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Performance of Supervised Artificial Neural Networks for Foreign Exchange Rate Prediction

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ABSTRACT

The purpose of this research is to develop Artificial Neural Network (ANN) based models for foreign exchange (FX) rate predictions. Since ANN are capable of recognizing nonlinear patterns by learning patterns of historical data and information. This study focuses on designing and developing models using two ANN techniques: (1) Multi-Layer Perceptron (MLP) with Error Back Propagation Algorithm (EBPA) and (2) Radial Basis Function Neural Network (RBFNN). Both ANN techniques use supervised learning to predict the output. The dataset used for this study are (1) Forex data namely Euro to US Dollar (EUR/USD) and (2) Euro to Japanese Yen (EUR/JPY) with daily and weekly data as three inputs high, low and close along with next day/week close as output. Experimental work is carried out with 10-Fold cross-validation technique and results obtained in the form of Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) proves that MLP is better than RBFNN for both exchange rate data in case of daily as well as weekly predictions. It has also been observed that ANN models performed better using the closing prices as compared to low or high prices.

KEYWORDS: Foreign Exchange, Artificial Neural Network, Multi-Layer Perceptron, Radial Basis Function Neural Network.

INTRODUCTION

The dynamics of the global foreign exchange market is ever evolving. Therefore, there is a need of continuous improvement in designing and developing models using the latest tools and techniques to capture the trends in foreign exchange (FX) rates. The FX market is also equally lucrative within financial markets (Baillie and McMahon, 1989). Therefore, investors are demanding sophisticated models to make better business decisions and minimize the risk due to fluctuations in exchange rates (Meese and Rogoff, 1983; Kilian and Taylor, 2003; Ni and Yin, 2009). Historically, there have been several forecast models developed using autoregressive coordinated moving average (ARIMA) (Box and Jenkins, 1976), autoregressive restrictive heteroskedasticity (GARCH) (Franses and Ghijsels, 1999) and smooth move autoregressive (STAR) (Sarantis, 2001). However, the models developed using traditional statistical techniques have not yielded satisfactory results during volatile economic conditions. Therefore, researchers are focusing on designing and developing models using the ANN techniques to predict FX rates integrating computational intelligence, signal processing as well as econometrics.

The literature review supports that ANN technique is a promising method for FX rate prediction. However, there are two different types of ANN techniques: supervised and unsupervised. Supervised ANN technique is used widely due to the availability of input as well as output (Target) data. Several authors have demonstrated the use of supervised ANN technique with other intelligent techniques for improved performance of predictive models. The prediction is dependent on training and testing samples. Some authors have used a static partition of training-testing samples which does not reflect the real strength of the predictive model and may be biased for a specific type of pattern. However, k-fold cross validation technique of data mining help designing a robust model by partitioning training and testing samples. This research work focuses on building FX rate prediction model with special emphasis on the selection of suitable input parameters using two ANN techniques: (1) MLP and (2) RBFNN with 10-fold cross validation. The performance of models was tested to validate the results in terms of Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE).

LITERATURE REVIEW

The literature reveals that ANN techniques are better than the conventional statistical methods in predicting non-linear patterns in data (Coats & Faut, 1993; Leonard et al., 1991; Fletcher & Goss, 1993; Salchengerger et al., 1992). Over the past two decades, several mathematical models in finance area have applied ANN to predict trends of foreign exchange rates successfully. Table 1 provides a summary of foreign currency rate models developed by several researchers.

