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Forecasting exchange rate of Solomon Islands dollar using artificial neural network and the purchasing power parity theory

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Forecasting exchange rate of Solomon Islands dollar using artificial neural network and the purchasing power parity theory

James Douglas Kimata

A thesis submitted in fulfilment of the
requirements for the degree of
Master of Science (M.Sc.) in
Mathematics

School of Computing, Information and
Mathematical Sciences
Faculty of Science, Technology and Environment
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Suva, Fiji

April, 2016

Declaration of Originality

Statement by Author

I, James Douglas Kimata, declare that this thesis is my own work and that, to the best of my knowledge, it contains no material previously published, or substantially overlapping with material submitted for the award of any other degree at any institution, except where due acknowledgment is made in the text.

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Statement by Supervisors

The research in this thesis was performed under our supervision and to our knowledge is the sole work of Mr. James Douglas Kimata.

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Dedication

Dedicated to my son Evans and my dear wife Rosemary and to my parents Douglas and Grace Kimata

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Contents

Abbreviations

AIC	Akaike Information Criterion
ANN	Artificial Neural Network
AR	Auto Regressive
ARCH	Auto Regressive Conditional heteroscedasticity
ARIMA	Auto Regressive Integrated Moving Average
AUD	Australian Dollar
CBSI	Central Bank of Solomon Islands
GARCH	General Auto Regressive Conditional Heteroscedasticity
GBP	Great Britain Pound
GRG	Generalized Reduced Gradient
HW	Holt– Winter
IMF	International Monetary Fund
JPY	Japanese Yen
LNESOUK	Natural logarithm of Solomon Islands dollar per United Kingdom pound
LNESOUS	Natural logarithm of Solomon Islands dollar per United States dollar
LNSOCPI	Natural logarithm of Solomon Islands Consumer Price Index
LNSOUKCPI	Difference of natural logarithm of Solomon Islands and United Kingdom Consumer Price Indexes
LNSOUSCPI	Difference of natural logarithm of Solomon Islands and United States Consumer Price Indexes
LNUKCPI	Natural logarithm of United Kingdom Consumer Price Index
LNUSCPI	Natural logarithm of United States Consumer Price Index

MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLR	Multiple Linear Regression
OARE	Online Access Research for Environment
PICs	Pacific Islands Countries
PPP	Purchasing Power Parity
RMSE	Root Mean Square Error
SBD	Solomon Bokolo Dollar (refers to, the Solomon Islands Dollar)
SDR	Special Drawing Rights
SIC	Schwarz Information Criterion
SPSS	Software Package for Social Science
SSE	Sum of Square Error
SST	Sum of Square Total
TS	Tracking Signal
UK	United Kingdom
USD	United States Dollar
USP	University of the South Pacific
VECM	Vector Error Correction Model

Figures

Tables

Abstract

With continual changes made and reviews of the exchange rate regime of Solomon Islands it is imperative that a proper forecasting modelling tool is established. The use of neural network models in exchange rate forecasting has received much attention in recent research. In this thesis we propose an artificial neural network (ANN) model for forecasting exchange rates of the Solomon Islands dollar (SBD) against all major trading currencies such as Australian dollar (AUD), Great Britain pound (GBP), Japanese yen (Yen) and EURO. We use daily exchange rate data during the period of January 5, 1998 to June 30, 2014. The proposed model is compared with a naive method as a benchmarked method. Further, it is compared with single exponential smoothing; double exponential smoothing with trend; and Holt-Winter multiplicative and additive seasonal and multiple linear regression models. The performance of the models was measured by using various performance metrics such as root mean square error, mean absolute error, and mean absolute percentage error. The validation tests of the models were also carried out using different goodness of fit measures such as R-square, bias and tracking signal. The empirical result reveals that the proposed model is an efficient tool for forecasting SBD against the major trading currencies more accurately than are regression and time series models. We have also tested the purchasing power parity hypothesis using the consumer price index of USA and UK against Solomon Islands for the sample monthly period from January 1993 to December 2013. This thesis uses co-integration and the error correction as methodologies as the data are found to be nonstationary. The result shows that the changes in Solomon dollars (SBD) per USD are influenced by the long-term trends in the price differential of Solomon Islands and the USA. We further investigate the changes in the price differential between Solomon Islands and the UK and establish that they have similar trends. The symmetry and proportionality of the strong version of PPP were found to be very significant for Solomon Islands against UK price only and not against US dollar. The price levels in an open small pegged exchange regime such as that of Solomon Islands are greatly determined by international prices, and interestingly, even the nominal exchange rates are determined by price differentials in the long-run.

Preface

This thesis entitled "*Forecasting exchange rate of Solomon Islands dollar using artificial neural network and the purchasing power parity theory*" is submitted to the University of the South Pacific, Suva, Fiji to fulfill the requirements of the Master of Science in Mathematics.

In this thesis an attempts is made to develop an ANN-based forecasting model of exchange rates for SBD against its major trading currencies such as AUD, GBP, Yen and Euro. The proposed model forecasts the rate that minimizes the sum of square error and is based on three neurons in input layer and four neurons in 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.

Our next study is to investigate if PPP hypothesis determines the exchange rate between the Solomon Islands dollar and the United States dollar, and the British pound. This study employs the co-integration and error correction methodologies in testing the PPP theory. We also test the causal relation between exchange rates and the prices. This testing through the error-correcting methodology implies whether the exchange rates and prices have common stochastic trends and if so, whether the current changes in one variable adjust to past trend and in lag level forms of the other variable. This thesis tries further investigation of the long-run PPP theory for the Solomon Islands dollar against the US dollar and the UK pound. We use the augmented Dick–Fuller tests (ADF) to test for the unit root and the Johansen co-integration test to determine the order of integration. We further adopt error correction estimates (ECE) to examine the speed of adjustment for the short-run and to ascertain the existence of the long-run PPP. To test the strength of the causation of the exchange rate and the price differential of local dollar against USA dollar and UK pound, we put restrictions on the coefficient of consumer price index (CPI) of local and the foreign prices and use the log likelihood test to determine the symmetry of the price differential.

The thesis is made up of eight chapters. **Chapter 1**, the introduction, presents the background, the study area, an overview of the Solomons exchange rate regime and forecasting, and the objectives. This chapter also comprises of the literature reviews of the artificial neural network and the purchasing power parity theories, respectively. **Chapter 2**, the methodology, focuses on the various sources used for collecting data and the statistical software required to analyse them. This chapter also includes the proposed model that will be built for experimentation and different error functions that are used to select the best model. Furthermore, this chapter covers the co-integration and the vector error correction model for the purchasing power parity. **Chapter 3** gives the forecasting using multiple linear regression models and **Chapter 4,** the forecasting using time series methods, in particular, single and double exponential smoothing, and Holt-Winter additive and multiplicative methods. **Chapters 5 and 6** respectively give the forecasting of the artificial neural network and the result of purchasing power parity. Finally, **Chapters 7** and **8** give the overall discussion and conclusions respectively.

Chapter 1: Introduction

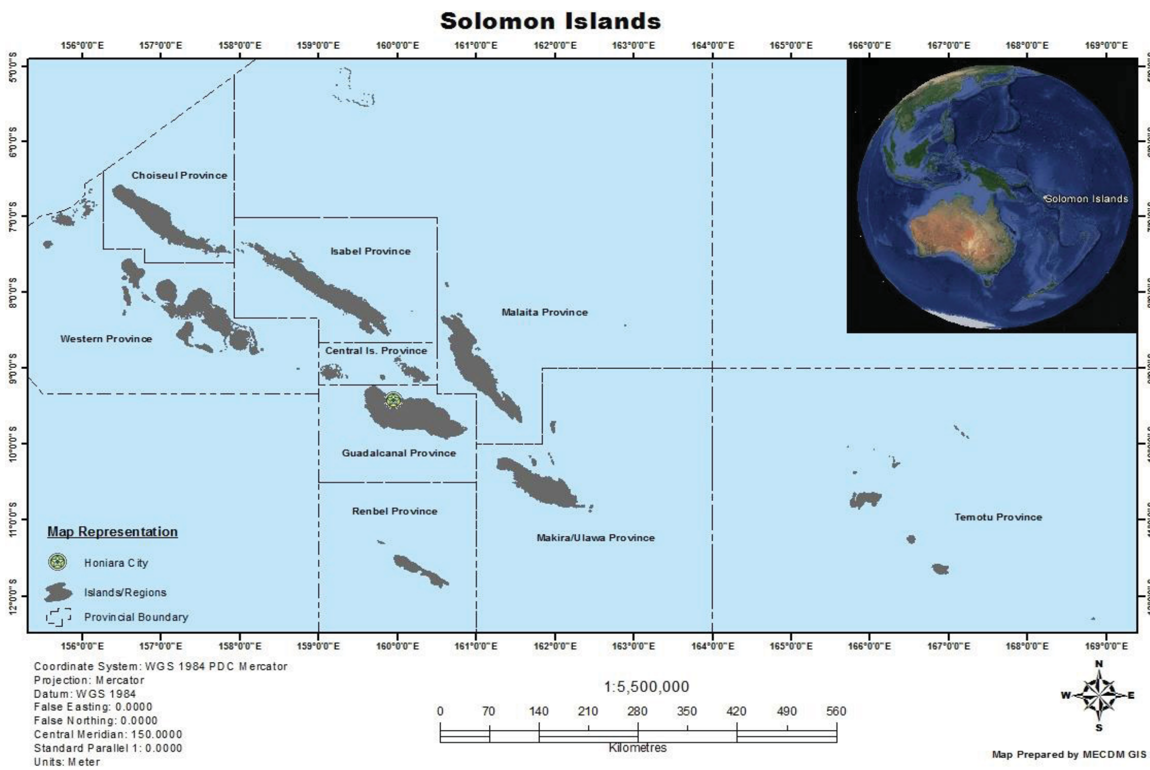
1.1. Background

A model for forecasting exchange rate has become a very important tool for prediction. In order to make sound monetary policy, a reliable model is needed. A good predictive model makes a significant contribution to investors' confidence in the local currency, entrepreneurship development and also the performance of the stock market (Abhyanker et al., 1997). Most of the earlier attempts used econometric models such as random walk (RW), autoregressive integrated moving average (ARIMA), autoregressive conditional heteroscedasticity (ARCH), and general autoregressive conditional heteroscedasticity (GARCH). However, these models are well known in the literature for their poor predictions, which are characteristically highly volatile, complex, noisy, nonstationary, nonlinear and chaotic (Abhyanker et al., 1997; Kamruzzaman & Sarker, 2004). For these reasons estimating exchange rate movement is always a difficult and challenging task, which has become one of the main concerns for academics and other researchers. Moreover, other time series and regressive models such as exponential smoothing models, Holt-Winter (HW) models and multiple linear regression models have been used but have some limitations and issues in their forecasting reliability and accuracy. For example, regression models require data to be stationary and normally distributed. However, most of the time series data fail to meet these two conditions which are adverse to the use of this regression model. Recent studies have shown that ANN has been an effective tool in forecasting exchange rates because it requires less assumptions, is nonlinear and data-driven (Kamruzzaman & Sarker, 2004; Winston & Venkataramanan, 2003). Exchange rate forecasting is done in many countries in the world but very little in the Pacific, in particular Solomon Islands where the focus of this research lies. For Solomon Islands, exchange rate forecasting is a real challenge, because there is no technical capacity or locally built model within the Central Bank of Solomon Islands (CBSI) that can capture the economic fundamentals of the country. Thus, most of the forecasting has relied on the United States forecasting and other international sources such as FX4cast.com and Bloomberg. This implies that its transmission or pass-through effect to the consumers is always lagging and not effective enough to stimulate economic activities.

The purchasing power parity (PPP) theory is an important field of study in international economics and finance. It is based on the law of one price. The law states that under the assumption of the absence of transportation costs and trade barriers, the price of a good in two countries should be equal if they are of the same quality and are expressed in terms of the same currency. The theory further state that on the basis of this law of one price, the exchange rates between any two countries will adjust over time to reflect changes in their respective price levels. Empirical economists have been using the PPP theory over a long time as a tool to compare the price differences between two countries. Other studies have been done in developed and developing countries, including other African countries, regarding the PPP theory but very little has been done in the Pacific Islands countries (PICs) (Paul & Motlaleng, 2006; 2008). In PICs the common challenges faced are limited, infrequency and incomplete data. This fact could be attributed to the islands' isolation and remoteness from their markets. Recently, Jayaraman and Choong (2014) did a study on validity of the PPP theory in five independent dollarized PCIs, namely Fiji, Samoa, Solomon Islands, Tonga and Vanuatu. They found a weak long-run PPP for all five countries but failed to establish evidence for a strong relationship between exchange rate and price level.

1.2.Study area

Solomon Islands is situated in the southwest Pacific Ocean, some 2000 km northwest of Australia and bordering Papua New Guinea to the west and Vanuatu to the southeast. Its geographical coordinates are 9° 26′ South and 159° 57′ East. The country is an archipelago consisting of a double chain of islands with a total land mass of approximately 28,000 km^2 and an ocean surface area of about 1.6 million km^2. The islands are of two types: mountainous with rugged terrain, and low lying coral atolls. The capital city Honiara is located on Guadalcanal, the largest island of the group. Solomon Islands, with an estimated population of 515,870, is a multiracial country, predominantly Melanesian (95.3%), followed by Polynesian (3.1%), Micronesian (1.2%) and others (SINSO, 2009). About 85% of the people live in the rural areas. English is the official language but Solomons Pidjin, the lingua franca for the majority of people, is a strong uniting bond. A constitutional monarchy with a democratically elected parliament, the country remains a member of the Commonwealth**.** Solomon Islands is rich with natural resources. However, the economic base is narrow and relies heavily on the export of raw materials, chiefly logs, palm oil, copra, fish, cocoa and gold. The growth of GDP is slow and projected to be 3.5% in the medium and long term. Dependency on subsistence continues to be very high.



Source: Ministry of Environment, Climate Change, Disaster Management and Meteorology.

Figure 1.1 Map of Solomon Islands showing Honiara the capital city.

1.3. Solomons exchange rate regime and forecasting

The Solomon Islands exchange rate regime is more of a fixed exchange regime, which has gone through a number of major reviews and developments during the past decade.

During this interval of time the Solomon Islands dollar (SBD) has been pegged to a basket of major trading currencies namely; the US dollar (USD), the Australian dollar (AUD), the New Zealand dollar (NZD), the Japanese yen (JPY) and the British pound (CBSI, 2005, 2014). The exchange rate is calculated based on the movement of the weighted basket of major trading currencies. The weights assigned to each currency reflect its importance in trade with Solomon Islands and add up to 1. USD and AUD constituted the greatest portion of the weight, adding up to around 80%, while the balance was shared by the remaining currencies.

For forecasting the exchange rate of SBD against these trading currencies there is no standard methodology developed yet. At the moment, a little has been done on regular forecasting, which is based on the FX4cast.com report that forecasts USD against major currencies on daily, weekly, monthly, semi-annual and annual bases. The Central Bank of Solomon Islands (CBSI) then calculates daily exchange rates on an ad-hoc basis based on key observations along the lines of the country's economic fundamentals.

1.4. Aims and objectives

The main aims of this thesis are: firstly, to develop an exchange rate forecasting model for forecasting exchange rates of Solomon Islands dollar against its major trading currencies such as AUD, GBP, JPY and EURO and; secondly, to find out whether the purchasing power parity hypothesis determines the exchange rate between the Solomon Islands dollar and the US dollar and the British pound. The objectives of this thesis are:

- to forecast the Solomons dollar against AUD, GBP, Yen and EURO using the multiple linear regressive model, the time series models and the proposed ANN model.
- to compare the proposed model with multiple regressive model, time series models and the major trading currencies such as AUD, GBP, JPY and EURO using various error measures, coefficients of correlation and the goodness of fit.
- to benchmark the proposed method with the naive method using RMSE, MAE and MAPE error measures.

- to determine the long-run and the strong version of the purchasing power parity using the consumer price indexes of Solomon Islands against USA and UK.

