Forecasting Tala-AUD Using Times Series and Artificial Neural Network Model

Shamsuddin Ahmed, MGM Khan, Biman Prasad, Avlin Prasad

Abstract**—**The paper compares the autoregressive time series Artificial Neural Network model, exponential smoothing with trend, and Winters Method model to forecast exchange rate of Samoan Tala/AUD during the period of January 3 2008 to September 28 2012. We use daily exchange rate data to do our study. The performance of the models was measured by using varies error functions such as Root Square mean error (RSME), Mean absolute error (MAE), and Mean absolute percentage error (MAPE). The empirical findings suggest that ANN model is an effective tool to forecast the Tala/AUD.

Keywords**—**Neural Network Forecasting Model, Autoregressive time series, Exchange rate, Tala/AUD, winters model.

I. Introduction

SAMOA is located half way between Hawaii and New Zealand in the South Pacific region with the geographic coordinates of 13° 35' South and 172° 20' west. It has a tropical climate. The total landmass area of Samoa is 2831 square kilometers with two main islands (Savaii and Upolu), and 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 194,320. 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 estimated data shows that the Samoa's 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 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. We compare autoregressive ANN model, moving average, exponential smoothing with trend, Winters method, and ANN with AR(1), AR (2) and AR (3) to forecast daily exchange rate of Samoan Tala against AUD.

Shamsuddin Ahmed is graduated School of Business, University of the South Pacific, USP, (Email: Dr_Shamsuddin_Ahmed@yahoo.com).

MGM Khan is with School of Computing, Information and Mathematical Science, USP, (E-mail: khan_mg@usp.ac.fj).

Biman Prasad is with School of Economics, USP, (E-mail: prasad_bc@usp.ac.fj).

Avlin Prasad is with School of Computing, Information and Mathematical Science, USP, (E-mail: prasad_avlin@yahoo.com).

II. Related Previous Studies

There are many ways to forecast exchange rate by using different models. 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) showed the exchange rate between Euro and USD using univariate model (autoregressive integrated moving average (ARIMA) and exponential smoothing method). He took 3202 observation of exchange rate between Euro and USD ranging from 4 January 1999 to 1 July 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 forecasting 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.

Many other authors such as Pradhan and Kumar (2010) , Pacelli, Bevilacqua and Azzollini M. (2011) Kamruzzaman and Sarker (2004), Huang, Lai, Nakamori and Wang (2004), Panda and Narasimhan (2003) , Andreou, Georgopoulos and Likothanssis (2002), Dunis and William. M. (2002) and Walczak (2001) also designed and tested the ANN model to predict exchange rate. The variable output designed in their techniques was either monthly or daily exchange rate. All these studies concluded that the ANN model is the better model to predict the exchange rate.

Nag and Mitra (2002) investigated hybrid artificial intelligence method based on neural network and genetic algorithm for modeling daily foreign exchange rate. They used time series data of deutsche mark/USD, YEN/ USD, USD/ GBP. The targeted rates were the closing exchange rate at the end of the next day. They concluded in their study that out of sample genetic algorithm is better than ANN model and a statistical time series modeling approach.

Recently, Azad and Mashin (2011) predicted the monthly average exchange rates of Bangladesh using ANN and ARIMA models. A feed forward multilayer neural network namely, exchange rate neural network (ERNN), has been developed and trained using back propagation 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.

III. Time Series Data

The study uses the daily real exchange rate of Samoan Tala against AUD from 3 January 2008 to 28 September 2012. This excludes the weekends and public holiday in Samoa. There are 1180 observations. The figure below shows the trend of the Tala/ AUD from 3 January 2008 to 28 September 2012. The Fig. 1 clearly shows that the Tala/AUD increased 21 October 2008 until 3 November 2008 and later Tala/AUD decreases. Thereafter, Tala/AUD maintained its fluctuating trend.

