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Prediction of Exchange Rate of EUR/USD by Using Lagged Models of ANN

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ABSTRACT

Predicting the market price movements and forecasting the projections about future price are challenging applications. To utilize the prediction process, it is aimed in this paper to improve the accuracy rate in the prediction of the market price movements and to determine the volatility pattern of exchange rate. We build 3 ANN Models to test the prediction power of ANN and compared these models to elicit the best model in exchange rates. Comparison of these models showed that input selection is very important. Furthermore, our findings show that the ANN model with three lagged values as input has the best capability to produce more accurate results than remaining models.

Keywords: *exchange rate prediction; exchange rate return; artificial neural networks*

INTRODUCTION

The financial market includes uncertainties and expectations of its future status in the short, medium and long terms. Proposed different prediction techniques have been applied to reduce the uncertainty of such a dynamic market. The ambiguity of the dynamic market has attracted the interest of academic researchers and market professionals.

According to the efficient market theory, demand and supply in the stock market is dominated by the expected future price, and it is impossible to forecast the changes in price (Parkin, 1999). Likewise, foreign exchange is also dominated by the expected future exchange rate and other various market factors. However, investors try to make the profit which depends on exchange rate. They plan to make a profit by buying at low price and selling at high price considering reflection of many factors that include local and global political conditions, economic conditions and other investors' sentiments. Consequently, financial analysts and investors need to observe the foreign exchange rate trends in order to obtain positive financial return on their transactions.

Predicting the market price movements and forecasting the projections about future price are challenging applications since supply and demand are not independent and they determine the exchange rate. Such a situation bolsters up its paradoxical structure and makes difficult to expect the future prices.The higher the expected future rate leads to the greater demand and the smaller supply in the foreign exchange market or vice versa. Therefore, it is difficult to make short and long term forecasting efficiently. The biggest challenge in this field comes from its complex and chaotic nature. Most prediction models are confined to determine the direction of future prices when undetermined fluctuations occur. However, the inherent difficulty in making accurate forecasting empowers the inventors to use the existing historical data and different methods in order to predict and evaluate price movements. New information about future price forms new expectations for future price or volatility, and enhances the interpretation of historical data and exterior conditions.

The existing inherent complexity is the major factor for this study that aims to improve the accuracy rate in the prediction of the market price movements and to gather the valuable information to the investors. Another aim is to determine the volatility pattern of exchange rate if possible. Like all predictions, the study has been based on to achieve best results using required input data and the least complex foreign exchange model.

It is certainly necessary to identify which variables help to predict the foreign exchange rate. This means which important variables may be used as an explanatory variable of the stock market price. The relationships between many variables are important issue to be considered. Furthermore, many other exterior factors, including political events and economic conditions interact within the financial market. Such as, Pargam and Jamshidi (2015) mentioned that exchange rates are affected by many correlated economic, political and even psychological factors. For this reason, accurate forecasting needs extra and valuable information from the economic environment in the global world.

Following the introduction, the rest of this paper is organized as follows. Section 2 introduces the literature, and followed by Section 3, Data, Methodology and Application. Section 4 covers the discussion points of the study. Finally, conclusions are given in Section 5.