1.5. Sources where information were collected

The literature gathered in this thesis was obtained by thoroughly searching from various online and offline scholarly data bases from the University of South Pacific, Laucala library. The main online data bases used for the review were pro-quest, OARE, pro-quest ebrary, IMF eLibrary data, google scholar and google search. The offline data were collected from the USP Library catalogue at the general collection and the Pacific collections. In addition, a search was made at the CBSI website www.cbsi.com.sb for bank annual reports, quarterly reports and monthly economic bulletin. Further reports and information were collected from the government and nongovernmental organisations in Solomon Islands.

1.6. Time series methods

Dumicic et al. (2008) define time series as a set of measurements or data points on a variable taken over an equally spaced interval of time in a sequential order. A time series is normally a collection of data $x_t(t=1,2,...,n)$ with the interval x_t and x_{t-1} is fixed and constant. Time series was used in many other areas including sociology, physiology, economics and meteorology. Many time series were used in finance as well, especially, the forecasting of the daily exchange rate, which is the main focus of this thesis. Researchers' primary concern for time series model is to decompose it into trend, cyclic seasonal and irregular components (Bleikh & Young, 2014, p. 7) or by using information from previous data (Dumicic et al., 2008). A univariate time series is one that consists of single observations over equal intervals of time. A multivariate time series on the other hand is one that consists of more than one set of observations or variables over an equal interval of time. The time series that are studied in this thesis are single and double exponential smoothing, Holt-Winter (HW) additive and multiplicative.

1.6.1. Exponential smoothing method

The exponential smoothing method was proposed by Holt in 1957 for nonseasonal without trend and in 1958 he offered a method that handled trend (Dumicic et al., 2008). In 1965, Winter generalized the model to include seasonality, hence the name Holt-Winter (Dumicic et al., 2008; Winter, 1960). Forecasts produced using exponential smoothing technique were weighted averages of past observations, with the weights decaying exponentially as the observations got older. In other words the most recent observations have higher associate weights, than the past distant observations (Dumicic et al., 2008). The value of the weight is controlled by the parameter α and is between 0 and 1. If the value of α is close to 1, then the majority of estimates favour more recent observations, whereas a low value of α suggests that past distant observations gain more importance.

As a group of forecasting techniques, exponential smoothing method was widely used to provide forecasts in situations in which there was no clear trend in the data. They were amongst the most successful methods for forecasting time series data. These models attempted to "smooth out" the random or irregular component in the time series by an averaging process. There were two frequently used smoothing-based forecasting techniques: single and double exponential smoothing methods.

Single exponential smoothing is a 1-parametric and is suitable for forecasting data with no clear trend or seasonal pattern (Ariffin et al., 2013; Chatfield & Yar, 1988). For example, Winter (1960) used single exponential smoothing to predict the expected sales of product that has no definite pattern or no long-run trend.

The equation for the single exponential smoothing according to the following authors (Ariffin et al., 2013; Chatfield & Yar, 1988) is given by

$$F_{t+m} = \alpha y_t + (1-\alpha) F_t ; t = 1, 2, ..., n \qquad \ldots (1.1)$$

where, F_{t+m} is the single smoothed value in period, $t+m$, for $m=1,2,...$ y_t is the actual in time period t, α is the smoothing parameter and is between [0,1] and F_t is forecasted value for t.

Double exponential smoothing is a modification of the single exponential smoothing method that attempts to capture the trend component of the data (Dumicic et al., 2008; Rani & Raza, 2012). The equation for the double exponential smoothing according to the following authors (Ariffin et al., 2013; Chatfield & Yar, 1988) is given by

$$S_t^{'} = \alpha y_t + (1-\alpha)S_{t-1}^{'} \qquad \ldots (1.2)$$

where, $S^{'}$ is double smoothing value of y_t at time t. Exponential smoothing produced better and more useful results than other complicated smoothing and forecasting methods even though it is numerically simple (Bleikh & Young, 2014; Cipra, 1992; Gardner, 1985). For example, Winter (1960) added that, exponential smoothing requires less information and responds rapidly to sudden changes in time series. It's robustness and accuracy have led to its wide spread use in many applications, particularly those involving a large number of series (Taylor, 2003), while some researchers find that exponential smoothing can be a better forecasting method when using a narrow range data points (Ariffin et al., 2013).

Although, exponential smoothing has an adaptive character due to exponential smoothing of past observations, Cipra (1992) and Ledolter (1989) noted that, the presence of outliers in the data contaminates the time series. This contamination was indicated by the presences of long-tail distribution in the time series. The authors stated that, identifying the outliers and interpolating the missing values were preferred methods of overcoming this problem. In addition, Chen and Liu (1993) noted in their literature that a two-step operation to alleviate the influence of outliers is to identify and locate the type of outliers and adjust its effect to use in model parameter estimation. Another weakness of exponential smoothing is that it cannot make better forecasts of a longer horizon (Ariffin et al., 2013). Choosing starting values and the smoothing parameters was also a problem in using exponential smoothing technique and Chatfield and Yar (1988) did some detailed study on this area.

1.6.2. Holt–Winter (HW) additive method

HW additive method is an extension of Holt's exponential smoothing that captures seasonality. This method produced exponentially smoothed values for the level, trend, and the seasonal adjustment to the forecast (Tratar, 2014). This seasonal additive method adds the seasonality factor to the trended forecast, producing the HW additive forecast. According to literature obtained by Tratar (2014) and Chatfield and Yar (1988), the seasonal additive is given by

$$F_{t+m} = L_t + b_t m + S_{t-S+m}; \quad t = 1,...,n \qquad \text{… (1.3)}$$

where, L_t is the level, b_t is the trend, S is the length of seasonality and m is the number of forecast ahead.

Additive HW technique was widely used and has been found to be robust, easy to use and somewhat successful in forecasting competitions (Chatfield & Yar, 1988; Lawton, 1998; Tratar, 2014). The HW additive method depends on three smoothing parameters, α, γ and δ; and a general approach in selecting the parameters is by estimating or by trial and error (Chatfield & Yar, 1988). These smoothing parameters α, γ and δ are coefficients for the level, trend and seasonal component of the times series. Similarly, to α, the values for β and δ are between 0 and 1. Similarly in the way in which we explained α, if the value is close to 1, it indicates that the estimation favours more recent observations than past, distant or initial data. Chatfield and Yar reported that estimation of these parameters, has been found to be more useful than trial and error. Using estimating approach, finding the optimum values of the parameters can be hampered partly because the likelihood functions are nonlinear and need not be concave (Snyder & Shami, 2001). For example, Lawton (1998) points that HW additive did not give a good estimate for level and seasonal time series partly due to the incorrect choice of its smoothing parameters. Chatfield and Yar (1988) after examining their literature suggested that good starting values of parameters are ($\alpha = \gamma = 0.3$, $\delta = 0.1$)

though it is entirely arbitrary. Recent, computer software packages such as Eviews have these values set automatically.

1.6.3. Holt–Winter (HW) multiplicative method

HW multiplicative is another version of HW additive method and is suitable when a time series has a linear trend with multiplicative seasonal variation. The seasonality factor is multiplied by the trended forecast, producing HW forecast (Chatfield & Yar, 1988; Koehler et al., 2001; Tratar, 2014).

The model for forecasting HW multiplicative according to the literature gathered by Tratar (2014) and Chatfield and Yar (1988) is given as

$$F_{t+m} = (L_t + b_t m) S_{t-s+m};\ t = 1, 2, ..., n \qquad \ldots (1.4)$$

where, L_t is the level, b_t is the trend, S is the length of seasonality and m is the number of forecast ahead. On average the multiplicative version is better than additive and has been used in many forecasting areas, and implemented more often in computer software (Koehler et al., 2001; Tratar, 2014). Tratar notes that an improved HW method produces good results for data with large fluctuation. However, HW multiplicative may not be used if the data series contains values equal to zero and it does not provide bounds for the forecasted error (Koehler et al., 2001; Tratar, 2014).

1.7. Regression models

1.7.1. Multiple linear regression (MLR)

MLR was the most commonly used statistical technique that uses two or more explanatory variables to predict the outcome of a response variable (Andrews, 1974; Jobson, 1991 see Ch4; Preacher et al., 2006). The goal of MLR is to model response and explanatory variables. The MLR according to Jobson (1991 see Ch4), is given as

$$y_t = \beta_0 + \beta_1 x_{t1} + \beta_2 x_{t2} + ... + \beta_p x_{tp} + \varepsilon_t;\ t = 1, 2, ..., n \qquad \ldots (1.5)$$

where $\beta_0, \beta_1, ..., \beta_p$ are the regression coefficients; ε_t is the error term and is independently identically distributed. When $p = 1$, it is a simple linear regression, the term linear is used because y (response variable) is directly a linear combination of the explanatory variables.

MLR analysis is used widely in almost every discipline; Andrews (1974) for instance, showed that more than half of the number of users of a computer program at the University of Toronto, in Canada were linear regression users. For example, Mahmoodabadia et al., (2013) used multivariate linear regression to model financial leverage relation with exchange rate changes and financial flexibility for Tehran stock exchange. The study found a significant relation between financial leverage and financial flexibility but not exchange rate.

1.7.2 Autoregressive (AR) Model

In an MLR model, the forecasted variable of interest uses the linear combination of predictors. To this end, for the AR model, the forecasted variable of interest uses a linear combination of past values of that variable. This implies that autoregression is a regression of the variable against itself. An AR of order p according to Hyndman and Athanasopoulos (2013) can be written as

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + \varepsilon_t ;\ t = 1, 2, ..., n \qquad .... (1.6)$$

where c is a constant and ε_t is white noise. Note that the lagged values of y_t were used as predictors instead of explanatory variables as in the case of multiple regression. This is referred to as an AR (p) model. Hyndman and Athanasopoulos further stated that autoregressive models were very flexible at handling a wide range of different time series patterns. Changing the parameters, $\phi_1, ..., \phi_p$, results in different time series patterns. The variance of the error term ε_t will only change the scale of the series, not the patterns. For an AR (1) model:

- when ϕ_1=1, y_t is equivalent to white noise.
- when ϕ_1=1 and c = 0, y_t is equivalent to a random walk.
- when ϕ_1=1 and $c \neq 0$, y_t is equivalent to a random walk with drift.
- when $\phi_1 < 0$, y_t tends to oscillate between positive and negative values.

Normally autoregressive models are restricted to stationary data, which requires some constraints on the values of the parameters in equation 1.6.

- for an AR (1) model: $-1 < \phi_1 < 1$.
- for an AR (2) model: $-1 < \phi_1 < 1, \quad \phi_1 + \phi_2 < 1, \quad \phi_2 - \phi_1 < 1$.

Restrictions are much more complicated when $p \geq 3$; in such case, a computer software R can be used to take care of these restrictions when estimating a model. Ahmed et al., (2013) used AR (1) and, AR (4) models to forecast the daily exchange rate of Samoan tala against USD and AUD. They used the daily exchange rate of Samoan tala against USD and AUD. The researchers found that AR (1) performed better than AR (4) models with the value of R^2 equals to 9.88×10^{-1} and 9.88×10^{-1} for AUD and USD respectively. Maniatis (2012) used AR (1) model as one of the candidate models to forecast the exchange rate of Euro against USD using non-stationary data.

The standard criterion for selecting the number of lags in an AR model is by observing the spikes in autocorrelation and partial autocorrelation functions (Ahmed et al., 2013; Maniatis, 2012). Another common lag length selection criterion for autoregressive models is the Akaike information criterion (*AIC*) and Schwarz information criterion (*SIC*). The *SIC* is an extension of the Bayesian information criterion (Akaike, 1974; Schwarz, 1978). Many researchers used *AIC* and *SIC* for lag length selection measure, which were used across most econometric and time series models (Lee & Boon, 2007; Mukhtar & Rasheed, 2010). The autoregressive model requires data to be stationary and normally distributed. But most of the time series data were not stationary and were not normal; this had affected the reliability and accuracy when using the AR models. There are other classes of autoregressive models such as ARCH, GARCH and ARIMA. This class of models will be studied in more detail in econometric models as discussed in the next section.

1.8. Econometric models

The methods discussed in this section, such as AR, ARIMA, GARCH and RW models, are widely used in finance and economics for forecasting. Before the seventies the exchange rate was determined by the balance of payments, and it was fixed. As the market became liberalized in the late 1970's, after the breakdown of the Bretton-Woods system between 1971 and 1973, most exchange rates were free-floating in the open market (Kiani & Kastens, 2008; Tambi, 2005). 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 (Ahmed et al., 2013; Lee & Boon, 2007; Maniatis, 2012; Meese & Rogoff, 1983; Tambi, 2005; Zhang, 2003). However, these models are well known in the literature for their poor predictions, which are characteristically highly volatile, complex, noisy, nonstationary, nonlinear and chaotic (Abhyanker et al., 1997; Gencay, 1999; Kuan & Liu, 1995; Maniatis, 2012; Meese & Rogoff, 1983; Tambi, 2005; Zhang, 2003). 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 based 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 (Ahmed et al., 2013; Kadilar et al., 2009).

The performance of these models was measured using the statistical error analysis from their residual such as RMSE, MAPE and MAE. Tambi (2005) reported that, ARIMA models gave a better forecasting of exchange rates than simple autoregressive or moving average models for forecasting exchange rate of the Indian rupee against SDR, USD, GBP, Euro and JPY. The random walk model did not perform better than other econometric models when predicting the exchange rate of US dollar against pound, mark and yen for weighted exchange rates for 1 to 12 months horizon (Meese & Rogoff, 1983). The empirical results vary from model to model

Most of these linear time series models had limitations in their ability to predict and performed poorly (Kuan & Liu, 1995; Meese & Rogoff, 1983). For example, Bararumshah and Liew (2006) used smooth transition autoregression (STAR) and linear autoregression (LAR) using quarterly data for the Japanese yen against six eastern Asian currencies. The results show that STAR outperformed the LAR model. GARCH and RW models in particular did not generate significant sign prediction (Gencay, 1999). Despite the use of new forecasting methods, some of the econometric models such as AR and ARIMA can still perform better in exchange rate forecasting and can still be useful (Ahmed et al., 2013). Most of the econometric models can be implemented by using Eviews, SPSS and R computer software.

1.9. Neural network models

1.9.1. Artificial neural network

Recently, ANN has become a popular model for forecasting (Egrioglu et al., 2012; Huang & Lai, 2004; Kadilar et al., 2009; Leung, Chen, & Daouk, 2000; Pradhan & Kumar, 2010; Walczak, 2001) and was found to be more effective than other econometric models, with higher percentage of ability to predict (Walczak, 2001). ANN is an information process technique, which is based on the construction of biological neural systems and is used for modelling mathematical relationships between input variables and output variables (Pradhan & Kumar, 2010; Zhang et al., 1998). It is computer software that emulates the brain's ability to learn, make decisions, recognize patterns and make forecasts based on past information or historical data (Talati, 2000). The technique is used broadly in financial markets, particularly to forecast inflation, interest rates, stock prices and exchange rates (Pradhan & Kumar, 2010).

ANN has three major components: the architectural structure, the learning algorithm and the activation function. The architectural structure consists of the input layers, the hidden layers and the output layers. These layers contain the many neurons that make up the network (Pacelli et al., 2011; Zhang et al., 1998; Zhang, 2003). The correct choice of the number of neurons in the input layers, and hidden layers, and the number of layers in the hidden layers plays a very important role in the successful application of the neural network (Pacelli et al., 2011; Zhang et al., 1998; Zhang, 2003). Some researchers used different variables while others used different exchange rate lag values as their input layer (Ahmed et al., 2013; Pacelli et al., 2011; Pradhan & Kumar, 2010; Walczak, 2001). For example, Pacelli et al. (2011), used seven economic variables inside the input layer while Walczak (2001) used 3 daily exchange rate lags for the input layer to predict daily exchange rate in the output layer. The hidden layer performs the complicated nonlinear mapping between the input nodes to the output nodes (Wu & Yang, 2007; Zhang et al., 1998). In most cases, the output layer consists of one layer and one neuron, which is the final predicted value.

