowJones Indices. The U.S. stock market index comes from the CEIC database; The oil index, the metals index, the iron ore price index for China imports from the IMF official statistics; Spot gold prices from the Wind data terminal. Finally, 33 influencing factors were selected in this paper, as shown in Table 1.

Table 1 Supply and demand and financial factors

The supply and demand factors	Communication industry index, industrial industry index, public sector index, electronic information index, material industry index, China iron ore import spot price index; The EU manufacturing Purchasing Managers' Index, the US ISM manufacturing Purchasing managers' Index, the PURCHASING managers' Index and the Japanese manufacturing Purchasing Managers' Index; Agricultural film (ten thousand tons), mobile phone production (ten thousand), Shenwan Industry Index: Medical equipment: month, automobile production (ten thousand), plate glass (ten thousand weight cases) (total 15 factors)
Financial factors	China stock Market index, American stock Market index, Japanese stock Market index, European Union stock Market index; Metals index, US dollar index, oil index, spot gold price (US dollar/ounce), China macroeconomic Sentiment Index; China’s M2 (millions of us dollars), the federal benchmark interest rate, money supply M2 (millions of us dollars) in Japan, the euro zone (millions of us dollars), China's money supply lend to interest rates (30 days), the United States the M2 measure of money supply, ZEW index in short-term interest rates: the United States, ZEW index of

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	short-term interest rates: the euro zone, ZEW index in short-term interest rates: Japan (total 18 factors)

3.2 Principal component extraction of influencing factors

Based on principal component analysis, the characteristics of data dimension can be reduced. In this paper, based on the analysis of variance, the data is projected onto the orthogonal principal component with the largest variance, so as to minimize the cross-correlation of multi-dimensional data and thus achieve dimensional reduction of multi-dimensional data. By combining principal component analysis method with neural network, the principal component of the influencing factors on the price can be analyzed first, which changes from multiple influencing factors to a few important principal components, and can still better express the original data information. As the input layer of the neural network, the principal component extracted by principal component analysis has significantly fewer input nodes than that without principal component extraction, which simplifies the structure of the neural network and improves the convergence speed and prediction accuracy of the model.

Before principal component analysis, relevant tests should be conducted on the data to determine whether the data can be processed with dimension reduction. The main test methods are KMO test and Bartlettt sphericity test. From the test results, it can be seen that the KMO test value is greater than 0.8 and the Bartlett sphericity test P value is 0.000, indicating that the 33 variables selected in this paper are suitable for factor analysis.SPSS was used for factor analysis of variables, and the factor variance was extracted as the standard with the eigenvalue greater than or equal to 1, as shown in Table 2. According to the total variance of factor interpretation, the cumulative variance contribution rate of component 1-5 reaches 81.982%, which provides enough original data information to reflect the variance change of a large part, and the result of factor analysis is relatively ideal. Therefore, the first five principal components were used for subsequent analysis.

Table 2 Total variance explains the results

composition	**Extract the sum of squares of loads**			
	cumulation %	**total**	**Percentage of variance**	**cumulation %**
1	48.451	15.989	48.451	48.451
2	62.949	4.784	14.498	62.949
3	73.112	3.354	10.163	73.112
4	78.311	1.716	5.199	78.311
5	81.982	1.211	3.671	81.982

IV. Ant Colony Optimization And Bp Neural Network Hybrid Model Design

4.1 Core logic and principle of ant colony algorithm and BP neural network

Ant colony algorithm was put forward in 1991 and applied to the area of path& parameters-seeking rapidly. How did it seeking the path? Suppose that the route chosen by all ants is an answer set of the optimization process of the problem to be solved. The route of ants is different in length, and ants constantly tell others the route information in a specific form. We assume that the concentration of pheromone released by ants with shorter walking path is much higher than that of ants with longer walking path. With the evolution, the concentration of pheromone varies on different paths. Ants constantly gather on the path with high pheromone concentration. In the end, the ant colony gathers on the road with the most pheromone to achieve the goal of the most demanding path. This process responds to the optimization problem and the solution of parameters. The specific process is shown in Figure 1:

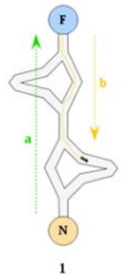

Fig 1. Flow chart of ant colony algorithm

BP neural network is a kind of multi-layer feedforward neural network, which is developed on the basis of single-layer perceptual network. It is proposed to solve the nonlinear problem. Use the multi-layer feedforward network, it can be enhanced the classification and recognition ability of the network and solved the nonlinear problem, that is, to add a hidden layer between the input layer and the output layer.

