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A Productivity Analysis of the Industrial Security in the Mineral Resources Mining Industry

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This study elaborates on the evaluating indicator system of mining industry security, and presents a method of combination between entropy and grey relation and makes an assessment of the security situation in China's mineral mining industry during the period from 2002 to 2009. Then, this study establishes a safety warning model for the mineral resources industry based on BP neural network and simulates the warning of related security conditions. The final analysis finds that warning effect simulation and empirical assessment results of the model are basically the same and this further demonstrate the effectiveness of this study.

Key words: Mineral Resources, Industrial Security, Assessment System, Early Warning

Introduction

Currently the safe supply of China's mineral resources is in a serious situation. The mineral resources of China are low in grade with more refractory mineral. The form of mineral is single and the associated mineral resources are excessive. Above circumstances make mining, ore-processing and comprehensive utilization much more difficult. He W D, Wu Y P&Liu R H studied that due to technological limited, the total recovery rate of China's mineral resources was only 30% and the rate of total associated minerals comprehensive utilization was about 35%[1]. Wang L F, Wen W&Lai M Y investigated that in 2009 the rate of tailings comprehensive utilization was only 13.3%, which was far behind that of developed countries[2].Yu D E, Qin J B&Sun Y B evaluated that being late of industrial security, most research had been from the perspective of national security or economic security, rather than industrial-security grounds[3]. In the meanwhile, He W D and Hao R estimated the economic security of logistics industry based on DEA model[4]. While researchers emphasize mineral resources security, they always focus on coal, oil, gas and other specific industries or several specific mineral security situations, so there is not as much attention on sufficient quantitative methods. According to the existing research view, this article attempts to construct a scientific evaluation index system of industrial safety in the mineral resources industry depending on the circumstances of development. Our study uses models to evaluate the situation of industrial security from the industrial level and investigate an early warning indicator system of security in the mineral resources industry.Ma J C, Liu G &Guo Y analyzed that industrial safety evaluation of mineral resources was a reflection of a country's mineral resources industry combined with security status indicators established on the basis of existing theories[5].

There exists three main evaluation systems: the first one is an evaluation system of China's manufacturing industrial safety by ESF, the second one is a security evaluation system of China's three main industries, which was introduced by He W D&He C[6], and the last one is an evaluation indicator system of industry, which was came up with Jing Y Q[7]. Taking the above three systems into account, we build an evaluation indication system for the industrial security of mineral resources mining industry from a macro level, meso level and micro level, which is showed in Table 1.

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Table 1—The early warning index system for the security of mining industry

First class indicators	Second class indicators	Third class indicators
Macro-index	Economic growth	Growth rate of GDP (X_1)
	Institutional environment	Institution (X_2)
	Government	Tax levels (X_3)
	Components	Capital intensity (X_4)
	Demands	Growth rate of domestic demand (X_5)
	Related supportive industry	Index of raw material costs (X_6)
Meso-index	Market share	Domestic market share (X_7)
		International market share (X_8)
	Enterprise scale	CR_4 (X_9)
	Competitive advantage	RCA (X_{10})
	Labor productivity	Overall labor productivity (X_{11})
	Foreign-trade dependence	Degree of dependence on import (X_{12})
		Degree of dependence on output (X_{13})
		Degree of dependence on capital (X_{14})
		Degree of dependence on technique (X_{15})
Micro-index	Enterprise strategy	Average ROA in nearly 3 years (X_{16})
	Enterprise competition	Average growth rate of total profit in nearly 3 years (X_{17})
	Technological innovative ability	R&D intensity (X_{18})
		R&D personnel intensity (X_{19})

Notice: The growth rate means year-on-year growth.

