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Artificial Neural Networks endowed with External Factors for Forecasting Foreign Exchange Rate

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Abstract

The successful key of trading in the forex market is the selection of correct exchange in proper time based on an exact prediction of future exchange rate. Foreign exchange rates are affected by many correlated economic, political and even psychological factors. Therefore, in order to achieve a profitable trade these factors should be considered. The application of intelligent techniques for forecasting has been proved extremely successful in recent years. Previous studies have mainly focused on the historical prices and the trading volume of one market only. In this paper, we have used Artificial Neural Networks (ANN) *to predict the exchange rate with respect to three external factors including gold, petroleum prices and FTSE 100 index. The result of forecasts is compared with the ANNs without external factors. The empirical results demonstrate that the proposed model can be an effective way of forecasting. For the experimental analysis phase, the data of exchange rate of GBP/USD is used.*

Keywords: *Forex market, GBP/USD, Artificial Neural Networks, Gold price, Petroleum price, FTSE*

1. Introduction

Regarding the size and importance of financial markets, foreign exchange market (forex) is the biggest and the most important one in the world. Individual investors who are considering participating in the forex market need to completely understand the market and its unique characteristics. Different parameters such as political, economic, and psychological ones affect the exchange rate fluctuations [1]. The interaction of these factors is in a very complex fashion. Therefore, forex trading is generally very risky and difficult. Like many other economic time series, forex has its own trend, cycle, season, and irregularity. Thus, in order to give a satisfactory forex forecasting the major challenge is to identify the model, extrapolate and recombine the aforementioned patterns. Technical and fundamental analyses are the basic and major forecasting methodologies which are in popular use in financial forecasting. Technical analysis means the analysis of fluctuations of price in the past is done with the help of diagram for the sake of predicting future movements. Every data, information and news that effects the supply and demand of the financial properties is straightly considered as a fundamental data. Fundamental analysis is a method that the effect of fundamental data on the economy situation, markets and industries is analyzed, so with that it could discover the reaction of capitalists and the common emotion of markets. Various kinds of forecasting methods have been developed by many researchers and experts [2], [3], [4], [5], [6], [7], [8], [9]. Regarding various methods of forecasting exchange rates, multivariate time series models have received much attention in the literature and tend to produce the best forecast for unseen data. The literature on multivariate time-series models is quite extensive. Specifically in the area of exchange rate forecasting Hoque and Latif [10], Liu et al. [11] showed that multivariate time-series models have some forecasting strength in predicting exchange rates and are able to produce forecasts that are superior to the random walk model.

Multilayer Perceptron neural networks (MLP) [12], radial basis function (RBF) [13] neural networks, and self-organizing map (SOM) [14] networks are three techniques used mostly and to a great degree in artificial neural networks [15], [16]. Sometimes a hybrid model of different types of artificial neural networks and statistical models are used to achieve a better prediction [1], [17], [18], [19]. According to a survey research conducted by Wong [20], more than 127 neural network business applications had been published in international journals up to September 1994. The number rose to 213 after a year Wong et al. [21]. The major advantage of neural networks is their flexible nonlinear modeling capability.

Many external and internal factors can affect exchange rate prediction. The influence of external factors has not been widely discussed in the literature. In [22] the gold price has been used as an external factor to predict exchange rate. In this paper we propose a neural network approach to the analysis and forecasting of financial time series based on a combination of external factors including gold, petroleum prices and FTSE 100 index.

The layout of this paper is as follows. In Section 2 the neural networks learning algorithm is reviewed and the structure of the proposed method is described. Section 3 discusses the data preparation process used as the input of the neural network model. Section 4 provides empirical results that demonstrate the performance of the proposed model. Finally, Section 5 summarizes the results of this work.

2. Neural networks in forecasting exchange rates

Artificial neural networks are a kind of dynamic Systems that by processing experimental data can transfer the knowledge or rules beyond the data to structure of the network. They can approximate any nonlinear function to an arbitrary degree of accuracy and have the potential to be used as forecasting tools in many different areas. In the following we describe the algorithm briefly.