The main characteristics of network operation are as follows: the signal propagates forward and the error propagates backward. Assuming that the neural network model has only one hidden layer, the process of BP neural network is mainly divided into two steps to achieve the goal. The first step is to process the information from the input layer into the hidden layer, then, to the output layer forward propagation process. The second step is the back propagation of the error. From the output layer to the hidden layer, and finally to the input layer, the weights and deviations from the hidden layer to the output layer and from the input layer to the hidden layer are adjusted in turn. The typical BP three-layer neural network topology is shown in Figure 2:

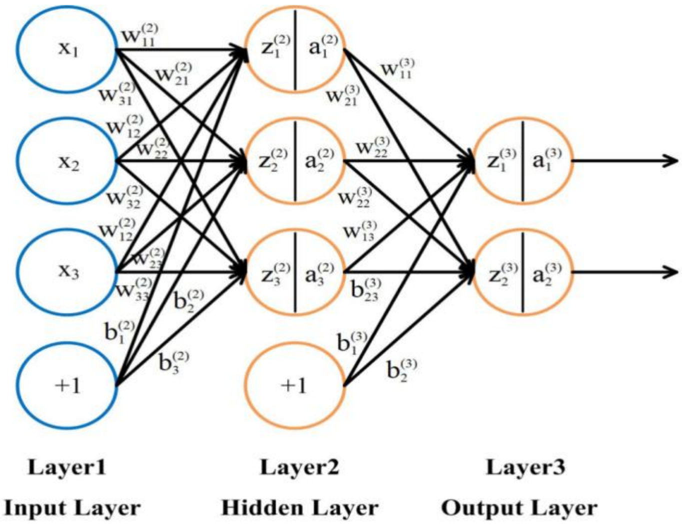

Fig 2. BP Three-layer neural network topology diagram

4.2 Design and principle analysis of ACO-BP model

The initial weight of the neural network is often randomly selected, and error information will be backpropagated in the learning and training of the neural network, and it is difficult to maintain a reasonable state due to constant dynamic adjustment. However, the ant colony algorithm, especially the well-designed ant colony system, can not only accelerate the search rate, but also be more conducive to finding the global optimal solution and Avoiding falling into local optimizations .This article use the ideas of the traveling salesman problem to set cities of 3 layers, the first layer is the starting cities, each layer has cities respectively, the numbers represent the tens place, the ones place, the tenth place after the decimal point, the hundredth place, and make an ant can only move from left to right, so that through a journey from city of origin to city of end, you can find your number. After a certain number of cycles to find of M aunts, you can find the required results. Since the ant colony system converts the direct search for

Numbers into a search for each number one by one, the optimization problem of continuous variables is transformed into a decision problem of several levels, which is more conducive to the complete search of the entire space of the ant colony.

The following information is calculated and specified in the design of the combined algorithm :(1) the element t_{ij} in the pheromone matrix is the pheromone between the current city i and a city j at the next layer. Therefore, in addition to the 1*10 matrix between the initial city and the next layer, the pheromone of each layer is a 10*10 matrix.(2) Path selection rule. Set NC as the number of iterations, and each ant selects a path according to the pheromone obtained by the NC-1 iteration. When the ant selects the path again, the system generates a random number q, which is compared with the parameter q_0 set between () and 1 to determine the path the ant chooses. The smaller the q_0, the higher the probability of random search. The formula of city selection probability is:

$$p(a,b)=\frac{t_{ab}^{k}}{\sum_{x-0}^{9} t_{ab}^{k}} \tag{1}$$

Where a is the current city, b is the next arriving city, t_{ab}^{k} is the pheromone between a and b, and t_{ab}^{k} is the pheromone between the current city and each city at the next layer. If $q > q_0$ then the path is chosen at random.(3) Updating of pheromones. In order to avoid the infinite accumulation of pheromones on a certain road energy, thus affecting the discovery of new and better solutions, each ant should update the pheromones on the path after completing an urban migration. The calculation formula is as follows:

$$t_{k,k-1}^{k} \leftarrow (1-\rho)t_{k,k-1}^{k} + \rho t_0 \tag{2}$$

Where, k is the number of layers where the city is located, ρ is the constant between (0,1), which is used to control the weakening speed of pheromone, and t_0 is the initial pheromone. In order to enable ants to approach better solutions faster, when all ants have completed a migration from the starting city to the ending city, they need to release more pheromones in a more optimal path, that is, to carry out global update. The calculation formula is as follows:

$$t_{ij} \leftarrow (1-\rho)t_{ij}^{k} + \frac{a}{f_{\min}} \tag{3}$$

a is the constant between (0,1), represents the importance of pheromone, and $f_{\min}$ is the minimum function value. The amount of pheromone increase is related to the size of the function value, which causes the ant to release more pheromones on the optimal path.

