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APPLICATION OF RADIAL BASIS FUNCTION NEURAL NETWORK TO PREDICT EXCHANGE RATE WITH FINANCIAL TIME SERIES

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Abstract: The literature indicates that exchange rates are largely unforecastable from the fact that the overwhelming majority of studies have employed linear models in forecasting exchange rates. In this paper, we applied Radial Basis Function Neural Network (RBFNN) to predict exchange rate, motived by the fact that RBFNN have the ability to implicitly detect complex nonlinear relationships between dependent and independent variables as it “learns” the relationship inherent in the exchange rate data presented to it. The model learning algorithm uses a diverse data set for training so as to adapt itself quickly for new exchange rate data. We apply the RBFNN to panel data of the exchange rates (USD/EUR, JPN/USD, USD/GBP, USD/CHY) are examined and optimized to be used for time-series predictions, some experiments testified the proposed method is effective and feasible.

Keywords: RBFNN, Exchange Rate Prediction, financial time series.

1. Introduction

The relative theory and technologies on financial time series are developed since the 1990's, and these methods aim to determine patterns of relationships in financial market data. Generally, these approaches are computationally intensive and characterized by the capacity of modeling nonlinear dynamic systems. The previous works indicates that exchange rates are largely unforecastable (Qi and Wu, 2003), but some researchers have employed linear models in forecasting exchange rates. Perhaps, the most widely cited paper in that category is that of Meese and Rogoff (1983). However, some studies such as Taylor and Peel (2000) argue that the relationship between exchange rates and macroeconomic fundamentals may be nonlinear. Subsequently, a number of studies have pursued nonlinear modelling using conventional nonlinear techniques, such as Markov switching models. However, generally the results suggest that conventional nonlinear modelling does not improve exchange rate forecasts (Engel and Hamilton, 1990). The problem with conventional nonlinear models is that they require the imposition of assumptions concerning the precise form of nonlinearity. But as discussed by Zhang et al. (1998), there are too many possible nonlinear patterns in a particular data set and the prespecified nonlinear model may not be broad enough to capture all the essential characteristics. An alternative way to deal with nonlinearities in data is to use NN models. In contrast to the aforementioned model-based nonlinear methods, NN models are data driven and are thus capable of producing nonlinear models without prior knowledge about the functional forms (Zhang et al., 1998). NN are also highly flexible as they can approximate any continuous function to any degree of accuracy (Hornik et al., 1989). There exist studies that have employed NN models for forecasting exchange rates. See, for example, Plasmans et al. (1998) and Qi and Wu (2003). The results from such analyses are generally mixed. Nagand Mitra (2002) argue that one of the reasons that NN models do not always outperform linear models, despite their theoretical appeal, is that constructing such models involves quite a lot of subjectivity as there do not exist any established procedures for choosing the parameters of the NN models. These parameters consist of, for example, the number of layers, number of input variables, number of hidden nodes and activation functions. However, Binner et al. (2005), Franses and Griensven (1998) and Bissoondeeal et al. (2008) show that NN models can perform better than linear models by experimenting over a range of parameter values. Therefore, we follow the procedure in these studies in developing our NN models. Another drawback of NN models is that due to their complex nature it is quite difficult, if not impossible, to interpret the NN weights in the way that we interpret the parameter estimates of a linear regression function. Consequently, NN models are sometimes referred to as black boxes. Given that this issue is beyond the scope of this paper, we will not explore it here, but refer the interested reader to studies such as Qiu and Jensen (2004), Setiono et al. (2000), Olden and Jackson (2002) which investigate how interpretation of weights can make NN models less of a black box.

In this paper, we applied Radial Basis Function Neural Network (RBFNN) to predict exchange rate, motived by the fact that artificial neural networks have the ability to implicitly detect complex nonlinear relationships between dependent and independent variables as it “learns” the relationship inherent in the data presented to it (Desai and Bharati, 1998). It is ensured that the model learning algorithm uses a diverse data set for training so as to adapt itself quickly for new exchange rate data. Furthermore, not only its error in prediction of rate is less than previous models but also this model can adapt itself to predict rate values for new exchange rate and still be accurate.

2. Proposed RBFNN-based exchange rate prediction

Artificial Neural Networks (ANNs) can be used for different purposes, including: monitoring, control, classification and prediction. ANNs have the ability to simulate important parameters based on past observations. There are many types of ANNs for modeling function approximation of the engineering problems (Park et al., 2005). NN models are composed of highly interconnected processing nodes that work simultaneously to solve specific problems. In time series analysis they are used as nonlinear function approximators. They take in a set of inputs and produce a set of outputs according to some mapping rules predetermined in their structure. In this paper the most popular form of NN models called the feedforward network is considered. Figure 1 depicts such a network that consists of layers of nodes. The input layer and output layer represent the input and output variables of the model. Between them lie one or more hidden layers that progressively transform the original input stimuli to final output and hold the networks ability to learn nonlinear relationships.

Radial basis networks can require more neurons than standard feedforward backpropagation networks, but often they can be designed in a fraction of the time it takes to train standard feedforward networks. They work best when many training vectors are available (Chen et al., 1991). RBFNNs (Radial Basis Function Neural Networks) have a very strong mathematical foundation rooted in regularization theory for solving illconditioned problems (Kashaninejad et al., 2009). In this paper GRNNs (Generalized Regression Neural Networks) was chosen instead of RB or RBE (Exact radial basis network) since all three of them were tested on the data set and the GRNNs results were far more accurate and acceptable than the other two. GRNNs are a kind of radial basis neural network that are often used for approximation. GRNNs can be designed very quickly (Wasserman, 1993). The structure of a basic GRNN consists of two-layer. The first layer has (radial basis) neurons, (Wasserman, 1993). The simplified architecture of the GRNN is shown in Figure 1.

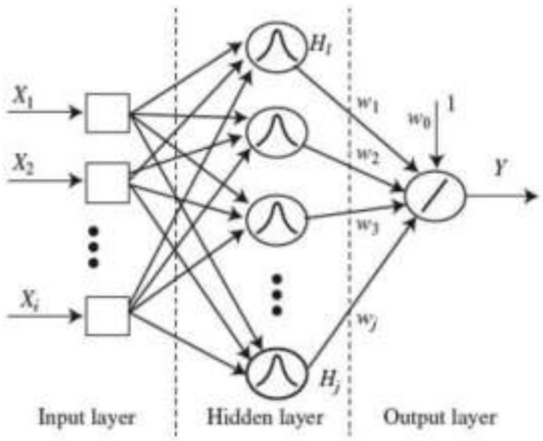

Figure 1. Architecture of the RBFNN used in this study.

