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AN APPROACH BASED ON MULTI-FEATURE WAVELET AND ELM ALGORITHM FOR FORECASTING OUTLIER OCCURRENCE IN CHINESE STOCK MARKET

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ABSTRACT

The prediction of outliers plays an important role in stock arbitrage and risk avoiding. While most of researches focused on detecting outliers and removing them to forecast time series data, few focused on forecasting the occurrence of outliers. The main goal of this work is to forecast outlier occurrence in Chinese stock market. Firstly, we detect abnormal points of two market indexes and six individual stocks based on multi-feature wavelet method. Compared with single feature wavelet method, multi-feature wavelet method was more reliable, since it captures more information of the market and avoids "masking effect". Moreover, according to the detected results, we construct an outlier forecasting model for the two market indexes and six individual stocks based on multi-feature extreme learning machine (ELM) algorithm. Finally, we find out the optimal number of hidden nodes to forecast when the mean of forecasting accuracy was the highest which approximately equals 98.255% and the variance of forecasting accuracy was only 0.000193.

Keywords: *Outlier Forecasting, Outlier Detection, Multi-feature Wavelet, Extreme Learning Machine (ELM)*

1. INTRODUCTION

People were paying close attention to the abnormal part of the data set, which was usually considered that it has polluted the data set, changed the original data information and the generated mechanism of the date set. However, abnormal points also contain information of the data set which can't be ignored. In financial field, abnormal points represent volatility of the market. Volatility plays an important role in risk management, market timing, derivative pricing, portfolio selection and many other financial activities [1]. Therefore, forecasting outlier occurrence of the stock market accurately is of great importance in theory and application.

Despite the vast variety of researches related to outlier detection [2]-[4], there were few works about forecasting the occurrence of outliers. Most scholars focused their attention on forecasting time series by detecting outliers and removing them from the data set [5][6]. However, anomaly is the result of quantitative accumulation and it reflects the fluctuation of the stock market, removing outliers directly may lost fluctuation information of the stock market. So we turn attention to the abnormal points which is an important feature of stock market. Wavelet analysis technology has been used in outlier detection field for a long time. Bilen and Huzurbazar used wavelet analysis to detect abnormal points in time series [7]. Grane and Veiga detected outliers in British and America market index using wavelet analysis based on Gaussian distribution hypothesis [8]. They found that wavelet analysis method was more reliable than other method for it didn't detect wrong abnormal points. Lu, Deng and Huo used wavelet analysis combined with boosting tree method to forecast the Australia electricity price [9]. But they used only single parameters to represent the stock market. Although dramatic fluctuation in share price (or index) represents abnormal fluctuation, studies have shown that stock price volatility was related to the trading volume [10][11]. Srinivasan found that trading volume contains information about market volatility [12]. Cheng and Oliver found that change in volume can provide information to forecast [13]. Scholars Zhu have integrated trading volume into

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their forecasting model [14]. In addition to price, trading volume is another important factor to analyze and forecast abnormal fluctuation in stock market. To represent the market comprehensively, we incorporate trading volume to wavelet outlier detection model and ELM outlier forecast model. Compared with single feature wavelet method, multi-feature wavelet method was more reliable, for it captures more information of the market and avoids "masking effect".

To forecast the occurrence of outliers, the forecasting algorithm must be appropriate. Neural network has been used in many fields because of its learning function of imitating neural frame of human being. Since the data is massive in stock market, the learning speed of neural network must be fast enough. Traditional feedforward neural network adjusts its learning weight parameter by gradient descent algorithm. However, its slow learning speed and poor generalization performance restricts its application. Based on this, Huang proposed a new learning algorithm called extreme learning machine (ELM) for single hidden layer feedforward neural networks (SLFNs) [15][16]. Compared to the traditional neural network, ELM algorithm has less optimal constraints because of its characteristic separability, randomly choosed input weights and hidden layer nodes offset. Moreover, the ELM algorithm solves output weight of the network only by one step calculation, the whole process needs no iteration, the speed improved significantly (usually 10 times) compared to the back propagation neural network (BP) [17]. Liu, Gao and Li found that extreme learning machine has great superiority in computational speed especially for large-scale sample compared to support vector machines [18]. Based on these advantages over other neural network, we adopt ELM algorithm to forecast stock market outlier combined with multiple features.