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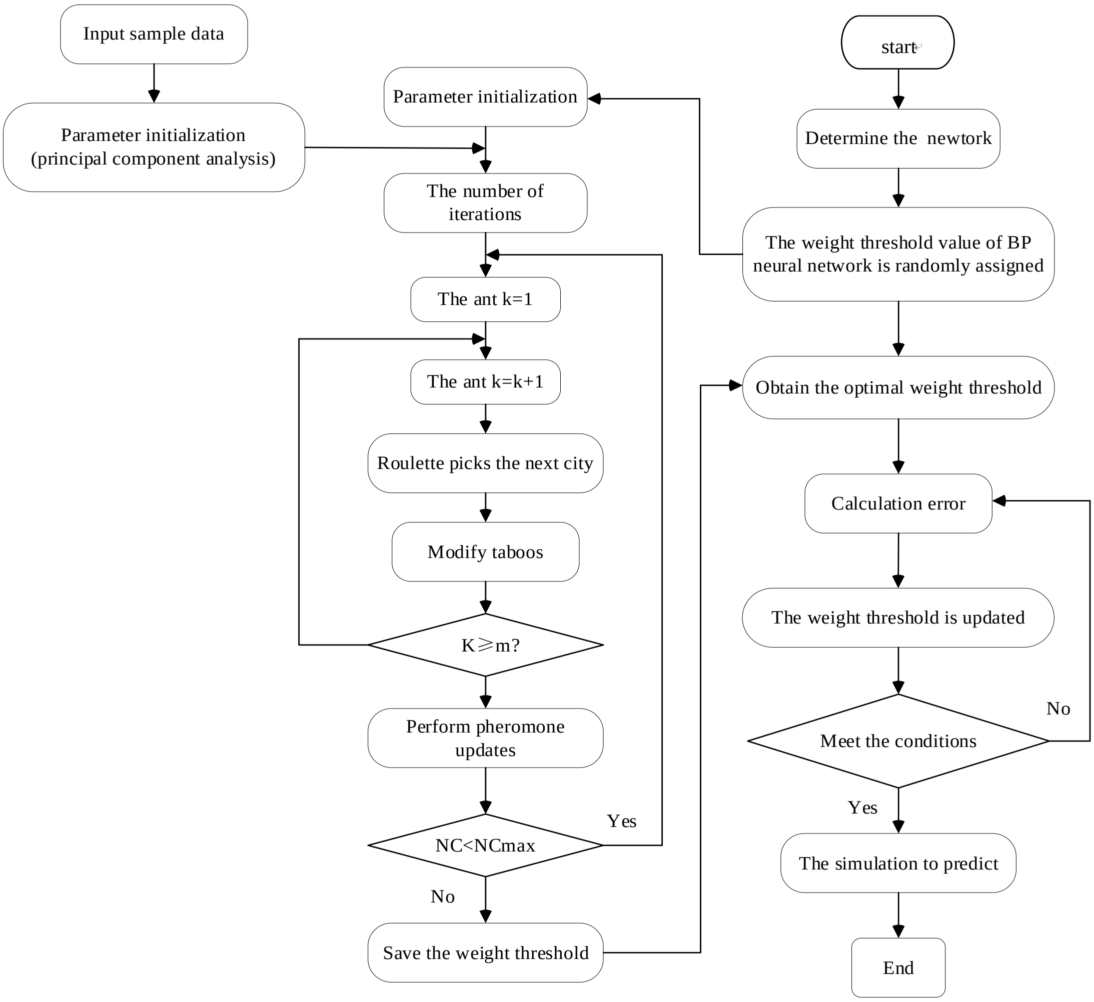

