Forecasting Tala/USD and Tala/AUD of Samoa using AR (1), and AR (4): A Comparative Study

Shamsuddin Ahmed
Graduate School of Business
MGM Khan
School of Computing, Information and Mathematical Science
Biman Prasad
School of Economics
The University of the South Pacific, Suva, Fiji

Shamsuddin_Ahmed@yahoo.Com

Abstract: - The paper studies the Autoregressive (AR) Models to forecast exchange rate of Samoan Tala/USD and Tala/AUD during the period of January 3 2008 to September 28 2012. We used daily exchange rate data to do our study. The performance of AR (1), and AR (4) model forecasting was measured by using varies error functions such as RSME Error, MAE, MAD, MAPE, Bias error, Variance error, and Co-variance error. The empirical findings suggest that AR (1) model is an effective tool to forecast the Tala/USD and Tala/AUD..

Key-Words: - AR (1), and AR (4) model, Exchange rate, RSME, MAE, MAD, MAPE, Bias error, Variance error, and Co-variance error

1 Introduction

Samoa is located half way between Hawaii and New Zealand with the geographic coordinates of 13 35 south and 172 20 west. The total area of landmass is 2831 square kilometers. Samoa has got a tropical climate. It has got two main islands (Savaii, Upolu) several smaller islands and uninhabited islets. Its major city is Apia. It natural resources are forest, fish and hydropower. Samoa gained independence on 1 January 1962 from New Zealand which was administered UN trusteeship.

The estimated population of Samoa in July 2012 is 194320. This includes Samoan, Euronesians (persons of European and Polynesian blood), Europeans and other ethnicity. Their official language is Samoan (Polynesian) and English. In 2012 the estimation shows that the Samoa population growth rate is 0.596%, birth rate is 22.1births/1,000, death rate is 5.34deaths/1,000 and Net migration is 10.81 migrant(s)/1,000.

Samoa has got a political system in which the legislature (parliament) selects the government - a prime minister, premier, or chancellor along with the cabinet ministers. According to party strength as expressed in elections; by this system, the government acquires a dual responsibility: to the people as well as to the parliament.

Remittances from Samoans working abroad are a key part of the economy. New Zealand is the main source of remittances, followed by Australia and the United States. The tourism sector has also been growing steadily over the past few years, although the 2009 tsunami caused extensive damage to several hotels and resorts. Foreign development assistance in the form of loans, grants and direct aid is an important component of the economy. Samoa is reliant on imports. The United States is Samoa’s largest export market, accounting for nearly 50% of Samoan exports. Its indigenous exports consist mainly of fish and agriculture products. A large proportion of the population is employed informally and works in subsistence agriculture or low-level commercial ventures.The gross domestic product (GDP) or value of all final goods and services produced within a nation for the 2nd quarter of 2012 shows 2.7%.

Daily exchange rate is fixed by the central bank of Samoa in relation with a weighted basket of currencies which includes United States of America dollar, New Zealand dollar, Australia dollar and the Euro.

In our study we used time series model such as autoregressive AR (1), and AR(4) model to forecast daily exchange rate of Samoan tala against AUD, and USD. Our study will uses the outcome of the two models mentioned to state the best AR model for predicting the exchange rates.

ISBN: 978-960-474-356-8

2 Literature Review

There are many ways to forecast exchange rate by using different models. The studies investigated below will show the best model used to forecast exchange rate.

Pacelli (2012) compared the ability of different mathematical models, such as artificial neural networks (ANN) and ARCH and GARCH models, to forecast the daily exchange rates Euro/U.S. dollar (USD). The researcher used time series data of Euro/USD from December 31, 2008 until December 31, 2009. The anticipated to ANN developed to predict the trend of the exchange rate Euro/ USD up to three days ahead of last data available. He concluded ARCH and GARCH models, especially in their static formulations, are better than the ANN for analyzing and forecasting the dynamics of the exchange rates. ARCH (2) model with a static approach showed the best predictive ability.

Maniatis (2012) studied the exchange rate between Euro and USD using univariate model (ARIMA and exponential smoothing method). He took 3202 observation of exchange rate between Euro and USD ranging from 4 January 1999 to July 1 2011. He concluded that there was a presence of unit root in exchange rate between Euro and USD and it failed to give non- trivial confidence interval for forecast of the exchange rate. When they differed the exchange rate between Euro and USD time series, this resulted in white noise, which could not be submitted to ARIMA or exponential smoothing method. However, The first difference followed Laplace distribution, and this distribution appeared different between two independent variables each followed exponential smoothing distribution..