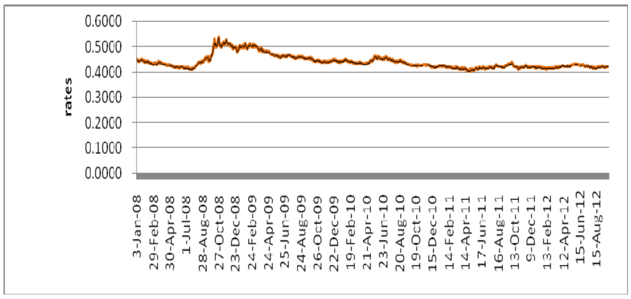


Fig. 1 Time series plot of Tala/AUD

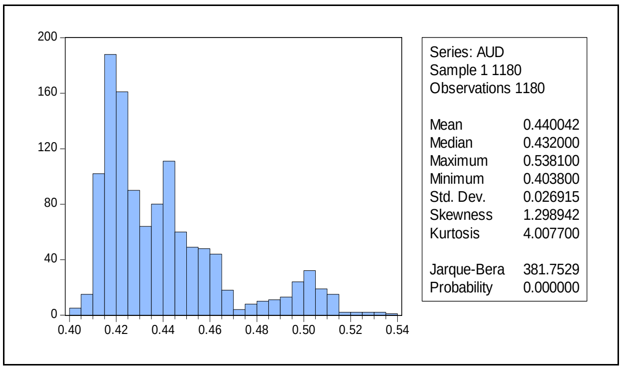


Fig. 2 Histogram and summary of Tala/ AUD

The average exchange rate of Tala against AUD over the study period is 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).This might imply that it is not advisble to use mean exchange rate value for business transactions. The coefficent of variance is 6.14%. Therefore, the Tala/AUD exchange rate is not highly volatile.

The preliminary test rejected stationary in AUD (-1) series. We carry out ADF test to check for the presence of unit root. The test suggested that there is a unit root present in AUD (-1) series. To test the presence of unit root we consider equation 1. For this purpose, we considered the model with constant, intercept and trend.

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

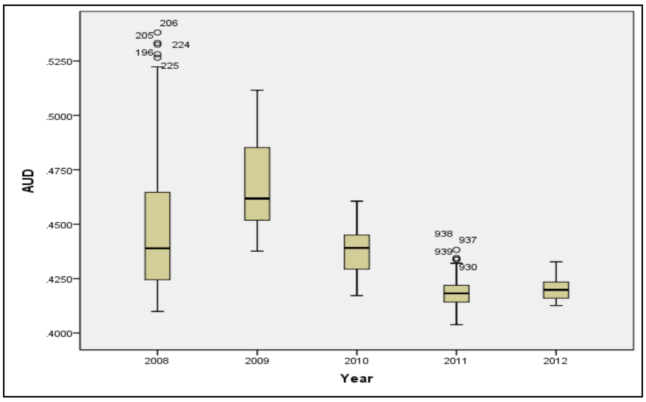


Fig. 3 Box Plot of Tala/AUD (-1) by Year

$$Y_t = a_0 + b_1 Y_{t-1} + b_2 t + \varepsilon ; (t = 1, 2, ..., n) \qquad (1)$$

where; Y_t= AUD with time; a_0 = constant; Y_{t-1}= lag of AUD; b_1, b_2 is the regression coefficient, ε is the error term and n=1179. The results are listed in Table I.

TABLE I
REGRESSION RESULT FOR TALA/AUD WITH LAG 1

Dependent Variable: AUD				
Method: Least Squares				
Included observations: 1179 after adjustments				
	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004280	0.001815	2.358179	0.0185
TIME	-4.55E-07	3.07E-07	-1.484719	0.1379
AUD(-1)	0.990837	0.003877	255.5619	0.0000
R-squared	0.987783			
Adjusted R-squared	0.987762			
S.E. of regression	0.002979			
Sum squared resid	0.010434			