Before a forecasting is carried out the data must be divided into two parts; training and testing parts. Many researchers split the data into 90% and 10% , 80% and 20% for training and testing respectively while few others use 50-50 (Andreou et al., 2002; Azad & Mahsin, 2011; Chand & Chandra, 2014; Hyndman & Athanasopoulos, 2014; Panda & Narasimhan, 2003). Again it is based on trial and error.

The various learning algorithm used in the literature include standard back propagation, scaled conjugate gradient and Bayesian reguralization (Kamruzzaman & Sarker, 2004) feedforward (Chand & Chandra, 2014; Leung et al., 2000) and feed forward and feed backward (Nag & Mitra, 2002). The descent-gradient algorithm is widely used as a learning algorithm. The network learns during training and changes its weight based on error information back propagated through the network from the output layer (Wu & Yang, 2007). Using this information, the algorithm moves exactly in the opposite direction by an amount proportional to the learning rate. It minimizes error by utilizing this downhill movement (Wu & Yang, 2007). Back propagation or decent-gradient algorithm is the one used in this thesis because it is commonly used in the literature and found to be markedly superior to other neural network algorithms (Walczak, 2001; Winston & Venkataramanan, 2003).

Zhang et al. (1998) point out that any function that is bounded, monotonic increasing and continuously differentiable can be used as a transfer function. Most researchers state that sigmoid and tangent hyperbolic transfer functions perform better than cosine,

sine and simple linear functions, and is widely used in the literature (Kadilar et al., 2009; Pradhan & Kumar, 2010; Zhang et al., 1998). As an activation function a nonlinear activation function such as a logistic or a tangent hyperbolic function was preferred over other linear and nonlinear functions because of its robust performance (Pacelli et al., 2011; Zhang et al., 1998). The activation function makes a nonlinear map from the input neurons to the output neurons. This is done by multiplying the input neuron signals by their corresponding weights, added and mapped via the transfer function to the output (Wu & Yang, 2007). A typical output bounded interval for sigmoid function is between [0,1] and tangent hyperbolic function is between [-1,1] (Pacelli et al., 2011; Zhang et al., 1998). The use of nonlinear activation function in the hidden layer has improved the percentage of predictability as compared to those using linear function (Kadilar et al., 2009; Zhang et al., 1998).

The advantage of ANN over other models is that it can model nonlinear and more complex relationships. Also it can be generalized and requires less assumptions to make accurate forecasting (Kadilar et al., 2009; Lapedes & Farber, 1987; Pacelli et al., 2011; Pradhan & Kumar, 2010; Walczak, 2001; Winston & Venkataramanan, 2003; Zhang, 2003).

Generally, ANN is a significant improvement in forecasting of the exchange rate and is used widely in many areas of finance and economics. For Walczak (2001), ANN can have a prediction accuracy as high as 60%, if given sufficient past data and knowledge. Many researchers realized that best performance of the neural network forecasting depends on the critical quantity of data fed to the layers (Kadilar et al., 2009; Kamruzzaman & Sarker, 2004; Walczak, 2001). Adding more of these training data would cause over fitting and deteriorate the predicting ability of the model. For example, Kamruzzaman and Sarker (2004) used a fixed six neurons for the input layer and observed that three neurons fed to the hidden layer gives best performance for all the models.

RMSE, MAPE, MAE and R^2 are the most commonly used statistical performance measure used by many researchers and practitioners. Based on these performance measures, researchers found a significant improvement in forecasting using ANN when comparing to the traditional conventional econometric models. However, ANN is prone to over fitting and bias, has no structural method, requires more data and computer time for training and has a large degree of uncertainty (Zhang et al., 1998; Zhang, 2003).

1.9.2. Mixture of time series and neural network model

Other researchers have used hybrids of some classical and neural network models such ARIMA and neural network (Kamruzzaman & Sarker, 2004; Rojas et al., 2008; Sallehuddin et al., 2007; Zhang, 2003), moving average (MA) and autoregressive artificial neural network (Ahmed et al., 2013) and ANN with ARCH and ARIMA (Kadilar et al., 2009). The researchers have found that there were some notable improvements on predictions performance compared to when integrating econometric and neural network models. For example, autoregressive ANN performs better than exponential smoothing and Winter time series models using daily exchange rates of Samoan Tala/USD and Tala/AUD from 2008 to 2012 (Ahmed et al., 2013).

Sallehuddin et al. (2007) used nonlinear grey relation artificial neural network (GRANN) and linear and ARIMA and obtained an accuracy of 99.85% for large scale data. Again, Kadilar et al. (2009) further noted that ANN has better forecasting accuracy over ARCH and ARIMA using Turkey's exchange rate data.

Conversely, ANN did not produce convincing forecast performance using four daily exchange rate returns against Dutch guilder, as reported by Franses and Homelen (1998). Sallehuddin et al. (2007) suggested that the hybridization of linear and nonlinear GRNN_ARIMA could reduce training time for an ANN learning algorithm and could be an alternative better forecasting tool for time series data. The researchers noted that the models may be better in predicting some currencies; but they were not consistent with other currencies and variables.

1.9.3. Hybrids of neural network model

In the most recent developments, researchers used hybrids of certain algorithms and applied them to the neural network to improve the predictable performance of ANN (Kuan & Liu, 1995; Leung et al., 2000; Nag & Mitra, 2002). These algorithms are based on optimization of the sum of square error, and they try to identify the sets of weights that converge to a global minimum. These sets of weights were used for test runs to identify the optimal combinations of neurons in architectural structure to obtain best prediction. The hybrids such as the general optimized neural network (GONN), the genetically optimized adaptive neural networks (GOANN), the general regression neural network (GRNN) (Andreou et al., 2002; Leung et al., 2000; Nag & Mitra, 2002) were employed to improve the application of ANN. For example, Leung et al. (2000) used GRNN to model monthly exchange rates of British pound, Canada dollar and Japanese yen using the non-linear kernel regression. Furthermore, GOANN was used to forecast the Greek exchange rate market for US dollar, British pound, Deutsche mark and French franc (Andreou et al., 2002) and GONN was used to model daily exchange rates of Deutsche mark/US dollar, Japanese yen/US dollar and US dollar/British pound. The algorithms mentioned earlier in this section are a set of iterative procedures used for training the network, in order to yield the optimum sets of weights (Nag & Mitra, 2002). The authors added that, these training algorithms could be backpropagation, feedforward network or recurrent backpropagation. Apart from the weights, other parameters to consider were optimum combination of weights in the hidden layers, number of inputs neurons, transfer function and learning rate as in the case of ANN (Nag & Mitra, 2002).

Leung et al. (2000) result strongly indicated that GRNN outperformed ANN and other econometric techniques for predicting monthly exchange rates of British pound, Canadian dollar and Japanese yen. In addition, GONN and GOANN gave successful results in their respective applications (Andreou et al., 2002; Nag & Mitra, 2002). Moreover, a survey reported by Huang and Lai (2004) and the finding of Rojas et al. (2008) indicate that using ANN with other forecasting methods produces a mixed result. The main weakness of all neural networks is that if the parameters or weights are not chosen carefully there is a high risk of their converging to a local minimum rather than to a global minimum as desired (Nag & Mitra, 2002).

1.9.4. Software used to analyse data

Data analysis employed a variety of computer software such as SPSS, R, Eviews and MATLAB (Ahmed et al., 2013; Kuan & Liu, 1995; Lee & Boon, 2007; Maniatis, 2012; Pacelli et al., 2011; Walczak, 2001). These software helped sort huge amounts of data to a manageable size, before they could be used for various test runs, simulations and to display statistical tests and parameters. These measured statistical parameters were tabulated on tables and plotted on graphs for interpretation. Such use, for the purpose of detail interpretation and analysis, of a graphical plot of actual rate, forecasted rate, currencies, and residuals against time is common in the literature (Ahmed et al., 2013; Kamruzzaman & Sarker, 2004; Maniatis, 2012). The graph attempted to visualize how the forecasted data try to mimic the actual data. The closer the graphs were the better the predictions. Statistical results were presented in tabular forms showing the values of test statistics, error values, regression values, analysis of variance, goodness of fit and other statistical metrics. In most cases, smaller error values indicate a model was predicting well compared with other models being studied.

1.10. Purchasing Power Parity

1.10.1 PPP hypothesis

Understanding PPP theory is the cornerstone of the monetary models of exchange rate determination (Anoruo et al., 2005; Dornbusch, 1976; Mussa, 1982) which attracts a lot of research in the vast literature. After the collapse of the Bretton–Wood system between 1970 and 1973, many countries' currencies became free floating and are exposed to exchange rate shocks. The PPP theory thus came into play. The law states that under the assumption of the absence of transportation costs and trade barriers, or low transport costs, the price of a good in two countries should be equal if they are of the same quality and are expressed in terms of the same currency (Jayaraman & Choong, 2014). This is often referred to as the law of one price.

Cassel's (1921) view of the PPP is that the exchange rate S is relative price of two currencies. Since the purchasing power of the home currency is $1/P$ and the purchasing power of the foreign currency is $1/P^{*}$, in equilibrium the relative value of two currencies should reflect their relative purchasing powers, that is, $S = P/P^{*}$. Further, the Casselian view suggests using the general price level proxies such as the CPI, in the empirical implementation of the theory. The theory implies that the log real exchange rate, $q = s + p^{*} - p$ is constant over time. However, international macroeconomists view Casselian PPP only as a theory of long-run determination of exchange rates.

The commodity arbitrage view of PPP, articulated by Samuelson (1964), simply says that the " law of one price" holds only for all internationally tradable goods. Thus the appropriate price index to study PPP may be the producer price index (PPI), or wholesale price index (WPI), since it may be weighted towards tradable goods rather than the CPI which includes items such as housing services, which do not trade internationally.

The PPP theory stipulates that the exchange rate adjusts overtime to accommodate inflation differentials between the two countries (Anoruo et al., 2005). The theory was tested by carrying out the hypothesis for short and long-run adjustments of the exchange rate and price differential. If no restriction was set on the coefficient of the domestic and foreign price and non-co-integration was rejected, then a weak version of PPP is favoured. To obtain a strong PPP, a 'restriction' was imposed by assigning unity (1) and minus unity (-1) to the coefficient of the domestic and foreign prices respectively and use the log likelihood test to determine the symmetry of the price differential (Jayaraman & Choong, 2014; Paul & Motlaleng, 2006; 2008).

Testing the PPP hypothesis is important firstly, because of its theoretical perspective in monetary economics, which assumes that there is a long-run relationship between money, price and exchange rate (Frenkel & Johnson, 1978); and secondly, because of the practical perspective of foreign exchange risk management by various economic agents in taking the long-run or short- run positions on foreign exchange related assets. Taking a long-run perspective is sometimes advised (Paul & Motlaleng, 2006; 2008).

When the floating exchange rate began, the relative prices between two countries are expected to reflect the changes in the nominal exchange rates. But as Paul and Motlaleng (2008) note in their literature, there was a substantial deviation of the exchange rates observed during this period, not only of the nominal exchange rates but more importantly of the real exchange rates. Furthermore, the high correlation between the nominal and real exchange rates has raised suspicions that nominal exchange rates do not revert to their stable equilibrium mean values.

The turning point for the PPP investigation began when Meese and Singleton (1982) found that the nominal exchange rates have a unit root. This means that nominal exchange rate follows a random walk, indicating that its impact is not mean-reverting. In other words, changes in the nominal exchange rates are expected to be permanent and as result fail to confirm the long-run PPP theory. Thereafter, many researchers were unable to reject the hypothesis of a unit root for real exchange rates, and of non-co-integration of nominal exchange rates and relative prices.

But, this has changed in the 1990's after many new studies have shown evidence of mean reversion and confirmed the long-run PPP theory (Lothian, 1997; Lothian & Taylor, 1996; Rogoff, 1996). Most authors agree that deviation from PPP frequently occurs in the short-run (Dornbusch, 1976; Frenkel, 1978). Dornbusch (1976) suggested that this deviation was due to different speed of adjustment in the asset market on the one hand and prices in goods market on the other hand. However, all studies focused on validity of PPP in the long-run and have produced mixed results (Anoruo et al., 2005). For example, several authors have evidence to support PPP theory in a long-run (Abuaf & Jorion, 1990; Jayaraman & Choong, 2014; Meese & Rogoff, 1988; Paul & Motlaleng, 2006; 2008) while Cooper (1994) and Ahking (1997) obtained evidence against it.

Paul and Motlaleng (2006) in their literature noted the validity of the long-run PPP theory using annual data of sixteen African countries covering the period 1981 to 1994. The authors noted twenty African countries using multilateral trade weighted exchange rate indices and panel unit root techniques and concluded that the PPP theory is valid for those countries, while Jayaraman and Choong (2014) used annual data from the period 1981 to 2011 to determine the validity of long-run PPP theory for five PICs.

On the contrary, Cooper (1994) investigated the validity of PPP by testing unit root and co-integration for Australian, New Zealand and Singaporean currencies from 1973-1992 and found that both tests fail to satisfy long-run PPP. Later, Ahking (1997) employed a more advanced Bayesian unit root approach and found that there is little probability that exchange rate and price level have a steady relationship in the long-run.

To determine the validity of PPP in the long-run, (Jayaraman & Choong, 2014; Paul & Motlaleng, 2008) used different econometric techniques such as panel unit root tests, as well as Pedroni's and Johansen's panel co-integration tests. Their results were based on the panel context of rejecting the null hypothesis of non-co-integration. The study has shown evidence that real exchange rates revert to long-run equilibrium.

To test the validity of a strong PPP hypothesis by panel analysis, the requirement is to have the existence of the two restrictive conditions relating to joint symmetry and proportionality. That is to set the coefficient of domestic price to unity (1) and on foreign price as of minus unity (-1). Khan and Parikh (1998) used the Johansen-Juselius approach in a bivariate context and reject the rand/pound and accept the rand/dollar exchange rate. While Jayaraman and Choong (2014) and Paul and Motlaleng (2008) use the Johansen multivariate approach, the former reject the exchange for five PICs while the latter accepts the Pula/dollar exchange rate for Botswana. The results indicate that domestic and foreign prices determine the exchange rate in the long run, but are mixed in the restrictive condition.

Many studies regarding PPP theory were done in developed and developing countries but far fewer in PICs. The result of these studies show that PPP theory deviates in the short-run but is mixed for long-run and restrictive conditions. PICs should continue to be guided by the PPP theory, to enable them to apply the appropriate measures with respect to price level and the exchange rate policy.

1.10.2. Nominal-exchange-regime neutrality

A broad and important class of theoretical models of exchange-rate determination embodies the property of nominal-exchange-regime neutrality. This property is that the behaviour of the real exchange rate between two countries should not be significantly and systematically affected by the nature of the regime controlling the nominal exchange rate between two countries. In particular, the behaviour of real exchange rates under a floating-exchange regime should not be significantly and systematically different from the behaviour under fixed or adjust-able-peg exchange regimes. However, instantaneous adjustments in asset and commodity market price levels may be possible only in pure theoretical models, and short-term deviations from the PPP may be frequently occurring in the floating exchange rate regimes. But, on the other side, some people believe that no such PPP theory can work in a pegged exchange rate regime such as in our country sample of the study; Solomon Islands, because exchange rates are controlled by the authorities, and such belief in the rightness of this may be due to the lack of proper understanding of the theory of the PPP, and the monetary theories of price determination in an open economy, and the implication of the hypothesis of nominal-exchange-regime neutrality. Against such a backdrop, a study of the PPP theory, along with the price determination for the small open economy of Solomon Islands, will be interesting.

1.10.3. Exchange rate policy in Solomon Islands

Solomon Islands dollar (SBD) followed a fixed exchange rate regime until 2012 when the “de facto” peg to the US dollar was changed to an invoice-based basket of currencies (Jayaraman & Choong, 2014). The basket of currencies consists of the US dollar, the Australian dollar, the Japanese yen and the British pound (CBSI, 2005). The weights assigned to each currency reflect their relative importance in trade with Solomon Islands, with US dollar having the largest proportion. The Central Bank of Solomon Islands (CBSI) administers and manages the exchange rate of Solomon Islands. SBD was devalued once during this sample period, by 20% in 1997, and revalued by 5% in June 2011.