Material and Methods

Data

According to the "China Statistical Yearbook", the mineral mining industry specifically includes coal mining and washing industry, oil and gas extraction industry, ferrous metal mining industry, non-ferrous metal mining industry, non-metallic mining industry and other mining industries. Since the output of other mining industries accounts for a very small proportion of the whole industry and lacks relative statistical data, we focus on coal mining and washing industry, oil and gas extraction industry, ferrous metal mining industry, non-ferrous metal mining industry, non-metal mining industry as research samples. All data in Table 2 is from "China Statistical Yearbook"[8], "China's Large Industrial Enterprises Yearbook"[9], "China Mining Yearbook"[10], "China Statistical Yearbook on Science and Technology"[11].

Mineral resources mining industry safety measure

Calculation with Entropy and Grey comprehensive evaluation theory

Determining the reference sequence and comparison data

We set a reference sequence as $X_0=\{x_0(1), x_0(2),\ldots,x_0(n)\}$, $i=1,2,\ldots,m,$ showing an evaluation of the year i, $j=1,2,\ldots,n,$ standing for the j-th index, and x_{ij} is the value of the j-th index in the year i. The equation describes as $Z=(X-\mu)/\sigma$, μ means average value, and σ means standard deviation.Forward indicators (the bigger index value is, the better results show) values are directly into the formula, while negative index (the smaller index value is, the better results are) uses opposite number instead. We apply dimensionless method to the data and then normalization processing is carried out for mapping [0, 1]. This can be rewritten as $X'_0=\{x'_0(1), x'_0(2),\ldots,x'_0(n)\}$, and the comparative data after processing is $x'_{ij}=(x_{ij})_{m\times n}$.

Calculation result of correlation is provided as

$S_{ij}=(min_i \quad min_j \mid x'_{ij}-x'_{0j} \mid +P \quad max_i \quad max_j \mid x'_{ij}-x'_{0j} \mid)/ (\mid x'_{ij}-x'_{0j} \mid + P\, max_i\, max_j \mid x'_{ij}-x'_{0j} \mid)$

Among that $|x'_{ij}-x'_{0j}|$ is the absolute difference of x'_{ij} and x'_{0j}.

The $\min_j |x'_{ij}-x'_{0j}|$ is the first stage of minimum difference, indicating the smallest difference between each spot and X'_0 in the sequence X'_i. The $\min_i \min_j |x'_{ij}-x'_{0j}|$ is the second stage of minimum difference and indicates to identify the smallest deviation in the sequence based on the smallest difference. The $\max_i \max_j |x'_{ij}-x'_{0j}|$ is the maximum difference between two stages with the similar meaning of minimum difference. As distinguishability, P is used for increasing significance of difference among the correlation coefficients so usually $P=0.5$ $(0\leq P\leq 1)$.

Table 2—The data of the mining industry

Year	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
2002	0.106152	4.68	-0.15351	22.80061	0.194005	-1	0.971823	0.017221	0.244468	0.343411
2003	0.115343	4.125714	-0.13438	21.60428	0.268896	-1.048	0.969634	0.018844	0.300196	0.326196
2004	0.132891	3.91	-0.15517	24.71714	0.540762	-1.167	0.964791	0.020062	0.254116	0.31173
2005	0.136314	4.41	-0.18272	26.725	0.332823	-1.264	0.967242	0.017889	0.187528	0.24626
2006	0.15233	3.57	-0.14929	33.24028	0.328288	-1.34	0.97128	0.016957	0.18276	0.211961
2007	0.172587	3.71	-0.13921	40.50361	0.258874	-1.4	0.969511	0.01575	0.157085	0.180902
2008	0.115621	4.2	-0.12422	49.80063	0.467897	-1.547	0.952806	0.015654	0.136166	0.175835
2009	0.091958	4.4	-0.10704	59.80676	-0.01894	-1.425	0.959777	0.01517	0.094456	0.178535

