TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.3, March 2014, pp. 2219 ~ 2226
DOI: http://dx.doi.org/10.11591/telkomnika.v12i3.4490

A Novel Efficient Adaptive Sliding Window Model for Week-ahead Price Forecasting

Zhu Quan-Yin*[1], Yin Yong-Hu[1], Yan Yun-Yang[1], Gu Tian-Feng[2]
[1]Faculty of Computer Engineering, Huaiyin Institute of Technology
[2]Hydrology-Water Resources and Hydraulic Engineering, Hohai University,
No.1 Meicheng East Road, Huaian 223005, China, +86-517-83591046/83591163
*Corresponding author, e-mail: hyitzqy@126.com

Abstract

In order to improve the accuracy of price forecasting by Web extracting, a novel efficient improved Adaptive Sliding Window (ASW) that the coefficients of the window width can be auto adjusts is proposed in this paper. Agricultural products price based on ASW is utilized to verify validity of adaptive Back Propagation (BP) neural network and adaptive Radial Basis Function (RBF) neural network model respectively. Experiments demonstrated that the Mean Absolute Error (MAE) on ASW model can be getting 99.62 percent accuracy rate. Experiment results proved that the proposed ASW model and adaptive BP neural network model are meaningful and useful to analyze and to research products market, but the proposed ASW model is the best one because of its speed is the fast one which can save time 80 percent than the adaptive BP neural network.

Keywords*: price forecasting, agricultural products, adaptive sliding window, adaptive BP neural network, adaptive RBF neural network*

1. Introduction

Forecasting is the process to make the statements about events whose actual outcomes that has not yet been observed. Predicts theory and method can be applied widely distributed in all kinds of areas of natural and social aspects. According to the areas covered, the different research objectives and tasks, forecasting can be classified with different areas of forecasting such as weather forecasting, scientific forecasting, military forecasting, technology forecasting, economic forecasting, and social prediction [1]. Price forecasting method can be find used widely scopes such as stock market [2], electricity market [3-5], old market [6], and so on. The price forecasting models usually include time series model [6], Sliding Windows Model (SWM) [4], various Neural Network (NN) [2,7-12], GM (1,1) [6], wavelet [13], support vector machine [3, 14], grey system theory [15], fundamental econometric model [5], fractal theory model [8], Fuzzy Multiple Attribute Decision [16] and Uncertain Measure [17]. Depend on the reported results; the different model has itself advantages and application markets.

Our team developed an application system to collect the agricultural products weekly price which is shown on bank service website. How to deal with those data and use it to forecast the agricultural products price and reduce the error as much as possible is a valuable work.

Take a wide view for the research result of agricultural products, we can find the agricultural products forecasting is the same as the other price forecasting. Because of these is all nonlinear system analysis. For example, if the power market or stock market changing, the agricultural products will be changed followed. That is the economic market is the same expressly now days of global economic integration. From the reported, we can summarize the forecasting models which include ANN [11, 18], RBF neural network [12], Wavelet model, support vector machine [3, 13, 14, 19], generalized auto regressive conditional hetero-skedasticity model [20, 21], probabilistic neural network model [9], linear moving average model [10], nonlinear genetic algorithm back propagation model [10], nonlinear autoregressive model [22], empirical mode decomposition model [11], DGM(2,1) model [15] and Markov model [21].

We use the ASW model, BP Neural Network (NN) and RBF NN model to build the agricultural products forecasting algorithm and verify the validity of the MAE rate on Web extracted data respectively. Furthermore, we research effect the results rely on the different

Received August 22, 2013; Revised September 26, 2013; Accepted October 17, 2013

number neurons on the BP and the different spreads on RBF NN model and different window width on the ASW model. We find the MAE rate can be reduced very small that used the Adaptive BP (ABP) NN and used the Adaptive RBF (ARBF) NN. But how to select variables of spreads on the BP NN model and the width on the Sliding Window Model (SWM) are very important.

2. Notations and Theory

Some definitions used in this paper are given as follows.

