

TL/EURO AND LEU/EURO EXCHANGE RATES FORECASTING WITH ARTIFICIAL NEURAL NETWORKS¹

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Abstract

Forecasting is a popular research topic that is getting more and more attention from researchers and practitioners in various fields. It is a well-known fact that exchange rate forecasting is an important and challenging task for both academic researchers and business practitioners. Therefore, various approaches have been suggested in the literature for exchange rate forecasting. The forecasting techniques range from Box-Jenkins models to artificial networks. Artificial neural networks have also been successfully applied to various time series forecasting problems since they can model both linear and non-linear parts of time series. In addition, artificial neural networks method does not require assumptions such as those of other commonly used conventional methods. In this study, artificial neural networks are utilized to forecast TL/EUR and LEU/EUR exchange rates. In order to reach high forecasting accuracy level, different artificial neural networks models are examined and the obtained best results are compared to those produced by Box-Jenkins models.

Keywords: Artificial neural networks, Box-Jenkins models, Exchange rates, Forecasting, Time series.

JEL Classification: C45, C51, C53, F37

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1. Introduction

Time series forecasting is a popular research topic of common interest in many disciplines such as statistics, economics, management, and so on (Aladag and Egrioglu, 2012). Therefore, both academicians and practitioners from the areas such as finance, accounting, marketing, operations management, human resource management, statistics, international business, information technology, environment, risk management, globalization and related areas have interested in this subject (Aladag, 2011a). Exchange rate forecasting is one of the most popular time series forecasting problems. Thus, various approaches have been proposed in the literature to reach better exchange rate forecasts. Kadilar et al. (2009) presents brief information about exchange rate forecasting given as follows:

“Along with the beginning of the application of the flexible exchange rate system, prediction of exchange rate movements gained importance. Changes in exchange rates have an effect on imports, volume of external trade, balance of payments, inflation and public debt. In this respect, exchange rate is an important factor in an economy as both an important indicator of total demand and also in the application of financial policies.

However, exchange rates may not always be completely predictable. This is because movements in exchange rates have highly varying, chaotic and noisy structures. This characteristic makes exchange rates difficult to predict. For this reason, estimating exchange rate movements is always a difficult and important topic in academic frameworks and business life and, therefore, this has been one of the main concerns of academics and other researchers in multi-national financing.”

One method to forecast exchange rates is utilizing artificial neural networks approach. Artificial neural networks method has the ability of forecasting both linear and non-linear structure of time series (Aladag et al., 2009a). In addition, artificial neural networks method does not require assumptions such as those of other commonly used conventional methods (Yolcu et al., 2012). Artificial neural networks approach has been already employed to forecast various kinds of time series (Aladag and Marinescu, 2011). Therefore, it would be wise to use artificial neural networks for forecasting exchange rates. In this study, Turkish liras (TL)/Euro (EUR) and Romanian Leu (RON)/EUR exchange rates are forecasted by using artificial neural networks. In order to get accurate forecasts, various artificial neural network models are examined for both time series. Also, both time series are forecasted utilizing Box-Jenkins models for the aim of comparison. As a result of the implementation, it is observed that using artificial neural networks produces the most accurate results for both time series.

In the next section, fundamental elements of artificial neural networks are reviewed. The implementation and the obtained results are presented in Section 3. Finally, last section concludes the paper.

2. Artificial Neural Networks

Artificial neural networks approach is an efficient forecasting tool(Aladag, 2011b). This method consists of algorithms that mimic the features of brain of human being. These features are generating new knowledge and exploring by learning (Egrioglu et al., 2009).ANN consist of some elements which effect the forecasting performance of the method. Therefore, determining the elements of ANN issue should be considered carefully. The fundamental elements of ANN can be given as follows (Egrioglu et al., 2008):

Architecture structure: Feed forward ANN has been widely used for forecasting problems because of their simple usage and success. The structure of multilayer feed forward ANN is basically given in Figure 1. Multilayer feed forward ANN as illustrated in the figure consist of three parts such as input, hidden, and output layers. Each layer consists of neurons. The architecture structure is determined based on deciding the number of neuron in each layer. These neurons are linked each other by weights. There is no link among the neurons in the same layer. For a forecasting problem, the inputs of the network are past lagged observations. One critical decision is to determine the appropriate architecture, that is, the number of layers, number of nodes in each layer (Zurada, 1992). However, in the literature, there are not general rules for determining the best architecture (Aladag et al., 2009b).