Table 1: Summary of Literature Review

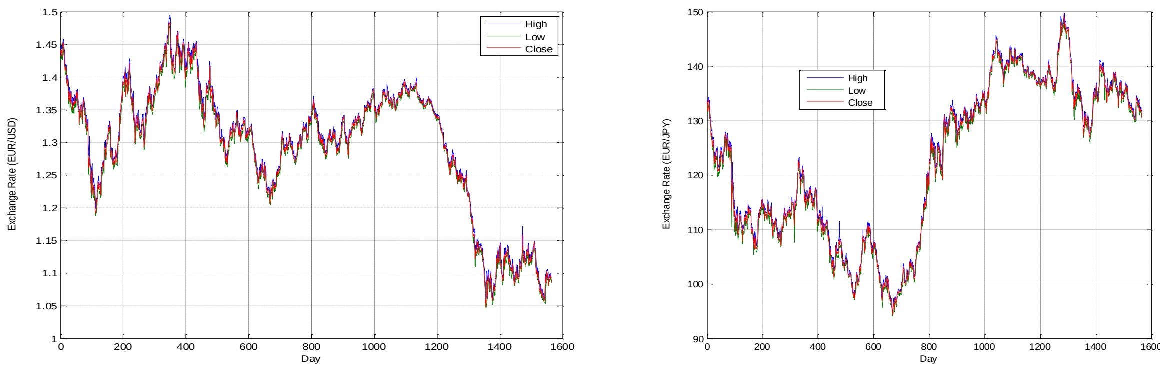
YEAR	REFERENCES	JOURNAL
1998	Zhang & Hu	International Journal of Management Science
1999	Hu et al.	Decision Sciences
2000	Leung et al.	Computers and Operations Research
2001	Davis et al.	International Journal of Intelligent Systems in Accounting
2003	Chun & Kim	Expert Systems with Applications
2004	Chen & Leung	Computers and Operations Research
2007	Panda & Narasimhan	Journal of Policy Modeling
2008	Lean et al.	Neurocomputing
2008	Yu et al.	Neurocomputing
2009	Ni & Yin	Neurocomputing
2013	Sermpinis et al.	European Journal of Operational Research
2013	Georgios et al.	European Journal of Operation Research
2016	Svitlana	Neurocomputing

DATA DESCRIPTION AND PREDICTION METHOD

Data Description

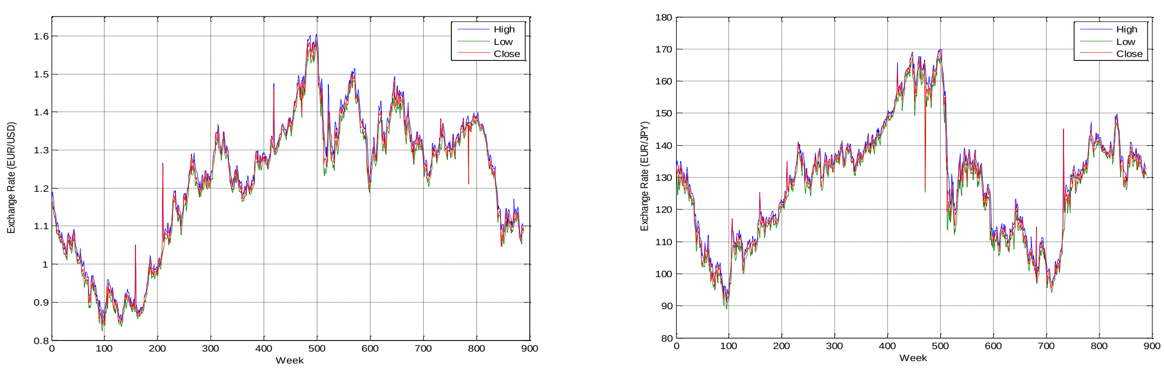
Sample size plays a significant role in designing models to ensure adequate data for learning patterns. Therefore, a large number of samples are necessary to develop exchange rate predictive models. Two foreign exchange rates data (EUR/USD and EUR/JPY) as shown in Table 2, was collected from the website (http://www.oanda.com/currency/historical-rates/) for daily rates from January 1, 2010, to December 31, 2015. The period for the weekly rate was extended from January 1, 1999, to December 31, 2015, to have a larger sample size. A total of 1565 samples for daily and 889 samples for weekly rates was used with three types of inputs: High, Low and Close rates and one output next day/week close rate for developing an exchange rate prediction model. The nonlinear trend of all the three inputs are shown in Figure 1(a) and (b) for exchange rate EUR/USD and EUR/JPY with daily step respectively and in Figure 2(a) and (b) for exchange rate EUR/USD and EUR/JPY with weekly step respectively. It can be observed from these figures that Forex data are highly nonlinear and varies from time to time.

Table 2: Data description of two Forex: EUR/USD and EUR/JPY				
Time Step	Range	Samples	Input	Output
Daily	Jan 1, 2010 to Dec 31, 2015	1565	High, Low, Close	Next Day close
Weekly	Jan 1, 1999 to Dec 31, 2015	889	High, Low, Close	Next Week close



(a) (b)

Figure 1: Trends of Exchange rate (a) EUR/USD (b) EUR/JPY with daily Step.