In the current research, the input layer of the network model comprised eight neurons (including Pol, J, ZM1, ZM1V, ZM2, ZM2V, W and Har), and the output layer had one output neuron (which was the rate). The new GRNN function creates a two-layer network with biases only for the first layer, a simple architecture of this model is shown in Figure 1.

The network was trained by different spreads from 0.1 to 1 and the training was stopped as the minimum root mean-square error (RMSE) was reached and coefficient of determination as follows.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i^* - y_p^{(i)}\right)^2}{\sum_{i=1}^{n}\left(y_i^* - y\right)^2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_p^{(i)} - y_i^*\right)^2}$$

where y is the average of y over the n data, and y* i and yð piÞ are the I th target and predicted responses, respectively.

By choosing a larger spread the radial basis function's slope becomes smoother and several neurons can respond to an input vector. The network then acts as if it is taking a weighted average between target vectors whose design input vectors are closest to the new input vector. As spread becomes larger more and more neurons contribute to the average, with the result that the network becomes smoother. Based on the theory of generalized regression artificial neural networks, simulation model of operational parameters was established, using the mathematical software program MATLAB (Version R2013a). The operating parameters, including topological descriptors (Pol, J, ZM1, ZM1V, ZM2, ZM2V, W, Har) were the inputs variable of the GRNN model as shown in Figure 2. These topological descriptors were employed to train GRNN in order to simulate rate.

Descriptors	Calculation
First Zagreb index	$\sum_{i=1}^{A}\delta_i^2$ [a]
Second Zagreb index	$\sum_{i=1}^{A-1}\sum_{j=i+1}^{A}a_{ij}\cdot(\delta_i \cdot \delta_j)$ [b]
ZM1V	$\sum_{i=1}^{A}(\delta_i^v)^2$ [c]
ZM2V	$\sum_{i=1}^{A-1}\sum_{j=i+1}^{A}a_{ij}\cdot(\delta_i^v \cdot \delta_j^v)$
Wiener index	$\frac{1}{2}\cdot\sum_{i=1}^{A}\sum_{j=1}^{A}d_{ij}$ [d]
Harary index	$\frac{1}{2}\cdot\sum_{i=1}^{A}\sum_{j=1}^{A}d_{ij}^{-1} = \frac{1}{2}\sum_{i=1}^{A}RDS_i$ [e]
Polarity number	(^3f) [f]
Balaban index	$\frac{B}{C+1}\cdot\sum_{i=1}^{A-1}\sum_{j=i+1}^{A}a_{ij}\cdot(\sigma_i\cdot\sigma_j)^{-\left(\frac{1}{2}\right)}$ [g]

Figure 2 Calculation of descriptors involved in the model

3. Experimental Results

3.1 Data Set

(a) Daily step of data

The data about exchange rates EUR/USD, GBP/USD, USD/JPY with daily step are gathered from site. Data are collected for the period from 01 Jan 2014 till 25 Apr 2014 in our experiments with daily step (83 valuese in total). The visualizations of gathered data for each exchange rate with daily step are depicted in Figure 3~Figure 5.

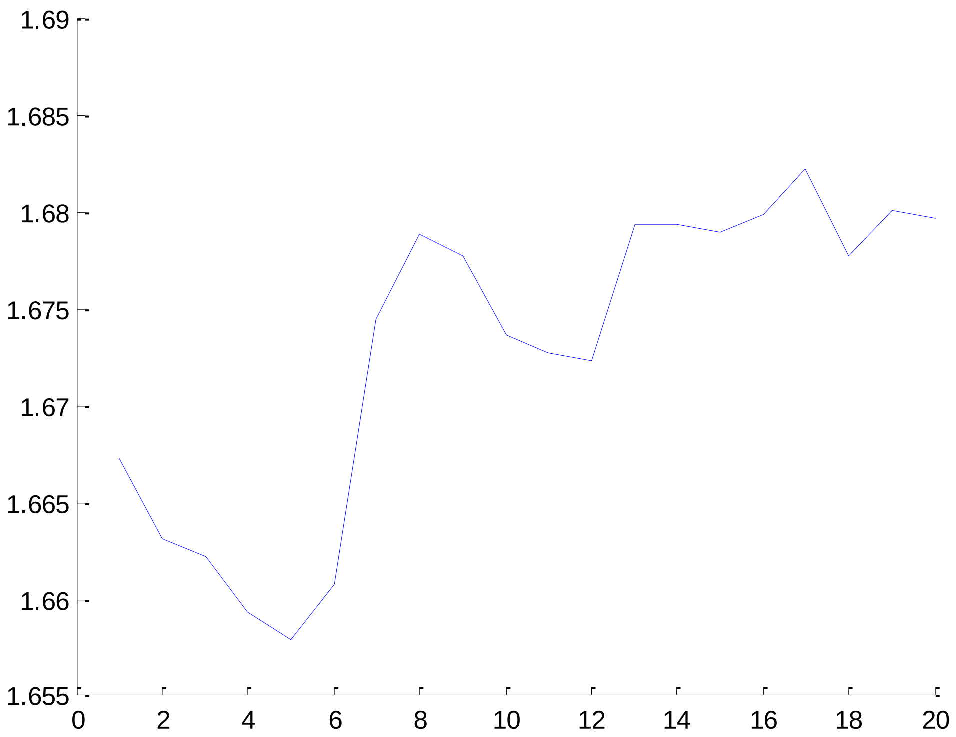

Figure 3. Graph of exchange rate GBP/USD with daily step.