Fig 3 ACO-BP model algorithm schematic diagram

After designing ant colony system, the parameters of ant colony optimization need to be assigned to BP neural network. Firstly, the weight and initial threshold of the neural network are given and the optimal value of the threshold is found and constructed by ant colony algorithm, so that the problem that the network weight can easily fall into the local optimal value due to the back propagation of errors is solved. Then the optimal solution input neural network constructed by ant colony algorithm is used for further optimization training to find the optimal solution of network weight threshold value. The above methods can not only improve the speed of neural network convergence and learning efficiency, but also improve the learning accuracy. The introduction of network gradient information also avoids the problem that the ant colony algorithm cannot find the optimal solution of threshold in a short time. The algorithm flow is as follows :(1) initialize the parameters, preprocess the training samples, and randomly select the threshold value of the neural network. Set the number of colony cycles *NC=1*, set the maximum number of cycles *NC=100*, the initial pheromone, the psychosomatic coefficient and the pheromone importance coefficient, and randomly place the ants in the spatial solution according to the parameter range.(2) Start all ants and select ants to start the movement. The path selection using state transition probability is conducted according to path selection rules, and the path is also recorded. (3) Pheromone evaporation and global update. The above formula is used to update the pheromone on the path.(4) When $NC = NC_{\max}$, it means that all ants converge to the same path, that is, the iteration reaches the maximum number, and the calculation is terminated; otherwise, the iteration continues. If the end condition is satisfied, the loop ends and the optimal parameter value is output. (5) The parameters obtained by ant colony algorithm were used to assign values to the neural network, and the test data were trained and calculated. The flow chart of ACO-BP algorithm is shown in Figure 3.

V. Simulation Of Multi-Factor Aco-Bp Combined Prediction Model

In order to meet the demand of network output for data, the input data were normalized. 80% of 98 samples were selected as training set samples, and the remaining 20% as test set samples. The ant colony algorithm was used for parameter optimization. The initial value of the parameter was selected. The maximum number of cycles was 1003, the number of ants was 30, the importance of pheromone was 5, the evaporation coefficient of pheromone was 0.1, and the strength coefficient of pheromone increased was 100.The target error of neural network training was set as 1E-10, the learning rate was 0.01, and the number of iterations was 1000. In order to demonstrate the effectiveness of the algorithm in this paper, BP neural network model and ACO-BP model were used to predict dysprosium oxide price respectively. Figure 4 shows the fitness curve. It can be seen from Figure 4 that when the number of iterations is 78, the optimal solution has been found and the obtained optimal threshold and weight can be input into BP neural network.

The optimized weight threshold value was assigned to the BP neural network, and the training set was optimized. The training set was the first 80% of the overall data set, marked as sample 1-80, and the time node was from 2010.01-2016.08. The optimized prediction results were shown in Figure 5, R^2 reaching 0.99, as shown in Figure 6.Indicates that the optimization parameter is effective and can be predicted in the next step.