In this study, we detect the abnormal points of two market indexes and six individual stocks in Chinese stock market based on multi-feature wavelet analysis method. To examine if multi-feature wavelet method outperforms single feature wavelet method, the experiment was conducted compared with single feature wavelet method. According to the detected results, we construct an outlier forecasting model based on multi-feature extreme learning machine (ELM) algorithm which can predict whether the abnormal fluctuation will appear today or not via its five days data before. Finally, we analyze the forecasting accuracy with different hidden nodes and find out the optimal number of hidden nodes to forecast.

The remainder of this paper proceeds as follows. Section 2 describes outlier detection methods as well as outlier forecasting model. In section 3, we apply the methods into Chinese stock market, compare multiple feature model outlier detection results with that of single feature model, then evaluate the forecasting performance of ELM algorithm. We conclude in section 4.

2. RESEARCH METHOD

2.1 Wavelet Transformation And Multi-Feature Wavelet Outlier Detection Method

Wavelet transformation provides a flexible time-frequency analysis method based on multiple resolution analysis. It can overcome the limitation of Fourier transformation which lack of locality in temporal domain.

2.1.1 wavelet transformation

Dealing with signal information, wavelet transformation solves the locality contradiction between temporal domain and frequency domain by adjusting the size of time window. For low frequency signal, it selects large time window to ensure accuracy of the signal frequency. While for high frequency signal, it selects small time window to improve its temporal resolution. Therefore, the wavelet function is:

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \quad (1)$$

Among them, $\psi(t)$ stands for the mother wavelet function, a is the expansion factor, b is the shift factor. The expansion factor a, also known as scale factor, defines the expansion degree of the base wavelet, $a>0$. The smaller the expansion factor a is, the narrower is $\psi(\frac{t}{a})$. When a becomes larger, $\psi(\frac{t}{a})$ becomes wider. The shift factor b is displacement component, $b \in R$. Wavelet function $\psi_{a,b}(t)$ is got from transformation by expansion factor and shift factor. $\psi_{a,b}(t)$ also represents the variability of temporal window and frequency window.

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2.1.2 multi-feature wavelet outlier detection method

Since trading volume is an important factor to analyze and forecast abnormal fluctuation in stock market. We incorporate it into wavelet outlier detection model to determine whether an observation is an outlier. The outlier detection procedure is as follows:

Step 1: According to equation 2, compute price (or index) yield rate r_t and trading volume changing rate m_t for each stock, then get the return rate sequence data of price (or index) $R=\{r_1,r_2,r_3,...r_t\}$ and the changing rate sequence data of trading volume $M=\{m_1,m_2,m_3,...,m_t\}$:

$$\begin{cases} r_t = 100*\log(p_t/p_{t-1}) \\ m_t = 100*\log(n_t/n_{t-1}) \end{cases} \tag{2}$$

Where t=1,2,3,…n, stands for number of days;

Step 2: Through primary wavelet decomposition, get sequence R 's low frequency R_L and high frequency R_D. Similarly, get sequence M 's low frequency M_L and high frequency M_D;

Step 3: To eliminate stochastic diffusion, set high frequency data R_D and M_D equals zero. Then make inverse wavelet transformation for low frequency data R_L and M_L to get the main trend of sequence R and M respectively: $\hat{R}$ and $\hat{M}$.

Step 4: Compute the absolute residual of sequence R and M : ε_R and ε_M respectively. Since the value of sequence ε_R and ε_M differs significantly, normalize sequence ε_R and ε_M :

$$\begin{cases} \varepsilon_R = \left|R-\hat{R}\right| \\ \varepsilon_M = \left|M-\hat{M}\right| \end{cases} \tag{3}$$

Where, ε_R residual of sequence R , ε_M is residual of sequence M . Residual of sequence R is generated by its original data sequence R subtracting main trend part of the sequence $\hat{R}$. So is the residual of sequence M .