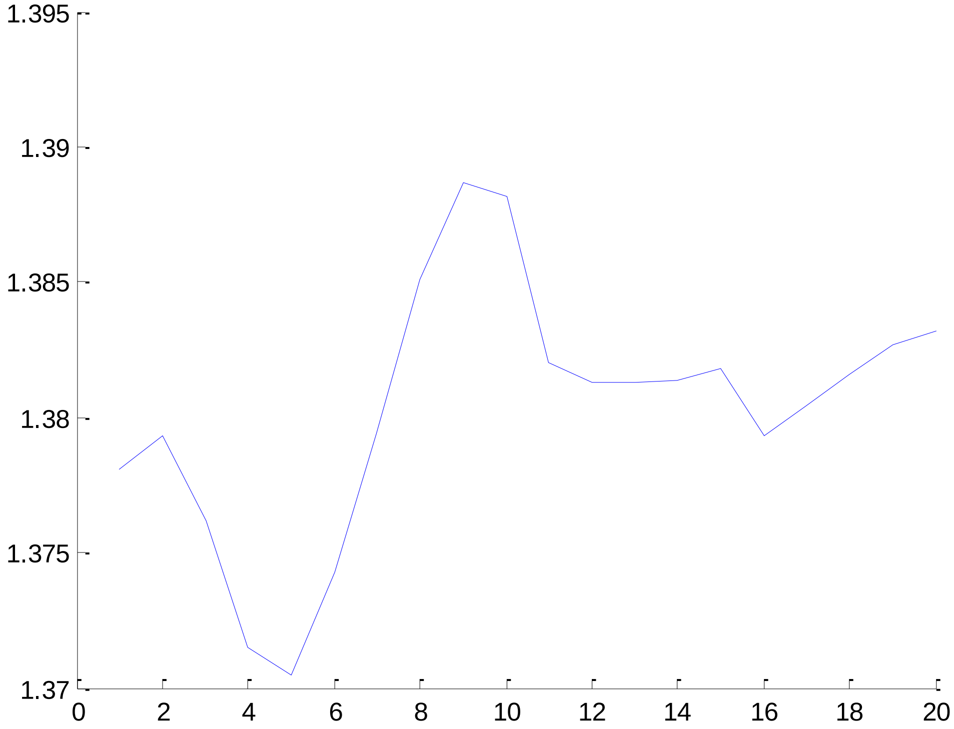

Figure 4. Graph of exchange rate EUR/USD with daily step

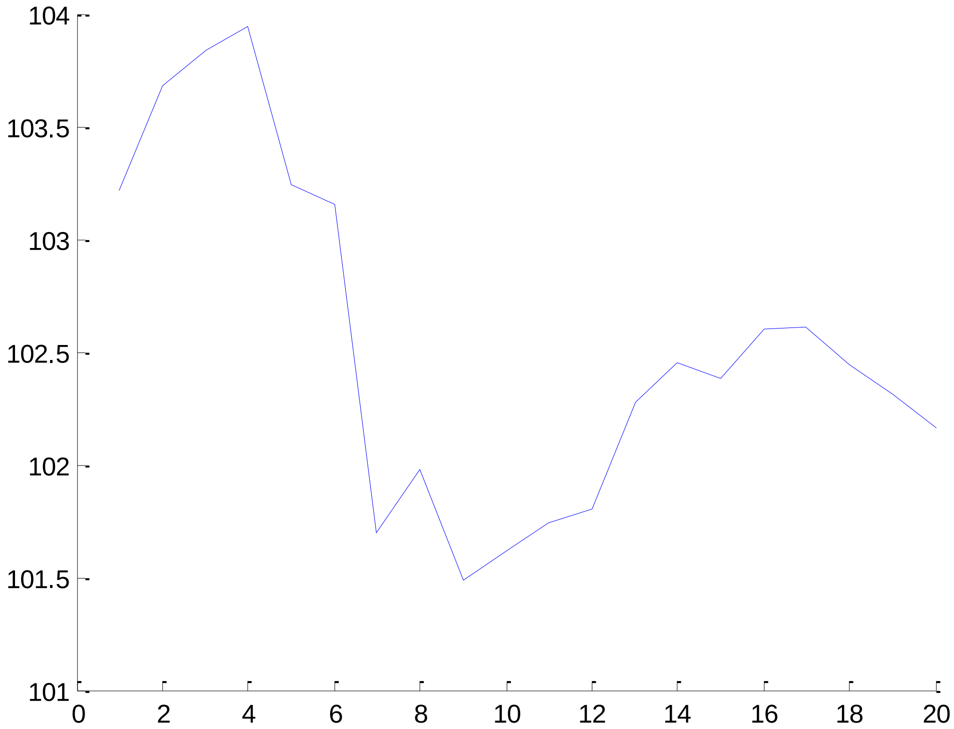

Figure 5. Graph of exchange rate USD/JPY with daily step.

(b) Monthly step

The data about exchange rates EUR/USD, GBP/USD, USD/JPY with monthly step are gathered from site http://www.oanda.com/currency/historical-rates/. Data are collected for the period from May 2009 till May 2014 in our experiments with monthly step. We have found 60 values of each exchange rate. The visualizations of gathered data for each exchange rate with monthly step are depicted in Figure 6, Figure 7 and Figure 8.

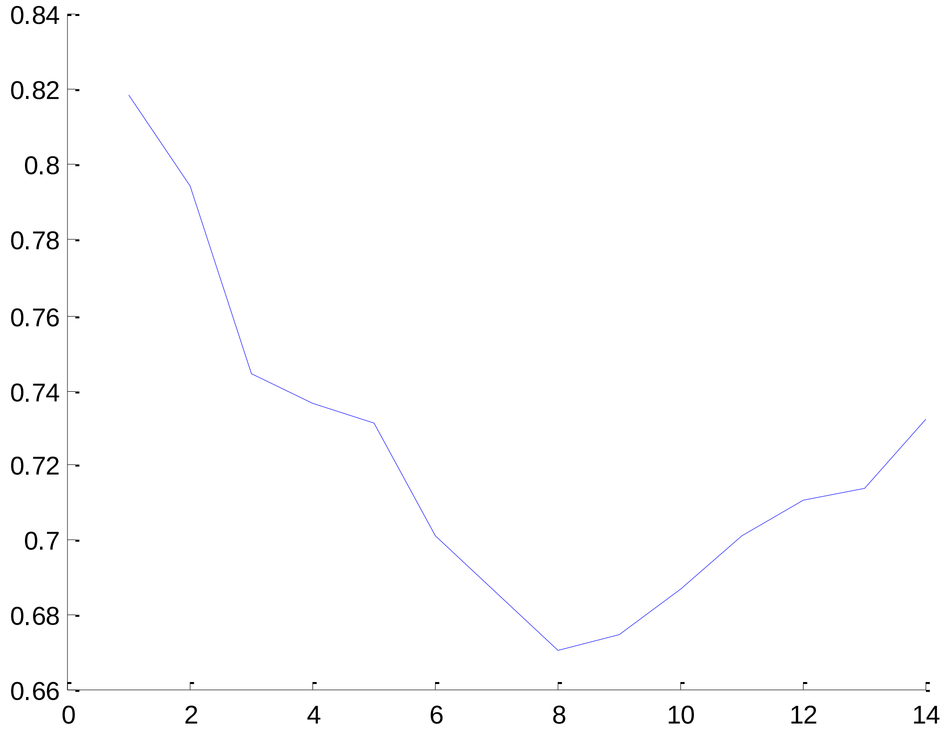

Figure 6. Graph of exchange rate EUR/USD with monthly step.