Pradhan and Kumar (2010) , Pacelli V., Bevilacqua V., Azzollini M. (2011) Kamruzzaman and Sarker (2004), HUANG, LAI, NAKAMORI and WANG (2004), Panda and Narasimhan (2003) , Andreou, Georgopoulos and Likothanssis (2002), Dunis C.L., and William. M. (2002) and Walczak, S. (2001) designed and tested the ANN model to predict exchange rate. The variable output designed was either monthly or daily exchange rate. All study concluded that the ANN model is the better model to predict the exchange rate.

Azad and Mashin (2011) predicted the monthly average exchange rates of Bangladesh using artificial neural network (ANN) and autoregressive integrated moving average (ARIMA) models. A feedforward multilayer neural network namely, exchange rate neural network (ERNN), has been developed and trained using backpropagation learning algorithm. The effect of different network and tuning parameters was examined during training session. The ARIMA model was executed using Box-Jenkins methodology and obtained the appropriate model. The results showed that the ANN model has better predictability than the ARIMA model.

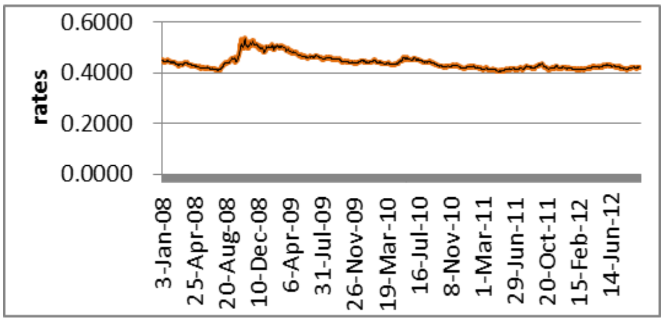
3 Data and variables

The study uses the daily real exchange rate of Samoan tala against AUD, and USD from 3 January 2008 to 28 September 2012. This excludes the weekends and public holiday in Samoa. There are 1180 observations.

3.1 Descriptive of Exchange rate

The graphs below show the trend of the tala against AUD, and USD from 3 January 2008 to 28 September 2012.

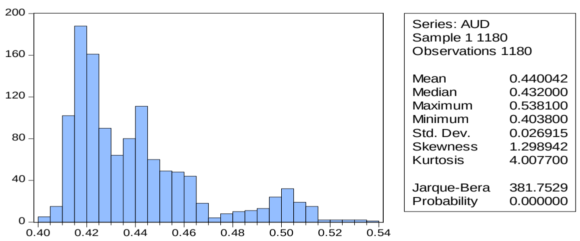
Figure 1 shows the time series plot of tala/AUD



The figure above clearly shows that the tala/AUD increased 21 October 2008 till 3 November 2008 and later Tala/AUD decreases. Thereafter, Tala/AUD maintained its fluctuating trend.

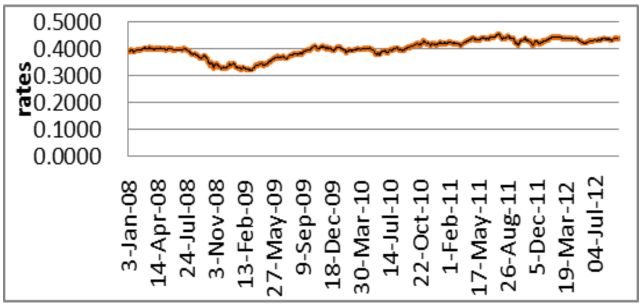
Figure 2 shows Histogram of Tala/ AUD with normal curve

ISBN: 978-960-474-356-8



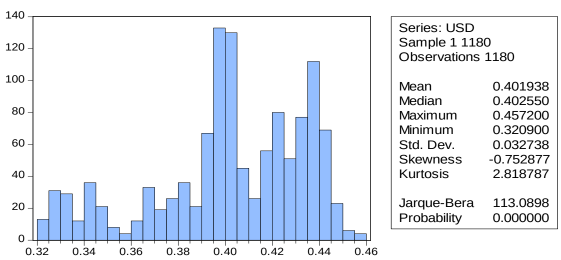
The average exchange rate of **Tala against AUD** over the study period was 0.44 with the standard deviation of 0.03. The table also reveals that the distribution is higly skewed to the right (skweness=1.30) and highly peaked (Kurtosis=4.00).