Step 5: Compute total residual of the two features:

$$\begin{cases} \varepsilon_0 = a_R\varepsilon_R + a_M\varepsilon_M \\ a_R + a_M = 1 \end{cases} \tag{4}$$

Where a_R and a_M is the weight of ε_R and ε_M respectively. In multi-feature model, assume that the impact of price (or index) to abnormal points is the same as the impact of trading volume, set a_R=0.5, a_M=0.5. In single feature model, set a_R=1, a_M=0.

Step 6: Sort ε_0 in descending order. Choose five percent maximum in ε_0. The corresponding date of the chosen data is when the abnormal fluctuation of individual stocks (or the whole market) happened.

2.2 Elm Algorithm And Multi-Feature Elm Outlier Forecasting Method

ELM algorithm solves output weight of the network only by one step calculation, the whole process needs no iteration, the speed improved significantly compared to BP neural network.

2.2.1 ELM algorithm

In order to solve BP neural network's slow training speed, sensitivity of parameter choosing and local optimum, Huang proposed ELM learning algorithm for single hidden layer feedforward neural network (SLFN) based on the following theorem:

Theorem 1 [15]: Given N different samples (x_i,t_i), where $x_i=[x_{i1},x_{i2},\cdots,x_{in}]^T \in R^n$ and $t_i=[t_{i1},t_{i2},\cdots,t_{im}]^T \in R^m$, SLFN with N hidden nodes and an activation function which is infinitely differentiable in any interval, $g: R \to R$, the hidden layer output matrix H of SLFN is invertible, where the error function $E(W)=0$. It means that the equation set has accurate solution.

Theorem 2 [16]: Given N different samples (x_i,t_i) , any small error $e>0$, an activation function which is infinitely differentiable in any interval, $g: R \to R$, there exists $N_0 \le N$ that the error function $E(W) \le e$ for SLFN with N_0 hidden layer nodes.

Theorems 1 and 2 show that SLFN whose input weights were assigned randomly can approximate

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any continuous function when the number of hidden nodes is big enough. The ELM algorithm only needs to adjust the number of hidden nodes N_0 compared with BP neural network.

2.2.2 multi-feature elm outlier forecasting method

According to sequence R and M we obtained above, construct an ELM abnormal predicting model which can predict whether abnormal fluctuation will appear today or not through data of its five days before based on the price (or index) and trading volume. In the procedure, take 95% of the total data as ELM training data, the rest as test data to test the forecasting accuracy. In this paper, we analyze the forecasting accuracy with number of different hidden nodes by experiment and find out the optimal hidden layer nodes number to forecast outliers.

3. EMPIRICAL RESULTS

To ensure universal application of the algorithm, we select two market indexes in Shanghai and Shenzhen, six other individual stocks which is representative of the market. The samples were collected as Table 1:

Table 1: Time Range Of Experiment Data And Number of Samples

Stock name	Stock code	Time range	Sample number
Shanghai stock index	000001	2000.02.17~ 2012.10.25	3075
Shenzhen component index	399001	2000.02.17~ 2012.10.25	3075
Vanke	000002	2000.01.05~ 2012.10.22	3030
Yunnan baiyao	000538	2000.01.05~ 2012.10.19	3025
China PetroChemi -cal	600028	2001.08.09~ 2012.10.19	2665
Baotou Rare Earth	600111	2000.01.05~ 2012.10.22	3040
Hefei Fengle Seed	000713	2000.01.05~ 2012.10.25	3045
China Satellite	600118	2000.01.05~ 2012.10.19	3030

3.1 Wavelet Outlier Detection Comparision

To examine if multi-feature model outperforms single feature model, contrastive analysis was conducted by comparing their detected results respectively.

3.1.1 multi-feature wavelet feature detection results

Combined with two features-price (or index) and trading volume, we detected outliers of the two market indexes and six individual stocks respectively. The market indexes outlier detection results were shown in Figure 1 and 3 where the plus sign represents detected abnormal points. To save space, the figures of individual stocks were not covered here. Comparing the detected abnormal dates with exceptional events at the corresponding dates, we analyze outlier detection accuracy of the two market indexes and six individual stocks respectively.