Single errors of predicted value:

$$e_t = Y_t - \hat{Y}_t , \quad t = 1, 2, \cdots , n \tag{1}$$

Relative errors of single predicted value:

$$\tilde{e}_t = \frac{e_t}{Y_t} = \frac{Y_t - \hat{Y}_t}{Y_t}, \quad t = 1, 2, \cdots , n \tag{2}$$

Mean Absolute Errors (MAE):

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |e_t| = \frac{1}{n}\sum_{t=1}^{n} \left|Y_t - \hat{Y}_t\right| \tag{3}$$

Mean Absolute Percentage Errors (MAPE):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{|e_t|}{Y_t} = \frac{1}{n}\sum_{t=1}^{n} \frac{\left|Y_t - \hat{Y}_t\right|}{Y_t} \tag{4}$$

3. Sliding Window Method

The basic idea of the Sliding Window (SW) method is as follows:

Setting the time sequence whose cycle is in the time observation period *t* as $x_1, x_2, \cdots, x_t, \cdots$, and $f_{t,1}$ as the prediction value of the next time is $t+1$, and setting $f_{t,1}$ to be the newest forecasting mean, namely the average value of $x_t, x_{t-1}, \cdots, x_{t-N+1}, \cdots$.

The method of the moving average is:

$f_{t,1} =$ the last observation average values = average value of $x_t, x_{t-1}, \cdots, x_{t-N+1}, \cdots$. *N* is appointed parameter.

N—The item of moving average (or called step size).

N determines the forecasting accuracy, which is generally obtained from the experimental data based on experience.

Forecasting value of the next time:

$$\hat{x}_{t+1} = f_{t,1} = \frac{x_t + x_{t-1} + x_{t-2} + \cdots + x_{t-(N-1)}}{N} \tag{5}$$

Through the data analysis according to different experimental sliding window value, it is obvious that under the slow and great change circumstance, a very good mean absolute error will be received when the value of the window width *N* is selected suitably.

4. RBF Neural Network

In a generic RBF NN is defined by an input vectors X^q and output as y^q, the inter-neural is defined by a particular real number, a synaptic weight $w1_{ij}$. The RBF NN's architecture shows as in Figure 1 which includes its input and output of inter-neural.

The input of ith neurons in inter-neural is:

$$k_i^q = \sqrt{\sum_j \left(w1_{ji} - x_j^q\right)^2} \times b1_i \tag{6}$$

The input of ith neurons in inter-neural is:

$$r_i^q = \exp\left(-\left(k_i^q\right)^2\right) = \exp\left(\sqrt{\sum_j \left(w1_{ji} - x_j^q\right)^2} \times b1_i\right) = \exp\left(-\left(\left\|w1_i - X^q\right\| \times b1_i\right)^2\right) \tag{7}$$

The output of the RBF NN is:

$$y^p = \sum_{i=1}^{n} r_i \times w2_i \tag{8}$$

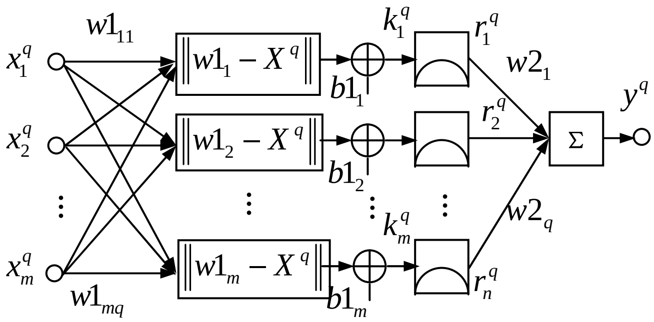


Figure 1. RBF NN Architecture and Its Inter-neural

5. BP Neural Network

A BP NN like the RBF NN, it also has an input layer, a hidden layer and an output layer. It is an error back propagation error learning process of back-propagation algorithm consists of two processes of the information forward propagation and error back-propagation. Through the hidden layer, depend on the weight error of the output layer, the error gradient descent back-propagation to the hidden layer and input layer, and so on. According to the layers of the weight adjustment process, the neural network is the learning and the training process. The BP NN's architecture shows as in Figure 2.

