# Forecasting of Currency Exchange Rate Using Artificial Neural Network: A Case Study of Solomon Island Dollar

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**Abstract.** The use of neural network models for currency exchange rate forecasting has received much attention in recent time. In this paper, we propose an exchange rate forecasting model based on artificial neural network. We tested our model on forecasting the exchange rate of Solomon Islands Dollar against some major trading currencies of the country such as, Australian Dollar, Great Britain Pound, Japanese yen, and Euro. We compared the performance of our model with that of the single exponential smoothing model; the double exponential smoothing with trend model; and Holt-Winter multiplicative and additive seasonal and multiple linear regression model. The performance of the models was measured using the error function, root mean square error (RMSE). The empirical result reveals that the proposed model is more efficient and accurate in forecasting currency exchange rate in comparison to the regression and time series models.

**Keywords:** Forecasting exchange rate · Neural network model · Multiple linear regression model · Time series models · Naive method

## 1 Introduction

Currency exchange rate plays an import role for a country in any international trading. Developing forecasting models for exchange rates is an on-going field of research because of its contribution to investors' confidence in the local currency, entrepreneurship development and also the performance of the stock market. Many time series models such as autoregressive integrated moving average (ARIMA), autoregressive (AR), Random Walk (RW), generalized autoregressive conditional heteroscedasticity (GARCH), and exponential smoothing models have been developed over the past decades to forecast exchange rates (Meese and Rogoff 1983; Zhang et al. 1998, 2003; Tambi 2005; Lee and Boon 2007; Maniatis 2012; Ahmed et al. 2013). However, these models are well known in the literature for their poor predictions, which are characteristically highly volatile, complex, noisy, nonstationary, nonlinear and chaotic (Meese and Rogoff 1983; Kuan and Liu 1995; Abhyanker et al. 1997;


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Gencay 1999; Zhang 2003; Tambi 2005; Maniatis 2012). In 1970, Box and Jenkins popularized ARIMA and researchers use it to forecast economic time series for years as a benchmark model (Kadilar et al. 2009). ARIMA is a general univariate model and it is developed on the assumption that the time series being forecasted, is linear and stationary. But most of the time series are nonlinear and nonstationary which makes ARIMA not a good technique for forecasting (Kadilar et al. 2009; Ahmed et al. 2013). Recently, ANN has become a popular model for forecasting (Leung et al. 2000; Walczak 2001; Huang and Lai 2004; Kadilar et al. 2009; Pradhan and Kumar 2010; Egrioglu et al. 2012) and was found to be more effective than other econometric models with higher percentage of accuracy to predict (Walczak 2001).

In this paper, we develop an ANN-based forecasting model of exchange rates for SBD against its major trading currencies such as AUD, GBP, JPY and EUR. The proposed model forecasts the rate that minimizes the sum of squared errors and is based on three neurons in the input layer and four neurons in the hidden layer. As a learning algorithm, a generalized reduced gradient (GRG) is developed, which uses a tangent hyperbolic transfer function and is solved using Excel Solver.

The rest of the paper is summarized as follows. First two sections discuss the methodology of ANN and time series models with the measures of model evaluation and validation. The next section describes the Solomon's exchange rate data followed by the presentation of results and discussion of the forecasting time series and proposed ANN models. The paper ends with the discussion of results and conclusion with future directions.

## 2 Solomon Islands Exchange Rate Data

This paper used the daily exchange rate of AUD against SBD (AUD/SBD) and the three other major trading currencies, namely GBP, JPY and EUR from January 5, 1998 to June 30, 2014 collected from the Central Bank of Solomon Islands (CBSI 2005, 2014). The data contain 4150 observations, out of this, 3750 (90%) will be used for training and the remaining 400 (10%) will be used for forecasting, which excludes weekends and public holidays.

## 3 Methodology

The purpose of this paper is to develop an artificial neural network for forecasting the exchange rate of a country against its major trading currencies and to compare its performance with other time series models. We use the naive method as a benchmark method for the comparison of the proposed ANN model.

