ARTICLE IN PRESS

Neurocomputing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Neural networks performance in exchange rate prediction

Svitlana Galeshchuk *

Ternopil National Economic University, 11 Lvivska str., 46000 Ternopil, Ukraine

ARTICLE INFO

Article history:
Received 25 September 2014
Received in revised form
1 February 2015
Accepted 18 March 2015

Keywords:
Neural networks
Multilayer perceptron
Currency exchange-rate changes
Foreign exchange rate prediction

ABSTRACT

Exploration of ANNs for the economic purposes is described and empirically examined with the foreign exchange market data. For the experiments, panel data of the exchange rates (USD/EUR, JPN/USD, USD/GBP) are examined and optimized to be used for time-series predictions with neural networks. In this stage the input selection, in which the processing steps to prepare the raw data to a suitable input for the models are investigated. The best neural network is found with the best forecasting abilities, based on a certain performance measure. A visual graphs on the experiments data set is presented after processing steps, to illustrate that particular results. The out-of-sample results are compared with training ones.

1. Introduction

Uncertainty is pervasive in everyday life and the forecasting of uncertain parameters is widely recognized to represent a very critical issue in every application context. This consideration is particularly true for the financial field, where wrong forecasts can produce very severe losses.

Prediction of different financial indices based on time series is one of the most urgent research directions in economic sciences nowadays [1]. Recent researches show that the application of computational intelligence methods as a base for predicting models, in particular, neural networks, evolutionary computations, fuzzy logic and others is very crucial due to their principal differences from existing mathematical approaches. For example, neural networks have inherent learning abilities that allow us to effectively capturing the dynamics of nonlinear and complicated features of financial data; their self-training and self-adaptation properties provide a universality of the prediction model within the class of forecasting problems [2]. While the prediction model based on mathematical expression should be re-calculated for every prediction case. Finally, some prediction tasks in economics cannot be predicted by mathematical methods due to a number and diversity of input parameters.

In the last years, more than thousand scientific contributions have been proposed on the application of neural networks (NNs or ANNs) in finance. Gurusen [3] provides a detailed survey of the 25 contributions available in scientific literature on the NNs application in the financial field for the last few years. Their conclusions have confirmed that NN-based solutions outperform other statistical and mathematic approaches in the most cases. The largest number of NN applications in finance is for exchange rate [4], stock price [3] and sales [5] predictions.

The literature indicates that exchange rates are largely unforecastable. The pessimism about the prediction of exchange rate becomes generally accepted after the publication of the seminal paper by Meese and Rogoff [6]. Meese and Rogoff puzzle states that there is no better economic model for exchange rates forecasting during floating exchange rates than the simple random walk. This result was updated later by the same authors, and the conclusions did not change [7]. Nevertheless, Alvarez-Diaz [8] highlights that Meese and Rogoff puzzle rely on the assumption of linearity; therefore, it must not be considered definitive or conclusive due to the possible existence of nonlinear structures in the exchange rates dynamics. Author assumes that the scarce forecasting ability of the structural and univariant approaches are well summarized in the competition conducted by Meese and Rogoff [6], where it was shown that the great majority of linear models could not beat the out-of-sample predictions of a simple random walk.

Subsequently, a number of studies have pursued nonlinear modeling using conventional nonlinear techniques, such as Markov switching models. However, generally the results suggest that conventional nonlinear modeling does not improve exchange rate forecasts. An alternative way to deal with nonlinearities in data is to use neural network (NN) models. In contrast to the abovementioned model-based nonlinear methods, NN models are data driven and are

* Corresponding author. Tel.: +380 967304326; fax: +380 352475059.
E-mail address: svitlana.galeshchuk@gmail.com

http://dx.doi.org/10.1016/j.neucom.2015.03.100
0925-2312/

thus capable of producing nonlinear models without prior knowledge about the functional forms. NN are also highly flexible as they can approximate any continuous function to any degree of accuracy.

The goal of this paper is to test prediction capacity of neural networks with the exchange rates of EUR/USD, GBP/USD and USD/JPY in daily steps to use them as the methods of the technical analysis of foreign market. The rest of the paper is organized as follows. The neural network used for our experiment is presented in Section 2. The input data preparation for NN training is described in Section 3. The NN models used for prediction are described in Section 4. The results of prediction are presented in Section 5. Section 6 concludes this paper.