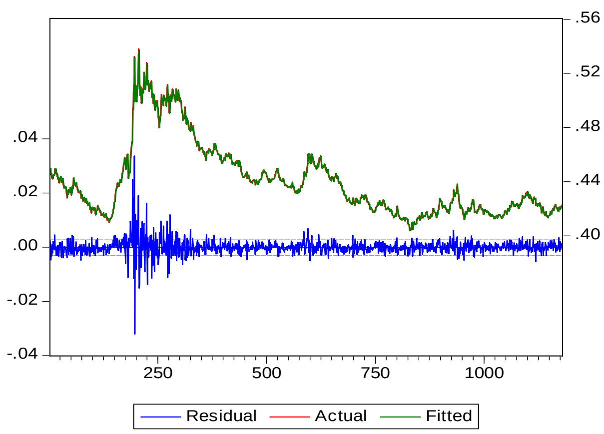
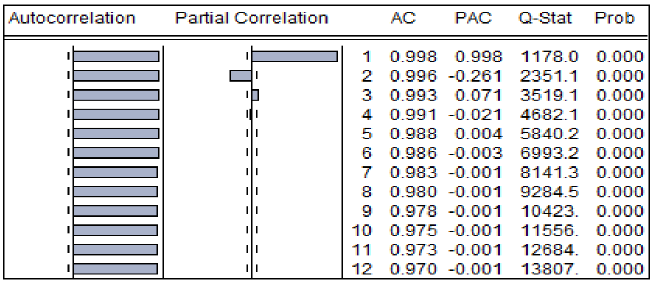


Fig. 4 Residual analysis from the regression of Tala/AUD

The regression result showed that the parameters of the model (constant and AUD (-1)) are significant (P values are less than 0.05) and R squared 0.994887. The Correlogram of forecasted values of Tala against AUD shows spikes at the 1st lag and slight spike at the 2nd lag. The Q- statistics are significant at all lags, indicating significant serial correlation in the residuals as shown in the corresponding figure.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.998	0.998	1178.0	0.000
		2	0.996	-0.261	2351.1	0.000
		3	0.993	0.071	3519.1	0.000
		4	0.991	-0.021	4682.1	0.000
		5	0.988	0.004	5840.2	0.000
		6	0.986	-0.003	6993.2	0.000
		7	0.983	-0.001	8141.3	0.000
		8	0.980	-0.001	9284.5	0.000
		9	0.978	-0.001	10423.	0.000
		10	0.975	-0.001	11556.	0.000
		11	0.973	-0.001	12684.	0.000
		12	0.970	-0.001	13807.	0.000

Fig. 5 Correlogram of forecasted Tala/AUD

Due to non-stationary of the Tala/ AUD daily exchange rate, the daily rate falls below the upper bound of the 95% confidence interval.

Fig. 6 shows an example of forecasting with an autoregressive model. The 95% confidence interval; are very board to help practical forecasting.

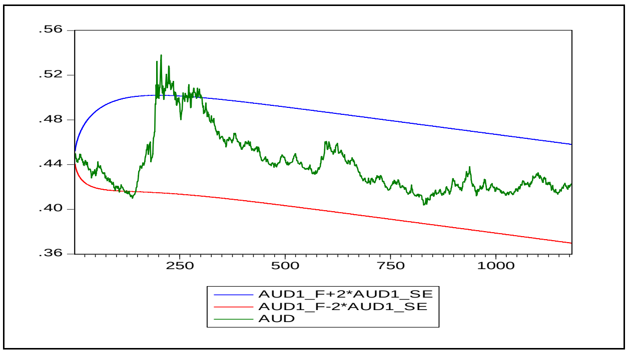


Fig. 6 The 95% confidence interval of forecasted AUD

III. TIME SERIES MODEL

The daily exchange data containing 1180 observations constitute the forecast model. Several time series models are considered.

a) Exponential Smoothing with Trend

The Exponential smoothing with trend is defined by:

$$S_t = \alpha y_t + (1-\alpha)\, s_{t-1} \qquad (2)$$

$$D_t = \alpha s_t + (1-\alpha)\, D_{t-1} \qquad (3)$$

where, S is the single smoothed series; D is the double smoothed series and Y_t is the AUD. Double smoothing is a single parameter smoothing method with damping factor $0 < \alpha \leq 1$.

