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Thermal Power Financial Environment Risk Forecast Model by Combined Stock Multi-indicators Basis on RBF Neural Network

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Abstract

It has an important significance for thermal power industry to take analysis and forecasting financial environment risk. With the scope of this paper, a RBF neural network model focus on risk analysis was constructed, and a series of input indicator combinations designed to get more accurate predictions.

Keywords: RBF, financial environment risk, forecast, Combined stock Multi-indicators

1. Introduction

As the most traditional and mature way of generating electricity in the power industry, thermal power has its own advantages, but the industry itself faces many risks. So, it is important to the thermal power industry to have a systematic study of these risks and it has an important significance for both industry operators and national macroeconomic. Power industry is moving from monopoly to competition under the influence of deregulation, as the market instability and security risks of the electricity market, caused by fluctuations of the electricity price and raw materials price, has become a prominent issue. At the same time, according to China's electric power system planning, electric market will be eventually fully opened, the relationship between financial markets and power industry will be more closely, and market participants are facing unprecedented

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market risks. Zheng Xinli considered that financial security is the core of industrial safety[1], so it is urgent and important to accelerate the improvement a modern financial system. Other researchers elaborated the basic framework of China's power financial markets, presented risk management strategies and methods[2-7]. Among above of these, the forecast of power financial environmental risk is a very important aspect, however, related literatures are very rare.

Radial basis function (for short, RBF) neural network is a network of local approximation. It can approximate any continuous nonlinear mapping accuracy[8], as for it is more suitable for dynamic system modeling and pattern classification, this paper choose RBF neural network to forecast market risk and build a forecast based on RBF neural network model to analyze the environmental risks by choosing impact indicators of MA5, BIAS6 and PSY12.

2. Financial environment risk

Financial environment risk is the risk of loss from adverse changes on financial products held by power generation companies, and the risk of fluctuations in the overall financial environment. Financial investments are risky, financial environment risk happens when the stock market's volatility not conducive to investors, so investors cannot obtain expected investment return or even get losses. For example, the expected rate of return of 25% equity investment, while the actual rate of return of 18%, 12% deviation to reflect the risks.

Different enterprises have appropriate investment strategies according to the characteristics of themselves. As the Power generation companies is very sensitive to changes in the prices of coal, Enterprises always hold investments Fuel-related stocks or futures to resolve the fuel market price fluctuations risk, which associated with risk.

This paper was based on the stock price data of November 2010, analyzed stock index futures data and forecasted by using the RBF neural network method to take the future direction of risk of the occurrence and transmission.

3. Radial basis function neural network

Radial basis function neural network is a three-layer feed-forward network, including the input layer, hidden layer and output layer. Input layer consists of source nodes; hidden layer is the second layer, the number of nodes is as required; output layer responds to the input mode. From the input layer to hidden layer transformation is nonlinear, while the transformation from hidden layer to output layer is linear. The activation function of hidden layer node is the radial basis function[9]. RBF neural network structure is shown in Fig. 1.
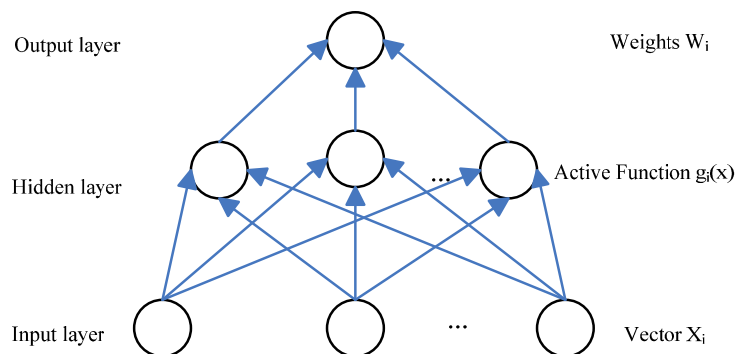

Fig.1. Process-core electricity corporation information system software model

Vector X=(x1, x2, ···, xm) is a m-dimensional input analog variable, W=(w1, w2, ···, wn) is the output layer weight vector. Activation function is the Gaussian function, denoted as gi(X) = gi(‖ X - Ci ‖) in which i=1, 2, ···,n and n is the number of hidden layer nodes, Ci is the i-th activation function of the center, ‖ * ‖ is the Euclidean norm.

The output function of the i'th node of RBF hidden layer shows as (1).

$$q_i = g_i(\|X - C_i\|) = \exp(-\frac{\|X - C_i\|^2}{2\sigma_i^2})$$

(1)

In which, σ_i is the width parameter.