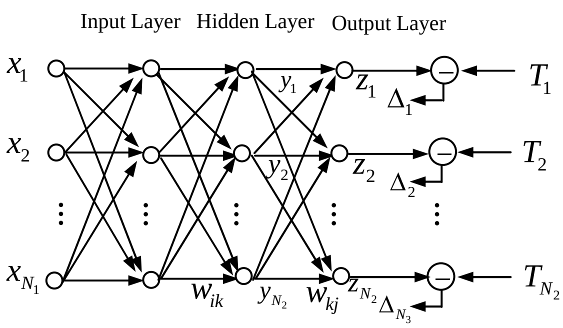


Figure 2. BP NN Architecture and Its Inter-neural

BP NN always uses activation function show as follows.
(1) Linear transfer function

$$f(x) = x \quad (9)$$

The function string is "purelin".
(2) Logarithmic sigmoid transfer function

$$f(x) = \frac{1}{1+e^{-x}} \qquad (0 < f(x) < 1) \quad (10)$$

The function string is "logsig".
(3) Hyperbolic tangent sigmoid transfer function

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \qquad (-1 < f(x) < 1) \quad (11)$$

6. Experiments Prepared

We select the ten agricultural products price which extracted from http://www.abchina.com/cn/RuralSvc/Information/RealtimePrice/AgriculturalMarkets_Information / at 1 Jan. 2011 to 31 Dec. 2011. The extracted method is a Web-extracting method and others price forecasting methods based on the authors' previous work [23-28]. The sample data show as the Figure 3. The experiment laptop configuration is ASPIRE 4738ZG (CPU Intel CPU P6200 @2.13GHz, RAM 2 G), the OS is Windows 7, Matlab is V7.0.

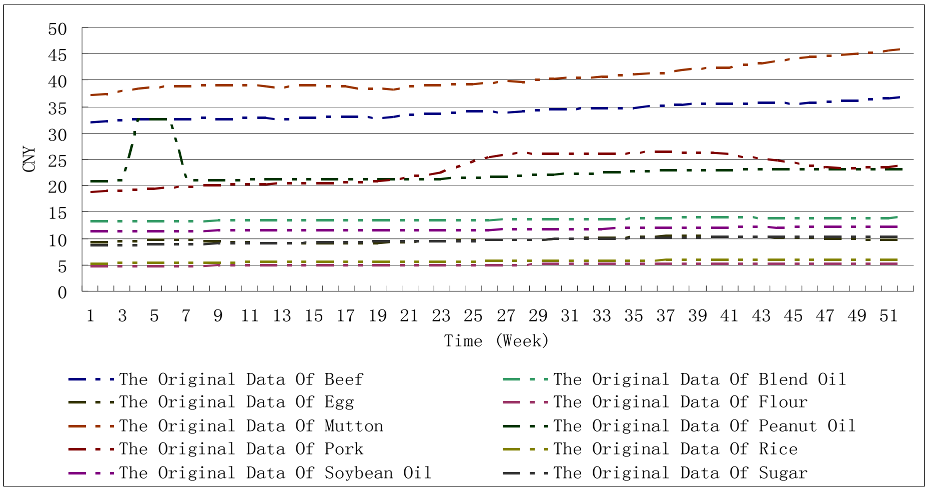
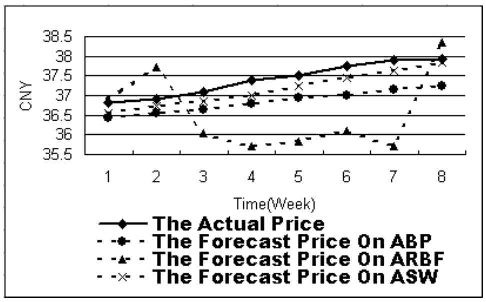


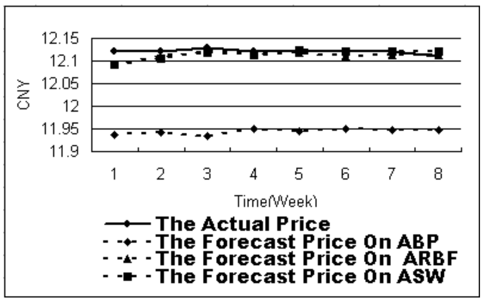
Figure 3. The Original Data of Agricultural Products Price Extracted from Web Page

