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Forecasting the BDT/USD Exchange Rate: An Accuracy Comparison of Artificial Neural Network Models and Different Time Series Models

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Abstract: Exchange rate is the price of one currency in terms of another currency. Exchange rates play an important role in controlling dynamics of the foreign exchange market. Predicting exchange rates has become one of the most challenging applications of financial time series forecasting due to its unpredictability and volatility. We selected to forecast the BDT against US Dollar because United States is the top trading partner of Bangladesh. This research study is to develop and compare the accuracy of different models; autoregressive Integrated Moving Average (ARIMA), Exponential smoothing models as the time series models and Feedforward neural network with the Backpropagation algorithm as the Artificial Neural Network (ANN) model for predicting monthly currency exchange rate of Bangladeshi Taka against US Dollar (BDT/USD). According to the performance of different models, it can be concluded that the ANN based model performs better when compared with the ARIMA model to predict the exchange rate of BDT/USD.

Keywords: Forecasting, Exchange Rate, ARIMA, Artificial Neural Network.

1 Introduction

Due to Globalization, the foreign exchange market has experienced unexpected development over the last few decades. Various economic factors such as inflation, economic growth, interest rates and monetary policies influence the value at which national currencies are traded in international markets. Therefore, the exchange rates play a vital role in controlling dynamics of the foreign exchange market.
Exchange rates prediction is one of the most challenging applications of modern time series forecasting. The rates are inherently noisy, non-stationary and deterministically chaotic [3].

2 Literature Review

The economic theory has not yet provided econometric models to produce efficient forecasts of exchange rates, although many studies have been devoted to the estimation of the equilibrium of exchange rates from the 20s to the recent years [Cassel (1923); Samuelson (1964); Mundell (1968); Dornbusch (1973 and 1979); Allen and Kenen (1980); Frankel and Mussa (1985); MacDonald (1999); Rogoff (1999); Alba e Papell (2007); Kim B.H., Kim H.K. and Oh (2009); Taylor (2009); Grossmann, Simpson e Brown (2009)]. In particular, Meese and Rogoff (1983) found that none of the forecasting models of the exchange rate established by economic theory has a better ability to forecast, over a period lower than 12 months, rather than the forward rate models or random walk, emphasizing the paradox that the variations of exchange rates are completely random. The likelihood to capture various patterns in the data as well as improvement of forecasting performance can be enhanced through combining different models. A number of researches are conducted on forecasting and trading financial series by the scholars and they suggest that by combining various models, forecasting accuracy can be enhanced over an individual model. Different methods are used in Exchange Rates prediction. These methods are distinguishable from each other by what they hold to be constant into the future. These methods include moving average (MA), autoregressive (AR), Exponential smoothing, autoregressive integrated moving

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average (ARIMA), vector autoregressive (VAR), autoregressive conditional heteroscedasticity (ARCH), generalized autoregressive conditional heteroscedasticity (GARCH) models.

Although in many forecasting applications the ARIMA model has been successfully used to predict seasonal time series, it suffers from limitation because of its linear form. However, due to its linearity, ARIMA is not always suitable for complex real-world problems. To overcome this limitation many of artificial intelligence (AI) models such as nonlinear regression model, artificial neural networks (ANN), support vector machines (SVM) and genetic algorithm (GA) have been used to provide powerful nonlinear solutions to forecasting problems. CoskunHamzacebi proposed an artificial neural network (ANN) structure for seasonal time series forecasting. The comparison of results found by the proposed model and the traditional statistical models shows that ANN model comes with lower prediction error than other methods.

The other important aspect is that ARIMA methodology is only suitable under the assumption that the time series is stationary. To overcome this limitation of the ARIMA methodology, Artificial Neural Networks (ANN) have also been used to forecast the prices as shown by KohzadiNowrouz et al. (1996), Tang et al. (1991) and Zoua et al. (2007). This is because Artificial Neural Networks do not make any assumption about the process from which a particular time series has generated. Therefore, Artificial Neural Networks effectively cover both linear and non-linear processes, stationary as well as non-stationary time series [1,2].