LITERATURE REVIEW

In economy where uncertainly is dominating other features, investors and academicians have been willing to predict the future of economical values. To be honest, it is complex and challenging task to predict the economical values in all aspects. Economic prediction is wide and consisting of many areas like commodity prices (oil, gas, gold, etc), markets, bonds, exchange rates, etc. Different methods have been applied to make predictions about the ûnancial market. Such methods may be grouped into four main categories: (i) Fundamental Analysis, (ii) Technical Analysis, (iii) Prediction of Time Series with Traditional Models and (iv) Machine Learning Methods (Oliveira et. al., 2013). ANN have been widely used in terms of prediction in the recent studies, like stock exchange (Hafezi *et al.*, 2015; Zahedi and Rounaghi, 2015; Kýlýç et. al., 2014; Ticknor, 2013; Oliveira *et al.*, 2013; Wang *et al.*, 2012; Guresen *et al.*, 2011; Kara *et al.*, 2011; Wang *et al.*, 2011; Yudong &Lenan, 2009), commodity prices (Lasheras *et al.*, 2015; Yu *et al.*, 2015; Kristjanpoller & Minutolo, 2015; Yu *et al.*, 2014; Salehnia *et al.*, 2013; Jammazi & Aloui, 2012; Yu *et al.*, 2008), exchange rates (Galeshchuk, 2016; Rehman *et al.*, 2014; Kýlýç, 2013; Sermpinis *et al.*, 2012a; Sermpinis *et al.*, 2012b; Majhi *et al.*, 2012; Majhi *et al.*, 2009; Ni & Yin, 2009; Panda & Narasimhan, 2007; Ince & Trafalis, 2006; Yu *et al.*, 2005; Yao &Tan, 2000; Zhang & Hu, 1998; Shazly & Shazly, 1999; Shazly and Shazly, 1997).

Researchers did not anchor in only ANN and its extensions to predict the economical values. The linear traditional models such as autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroscedastic (GARCH) models and their extensions are also excelling in literature. Recently, Zhang *et al.* (2015) used the ensemble empirical mode decomposition (EEMD) method to decompose international crude oil price into a series of independent intrinsic mode functions (IMFs) and the residual term. Then, the least square support vector machine together with the particle swarm optimization (LSSVM–PSO) method and GARCH model are developed to forecast the nonlinear and time-varying components of crude oil prices.

Sharma and Vipul (2015) compared the forecasting ability of the Realized GARCH model with that of the standard GARCH models that use only the daily returns and the other time series models based on the realized measures of volatility. Each model is used for forecasting the conditional variance of several international stock indices, for a sample period of about 14 years. Bentes (2015) applied three volatility models of the GARCH family (GARCH, IGARCH and FIGARCH) to examine the volatility behavior of gold returns. The results showed that the FIGARCH was the best model to capture linear dependence in the conditional variance of the gold returns as given by the information criteria. FIGARCH was also found to be the best model among these methods to forecast the volatility of gold returns.

Babu and Reddy (2015) proposed a hybrid model of ARIMA-GARCH that provided scope for preserving data trend across the forecast horizon while maintaining good prediction accuracy. Tian and Hamori (2015) proposed a realized GARCH (RGARCH) model to estimate the daily volatility of the short-term interest rate in the euro-yen market. The model better ûtted the data and provided more accurate volatility forecasts by extracting additional information from realized measures. In addition, they proposed the ARMA-RGARCH model to capture the volatility clustering and the mean reversion effects of interest rate behavior. It was found that ARMA-RGARCH model ûtted the data better than the simple RGARCH model, but it didn't provide superior volatility forecasts.

While these models are used by researchers mainly, there are also hybrid methods of ARIMA and GARCH models with ANN. These hybrid metods are used to predict different economical values like commodity prices (Kristjanpoller & Minutolo, 2015; Lasheras *et al.*, 2015), exchange rates (Sermpinis *et al.*, 2012a; Sermpinis *et al.*, 2012b; Ince & Trafalis, 2006) and stock exchange (Wang *et al.*, 2012; Guresen *et al.*, 2011).

In this study, we will focus on ANN to predict the future of exchange rates because in recent years, ANN has been demonstrated to be successful research models to forecast the economical values. ANN models were developed to forecast, detect and summarize the structure of financial variables without relying too much on specific assumptions and error distributions (Duan & Stanley, 2011).

METHODOLOGY

This research utilized the process which used the historical data of several indicators as, exchange rate of EUR/USD, oil prices, gold prices and Dow Jones stock exchange prices to predict the exchange rate. The data about this research with daily step are gathered from site *http://tr.investing.com*. Data are collected for the period from 3 th December 2010 till 30 th August 2015. Fluctuation character of the inputs made this research more interesting and challenging as the non-linear volatile nature of inputs are varying due to several impacts in the selected time era. Examples of the visualization of gathered data for prediction of exchange rate of EUR/USD are depicted in the following figures from Figure 1 to Figure 3 for the period 2011-2015.