SBD was temporarily pegged to USD from 1998 to 2003, a move to control inflation pressure and sustain imports due to low export volumes (CBSI, 2000). This temporary measure was later removed and SBD was allowed to fluctuate with other traded currencies (CBSI, 2007). The current fixed exchange regime monetary policy generally meant to provide an avenue for exchange control and avoid exogenous shocks to the bank. But this does not mean that SBD is immune from external shocks coming from the basket of currencies in which it is pegged, such as the US dollar. For instance, an increase in the price of oil would affect the US dollar and the shock will then transmit to the Solomon Islands dollar. This becomes evident during the global economic recession in 2008, which has forced the exchange rate of the local dollar to decline by 3% due to its pegging to the US dollar.

In 2006, SBD was maintained under a managed crawling pegging regime, with the value derived from the basket of foreign currencies (CBSI, 2006). CBSI and the national government have agreed to maintain the peg with the emphasis on stabilizing SBD against USD. The Government revalued SBD by 5% in June 2011 (CBSI, 2011) in a move to arrest inflationary pressure in the economy. This resulted in the appreciation of 15% the real effective exchange rate against the traded basket of currencies. The real effective appreciation has forced the exports to be less competitive, while imports, on the other hand, become more competitive, which then helped ease the inflationary pressure during the year. Another direct impact of this appreciation is the consequent reduction of Solomon Islands foreign debts and income.

In October 2012, the bank changed the exchange rate regime, from the "de facto" peg to USD to an invoice-based basket of currencies (CBSI, 2012). This change will allow more flexibility and management of the exchange rate, to be more in line with economic fundamentals. Under this regime SBD is allowed to fluctuate within the narrow band of ±1% with respect to a base currency and then to the components of the basket of currencies.

1.10.4. Price levels and inflation in Solomon Islands

Inflation in Solomon Islands is relatively high compared to its major trading partners and it is rated as one of the highest in the developing PICs (CBSI, 2011, 2012). For instance, the highest average annual inflation rate during this period was recorded at 15.4% and 19.4% in 2002 and 2008 respectively (CBSI, 2002, 2008). Despite the fall in the inflation rates of SBD major trading partners the inflation rate known as the Honiara retail price index (HRPI) still remains higher, which reflects the high cost of doing business in Solomon Islands. This is a classic example of why nominal exchange rate changes may not pass through to domestic prices as claimed in the literature (Paul & Motlaleng, 2008). After 2003, the inflation rate seems to be stable at around 6%. This is due to the government policy of maintaining the inflation rate at a single digit (CBSI, 2006) and pegging the Solomons dollar to the US dollar. It was noted in this annual report that the oil prices were the main factor that drives other prices and contributes to the increase in inflation for imported items. The effect of a 5% revaluation of the local currency on June 2011 has only helped to cushion the domestic prices against high global fuel prices but did not pass on the effect to the consumers. This effect was noted by Paul and Motlaleng (2008) in Botswana's wholesale sector, where the lack of competition enabled importers to absorb the beneficial impact of currency appreciation in their profit margins, only passing the negative impact of depreciation to consumers. In 2012, the CBSI board passed the Price Stability Act that came into effect on January 2013 (CBSI, 2012). The Act gave a mandate to the CBSI board to develop a 5-year strategic change agenda for 2013-2017 with an aim of bring Solomon Islands inflation on par with developing PICs.

Chapter 2: Methodology

2.1. Introduction

This chapter discusses briefly all the methods and the variables that will be used in this thesis. The chapter is made up of Solomons exchange data and variables, time series method, regression method, ANN method and the purchasing power parity method.

2.2. Data and variables

2.2.1. Variables

The variables that are used in this thesis are the daily exchange rates data of the Solomon dollar (SBD) against its major trading currencies such as AUD, GBP, JPY and EURO, in which time is the independent variable and exchange rate is the dependent variable. The factors that might influence exchange rate are micro and macroeconomic factors. Exchange rates are correlated with inflation and interest rates. Interest rates adjusted by the central bank can have an impact on currency values, for instance a lower inflation rate can make itself evident in a higher currency value. The current account balance between countries may suggest that it requires more foreign currency than it collects during sales of exports. Additional demand for foreign currency drops the exchange rate. Substantial debt pushes inflation and the currency value declines. If exports are higher than imports in a country, then the trade balance is the country's favour and influences the currency rate. In this study, the exchange rate (Y) is set as a function of time. Alternatively, it can be stated as: $Y = Y_t$.

2.2.2. Data collection

The daily mid-rate exchange rate data used in this thesis were collected from the International Department at CBSI in Honiara. An additional set of data from July to December 2005 was collected from the bank's June 2005 quarterly bulletin. Furthermore, a questionnaire consisting of three open-ended questions (see Appendix 1) was sent to the correspondent at the bank's International Department regarding the basket of currencies and forecasting techniques used by the bank. After a short interview with the researcher regarding questionnaires and future collaboration, the correspondent agreed and sent the data over for verification. An exchange of emails over some 3 months enabled finalization of data ready for sorting. In all, 4150 pieces of data were collected, these daily exchange rate data excluding weekends and public holidays.

2.2.3. Data storage and sorting

Data were saved in three different storage devices; mass storage; online student account and computer laptop for safe keeping and security purposes. The data were then numbered, coded and copied to Excel spreadsheet, 2010 version. The bank corrected the values to 4 significant digits, according to their calculations of exchange rate formulae.

2.2.4. Data processing and analysis

Microsoft Excel 2010 was used to process the data and from here it was exported to Eviews, SPSS, R and MATLAB for analysis. Most of the time series and regression models, namely: multiple linear regression, exponential smoothing, HW additive and HW multiplicative, were implemented using Eviews_8 (x 64) version. These computer software packages analyse and display the following parameters: unit root, descriptive statistics and histogram summary, regression parameters, and AIC and SIC lag length selection criteria.

IBM SPSS statistics 21 version was used for analyzing the normality tests: the Shapiro-Wilk test, Kolmogorov-Smirnov test and the Q–Q plot.

MATLAB R2008a version, Eviews_8 (x64) version and Microsoft Excel 2010 were used to plot the graph of Solomon dollar exchange rates against its major trading currencies. The graph displayed actual, forecasted and residuals. The software R was used for calculating the naive method error measures, that is, RMSE, MAE and MAPE.

Microsoft Excel 2010 was used for ANN model building and processing. Two worksheets were created, one for model building and the other for processing the error functions. A function solver was used to find the optimum value of weights by minimizing the sum of square error (SSE) and hence corrected the predicted value. The generalized reduced gradient (GRG) was the engine employed to run the solver. The final output of the ANN was the predicted values. Once GRG had converged to an assumed global minimum, the predicted values were accepted and copied to the second worksheet, where the values of MAPE, MAE, RMSE and coefficient of determination R^2 were processed. The algorithm used to implement this process is discussed in Section 2.4.1.

2.2.5. Solomon Islands exchange rate data

This thesis used the daily exchange rate of AUD against SBD (AUD/SBD) and the three other major trading currencies, namely GBP, JPY and EURO, from January 5, 1998 to June 30, 2014 collected from the Central Bank of Solomon Islands. The data contain 4150 observations, out of which, 3750 (90%) will be used for training and the remaining 400 (10%) will be used for forecasting, which excludes weekends and public holidays. Figure 2.1 shows a trend of the exchange rates of AUD, which is one of the largest trading currencies against SBD and other major currencies. Initially, it is strengthening, reaching its peak around February of 2001. After this period, SBD declines exponentially and then slowly fluctuates around 0.15 AUD against SBD.

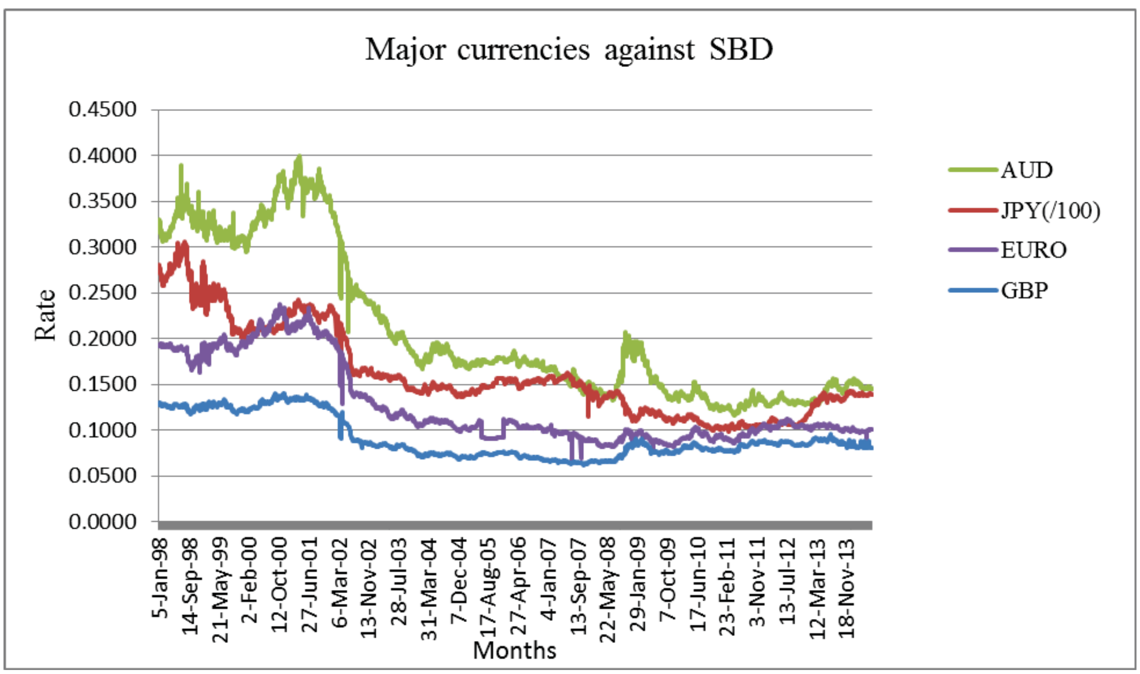


Figure 2.1: Time series plot of actual AUD/SBD and other major currencies.

The preliminary test rejected stationary in AUD (-1) series. We carry out the Augmented Dick-Fuller (ADF) test to check for the presence of unit root. The test indicated that there is a unit root present in AUD of lag 1 series. To test the presence of a unit root we consider the model with constant, intercept and trend as follows.

$$Y_t = a_o + b_1 Y_{t-1} + b_2 t + \varepsilon_t;\ t = 1, 2, ..., n \quad \text{… (2.1)}$$

where, Y_t is the AUD/SBD with time *t*; a_0 is a constant; Y_{t-1} is the lag of AUD/SBD; b_1 and b_2 are the regression coefficients, ε_t - is the error term and *n* = 3750. The test shows that the null hypothesis (Null Hypothesis: AUD has a unit root) cannot be rejected at the 1% level of significance. Thus, this implies the variables are non-stationary. Table 2.1 shows results of ADF tests for unit root from Eviews with other statistics metrics. Further test shows using ADF test confirms that the data are stationary after the first difference.

Table 2.1: Augmented Dickey-Fuller test for unit root

Null Hypothesis: AUD has a unit root
Exogenous: Constant
Lag Length: 5 (Automatic - based on SIC, max lag=29)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.91	0.79
Test critical values:	1% level	-3.43	
	5% level	-2.86	
	10% level	-2.57	

*MacKinnon (1996) one-sided p-values.

2.3. Regression and time series models

The thesis considers several regression and time series models that are discussed below:

2.3.1 The multiple linear regression; MLR (*p*)

The multiple linear regressive model with *p* time-lagged period is defined by

$$Y_t = \beta_0 + \beta_1 Y_{t1} + \beta_2 Y_{t2} + ... + \beta_p Y_{tp} + \varepsilon_t;\ t = 1, 2, ..., n \quad \text{… (2.2)}$$

where, Y_t is the AUD against SBD with time t; β_0 is a constant; Y_{t1} is the AUD against SBD with time lag 1, Y_{t2} is the AUD against SBD with time lag 2 and so on; β_0, β_1, $\beta_2,\ldots,$ β_p are the regression coefficients, ε_t is the error term and *n* is the number of observations.

2.3.2 Exponential smoothing

The Exponential smoothing with trend is defined by:

$$S_t = \alpha Y_t + \alpha(1-\alpha)S_{t-1} \qquad \ldots (2.3)$$

$$D_t = \alpha S_t + \alpha(1-\alpha)D_{t-1} \qquad \ldots (2.4)$$

where, S is the single smoothed series; D is the double smoothed series and Y_t is the AUD against SBD. The double smoothing described in (2.4) is a single parameter smoothing method with damping factor $0 \le \alpha \le 1$.

2.3.3 Holt–Winter additive

This model is used when the series exhibits additive seasonality. In this model, the exchange rate data are represented by the model

$$Y_t = a + bt + S_t + \varepsilon_t \qquad \ldots (2.5)$$

where, *a* is the permanent component; *b* is the trend component; S_t is the additive seasonal factor; and ε_t is the error component.

2.3.4 Holt–Winter multiplicative

This method is appropriate when the exchange rate data exhibit a linear trend and multiplicative seasonal variation. Then, the smooth time series is represented by

$$Y_t = (a + bt)S_t + \varepsilon_t \qquad \ldots (2.6)$$

Where, *a* is the intercept called permanent component; *b* is the trend component; S_t is the multiplicative seasonal factor; and ε_t is the error component.

2.4 Model evaluation

The performance of exchange forecasting models is compared using the following error functions:

Mean Absolute Error:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\hat{Y}_t - Y_t\right| \qquad \dots (2.7)$$

Mean Absolute Percentage Error:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{\hat{Y}_t - Y_t}{Y_t}\right| \qquad \dots (2.8)$$

Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{n}(\hat{Y}_t - Y_t)^2} \qquad \dots (2.9)$$

where, Y_t is the actual value at time *t*; and $\hat{Y}_t$ is the forecasted value at *t* during the forecasting period ($t = 1, 2, ..., n$).

The following diagnostics measures are also used to test the validity of the forecasting exchange rate models:

Pearson correlation:

$$r = (\sum_{t=1}^{n}(Y_t - \bar{Y})(\hat{Y}_t - \bar{\hat{Y}})) / \left(\sqrt{\sum_{t=1}^{n}(Y_t - \bar{Y})^2}\sqrt{\sum_{t=1}^{n}(\hat{Y}_t - \bar{\hat{Y}})^2}\right) \qquad \dots (2.10)$$

Goodness of fit:

$$R^2 = 1 - (\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2 / \sum_{t=1}^{n}(Y_t - \bar{Y})^2) \qquad \dots (2.11)$$

Tracking signal:

$$TS = \frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)}{\sum_{t=1}^{n}\left|Y_t - \bar{Y}\right| / n} \qquad \dots (2.12)$$

and

$$Bias = \sum_{t=1}^{n}(Y_t - \hat{Y}_t) \qquad \text{… (2.13)}$$

Forecast bias in (2.13) gives the direction of the error. If the value of the bias is positive the forecasting method is underestimating and the negative values imply that the forecasting is overestimating. By adding the error terms if there is no bias, the positive and negative error terms 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 the value of TS in (2.12) is zero or close to zero. In such a case, the forecasting method does not result in bias implying that there is no underestimation or overestimation.

2.5 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 by any nonlinear function with higher accuracy and has greater ability to be used in many different areas (Kadilar et al., 2009; Kamruzzaman & Sarker, 2004; Winston & Venkataramanan, 2003). This section gives the algorithm, architecture, computation and activation function that is required to build ANN model.

2.5.1 ANN Algorithm

To develop a self-adaptive iterative training algorithm for exchange rate in Solomon Islands, consider an autoregressive model of lag 2 (i.e, AR (2)) and natural log activation function in the hidden layer. Suppose we have a neural network (NN) iterative algorithm with initial arbitrary weight vector w_k. At the beginning of iteration k, the logarithm generates a sequence of vectors $w_{k+1} + w_{k+2},...$ during epoch $k+1, k+2,...$ and henceforth. The iterative algorithm is convergent if the sequence of vectors converges to solution set Ω. Consider for example the following training problems, where w is defined over the dimension E^m.