(1) Accuracy analysis of market index outlier detection

Firstly, we detect abnormal points of Shanghai index and Shenzhen component index respectively. Then take 5% of their maximum fluctuation points. Each index has 154 abnormal fluctuation dates. To see on those dates if abnormal fluctuation really happened, examine index volatility and trading volume volatility at the corresponding date. We found that with large trading volume, the index volatility was about 3% more or less. For market index, 3% was dramatic pricing volatility. Finally, we analyze detection accuracy by comparing the detected abnormal date with exceptional events in domestic environment. The result show that the two indexes were subject to domestic environment significantly and the abnormal dates were matched with the exceptional events largely. To explore the reasons why they were matched, we found that the abnormal dates were related to dates of security policies issued by Chinese government.

Specifically, for instance, the abnormal dates were: March 16, 2000; October 22, 2001; June 19, 2002; June 11, 2003; September 16, 2004; May 10, 2005; May 16, 2006; May 31, 2007; January 23, 2008; August 29, 2008; October 10, 2008; December 21, 2009; January 15, 2010; January 17, 2011; January 17, 2012. Compared with the exceptional events at the corresponding dates, we found that on March 16, 2000 the western development office was established formally by the state council. On October 23, 2001 securities regulatory commission announced that stop selling state-owned shares which issued for the first time. On June 20, 2002 Shanghai stock exchange intended to change the constituent stock index. On June 11, 2003, the national social security fund

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entered the security market officially. On September 14, 2004, premier Wen jiabao presided the state council executive meeting, calling for carrying out the nine-point guidelines. On May 9, 2005, the equity division reform pilot started officially. On May 17, 2006, the new regulation of IPO began to initiate. On May 31, 2007, the security transaction stamp tax rate increase to 3‰. On January 23, 2008, four ministries issued “notice on inquiry, freeze and deduct securities and relevant questions of security transaction settlement funds” jointly. On August 29, 2008, Shanghai and Shenzhen stock exchange issued guidance to standardize the behavior of big shareholders and their consistent person increasing shares. On October 9, 2008, the central bank announced to cut down lending rate and deposit reserve ratio, exempt investors from interest tax temporarily. On December 24, 2009, the central bank issued monetary policy: to guide financial institutions to achieve loan balance and avoid big fluctuation. On January 13, 2010, China Financial Futures Exchange was approved to trade index futures by China Securities Regulatory Commission (CSRC), the central bank raised 0.5% of deposit reserve ratio. On January 17, 2011, the central bank raised 0.5% of deposit reserve rate again. On January 17, 2012, the national bureau of statistics released that Chinese economy has increased 9.2% computed by the comparable price compared with 2011. These are part of the matching results which show that the matching degree between detected abnormal points and actual abnormal points is extremely high.

(2) Accuracy analysis of individual stocks outlier detection

For individual stocks, because of the limitation of length, only take Vanke, Yunnan baiyao and China petrochemical whose stock code is 000002, 000538, 600028 for example. Extract two abnormal points of every stock and find out its corresponding events to analyze the accuracy of outlier detection respectively.

In the samples, there are 152 abnormal points in Vanke. Take July 17, 2007 and April 24, 2008 for example. Enquiry about the major issues of the company, we find that on July 16, 2007, increasing issues in A share market was passed by CSRC issuance examination committee conditionally. On April 24, 2008, the general meeting of shareholders made decision to add 6 shares for every 10 share and pay dividends 1 yuan per share (including tax), change part funds of “Vanke turn 2” into Shanghai shippo 53# project, elect new board of directors, adjust the salary of board of directors and supervisors, appointed annual auditor in 2008.

For Yunnan baiyao, there are 152 abnormal points in samples. Take April 7, 2010, April 27, 2011 for example. Enquiry about the major issues of the company, we find that On April 9, 2010 the company got approval exemption offer from CSRC about controlling shareholder state-owned equity transfer freely. On April 30, 2011, the company announced their first quarter of 2011 financial report, per share earning was 0.32 yuan.