2. Literature overview

The ANNs as a tool in the exchange rate prediction is used quite rarely due to the popularity of the statistical methods and the lack of the experts in the field of artificial intelligence among those who practice economic forecasting. However, there are several major pros of ANN usefulness that distinguish them from the other existed prediction methods. The most powerful feature of artificial neural network technology is solving nonlinear problems that other classical techniques do not deal with. The ANN technology does not require assumption about data distribution and missing, noisy and inconsistent data do not possess any problems. Another important aspect of the ANN is its ability to learn from the data. Moreover, according to Lam [9] neural networks are numeric in nature, which is especially suitable for processing numeric data such as financial information and economic indicators. Because numeric data must be converted into nominal values before they can be used as input to symbolic manipulation techniques, there are the problems of losing information, inappropriate data intervals, and different conversion methods leading to different mining results. Neural networks, on the other hand, can accept numeric data directly as input for mining purpose. Thinyane and Millin [10] in their article describe the creation, optimization and testing of an intelligent technical trading tool. According to their conclusions ANNs prove to be good signal amalgamators, with overtraining being their only downfall. Having said that, they also find that the more complex the ANN, the more specialized the resulting system; generating increasing profits on the training sets. This specialization however, cause a decrease in profits in the test sets, as the resulting system is not finding general optimums, but rather unique and highly profitable solutions limited to the training set. Thus the least complex ANN turn out to be the most profitable, as it is unable to specialize as highly, and is thus a more general solution.

An evidence that ANNs outperform a sort of non-linear approaches in terms of out-of-sample prediction accuracy is investigated and confirmed by the number of economists such Önder et al. [11] who make the comparison between neural networks implementation and the other time series techniques. Based on empirical analysis the authors find that neural networks are universal functions approximation and they can model any continuous and nonlinear function with desired accuracy, and do not have any assumption about input or residual probability distribution as regression analyze.

There exist studies that have employed artificial neural networks (ANNs) models. During the last several years, ANNs have been applied successfully in many fields, mainly in biology, physics, and statistics and increasingly are being used in economics as well as in economic modeling. Among those who investigated neural networks and their implication for forecasting of financial markets were Kuan and White [12], as well as Swanson and White [13] who prove usefulness of neural networks in economic time series., Qi and Madala [14] show its usefulness for the stock market, and Gencay [15] for exchange rate forecasting.

Santos et al. [16] in their work use series of first difference of 15 min, 60 min and 120 min log-returns from 01/01/2002 to 01/01/2003 and daily and weekly log-returns from 01/01/2000 to 01/01/2004 of the Brazilian exchange rate (R$/US$). The most important result is that ANNs performed better than linear models in all series. Another empirical experiment in favor of ANN is done by Ozkan [17] who compares the prediction performances of artificial neural networks, which he finds as an effective tool of prediction, and the monetary model, which is one of the methods to predict exchange rates. In his study exchange rates of Turkish Lira against US Dollar and Euro are predicted. Results of this study show that ANN, which is recently being used for the prediction problems, reached a high level prediction performance. Dunis and Huang, [18] applies MLP to a 1-day-ahead forecasting and trading task of the EUR/USD exchange rate using the ECB fixing series with only autoregressive terms as inputs. As it turns out, the MLP model clearly outperforms the traditional models in both out-of-sample periods in terms of annualized return. Bissoondeeal et al. [19] evaluate the exchange rate forecasting performance of neural network models against the random walk, autoregressive moving average and generalized autoregressive conditional heteroskedasticity models. They warn that there are no guidelines available that can be used to choose the parameters of neural network models and therefore, the parameters are chosen according to what the researcher considers to be the best. In spite of these disadvantages in the paper their results still show that in general, neural network models perform better than the traditional time series models in forecasting exchange rates.

I agree with the disadvantages of ANN called by the researches mainly with the subjectivity in the selection of hidden layers, neurons, etc. Nevertheless, in most cases the implementation of ANN with experienced users as well as special programming environment gives quite good prediction results. It brings us to the idea to use the ANNs mainly the MLP in the experiment with the forecasting of exchange rates of three currency pairs. The originality of the research is in comparison the forecasting capacity of the ANN not with other methods like it is done in the most papers but with different currencies (EUR/USD, GBP/USD and USD/JPY in daily, monthly and quarterly steps was predicted). In the other words, in this paper the idea that it is possible to apply one proposed neural network model (with the example of MPL) to the prediction of the different exchange rates for the different periods is considered as a novelty of the research.

3. Description of used neural network model

The multi-layer perceptron is used as a model to predict exchange rates. This kind of neural network has the advantage of being simple and provides nice generalized properties.

The output value y of three-layer perceptron (Fig. 1) can be formulated as

$$y = F_3\left(\sum_{i=1}^{N} w_{i3} h_i - T\right) \tag{1}$$

where N is the number of neurons in the hidden layer, w_{i3} is the weight of the synapse from neuron i in the hidden layer to the output neuron, h_i is the output of neuron i, T is the threshold of the output neuron and F_3 is the sigmoid activation function (3) of the output neuron.

Please cite this article as: S. Galeshchuk, Neural networks performance in exchange rate prediction, Neurocomputing (2015), http://dx.doi.org/10.1016/j.neucom.2015.03.100

The output value of neuron j in the hidden layer is given by

$$h_j = F_2\left(\sum_{i=1}^{M} w_{ij}x_i - T_j\right), \tag{2}$$

where w_{ij} are the weights from the input neurons to neuron j in the hidden layer, x_i are the input data and T_j is the threshold of neuron j, and F_2 is the sigmoid activation function (3) of the hidden neuron. The number of input neurons is defined in Table 1 below. The number of output neurons in our experiments is equal to 1.