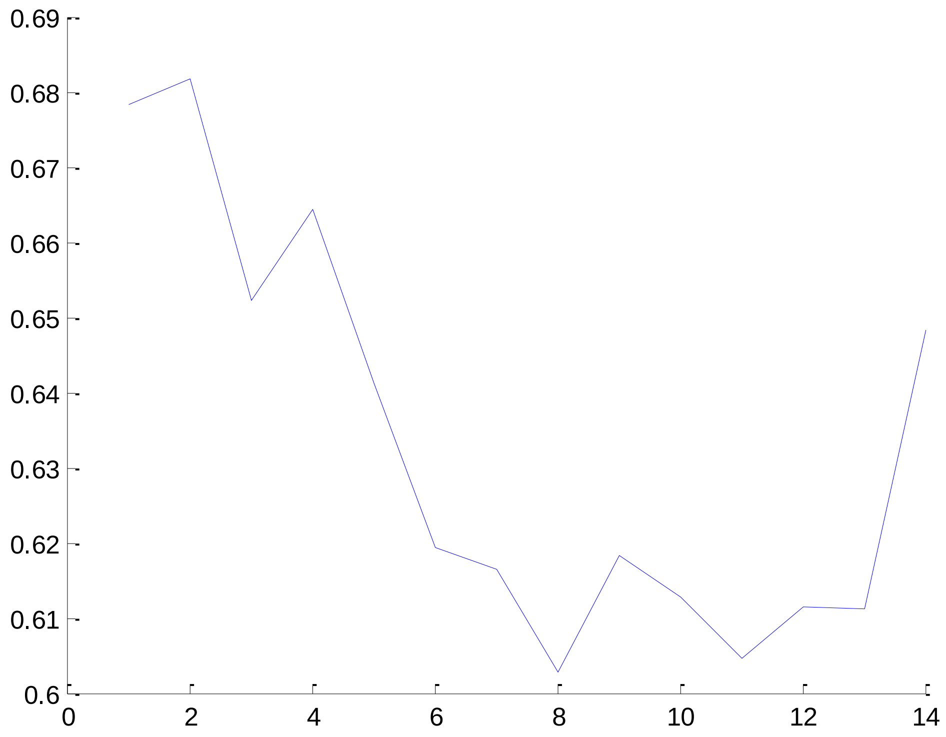

Figure 7. Graph of exchange rate USD/GBP with monthly step.

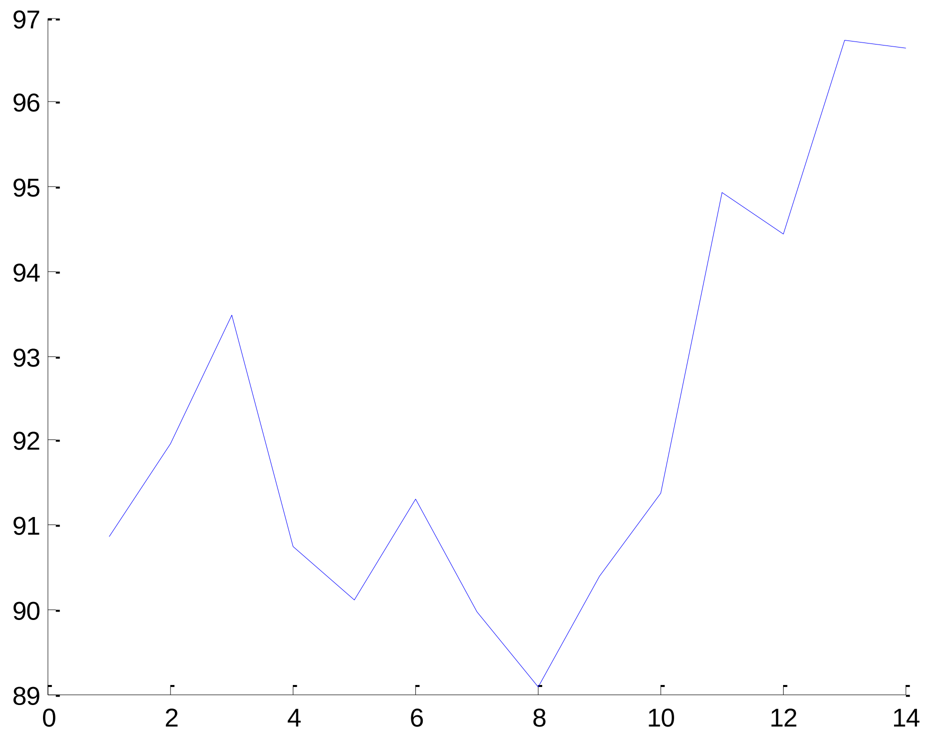

Figure 8. Graph of exchange rate USD/JPY with monthly step.

(c) Quarterly data

The data about exchange rates EUR/USD, GBP/USD, USD/JPY with quarterly step are gathered from site http://www.oanda.com/currency/historical-rates/. as well. Data are collected for the period since May 1999 till May 2014 in our experiments with quarterly step. We have gotten 59 values of each exchange rate. The visualizations of gathered data for each exchange rate with quarterly step are depicted in Fig. 14 for EUR/USD, in Fig. 16 for GBP/USD and in Fig. 18 for USD/JPY.

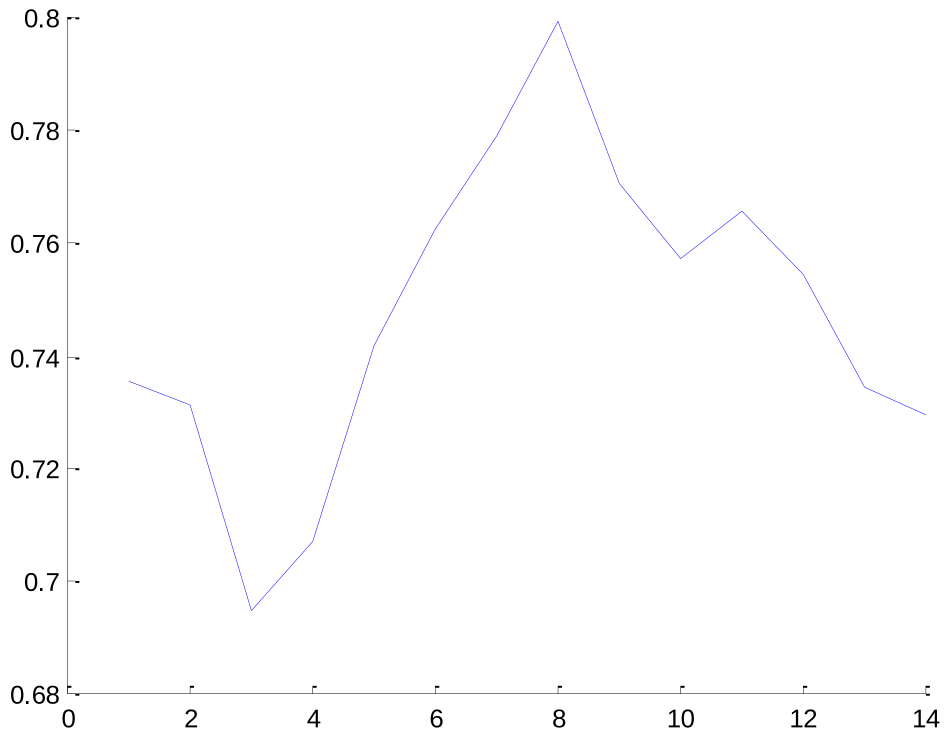

Figure 9. Graph of exchange rate EUR/USD with quarterly step.