For China petrochemical, there are 134 abnormal points in samples. Take July 18, 2008, October 30, 2008 for example. Enquiry about the major issues of the company, we find that On July 18, 2008 the company expected that their net profit will decrease more than 50% in the first half of 2008 compared with the same period in 2007. On October 30, 2008, the company announced their financial report in the third quarter of 2008, per share earning was 0.096 yuan, according to the relevant provisions of the dealers association, the application for registration in China and issuing less than 30 billion mid-term bill once or several times were approved by the board of directors.

The accuracy analysis results of individual stocks show that individual stocks were correlated to the information issued by the government and their earning ability.

3.1.2 single feature wavelet outlier detection results

When using only one feature of the market-price, the detected results were different from above multi-feature model results, In order to save space, only take two market indexes for instance, the results were shown in Figure 2 and Figure 4 where the plus sign represents detected abnormal points.

Comparing Figure 2 and Figure 4 with multi-feature model results: Figure 1 and 3, we can find that single feature model easily trapped into local outlier. Whereas multi-feature outlier detection model can avoid “masking effect”, it was more reliable than single feature model.

Take Shanghai index for instance, the abnormal dates which single feature model didn’t detect, while multi-feature model detected were: November 19, 2001; May 21, 2002; October 10, 2002; August 19, 2008; November 27, 2008; January 17, 2012. To examine if these dates were really abnormal points, we found that on those surrounding detected days, the index volatility was 1% more or less. This degree of fluctuation is

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enough to count as abnormal points. To explore the reason behind these fluctuations, examine exceptional events in domestic environment at the corresponding dates. we found that on November 16, 2001, CSRC cut down security transaction stamp tax rate. On May 22, 2002, CSRC issued “notice on listing requirement of acquired company which were involved acquisition deals”. October 8, 2002, CSRC issued measurements about information disclosure on acquisition of listed companies and changes in proportions of shareholders. On August 22, 2008, the state asset regulatory commission and CSRC jointly started to monitor state-owned shares in real time. On November 27, 2008, the central bank announced to cut down benchmark interest rate and deposit reserve ratio. On January 17, 2012, the national bureau of statistics released that Chinese economy has increased 9.2% computed by the comparable price compared with 2011.

The above analysis of outlier detection results shows that multi-feature wavelet method was more reliable than single feature wavelet method. Since multi-feature wavelet method can capture more information of the market, it can avoid “masking effect”.

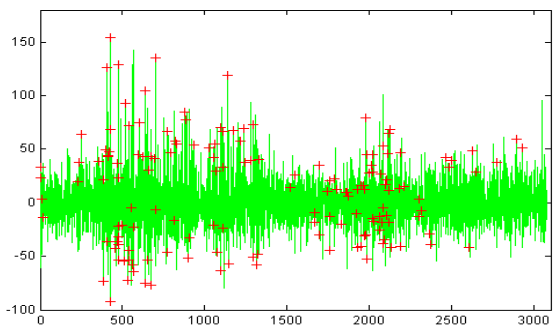

Figure 1: Outlier Detection Results Of Shanghai Index By Multi-feature Model

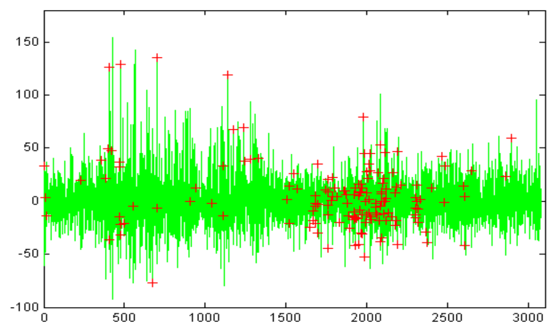

Figure 2: Outlier Detection Results Of Shanghai Index By Single Feature Model

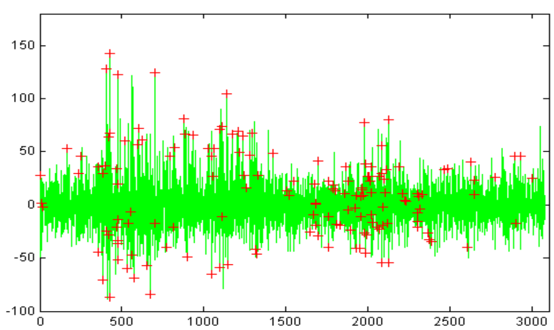

Figure 3: Outlier Detection Results Of Shenzhen Component Index By Multi-Feature Model