7. Experiments

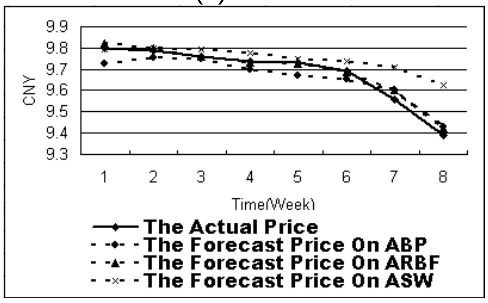
In order to get higher accuracy of agricultural products on price forecast, we select different window width for SW to forecast ten type agricultural products price. Then use the window width of the highest accuracy of agricultural products price as the SW model, so we called this model as ASW model. The Table 1 is the examples for MAPE of best and worst window widths using SW. When we use this model, we can train the window width as the forward period of time. As an example, we select *N*=28 (four weeks) and *N*=14 (four weeks) and using the Equation (1) to (5). The sample data use the Figure 3 from 1 Jan. 2011 to 30 Nov. 2011.The agricultural products price forecast from 30 December 2011 to 17 February 2012 (total 8 weeks). The ten types of agricultural products price forecasting results of MAE for the best window widths are show as Figure 4(a) to Figure 4(j) respectively. The accuracy rate for ten types of agricultural products price obtain 99.62 percent. Figure 5 shows the average MAE on price forecast using ASW, ABP NN and ARBF NN.