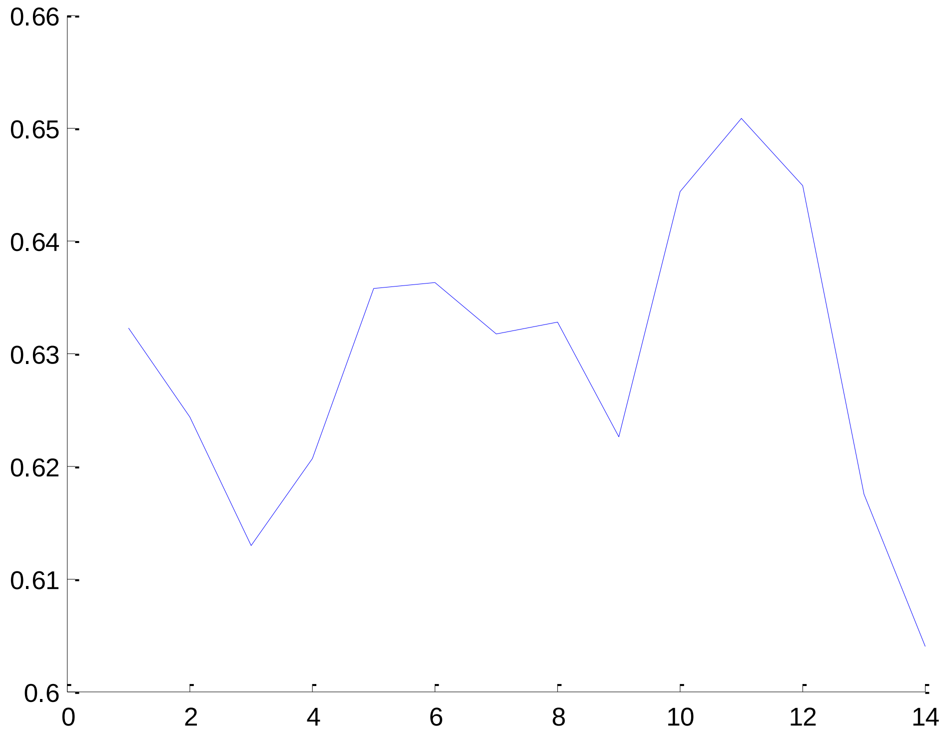

Figure 10. Graph of exchange rate GBP/USD with quarterly step.

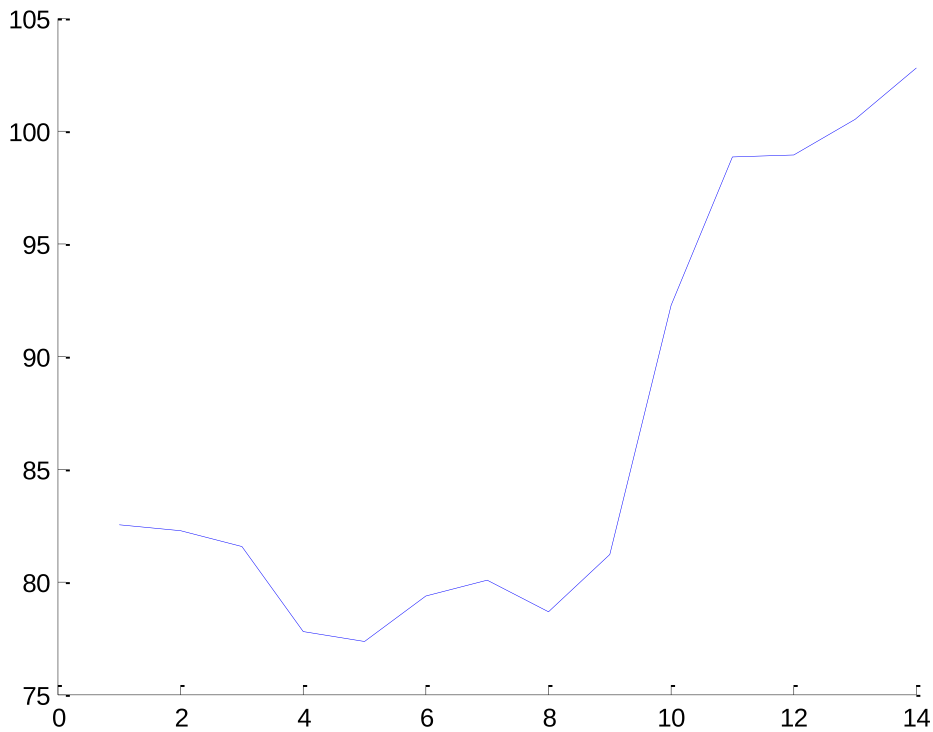

Figure 11. Graph of exchange rate USD/JPY with quarterly step.

3.2 Results

(a) Daily data

Firstly, we testify the proposed algorithm on the exchange rate prediction on daily data. The training set contains 78 training vectors for the exchange rate prediction with daily step. It was used 60 vectors for the training and 18 for the testing of accuracy of the prediction. Within the real time it means that the values of the exchange rate gathered from 8 January 2014 till 31 March 2014 are used for the training, and the period 1–25 April 2014 is used for the prediction. We have used the Radial Basis Function based Neural Network to predict the short period of time. The prediction results with daily step are depicted in Figure 12 for exchange rate EUR/USD, in Fig. 14 for the exchange rate GBP/USD and in Fig. 13 for the exchange rate USD/JPY.