TABLE II
FORECAST RESULT DOUBLE EXPONENTIAL OF TALA/AUD

Method: Double Exponential		
Original Series: AUD		
Forecast Series: AUDSM		
Parameters: Alpha		0.4200
Sum of Squared Residuals		0.011756
Root Mean Squared Error		0.003156
End of Period Levels:	Mean	0.422117
	Trend	0.000193

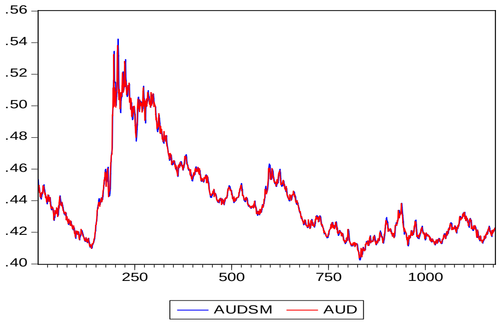


Fig. 7 Actual AUD vs. Forecasted AUD (exponential)

b) Holt-Winters—Multiplicative

This method is appropriate for series with Additive and multiplicative seasonal variation. The smoothed $\hat{Y}_t$ series is given by:

$$\hat{Y}_{t+k} = \left(a + bk\right)c_{t+k} \tag{4}$$

where, a is the intercept; b *is the* trend and c_t *defines the* multiplicative seasonal factor. The forecasts are computed by:

$$\hat{Y}_{t+k} = \left(a\left(T\right) + b\left(T\right)k\right)c_{T+k-s} \tag{5}$$

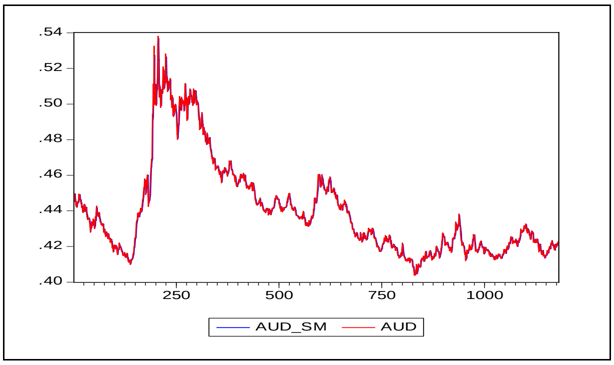


Fig. 8 Actual AUD vs. Forecasted AUD (Holt-winters Multiplicative)

Holt- Winters Additive method

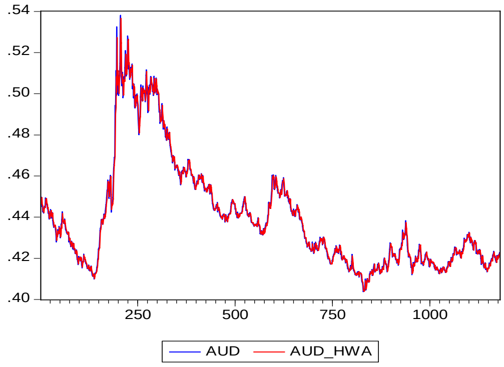


Fig. 9 Actual AUD vs. Forecasted AUD (Holt-winters Additive)

c) ANN Model

The model is designed as multi-layer perception. The model consists of three layers: an input layer, a hidden layer, and an output layer. This study used Activation function “TANH” the performance and predictability. For the first lag of Tala/AUD, the input layer has 4 variables; the hidden layer had 5neurons (the neurons in this layer can be changed depending on the performance of the result). The output layer has 1 variable- the exchange rate of Tala/AUD with 1179.The 2nd lag of Tala/AUD, the input layer has 3 variables; the hidden layer had 4neurons (the neurons in this layer can be changed depending on the performance of the result). The output layer has one variable- the exchange rate of Tala/AUD with 1178. The third lag of Tala/AUD, the input layer has five variables; the hidden layer had 5neurons (the neurons in this layer can be changed depending on the performance of the result). The output layer has one variable- the exchange rate of Tala/AUD with 1178.Neural network is often pictured as layer of functional node. The graph below shows the back propagation neural network. To experiment with the exchange rate time series ANN model, the author developed Microsoft Excel neural network software. The computational method employs conjugate gradient algorithm but with additional bias term in ANN model. This is to structure the favorable error surface for computational convenience.