The main goal of a neural network is to make an accurate prediction in the dependent variable (output cell). The advantage of a neural network is that it uses less assumptions; it can fit a nonlinear model that can approximate any nonlinear function with higher accuracy; and has greater ability of prediction to be used in many different areas (Kamruzzaman and Sarker 2004; Wu and Yang 2007; Kadilar et al. 2009).

The ANN model designed in this paper is a multi-layered perception. The proposed model considers the most widely used neural network, known as the back propagation network. The network consists of one-hidden layer with different lags of exchange rate as neurons in the input layer. We used 2 to 6 (lag 2 to lag 6) nodes for the input layer, 3 to 5 nodes for the hidden layer and one output in the model topology. We experiment on different transformation or activation functions to map the inputs into the outputs and found that the tangent hyperbolic *tanh* function gives better performance so we use it in our model. The optimum weights and biases that yield the best forecasts are obtained by minimizing the sum of square error (SSE). Using the training data with the RMSE error measure for different number of nodes in the input and hidden layers we found ANN (3, 4, 1) to be the best so we take it as our final model.

We also constructed the multiple linear regression (MLR) and time series models for comparison purposes. For the selection of the number of time-lags that fits best a multiple linear regression model for forecasting AUD/SBD exchange rate, we consider the Akaike information criteria (AIC) and the Schwarz information criteria (SIC) and found that MLR (6), the multiple linear regression with 6 lags is the most preferred model because it is significant at the 1% level of confidence, and has the lowest values of AIC and SIC. We also generate the time series models using the exponential single and double smoothing models as well as the Holt–Winters (HW) additive and multiplicative models for the training sample.

## 4 Forecasting Results and Discussion

We use the testing sample to forecast the Solomon Islands exchange rates against AUD, GBP, JPY and EUR using all the methods discussed above. For the comparison of various forecasting models and exchange rate series, we present the error measures in Table 1 for AUD, GBP, JPY and EUR. The results of the proposed ANN (3, 4, 1) model are presented in the last row of the table. It reveals that the proposed ANN (3, 4, 1) is the preferred model with lowest RMSE. We further benchmarked our proposed model with the naive method, which may appear to be the best forecasting method in many cases. Thus, the proposed ANN method should be compared to this simple method to ensure that the new method is better (Hyndman and Athanasopoulos 2014). The results for the naive method along with the proposed method are presented in Table 2. The table reveals that the proposed method outperformed the benchmarked method in all of the four exchange rate.

**Table 1.** RMSE measures for different models and exchange rate series using the testing sample.

| Model | AUD ($\times 10^{-4}$) | GBP ($\times 10^{-4}$) | JPY ($\times 10^{-4}$) | EUR ($\times 10^{-4}$) |
|---|---|---|---|---|
| Single | 10.49 | 12.33 | 12.74 | 7.26 |
| Double | 10.60 | 13.25 | 10.13 | 7.63 |
| HW additive | 9.31 | 12.33 | 8.53 | 7.20 |
| HW multiplicative | 9.31 | 12.33 | 8.53 | 7.20 |
| MLR(6) | 9.37 | 12.81 | 8.74 | 7.39 |
| **ANN (3, 4, 1)** | **9.23** | **11.95** | **8.52** | **6.96** |

**Table 2.** RMSE measures for benchmarking the proposed ANN model using the naive method for different currencies exchange rate.

| Accuracy measure | AUD/SBD | | GBP/SBD | | Japanese Yen/SBD | | EUR/SBD | |
|---|---|---|---|---|---|---|---|---|
| | Naive | ANN | Naive | ANN | Naive | ANN | Naive | ANN |
| RMSE ($\times 10^{-4}$) | 164.91 | **9.23** | 37.61 | **11.95** | 246.66 | **8.52** | 36.95 | **6.96** |

## 5 Conclusion

In this paper, we propose an ANN model for forecasting Solomon exchange rates against four major trading currencies. The result of this study reports that the ANN (3, 4, 1) produces least values of RMSE. This proposed model is compared with regression and time series models and is found to be robust and superior. The proposed model also has the least value of RMSE over the benchmarked method for all the currencies. These empirical findings strongly indicate that ANN is an efficient tool for the forecasting the currency exchange rates more accurately. The immediate future direction is to use other exchange rate datasets with ANN or its variations such as recurrent neural network and cooperative coevolution neural network.