The back propagation error algorithm [9] is used for the training algorithm. It is based on the gradient descent method and provides an iterative procedure for the weights and thresholds updating for each training vector p of the training sample

$$\Delta w_{ij}(t) = -\alpha\frac{\partial E^p(t)}{\partial w_{ij}(t)}, \qquad \Delta T_j(t) = -\alpha\frac{\partial E^p(t)}{\partial T_j(t)}, \tag{3}$$

where α is the learning rate, $\frac{\partial E^p(t)}{\partial w_{ij}(t)}$ and $\frac{\partial E^p(t)}{\partial T_j(t)}$ are the gradients of the error function on each iteration t for the training vector p with $p \in \{1, ..., P\}$, where P is the size of the training set.

The Sum-Squared Error (SSE), for training iteration t, is calculated as

$$E^p(t) = \frac{1}{2}\left(y^p(t) - d^p(t)\right)^2, \tag{4}$$

where for the training vector p, $y^p(t)$ is the output value of the MLP on iteration t and $d^p(t)$ is the target output value.

During training, the total error is calculated as

$$E(t) = \sum_{p=1}^{P} E^p(t) \tag{5}$$

The error of neuron i with logistic activation function can be determined by the relation

$$\gamma_i^p(t) = \sum_{j=1}^{N} \gamma_3^p(t) w_{i3}(t) h_j^p(t)(1 - h_j^p(t)), \tag{6}$$

where $\gamma_3^p(t) = y^p(t) - d^p(t)$ is the error of the output neuron of the MLP, $w_{i3}(t)$ is the weight of the synapses between the neurons of the hidden layer and the output neuron.

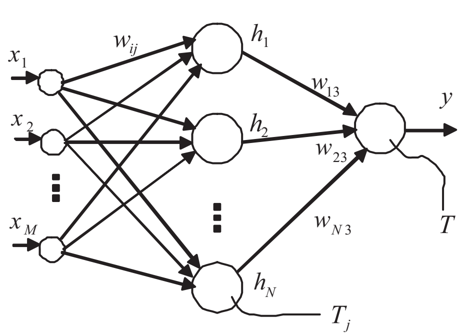

Fig. 1. Structure of multi-layer perceptron.

Table 1
The summary of prediction results with neural networks.

Exchange rate	Daily step		Monthly step		Quarterly step	
	Relative prediction error, %					
	Average	Maximum	Average	Maximum	Average	Maximum
EUR/USD	0.2	0.4	1.3	3.3	2.3	5.1
GBP/USD	0.2	0.9	2.2	4.5	1.9	5.0
USD/JPY	0.3	1.3	0.3	1.3	3.5	10.2

4. Getting data about exchange rates

4.1. Daily step

The data about exchange rates EUR/USD, GBP/USD, USD/JPY with *daily step* are gathered from site http://www.global-view.com/forex-trading-tools/forex-history/index.html. Data are collected for the period from 01 Jan 2014 till 25 Apr 2014 in our experiments with daily step (83 values in total). The visualizations of gathered data for each exchange rate with daily step are depicted in Fig. 2 for EUR/USD, in Fig. 4 for GBP/USD and in Fig. 6 for USD/JPY.

4.2. 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 Fig. 8 for EUR/USD, in Fig. 10 for GBP/USD and in Fig. 12 for USD/JPY.

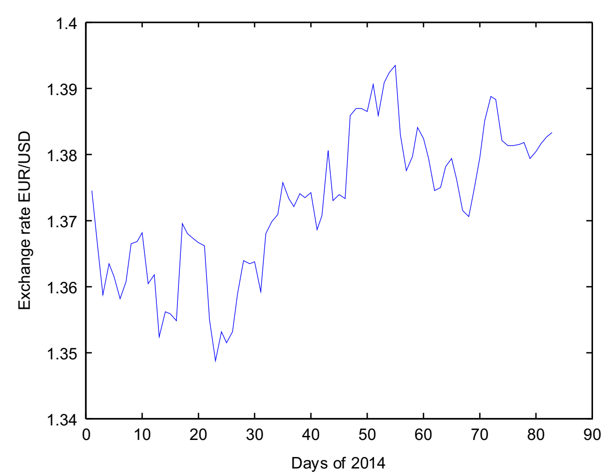

Fig. 2. Graph of exchange rate EUR/USD with daily step.

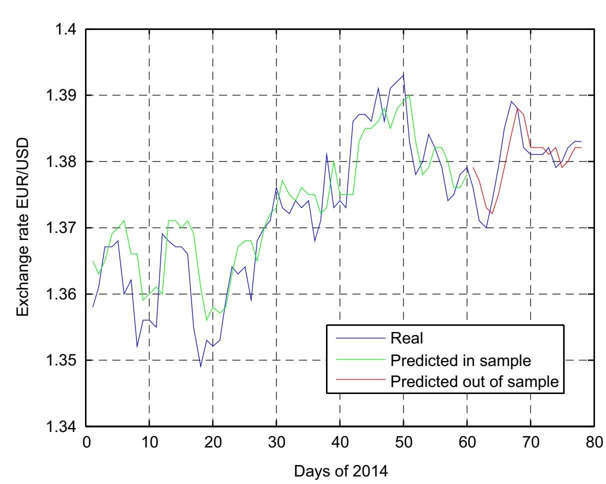

Fig. 3. Prediction of exchange rate EUR/USD with daily step.