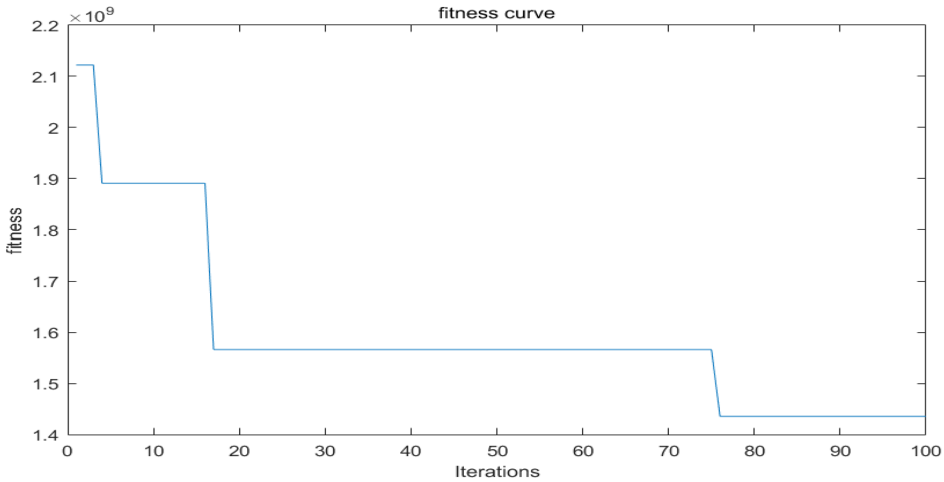

Figure 4 Fitness curve

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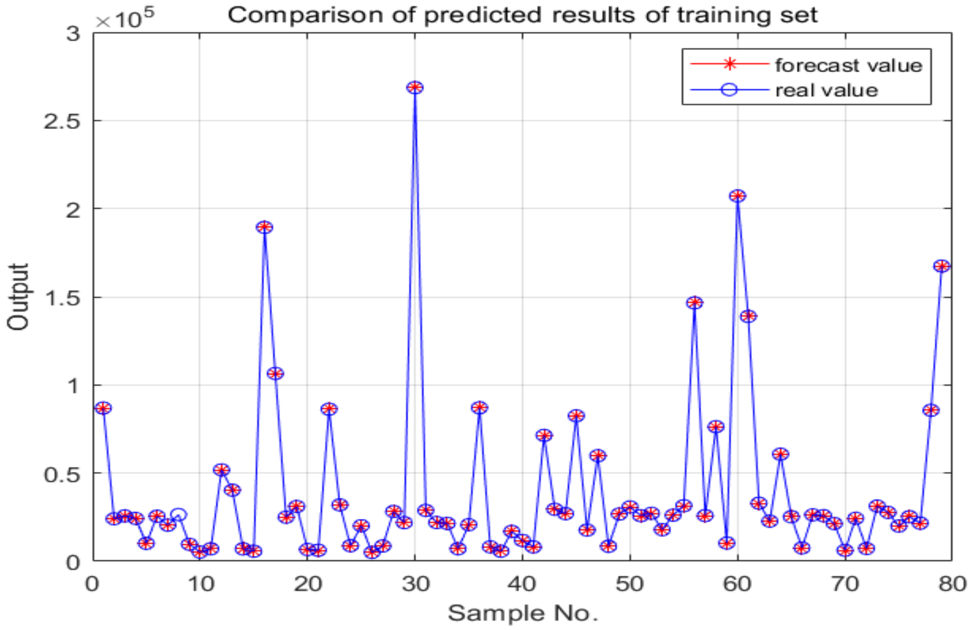

Figure 5 Comparison of dysprosium oxide training set prediction results

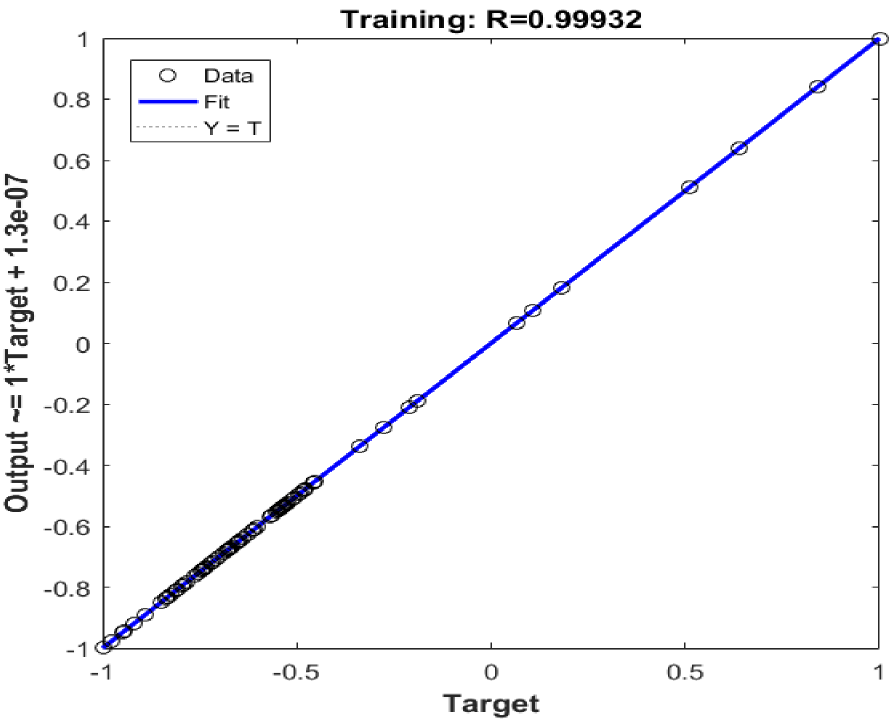

Figure 6 Fitting degree of dysprosium oxide training set

After repeated tests, it was found that the number of cycles exceeded 100 had no influence on the results, so this paper chose the maximum number of cycles to be 100.

Compared with the original BP neural network, the fitting degree of the prediction experiment is improved, the results show that the use of ant colony algorithm have an initial threshold of BP neural network and optimize the weights of location is reasonable, model simulation accuracy is higher, after training the BP neural network prediction based on ant colony optimization effect is better, faster convergence speed to better reflect the variation of dysprosium oxide price regulation.