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## References

Abhyanker, A., Copeland, L.S., Wong, W.: Uncovering nonlinear structure in real-time stock-market indexes: the S&P 500, The Dax, the Nikkei 225, and the FTSE-100. J. Bus. Econ. Stat. **15**, 1–14 (1997)

Ahmed, S., Khan, M.G.M., Prasad, B.: Forecasting Tala/USD and Tala/AUD of Samoa using AR (1), and AR(4): a comparative study. Math. Comput. Contemp. Sci., 178–186 (2013)

CBSI: CBSI quarterly review, vol. 17. Central Bank of Solomon Islands, Honiara, June 2005

CBSI: CBSI quarterly review, vol. 27. Central Bank of Solomon Islands, Honiara, June 2014

Egrioglu, E., Aladag, H.C., Yolcu, U.: Comparison of architect selection criteria in analysing long memory time series. Adv. Time Ser. Forecast. **3**, 18–25 (2012)

Gencay, R.: Linear, non-linear and essential Foreign exchange rate prediction with simple technical trading rules. J. Int. Econ. **47**, 91–107 (1999)

Huang, W., Lai, K.K.: Forecasting Foreign exchange rates with artificial neural networks: a review. Int. J. Inf. Technol. Decis. Mak. **3**, 145–165 (2004)

Hyndman, R.J., Athanasopoulos, G.: Forecasting: Principles and Practice. OTexts (2014)

Kadilar, C., Muammer, S., Aladag, H.C.: Forecasting the exchange rate series with ANN: the case of Turkey. Istanb. Univ. Econ. Stat. E-J. **9**, 17–29 (2009)

Kamruzzaman, J., Sarker, R.A.: ANN-based forecasting of Foreign currency exchange rates. Neural Inf. Process. Lett. Rev. **3**, 49–58 (2004)

Kuan, C.M., Liu, T.: Forecasting exchange rates using feedforward and recurrent neural networks. J. Appl. Econ. **10**, 347–364 (1995)

Lee, C.L., Boon, H.T.: Macroeconomic factors of exchange rate volatility evidence from four neighbouring ASEAN economies. Stud. Econ. Financ. **24**, 266–285 (2007)

Leung, M.T., Chen, A.S., Daouk, H.: Forecasting exchange rates using general regression neural networks. Comput. Oper. Res. **27**, 1093–1110 (2000)

Maniatis, P.: Forecasting the exchange rate between Euro and USD: probabilistic approach versus ARIMA and exponential smoothing techniques. J. Appl. Bus. Res. **28**, 171–192 (2012)

Meese, R.A., Rogoff, K.: Empirical exchange rate models of the seventies. Do they fit out of sample? J. Int. Econ. **14**, 3–24 (1983)

Pradhan, R.P., Kumar, R.: Forecasting exchange rate in India: an application of artificial neural network model. J. Math. Res. **2**, 111–117 (2010)

Tambi, M.K.: Forecasting exchange rate: a univariate out of sample approach. IUP J. Bank Manag. **0**(2), 60–74 (2005)

Walczak, S.: An empirical analysis of data requirements for financial forecasting with neural networks. J. Manag. Inf. Syst. **17**, 203–222 (2001)

Wu, W.P., Yang, H.L.: Forecasting New Taiwan/United States dollar exchange rate using neural network. Bus. Rev. **7**, 63–69 (2007)

Zhang, G., Patuwo, B.E., Hu, M.Y.: Forecasting with artificial neural networks: The state of the art. Int. J. Forecast. **14**, 35–62 (1998)

Zhang, G.P.: Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing **50**, 159–175 (2003)