Figure 3 shows times Plot of Tala/USD



From 8 October 2008 Tala/ USD decreased and then it increased again from 4 May 2009. From there onwards the graph above shows an increase trend.

Figure 4 shows Histogram of Tala/ USD with normal curve



The average exchange rate of **Tala against USD** over the study period was 0.40 with the standard deviation of 0.03. the table also shows that the distribution is slighly skewed to the left (Skweness= -0.75) and is peaked (kurtosis =2.82)

4 Result of AR (1)

In attempt to check the data is at least stationary, the data was split into 5 categories as per year. The ADF test was done by taking 22 lags of the variables to check for unit root for Tala/ AUD, and USD. The test shows that the Null hypothesis (Null Hypothesis: AUD and USD has a unit root) cannot be rejected. Thus this states that the variables are non-stationary.

Figure 5 shows the Box Plot of Tala/AUD (-1) by Year

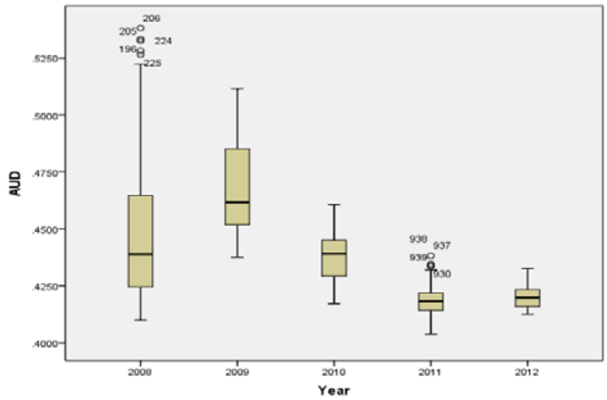
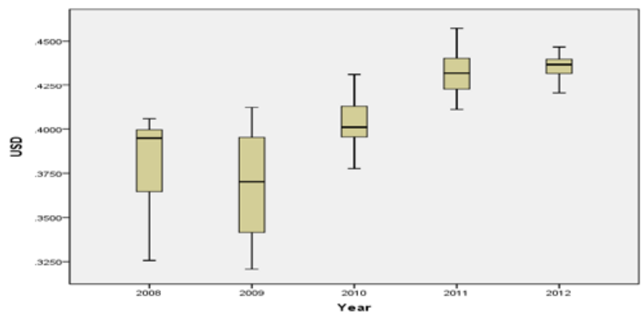


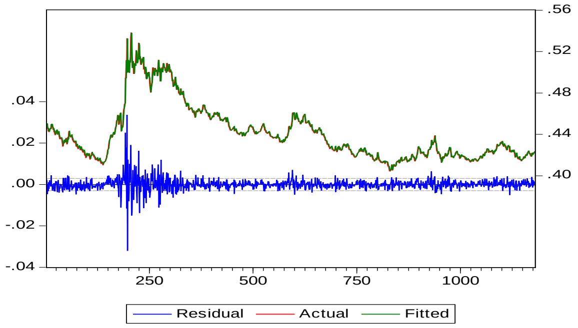
Figure 6 shows Box Plot of Tala/USD (-1) by Year



To tailor for the presence of unit root we developed an equation. The result for regression is shows AUD (-1), and constant are significant (P value <0), where else, time is not significant. The R-squared is 0.987783.

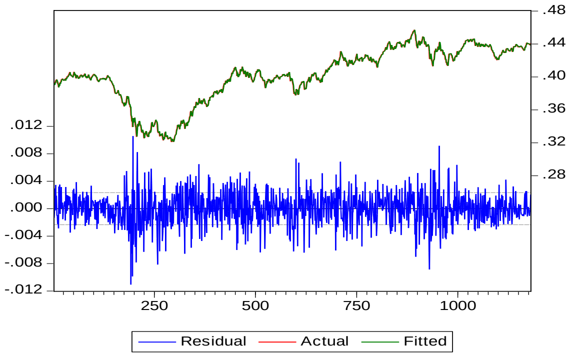
ISBN: 978-960-474-356-8

Figure 7 shows the plot of the residual analysis from the regression of tala/AUD



The result for regression is shows USD (-1), time and constant are significant (P value <0), The R-squared is 0.987783.

