Compare with Three Models for Price Forecasting on Steel Market

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Abstract—**In order to get the excellent accuracy for price forecast in the steel market, the adaptive Radial Basis Function (RBF) Neural Network (NN) model, Back Propagation (BP) NN model and Sliding Window (SW) model are utilized to forecast the price of the steel products in this paper. Eight steel products, which extracted from Shanghai Baoshan steel market of China at January, 2011 to December 2011, are selected to forecast the price about one week and compare the Mean Absolute Errors (MAE) by RBF model, BP model and ASW model respectively. One main parameter of each model's is changed step size by programs automatically. Experiments demonstrate that the ASW model is best model which can get lowest Mean Absolute Errors (MAE). Experiment results prove that the proposed ASW model is meaningful and useful to analyze and to research the price forecast in the steel products market.**

***Keywords-** price forecast; steel market; MAE; RBF; BP; ASW*

I. INTRODUCTION

The price forecast is based on the rules of market economy on the basis of price monitoring, the use of scientific methods, analysis and judgment of future price changes. That is according to the relevant price information and data, using scientific methods, analysis and judgment on the dynamics of changes in commodity prices, or an integral part of socio-economic forecast. An important foundation and prerequisite for extensive collecting domestic and foreign price data, accurate knowledge of the important information about the market price, and then, depending on the requirements, the preparation of calculation model. Due to the development of network technology and the popularity of the online store, so in recent years, there is a growing emphasis on the prediction method of commodity prices. Commodity price forecasts can be seen as based on time series of data processing and data analysis that is divided into data acquisition, data processing and forecasting model in three aspects. Stock market, futures market, the electricity market open price data for relatively easy for the price forecasting model. RBF NN has many applications, such as discrete fuzzy control [1], encrypting algorithm [2], network flow prediction [3], and robot behavior learning [4] and so on. Of course, BP neural network also has many applications, for example, forecasting chaotic time series [5], segmentation of rice disease spots [6], lossless image compression [7], research on building electricity saving [8], ECG signal classification [9]. In recent years, many researchers in the world pay more attention to the price of agriculture products. To successfully know the price of agriculture products requirements an accurate forecast. If we can predict the price, then the market participants will have a correct grasp of the trend of commodity prices.

In this paper, basis of previous studies of Web data mining and price forecasts [10-13] on this area, we use RBF neural network Model (RBFM), BP neural network Model (BPM) and SW Model (SWM) to build the steel price forecast algorithm and calculate the MAE respectively.

II. NOTATIONS AND SLIDING WINDOW

Definition 1: Let the cycle time within the time observation period t sequence $x_1, x_2, \cdots, x_t, \cdots$, $f_{t,1}$ is the predictive value of the $t+1$.

$f_{t,1}$ = latest forecast mean $= x_t, x_{t-1}, \cdots, x_{t-N+1}$ the average, N for a given parameter, the forecast window, also known as step; N determines the prediction accuracy of the experimental data are generally based on experience.

Definition 2: x_t is the actual value of the time t, where $\hat{x}_t$ is the predictive value of time t.

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):

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

III. RBF NN AND BP NN

The RBF NN is a three-layer feed forward network which is composed by input layer, hidden layer and output layer. Figure 1 shows the RBF network topology, the hidden layer takes the RBF function as the activation function, and

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generally we use Gaussian function. The nodes of input layer only transfer the input signal to the hidden layer. The node of hidden layer is composed of action function such as Gauss function etc.[14].