2.1 Learning Algorithm

The back-propagation algorithm [22], [23] has emerged as one of the most used learning procedures for multilayer networks as shown in figure 1. The algorithm looks for the minimum of the error function in the weight space using the method of gradient descent. The combination of weights which minimizes the error function is considered to be a solution of the learning problem. It has been shown that they have great potentials for financial forecasting and they can be used to approximate any spatially finite function given a set of hidden nodes. There are many different neural net learning algorithms found in the literature. The method according to [22] is based on determining the error between the predicted output variables and the known values of the training data set. The error parameter is commonly defined as the root mean square of the errors that for all the processes take the form of determining the partial derivatives of the errors with respect to each of the weights. It consists of an input layer, an output layer and one or more intermediate layer called hidden layer. All the nodes at each layer are connected to each node at the upper layer by interconnection strength called weights. A training algorithm is used to attain a set of weights that minimizes the difference between the target and actual output produced by the network. Each training epoch involves one exposure of the network to a training sample from the training set, and adjusting each of the network weights layer by layer. The back-propagation training algorithm is described in the following.

Back-propagation learning algorithm

S0. Create a feed-forward network with n_i inputs, n_h hidden units, and no output units.
S1. Initialize all weights to small random values (e.g. between -0.1 and 0.1)
S2. Until termination condition is met, do
S3. For each training sample vector (x, t) do
S4. Compute the output O_u for every unit of x
S5. For each output unit k, calculate
$\boldsymbol{\delta}_k=O_k(1-O_k)(t_k-O_k)$
S6. For each hidden unit calculate
$\boldsymbol{\delta}_h=O_h(1-O_h)\sum\boldsymbol{\delta}_k w_{kh}$ $\quad (k \in \text{downstream } (h))$
S7. Update each network weight w_{ji} as follows:
$W_{ji}=w_{ji}+\Delta w_{ji}$ where $\Delta w_{ji}=\eta\boldsymbol{\delta} x_{ji}$

Each training sample is of the form (x, t) where x is the input vector and t is the target vector and η is the learning rate. The parameters n_i, n_h and n_o are the number of input, hidden and output nodes respectively. The input i to the unit j and its weighs are denoted by x_{ij} and w_{ij} , respectively. The process of adjusting weights is continued until the error is less than a user defined threshold. Once the trained phase is completed, new input data can be fed to the network to get the desired output [16], [24].

2.2 The proposed model

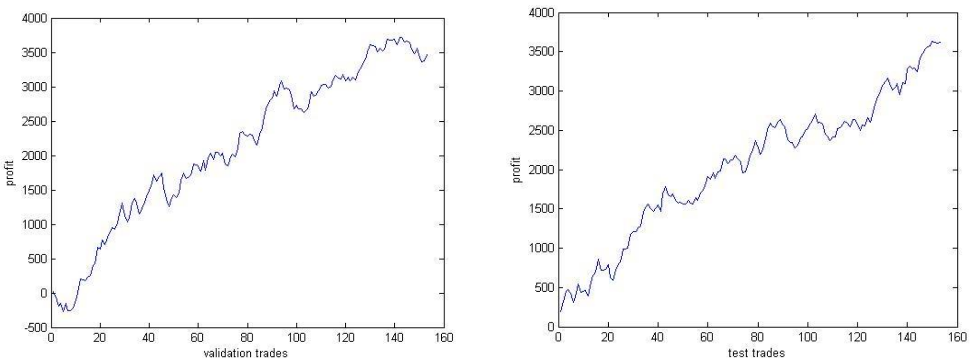
In order to create the model, first a proper neural network training algorithm should be selected and then the inputs, outputs, the number of layers and the number of neurons in each layer should be defined in a way to produce the best results. Our proposed model employs a feed forward back-propagation network including two hidden layers. At first, network weights are selected randomly in the range of *[0, 1]* that would be a convenient choice because we have normalized the data in the same range. There are 10 and 3 neurons in the first and second hidden layers respectively, and 1 neuron in the output layer. The Pureline function is used as an activation function for the first hidden layer and the activation function used for the second hidden layer and output layer was selected as Sigmoidal. We remark that Pureline is an identity function that maps the inputs to the outputs changelessly and the Sigmoidal function maps the inputs to the interval *[0, 1]*. The Trainlm function is employed to train the network. Note that trainlm is a network training function that updates weight and bias values based on Levenberg-Marquardt optimization method [25]. The dividing function was set to the Divide Block function that separate the data into three parts including training set, validation set and testing set. 60 percent of the data is used to train the network and the remaining 40 percent of the data is divided into half for validating and testing the model. Validation set is used to stop training early if the network performance on the validation data fails to improve or remains the same for a user defined maximum epochs. The testing set does not have any effect on training and it is used to assess how well the network generalizes. The aim is to discover the relationship between present, past and future observations. The algorithm has been implemented using the Matlab software.