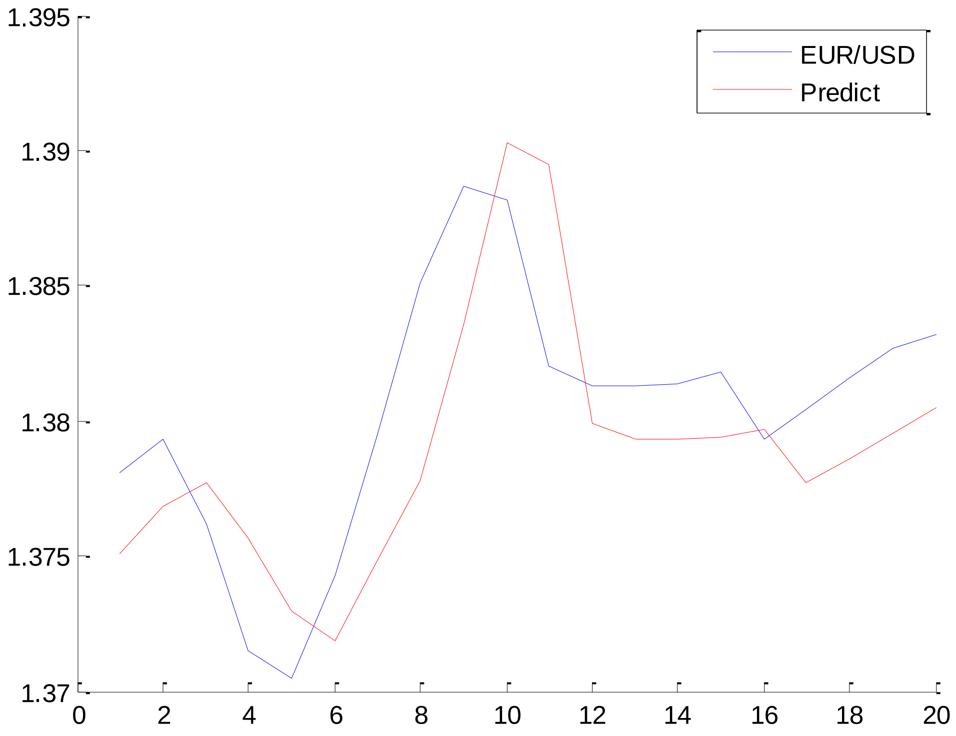

Figure 12 Exchange rate prediction results on EUR/USD of daily step data

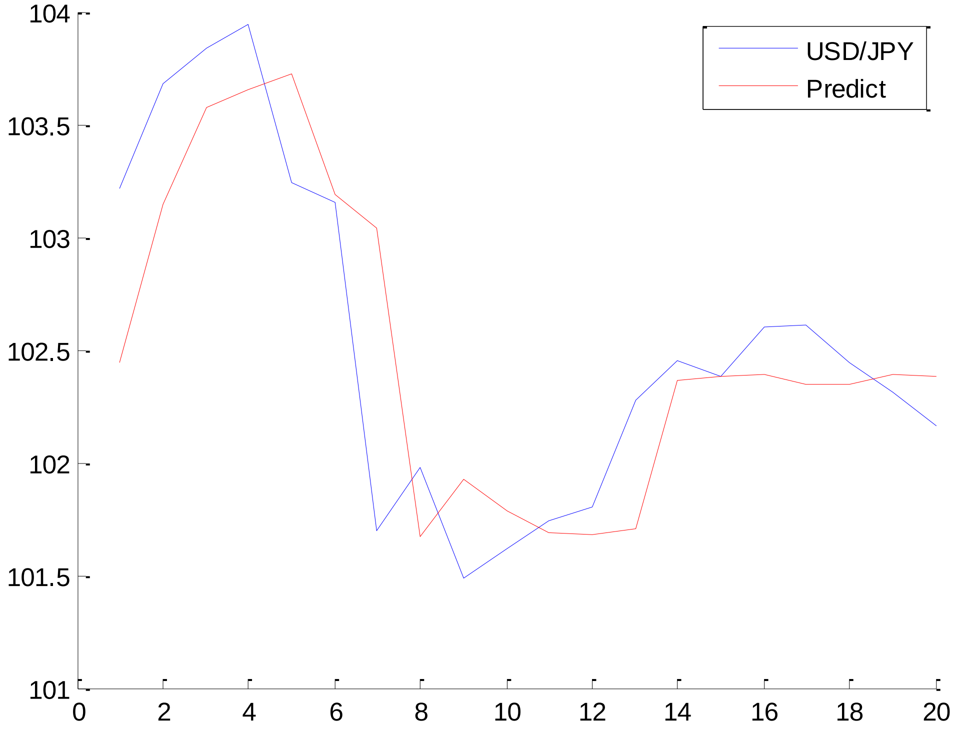

Figure13 Exchange rate prediction results on USD/JPY of daily step data

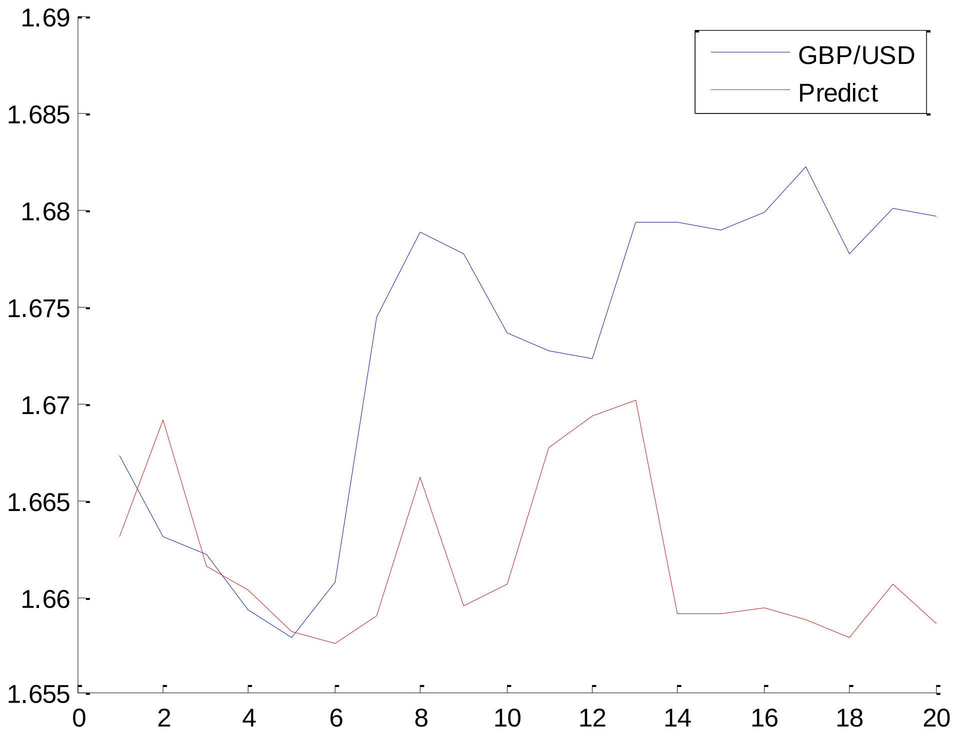

Figure14 Exchange rate prediction results on GBP/USD of daily step data

(b) Monthly data

We have formed the training set containing 55 training vectors for the exchange rate prediction with monthly step.We have used 40 vectors for the training and 15 for the testing of accuracy of the prediction. Within the real time it means that the values of the exchange rate gathered from May 2009 till January 2013 are used for the training, and the period February 2013–April 2014 is used for the prediction. We have used the Radial Basis Function in LS-SVM to predict the short period of time.The prediction results with monthly step are depicted in Fig. 15 for exchangerate EUR/USD, in Fig. 16 for the exchange rate GBP/USD and in Fig. 17 for the exchange rate USD/JPY.