d) ANN Computations

Step 1: Evaluate the net input to the j^{th} node and that to the k^{th} node in the output layer as follows:

$$net_j = \sum_{i=1}^{n} W_{ij}Y_i - \theta_j \tag{6}$$

$$net_k = \sum_{j=1}^{n} W_{jk}Y_j \tag{7}$$

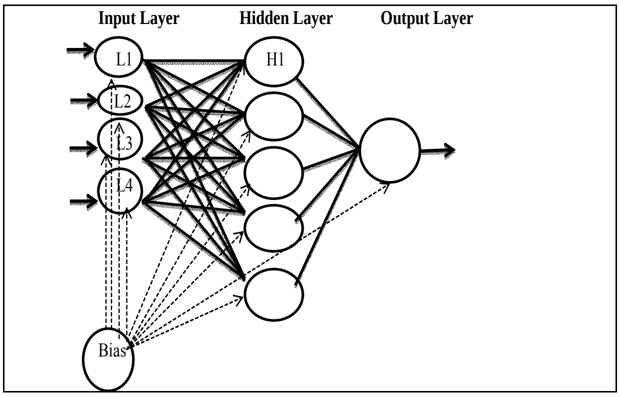


Fig. 10 ANN structure (AR model)

where i is the input node, j is the hidden layer node, k is the output layer node, w_{ij} is the weights connecting the i^{th} input node to the j^{th} hidden layer node, w_{jk} is the weights connecting the j^{th} hidden layer node to the k^{th} output layer node, θ_j is the threshold between the input and hidden layers.

Step2: Evaluate the output of the jth node in the hidden layer and the output of the kth node in the output layer as follows:

$$h_j = f_h(\sum_{i=1}^{n} W_{ij}Y_i - \theta_j) \tag{8}$$

$$k_j = f_k(\sum_{j=1}^{n} W_{jk}Y_j) \tag{9}$$

Define TANH activation function as: $\dfrac{e^{y}-e^{-y}}{e^{y}+e^{-y}}$ (10)

where, h_j is the vector of hidden-layer neurons, f_h and f_k are logistic activation functions from input layer to the hidden layer and from hidden layer to output layer respectively. The output of each neuron is obtained by applying an activation functions f_h and f_k. The nodes are used to perform the nonlinear input/output transformations using an activation function. Since the actual adaptation seems to be a non-linear form, the activation function influences strongly the ANN predictions in this study.

Step 3: For the calculation of errors in the output and hidden layers can be expressed as follows:

The output layer error between the target and the observed output is expressible as

$$\delta_k = -(d_k - y_k) f_k' \tag{11}$$

$$f'_k = \frac{4}{\left(e^{x}+e^{-x}\right)^2} \tag{12}$$

where δ_k is the vector of errors for each output neuron (y_k) and d_k the target activation of output layer. The term δ_k depends only on the error ($d_k - y_k$) and f'$_k$ is the local slope of the node activation function for output nodes. The hidden layer error is expressible as

$$\delta_j = f_h' \sum_{k=1}^{n} W_{kj}\delta_k \tag{13}$$

where δ_j is the vector of errors for each hidden layer neuron, δ_k is a weighted sum of all nodes and f'_h the local slope of the node activation function for hidden nodes.

Step 4: Considering the ANN error equation as 12, the Newton based optimization scheme is applicable to optimize neural network weights as discussed next. In this study, quasi Newton based algorithm such as Davidon (1959), Fletcher and Powell (1963) is employed. This method falls under the general class of quasi-Newton procedures, where the search directions are of the form:

$$d_j = -D_j \nabla f(Q). \tag{14}$$

The gradient direction is deflected by multiplying $-D_j$, where D_j is $m \times m$ positive definite symmetric matrix. It approximates the inverse of the Hessian Matrix of the neural network error function of type as shown in equation 12.

Let $\varepsilon > 0$ be the small scalar quantity set as termination criteria. Choose and initial m dimensional weight w_i (1=1,2,…m) resulting from an ANN error function and the initial symmetric positive definite matrix D_1. Let Q_1=w_1, $k = j = 1$, and go to the main step.

a) If $\left\|\nabla f(Q_j)\right\| < \varepsilon$, stop, otherwise, let $d_j = -D_j \nabla f(Q_j)$ and let λ_j be an optimal solution to the problem:

Minimize $f(Q_j + \lambda d_j)$; Subject to $\lambda \geq 0$.