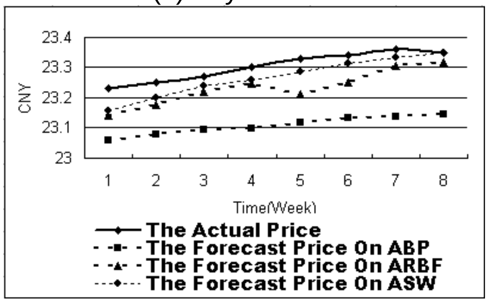
(a) Beef



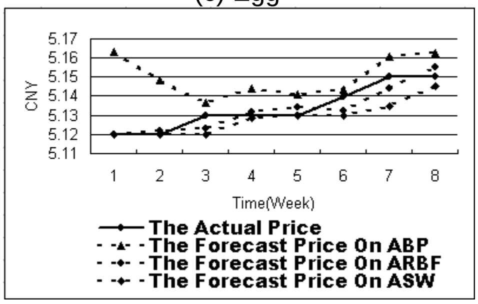
(b) Soybean oil



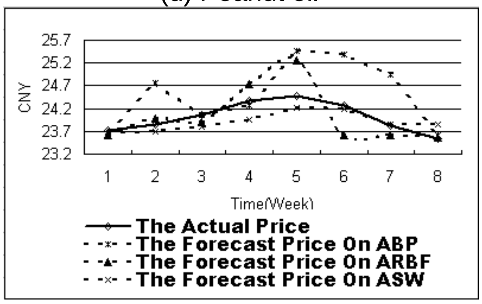
(c) Egg



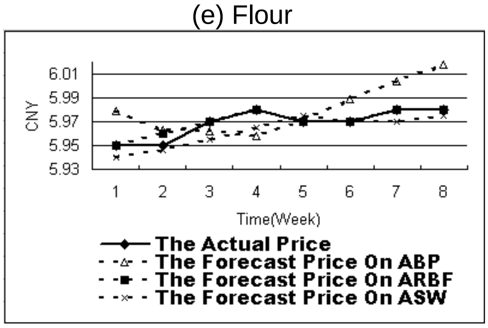
(d) Peanut oil



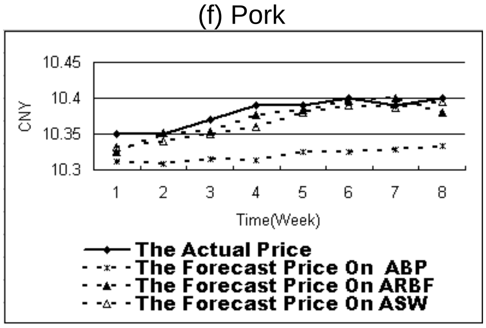
(e) Flour



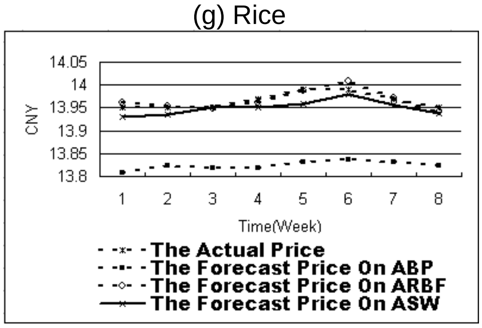
(f) Pork



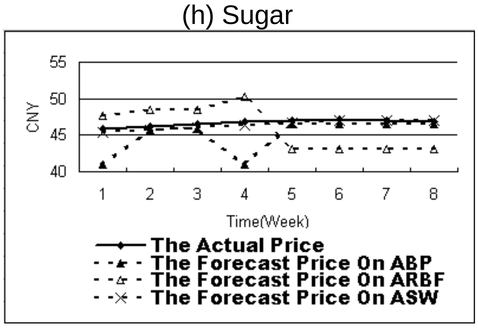
(g) Rice



(h) Sugar



(i) Blend oil



(j) Mutton

Figure 4. The Agricultural Products Price Forecast using ASW, ABP NN and ARBF NN

As the same way, we select different number of neurons for BP NN model and different spreads for RBF NN model to forecast same ten type agricultural products price. Then use the number of neurons for BP NN model and different spreads for RBF NN model of the highest accuracy of agricultural products price as the BP NN and RBF NN model, so we called these two models as ABP NN and ARBF NN model. The Table 2 is the examples for MAPE of best and worst number of neurons using BP; and The Table 3 is the examples for MAPE of best and worst spread using RBF. The ten types of agricultural products price forecasting results of MAE for the ABP NN and the ARBF NN are show as Figure 4(a) to Figure 4(j) respectively too. The accuracy rate for ten types of agricultural products price achieve 99.20 and 98.82 percent respectively.

In order to compare with each model's efficiency, we use the different window widths as 2, 4, 8, and 12 for SW model; the different number of neurons as 10, 15, 20 for BP NN model; and different spreads as 0.01, 10, 20 and 100 for RBF NN model. The averages time of forecasting for three models show in Table 4.

Form the Table 4 we can find that for different agricultural products forecast price the best spread is different. The experiments show us that the ASW model is fast one. So the ASW model not only can get the best accuracy on price forecasting but also can save time.

Table 1. The Examples for MAPE of Best and Worst Window Widths using SW

Agricultural Products	Best		Worst	
	N	MAPE	*N*	MAPE
Beef	2	0.26%	12	3.20%
Soybean Oil	2	0.00%	12	0.15%
Egg	2	0.70%	12	2.92%
Peanut Oil	2	0.16%	12	0.81%
Flour	12	0.11%	8	0.29%
Pork	2	1.10%	8	2.99%
Rice	4	0.00%	12	0.29%
Sugar	8	0.18%	12	0.39%
Soybean Oil	4	0.04%	12	0.27%
Mutton	2	0.70%	12	4.11%
Average MAPE		0.33%		1.54%

Table 2. The Examples for MAPE of Best and Worst Window Widths using BP

Agricultural Products	Best		Worst	
	Neurons	MAPE	Neurons	MAPE
Beef	20	1.51%	15	3.22%
Soybean Oil	15	1.45%	20	1.90%
Egg	20	0.44%	15	1.77%
Peanut Oil	15	0.84%	10	1.06%
Flour	15	0.32%	20	1.48%
Pork	15	0.64%	20	3.49%
Rice	15	0.30%	10	3.12%
Sugar	10	0.58%	15	1.73%
Soybean Oil	20	1.01%	15	1.69%
Mutton	20	1.51%	10	12.23%
Average MAPE		0.86%		3.17%

Table 3. The Examples for MAPE of Best and Worst Window Widths using RBF

Agricultural Products	Best		Worst	
	Spreads	MAPE	Spreads	MAPE
Beef	100	4.47%	10	28.47%
Soybean Oil	100	0.11%	0.01	0.25%
Egg	100	0.30%	0.01	6.93%
Peanut Oil	20	3.23%	0.01	9.07%
Flour	100	0.09%	0.01	0.18%
Pork	0.01	1.72%	10	13.03%
Rice	0.01	0%	100	0.11%
Sugar	100	0.12%	0.01	7.52%
Soybean Oil	0.01	0.11%	20	0.16%
Mutton	0.01	7.55%	20	780.21%
Average MAPE		1.77%		84.59%

Table 4. The Averages Time of Forecasting for SW, BP NN and RBF NN

SW		BP		RBF	
N	Time(s)	Neurons	Time(s)	Spreads	Time(s)
2	18.36	10	42.25	0.01	18.44
4	19.41	15	92.94	10	18.39
8	18.32	20	144.82	20	18.52
12	18.65			100	18.46