Learning algorithm: There have been many learning algorithms in order to determine weights. The one of the most employed algorithm is called Back Propagation Learning Algorithm. This learning algorithm updates the weights based on difference between real value and output value of the ANN. However, back propagation networks have some disadvantages mentioned in the introduction. In light of the weakness of the conventional back propagation algorithm, a number of variations or modifications of this algorithm, such as the adaptive method, quickprop, and second-order methods etc., have been proposed (Zou et al., 2007). Among them, the second-order methods such as Levenberg Marquardt method are more efficient nonlinear optimization methods and are used in most optimization packages. Their faster convergence, robustness, and the ability to find good local minima make them attractive in ANN training (Zou et al., 2007). Therefore, Levenberg Marquardt method is used as training algorithm in the implementation.

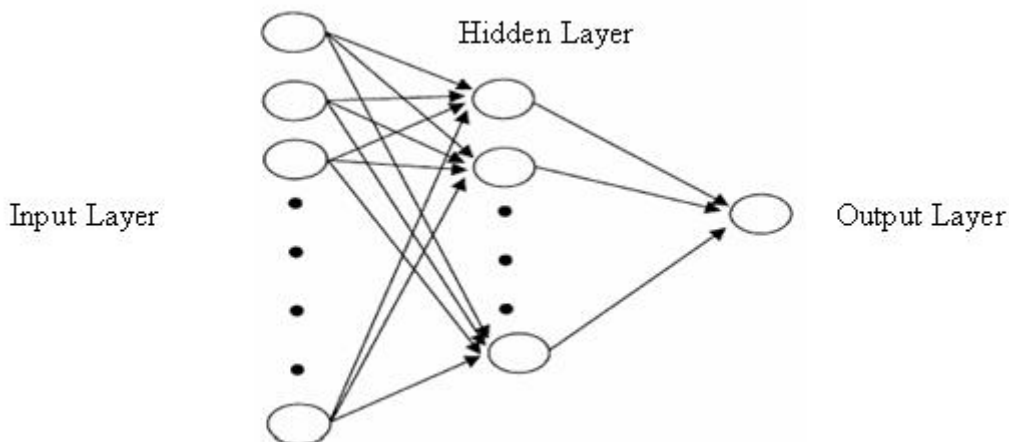


Fig. 1. Multilayer feed forward ANN with one output neuron

Activation function: Activation function provides the non-linear mapping between input and output. The performance of networks depends on the proper choice of activation function. Activation function can be chosen as either linear or double polarized, or one polarized. Slope parameter should be determined when the activation is non linear. Also, slope parameter plays a key role in reaching desired output values.

3. Forecasting Exchange Rate Series

For the exchange rate series, we take the monthly rates of TL/EURO and RON/EURO series between the period January, 2005 and August, 2012. Both time series have 92 observations and the graphs of time series are shown in Fig. 2. The first 84 and the last 8 observations are used for training and test sets, respectively.

Determination of a network structure involves the selection of an input parameters input layer, the number of hidden layer neurons and also a combination of transfer functions between the layers (Park and Lee, 2011). Logistic activation function was used in all neurons of a network. As mentioned before, Levenberg Marquardt method was used as training algorithm. In order to obtain accurate forecasts, numbers of neurons in both the input and the hidden layers were varied between 1 and 12. And, one neuron was used in the output neuron. Thus, 144 network architectures were totally examined for each time series.