Artificial Neural Networks (ANNs) are a very powerful tool in modern quantitative finance and have emerged as a powerful statistical modeling technique. ANNs provide an attractive alternative tool for both researches and practitioners. They can detect the underlying functional relationships within a set of data and perform tasks such as pattern recognition, classification, evaluation, modeling, prediction and control (Anderson and Rosenfeld, 1988; Hecht-Nielsen, 1990; Hertz et al., 1991; Hiemstra and Jones, 1994). Several distinguishing features of ANNs make them valuable and attractive in forecasting. First, ANNs are nonlinear data-driven. They are capable to perform nonlinear modeling without an a priori knowledge about the relationships between input and outputs variables. The non-parametric ANN model may be preferred over traditional parametric statistical models in situations where the input data do not meet the assumptions required by the parametric model, or when large outliers are evident in dataset (Lawrence, 1991; Rumelhart and Mcclelland, 1986; Waite and Hardenbergh, 1998; Wasserman, 1993). Second, ANNs are universal functions approximation. It has been shown that a neural network can approximate any continuous function to any desire accuracy (Hornik, 1993; Horniket al., 1989). Third, ANNs can generalize. After learning the data presented to them, ANNs can often correctly infer the unseen part of a population even if the sample data contain noisy information. Neural Networks are able to capture the underlying pattern or autocorrelation structure within a time series even when the underlying law governing the system is unknown or too complex to describe [4,5,6].

Present paper uses Artificial Neural Network as an alternative model for forecasting exchange rate in Bangladesh in both technical and fundamental approaches.

3 Data Source

Data used in this study were records of Bangladesh exchange rate (BDT vs. USD) movement for the period from August 2004 to March 2016 from Bangladesh Bank on monthly basis.

4 Results and Discussion

4.1 Exponential Smoothing Method

We analyze a sequence of 140 monthly exchange rate observations. The data indicates an upward trend. This trend however does not appear to be constant but seems to change over time. A constant linear trend model would therefore not be appropriate. Because of the growing trend pattern of the series we decide to use double exponential smoothing. To decide on the smoothing constant, we simulated the forecast errors for several different smoothing coefficients, sum of the squared errors and root mean squared error. To forecast the exchange rate BDT/USD using double exponential smoothing at first we have to choice the initial value for smoothed statistic S_0 . To find out the initial value of smoothed statistic we take the simple arithmetic average of the available historical data. Such choice also has been suggested by Brown (1962) and Montgomery and Johnson (1976). The arithmetic average will perform well, provided that the mean level changes only slowly. Subsequently we will get the value of smoothed statistic by the following equation:

$$S_t = \alpha y_t + (1-\alpha) S_{t-1}$$

Table 1. Sum of Squared Errors (α) and Root Mean Squared Errors (α) for different values of smoothing constant (α); Double Exponential Smoothing- Exchange Rate BDT/USD.

Smoothing Constant(α)	**Sum of Squared Error(α)**	**Root Mean Squared Error(α)**
0.10	387.93	1.75
0.15	248.58	1.40
0.20	182.05	1.20
0.25	146.91	1.08
0.30	126.77	1.00
0.35	114.41	0.95
0.40	106.46	0.92
0.45	101.24	0.90
0.50	97.92	0.88
0.55	96.03	0.87
0.60	95.32	0.86
0.65	95.67	0.87
0.70	96.99	0.88
0.75	99.29	0.89
0.80	102.57	0.90
0.85	106.91	0.92
0.90	112.42	0.94
0.95	119.27	0.97

From the above table, we observe that the smoothing constant which minimizes the sum of the squared forecast errors and root mean squared errors is then used as smoothing constant in the derivation of the future forecast. From above table we see that smoothing constant 0.60 is used in the derivation of the future forecast.

