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Study on Energy Finance Risk Warning Model --- Based on GABP Algorithm

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Abstract.

Based on the developing features of the energy finance in our country, this paper designs the warning index system covering the systematic features of energy finance risks, which is BP neural network method based on genetic algorithm optimization; the energy finance risk warning model can provide information on risk recognition and risk warning for government and relevant management departments.

Introduction

During recent years, the energy consumption in our country increases with the speed twice of GDP of that year, indicating that the energy consumption level will keep going up during a relative long time and it is necessary to build an improved energy finance risk warning model with strong adaptation.

Indicator system of energy finance risk warning

Energy finance is a kind of new finance with the combination of energy and finance; generally speaking, energy finance risk refers to a series of paradoxes, problems and various adjusting measures displacements appearing in the energy finance development caused by objective or subjective reasons. This paper builds the energy fiance warning index system suitable for the energy finance development in our coulntry, which can be seen in Table 1.

Table 1: Indicator system of energy finance risk warning

First level	Second level	Significance of indicators
Index group of macroeconomy	GDP growth rate	Measuring the quality of macroeconomic environment
	GDP deflator	Measuring the inflation level of a country
	Exchange rate volatility	Measuring the risk state of finance risk
	Shanghai composite index	Measuring the security market financing of energy enterprises
Index group of energy industry	Price index of commercial fuel	Measuring the supply and demand state of global energy
	Prosperity index of energy enterprises	Measuring the entire state of production and opeartion of energy industries
Index group of banks and energy enterprises	Interest coverage multiple	Measuring the interest payment competence of energy enterprises
	Non-performing loan ratio	Measuring the debt quality of energy enterprises
	Aasset-liability ratio	Measuring the debt burden state of energy enterprises

Study method of energy finance risk

This paper divides the energy industry into oil and gas mining, coal mining and washing, and power generation industries and uses the neural network GABP algorithm optimized by genetic algorithm to study energy finance risk warning model based on the warning indicator data from WIND database. GABP algorithm is the best warning method at present and also the optimal choice to study energy finance risk warning. There are three reasons: firstly, the energy finance risk warning in our country just starts and relevant data is not complete, while GABP algorithm has strong information processing function; secondly, energy finance risk warning model is a complicated and large system with complex non-linear relations among different factors, while GABP algorithm can deal with plenty of non-linear relations; thirdly, during learning and training, GABP algorithm can recognize the internal relationship between input and output, so as to get rid of the inappropriate part during manual handling data and deal with data objectively.

Regional finance risk indicators selection and research methods

I. Regional finance risk indicators

It is necessary to consider the universality of financial risk factors and the regional feature of fiance development in the selection of regional finance risk indicators, and the phase characteristics of local finance development should be reflected. Principles of selection indicators: firstly, selected indicators hould be as simple as possible and representative; secondly, the availability of data should be considered; thirdly, the selection cost of data and the practicability of model prediction should be balanced. The selected indicators can be seen in Table 2.

Indicators	Variable	Economic significance
GDP growth rate	X1	If the growth rate is too high, it indicates the economy is overheated and inflation is easy to take place; if it is too low, it indicates that recession may occur.
Growth rate of fixed-asset investment	X2	Decreasing investment is the sign of economic weakness; over-expansion of investment may cause inflation.
Export growth rate	X3	It reflects the international comopetitiveness of local products, influencing the foreign countries' demand of domestic currency.
Inflation rate	X4	It influences the economic growth rate and real growth rate. Inflation and deflation are not benefitial for the economic development.
Industrial structure	X5	It is indicated with the weights of three industries. It reflects the quality and degree of economic development.
Fiscal expenditure growth rate	X6	It reflects the ability of llocal governemtn finance supporting economy. If this indivator is too low, it shows the fiscal support is weak; if the indicator is too high, the fiscal support is non-sustainable.
Fiscal revenue / fiscal expenditure (fiscal self-sufficiency degree)	X7	It reflects the self-supporting competence of local finance. The higher the indicator value is, the stronger is the self-supporting competence; the lower the indicator value is, it is possible to have local debt risk.
Bank loan growth rate	X8	It reflects the support degree of finance on economic development.
Bank loan / deposit	X9	It reflects the ratio of local loans in bank deposit. The smaller the ratio is, the more the deposit outflow, which may damages the local economic development.
Housing price growth rate	X10	Fast increase in housing price will generate property value bubbles and cause bank financial risks.

II. Factor analysis

Factor analysis mainly reaches simplified multi-dimensional data through dimension reduction, which means to find out the basic variables (common factors) of relevant representative multidimensional variales. The factor analysis model is as following:

$$\begin{cases} X_1=a_{11}F_1+ a_{12}F_2+\ldots.+ a_{1m}F_m+a_1\varepsilon_1 \\ X_2=a_{21}F_1+ a_{22}F_2+\ldots.+ a_{2m}F_m+a_2\varepsilon_2 \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ X_n=a_{n1}F_1+ a_{nn}F_n+\ldots.+ a_{nm}F_m+a_n\varepsilon_n \end{cases}$$

In the formula, multidimensional variables are X_1、X_2 、 …….. 、 X_n; m factor variables are F_1, F_2 , …….. F_n , m<n; ε is special factor, which is the part that cannot be explained by factors in original random variables. As for factor analysis, it means to select lesser factors to show more original variables according to certain method, to reach simplification and dimension reduction.