Continued Table 2—The data of the mining industry

Year	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}	X_{19}
2002	6.769142	-0.47275	0.138852	-0.01583	-0.75987	-58106	0.110611	0.891948	0.005662
2003	7.059752	-0.56808	0.130909	-0.01254	-0.80437	-33236.2	0.106071	0.065265	0.005164
2004	10.37137	-0.47808	0.079074	-0.01319	-0.79524	-51165	0.124691	0.298025	0.006316
2005	12.52009	-0.638	0.098853	-0.02614	-0.69529	-33160.5	0.166637	0.522134	0.004656
2006	14.92496	-0.6555	0.067588	-0.02431	-0.87032	-42385.6	0.199965	0.498382	0.00425
2007	16.84071	-0.65011	0.039647	-0.03045	-0.76496	-42986.1	0.209512	0.318875	0.004755
2008	16.13497	-0.58948	0.033771	-0.03863	-0.54588	-47506.2	0.20547	0.239646	0.004345
2009	18.07732	-0.48254	0.037292	-0.03727	-0.64629	-41809.9	0.170434	0.032611	0.007244

Original data processing

To solve how to evaluate m evaluation objects and n evaluations, the data needs to satisfy the following:

$$X_1 = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \quad \ldots(1)$$

Using dimensionless method and normalization processing with the evaluation matrix X_1, we can find a rewritten matrix $Y=(y_{ij})_{n\times m}$, $y_{ij}\in[0,1]$.

Entropy calculation

The i-th entropy is defined as: $H_i= -k \sum_{j=1}^{m} f_{ij}\, lnf_{ij}$

Determine the weights

The entropy weigh of the i-th index is defined as: $W_i =1-H_i/\sum_{i=1}^{n}(1-H_i)$

Comprehensive evaluation value

Comprehensive evaluation value is calculated as: $\zeta_i=\sum_{j=1}^{n}\omega_j s_{ij}$

Early warning line identification based upon 3σ and Bootstrap sampling methods

3σ method refers to calculate the expected value μ and standard deviation σ_1 of each evaluation index, after that sets [μ-σ, μ+σ] as a safe interval, [μ-2σ, μ-σ] and [μ+σ, μ+2σ] as basic safe intervals, [-∞, μ-2σ] and [μ+2σ, +∞] as unsafe intervals. After calculation, AWACS range of mineral resources mining industry for safety is described as: safe interval: [μ-σ, μ+σ]=[0.496810, 0.577679]; basic safe intervals: [μ-2σ, μ-σ]=[0.458571, 0.496810] and [μ+σ, μ+2σ]=[0.577679, 0.615918]; unsafe intervals: [-∞, μ-2σ]=[-∞, 0.458571] and [μ+2σ, +∞] =[0.615918, +∞].The specific results are shown in the Table 3.

Table 3—The safe evaluation results of mining industry

Year	2002	2003	2004	2005	2006	2007	2008	2009
Safe state	unsafe	safe	safe	safe	safe	safe	safe	safe

BP neural network model

BP neural network is a multilayer feed forward neural network. Shi F, Wang X C &Yu L find that the main feature of the network is to transmit the signal before the error back-propagation[12].

Determination of hidden node

Jia Q argues that if hidden nodes of BP neural network are not enough, training accuracy of networks will also be affected. On the contrary, it will increase training time to make the neural network overfitting[13]. Choose the best hidden nodes usually refer to $l=log_2 n$ and $l< n-1$, l is the number of hidden layer nodes. m refers to the number of output layer nodes. n means the number of input layer nodes. α is a constant between 0 and 10. In the warning model of mineral resources mining industrial security, $m=3$, $n=7$. From the above we can make sure that the best hidden nodes' numbers are roughly between 3 and 5.So we can infer that the best number is 5.

Operation of BP neural network model

With MATLAB7.0 BP neural network model is established by FUNC newff. In the warning model of mineral resources mining industrial security, FUNC newff is written as following:

net=newff((minmax(p)),[3,3],{'logsig','logsig'},'trainrp')

net=newff indicates to create a BP neural network.

minmax(p)-value of input matrix P. 7×2 dimension matrix is composed by the maximum and minimum values of each group (total of 7 sets of input) element.

[3,3]-the first data shows hidden nodes and the second one represents the output nodes.