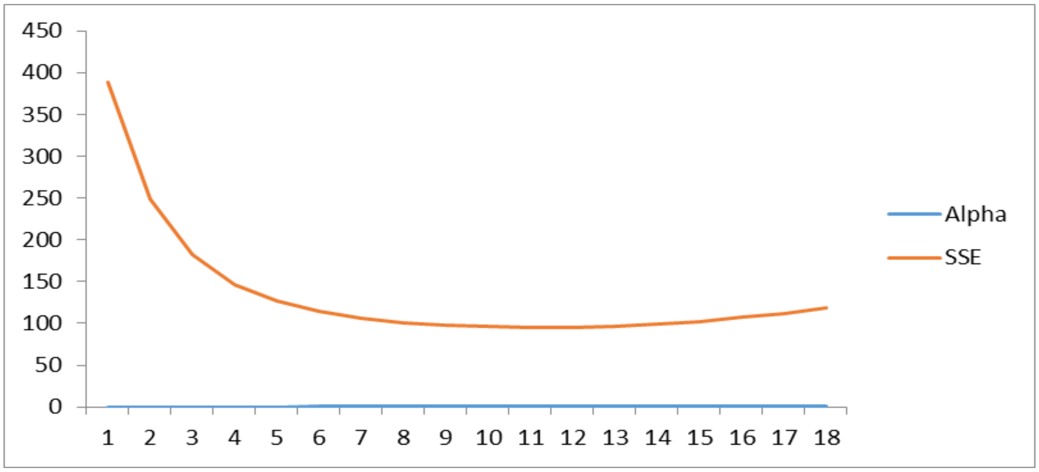

Figure 1. Plot of SSE (α), for double exponential smoothing-exchange rate BDT/USD.

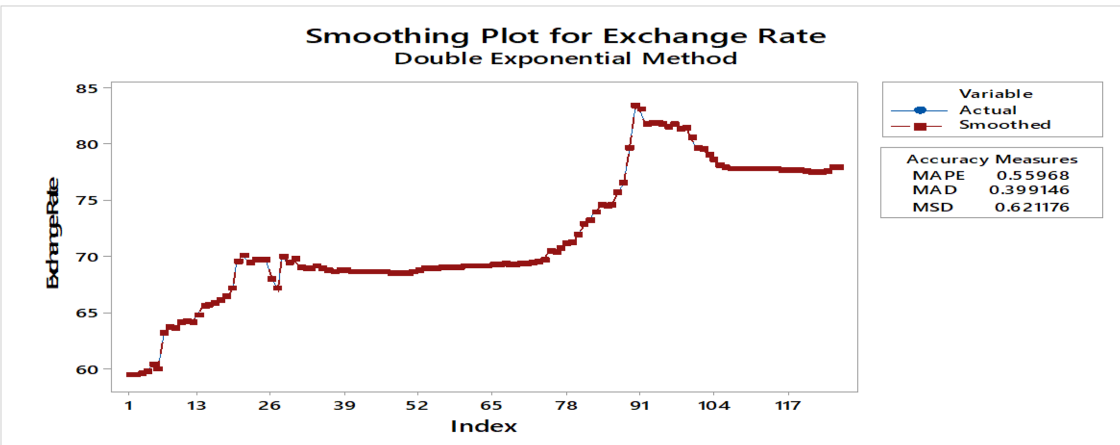

Figure 2. Double Exponential Smoothing Series.