3. Data preparation

The time series of GBP/USD, is used as the input of the network. Furthermore, Gold, Petroleum and FTSE 100 index are fed to the model as external factors. Gold is a valuable good that is considered as a bankroll for countries. Hence, the currency market is affected by changing the price of gold. Petroleum is another important substance and the source of providing energy that dedicates an extensive volume of transaction to itself in all over the world and also its price fluctuations is in the head of news in the world's media. The FTSE 100 index is a capitalization-weighted index of the 100 most highly capitalized companies traded on the London Stock Exchange. It is one of the most widely used stock indices and is considered as a gauge of business prosperity. Undoubtedly, variation in the prices of gold, Petroleum and FTSE 100 index has noticeable effects on the currency exchange. In this study the entire data set covers daily periods running from January 2004 through December 2011. The Saturday and Sunday holidays were missing data of the time series. 28 previous daily periods of GBP/USD, gold, Petroleum and FTSE 100 and their volume of trading are used in order to predict future price of GBP/USD.

4. Discussion and results

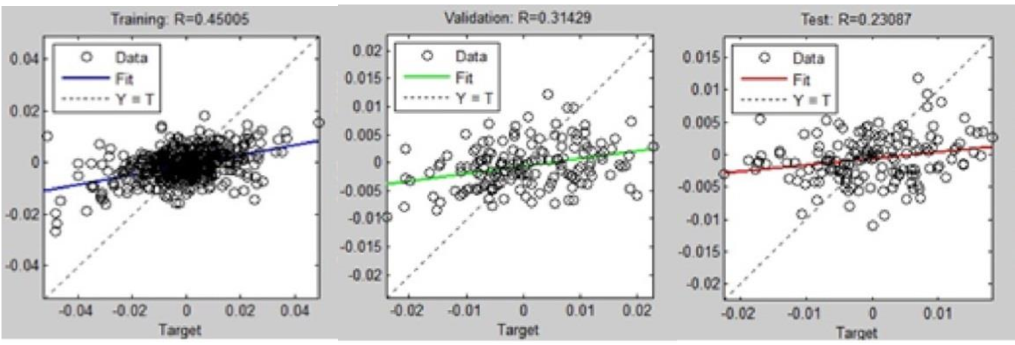
In this section the performance of the proposed model is illustrated. In order to show that the proposed model is profitable we have used a simple strategy, in the way that, a trade is opened based on the network prediction and it is closed at the end of the day and then the profit diagram which comes from cumulative series of profit and loss is depicted. Figure 1. (a) and (b) plot the profit diagram according to our simple trading strategy for the validation and testing set, respectively. It reveals that the amount of profit is uniformly increased by time. The profitability is evaluated in terms of pip.