III. Neural network model

Neural network model. Artificial neural network, a model to realize intelligent computation through imitating the working principle of neural network processing outer information.

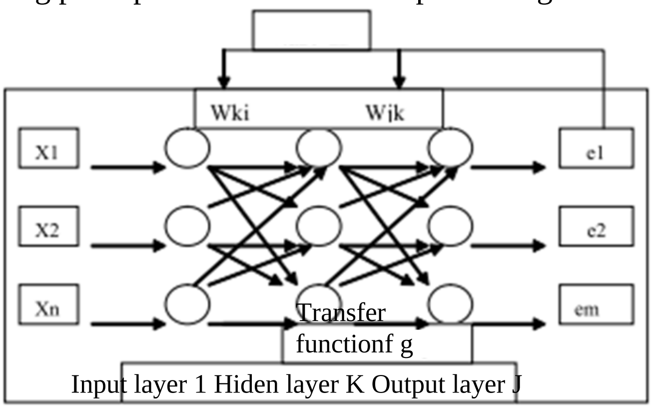

Figure 1 Working principle of BP neural network

Note: Wki is the weight from input layer to hidden layer; Wjk is the weight from hidden layer to output layer; there are numerous nerve cells in each layer, which are indicated with circles; f and g stand for the transfer functions of hidden layer and output layer.

Study on energy finance risk warning model

Before using BPGA algorith to study energy finance risk warning model, this paper needs to make normalization processing on relevant data.

I. Experimentation of warning model

1. Set weight and valve value of the model. Define the quarter data during 2005-2013 as training sample set, and the quarter data during 2006-2013 as test sample set; import training sample set and test sample set into MATLAB respectively; use NEWFF function to generate a multilayer feedforward BP neural network and adopt following steps to optimize.

(1) Initialize BP neural network. (2) Encode genetic algorithm: S=R*S1+S1*S2+S1+S2, where S1 stands for node number in hidden layer, S2 for input node number, R for output node number. (3) Set genetic algorithm parameters: population size is 50, copy operation 0.09, interlace operation 2, mutation operation［2 gen 3］, genetic algebra 100. (4) Set GABP network fitness function. (5) Assign value for BP neural network.

2. Training and learning neural network

(1) Stipulate training function as TRAINGDX, learning function as LEARNGDM, activation function of hidden layer and output layer as hyperbolic tangent function SIGMOID function. (2) Learning rate is 0.9, training goal 10~4, the largest number of times of training is 104. (3) Training and learning: net input is the normal data of training sample set after normalization processing during 2008-2015, with expected output is the quarter data during 2009-2016.

3. Select nodes of neural network. In the training and learning process of neural network, the number of nodes in hidden layer of network has great influence on network performance; this paper sets the node number in hidden layer of GABP network of energy finance risk warning as 9.

4. Inspect warning model. Based on above, use the sample data in 2016 to examine the energy finance risk warning GABP network with good performance after training and learning; adopt POSTMNMX function to do anti-normalization on the output data of energy finance risk warning GABP network; if the error absolute value of other index is within 0.2, it indicates that the expected output matches real output well.

Table 3 Test data and model output of finance risk warning of oil and gas

	GDP growth rate	GDP deflator	Exchange rate volatility	Shanghai composite index	Commercial fuel price index	Enterprise prosperity index	Interest coverage ratio	Non-performing loan ratio	Asset-liability ratio
Test input	0.0780	0.0230	0.8280	2.0535	1.9455	1.6308	6.9500	0.0096	0.0409
	0.0750	0.0205	0.8414	2.0899	1.8460	1.6594	6.5000	0.0096	0.0409
	0.0790	0.0210	0.8237	2.1073	1.9571	1.6714	6.0500	0.0097	0.0409
	0.0760	0.0222	0.8280	2.1069	1.9206	1.5446	5.6000	0.0100	0.0409
Expected output	0.0730	0.0048	0.8272	2.1017	1.9091	1.5210	5.4250	0.0104	0.0409
	0.0740	0.0102	0.8343	2.1128	1.9424	1.4910	5.2500	0.0108	0.0409
	0.0720	0.0101	0.8496	2.1251	1.8317	1.4000	5.0750	0.0116	0.0409
	0.0720	0.0079	0.8499	2.1231	1.4142	1.0710	4.9000	0.0125	0.0409
Real output	0.0726	0.0218	0.7659	1.8988	1.7556	1.5080	6.4250	0.0094	0.0383
	0.0773	0.0207	0.8733	2.1699	1.8706	1.7228	6.7500	0.0094	0.0419
	0.0906	0.0227	0.9617	2.4631	1.9045	1.9532	7.0750	0.0095	0.0460
	0.0968	0.0256	1.0910	2.7818	1.2531	2.0384	7.4000	0.0095	0.0504