Table 2:Summary result of double exponential smoothing model

Model	SSE	RMSE	MAE	MAPE	R
Double Exponential Smoothing	54.2141	0.6639	0.3991	0.5597	0.99

4.2 ArimaModel

Now we consider the different types of tentative models as much as possible from which we select the best model using the model selection criterion. Since the characteristics of a good ARIMA model is parsimonious ignoring the higher order of p and q, the tentative models on the basis of model selection criterion are as follows:

Table 3: Different ARIMA models for exchange rate in Bangladesh

Model	R^2	Adjusted R^2	AIC	Normalized BIC
ARIMA (1,1,0)	0.996737	0.996713	0.116021	-1.782009
ARIMA (0,1,1)	0.996751	0.996727	0.116523	-1.739059
ARIMA(1,1,1)	0.997000	0.996934	0.108345	-1.818889

From the above table we see that for the model ARIMA (1, 1, 1); AIC, Normalized BIC i.e. SIC are smaller than other models and R^2 adjusted R^2 is high. So the model ARIMA (1,1,1) is the best tentative model and we use this model for our forecasting purposes.

4.2.1 Out of Sample Model Adequacy

We will compare different models with each other by the following statistical measure of criterion.

Table 4. Statistical summary measures of a model's forecast accuracy (Post evaluation criterion).

Model	RMSE	MAE	MAPE
ARIMA(1,1,0)	0.338194	0.215526	0.299250
ARIMA(0,1,1)	0.338925	0.230093	0.319581
ARIMA(1,1,1)	0.325664	0.208359	0.288887

We observe from the above table that RMSE, MAE and MAPE are smaller for ARIMA (1,1,1) model than the others. So we can conclude that the ARIMA (1,1,1) model is the best fitted model among all the tentative models.

4.3 Neural Network Models

To forecast exchange rate in Bangladesh we analyzed a sequence of 141 monthly exchange rate observations.To fit a feed forward neural network we need appropriate number of input layer, hidden layer and output layer. In this paper a feed forward neural network was fitted to the data, where lag values of dependent variable were taken as independent variable or covariates and the value to be forecast (i.e. exchange rate) was the dependent variable or output layer. From the result of autocorrelation and autocorrelation analysis we use lag1 as a covariate or independent variable.
Now we consider the different types of tentative models as much as possible from which we select the best model using the model selection criterion. Since the characteristics of a good neural network model depends on the out sample criteria, the tentative models on the basis of model selection criterion are as follows:

Table 5. Different tentative artificial neural network models for exchange rate BDT/USD

Model	RMSE	MAE	MAPE	Z
ANN(1,1)	0.355049	0.323585	0.414956	100
ANN(1,2)	0.240281	0.175938	0.224938	100
ANN(1,3)	0.286467	0.226685	0.080677	100
ANN(1,4)	0.244748	0.226685	0.169464	100

We observe from the above table that, MAPE, SSE and RMSE are smaller for NN (1,2) model than the others and the correlation coefficient is 1.0. So we can conclude that the NN (1,2) model is the best fitted model among all the tentative model and we use this model for our forecasting purposes.

4.4 Accuracy Comparison For Different Forecasting Models

Accuracy measurement of the different forecasting method is based on mean absolute percentage error (MAPE), mean absolute error (MAE) and Root mean squared error (RMSE). We will compare different models on the basis of the value of in sample model selection criteria.

Table 6: An accuracy comparison in sample for different forecasting models.

Period	Month	Actual Value	Forecast Value using ARIMA	Forecast Value using Exponential Smoothing	Forecast Value using Artificial Neural Network
2016	April	78.4	78.4544	78.4327	78.2253
	May	78.4	78.6134	78.5292	78.3583
	June	78.4	78.7435	78.6257	78.4283
	July	78.4	78.8808	78.7222	78.4583
	August	78.4	79.0164	78.8187	78.5083
	September	78.4	79.1523	78.9152	78.5583
	October	78.4	79.2882	79.0117	78.6283
	November	78.54	79.4241	79.1083	78.7483
	December	78.8	79.5600	79.2048	78.8355
2017	January	78.86	79.6959	79.3013	78.9467
	February	79.24	79.8318	79.3978	79.1459
	March	79.54	79.9677	79.4943	79.3547

Table 7. An accuracy comparison in sample for different forecasting models.