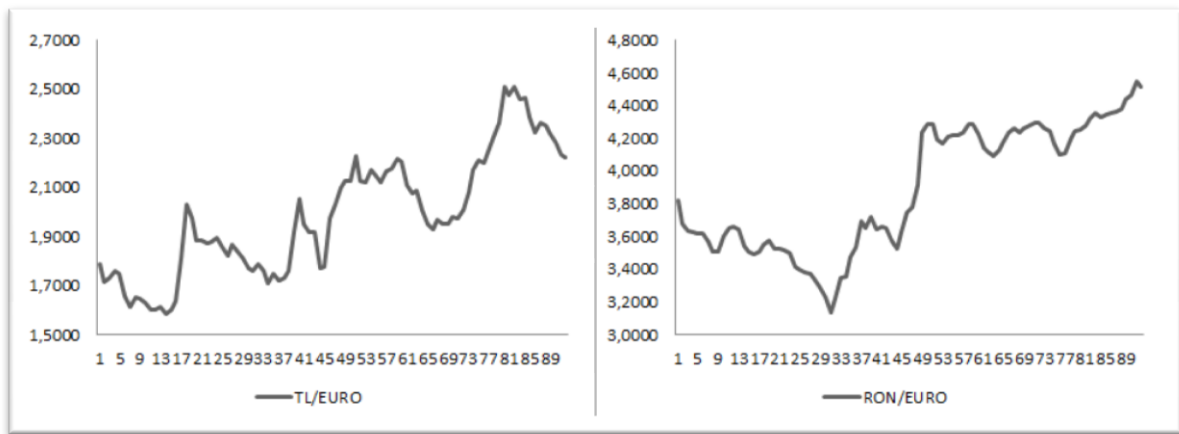


Fig. 2. The graphs of exchange rates time series

In the literature, the most preferred performance measure is root mean square error (RMSE) so RMSE values calculated over the sets were used to evaluate the forecasting performance of the models. The expression of RMSE is given as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (forecast_t - actual_t)^2}{n}} \quad (1)$$

where t represents the time and n is the number of observations in the test set. $forecast_t$ is the forecast at t from any mentioned model and $actual_t$ is the observed value at t .

These exchange rates were also analyzed by Box-Jenkins models for comparison. As a result of the implementation, all obtained forecasting results are summarized in Table 1. In the table, the best models for Box-Jenkins and artificial neural networks (ANN) methods and the corresponding RMSE values are presented. For example, when RON/EUR exchange rates are forecasted by artificial neural networks, the best forecasts are obtained from the architecture 4-8-1, which means that this architecture has 4 and 8 neurons in the input and hidden layers respectively, with 0.00865RMSE value.

According to Table 1, it is clearly seen that the most accurate forecasts for both time series were obtained when artificial neural networks were utilized. For both exchange rate series, artificial neural networks produced very accurate forecasts in terms of RMSE criterion. As a result of the implementation, it can be said that artificial neural networks should be preferred instead of conventional Box-Jenkins models when TL/EUR and RON/EUR exchange rates are tried to be forecasted.

Table 1. The obtained forecasting results

Time Series	The best models	
	Box-Jenkins	ANN
TL/EUR	ARIMA(1,1,0)(0,0,0) (0.01849)	12-4-1 (0.00335)
RON/EUR	ARIMA(0,1,0)(0,0,0) (0.04127)	4-8-1 (0.00865)

4. Conclusion

Exchange rate forecasting is an important and a hard forecasting problem. This forecasting problem is getting more and more attention from researchers and practitioners. In the literature, there have been different forecasting approaches for exchange rates. Recently, artificial neural networks have been also utilized to forecast such time series. In this study, in order to reach high forecasting accuracy level, different artificial neural network models are employed to forecast TL/EUR and RON/EUR exchange rates time series. In addition, Box-Jenkins models are used to analyze these two series for the aim of comparison. As a result of the implementation, it is observed that artificial neural networks give very accurate forecasts for both time series in terms of RMSE measure. Besides, it is seen that artificial neural networks produce more accurate results than those obtained from Box-Jenkins models. Consequently, it can be said that artificial neural networks should be employed to forecast both TL/EUR and RON/EUR exchange rates instead of using Box-Jenkins models.

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