(a) (b)

Figure 2: Trends of Weekly Exchange rate (a) EUR/USD (b) EUR/JPY

Prediction Method

The development of a prediction model for financial data requires techniques like Artificial Neural Network (ANN) because of its capabilities to capture nonlinear nature of data pattern as well as to store a large amount of patterns in the form of weights on its connections. Among several ANN techniques reported in the literature two ANN techniques (Multi-Layer Perceptron (MLP) and Radial Basis Function Neural Network (RBFNN)) are widely used for a nonlinear pattern recognition. Therefore, these techniques are suitable for the development of FX rate prediction model. MLP is a multi-layer neural network with at least one hidden layer along with multiple input and output layers. The number of processing units (Neurons) at input and output layers are equal to the number of elements in input and output vectors respectively. The number of processing units at the hidden layer is decided according to the complexity and level of non-linearity nature of the data (Georgios et al., 2013). MLP is trained with popular Error Back Propagation Algorithm (EBPA) which is calculated based on the gradient descent and maps the input patterns to its corresponding output patterns in a supervised manner by sending back the error signals to adjust weights of the connection. On the other hand, RBFNN also works in a supervised manner with radial basis function as an activation function at the hidden layer. RBFNN generally consists of three layers (Input, hidden and output). The hidden layer of RBFNN differs from MLP because each node represents a cluster of data centered at a particular point within a given radius. Each node in the hidden layer calculates the distance from the input vectors to its own using Euclidian distance formulae (Yu et al., 2008). However, characteristics of input and output layers are very similar in of both type of ANNs.

There are several parameters that influence the performance of both techniques. For example, in MLP, the value of learning rate and the momentum that lies between 0 and 1 may affect the predictive performance of the model as well as avoid the problem of local minima and overfitting. Similarly, in RBFNN, Gaussian function works as an activation function, the value of which depends on the suitable value of its center and width. These parameters may be optimized either using the self-experiment of ANN technique or by any optimization techniques including Particle Swarm Optimization (PSO), Genetic Algorithms (GA) and others. In the proposed research work hidden layer neurons and other parameters as explained above are decided through the experiment. Also, ANN architecture with three neurons in the input layer and one neuron in the output layer is designed.

In order to train and to validate the models popular K-fold cross validation method is used which produces more reliable results since it uses all the parts of the samples as training as well as testing. K-fold is a common technique for estimating the accuracy of prediction models in which entire samples are eventually used for both training and testing. In this method original data is splits into k equal size subsamples out of which k-1 sub-samples are used to train the model, and one subsample is used to validate the trained model, the final result is the average of all the folds. In this research work 10-fold cross validation method is used. In which nine folds are used for training the model while one fold is used for testing the model, and the process is repeated 10 times considering another nine folds as training and one fold as testing.

SIMULATION STUDY

Simulation of the work is carried out with WEKA (http://www.cs.waikato.ac.nz/ml/weka/), which provides many machine learning techniques like a decision tree, ANN, association rule mining, clustering, classification and regression along with data preprocessing tools like K-fold cross-validation, etc. A Graphical User Interface (GUI) feature of WEKA allows a developer to choose machine learning methods by importing data from excel sheet. Exchange rate data explained in the previous section are normalized using simple normalization formulae by dividing each data with a maximum value of data set to produce data ranging from 0 to 1. MLP and RBFNN with 2 to 3 number of input neurons and one output neuron as network topology were used to develop the models, parameters of these two techniques are set as default value. These models are tested using a ten-fold cross-validation and produces average testing results in terms of Mean absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) as shown in Tables 3-6 for different model with different input parameters as High-Low-Close (H-L-C), Low-Close (L-C), High-Close (H-C) and High-Low (H-L) for both the exchange rate data. Out of two ANN techniques considered in this research work, MLP is performing better than RBFNN. Also, the close value is playing a crucial role in the prediction of FX rate in the combination of High and Low parameters for both FX data. Table 7 entails the consolidated results of EUR/USD FX data. The results reveal that model with L-C and H-C parameters performed equally well (MAPE= 0.621 and 2.917 respectively for MLP and RBFNN) for daily FX data while for weekly FX data model with L-C as input parameters is performing well with MAPE = 1.624 and 6.054 respectively for MLP and RBFNN. On the other hand Table 8 contains EUR/JPY FX results. The results reveal that model with L-C and H-C input parameters is again equal (MAPE= 0.848 and 4.053 for MLP and RBFNN respectively) for daily FX data while it is 2.028 and 5.714 using L-C and 2.217 and 5.737 using H-C respectively for MLP and RBFNN for weekly FX data. Comparative results shown in above tables reveals that close value of is more important than others. A graphical view of comparative prediction results in terms of MAPE for various models with different input parameters is given in Figures 3 (a), (b) and 4 (a), (b) for daily and weekly time step for exchange rate EUR/USD and EUR/JPY respectively. These figures clearly reflect that MLP is performing better than RBFNN for FX data.