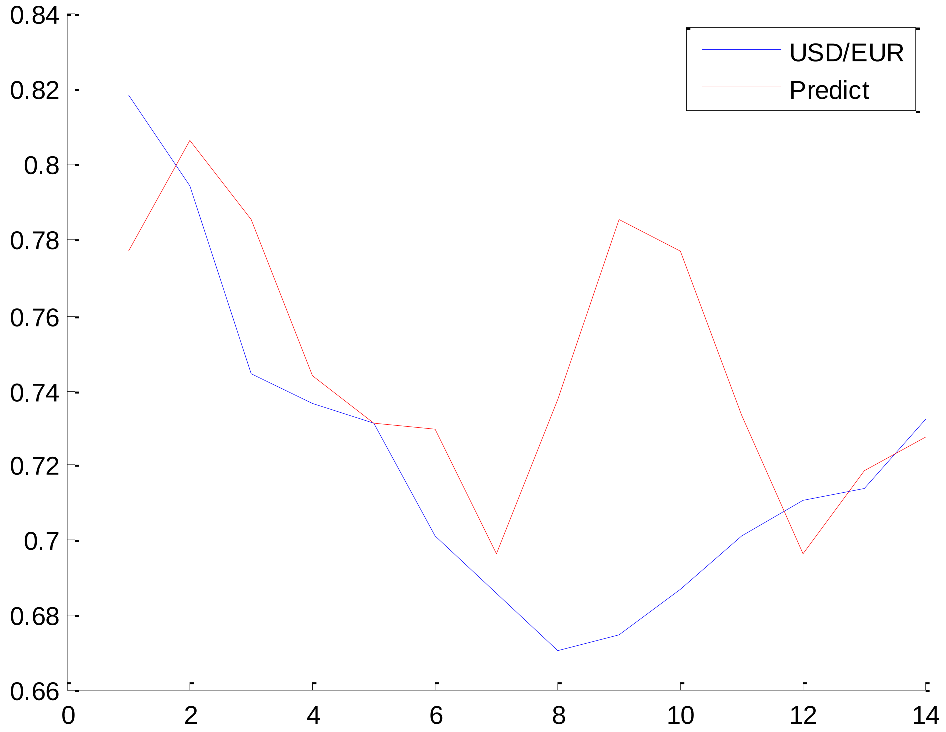

Figure 15 Exchange rate prediction results on USD/EUR of monthly step data

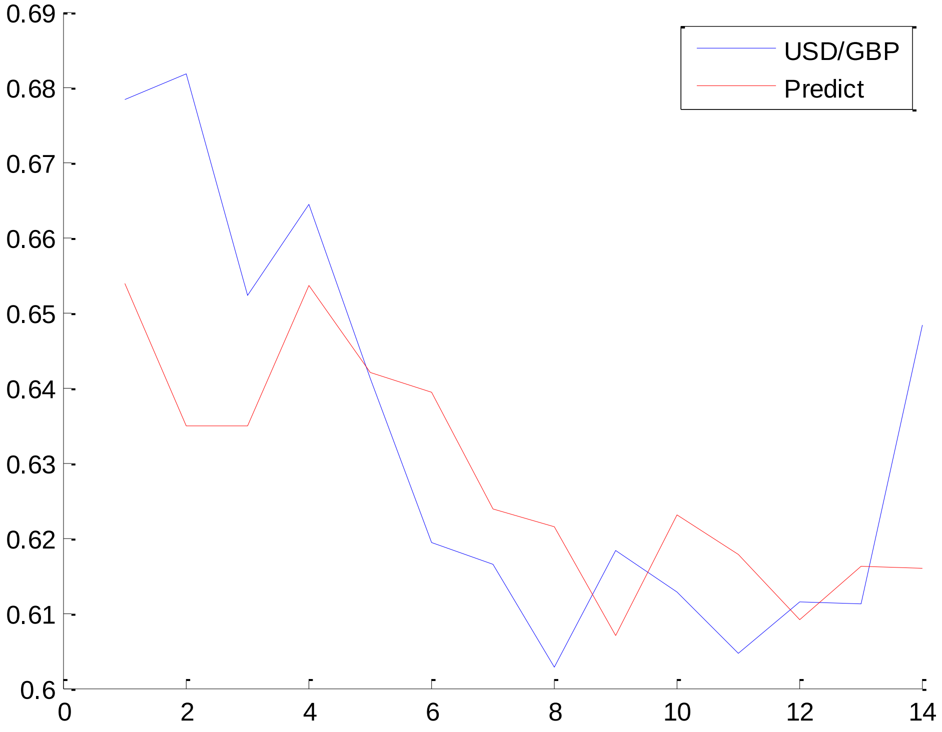

Figure 16 Exchange rate prediction results on USD/GBP of monthly step data

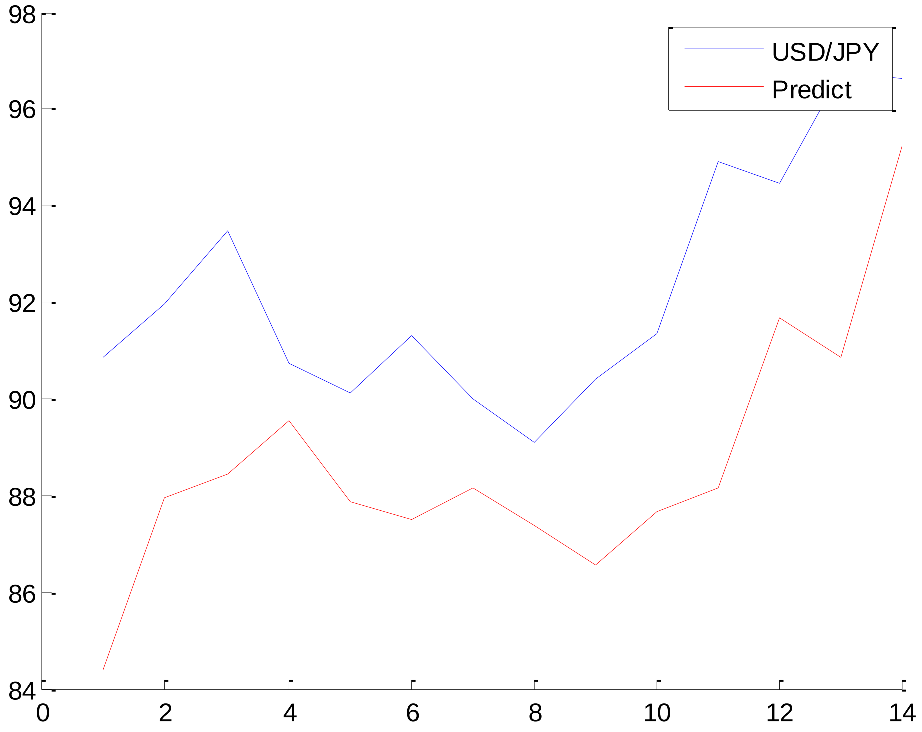

Figure 17 Exchange rate prediction results on USD/JPY of monthly step data

(c) Quarterly data

We have formed the training set containing 54 training vectors for the exchange rate prediction with quarterly step. We have used 42 vectors for the training and 12 for the testing of accuracy of the prediction. Within the real time it means that the values of the exchange rate gathered from 1st quarter of 1999 till 1st quarter 2011 are used for the training, and the period from 1st quarter 2011 till 1st quarter 2014 is used for the prediction. We have used the We have used the Radial Basis Function in LS-SVM to predict the short period of time.. The prediction results with quarterly step are depicted in Fig. 18 for exchange rate EUR/USD, in Fig. 19 for the exchange rate GBP/USD.