The output of output layer is the linear combination of nodes in the hidden layer as illustrated in (2).

$$y = \sum_{i=1}^{n} w_i q_i$$

(2)

In which, w_i is the connection weights between the hidden layer and output layer.

4. Forecasting and Results Analysis

4.1. Data choose and preprocessing.

In order to describe the state of the financial environment, this paper chooses the stock price index as forecast target, which describes the general stock market price level changes. Based on data in stock index futures market, the paper examined the relationship between closing price and other indicators of BIAS6, MA5 and PSY12, then the RBF neural network model constructed to forecast stock price index on the stock index futures market during fixed period of time.

The RBF neural network structured and trained by data from 2010-11-30 to 2010-11-02, to forecast data from 2010-12-01 to 2010-12-14, after that, the forecasted and actual data were analyzed.

The data pretreatment is needed for the input data. In this paper, BIAS6 and PSY12 are pretreated by (3), and (4) is set for MA5.

$$X' = (X - \mathrm{E}(X))/(m*\sigma)$$

(3)

$$X' = (X - \mathrm{E}(X))/m$$

(4)

In which, X is the original input vector, $\mathrm{E}(X)$ is expectations of X, σ is the standard deviation of X, m could be the product of columns number of training samples' input vector X1 and forecast input vector X2, that is m=(n1 + n2) * 4.5. X' is the treated input vector.

4.2. Forecast results show.

This Paper takes predictive analysis mainly in the MA5, BIAS6 and PSY12 indicators. The following three steps are used in the analysis of the data:

(1) Forecasting by using a single indicator one by one.

(2) Forecasting by combining two indicators to form two-dimensional input vector.

(3) Forecasting by combining three indicators to form three--dimensional input vector.

In summary, this trial will generate seven groups of forecast data. This paper will give the graphic of corresponding forecast data and actual data, as well as the comparative analysis table of seven groups of data.

4.3. Analysis of forecast results.

(1) BIAS6 indicators. Take BIAS6 data and the corresponding closing price data as training samples, structure the network and train it. Based on this, input 10 groups of BIAS6 data to the network, obtain the corresponding 10 output groups of forecasted data, shown in Fig. 2.

(2) MA5 indicators. Take MA5 data and the corresponding closing price data as training samples, structure the network and train it. Based on this, input 10 groups of MA5 data to the network, obtain the corresponding 10 output groups of forecasted data, shown in Fig. 3.

(3) PSY12 indicators. Take PSY12 data and the corresponding closing price data as training samples, structure the network and train it. Based on this, input 10 groups of PSY12 data to the network, obtain the corresponding 10 output groups of forecasted data, shown in Fig. 4.

(4) Combined BIAS6 and MA5, shown in Fig. 5.

(5) Combined BIAS6 and PSY12, shown in Fig. 6.

(6) Combined MA5 and PSY12, shown in Fig. 7.

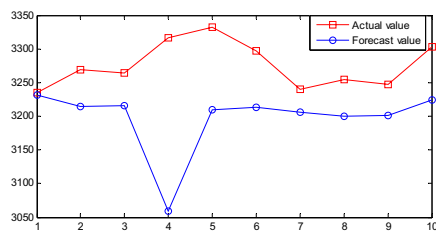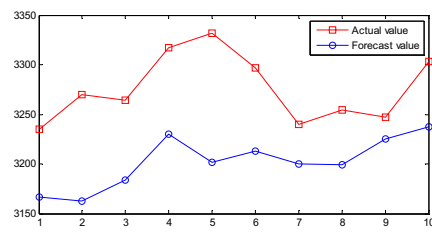(4) Combined MA5, BIAS6 and PSY12, shown in Figure 8.