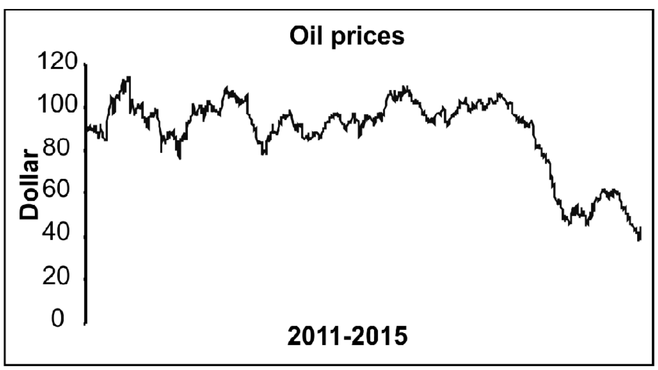

Figure 1: Oil Prices

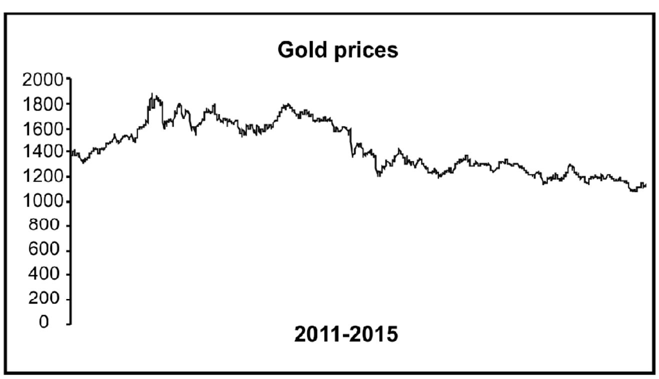

Figure 2: Gold Prices

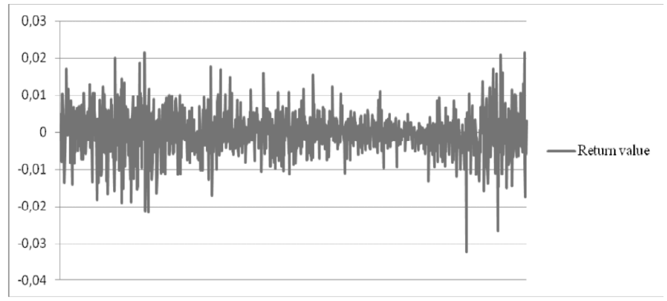

Figure 3: Return Value of Exchange Rate of EUR/USD

In this study, at most three lagged values of daily returns of indicators; exchange rate of EUR/USD, oil prices, gold prices and Dow Jones stock exchange prices are used as input variables in ANN models to predict daily movements of exchange rate of EUR/USD. The output of the ANN models is denoted as $RDIR_t$ and defined by the following functions (1) and (2);

$$R_t = (P_t - P_{t-1}) / P_{t-1},\ t = 1\ldots1180 \quad (1)$$

Here R_t denotes the return rate of EUR/USD exchange rate, t resembles the date while P_t shows the closing price of the data. Direction of return rate, $RDIR_t$ will be acquired through eq. (2) by the help of daily returns of eq. (1).

$$RDIR_t = \begin{cases} 0, & R_t < 0 \\ 1, & R_t \geq 0 \end{cases} \quad (2)$$

The values of return rate in eq. (2) as 0 and 1 represent the price decline and increment respectively. In the study, we created different models of ANN to test the efficiency of the prediction power of each models. Lagged models (R_{t-1}), (R_{t-2}) and (R_{t-3}) will be tested and the results will be compared with conventional ANN approach. In all ANN models, daily returns of the exchange rate of EUR/USD are characterized with (0) for negative income and with (1) for positive income in the forms of $RDIR_t$, $RDIR_{t-1}$, $RDIR_{t-2}$ and $RDIR_{t-3}$. Daily returns are shown in eq. (2) in two different category since there are only 14 $R_t = 0$ in data set. And finally, the whole sample data covers 1180 daily returns for considered period.