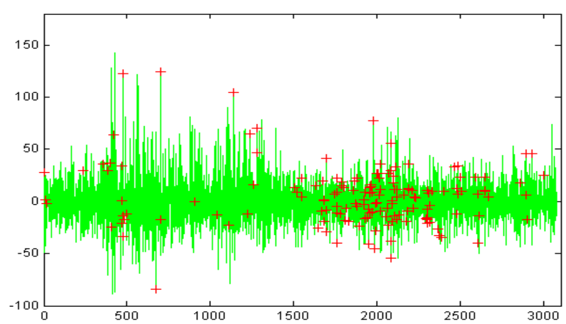

Figure 4: Outlier Detection Results Of Shenzhen Component Index By Single Feature Model

3.2 Multi-Feature Elm Outlier Forecasting Model And Hidden Nodes Selection

The number of hidden nodes is the key to ELM algorithm. With different number of hidden nodes, the training accuracy and forecasting accuracy of ELM algorithm were different. To find out how many hidden nodes was the best to forecast, set the hidden nodes of market index from 50 to 2500 by the increasing step length of 10. The result of training accuracy and forecasting accuracy was shown in Figure 5 and Figure 6, the horizontal axis stands for the number of hidden nodes and the vertical axis stands for the accuracy of training and forecasting.

For individual stocks, the experiment method was similar to the market indexes. Set the hidden nodes of market index from 50 to 2500 by the increasing step length of 10 to get training accuracy and forecasting accuracy. In order to guarantee validity of the data in the graph, we removed the hidden nodes whose training accuracy was lower than 0.97. According to Figure 5 and Figure 6, when hidden nodes were big enough, the forecasting accuracy declined, so we got rid of the hidden nodes which were too big to increase forecasting accuracy. Finally, we got Figure 7, 8, 9,

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10, 11, 12 correspondingly. The horizontal axis stands for the number of hidden nodes and the vertical axis stands for the accuracy of training and forecasting.

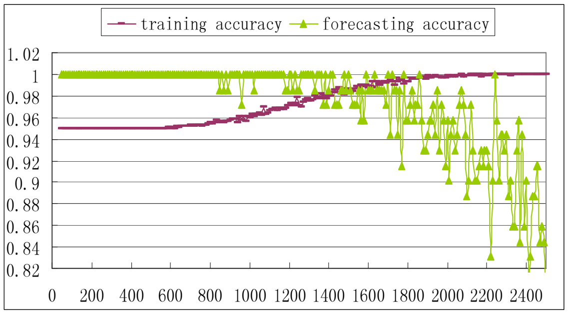

Figure 5: Training Accuracy And Forecasting Accuracy Of Shanghai Index By ELM Model

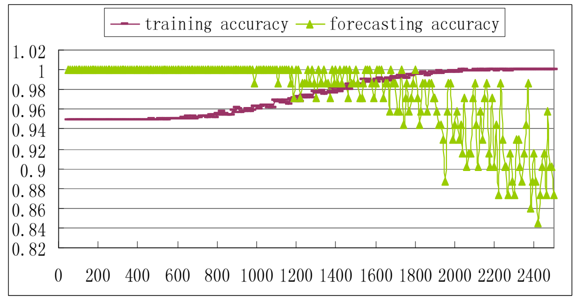

Figure 6: Training Accuracy And Forecasting Accuracy Of Shenzhen Component Index By ELM Model