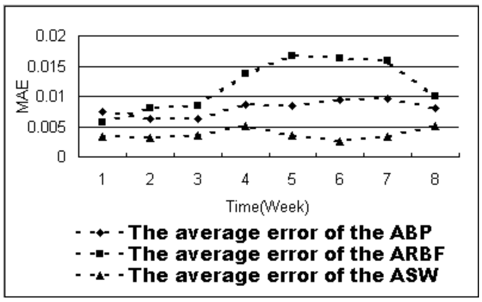


Figure 5. The Average MAE on Price Forecast using ASW, ABP NN and ARBF NN

8. Conclusion

In this paper, the new idea for SWM, ABP NN and ARBF NN models are used for agricultural products forecasting is introduced. Furthermore this paper applies this method to agricultural products of the ten types of market which increases the accuracy rate. At the same time by the proposed model the adaptive parameter for the ASW model, ABP NN and ARBF NN model are introduced in detailed. Thus the three models demonstrated in this paper have a high practical value.

Three proposed agricultural products forecasting methods not only can be applied to agricultural products market and sales areas, but also can be used for other types of other commodities to do price forecasting fields.

Acknowledgments

This research was supported in part by the National Sparking Plan Project of China (2011GA690190), the Major Program of the Undergraduate Innovations Foundation of the Jiangsu Higher Education Institutions of China (201311049005); the fund of Huaian Industry Science and Technology, China (HAG2011052, HAG2011045, HAG2012086, HASZ2012046, HASZ2012050).

References

[1] Zhang Gui-xi, Ma Li-ping Editor. An Introduction to Forecast and Decision. Beijing: Economic and Trade University Press. 2006.
[2] Chih-Ming Hsu. *Forecasting Stock/futures Prices by Using Neural Networks with Feature Selection*. Proceedings of the 6th IEEE Joint International Information Technology and Artificial Intelligence Conference (ITAIC). Chongqing. 2011; 1: 1-7.
[3] Jianhua Zhang, Jian Han, Rui Wang, Guolian Hou. *Day-ahead Electricity Price Forecasting Based on Rolling Time Series and Least Square-support Vector Machine Model*. Proceedings of the Chinese Control and Decision Conference (CCDC). Mianyang. 2011: 1065-1070.
[4] Ruiqing Wang. *Review of Application Research on Options in Electricity Market*. Proceedings of the International Conference on Mechanic Automation and Control Engineering (MACE). Wuhan. 2010: 5227-5230.
[5] Gonzalez V, Contreras J, Bunn DW. Forecasting Power Prices Using a Hybrid Fundamental-econometric Model. *IEEE Transactions on Power Systems*. 2012; 27(1): 363-372.
[6] Hadavandi E, Ghanbari A. Abbasian-Naghneh, S. *Developing a Time Series Model Based on Particle Swarm Optimization for Gold Price Forecasting*. Proceedings of the Third International Conference on Business Intelligence and Financial Engineering (BIFE). Hongkong. 2010: 337-340.
[7] Patricia Melin, Victor Herrera, Danniela Romero, Fevrier Valdez, Oscar Castillo. Genetic Optimization of Neural Networks for Person Recognition based on the Iris. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(2): 309-320.
[8] He-rui Cui, Li Yang. *The Wrong Analysis of the Price Forecast Model Based on Fractal Theory in Commodity Price Forecasting*. Proceedings of the IITA International Conference on Services Science, Management and Engineering (SSME). Zhangjiajie. 2009: 329-332.