ANN is one of the relevant techniques to model the data which does not contain standard formulas in fluctuating market, and may be easily adapted to market changes (Ince & Trafalis, 2006; Oliveira *et al.*,2013). ANN has the ability to learn by example and make interpolations and extrapolations of what they learned. The use of ANN in the solution of a task initially involves a learning phase to extracts the patterns, thereby creates a specific representation of the problem (Oliveira *et al.*, 2013). ANN has many different neural network models to process the training and learning stage. Multiplier perception (MLP) network is the one of the most popular networks. It is widely applied to extract ANN model for the complex and mathematically non-modeled problems since it has the learning capability to obtain the best weights, used in the layers of neural network. A neural network has at least three layers such as input, hidden and output. MLP network has the capability to identify the complex map between the initial layer and last layer.

The major advantage of neural networks is the ability to produce a flexible mapping. Having a general map between the input and output layers eliminates the need for unjustified restrictions that are needed in conventional statistical and econometric modeling (Yu *et al.*, 2007). The ANN architecture represents this relationship between initial and last layer, and the relation between input and output is determined with transfer function in nodes (Chen *et al.*, 2014). A typical artificial neuron model in Figure 4 is widely used in neural networks with minor variations. The figure includes n inputs and n weights which are denoted as $X_1 \ldots X_n$ and $W_1 \ldots W_n$ respectively, summing function and activation function as well. In the input layer, each weighted input is summed and activated with an activation function to produce the output to the next layer. The output y of input layer is the input of the next layer, named hidden, since the order of layers are input, hidden and output in the ANN architecture. Similarly, the output of the output layer is the predicted value of the ANN algorithm.

$$u = \sum_{i=1}^{n} x_i \, w_i + \theta$$

Here, θ is the activation function.

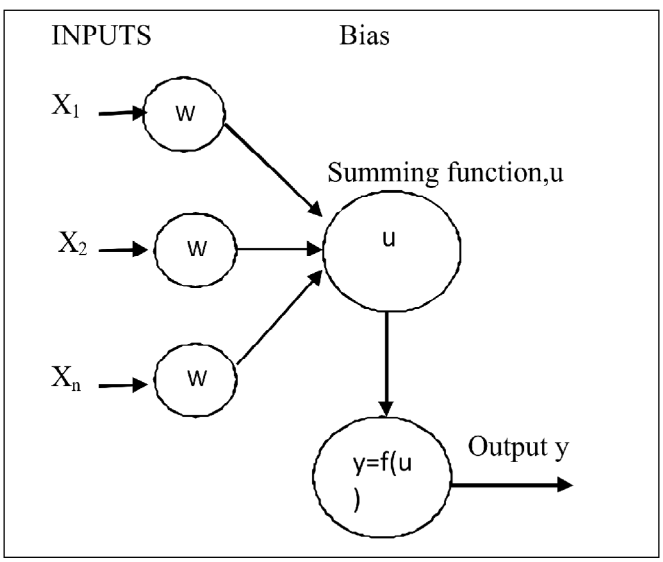

Figure 4: An Artificial Neuron Model (Source: Akhmet & Yılmaz, 2014)

Another important parameter in ANN is the learning algorithm which is an iterative process with learning ratio. Back propagation algorithm is used to search the optimal weights in the network which combines feed forward networks and error estimation process (Yu *et al.*, 2007). The training of network is checked by the learning ratio of algorithm and weight matrices are updated (Chen *et al.*, 2014). Value of weights is real numbers but positive value for weights shows an excitatory connection while negative value shows an inhibitory one (Akhmet &Yýlmaz, 2014). For that reason, updating weight matrices systematically during back propagation process is highly important and beneficial for accurate predicting.