The parameter λ is obtained by line a suitable search method. Let $Q_{j+1} + Q_j + \lambda_j d_j$. If j<m, go to step b. If j=m, let $Q_1 = x_{i+1} = Q_{m+1}$, replace i by i+1, let j=1, and repeat step a.

b) Construct D_{j+1} as follows:

$$D_{j+1} = D_j + \frac{P_j P_j^t}{P_j^t q_j} - \frac{D_j q_j q_j^t D_j}{q_j^t D_j q_j}$$

where

$P_j = \lambda_j d_j \equiv Q_{j+1} - Q_j$ And

$q_j = \nabla f(Q_{j+1}) - \nabla f(Q_j)$

Repeat j by j+1 and repeat step a.

IV. ANN Model Simulation

The importance of normal distribution of error vector is undeniable since the underlying assumption of many statistical procedures such as t-test, regression analysis, and analysis of variance (ANOVA) (Razali and Wah, 2011). The Anderson-

Darling test is used to test if a sample of data came from a population with a specific distribution. The Anderson-Darling (1954) test makes use of the specific distribution in calculating critical values. This has the advantage of allowing a more sensitive test and the disadvantage that critical values must be calculated for each distribution. The Anderson darling test and Shapiro and Wilk (1965) test exhibit similar results when the necessarily sample size is 500 or less. In our case, the data tide exceeds 1000 and therefore, Anderson Darling test is robust. Further, Anderson darling (1954) test is competitive with better known Shapiro and Wilk (1965) but has the advantage that the critical values of each sample size is not needed. It is an omnibus test, in sense that it is sensitive to all types of deviation to normality, but it is somewhat more sensitive to deviation in the tails of the distribution-which is that way non normality makes itself known. The microsoft excel based computational software is developed by the author.The graph below shows the normal probalbity plot through Aderson Darling Normality Test AR model.

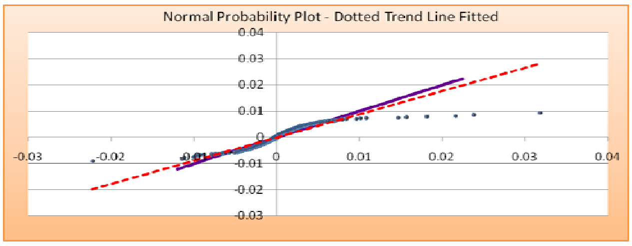


Fig. 11 Normal Probablity Plot from Anderson Darling Test AR model for Tala/AUD

The Aderson Darling Normality Test exhibit the p- value less than 0.05 and it implies that the data is sampled from a population that is not normally distributed.The AR time series exchange rate is a multi-layer perception model.

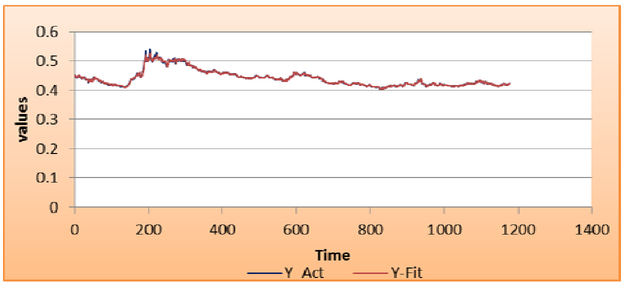


Fig. 12 Actual AUD vs. Forecast (ANN AR time series)

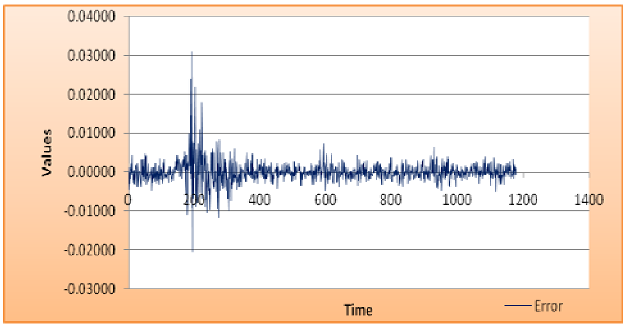


Fig. 13 Error distribution ANN AR model Tala/AUD

V. Diagnostic Error Terms

To test the validity of the exchange rate estimation model, the following diagnostics measures were considered:

Mean Absolute Error:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\hat{Y}_t - Y_t\right| \tag{15}$$

Mean Absolute Percentage Error:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{\hat{Y}_t - Y_t}{Y_t}\right| \tag{16}$$

Root Mean Square Deviation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\hat{Y}_t - Y_t\right)^2} \tag{17}$$

Thiel's U:

$$U = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\hat{Y}_t - Y_t\right)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\hat{Y}_t\right)^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t\right)^2}} \tag{18}$$

Where, Y_t is the actual value and time t; $\hat{Y}_t$ is the forecast value with t=1, 2…, n for the forecast period.

To test the validity of the exchange rate using ANN model, some other diagnostics measures are used:

Pearson Correlation:

$$r = \frac{\left(\sum_{i=1}^{n}(Y_i - \bar{Y})(\hat{Y}_i - \bar{\hat{Y}})\right)}{\left(\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}\sqrt{\sum_{i=1}^{n}(\hat{Y}_i - \bar{\hat{Y}})^2}\right)} \tag{19}$$

Goodness to fit:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{20}$$

Tracking Signal:

$$TS = \frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)}{\frac{\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right|}{n}} \quad (21)$$

To develop a forecast accuracy measures, two types of errors are considered. The one is forecast bias where the direction of the error was considered. If the value of the error is negative, then forecasting method is overestimating. Positive values imply that forecasting is underestimating. By adding error term, if there is no bias the positive and negative error term will cancel each other out and the mean error term will be zero. If the positive and negative values tend to cancel each other, then TS (tracking signals (cumulative forecast running error/ mean absolute deviation) is zero or near to zero. In such case, forecasting methods does not result in bias implying that there is no underestimation or overestimation. Even if there is no bias, it is likely that the estimation result is significant variation from the actual value. The aim of identifying accuracy in estimation is to determine how well the forecasting method estimates the actual value without evaluating forecast bias. The utilization of mean square error (MSE) as a criterion in determining the accuracy of forecast has drawbacks. Some of the errors measures listed above are MAE, RSME, and MAPE. The scaling of U will always lie between 0 and 1. If U = 0, Yt = ft for all forecasts and there is a perfect fit; if U = 1 the predictive performance is as bad. Theil's U statistic can be rescaled and disintegrated into 3 proportions of inequality bias, variance and covariance. The bias + variance + covariance = 1. The interpretations of the three proportions are explained next: Bias indicates systematic error. Bias should be close to zero if the bias large this suggests a systematic over or under prediction. Variance indicates the ability of the forecasts to replication degree of variability in the variable to forecast. If the variance proportion is large then, the actual series has fluctuated considerably whereas the forecast has not. Covariance is the proportion that measures unsystematic error. Ideally, this should have the highest proportion of inequality.

VI. Results

The result shown in table illustrates a comparison of ANN model, exponential smoothing, and Winters Method model**.** The ANN model shows a smaller RSME, MAE, MAPE compared to other model. The fitted value of Neural Network model have higher correlation value (CORR=0.99456) with the actual series.

TABLE III
SHOWS THE COMPARISON OF DIFFERENT MODEL RESULTS OF TALA/AUD

Model	RSME	MAE	MAPE	Bias	TS	R^2
AR (1)	0.0334	0.0150	0.0334	-0.0071	-56.0250	0.9878
Exponential Smoothing	0.0032	0.0020	0.0003	0.0000	0.5485	0.9862
Holt-Winters—Multiplicative	0.0029	0.0017	0.0022	0.0000	0.1382	0.9881
Holt- Winters Adaptive method	0.0029	0.0017	0.0022	0.0000	0.1361	0.9881
ANN (AR 2) model	**0.0028**	**0.0000**	**0.0037**	**0.0000**	**-0.1963**	**0.9891**

VII. Conclusion

The Anderson Darling normality test for the error distribution of the ANN time series shows that the data comes from a population that is not normally distributed. This assumption deviated from the traditional central limit theorem for error distributions in statistical models. The ANN time series model forms a multi-layer perception with "TANH" activation function. The input layer of the ANN with four neurons receives the lagged daily exchange rate time series signals. The hidden layer has five neurons with trigonometric activation function. The output layer has one neuron and transforms the signal to daily forecasted exchange rate of Tala/AUD. The series is non-stationary and hence exhibit challenge to construct forecasting model.