Figure 8 shows the plot of the residual analysis from the regression of tala/USD

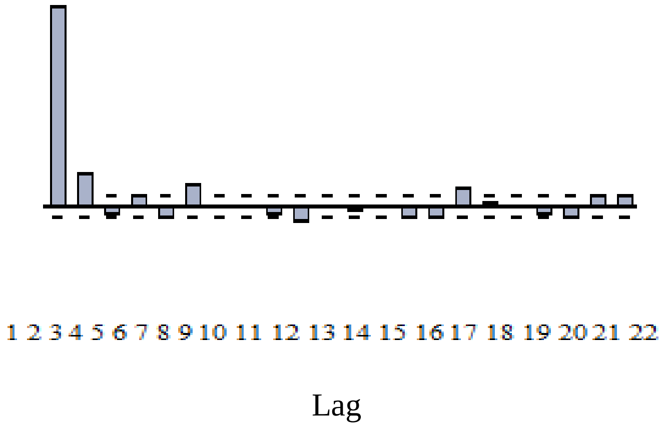


We retained 1179 observation and demanded to forecasts for AUD and USD using AR (1) method.

4.1 Forecasting with AR (1)

The Partial Autocorrelation function of tala/ AUD (-1) and USD (-1) showed the first spike (as shown in figure 9) and this justifies that the use of AR (1) model as the candidate for forecasting.

Figure 9 shows the Partial Autocorrelation Graph of Tala/AUD (-1)



The result AR (1) forecasting shows both the graph of the forecasts and the statistics evaluation the equality of the fit to the actual data of tala against AUD (-1) and USD (-1).

Figure 10 shows the forecasted graph with the error of Tala/AUD

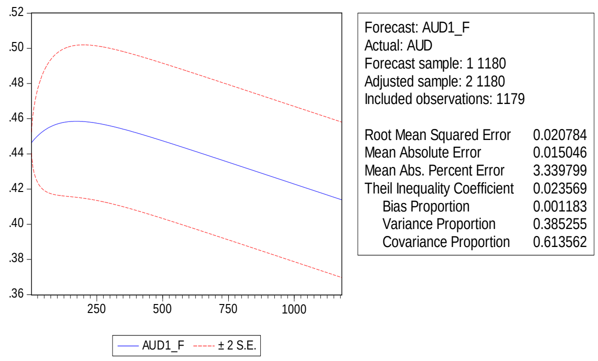
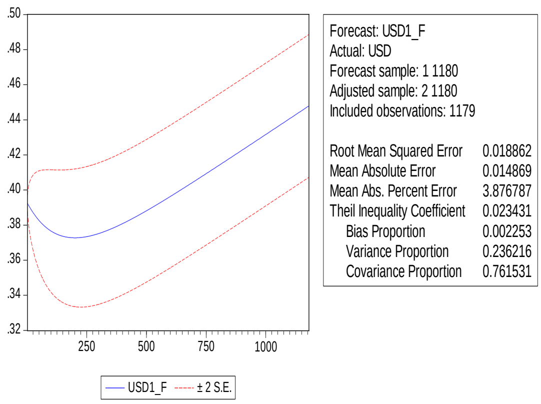


Figure 11shows the forecasted graph with the error of Tala/USD



ISBN: 978-960-474-356-8

The graph below shows forecasting with AR (1) model; the 95% confidence interval; are very board to help practical forecasting.