Minimize $f(w)$

Subject to : $w \in E^m$

Let $\Omega \in E^m$ be the solution set. Consider an NN algorithm applied over an error function to generate the sequence $w_{k+1}, w_{k+2}, \ldots$ starting with the weight vector w_k such that $(w_k, w_{k+1}, w_{k+2}, \ldots,) \in \Omega$, then the algorithm converges to a solution set Ω. The exchange rate error function is viewed as a minimization problem; since it is possible to construct an error function with an AR (2) model subject to the square error minimization criterion. Let Ω be a nonempty compact subset of E^m, and if the algorithm generates a sequence: $\{w\} \in \Omega$ such that $f(w)$ decreases at each iteration while satisfying the network weight inequality in order: $f(w_k) > f(w_{k+1}) > f(w_{k+2}) >, \ldots$ then the error function $f(w)$ is implicitly a descent function. In NN computation $f(w)$ is assumed to possess descent properties and hence the error function is convex in nature. Therefore, it is feasible to define a descent direction along which error function can be trained.

2.5.2 ANN structure

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 (Kadilar et al., 2009; Kamruzzaman & Sarker, 2004; Winston & Venkataramanan, 2003).

The ANN model designed in this thesis is a multi-layered perception. The proposed model considers the most widely used neural network, known as the back propagation network, as illustrated in Figure 2.2. The network consists of one-hidden layer with different lags of exchange rate as neurons in the input layer. The layer of *p* lags (L1,…, L*p*) as shown in the first column and L0 may be viewed as analogous to a constant or bias. There is one hidden layer consisting of *q* neurons as shown in second column. The final number of neurons in this layer depends on the performance of forecasting. The last column is the output layer with one output cell, which represents the exchange rate that we want to forecast. The layer is also connected with bias (H0) from the hidden layer. All the neurons on the lower layer in the network are connected to upper layer by the corresponding weights.

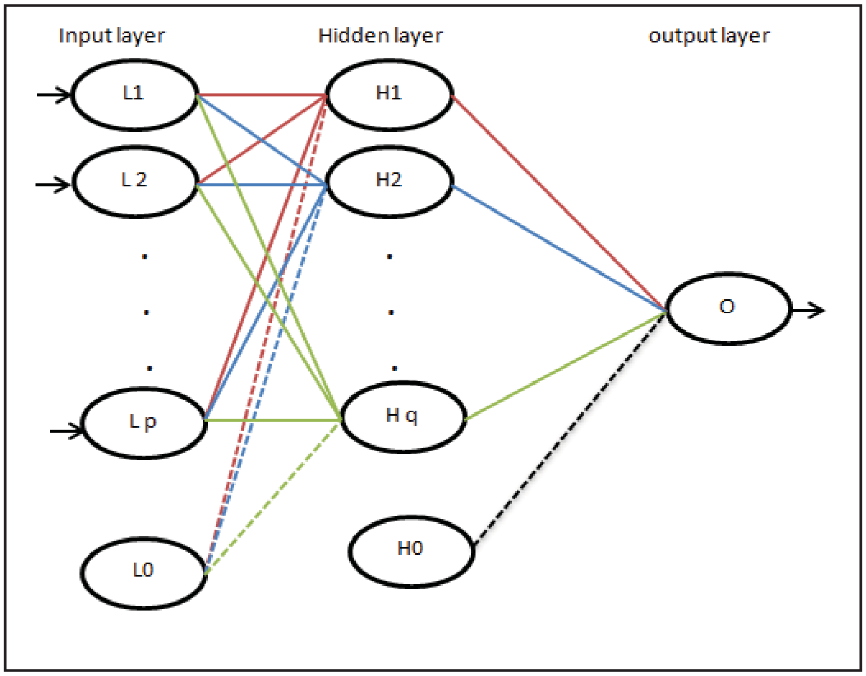


Figure 2.2: ANN structure for forecasting exchange rate.

2.5.3 ANN computations

The computational procedures for the ANN model are described below:

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

$$net_j = \sum_{i=1}^{p} W_{ij} Y_i - \theta_i,\ j = 1, 2, ..., q \qquad \dots (2.14)$$

$$net_o = \sum_{j=1}^{q} W_{jo} Y_j \qquad \dots (2.15)$$

where, i is the input node $(i = 1, 2, ..., p)$, j is the hidden layer node $(j = 1, 2, ..., q)$, o is the output layer node, W_{ij} is the weights connecting the i^{th} input node to the j^{th} hidden layer node, W_{jo} is the weights connecting the j^{th} hidden layer node to the o output layer node, Y_i is the output from the i^{th} input node, Y_j is the output from the j^{th} hidden node and θ_i is the threshold between the input layer and the hidden layer.

Step 2: Evaluate the output of the j^{th} node in the hidden layer and the output of the o node in the output layer as follows:

$$h_j = f_h(\sum_{i=1}^{p} W_{ij} Y_i - \theta_i) = f_h(net_j); j = 1, 2, ..., q \qquad \text{... (2.16)}$$

$$o_t = f_o(\sum_{j=1}^{q} W_{jo} Y_j) = f_o(net_o) \qquad \text{... (2.17)}$$

where, h_j is the vector of the hidden-layer cell (or output) from the j^{th} hidden layer node to the o output layer node, o_t is the final output for the o output layer node for the t^{th} observation $(t = 1, 2, ..., n)$. f_h and f_o are the activation function that maps the input layer to the hidden layer and the hidden layer to the output layer, respectively. The output of each cell (neuron) is obtained by performing transformations using the activation functions f_h and f_o that are discussed in Section 2.1.2.

Step 3**:** Calculate the errors in the output and the hidden layers for the t^{th} observation as follows:

$$E_t = o_t - a_t; t = 1, 2, ..., n \qquad \text{... (2.18)}$$

where, a_t is the actual value of the output node for the t^{th} observation.

Step 4: Determine the optimum weights W_{ij} and W_{jo} by minimizing the sum of the squares of the errors (SSE) in (2.18), that is

$$\text{Minimize } SSE = \sum_{t=1}^{n}(o_t - a_t)^2 \qquad \dots (2.19)$$

The optimum weights W_{ij} and W_{jo} can be computed by solving (2.19) using a gradient method. In this thesis, we use a Generalized Reduced Gradient Method (GRG) which is implemented in Excel Solver.

2.5.4 The transformation functions

We experiment on different transformation or activation functions to map the inputs into the outputs as given below:

i) Sigmoid (logistics) function

The sigmoid transformation function is given by

$$f(y) = 1/(1+e^{-y}) \qquad \dots (2.20)$$

This sigmoid function squashes the input values on the interval [-∞, +∞] to the unit interval [0, 1] and thus prevents any output from reaching a very large value that can paralyze ANN models. The output of the sigmoid function ranges from 0 to 1.

ii) Cosine or sine function

The cosine transformation function is given by

$$f(y) = \cos(y) \qquad \dots (2.21)$$

The sine transformation function is given by

$$f(y) = \sin(y) \qquad \dots (2.22)$$

Functions (2.21) and (2.22) also squash the input values on the interval [-∞, +∞] to the unit interval [0, 1]. Their outputs range from -1 to 1.

iii) Tangent hyperbolic function

The tangent hyperbolic function, is a rescaling of the logistic sigmoid, such that its outputs range from -1 to 1. We use the tangent hyperbolic function as the transformation function given in (2.23) to map the inputs into the outputs. That is, for each hidden node the output associated with the hidden node for an input level y is given by

$$tanh(y) = (e^{y} - e^{-y}) / (e^{y} + e^{-y}) \qquad \ldots (2.23)$$

Function (2.23) is preferred over other nonlinear functions that produce best prediction found in this study. It also "squashes" values on the interval [$-\infty$, $+\infty$] to the unit interval [0, 1] and thus prevents any output from reaching a very large value that can paralyze ANN models. The slope of the tangent hyperbolic function for the [0, 1] interval is given by

$$f'(y) = f(y)[1 - f(y)]$$

This means that the tangent hyperbolic function is very steep for intermediate values of the input (y) and flat for extreme input (y) values.

2.6 Purchasing Power Parity theory

2.6.1 Data and variables

The study has used the monthly average period observation from January 1993 to December 2013 for exchange rate and Consumer Price Index for United States and United Kingdom against Solomon Islands. The data seasonally unadjusted are obtained from IMF's international financial statistics. Exchange rates were given as number of Solomon dollars per US dollar and Solomon dollars per UK pound. We take the natural logarithms of them respectively which are represented by R^{US} (or $LNESOUS$) and R^{UK} (or $LNESOUK$). The natural logarithm of US and UK Consumer Price Indexes are subtracted from the natural logarithm of Solomon Islands and are represented by P^{US} (or $LNUSCPI$) and P^{UK} (or $LNUKCPI$) respectively. CPI is indexed to 2010.

2.6.2 Unit root test

The unit-root analysis figure is very important in exchange rate studies. The presence of a unit root indicates that a time series is not stationary. To test the stationarity of a time series, we utilize the co-integration analysis. Since this study use multivariate co-integration, it is appropriate to employ the Augmented Dick-Fuller (ADF) (Dickey & Fuller, 1979) test based on t-ratio of the parameter as given in equation (2.24)

$$\Delta q_t = \beta_0 + \beta_1 + \pi_i q_{t-i} + \sum_{i=1}^{p} \Gamma_i \Delta q_{t-1} + \varepsilon_t \qquad \dots (2.24)$$

where, q is the dependent variable, that is, the exchange rate, Δ is the first difference operator, t is the time trend and ε is the random error and p is the maximum lag length. The optimal lag length is chosen so that the lag length $\varepsilon_t \sim n(0,\sigma_{\varepsilon_t}^2)$ is independent and identical distributed (i.i.d) with mean zero and constant standard deviation, while β_0, β_1, π and Γ are parameters to be estimated. Under the null hypothesis, Δq_t is in level form or I(0) which implies that $\pi = 0$, then we conclude that the series under consideration has a unit root and is therefore nonstationary. To achieve stationarity further differencing is required so that $0 < \pi < 1$ or is inside the unit circle.

2.6.3 Co-integration

The unit root processes $\{q_t\}$ and $\{f_t\}$ will be co-integrated if there exists a linear combination of the two time series that is stationary. To understand the implications of co-integration, let's first look at what happens when the observations are not co-integrated.

2.6.3.1 No co-integration

Let $\xi_t = \xi_{qt-1} + \mu_{qt}$ and $\xi_t = \xi_{ft-1} + \mu_{ft}$ be two independent random walk processes, where $\mu_{\mathrm{qt}} \sim \mathrm{n}\left(0,\sigma_{\mathrm{q}}^2\right)$ and $\mu_{\mathrm{ft}} \sim \mathrm{n}(0,\sigma_{\mathrm{f}}^2)$ are independent and identical distributions (i.i.d). Let $\underline{z}_t = (z_{qt}, z_{ft})'$ follow a stationary bivariate process such as vector autoregressive (VAR). The next process for $\underline{z}_t$ does not need to be explicitly modelled at this point. Now consider the two unit root series built up from these components:

$$q_t = \xi_{qt} + z_{qt} \qquad \dots (2.25)$$

$$f_t = \xi_{ft} + z_{ft} \qquad \dots (2.26)$$

Since q_t and f_t are driven by independent random walks, they will drift arbitrarily far apart from each other over time. If we try to find a value of β to form a stationary linear combination of, q_t and f_t, we will fail, because

$$q_{\mathrm{t}} - \beta f_{\mathrm{t}} = (\xi_{\mathrm{qt}} - \beta \xi_{\mathrm{ft}}) + \left(z_{\mathrm{qt}} - \beta \mathrm{z}_{\mathrm{ft}}\right) \qquad \ldots (2.27)$$

For any value of β, $(\xi_{qt} - \beta\xi_{ft}) = (\tilde{u}_1 + \tilde{u}_2 + \ldots + \tilde{u}_t)$, where $\tilde{u}_t = u_{qt} - \beta u_{ft}$ so the linear combination itself is random walk, $\{q_t\}$ and $\{f_t\}$ clearly do not share a long-run relationship. There may, however, be short-run interactions between their first differences:

$$\begin{pmatrix} \Delta q_t \\ \Delta f_t \end{pmatrix} = \begin{pmatrix} \Delta z_{qt} \\ \Delta z_{ft} \end{pmatrix} + \begin{pmatrix} \varepsilon_{qt} \\ \varepsilon_{ft} \end{pmatrix} \qquad \ldots (2.28)$$

If $\underline{z}_t$ follows a first-order VAR, we can show that equation (2.28) follows a vector ARMA process. Thus, when both $\{q_t\}$ and $\{f_t\}$ be first order differenced to induce stationarity and then their first differences modelled as a stationary vector process.

2.6.3.2 Co-integration

$\{q_t\}$ and $\{f_t\}$ will be co-integrated if they are driven by the same random walk, $\xi_t = \xi_{t-1} + \varepsilon_t$, where $\varepsilon_t \sim n\left(0, \sigma^2\right)$ and is i.i.d. For example,

$$q_t = \xi_t + z_{qt}$$

$$f_t = \phi(\xi_t + z_{ft}) \qquad \ldots (2.29)$$

And we look for a value of β in equation (2.30) that renders stationary

$$q_t - \beta f_t = (1 - \phi\beta)\xi_t + z_{qt} - \phi\beta z_{ft} \qquad \ldots (2.30)$$

we will succeed by choosing $\beta = 1/\phi$, since $q_t - f_t/\phi = z_{qt} - z_{ft}$ is the difference between two stationary processes , so it will itself be stationary. $\{q_t\}$ and $\{f_t\}$ will share a long-run relationship. We say that they are co-integrated, with co-integrating vector $(1, -1/\phi)$. Since the random walks are sometimes referred to as stochastic trend processes, when two series are co-integrated we sometimes say they share a common trend.

2.6.4 Vector error correction representation (model)

For the univariate AR (2) process, we can write $q_t = \rho_1 q_{t-1} + \rho_2 q_{t-2} + u_t$ in Augmented Dick-Fuller test equation as

$$\Delta q_t = (\rho_1 + \rho_2 - 1) q_{t-1} - \rho_2 \Delta q_{t-1} + u_t \qquad \ldots (2.31)$$

where $\mu_t \sim n(0, \sigma_u^2)$ and is i.i.d. If q_t is a unit root process then $(\rho_1 + \rho_2 - 1) = 0$, and $(\rho_1 + \rho_2 - 1)^{-1}$ clearly does not exist. There is a sense of singularity in q_{t-1} because Δq_t is stationary and this can be true only if q_{t-1} drops out from the right-hand side of the equation (2.31).

By analogy, suppose that in the bivariate case the vector (q_t, f_t) is generated according to

$$\begin{bmatrix} q_t \\ f_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} q_{t-1} \\ f_{t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} q_{t-2} \\ f_{t-2} \end{bmatrix} + \begin{bmatrix} \mu_{qt} \\ \mu_{ft} \end{bmatrix} \qquad \ldots (2.32)$$

where $(\mu_{qt}, \mu_{ft}) \sim n(0, \Sigma_u)$ and is i.i.d. Rewrite equation (2.32) as a vector analog of the Augmented Dick–Fuller test equation,

$$\begin{bmatrix} \Delta q_t \\ \Delta f_t \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} \begin{bmatrix} q_{t-1} \\ f_{t-1} \end{bmatrix} - \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \Delta q_{t-1} \\ \Delta f_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_{qt} \\ \mu_{ft} \end{bmatrix} \qquad \ldots (2.33)$$

where $\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} = \begin{bmatrix} a_{11} + b_{11} - 1 & a_{12} + b_{12} \\ a_{21} + b_{22} & a_{22} + b_{22} - 1 \end{bmatrix} \equiv R$

If $\{q_t\}$ and $\{f_t\}$ have unit-root processes, their first difference are stationary. This means that the terms on the right hand side of equation (2.33) are stationary. Linear combinations of levels of the variables appear in the system $r_{11}q_{t-1} + r_{12}f_{t-1}$ appears in the equation for Δq_t and $r_{21}q_{t-1} + r_{22}f_{t-1}$ appears in the equation for Δf_t.