Please cite this article as: S. Galeshchuk, Neural networks performance in exchange rate prediction, Neurocomputing (2015), http://dx.doi.org/10.1016/j.neucom.2015.03.100

4.3. Quarterly step

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.

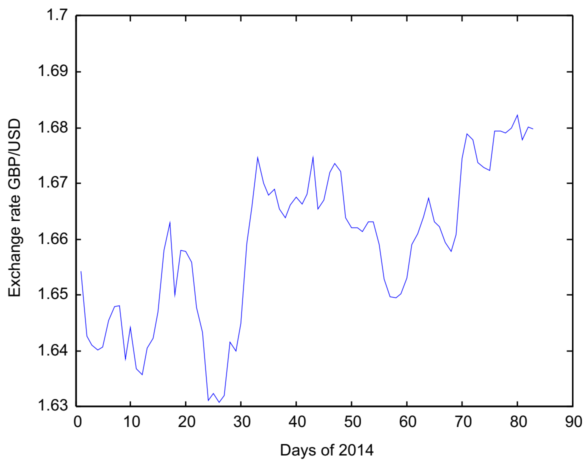

Fig. 4. Graph of exchange rate GBP/USD with daily step.

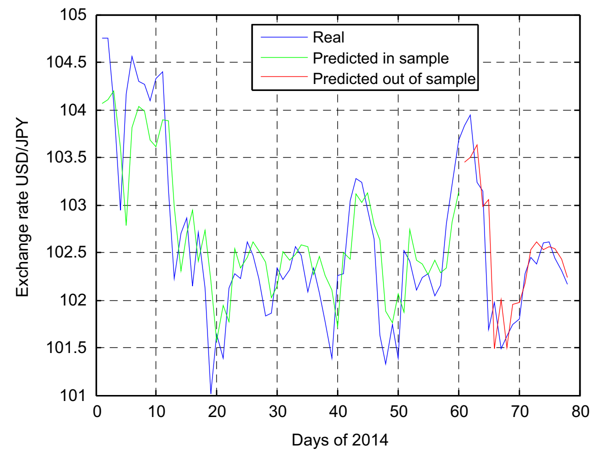

Fig. 7. Prediction of exchange rate USD/JPY with daily step.

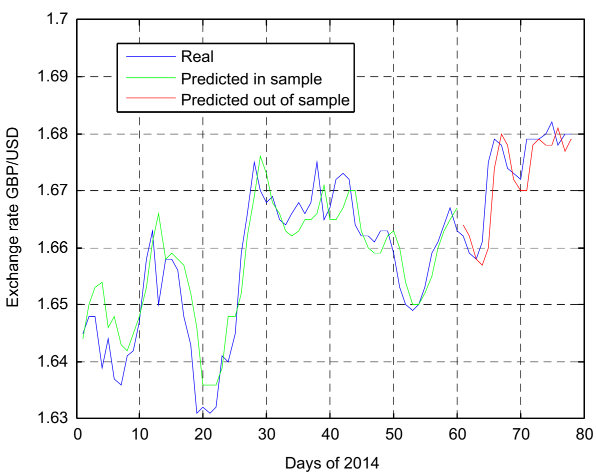

Fig. 5. Prediction of exchange rate GBP/USD with daily step.

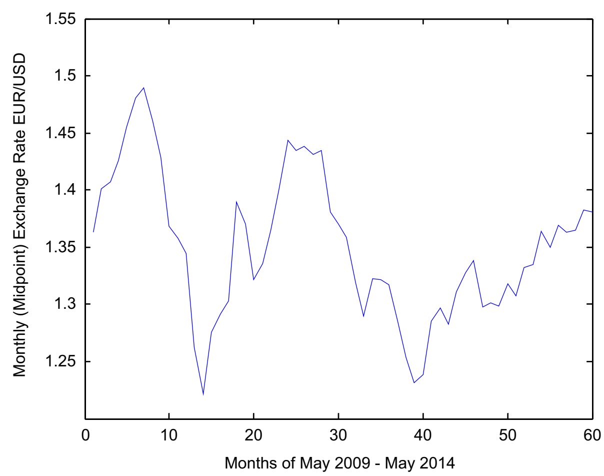

Fig. 8. Graph of exchange rate EUR/USD with monthly step.