Figure 12 shows the 95% confidence interval graph of forecasted AUD

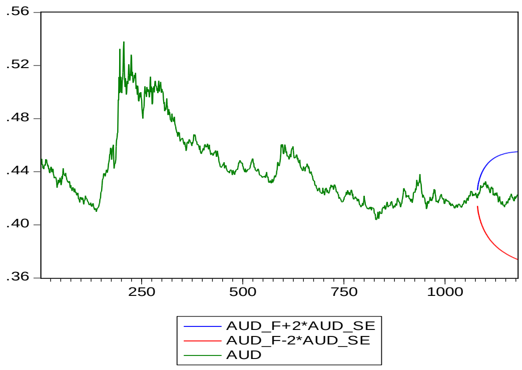
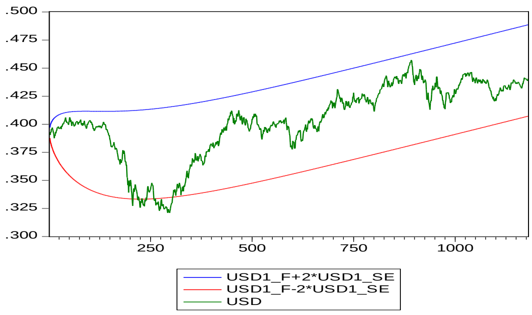


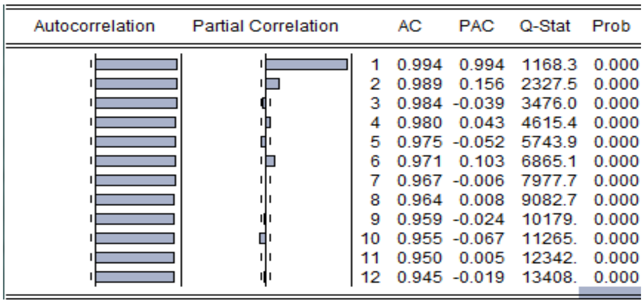
Figure 13 shows the 95% confidence interval graph of forecasted USD



The graph above shows that the AUD is within the forecast interval for most of the forecast period. Where else, USD is within the forecast interval except between 20 November 2008 and 28 November 2008 (time 222-228).

The Correlogram of forecasted values of tala against AUD (AUD1_f), and USD (USD1_f shows spikes at the 1st lag and the Q- statistics are significant at all lags, indicating significant serial correlation in the residuals as shown in the figure below:

Figure 14 shows Correlogram of forecasted Tala/AUD



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.994	0.994	1168.3	0.000
		2	0.989	0.156	2327.5	0.000
		3	0.984	-0.039	3476.0	0.000
		4	0.980	0.043	4615.4	0.000
		5	0.975	-0.052	5743.9	0.000
		6	0.971	0.103	6865.1	0.000
		7	0.967	-0.006	7977.7	0.000
		8	0.964	0.008	9082.7	0.000
		9	0.959	-0.024	10179.	0.000
		10	0.955	-0.067	11265.	0.000
		11	0.950	0.005	12342.	0.000
		12	0.945	-0.019	13408.	0.000

The diagram also suggests that there is no presence of white noise indicating tala against AUD, and USD is correlated over time with a constant variance and mean zero.

5 Result of AR (4)

In attempt to check if the data is at least stationary the data is divided into 5 years. The box plot shows the distribution of 4 lag variables (Tala/AUD and Tala/USD) over the 5 year period. The ADF test was also performed to by taking 22 lags of the variables to check for the unit root.

Figure 15 shows the Box Plot of AUD (-4)

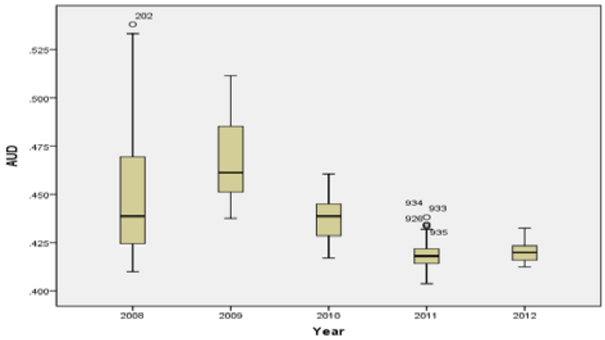
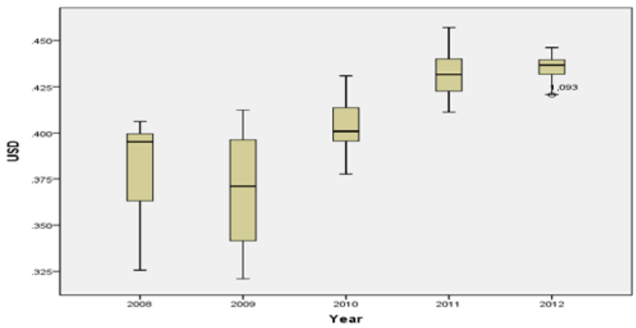