{'logsig','logsig'}-The first 'logsig' indicates the selection of a logarithmic function S-type transfer function from the input layer to the hidden layer. In FUNC logsig the input of neuron is mapped to the interval [0, 1]. The second 'logsig' presents the selection of a S-type logarithmic function transferring from hidden layer to output layer.

Trainrp-represents training algorithm selects resilient BP algorithm. The feature of S-type transferring function is when the input is too large or too small, and the slope is close to zero. This makes that the calculated gradient will be small when training for BP network with S-type multi-layer neurons. Then the network variable weights and thresholds will be small, thus affecting the speed of the network training. The purpose of resilient BP algorithm is to solve this problem so that we can eliminate the influence of gradient modulus. In this algorithm, via a separate parameter the weights and thresholds network is updated. When the network performance function of a power differential value has the same sign in two consecutive training cycles, this variable will be increased by parameters delt_inc, on contrary to be reduced by parameter delt_dec.

Test of BP neural network warning model

BP neural network training

In the mineral resources mining industrial safety warning model, we use the following command to train the network:

net.trainParam.epochs=100
net.trainParam.goal=0.000001
net=train(net,p,t)
The training results as following:
TRAINRP, Epoch 0/100, MSE 0.555975/1e-006, Gradient 0.164704/1e-006
TRAINRP, Epoch 25/100, MSE 0.00875311/1e-006, Gradient 0.00872894/1e-006
TRAINRP, Epoch 50/100, MSE 1.47672e-006/1e-006, Gradient 3.23376e-006/1e-006
TRAINRP, Epoch 51/100, MSE 3.65704e-007/1e-006, Gradient 8.25443e-007/1e-006
TRAINRP, Performance goal met.

After 51 times, MSE=3.65704e-007. From the following error curve, we can find the error remains small. We can see the results curve in Figure 1.

Test results

Test data input and output functions are as follows:

p_test=[0.15537 0.69493 0.91675 0.96499 0.034276 0.30573 0.27165 0.20206 0.13021 0.26129 0.81439 0.78048 0.25639 0.19892 0.73127 0.56104 0.20862 0.98443 0.51647]'

y=sim(net,p_test);

The output is:

$$y = \begin{bmatrix} 0.99975 \\ 2.0813\text{e}-007 \\ 1.5862\text{e}-009 \end{bmatrix} \quad \ldots (2)$$

Based on the previous results, in the year 2008 mineral resources mining industry is in a safe state for the green signal (100). Test results show that the safety warning model is consistent with safety assessment results. Besides, the prediction error can meet the requirements

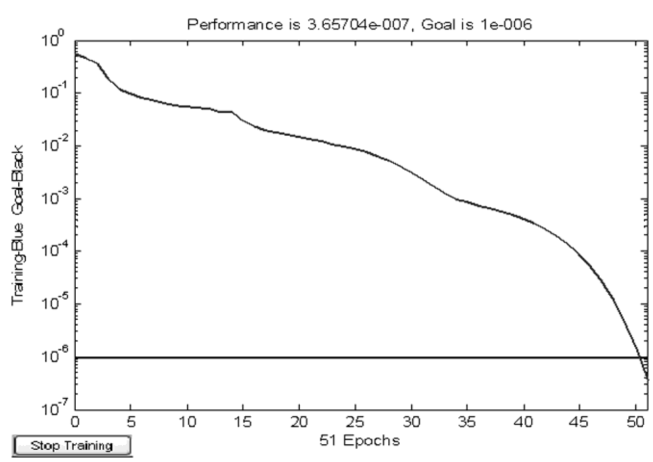

Fig.1—The error curve of back-propagation network

Conclusion

This paper presents the early warning index system for the security of Chinese mining industry. It also measures the safety situation of mining sub-industries form 2002-2009 by the combination of Information entropy and grey theory. The research results show that during 2002-2009, the mining sub-industries were safe, except in 2002. By establishing the BP neural network warning model for security based on the mineral resources industry, the security situation of mineral resources mining industry sub-sectors are simulated warning. Warning simulation results show that the effect of the model and empirical evaluation results are basically the same.

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