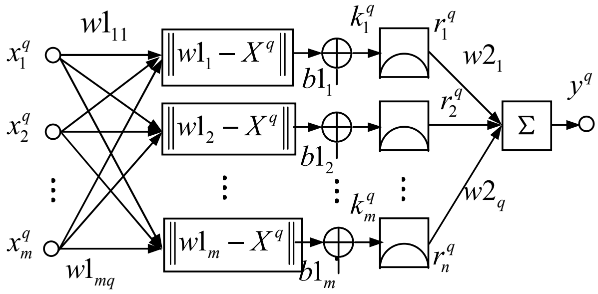

Figure 1. RBFNN architecture and its inter-neural

Suppose the network has m inputs and 1 output, the hidden layer has n neurons, the connection weight between the input layer and the hidden layer is $w1_{ji}$, the threshold value of the hidden layer is $b1_i$, the connection weight between the hidden layer and output layer is $w2_q$, the input of the hidden layer's *i*th neuron is:

$$k_i^q = \sqrt{\sum_j (w1_{ji} - x_i^q)} \times b1_i \quad (i = 1,2,\ldots,m; j = 1,2,\ldots,n) \quad (4)$$

Where q is represent the *q*th vector. The output of the *j*th neuron is hidden layer is:

$$r_i^q = \exp\left(-\left(k_i^q\right)^2\right) = \exp\left(\sqrt{\sum_j \left(w1_{ji} - x_j^q\right)^2} \times b1_i\right) = \exp\left(-\left(\left\|w1_i - X^q\right\| \times b1_i\right)^2\right) \quad (5)$$

The input of the output layer are the weighting sum of the neuron's output of each hidden layer, the activation function is a pure linear function, and the output is:

$$y^p = \sum_{i=1}^{n} r_i \times w2_i \quad (6)$$

The training process of RBF NN can be divided into two steps, the first step is to identify the weight $w1$ without teacher, and the second step is to identify the weight $w2$ with teacher. It is a key problem to identify the number of the hidden layer's neurons, usually it starts to train from 0 neuron, the hidden layer neuron is increased automatically by checking the error, and repeats this process until the requested precision, or the largest number of hidden layer's neurons is achieved.

The BP NN is the network that can establish relationships between layers orderly from inputs to outputs. It has an input layer, an output layer and some hidden layers. There are some nerve cells called nodes in each layer. Its learning process is made up of two parts: One is from input to output, called forward process, and the other is from output to input, called backward process. In the forward process, the input signals are processed from the input layer to the output layer and the states of the layer's nodes can only influence the states of the next layer's nodes. At the output layer, the value of the output is compared with the anticipant value. If there is any error, the error will be returned along the quondam way, and the weight values of the nodes between layers are modified to reduce the error. So the error will be controlled in the range given in advance.

IV. EXPERIMENTS PREPARED

For the price data, we can regard three days as a period. The one weeks' price is the input vector and the output vector is the forecasting daily price. Therefore the number of the input layer neurons is $N = 3$, the number of the output layer neurons is $M = 1$, and the number of sample is determined by Equation (1).

$$K = L - (M + N) + 1 \quad (7)$$

The L is the length of the all data. The code of the creation of the RBF NN is as following.

$$net = newrbe(P, T, spread) \quad (8)$$

Where P is the input vector, T is the output vector.

In order to verify the validity prediction model, select the Shanghai Baoshan steel market (www.sinometal.com/) prices from January 4, 2011 to December 30, 2011, shown Figure 2, and extract 8 different commodities in model tests.

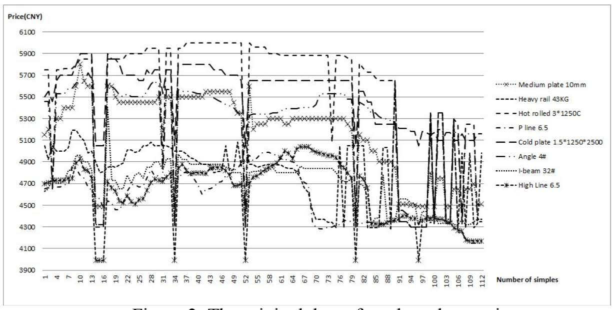

Figure 2. The original data of steel products price

V. COMPARISONS OF THREE MODELS

The different spreads are auto opted for each steel product data. The experiments results of comparison showed as Fig. 3 to Fig. 10. In order to display the accuracy of the two models, the MAE of the three models is sketched in the same figure.