Figure 16 shows the Box Plot for USD (-4)

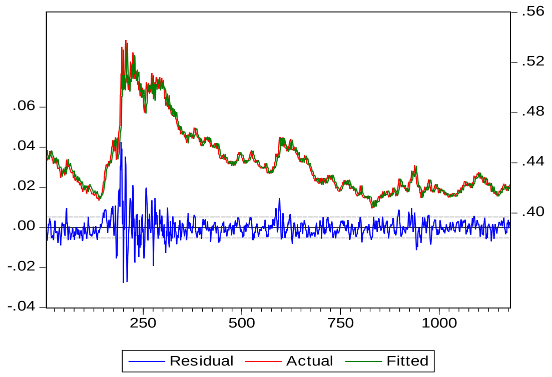


ISBN: 978-960-474-356-8

The test showed that the USD (-4) and AUD (-4) series are non-stationary. The ADF test showed the presence of unit root in AUD (-4) and USD (-4) series. To tailor for the presence of unit root we developed an equation.

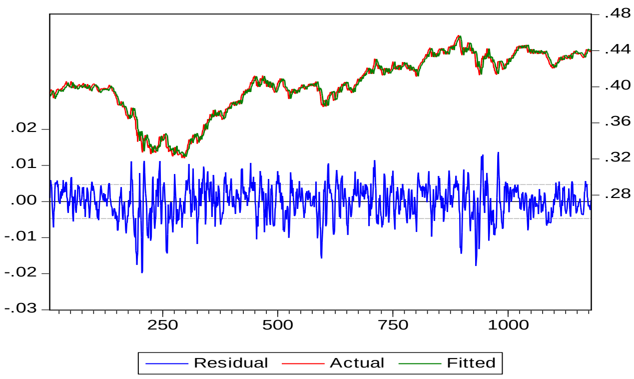
The result for regression for AUD (-4) shows constant, AUD (-4), and time is significant (P value <0). The R-squared is 0.962440.

Figure 17 shows the plots of the residual analysis from the regression of tala/AUD (-4)



The result for regression for USD (-4) shows constant, AUD (-4), and time is significant (P value <0). The R- squared is 0.979521.

<u>**Figure 18 shows the plots of the residual analysis from the regression of tala/USD (-4)**</u>



5.1 Forecasting with AR (4)

The Partial Autocorrelation function of tala/AUD (-4) and USD (-4) showed the first spike (as shown in figure 55) and this justifies that the use of AR (4) model as the candidate for forecasting.

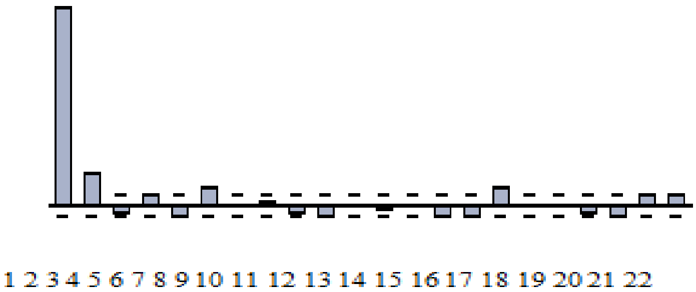
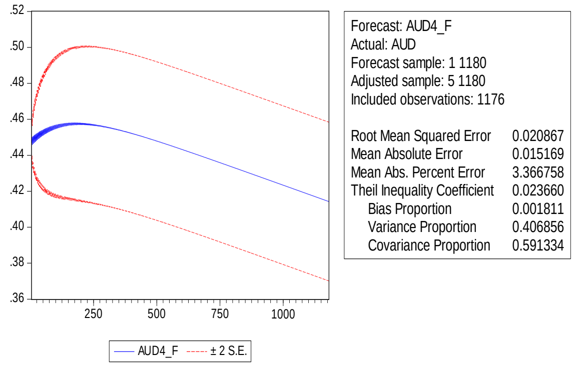