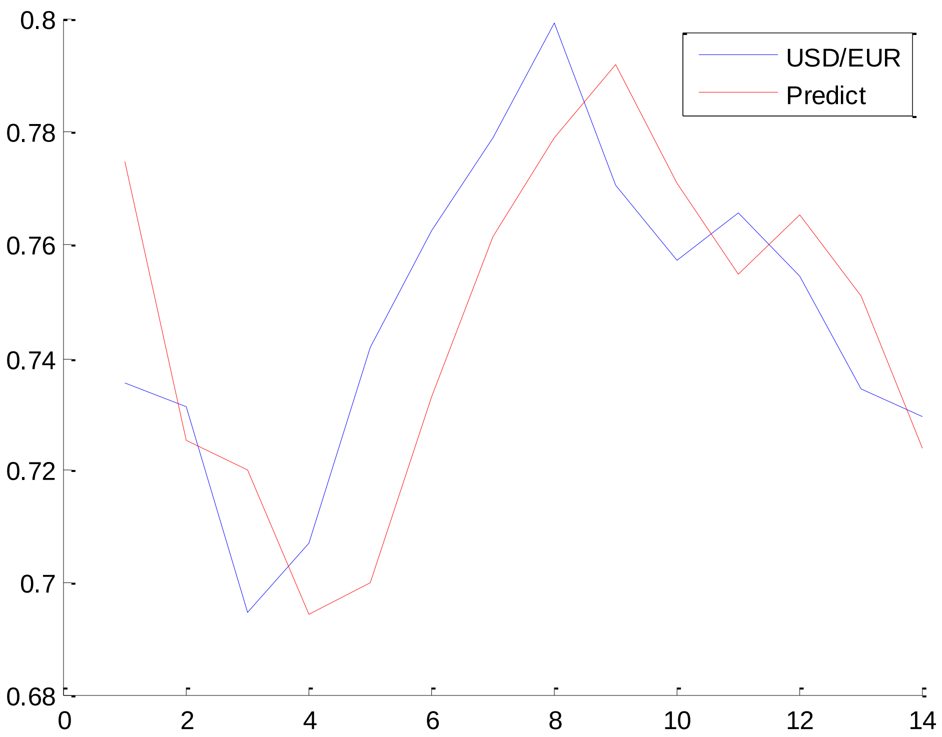

Figure 18 Exchange rate prediction results on USD/EUR of quarterly step data

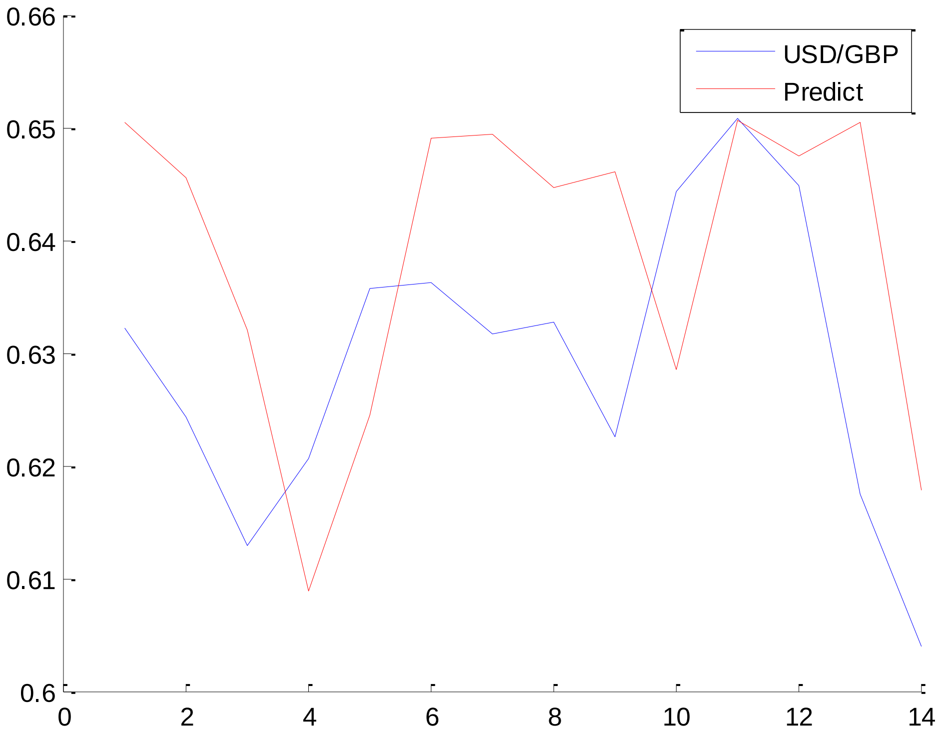

Figure 19 Exchange rate prediction results on USD/GBP of quarterly step data

4 Conclusion

Radial Basis Function Neural Network (RBFNN) is applied to predict exchange rate with financial time series. Since RBFNN have the ability to implicitly detect complex nonlinear relationships between dependent and independent variables as it "learns" the relationship inherent in the exchange rate data, the RBFNN performs well on the exchange rate prediction. The experiments on daily data, monthly step data and quarterly step data are to testify the performance of the proposed algorithms. The RBFNN is effective to predict exchange rate with financial time series. The procedural parameters are chosen with cross-validation method, the future work is attempted to choose them automatically according to the input training data.

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