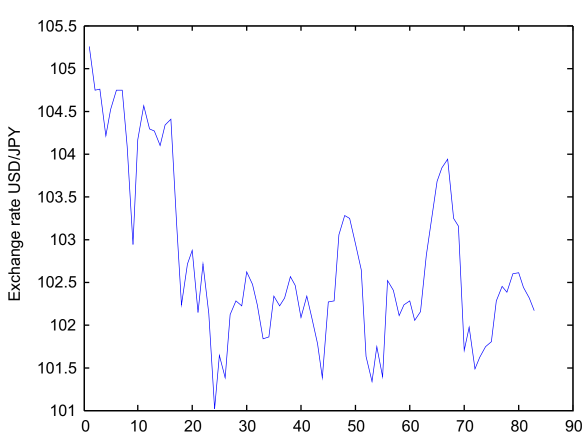

Fig. 6. Graph of exchange rate USD/JPY with daily step.

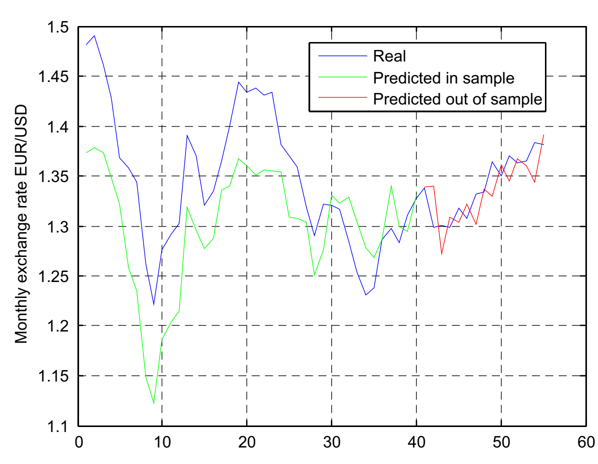

Fig. 9. Prediction of exchange rate EUR/USD with monthly step.

Please cite this article as: S. Galeshchuk, Neural networks performance in exchange rate prediction, Neurocomputing (2015), http://dx.doi.org/10.1016/j.neucom.2015.03.100

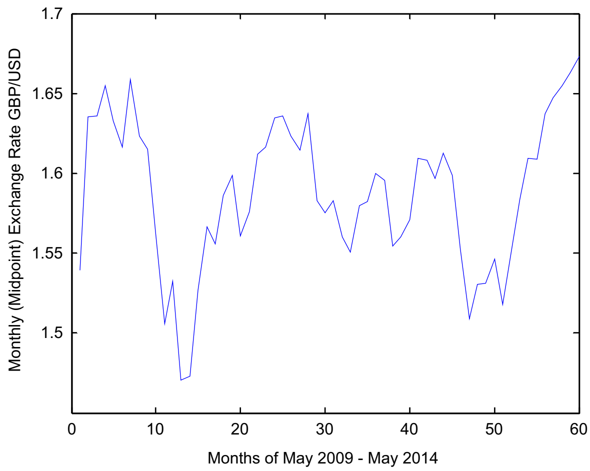

Fig. 10. Graph of exchange rate GBP/USD with monthly step.

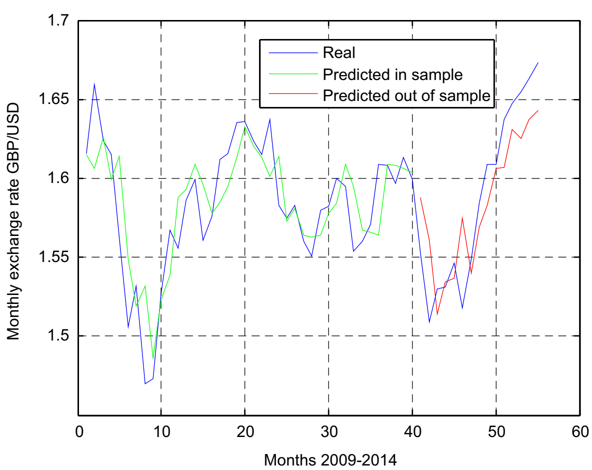

Fig. 11. Prediction of exchange rate GBP/USD with monthly step.

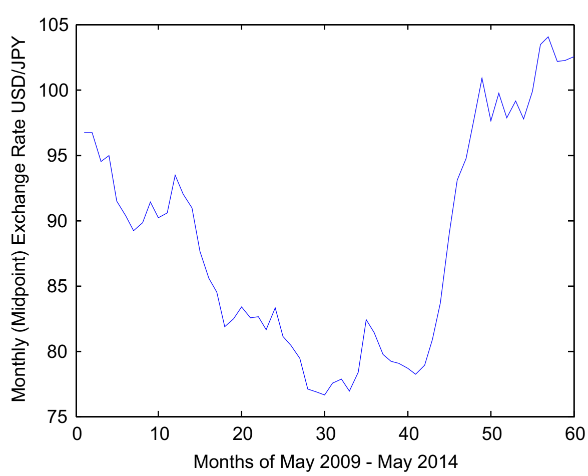

Fig. 12. Graph of exchange rate USD/JPY with monthly step.