Step size is used to control the learning speed and real convergence (Yu *et al.*, 2007).

The crux of the ANN is the ability to learn and then improve its performance from data. There are various learning method used in ANN. Back propagation learning mechanism, one of them, consists of two phases: forward propagation and backward propagation phase. In the forward phase, data is feed into the input layer, and an output is generated depending on the initial weights of the layers. Since the aim is to minimize the error function S on the output (y),

$$S = \sum_{i=1}^{1180} (y_i - \hat{y}_i)^2$$

in the backward phase the gradient descent is performed on the weights space to locate the optimal solution . The direction and magnitude change of weights (Δw_{ij}) are changed as

$$\Delta w_{ij} = -\frac{\partial S}{\partial w_{ij}} \varepsilon$$

where $0 < \varepsilon < 1$ is a learning parameter which controls the convergence rate of the algorithm during each iteration of BPNN algorithm until E converges (Chen *et al.*, 2014). As shown in the above formulas, sum of square of the difference between actual value and predicted value has a crucial impact on determining the new and better weights than previous ones. Weight adjustments are performed on the way of propagation at each level and layer in the iterations. Therefore, the learning algorithm is known as the process of determining the optimal weights between nodes of ANN (Kılıç, 2013; Yu *et al.*, 2007) since the strength of neurons' connection depends upon the weight.

On the other side, neurons are storing the weights and biases of nodes through data from learning stage. Depending on this knowledge, ANN is a model which has capacity to depict the nonlinear relation of inputs and outputs. The relation between input and output is determined with transfer function in nodes and transferred to the following node with function (Chen *et al.*, 2014). The activation function in each layer should be differentiable function theoretically (Kılıç, 2013; Chen *et al.*, 2014) such as threshold function, linear function, tangent hiperbolic and sigmoid function.

In this study, sigmoid function is selected for the activation function and BPNN is preferred for the learning algorithm. The number of hidden layers is adjusted by the system during testing the ANN models.

RESULTS

Exchange rate forecasting is a difficult task due to a large number of factors that influence the daily value. Therefore 4 different ANN models are tested to predict the direction of EUR/USD exchange rate. ANN Model 0, which uses exchange rate of EUR/USD, oil prices, gold prices and Dow Jones Stock Exchange closing prices as inputs is tested at the initial state. After training the model, test results mainly demonstrate that the outcomes are not consistent. To overcome this inconsistency and to obtain more detailed research we have needed data transformation process. Data transformation mainly aims to transform time series data into a training form so as to satisfy the basic condition of neural network learning (Yu *et al.*, 2007). So data is transformed into lagged values with lag periods (one day, two day and three day) of all variables of this study. ANN is executed and trained for each transformed data separately and ANN models are named as Model 1, Model 2 and Model 3, according to lagged days.

The main reasons of lagged models are both testing the reliability of the models and giving freedom to the investors for choosing a method. Also it was aimed to compare the results of the models. The inputs of the Model (0) were mentioned above but for the Model (1), we also used one day lagged values of oil prices, gold prices and Dow Jones Stock Exchange closing prices in addition to Model (0) inputs. Similar to Model (1), we included two day lagged values of aforementioned values for the Model (2). The same logic was followed for Model (3) and all models were tested to predict the direction of exchange rate of EUR/USD.

We demonstrated the best results for each ANN models in Table 1 for the all ANN models which include different trends. Table 1 shows the best prediction values for the training and the testing trials for each method. In Table 1, the direction of the prediction is named upward for the increase, downward for the decrease and moderate trend which shows a slight increase or decrease.