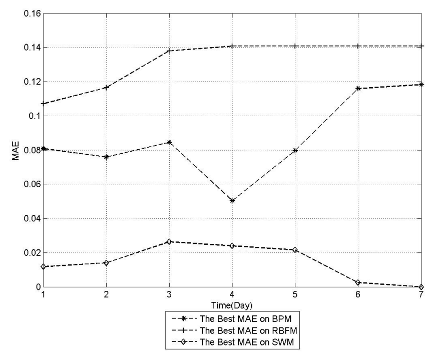

Figure 3. The best MAE of High line.

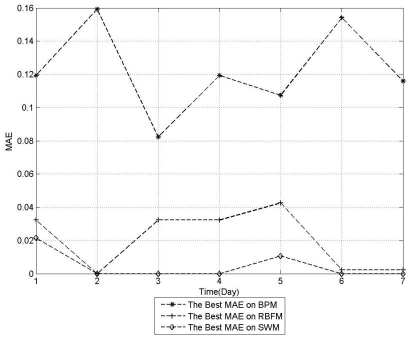

Figure 4. The best MAE of Medium plate

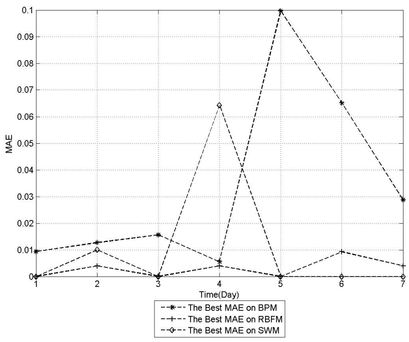

Figure 5. The best MAE of Heavy rail.

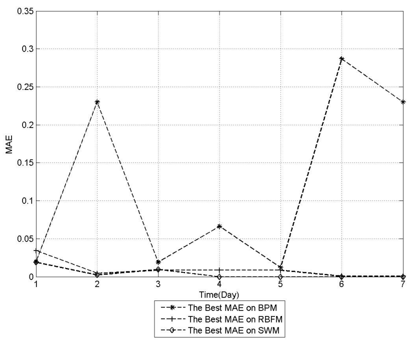

Figure 6. The best MAE of Hot rolled.

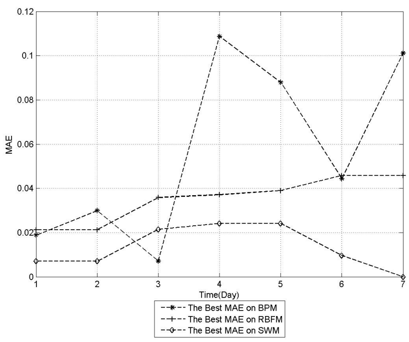

Figure 7. The best MAE of Pline.

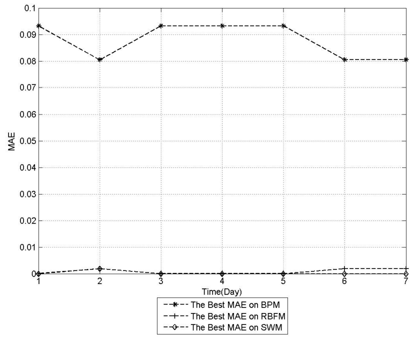

Figure 8. The best MAE of Cold plate.

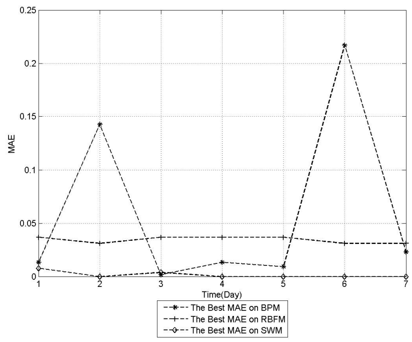

Figure 9. The best MAE of Angle.