Table 4 Test data and model output of finance risk warning of coal mining and washing

	GDP growth rate	GDP deflator	Exchange rate volatility	Shanghai composite index	Commercial fuel price index	Enterprise prosperity index	Interest coverage ratio	Non-performing loan ratio	Asset-liability ratio
Test input	0.0780	0.0230	0.8280	2.0535	1.9455	0.9520	3.9750	0.0096	0.6200
	0.0750	0.0205	0.8414	2.0899	1.8460	0.7200	3.6500	0.0096	0.6400
	0.0790	0.0210	0.8237	2.1073	1.9571	0.7944	3.3250	0.0097	0.6600
	0.0760	0.0222	0.8280	2.1069	1.9206	0.8472	3.0000	0.0100	0.6800
Expected output	0.0730	0.0048	0.8272	2.1017	1.9091	0.7740	2.5250	0.0104	0.6600
	0.0740	0.0102	0.8343	2.1128	1.9424	0.7050	2.0500	0.0108	0.6400
	0.0720	0.0101	0.8496	2.1251	1.8317	0.7120	1.5750	0.0116	0.6200
	0.0720	0.0079	0.8499	2.1231	1.4142	0.7060	1.1000	0.0125	0.6000
Real output	0.0716	0.0188	0.5688	2.1717	1.2920	1.7792	2.0250	0.0198	0.6853
	0.0737	0.0119	0.5319	2.0881	1.2709	1.7709	2.0500	0.0109	0.6605
	0.0728	0.0187	0.4969	2.0515	1.2730	1.7730	2.0750	0.0111	0.6363
	0.0815	0.0187	0.4814	2.0095	1.2697	1.7697	2.1000	0.0124	0.6154

Figure 2 and Figure 3 provide the error curve between expected output and real output of different indicators of oil and gas during four quarters in 2016

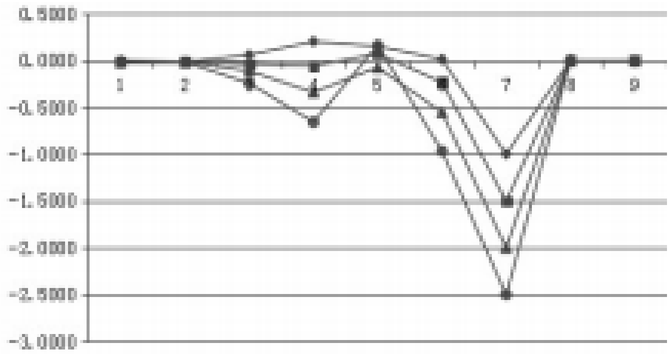

Figure 2 Output error of finance risk warning model of oil and gas in 2016

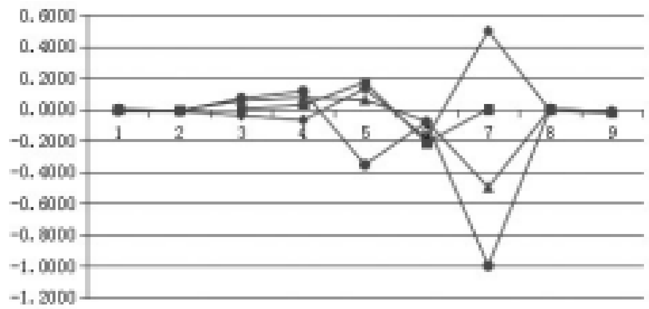

Figure 3 Output error of finance risk warning model of coal mining and washing in 2016

Table 5 Indicator value section of energy finance risk warning

Warning indicator	Safety value	Risk contribution weight	Indicator section of energy finance risk condition indicator			
GDP growth rate	6.5~9.5	0.15	Safety	Basic safety	Alarm	Unsafety
GDP deflator	2~5	0.15	[6.5,9.5]	[5,6.5]∪[9.5,11]	[3.5,5∪[11,12.5]	[-100,3.5]∪[12.5,100]
Exchange rate volatility	<3	0.15	<3	[3,5]	[5,7]	>7
Shanghai composite index	3000~4500	0.15	[0,1.5]	[-5,0]∪[1.5,3]	[-10,-5]∪[3,5]	[-50,-10]∪[5,50]
Commercial fuel price index	150~200	0.08	[3000,4500]	[4500,5500]∪[2500,3000]	[1000,2500]∪[5500,6000]	[0,1000]∪[6000,+∞)
Enterprise prosperity index	150~200	0.08	150~200	100~150	50~100	0~50
Interest coverage ratio	2.5	0.08	150~200	100~150	50~100	0~50
Non-performing loan ratio	0~2	0.08	>2.5	[1,2.5]	[0.1,1]	<0.1
Asset-liability ratio	6	0.08	0~2	2~5	5~8	8~10

Summary

The method of energy finance risk warning model is scientific and effective, suitable for the reality of Chinese energy finance development, with strong operability, which can provide information on energy finance risk recognition and risk warning for government and relevant administrative departments.

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