Table 3: Experimental results with High, Low and Close (H-L-C) as input

ANN Technique	Time Step	EUR/USD		EUR/JPY	
		MAE	MAPE	MAE	MAPE
MLP	Daily	0.005	0.623	0.007	0.870
	Weekly	0.012	1.643	0.015	2.085
RBFNN	Daily	0.026	3.016	0.033	4.141
	Weekly	0.046	6.273	0.045	5.848

Table 4: Experimental results with Low and Close (L-C)as input

ANN Technique	Time Step	EUR/USD		EUR/JPY	
		MAE	MAPE	MAE	MAPE
MLP	Daily	0.005	0.621	0.006	0.848
	Weekly	0.012	1.624	0.015	2.028
RBFNN	Daily	0.025	2.917	0.032	4.053
	Weekly	0.045	6.054	0.044	5.714

Table 5: Experimental results with High and Close (H-C) as input

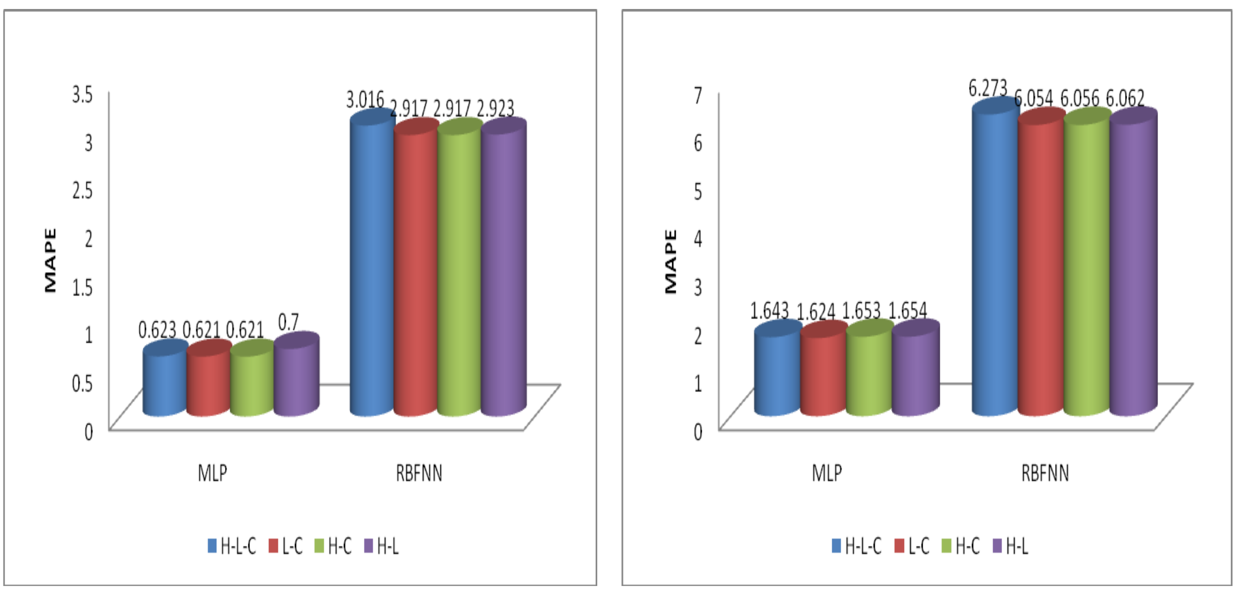
ANN Technique	Time Step	EUR/USD		EUR/JPY	
		MAE	MAPE	MAE	MAPE
MLP	Daily	0.005	0.621	0.006	0.848
	Weekly	0.012	1.653	0.016	2.217
RBFNN	Daily	0.025	2.917	0.032	4.053
	Weekly	0.045	6.056	0.044	5.733

Table 6: Experimental results with High and Low (H-L) as input

ANN Technique	Time Step	EUR/USD		EUR/JPY	
		MAE	MAPE	MAE	MAPE
MLP	Daily	0.006	0.700	0.007	0.891
	Weekly	0.012	1.654	0.014	1.979
RBFNN	Daily	0.025	2.923	0.032	4.062
	Weekly	0.045	6.044	0.044	5.737