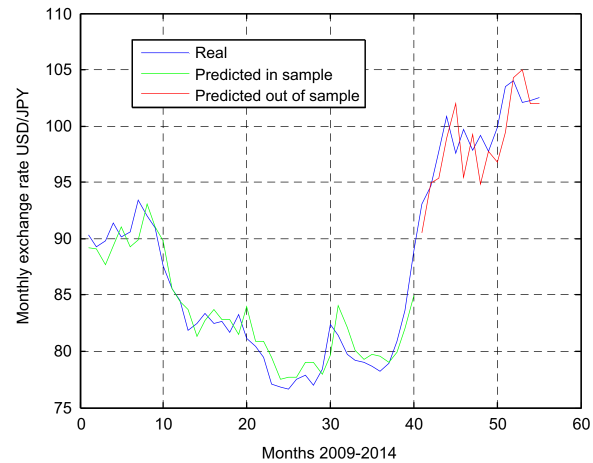

Fig. 13. Prediction of exchange rate USD/JPY with monthly step.

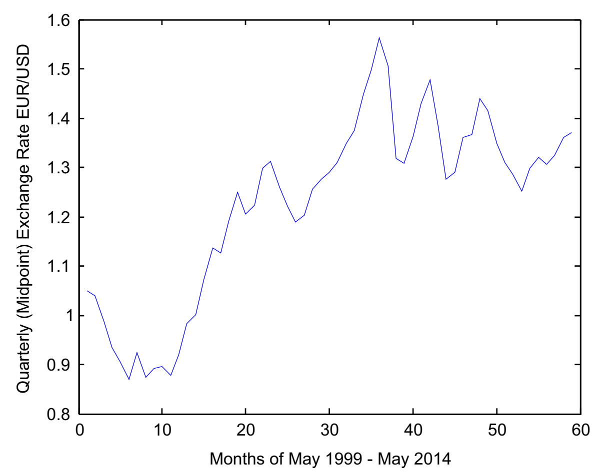

Fig. 14. Graph of exchange rate EUR/USD with quarterly step.

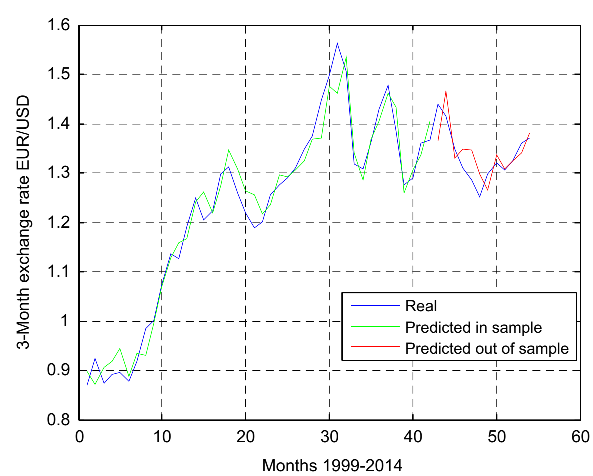

Fig. 15. Prediction of exchange rate EUR/USD with quarterly step.

5. Prediction results

5.1. Exchange rate prediction with daily step

We have formed the training set containing 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 multilayer perceptron model 5-10-1 and one-step prediction mode. The prediction results with daily step are depicted in Fig. 3 for exchange rate EUR/USD, in Fig. 5 for the exchange rate GBP/USD and in Fig. 7 for the exchange

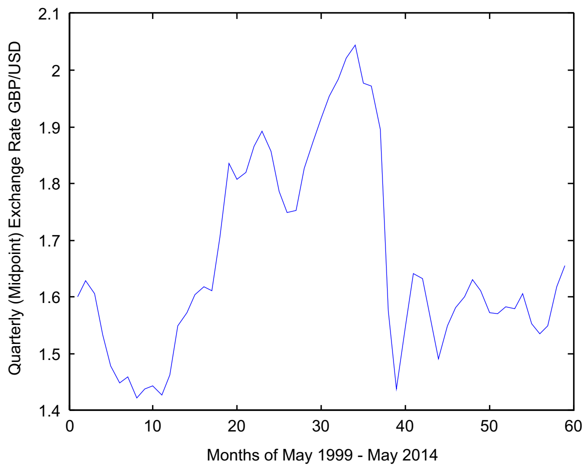

Fig. 16. Graph of exchange rate GBP/USD with quarterly step.

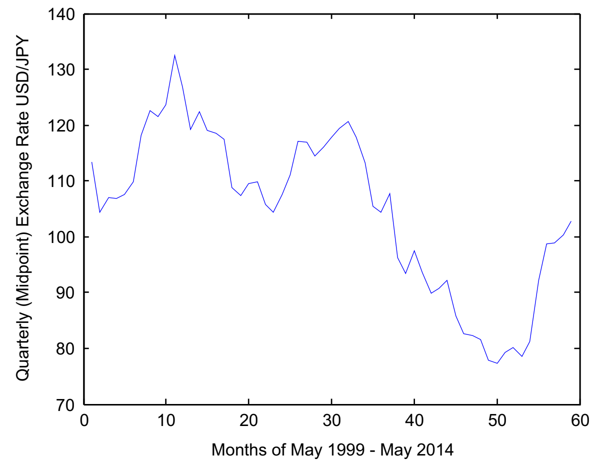

Fig. 18. Graph of exchange rate USD/JPY with quarterly step.