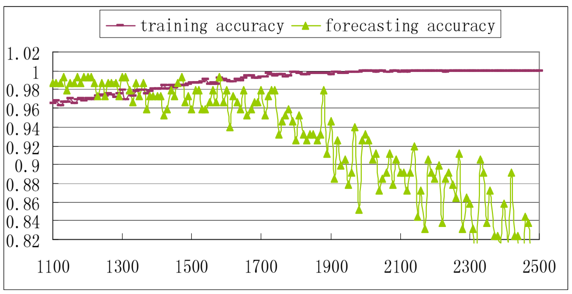

Figure 7: Training Accuracy And Forecasting Accuracy Of Vanke By ELM Model

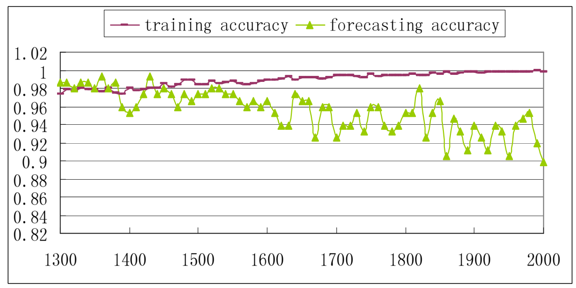

Figure 8: Training Accuracy And Forecasting Accuracy Of Yunnan Baiyao By ELM Model

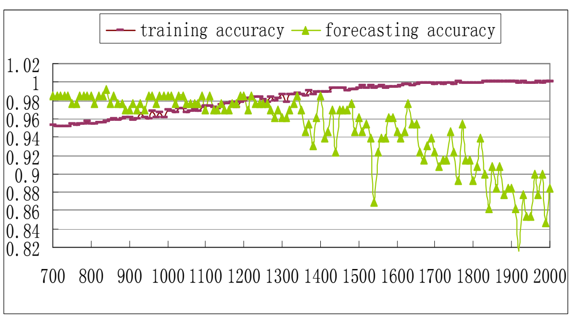

Figure 9: Training Accuracy And Forecasting Accuracy Of China PetroChemical By ELM Model

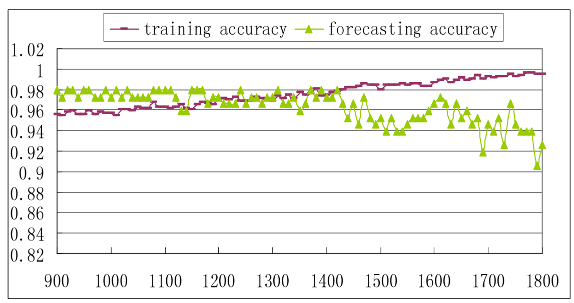

Figure 10: Training Accuracy And Forecasting Accuracy of Baotou Rare Earth By ELM Model

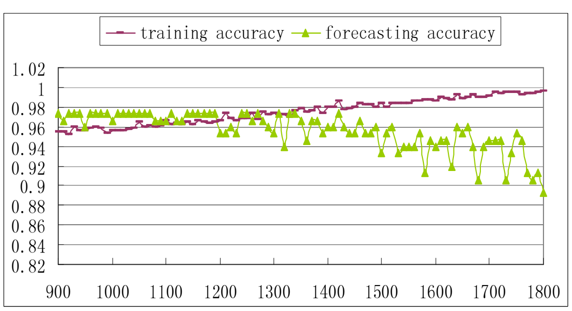

Figure 11: Training Accuracy And Forecasting Accuracy Of Hefei Fengle Seed By ELM Model

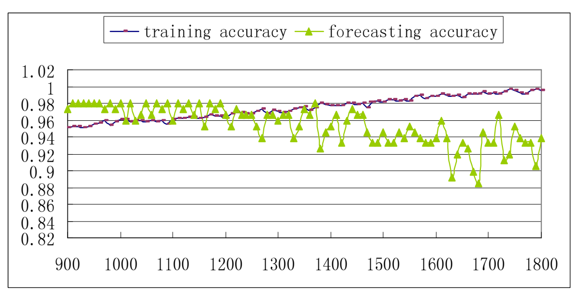

Figure 12: Training Accuracy And Forecasting Accuracy Of China Satellite By ELM Model