Table 7: Comparative experimental results with different input parameters for EUR/USD FX					
ANN Technique	Time Step	H-L-C	L-C	H-C	H-L
MLP	Daily	0.623	0.621	0.621	0.700
	Weekly	1.643	1.624	1.653	1.654
RBFNN	Daily	3.016	2.917	2.917	2.923
	Weekly	6.273	6.054	6.056	6.062

Table 8: Comparative experimental results with different input parameters for EUR/JPY FX					
ANN Technique	Time Step	H-L-C	L-C	H-C	H-L
MLP	Daily	0.870	0.848	0.848	0.891
	Weekly	2.085	2.028	2.217	2.312
RBFNN	Daily	4.141	4.053	4.053	4.062
	Weekly	5.848	5.714	5.733	5.737



(a) (b)

Figure 3: A comparative graph of MAPE for two ANN techniques for prediction of EUR/USD FX data with various input parameters (a) For daily time step (b) For weekly time step

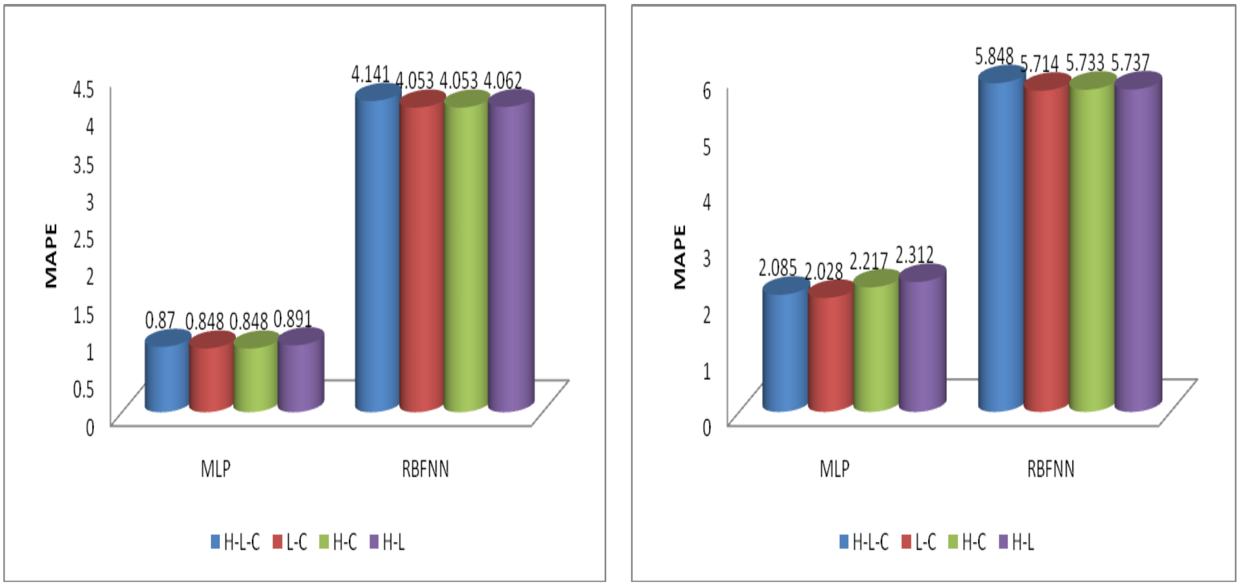


Figure 4: A comparative graph of MAPE for two ANN techniques for prediction of EUR/USD FX data with various input parameters (a) For daily time step (b) For weekly time step

CONCLUSION

Foreign exchange rates prediction is possible with nonlinear models due to nonlinear nature of exchange rates data. ANN techniques are suitable for this type of prediction. Two ANN techniques namely: MLP and RBFNN are used in this research work for predicting two exchange rates EUR/USD and EUR/JPY. Models were trained with default parameters of both the methods with 10-fold cross validation method to obtain more authentic results. The performance of ANN-based models was evaluated regarding MAPE and MAE. It has been observed that MLP outperformed than RBFNN in predicting both exchange rates with daily as well as weekly step with Low and Close as input parameters, It is also noted that models with close as one of the input parameter in the combination of others are performing better than the input parameters without close. This study, as well as previous literature, proves that ANN may be the best choice as an independent model or in a combination of other intelligent techniques for foreign exchange rate prediction. The future scope of extension of this study may include hybridization of the predictive model, feature extraction from exchange rates data and optimization of various parameters of ANN as well as input parameters using evolutionary techniques.

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