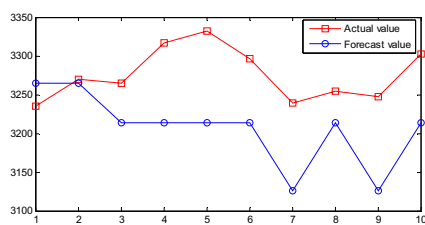

Fig.2. Forecast by BIAS6

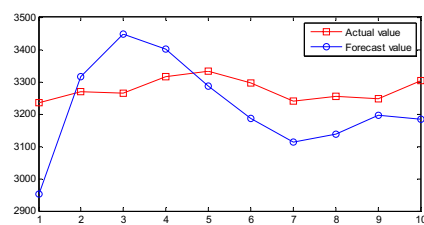Fig.3. Forecast by MA5

Fig.4. Forecast by PSY12
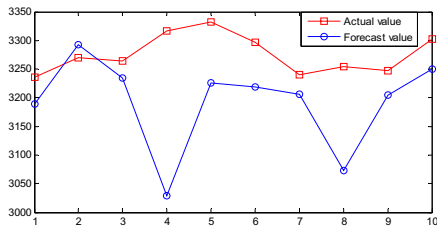

Fig.5. Forecast by BIAS6 andMA5
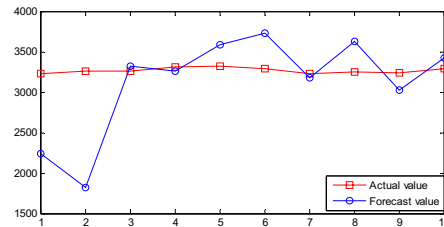
Fig.6. Forecast by BIAS6 and PSY12
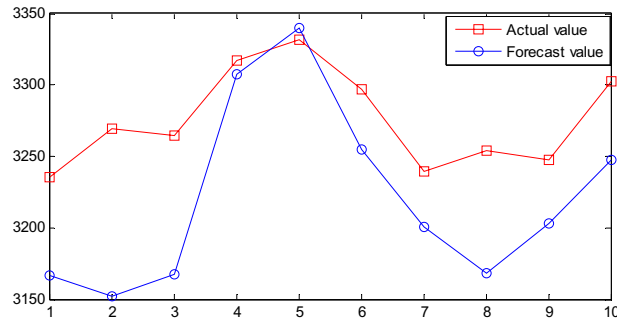

Fig.7. Forecast by MA5 and PSY12

Fig.8. Forecast by MA5, BIAS6 and PSY12

The comparative analysis table of seven groups of data show as table 1.

Table 1. Forecasted and Actual data analysis summary table (1.0e+003 *)

	12/01	12/02	12/03	12/04	12/07	12/08	12/09	12/10	12/11	12/14	average error
Actual data	3.1665	3.1523	3.1671	3.3079	3.3400	3.2546	3.2007	3.1680	3.2032	3.2475	——
BIAS6	3.2321	3.2143	3.2162	3.0589	3.2099	3.2128	3.2056	3.2004	3.2015	3.2247	2.3746
MA5	3.1670	3.1625	3.1837	3.2303	3.2018	3.2134	3.2001	3.1990	3.2249	3.2371	2.2514
PSY12	3.2652	3.2652	3.2140	3.2140	3.2140	3.2140	3.1258	3.2140	3.1258	3.2140	2.2941
BIAS6+MA5	2.9514	3.3167	3.4474	3.4023	3.2867	3.1874	3.1139	3.1367	3.1955	3.1838	3.5750
BIAS6+PSY12	3.1890	3.2931	3.2348	3.0293	3.2252	3.2182	3.2066	3.0723	3.2048	3.2504	2.6826
MA5+PSY12	2.2401	1.8177	3.3245	3.2714	3.5956	3.7358	3.1822	3.6369	3.0362	3.4281	12.3436
MA5+BIAS6+PSY12	3.1665	3.1523	3.1671	3.3079	3.3400	3.2546	3.2007	3.1680	3.2032	3.2475	1.7391

By comparing data in the table, It can be concluded that, the forecast result by RBF neural network from three latitude input vector combined by the three indicators is better than the other models. It's a general approach of forecasting calculation based on the RBF, therefor, when this method approached to analysis of other indicators related to stock market factors, some more accurate and useful combinations should be draw out. Based on the data above, combined with the current macroeconomic environment and the latest financial policy, we can make a comprehensive assessment of financial environment risk.

5. Summary

This paper constructed data forecast model based on RBF neural network which considered several impact indicators. To verify the validity of the forecast model, three indicators, MA5, BIAS6 and PSY12, were chosen to make the composition of the input vector, which provides an effective algorithm model for the thermal power industry making analysis and forecasting of the financial environmental. In the technical indicator group, BIAS6 and MA5 outperformed other indicators. Using a single indicator to forecast stock closing indices, whether it was a technical indicator, an average stock yield indicator or a closing index indicator, the accuracy was lower than that achieved with group indicators. Of all the hybrid combinations, BIAS6 + MAS5 + ASY12 were the optimum group with the smallest forecasting errors.

In this paper, quantitative indicators were used to forecast the closing indices. However, stock movements are affected not only by quantitative factors, but also by non-quantitative factors, such as macroeconomic policies, regulations and psychological factors, etc. How to integrate these non-quantitative factors into mathematical algorithms using mining techniques to effectively increase forecast accuracy will be left to future research.

Acknowledgements

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