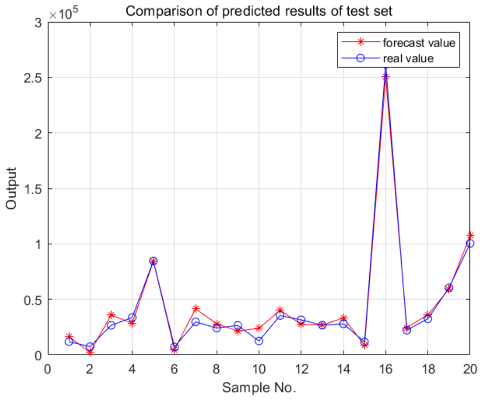

Figure.7 Comparison of predicted results of ACO-BP model test set

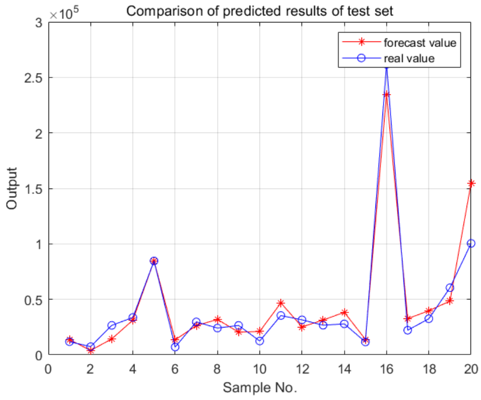

Figure.8 BP neural network model test set prediction result pair

The mean square deviation of test set and training set of BP neural network model and ACO-BP combined model under the same number of training iterations is further compared, as shown in Table 3.

Table 3. Model mean square deviation comparison

	Mean square deviation of training set	**Mean square deviation of test set**
ACO-BP	3290766	1831075283
BP	2210251	17514281433

According to the comparison results in Table 3, although the ACO-BP combination prediction model of training set is slightly higher than the simple BP neural network, in terms of the mean square deviation of test set, the optimized ACO-BP combination prediction model is much smaller than the BP model by an order of magnitude, and its prediction stability and accuracy are significantly improved. It shows that it is feasible to use ant colony algorithm to optimize BP neural network. The ACO-BP combined prediction model has stronger simulation capability, the network output value is closer to the actual value, and the prediction error, convergence speed and convergence accuracy are all better than BP neural network, which has certain guidance to the actual price change trend of dysprosium oxide, and can be used as the basis to judge the change trend of dysprosium oxide price.

Ⅵ. Conclusion

In this paper ,we constructed a method to predict the price of rare earth products benefits for Rare Earth industry after the COVID-19 epidemic. In the process of prediction, ant colony algorithm was introduced into dysprosium oxide price prediction model, and monthly dysprosium oxide price data were used for empirical analysis. By comparing the prediction effect of ACO-BP model and BP neural network model, the following conclusions were drawn:

First of all, when the number of input layers of BP neural network is too large and each parameter has a certain linear relationship, the accuracy of the network will decrease and the training time will be prolonged. The input variables in BP neural network are optimized by principal component analysis to reduce the dimension of input variables and reduce the structural complexity of the neural network. By combining the advantages of factor analysis and neural network, the prediction accuracy of the neural network is effectively improved.

Secondly, through the simulation results, we can conclude the ACO - BP combined forecasting model is superior to the BP neural network model. On the one hand, the ACO - BP combination model inherits the self-learning and nonlinear mapping capability of BP neural network , on the other hand, the BP neural network optimized by ant colony algorithm solves the problems of the traditional BP neural network, such as slow convergence rate, easy to fall into extreme minimization, etc., and has the advantages of stable output, fast convergence and high prediction accuracy. Aco-bp combined model is superior to BP neural network in simulation capability, error level, convergence precision and iteration times, and has more outstanding simulation capability and better data fitting capability. The combination model has a stronger ability to explain the dysprosium oxide price, which indicates that the dysprosium oxide price prediction is more applicable. It also provides a feasible and effective method for the prediction of other time series data.

Third, through various influencing factors of dysprosium oxide price, an ACO-BP combined prediction model based on multi-factor principal component dimension reduction was constructed., and monthly data are used for price forecasting, simulation results show that the price of dysprosium oxide prediction error is very small, it shows that the ACO-BP neural network combination model with multiple inputs based on monthly data can accurately predict its variation trend., the judgment about dysprosium oxide price movements has a certain guiding significance.

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