The "trend" columns show the result of each model after several trials. The determined results are best results of the trials. Table 1 shows that Model (0) predicts the direction of exchange rate of EUR/USD upward with 65,6% while 72,8% downward in other trial. For each upward and downward predicition, the estimation power seems close to each other with the results, 55,1% and 52,7 %. The estimation power of moderate trend for Model (0) is 54,1%.

The estimation power of Model (1) and Model (2) is better than Model (0) for the three trends. But it is also obvious that this estimation power of these models is not dominanat in each trend.

This situation leads us to develop the Model (3) and to compare with the previous models. After several trials, Model (3) test results showed that the outcomes of the trials are close to each other. Regarding to this results, estimation power of Model (3) is the most strongest among others with approximate 65%. It can be inferred that there is a modest improvement in the prediction of exchange rate movement.

We believe that interpreting the table is very important because Decision Maker (DM) can decide by looking the highest result of the table with 72%. It

Table 1: Best Prediction Results for Each ANN Models.

Models		*Upward trend %*			*Downward trend %*			*Moderate trend %*		
		0	*1*	*Correct*	*0*	*1*	*Correct*	*0*	*1*	*Correct*
Model 0	Training %	36,3	63,7	54,0	73,4	26,6	54,1	58,0	42,0	55,2
	Testing %	34,4	65,6	55,1	72,8	27,2	52,7	51,5	48,5	54,1
Model 1	Training %	44,5	55,5	61,9	62,3	37,7	59,3	54,0	56,0	62,8
	Testing %	41,5	58,5	66,9	62,4	37,6	61,0	50,1	49,9	64,2
Model 2	Training %	34,7	62,6	60,1	59,9	40,1	59,5	49,7	50,3	64,2
	Testing %	40,5	59,5	61,3	64,9	35,1	60,0	48,5	51,5	62,2
Model 3	Training %	50,9	49,1	65,5	53,5	46,5	60,8	49,8	50,2	62,2
	Testing %	48,0	52,0	64,9	55,4	44,6	64,6	50,4	49,6	65,0

is beyond our suggestion since the DM should consider all the prediction ratios and estimation power.

DISCUSSION OF RESULTS

In this research, after many trials, upward, downward and slight up-downward estimation results are obtained. Overall results show that exchange rate of EUR/USD is highly affected by the fluctuation of inputs. Model (0) presents that exchange rate of EUR/USD is affected excessively by the daily fluctuation of inputs. Although Model (1) and Model (2) contributed more to the training process of predicting exchange rate of EUR/USD, the gap between upward and downward trend is increasingly diminished. It profoundly affects to make decision, and causes a doubt in expressing the direction of the price movement. When the Model (3) have been put forth for the consideration, it is seen that accuracy percent of the predicted model has increased. As to model (3), low price probability and high price probability of exchange rate of EUR/USD are close to each other with a relatively higher accuracy percent than the accuracy percent of Model (1) and Model (2). In this sense, Model (3) reveals that decision makers or investors should be more cautious. Model (3) also indicates that the other parameters should be taken into consideration in the prediction of exchange rate of EUR/USD.

CONCLUSION

Empirical results show that fluctuations involved in the data inevitably influences the performance of trained ANN models. These findings may result from the possibility that economic conditions and political decisions not considered in framework of the study play an important role.

Additionally, empirical results verify the validity of rational expectations theory which attempts to explain how economic agents have formed the financial expectations. Efficiency market theory which is the application of theory of rational expectations in financial market suggests that optimal prediction is possible using all available information (Mishkin, 1998). Despite of the efficiency market theory, people who have better forecasts about the future get financial advantages in financial market. This follows that the more reliable information is obtained, the better predictions are available.

The results of ANN models with three trends may enlighten investors or DMs who have need the reasonable information that may be used to make a prediction on EUR/USD exchange rate direction. However it should be noted that the results can be regarded as providing extra information only which may be useful in predicting the future value of EUR/USD direction.

We used daily data in this research. Further similar analysis can also be performed by smaller time intervals, such as hourly changes. It will be possible to gather more useful information by using small time intervals.

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