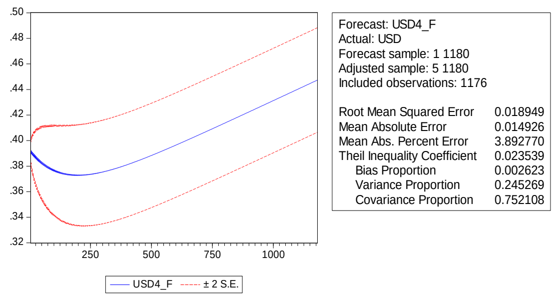
Figure 19 shows the Partial Autocorrelation Graph of Tala/AUD (-4)

The result AR (4) forecasting shows both the graph of the forecasts and the statistics evaluation the equality of the fit to the actual data of tala against AUD (-4) and USD (-4).

Figure 20 shows the forecasted graph with the error of Tala/AUD



<u>Figure 21 shows the forecasted graph with the error of Tala/USD</u>



ISBN: 978-960-474-356-8

Figure 22 shows the approximate 95% confidence intervals for forecasted AUD

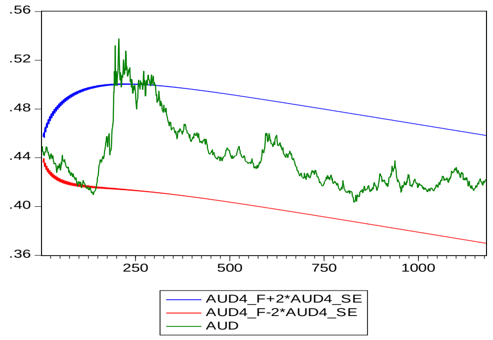
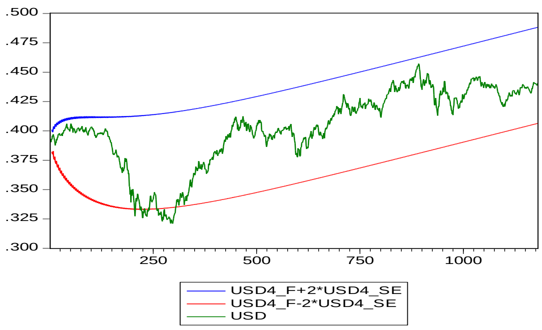


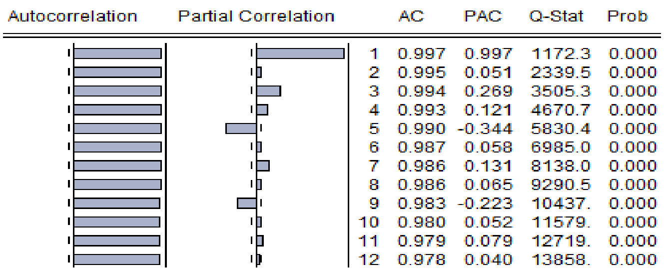
Figure 23 shows the approximate 95% confidence intervals for forecasted USD



The graph above shows that the AUD is within the forecast interval for most of the forecast period excepts on 10, 15 October 2008, 17-21 October 2008, 23 October- 5 November 2008, 10 November -12 December 2008, 16 December- 17 December 2008 , 25 June- 1 July2008, 4 -8 July 2008, and 10- 31 July 2008 . Where else, USD is within the forecast interval except between 20-28 November 2008, 3- 12 December 2008 and on 16 December 2008.

The Correlogram of forecasted values of tala against AUD (AUD4_f), and USD (USD4_f) shows spikes at the 1st lag and the Q- statistics are significant at all lags, indicating significant serial correlation in the residuals as shown in the figure below:

Figure 24 shows Correlogram of forecasted Tala/AUD (-4)



5 Conclusions

The Exchange rate of Tala/AUD and Tala/USD has been forecasted based on four AR performance measure and a comparison has also been made with the different AR model which is shown in the table 4. The table clearly represents that for Tala/AUD and Tala/USD daily exchange rate, AR (1) leads to minimum error in forecasts than the corresponding AR (4) models.