If $\{q_t\}$ and $\{f_t\}$ do not co-integrate, there are no values of the r_{ij} coefficients that can be found to form stationary linear combination of $\{q_t\}$ and $\{f_t\}$. The level terms must drop out. R is the null matrix, and $(\{q_t\},\{f_t\})$ follows a vector autoregression.

If $\{q_t\}$ and $\{f_t\}$ do co-integrate, then there is a unique combination of the two variables that are stationary. The levels enter on the right-hand side, but do so in the same combination in both equations. This means that the column of R**,** which is singular, and can written as

$$R = \begin{bmatrix} r_{11} - \beta r_{11} \\ r_{21} - \beta r_{21} \end{bmatrix}$$

Equation (2.33) can be written as

$$\begin{bmatrix} \Delta q_t \\ \Delta f_t \end{bmatrix} = \begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} (q_{t-1} - \beta f_{t-1}) - \begin{bmatrix} b_{11}\, b_{12} \\ b_{12}\, b_{22} \end{bmatrix} \begin{bmatrix} \Delta q_{t-1} \\ \Delta f_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_{qt} \\ \mu_{ft} \end{bmatrix}$$

$$= \begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix} z_{t-1} - \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \Delta q_{t-1} \\ \Delta f_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_{qt} \\ \mu_{ft} \end{bmatrix} \qquad \ldots (2.34)$$

Where $z_{t-1} \equiv q_{t-1} - \beta f_{t-1}$ is called the error-correcting term, and equation (2.34) is the vector error-correction representation.

A VAR in first difference would be misspecified, because it omits the error-correction term. To express the dynamics governing z_t, multiply the equation by Δf_t by β and subtract the result from the equation for Δq_t, to give

$$z_t = \left(1 + r_{11} - \beta r_{21}\right) z_{t-1} q_{t-1} - \left(b_{11} - \beta b_{21}\right) \Delta q_{t-1} - (b_{12} + \beta b_{22}) \Delta f_{t-1} + \mu_{qt} - \beta \mu_{ft} \qquad \ldots (2.35)$$

The entire system is given by

$$\begin{bmatrix} \Delta q_t \\ \Delta f_t \\ \Delta z_t \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & r_{11} \\ b_{21} & b_{22} & r_{12} \\ -(b_{11}+\beta b_{21}) & -(b_{12}+\beta b_{22}) & 1+r_{11}-\beta r_{21} \end{bmatrix} \begin{bmatrix} \Delta q_{t-1} \\ \Delta f_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_{qt} \\ \mu_{ft} \\ \mu_{qt}-\beta\mu_{ft} \end{bmatrix} \quad \ldots (2.36)$$

$(\Delta q_t, \Delta f_t, z_t)'$ is stationary vector, and (2.36) looks like a VAR(1) in these three variables, except that the columns of the coefficient matrix are linearly dependent. In many applications, the co-integration vector $(1,-\beta)$ is given a priori by economic theory and does not need to be estimated. In these situations, the linear dependence of the VAR in (2.36) tells us the information contained in the VECM is preserved in bivariate VAR form z_t and either Δq_t *or* Δf_t.

Suppose that we know this strategy. To obtain the VAR for $(\Delta q_t, \Delta f_t)$ substitute $f_{t-1} = (q_{t-1} - z_{t-1})/\beta$ into the equation (2.31) for Δq_t, to get

$$\Delta q_t = b_{11}\Delta q_{t-1} + b_{12}\Delta f_{t-1} + r_{11} z_{t-1} + \mu_{qt}$$

$$= a_{11}\Delta q_{t-1} + a_{12} z_{t-1} + a_{13} z_{t-2} + \mu_{qt}$$

where, $a_{11} = b_{11} + b_{12}/\beta$, $a_{12} = r_{11} - b_{12}/\beta$ and $a_{13} = b_{12}/\beta$ Similarly, substitute f_{t-1} out of the equation for z_t, to give

$$z_t = a_{21}\Delta q_{t-1} + a_{22} z_{t-1} + a_{23} z_{t-2} + (\mu_{qt} + \mu_{ft})$$

where, $a_{21} = -(b_{11} + \beta b_{21} + b_{12}/\beta + b_{22})$, $a_{22} = 1 + r_{11} - \beta r_{21} + b_{22} + b_{12}/\beta$, and $a_{23} = -(b_{22} + b_{12}/\beta)$.

Together, we have the VAR (2)

$$\begin{bmatrix} \Delta q_t \\ z_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \Delta q_{t-1} \\ \Delta f_{t-1} \end{bmatrix} + \begin{bmatrix} 0 & a_{13} \\ 0 & a_{23} \end{bmatrix} \begin{bmatrix} \Delta q_{t-2} \\ z_{t-2} \end{bmatrix} + \begin{bmatrix} \mu_{qt} \\ \mu_{qt}-\beta\mu_{ft} \end{bmatrix} \quad \ldots (2.37)$$

Equation (2.37) is easier to estimate than the VECM and the standard forecasting formulae for VARs can be employed without modification.

2.6.5 Models for exchange rate, CPI

In this section we present the empirical models and the variable description.

Model 1

$$E(R_{t+1}) = \alpha + \beta S + U_t; \beta > 0 \qquad \text{… (2.38)}$$

where, $E(R_{t+1})$ is the expected nominal exchange rate (defined as the log of the number of Solomon Islands dollars per foreign currency). R = log of the Solomon dollar per foreign currency, S = log of Solomon Islands consumer price index (P) minus log of the foreign consumer price index (P^*) and U_t is the stochastic disturbance term and t is the time captured.

The foregoing models approximate the relative version of the PPP theory even though the dependent variable is not exactly the changes in exchange rate.

Model 2

$$R_t = \alpha + \beta_1 P_t + \beta_2 P_t^* + U_t; \beta_1 > 0; \beta_2 < 0 \qquad \text{…. (2.39)}$$

Variables are in natural logarithms.

Using restriction for the absolute version $-\beta_1 = \beta_2$, equation (2.39) becomes

$$R_t = \alpha + \beta(P_t - P_t^*) + U_t \qquad \text{… (2.40)}$$

The empirical estimation of equation (2.40) amounts to the testing of the absolute version hypothesis of the PPP theory. Model 2 does not follow from model 1 and it is independent. The symmetry and the proportionality assumptions of the PPP theory can be rigorously examined by equation (2.40).

Even though in strict PPP theory of the absolute version $\beta_1 = 1$ and $\beta_2 = -1$ the orders of the magnitude can deviate slightly from unit coefficient and still maintain the proportionality and symmetry in strong version of the PPP theory.

2.7 Conclusion

In this chapter we discuss the methodologies used in carrying out the present research. Firstly we discuss the method of collecting Solomon exchange rate data and the various software used. Then we discuss in-depth of various time series methods, regression method, ANN method and the purchasing power parity method.

Chapter 3:

Forecasting exchange rates using multiple linear regression

3.1. Introduction

In this chapter, the forecasting of Solomon dollar exchange rates against its major trading currencies such as AUD, GBP, Yen and EURO were carried out using multiple linear regression of various time-lagged exchange rates. For the purpose of illustrations, the results for AUD exchange rates are reported in this chapter. The results for the forecasting of Great Britain pound, Japanese yen and Euro exchange rates are reported in Chapter 7 and Appendices 2-4 for the discussion about the comparison of various forecasting models the thesis considers.

The various error measures, and the lower values of both the Akaike and the Schwarz information criteria, S_p^2 and the higher value of R_{adj}^2 suggest that the multiple linear regression with 6 lags is to be considered best for the forecasting of the AUD/SBD exchange rate. For the selection of the number of time-lags that fits best a multiple linear regression model for forecasting the AUD/SBD exchange rate, we consider the following criteria.

3.2. Model selection criteria

3.2.1 AIC and SIC model selection criteria

Determining optimal lag length is crucial in multiple linear regressions because they are sensitive to lag length (p). To maximize normal likelihood we choose p to minimize (SSE_p / n) which is the estimated error in the covariance in the sample n. Akaike information criterion (AIC) is the most popular information criterion used to determine the preferred model. AIC modifies the likelihood $\ln(SSE_p / n)$ by adding a penalty on each additional lag and is given by

$$AIC_p = \ln(SSE_p / n) + 2r / n \qquad \dots (3.1)$$

where, r = p+1 is the number of parameters in the model, n is the number of observations, p is the lag length, and (SSE_p / n) is the maximum likelihood.

Another model selection criterion is Schwarz information criterion (SIC), which is an extension of Bayesian information criterion. This criterion suggests that p values are too large by adding greater penalty on the parameters (r) and is given by

$$SIC_p = \ln(SSE_p / n) + r\ln(n) / n \qquad \dots (3.2)$$

The preferred model is one with the minimum value of AIC and SIC from their corresponding candidate models.

3.2.2 Adjusted r-square $R^2_{Adj,p}$ and mean square error S^2_p information criteria

Let R^2_p denote the R^2 from a model containing p variables, $(p+1)$ regression coefficients and the intercept (constant). The R^2_p is given by $R^2_p = 1-(SSE_p / SST)$, where SSE_p is the error sum square and SST is the total sum square.

R^2_p increases with p; if we continue to add variables to the model then SSE_p will decrease. Consequently, one can get R^2_p close to 1 by adding increasingly more variables. In the limit, where there are n observations and the model contains n parameters, $SSE = 0$ and $R^2 = 1$. For this reason, we use adjusted R^2_p, which applies a penalty for each estimated coefficient. The sums of squares are adjusted by their degrees of freedom: SSE_p by $n-p-1$ and SST by $n-1$. The adjusted R^2_p is given by

$$R^2_{Adj,p} = 1-(S^2_p / S^2_y) \qquad \dots (3.3)$$

where, $S_p^2 = SSE_p / n - p - 1$ is the mean square error of the residuals and $S_y^2 = SST / n - 1$ is the variance of the dependent variable. Equation (3.3) shows that $R_{Adj,p}^2$ does not necessarily increase with p anymore. The term $(n-1)/(n-p-1)$ lowers $R_{Adj,p}^2$ when there is no improvement to R_p^2. Therefore, by examining the smaller value of S_p^2 and the higher value of $R_{Adj,p}^2$ one can select the best time-lag model (Abraham & Ledolter, 2005).

3.3 Results of model selection using the training sample

The results on model selection criteria and for error measures are given in Table 3.1 and Table 3.2 respectively. The first column in Table 3.1 represents various time-lagged models of AUD/SBD from lags 1 to 12. The rest of the columns are the lag length selection measures criteria and the last column gives the probability. The value of S_p^2 and R_{Adj}^2 is calculated using equation 3.3. The values of *AIC, SIC,* R^2 and probability are obtained using Eviews software. As an example, the result for lag 6 is displayed in Table 3.2.

Table 3.1: Model selection criteria of MLR for AUD/SBD

Model with lags (p)	AIC_p $(\times 10^{-3})$	SIC_p $(\times 10^{-3})$	S_p^2 $(\times 10^{-7})$	$R_{adj,p}^2$ $(\times 10^{-4})$	Probability $(\times 10^{-1})$
Lag 1	-8488.56	-8485.24	120.40	9982.66	<0.01
Lag 2	-8557.30	-8552.32	112.34	9983.81	<0.01
Lag 3	-8567.09	-8560.45	111.19	9983.97	<0.01
Lag 4	-8566.81	-8558.51	111.17	9983.96	1.71
Lag 5	-8571.39	-8561.43	110.60	9984.04	<0.01
Lag 6	**-8573.62**	**-8561.99**	**110.29**	**9984.07**	**<0.01**
Lag 7	-8573.58	-8560.28	110.24	9984.07	0.91
Lag 8	-8574.18	-8559.23	110.11	9984.08	0.36
Lag 9	-8574.23	-8557.63	110.05	9984.09	0.83
Lag 10	-8573.54	-8555.25	110.07	9984.08	6.60
Lag 11	-8573.85	-8553.90	109.97	9984.08	5.75
Lag 12	-8573.35	-8551.73	109.97	9984.08	9.90

The results in Table 3.1 reveal 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, even though a few models have a slightly higher value of R^2_{adj}. Furthermore, the lowest values of AIC_p and SIC_p strongly indicate that the lag 6 is the optimal lag. Table 3.2 gives the Eviews results for forecasting the exchange rate of AUD/SBD in Section 3.5.

Table 3.2 Results of MLR (6) from Eviews software.

Dependent Variable: AUD
Method: Least Squares
Sample (adjusted): 7 3756
Included observations: 3750 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.81E-05	1.50E-04	0.39	0.70
AUD(-1)	0.71	1.63E-02	43.29	<0.01
AUD(-2)	0.18	2.00E-02	8.79	<0.01
AUD(-3)	0.07	2.02E-02	3.36	<0.01
AUD(-4)	-0.04	2.02E-02	-1.94	0.05
AUD(-5)	0.03	2.00E-02	1.72	0.09
AUD(-6)	0.05	1.63E-02	3.33	<0.01

R-squared	0.998410	Mean dependent var	0.214747
Adjusted R-squared	**0.998407**	S.D. dependent var	0.083283
S.E. of regression	0.003324	Akaike info criterion	-8.573615
Sum squared resid	0.041349	**Schwarz criterion**	**-8.561987**
Log likelihood	16082.53	Hannan-Quinn criter.	-8.569480
F-statistic	391691.9	Durbin-Watson stat	2.003000
Prob(F-statistic)	0.000000		

3.4 Dicussion on the lag selection

Table 3.1 shows the results of fitting all possible regressions. The best three competing models based on a 1% level of significance are multiple linear regressions with 3, 5 and 6 lags. In this discussion p may be used interchangeably with the lag length. For 3 lags, the values of $R^2_{Adj,3}$ and S^2_3 are $9983.97\,(\times 10^{-4})$ and $111.19\ (\times 10^{-7})$ respectively. For 5 lags, the values of $R^2_{Adj,5}$ and S^2_5 are $9984.04\,(\times 10^{-4})$ and $110.60\ (\times 10^{-7})$ respectively. For 6 lags, the values of $R^2_{Adj,6}$ and S^2_6 are $9984.07\,(\times 10^{-4})$ and

$110.29\,(\times 10^{-7})$ respectively. The value of $R^2_{Adj,p}$ is highest for 6 lags followed by 5 lags and 3 lags and the value of S^2_p is smallest for 6 lags followed by 5 lags and then 3 lags. The values of AIC and SIC for 3 lags are -8567.09$\,(\times 10^{-3})$ and -8560.45$\,(\times 10^{-3})$ respectively. For 5 lags, the respective values of AIC and SIC, are -8571.39$\,(\times 10^{-3})$ and -8561.43$\,(\times 10^{-3})$. For 6 lags, the respective values of AIC and SIC, are -8573.62$\,(\times 10^{-3})$ and -8561.99$\,(\times 10^{-3})$. The values of AIC and SIC are smallest for 6 lags followed by 5 lags then 3 lags. All the model selection criteria; $R^2_{Adj,p}$, S^2_p, AIC and SIC suggests that the model with 6 lags is preferred over models with 5 lags and then 3 lags.

As the variable increases beyond 6 lags, the rate of convergence is very slow. In addition, adding more AUD/SBD exchange rate lags tends to reduce the sum of square error to zero and hence will push R^2 very close to 1. Therefore, for higher lags, we rely on the adjusted $R^2_{adj,p}$ as our performance measure rather than relying on the normal R^2_p. And as such we report only the values of adjusted R^2 in Table 3.1. After this, it fluctuates very slowly and remains steady at this level. In most cases, SIC is a more reliable lag selection criterion than AIC as given in equation 3.2 (Mukhtar & Rasheed, 2010). In Table 3.1 the smallest value of SIC is -8561.99 $(\times 10^{-3})$ and this occurs at 6 lags. The smallest value of SIC and largest value of $R^2_{adj,p}$ strongly suggests that MLR (6) is the most favourable. These two selection criteria can be relied upon if the lag length grows bigger and bigger.