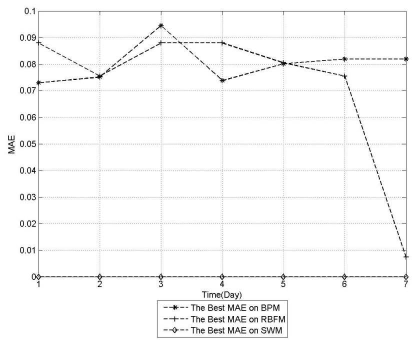

Figure 10. The best MAE of Ibeam.

From the Fig. 3 to Fig. 10 we can find that for the three different models, the accuracy is different. For the most steel products, the accuracy of SWM is better than RBFM, but RBFM is better than BPM. While the BPM can gets the best forecast price for Pline at the third day, and the RBFM can gets the best forecast price for Angle at the second day.

In order to compare the results with three models clearly, Figure 11 to Figure 13 show as the best forecast for three models respectively, and the Figure 14 shows the average MAE for the three models.

From the Fig.14, we can get that the SWM is best model for the steel products price forecasting.

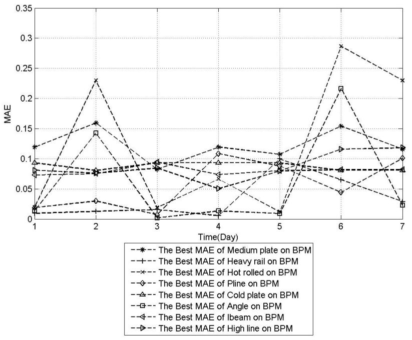

Figure 11. The best MAE of eight types of steel products using BPM

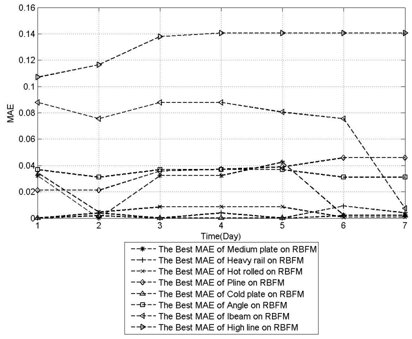

Figure 12. The best MAE of eight types of steel products using RBFM

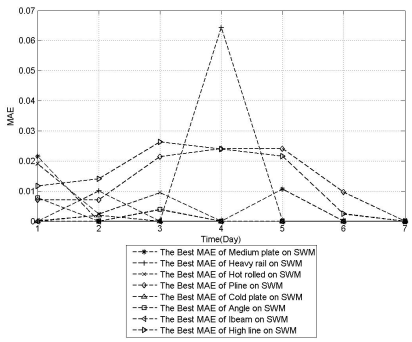

Figure 13. The best MAE of eight types of steel products using AWM

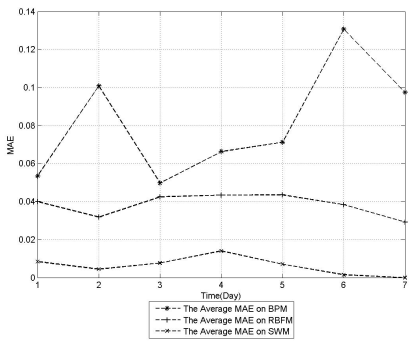

Figure 14. The best MAE compare with BPM, RBFM and SWM

VI. CONCLUSION

In this paper, the BPM, RBFM and SWM models are used for forecasting the price of steel products. Through the comparison of the three models, we can find that SWM can be achieving the best forecasting accuracy rate, It can get higher accuracy (more than 99.3%), the RBFM model is better than the BPM, it can obtain 96.1 averages percent accuracy as well. Furthermore, the RBFM and BP need more time to training that means it is also the lower on time.

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