This paper compared the daily exchange forecast results derived from ANN time series, exponential smoothing and winters time series model. We conclude that the autoregressive time series exchange rate of Tala vs AUD is the best model to do daily exchange rate forecast.

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Shamsuddin Ahmed is Professor of Operations Management at the Graduate School of Business, The University of the South Pacific, Fiji. His research works are in the areas of biological neural computation, applied statistical computations, six sigma, process analysis, simulation, and service quality in health care management. He obtained a PhD degree in applied operations research from Edith Cowan University. He is a trained graduate engineer with honours degree in mechanical engineering. He holds MS degree in industrial engineering from Dalhousie University.

Previously he served KIMEP as the director of research at the Bang College of Business and American University of the Middle East in affiliation with Purdue University, USA. Outside academia, he worked as systems analyst in Middle East and industrial engineer in production industries in India. Ahmed is recipient of the KIMEP faculty research awards several times for excellence in research leadership at the Bang College of Business, KIMEP. He serves the editorial board of several international journals. Recently, Ahmed was awarded the "Best Professor in Operations Management" for excellence in education, leaderships, and teaching, The World Education Congress, 2012, India, governed by the Global Advisory Council: the Jury and Council of Board members, July, 2012.

MGM Khan is an Associate Professor in Statistics at the University of the South Pacific (USP), Suva, Fiji. The main research interest of Dr. Khan is in the areas of Mathematical Programming and its Applications, Sampling Theory and Survey Sampling, Statistical Modelling and Simulation, Optimization, Software Reliability, Estimation Theory and Design of Experiment.

Dr. Khan graduated from the University of Calcutta in 1985. He obtained his M.Sc. from the Aligarh Muslim University in 1989. In 1992 he awarded M.Phil. Degree in Statistics followed by Ph.D. Degree in 1996 from the Aligarh Muslim University.

Previously, he served as a Lecturer in Statistics during 1996-1997at Poona College affiliated by the University of Pune, India. Then he joined as a Lecturer in Statistics in 1998 at Mohamed Sathak College affiliated by University of Madras, Chennai, India before he joined at USP in 2001. He was Visiting Scholar at the Department of Statistics, Iowa State University, Ames, USA during August 2007 to January 2008. As an administrator, he served as the Coordinator of Mathematics and Statistics Division during 2006-2010 and as the acting Head of the School of Computing, Information and Mathematical Sciences at USP during 2010-2012.

Dr. Khan serves as member of several editorial boards of international journals. He is an elected member of the International Statistical Institute and also active member of International Association of Survey Statistician and American Statistical Association. He is also Representative of Fiji to the Survey Statistician, Newsletter of International Association of Survey Statisticians since 2012.

Biman Prasad is Professor Economics at the University of the South Pacific and Adjunct Professor at the Griffith University and James Cook University in Australia. He was the Dean of the Faculty of Business and Economics at the University of the South Pacific from 2007 to 2011 and Head of School of Economics from 2003 to 2007. He is an Associate Editor for the Journal of Fijian Studies and Editor-in-Chief of the Journal of Pacific Studies. He has held visiting appointments at the Kagoshima University in Japan, Otago University in New Zealand and Jawaharlal Nehru University in India. His current research interests include economic growth, trade, development and economic integration in the Pacific Islands.

Avlin Pritishna Prasad is a Research Assistant of Research Cluster "Economic Growth, Trade and integration" at University of the South Pacific (USP), Suva, Fiji. The main research interests of Ms. Prasad are in the area of econometrics, forecasting, economic statistics, economic analysis, and economics of growth and Development.

Ms. Prasad graduated from University of the South Pacific in 2010 with BCom. She obtained her PGDip in Economics from USP in 2013.

Earlier, she served as a Research Assistant-statistics from October 2010-April 2012 at Fiji Commerce Commission, Suva, Fiji. She also served Fiji National University as temporary student assistant and Graduate Assistant/Mentor from April 2010-September 2010.