Again it is interesting to note that the model with 9 lags has the smallest value of AIC and the model with 11 lags has the highest value of R^2, and smallest value of S^2_p. Further, the model with 8 lags has the lowest value of R^2_{adj}. These models were dropped off from the competition because they are not significant at the 1% level of significance.

We, therefore, select multiple linear regression of lag 6 as our preferred model because other exchange rate time-lags are not significant at the 1% level of confidence (see Table 3.1). Based on the three competitive models, the lowest values of AIC and SIC strongly indicate that model with 6 lags is the optimal lag.

Figure 3.1 presents the actual vs predicted exchange rates along with the residuals values for MLR (6) model using the training sample.

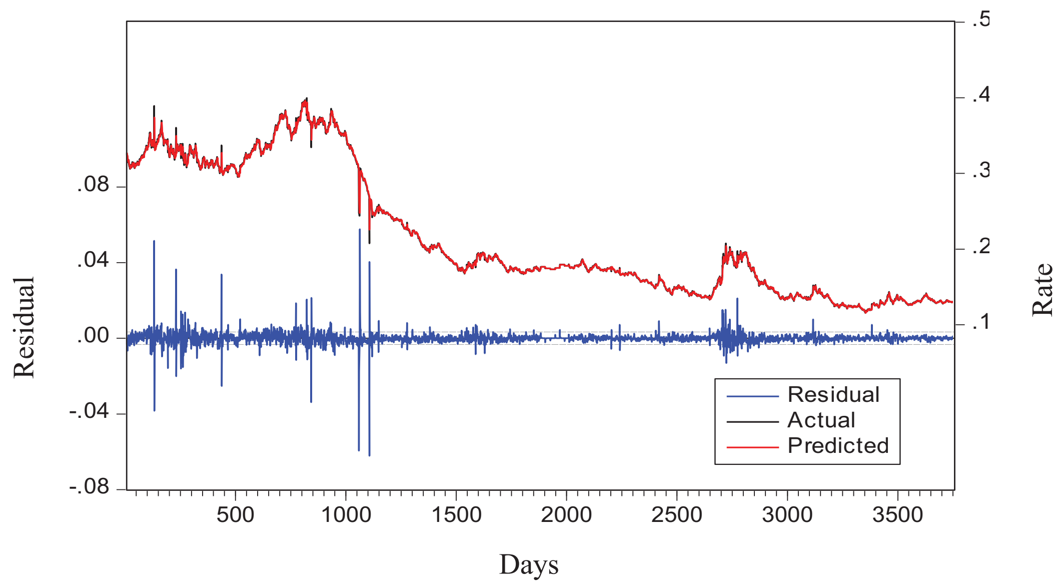


Figure 3.1: Actual, predicted and residual exchange rate values for AUD/SBD for MLR (6) model for training sample.

3.5 Normality tests for MLR model

A histogram with a summary table (Figure 3.2) clearly indicates that the average exchange rate of AUD/SBD over the sample period is 0.21 with the standard deviation of 0.08. It also shows that the distribution is positively skewed (skewness = 0.70) and its peakness is very high (kurtosis = 1.93). This might imply that it is not advisable to use the mean exchange rate value for business transactions. Moreover, the Jarque–Bera statistics for normality is highly significant and, therefore rejected.

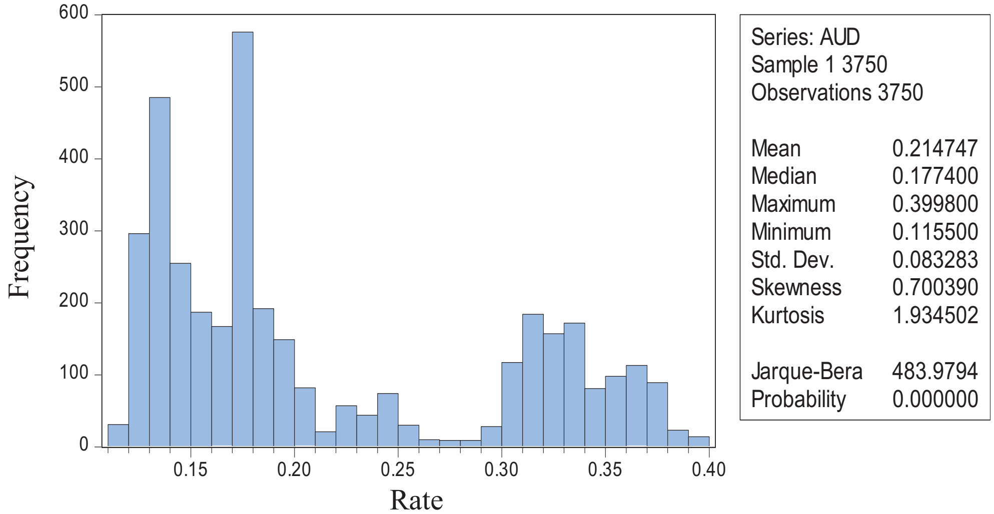


Figure 3.2: Histogram and summary of AUD/SBD

The Shapiro-Wilk test ($p < 0.01$), the Kolmogorov-Smirnov test ($p < 0.01$) and the normal Q–Q plot (see Figure 3.3 and Table 3.3) of the residuals also reveal that the MLR model fails to meet the normality assumption of residuals. Thus, these findings are contrary to the use of MLR models.

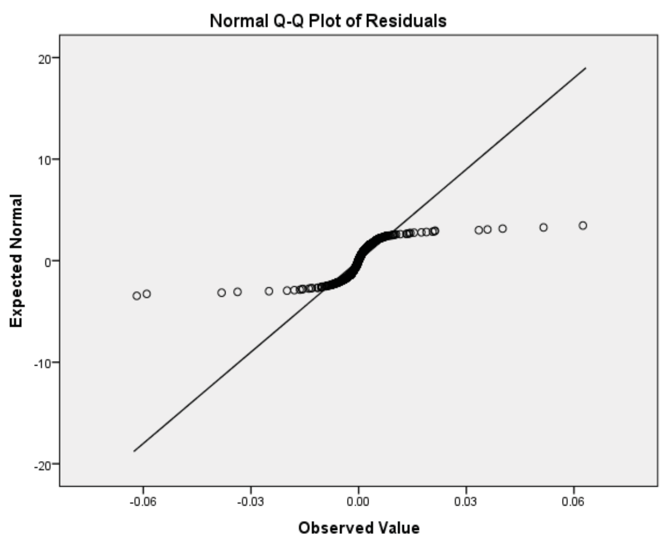


Figure 3.3: Normal Q–Q plot of residuals

Table 3.3: Test for normality (Kolmogorov-Smirnov and Shapiro-Wilk).

	Kolmogorov-Smirnov [a]			Shapiro-Wilk		
	Statistics	df	Sig.	Statistics	df	Sig.
Residuals	0.18	3750	<0.01	0.56	3750	<0.01

[a] Lilliefors Significance Correction.

3.6 Forecasting MLR model using the testing sample

The forecasted equation for MLR (6) estimated using the least squares method as estimated by Eviews software using equation 2.2 in Chapter 2 and results in Table 3.2 is given as

$$\hat{y}_t = 5.81E - 0.05 + 0.71y_{t-1} + 0.17y_{t-2} + 0.07y_{t-3} - 0.04y_{t-4} + 0.03y_{t-5} + 0.05y_{t-6} \quad \text{... (3.4)}$$

We use this equation to forecast the exchange rate of AUD/SBD for the testing period given in Figures 3.4 and 3.5. The forecasted result is reported in Table 7.1(a) in Chapter 7 for comparison with other models.

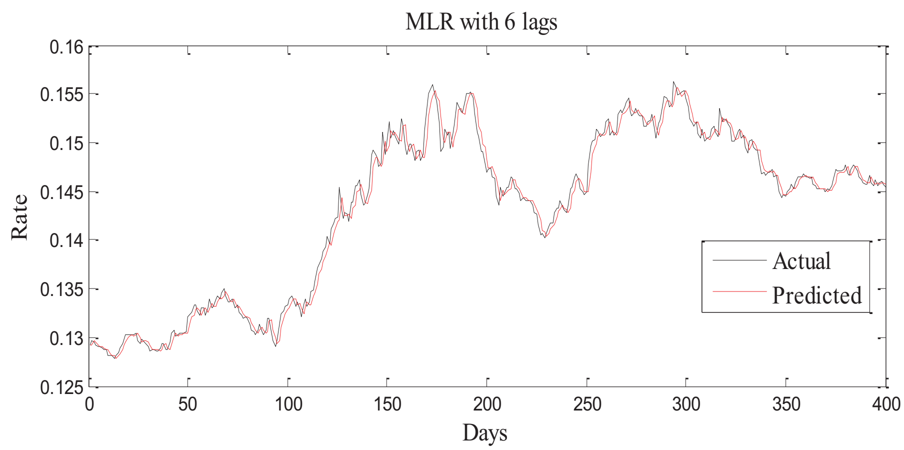


Figure 3.4: Graph of actual vs predicted for MLR with 6 lags for testing sample.

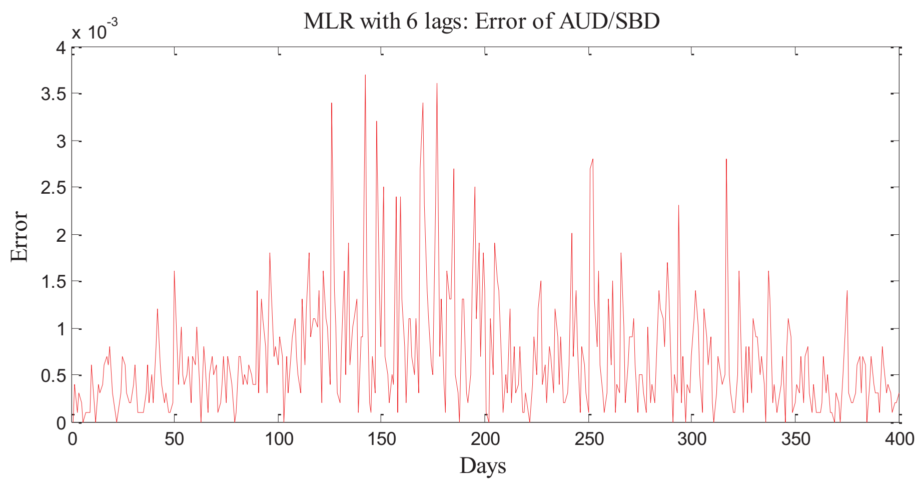


Figure 3.5: Residual of MLR(6) for testing AUD/SBD.

3.7 Conclusion

This chapter gives the results of forecasting SBD against AUD using multiple linear regression using the weights obtained from the training set. MLR (6) was selected based on the lower values of AIC, SIC, S_p^2 and higher value for the adjusted $R_{Adj,p}^2$ using the training set.

Chapter 4:

Forecasting exchange rates using time series models

4.1 Introduction

This chapter discusses the forecasting results of single exponential smoothing; double exponential smoothing with trend, HW additive and multiplicative seasonal. For the purpose of illustrations, the results for AUD exchange rates are reported in this chapter. We repeat this method for Great Britain pound, Japanese yen and Euro exchange rates and their results are presented in Chapter 7 and Appendices 2-4 for the comparison of various models.

4.2. Single exponential smoothing

Forecasting AUD/SBD is carried out using exponential single smoothing model given in equation (2.3) in Chapter 2. The following sections firstly trains the value of alpha and this value is then used to forecast the exchange rate of AUD/SBD using the testing sample.

4.2.1 Forecasting single smoothing using the training sample

This section reports the result of training single exponential smoothing using the Eviews computer software. Table 4.1 presents the result of single exponential smoothing for AUD/SBD.

Table 4.1: Shows result of training single exponential smoothing

Sample: 1 3750		
Included observations: 3750		
Method: Single Exponential		
Original Series: AUD		
Forecasted Series: AUDSINGLE		
Parameters:	Alpha	0.71
Sum of Squared Residuals		4.41E-02
Root Mean Squared Error		3.43E-03
End of Period Levels:	Mean	0.13

The parameters reported in Table 4.1 gives the values of alpha, $\alpha = 0.71$, sum of square residuals (or errors), $SSR = 4.41\times10^{-2}$, and root mean square error, $RMSE = 3.43\times10^{-3}$. The mean value for AUD/SBD exchange rate at the end of each period level is 0.13. The single exponential smoothing does not capture linear trend and seasonal variation. The value of α is close to 1 which indicates that the estimate favours more recent data than the far distant observations (Dumicic et al., 2008). Figure 4.1 show graphs of AUD/SBD for actual vs predicted and residuals using single exponential smoothing on the training data set.

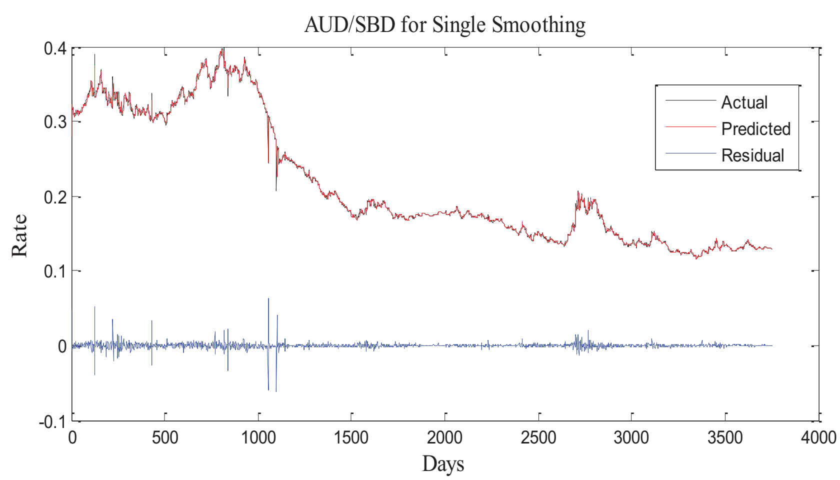


Figure 4.1: Actual, predicted and residual for training AUD/SBD for single smoothing.

4.2.2 Forecasting single smoothing using the testing sample

We use the weights in Table 4.1 to get the result in the Table 4.2 using the testing sample for our forecasting. Figures 4.2 and 4.3 shows the actual vs forecasted and the residuals for forecasting AUD/SBD exchange rate for single smoothing.

Table 4.2: Shows result of testing single exponential smoothing

Sample: 1 400		
Included observations: 400		
Method: Single Exponential		
Original Series: AUD		
Forecasted Series: AUDSINGLE		
Parameters:	Alpha	**0.71**
Sum of Squared Residuals		4.40E-04
Root Mean Squared Error		1.05E-03
End of Period Levels:	Mean	0.15

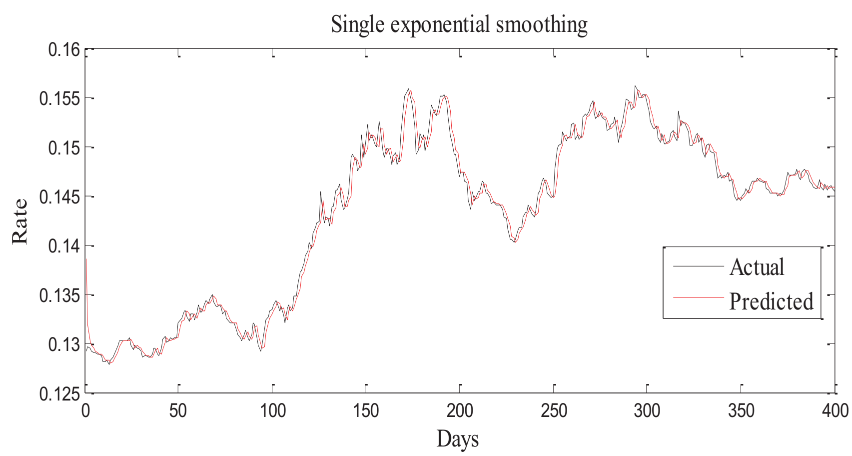


Figure 4.2: Performance of single smoothing for AUD/SBD using the testing sample.