[9] Wang Hua, Liu Bing-xiang, Cheng Xiang, Xiao Xuan. *An Exchange Rate Forecasting Method Based on Probabilistic Neural Network*. Proceedings of the International Conference on Electronic and Mechanical Engineering and Information Technology (EMEIT). Harbin. 2011; 6: 3124-3126.
[10] Huang Zhigang, Zheng Guozhong, Jia Yaqin. *Forecasting Exchange Rate Volatility with Linear MA Model and Nonlinear GABP Neural Network*. Proceedings of the Fourth International Conference on Business Intelligence and Financial Engineering (BIFE). Wuhan. 2011: 22-26.
[11] Heng-Li Yang, Han-Chou Lin. *Applying EMD-based Neural Network to Forecast NTD/USD Exchange Rate*. Proceedings of the 7th International Conference on Networked Computing and Advanced Information Management (NCM). Gyeongju. 2011: 352-357.
[12] YU Zhijun. RBF Neural Networks Optimization Algorithm and Application on Tax Forecasting. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013; 11(7): 3491-3497.
[13] Fan-Yong Liu. *The Hybrid Prediction Model of CNY/USD Exchange Rate Based on Wavelet and Support Vector Regression*. Proceedings of the 2nd International Conference on Advanced Computer Control (ICACC). Shenyang. 2010; 4: 561-565.
[14] Lixia Liu, Wenjing Wang. *Exchange Rates Forecasting with Least Squares Support Vector Machine*. Proceedings of the International Conference on Computer Science and Software Engineering (CSSE). Wuhan. 2008; 5: 1017-1019.
[15] Hong Wu, Fuzhong Chen. *Chinese Exchange Rate Forecasting Based on the Application of Grey System DGM (2,1) Model in Post-crisis Era*. Proceedings of the International Conference on Information Management, Innovation Management and Industrial Engineering (ICIII). Kunmingy. 2010; 1: 592-595.
[16] Haining Wang, Shouqian Sun. A Method for Intuitionistic Fuzzy Multiple Attribute Decision Making with Incomplete Weight Information. *Information*. 2011; 14(2): 315-322.
[17] Zixiong Peng, Kakuzo Iwamura. A Sufficient and Necessary Condition of Uncertain Measure. *Information*. 2012; 15(4): 1381-1392.
[18] Quanyin Zhu, Suqun Cao, Jin Ding, Zhengyin Han. *Research on the Price Forecast Without Complete Data Based on Web Mining*. Proceedings of the 10th International Symposium on Distributed Computing and Applications to Business, Engineering and Science (DCABES). Wuxi. 2011: 120-123.
[19] Zhang Xinfeng, Zhao Yan. Application of Support Vector Machine to Reliability Analysis of Engine Systems. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013; 11(7): 3552-3560.
[20] Huaijin Gao, Jianan Sun. *The EUR/CNY Exchange Rate Forecast Based on GARCH Model*. Proceedings of the IEEE International Conference on Computer Science and Automation Engineering (CSAE). Shanghai. 2011; 4: 447-450.
[21] Banik S, Anwer M, Khan AFMK. *Predictive Power of the Daily Bangladeshi Exchange Rate Series Based on Markov Model, Neuro Fuzzy Model and Conditional Heteroskedastic Model*. Proceedings of the 12th International Conference on Computers and Information Technology (ICCIT). Seoul. 2009: 303-308.
[22] Chuanjin Jiang, Fugen Song. *Forecasting Chaotic Time Series of Exchange Rate Based on Nonlinear Autoregressive Model*. Proceedings of the 2nd International Conference on Advanced Computer Control (ICACC). Shenyang. 2010; 5: 238-241.
[23] Quanyin Zhu, Yunyang Yan, Jin Ding, Jin Qian. *The Case Study for Price Extracting of Mobile Phone Sell Online*. Proceedings of the 2nd IEEE International Conference on Software Engineering and Service Sciences (ICSESS). Beijing. 2011: 282-285.
[24] Quanyin Zhu, Hong Zhou, Yunyang Yan, Jin Qian, Pei Zhou. *Commodities Price Dynamic Trend Analysis Based on Web Mining*. Proceedings of the Third International Conference on Multimedia Information Networking and Security (MINES). Shanghai. 2011: 524-527.
[25] Quanyin Zhu, Yunyang Yan, Jin Ding, Yu Zhang. *The Commodities Price Extracting for Shop Online*. Proceedings of the International Conference on Future Information Technology and Management Engineering (FITME). Changzhou. 2010; 2: 317-320
[26] Jianping Deng, Fengwen Cao, Quanyin Zhu, Yu Zhang. The Web Data Extracting and Application for Shop Online Based on Commodities Classified. In: Yanwen Wu. *Editor*. Computing and Intelligent Systems. Chennai: Springer-Verlag Berlin Heidelberg. 2011; 234: 189-197.
[27] Su-Qun Cao, Quan-Yin Zhu, Bo-Kui Li, Rong Gao, Hai-Fei Zhai. Fuzzy Fisher Criterion Based Edge Detection. *International Journal of Digital Content Technology and its Applications*. 2011; 5(8): 381-388.
[28] Su-Qun Cao, Xiang-Zhi Chen, Jun-Min Wang, Quan-Yin Zhu. A Novel Intelligent Fault Diagnosis Method for Turbine Generator Sets. *International Journal of Advancements in Computing Technology*. 2011; 3(10): 357-363.