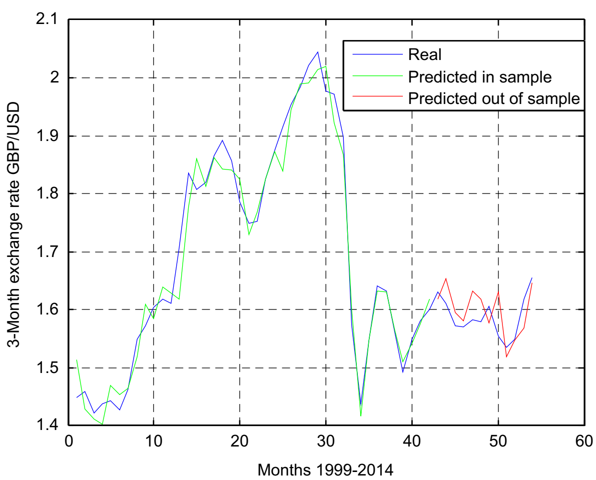

Fig. 17. Prediction of exchange rate GBP/USD with quarterly step.

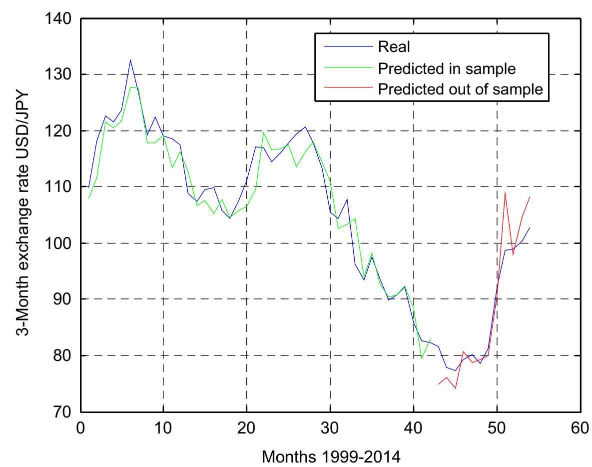

Fig. 19. Prediction of exchange rate USD/JPY with quarterly step.

rate USD/JPY. The analysis of the predicting results shows that the average and maximum relative prediction errors within short-term prediction are 0.2–0.4% for the exchange rate EUR/USD, 0.2–0.9% for the exchange rate GBP/USD and 0.3–1.3% for the exchange rate USD/JPY respectively.

5.2. Exchange rate prediction with monthly step

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 multilayer perceptron model 5-10-1 and one-step prediction mode. The prediction results with monthly step are depicted in Fig. 9 for exchange rate EUR/USD, in Fig. 11 for the exchange rate GBP/USD and in Fig. 13 for the exchange rate USD/JPY. The analysis of the predicting results shows that the average and maximum relative prediction errors within short-term prediction are 1.3–3.3% for the exchange rate EUR/USD, 2.2–4.5% for the exchange rate GBP/USD and 0.3–1.3% for the exchange rate USD/JPY respectively.

5.3. Exchange rate prediction with quarterly step

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 multilayer perceptron model 5-10-1 and one-step prediction mode. The prediction results with quarterly step are depicted in Fig. 15 for exchange rate EUR/USD, in Fig. 17 for the exchange rate GBP/USD and in Fig. 19 for the exchange rate USD/JPY. The analysis of the predicting results shows that the average and maximum relative prediction errors within short-term prediction are 2.3–5.1% for the exchange rate EUR/USD, 1.9–5.0% for the exchange rate GBP/USD and 3.5–10.2% for the exchange rate USD/JPY respectively.

Exchange rate prediction with monthly step is shown in Figs. 8–13.

Exchange rate prediction with quarterly step is shown in Figs. 14–19.

The summary of the prediction results are collected in Table 1.

6. Conclusions

The application of neural networks to predict exchange rates EUR/USD, GBP/USD and USD/JPY in daily, monthly and quarterly

Please cite this article as: S. Galeshchuk, Neural networks performance in exchange rate prediction, Neurocomputing (2015), http://dx.doi.org/10.1016/j.neucom.2015.03.100

steps is considered in the paper. The results of exchange rate prediction using short-term prediction method are summarized in Table 1. These results show that the short-term prediction method provides good accuracy of the prediction and can be used in practical systems to predict the exchange rate for one step ahead.

In the conditions of the modern financial technologies and evolution of financial markets the competition among the participants of financial world becomes more and more significant. Despite the EMH technical analysis is still in demand as traders refuse to give up with naive strategy and they still gain their profits. In the time quick development of the computation systems, we are convinced, will create the yet non-studied technological bias. This would require further research on the topic that points to the direction of ANNs. By imitating the biological evolution process, neural networks try to find optimal or new optimal solutions with relatively modest computational requirements.