(a) (b)

Figure 1. (a) Profitability of the proposed method on validation data (b) Profitability of the proposed method on testing data

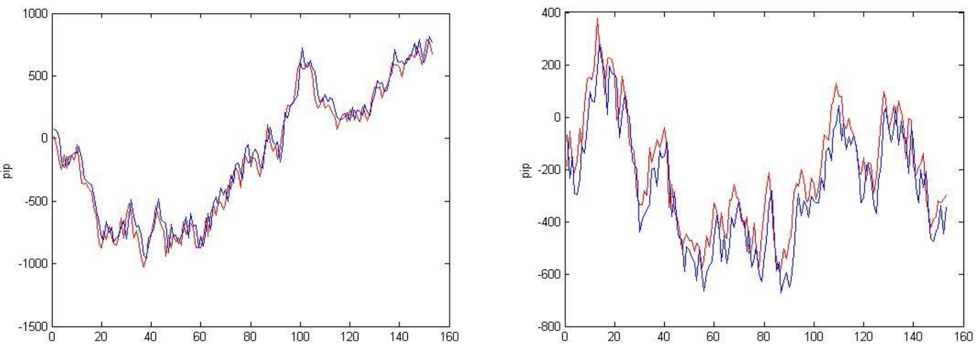
Figure 2. shows the correlation (R) between network output and real output for validation and testing data. Whatever these numbers are more closed to 1, the network can obtain more accurate results.



(a) (b) (c)

Figure 2. Correlation between network output and real output. (a) Training data (b) Validation data (c) Testing data

After the learning phase and building the model, the graph of the original and predicted time series for the last 160 data of the test set are shown in the figure 3. Note that the blue line and red line represent actual outputs and predicted values, respectively.



(a) (b)

Figure 3. Actual and neural network predicted values for GBP/USD on (a) validation data (b) testing data

There are several important evaluation criteria for the prediction of financial time series. In statistics, the mean squared error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. MSE measures the average of the square of the error. The error is the amount by which the value implied by the estimator differs from the estimated quantity. Taking the square root of MSE yields the root mean square error or root mean square deviation (RMSE) which has the same units as the quantity being estimated. The second evaluation method is more practical in financial time series prediction. The third evaluation method is the median absolute deviation (MAD) is a robust measure of the variability of a univariate sample of quantitative data. Indeed, MAD is a measure of statistical dispersion. Moreover, the MAD is a robust statistic, being more resilient to outliers in a data set than the standard deviation. The aforementioned criteria are among the most important evaluation methods for the prediction of financial time series. The forecasting results for GBP/USD based on the aforementioned criteria are shown in Table 1. The results of the proposed model are compared with the neural network model without external factor and the ANN endowed with gold price as the only external factor. The best results have been shown in bold face.

Table 1. Forecasting accuracy of neural network model for GBP/USD based on MSE criterion

Algorithm\Set	**Train**	**Validation**	**Test**
Proposed model	**0.00017**	**0.000082**	**0.000067**
ANN with gold price	**0.00017**	0.000094	0.000082
ANN without external factor	0.000255	0.000113	0.000129

Table 2. Forecasting accuracy of neural network model for GBP/USD based on RMSE criterion

Algorithm\Set	**Train**	**Validation**	**Test**
Proposed model	**0.0132**	**0.0091**	**0.0082**
ANN with gold price	**0.0132**	0.0097	0.0091
ANN without external factor	0.0160	0.0107	0.0112

Table 3. Forecasting accuracy of neural network model for GBP/USD based on MAD criterion

Algorithm\Set	**Train**	**Validation**	**Test**
Proposed model	**0.0100**	**0.0074**	**0.0065**
ANN with gold price	0.0101	0.0078	0.0073
ANN without external factor	0.0125	0.0086	0.0091

As can be seen in Table 1, our proposed method has obtained acceptable results in comparison with other approaches. In Table 2, this comparison has been made according to the RMSE criterion. It turns out that the proposed model outperformed all other methods. Table 3 cites the MAD comparison and it reveals that proposed method has significantly produced better results.

5. Conclusion

This study introduces a neural network model to forecast exchange rates with respect to three external factors including gold and petroleum price and FTSE100 index. The results of the proposed model are compared with the neural network model without external factor and the ANN endowed with gold price as the only external factor. Empirical results show that our proposed model significantly produces acceptable results and outperforms all other approaches. Several important criteria are used to show the effectiveness of the proposed method.

In the future, it would be interesting and beneficial to verify the predictive strength of the new approach based on the GRNN and RBF neural networks. Furthermore, the influence of other economical indexes such as inflation rate, gross national product, interest rate and etc. can be considered.

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