Forecasting Model	**Error Measures**	**In Sample Set**	**Out of Sample Set**
ARIMA	RMSE	0.3257	1.0425
	MAE	0.2084	0.8448
	MAPE	0.2889	1.0815
Exponential Smoothing	RMSE	0.6639	0.3797
	MAE	0.3991	0.2725
	MAPE	0.5597	0.3479
Artificial Neural Network	RMSE	0.2403	0.3386
	MAE	0.1759	0.2682
	MAPE	0.2249	0.3424

It is clear that neural networks model is the best to forecast the future values, because it has minimum measures of forecasting errors such as MAPE, RMSE and MAE. The low MAPE indicates that the deviation between the discrepancies between the predicted values derived by the neural networks and the actual values are very small

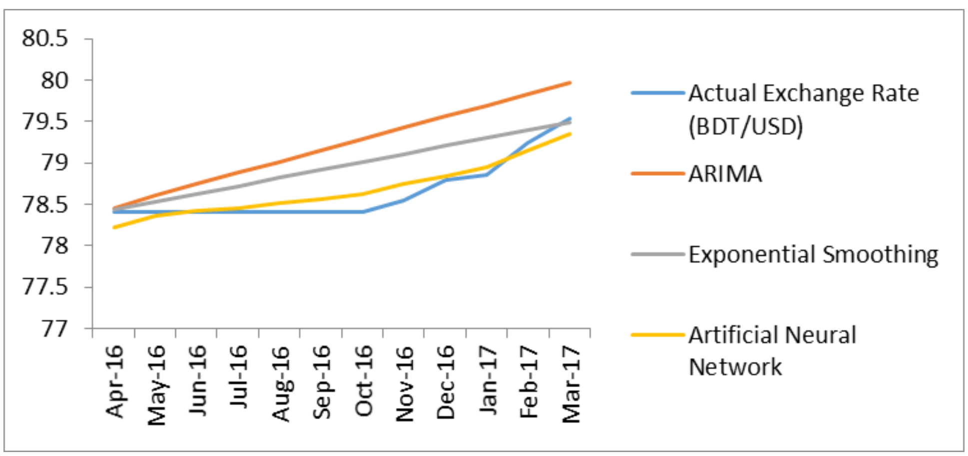

Figure 3. Graphical representations of different forecasting methodsFindings

Figure 3 displays plot among actual values of exchange rate, forecast values using exponential smoothing model, ARIMA model and Artificial Neural Network (ANN) model. These plot shows that forecast values from Artificial Neural Network (ANN) are almost equal to actual values of exchange rate than other two model. Therefore we say that Artificial Neural Network give more accurate result than Exponential Smoothing and ARIMA model.

5 Summary and Conclusion

In this paper, we examine and compare different time series and Artificial Neural Network (ANN) model for forecasting exchange rate in Bangladesh. Analyzing a time series behavior of the exchange rate data is very helpful to forecast exchange rate series.

From the discussion of different parametric and non-parametric models, we see that the various information criterion such as AIC, SIC (Normalized BIC), RMSE and MAE and MAPE for the model ARIMA (1,1,1) are 0.1083, -1.8189, 0.3257, 0.2084 and 0.2889 respectively, which are very less but adjusted R^2 (=0.9969) is very high compared to the other models.. In exponential smoothing method RMSE, MAPE, MAE and r are 0.6639, 0.3991, 0.5597 and 0.99 respectively. On the other hand, in neural network model (1,2) RMSE, MAE, MAPE, Z and r are 0.2403, 0.1759, 0.2249, 100 and 1.00 respectively, which is minimum among all models.

Empirical results suggest that neural network model fits the exchange rate well and it is capable of forecasting the future trend of the exchange rate movement. According to the minimum in sample criteria neural network model is considered the best model for predicting exchange rate (Taka per US Dollar).

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