However, exchange rate forecasting is not only interesting for correction traders but also for international companies which want to decrease exchange exposure. In fact, exchange rate prediction is relevant to all sorts of firms, disregarding its size, geographic dispersion, or core business. The reason is that whether or not a firm is directly involved in international business through imports, exports, and direct foreign investment, its purchases of imported products or services may require payment in a foreign currency. This opens another research question how to find the best strategy to diminish currency risks for the enterprises in the conditions of the current exchange-rate markets. In the light of our researches it is promising to work out a number of prediction approaches as well as neural networks methods with multi-step prediction mode (in this paper we used one-step mode) to find the forecasted exchange rate on the given date. We consider this as our further research question.

References

[1] M. Štěpnička, P. Cortez, J. Peralta Donate, L. Štěpničková, Forecasting seasonal time series with computational intelligence: on recent methods and the potential of their combinations, Expert Syst. Appl. 40 (6) (1981–1992).

[2] Haykin, S. Simon, Neural networks and learning machines, 3, Pearson Education, Upper Saddle River, 2009 http://www.mif.vu.lt/~valdas/DNT/Literatura/Haykin09/Haykin09.pdf.

[3] E. Gurusen, G. Kayakulu, T. Daim, Using artificial neural network model in stock market index prediction, Expert Syst. Appl. 38 (8) (2011) 10389–10397.

[4] Y.-Q. Zhang, X. Wan., Statistical fuzzy interval neural networks for currency exchange rate time series prediction, Appl. Soft Comput. 7 (4) (2007) 1149–1156.

[5] V. Golovko, Y. Savitsky, T. Laopoulos, A. Sachenko, L. Grandinetti, Technique of learning rate estimation for efficient training of MLP, in: Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks IJCNN, vol. 1, 2000, pp. 323–328.

[6] R. Meese, K. Rogoff, Empirical exchange rate models of the seventies: do they fit out of sample? J. Int. Econ. 14 (1/2) (1983) 3–24.

[7] R. Meese, K. Rogoff, The out-of-sample failure of empirical exchange rate models: sampling error or misspecification? Exchange Rates and International Macroeconomics, 4 (1) 1983b, pp. 67–112.

[8] M. Alvarez-Diaz, R. Bissoondeeal, J. Binner, M. Bhuruth, A. Gazely, V. Mootanah, Forecasting exchange rates with linear and nonlinear models, Appl. Econ. 40 (2) (2008) 1969–1984.

[9] M. Lam, Neural network techniques for financial performance prediction: integrating fundamental and technical analysis, Decis. Support Syst. 37 (4) (2004) 567–581.

[10] H. Thinyane, J. Millin, An investigation into the use of intelligent systems for trading, Comput. Econ. 37 (4) (2011) 363–374.

[11] E. Önder, B. Fırat, A. Hepşen, Forecasting macroeconomic variables using artificial neural network and traditional smoothing techniques, J. Appl. Finance Bank. 3 (4) (2013) 3–104.

[12] C. Kuan, H. White, Artificial neural networks: an econometric perspective, Econom. Rev. 13 (1) (1994) 1–91.

[13] N. Swanson, H. White, Forecasting economic time series using flexible versus fixed specification and linear versus nonlinear econometric models, Int. J. Forecast. 13 (4) (1997) 439–461.

[14] M. Qi, G. Madala, Economic factors and the stock market: a new perspective, J. Forecast. 18 (1999) 151–166.

[15] R. Gencay, Linear, nonlinear and essential foreign exchange prediction with simple technical trading rules, J. Int. Econ. 47 (1999) 91–107.

[16] A. Santos, N. da Costa, L. dos Santos Coelho, Computational intelligence approaches and linear models in case studies of forecasting exchange rates, Expert Syst. Appl. 33 (4) (2007) 816–823.

[17] F. Ozkan, A comparison of the monetary model and artificial neural networks in exchange rate forecasting, Bus. Econ. Res. J. 3 (1)) (2012).

[18] C. Dunis, X. Huang, Forecasting and trading currency volatility: an application of recurrent neural regression and model combination, J. Forecast. 21 (5) (2002) 317–354.

[19] R.K. Bissoondeeal, M. Karoglou, A.M. Gazely, Forecasting the UK/US exchange rate with divisia monetary models and neural networks, Scott. J. Political Econ. 58 (1) (2011) 127–152.

Svitlana Galeshchuk is a Ph.D. candidate at Ternopil National Economic University (Ukraine). She got MSc in Banking at Ternopil National Economic University (Ukraine) and Master 2 in Management of European Affairs at Lille 1 University – Science and Technologies (France). Eiffel Excellence grand holder (2013, France). The key areas of her scientific interests include the specific areas of financial indices prediction with a number of computation methods.

Please cite this article as: S. Galeshchuk, Neural networks performance in exchange rate prediction, Neurocomputing (2015), http://dx.doi.org/10.1016/j.neucom.2015.03.100