Figure 5 to 12 show that each stock's training accuracy and forecasting accuracy changed as the number of hidden nodes varied. In order to find out the optimal number of hidden nodes, Select effective hidden nodes whose training accuracy rate was greater than 0.97 and compute mean and

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variance of the two market indexes' and six individual stocks' prediction accuracy. Find out the optimal hidden nodes whose mean of prediction accuracy was the highest and variance was the lowest. The result was shown in Table 2:

Table 2: The Training Accuracy And Forecasting Accuracy With Different Hidden Nodes

Number of hidden nodes	Mean of forecasting accuracy	Variance of forecasting accuracy	Number of hidden nodes	Mean of forecasting accuracy	Variance of forecasting accuracy
1300	0.97481875	0.000251	1560	0.96005125	0.000395
1310	0.98254625	0.000193	1570	0.96187125	0.000410
1320	0.97333125	0.000276	1580	0.95781875	0.000604
1330	0.97250375	0.000221	1590	0.96215625	0.000336
1340	0.9820525	0.000214	1600	0.96361875	0.000343
1350	0.97584	0.000140	1610	0.96187625	0.000444
1360	0.97381875	0.000376	1620	0.96199375	0.000462
1370	0.970325	0.000084	1630	0.95495375	0.001279
1380	0.969415	0.000700	1640	0.9611125	0.000342
1390	0.9663025	0.000163	1650	0.96372375	0.000320
1400	0.97270125	0.000254	1660	0.95733875	0.000490
1410	0.96946625	0.000299	1670	0.94104875	0.000669
1420	0.96964125	0.000524	1680	0.94828125	0.001329
1430	0.97063625	0.000142	1690	0.953295	0.000407
1440	0.9657875	0.000458	1700	0.9548875	0.000767
1450	0.9724025	0.000160	1710	0.939865	0.000204
1460	0.97063125	0.000143	1720	0.956315	0.000546
1470	0.97247375	0.000329	1730	0.94720125	0.001222
1480	0.9675225	0.000397	1740	0.95074	0.000507
1490	0.96191125	0.000334	1750	0.94776625	0.000204
1500	0.96568875	0.000512	1760	0.94928125	0.000782
1510	0.96191625	0.000413	1770	0.93791875	0.000254
1520	0.96272875	0.000231	1780	0.944595	0.000837
1530	0.9549175	0.000287	1790	0.93347	0.000733
1540	0.94717375	0.001148	1800	0.93574125	0.001108
1550	0.960805	0.000563			

From Table 2 we can see that the highest mean of forecasting accuracy was 0.98254625 when the number of hidden nodes was 1310. In this situation, the variance of forecasting accuracy was 0.000193. The lowest variance of forecasting accuracy was 0.000142 when the number of hidden nodes was 1430. In this situation, the mean of hidden nodes was 0.97063625. Since the former mean of forecasting accuracy was higher than the latter, and the former variance of forecasting accuracy was a little larger than the lowest, choose the former whose number of hidden nodes was 1310 as the optimal forecasting model. In consequence, the mean of optimal forecasting model was 0.98254625 and the variance of optimal forecasting model was 0.000193. The ELM algorithm forecasting model whose mean of forecasting accuracy approximately equals to 98.255% was effective.

4. CONCLUSION

In this paper, we firstly detect abnormal points of two market indexes and six individual stocks based on multi-feature wavelet method. Compared with single feature wavelet method, the detected results were more reliable, for it captures more information of the market and avoid "masking effect". The reliable outlier detection results ensured the effectiveness of training data set. Moreover, we construct an outlier forecasting model based on multi-feature extreme learning machine (ELM) algorithm which can predict whether the abnormal fluctuation will appear today or not via its five days data before. The model was successfully conducted on two market indexes and six individual stocks in Chinese stock market. Finally, we analyze the accuracy of the forecasting model and find out the optimal number of hidden nodes to forecast. When the number of hidden nodes was 1310, the mean of

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forecasting accuracy was the highest which approximately equals to 98.255% and the variance of forecasting accuracy was only 0.000193. The forecasting accuracy of 98% proved the effectiveness of the ELM outlier forecasting model combined with two features of the market.

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