Table 4 Comparison among AR (1) and AR (4)

Currency	AR model	Performance Metrics					
		RSME	MAE	MAPE	Bias Error	Variance Error	Co-variance Error
Tala/AUD	AR(1)	**0.0209**	**0.015**	**3.3398**	**0.0012**	**0.3853**	**0.6136**
	AR(4)	0.0209	0.0152	3.3668	0.0018	0.4069	0.5913
Tala/USD	AR(1)	**0.0189**	**0.0149**	**3.8768**	**0.0022**	**0.2362**	**0.7615**
	AR(4)	0.0189	0.0149	3.8927	0.0026	0.2452	0.7521

ISBN: 978-960-474-356-8

The bias error should be close to 0, if the bias error is large it indicates systematic over or under prediction. In the table it shows AR (1) bias error is closer to 0 when compared to AR (4) models. Variance error should be small; if the error is large it indicates the actual series has fluctuated considerably whereas the forecast has not. In this case AR (1) also shows a smaller variance error compared to other AR models. Co-Variance error should have the highest proportion of inequality and this is higher in AR (1) as compared to AR (4) models.

References:

[1] Steven, W. 2001,"An Empirical Analysis of data requirement for financial forecasting with Neural Network Model," Journal of Management Information system, vol. 17, no. 4, pp. 203-222.

[2] Ashok, K.N. & Mitra, A. 2002, "Forecasting daily foreign exchange rates using genetically optimized neural networks", Journal of Forecasting, vol. 21, no. 7, pp. 501-511.

[3] Andreou, A.S., Georgopoulos, E.F., & Likothanassis, S.D., 2002, "Exchange rate forecasting: A hybrid algorithm based on genetically optimized adaptive neural network", Computational Economics, vol. 20, no. 3, pp. 191-210.

[4] Dunis, C.L., & William, M., 2002, "Modeling and trading the euro/us dollar exchange rate: Do neural network model perform better?" Derivative Use, Trading & Regulation, vol. 8, no. 3, pp. 211-239.

[5] Panda, C, & Narasimhan, V 2003, 'FORECASTING DAILY FOREIGN EXCHANGE RATE IN INDIA WITH ARTIFICIAL NEURAL NETWORK', Singapore Economic Review, 48, 2, pp. 181-199.

[6] Huang, W., Lai K.K., Nakamori, Y., and Wang, S. 2004, "Forecasting Foreign Exchange rates With Artificial Neural Network: A Review", International Journal of Information Technonlogy & Decision Making, Vol. 3, no. 1, pp. 145-165.

[7] Kamruzzaman, J., and Sarker R.A. 2004, "ANN Based Forecasting of Foreign Currency Exchange Rates", Neural Information Processing - Letters and Reviews, Vol. 3, no. 2, pp.49-58.

[8] Chong Lee-Lee, Tan Hui-Boon, (2007) "Macroeconomic factors of exchange rate volatility: Evidence from four neighboring ASEAN economies", Studies in Economics and Finance Vol. 24 Iss: 4, pp.266 – 285.

[9] Wei-Pang Wu & Hui-Ling Yang 2007, "Forecasting New Taiwan Dollar/United States Dollar Exchange Rate Using Neural Network", The Business Review, Cambridge, vol. 7, no. 1, pp. 63-69.

[10] Rudra, P.P. & Kumar, R. 2010, "Forecasting Exchange Rate in India: An Application of Artificial Neural Network Model", Journal of Mathematics Research, vol. 2, no. 4, pp. 111-117.

[11] Kadilar, C. & Simsek, M. 2009, "Forecasting the Exchange rate series with ANN: The case of Turkey", Intanbul U. Econ. Statist. J., vol. 9, no. 1, pp. 17-29.

[12] Malik, K 2011, 'Exchange Rate Forecasting and Model Selection in Pakistan (2000-2010)', Journal Of Business & Economics, 3, 1, pp. 77-101.

[13] Azad, A. K., and Mahsin M. 2011, "Forecasting Exchange rates of Bangladesh using ANN and ARIMA Model: A Comparative Study", International Journal of Advanced Engineering Science and Technologies, Vol. 10, no.1, pp.31-36.

[14] Pacelli V., Bevilacqua V., Azzollini M. (2011), "An Artificial Neural Network Model to Forecast Exchange Rates", in Journal of Intelligent Learning Systems and Applications, Vol. 3, n. 2/2011, pp. 57-69, Scientific Research Publishing, Inc. USA;

[15] Pacelli, V. 2012, "Forecasting Exchange Rates: a Comparative Analysis", International Journal of Business and Social Science, vol. 3, no. 10