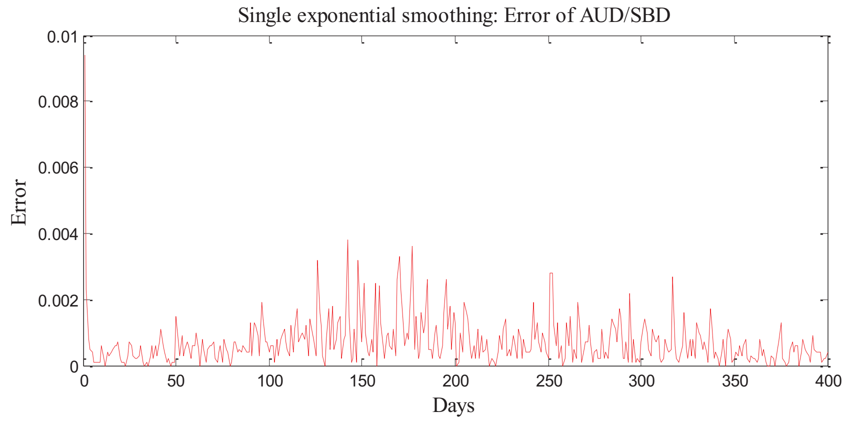


Figure 4.3: Residual for single smoothing for testing AUD/SBD.

4.3 Double exponential smoothing

Forecasting AUD/SBD is carried out using exponential double smoothing model given in equation (2.4) in Chapter 2. The following sections firstly trains the value of alpha and this value, is then used to forecast the exchange rate of AUD/SBD using the testing sample.

4.3.1 Forecasting double smoothing using the training sample

This section reports the result of training the double exponential smoothing using Eviews computer software. Table 4.3 presents the result for double exponential smoothing for AUD /SBD exchange rate. Figure 4.4 show the actual vs predicted and the residuals for forecasting AUD/SBD exchange rate for double exponential smoothing.

Table 4.3: Shows result of training double exponential smoothing.

Sample: 1 3750		
Included observations: 3750		
Method: Double Exponential		
Original Series: AUD		
Forecasted Series: AUDDOUBLE		
Parameters: Alpha		0.35
Sum of Squared Residuals		5.13E-02
Root Mean Squared Error		3.70E-03
End of Period		
Levels:	Mean	0.13
	Trend	-1.56E-04

The parameters reported in Table 4.3 gives the values of $\alpha = 0.35$, $SSR = 5.13\times10^{-2}$, and $RMSE = 3.70\times10^{-3}$. The exponential double smoothing model captures the trend component in the data unlike the single smoothing model. The mean value at the end of its period level is 0.13 and the trend coefficient is -1.56×10^{-4}. The negative coefficient of the trend indicates that there is a general decreasing in the AUD/SBD exchange rate. This general trend shows that SBD continues to weaken against AUD. Mathematically, the current trend tells us that every day SBD will be weakening against AUD by -1.56×10^{-4}. This effect may appear insignificant in a short run, but the impact will be severe in the long-run. For example, if we multiply this trend coefficient by n =1500 which is approximately 5 years, then SBD will be weakened by 0.23 AUD. Using the current mean value, the exchange rate after 5 years will become 0.03 AUD/SBD. This type of scenario will not likely to happen in a fixed exchange regime as in the Solomon Islands because currency movement is controlled by the authority. In such situation, the regime will come up with certain monetary policy measure to ensure that the currency is in line with the country's economic fundamentals. Note that the value of $\alpha < 0.5$, this means that the estimation favours past distance observation in contrast to single smoothing. The error values show that single smoothing is better than double smoothing for forecasting AUD/SBD exchange rate. This is a bit surprise because the former is expected to forecast better that the latter. Chand and Chandra (2014) pointed out in their literature that in order to make a right selection of forecasting models, one must identify the features of the time series data so that a proper method can be applied to give prediction accuracy.

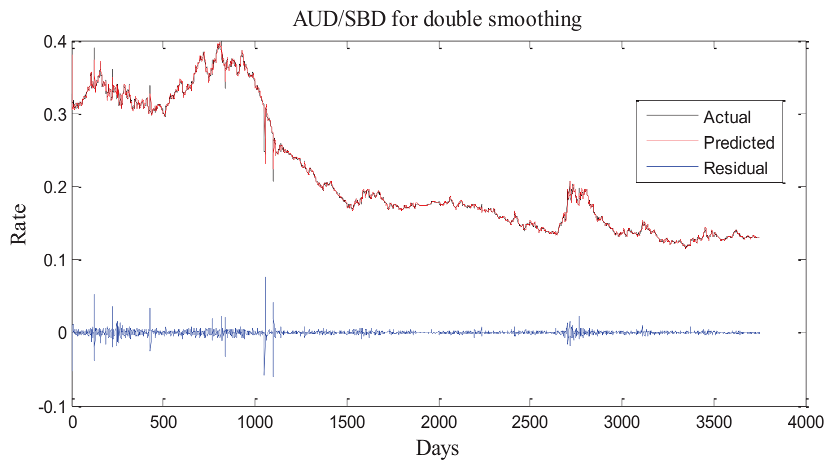


Figure 4.4: Actual vs predicted and residual for training AUD/SBD for double smoothing.

4.3.2 Forecasting double smoothing using the testing sample

We use the training weights from Table 4.3 to get the results on Table 4.4 that will be used for forecasting using the double smoothing method. Figures 4.5 and 4.6 shows the actual vs forecasted and the residuals for forecasting AUD/SBD exchange rate for double smoothing.

Table 4.4: Shows result of testing double exponential smoothing

Sample: 1 400		
Included observations: 400		
Method: Double Exponential		
Original Series: AUD		
Forecasted Series: AUDDOUBLE		
Parameters:	Alpha	**0.35**
Sum of Squared Residuals		4.50E-04
Root Mean Squared Error		1.06E-03
End of Period Levels:	Mean	0.15
	Trend	-7.24E-05

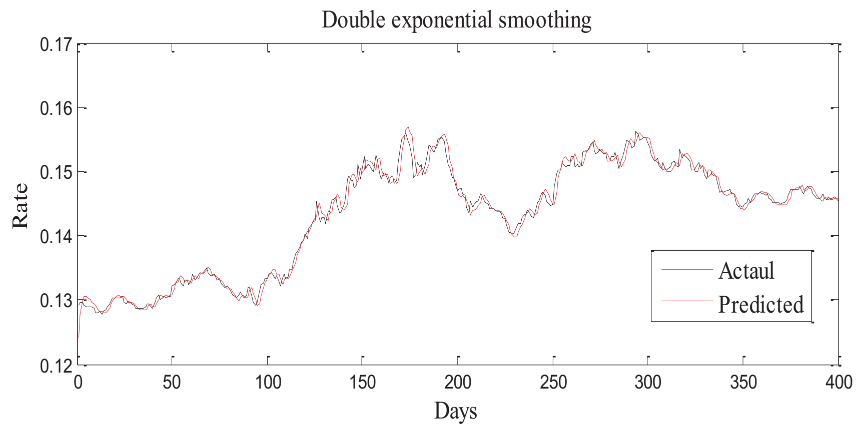


Figure 4.5: Performance of double smoothing for AUD/SBD using the testing sample.

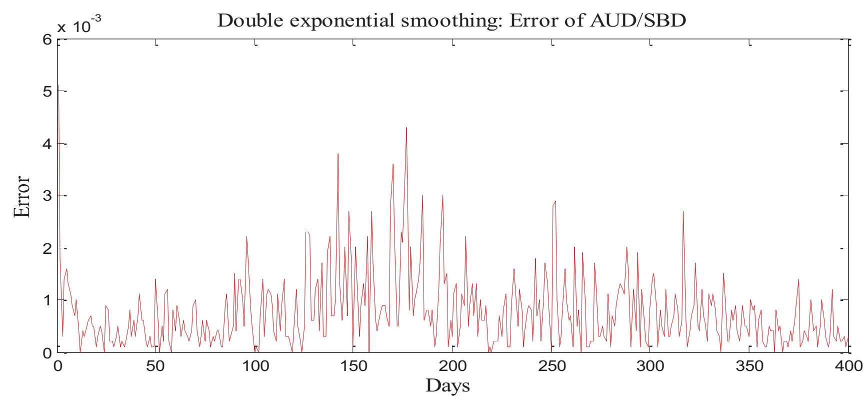


Figure 4.6: Residual for double smoothing for testing AUD/SBD.

4.4 Holt–Winter (HW) additive seasonal method

HW additive method is a modification from the exponential smoothing that captures average, trend, and seasonality. Using equation (2.5) in Chapter 2, we carry out the forecast of AUD/SBD for HW additive model. The following sections firstly train the values of alpha, beta and gamma, and these values are then used to forecast the exchange rate of AUD/SBD using the testing sample.

4.4.1 Forecasting HW additive seasonal using the training sample

Table 4.5 presents the result of training HW additive seasonal for AUD against SBD. The model attempts to capture the average, trend and seasonal effect at the end of each period level for additive seasonal. The seasonal effect is set at 5 seasonal cycles which means that only 5 most recent seasonal cycle values are shown on the bottom 5 rows of Table 4.5. This seasonal effect was automatically set by the Eviews software because in most cases the most recent observations give better predictions. This explanation is the same for Section 4.5.

Table 4.5: Shows result of HW additive seasonal

Sample: 1 3750
Included observations: 3750
Method: Holt-Winters additive seasonal
Original Series: AUD
Forecasted Series: AUDADD

Parameters:	Alpha		0.70
	Beta		0.00
	Gamma		0.00
Sum of Squared Residuals			4.17E-02
Root Mean Squared Error			3.33E-03
End of Period Levels:	Mean		0.13
	Trend		-5.15E-05
	Seasonals:	3746	-1.56E-05
		3747	3.66E-05
		3748	-4.63E-05
		3749	2.51E-05
		3750	1.48E-07

The parameters reported in Table 4.5 gives the value of $\alpha = 0.70$, $\beta = \gamma = 0$ $SSR = 4.17 \times 10^{-2}$ and $RMSE = 3.33 \times 10^{-3}$. The mean value for each period at the end of its level is 0.13 and the trend is -5.15×10^{-5}. The coefficient of trend component is negative which indicates that there is a general down ward trend AUD/SBD exchange rate data similar to double exponential smoothing. The seasonal effect is very small and oscillating also indicates little seasonal influence on the series data. The low value of SSR and RMSE imply HW additive forecast better than single and double exponential smoothing for Solomon exchange rate forecasting. The parameters α, β and γ are the weighting for smoothing for mean, trending component and component of seasonal effect respectively and are estimated using the Eviews software. Note that, parameters $\beta=\gamma=0$ strongly indicate that the estimate on trend component and seasonal effect favours far distance value of the independent variable than the more recent ones. Conversely, the value of $\alpha>0.5$ imply that the estimation for mean favours recent values of observations than past distance ones. This agrees with the single exponential smoothing method. Figure 4.7 shows the actual vs predicted and the residuals for forecasting AUD/SBD exchange rate for HW additive.

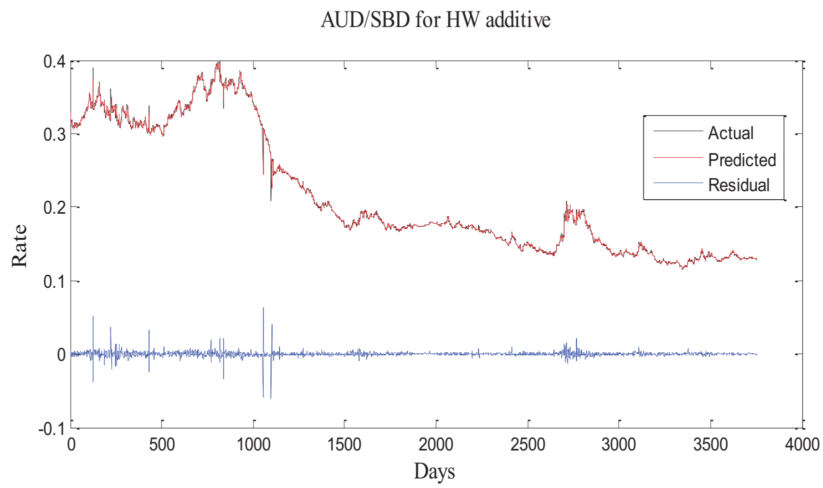


Figure 4.7: Actual vs predicted and residual for training AUD/SBD for HW additive.

Figure 4.8 shows the seasonal variation on the recent 5 cycles, it indicates that the AUD/SBD fluctuated around 0, which might imply that the SBD seems to be stable around this current mean value. Note that the variation alternatives from positive and negative value around 0. The average amplitude of the additive seasonal variation is around 4.00×10^{-5}.

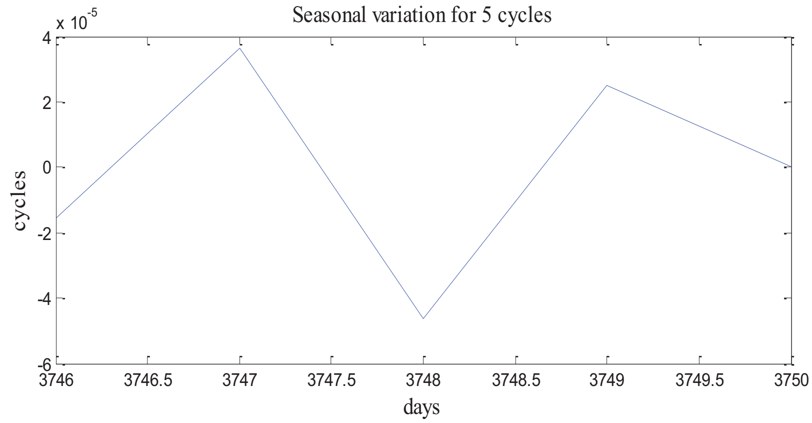


Figure 4.8: Seasonal variation for HW additive for recent 5 cycles

4.4.2 Forecasting HW additive seasonal using the testing sample

We use the training weights from Table 4.5 to get the results in Table 4.6 that will be used for forecasting using the HW additive method. Figures 4.9 and 4.10 shows the actual vs forecasted and the residuals for forecasting AUD/SBD exchange rate for HW additive seasonal.

Table 4.6: Shows result of testing HW additive seasonal

Sample: 1 400
Included observations: 400
Method: Holt-Winters Additive Seasonal
Original Series: AUD
Forecasted Series: AUDADD

Parameters:	Alpha			**0.70**
	Beta			**0.00**
	Gamma			**0.00**
Sum of Squared Residuals				3.47E-04
Root Mean Squared Error				9.31E-04
End of Period Levels:	Mean			0.15
	Trend			4.15E-05
	Seasonals:	396		3.95E-05
		397		1.68E-05
		398		1.03E-05
		399		-6.63E-05
		400		-2.88E-07

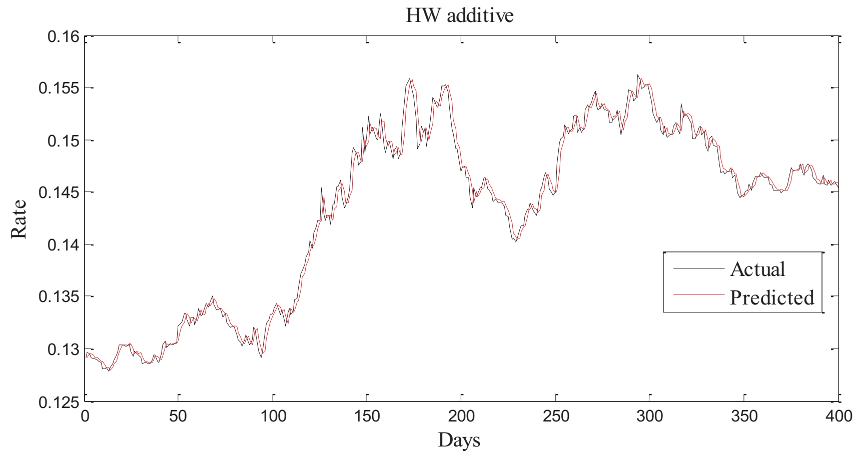


Figure 4.9: Performance of HW additive for AUD/SB using the testing sample

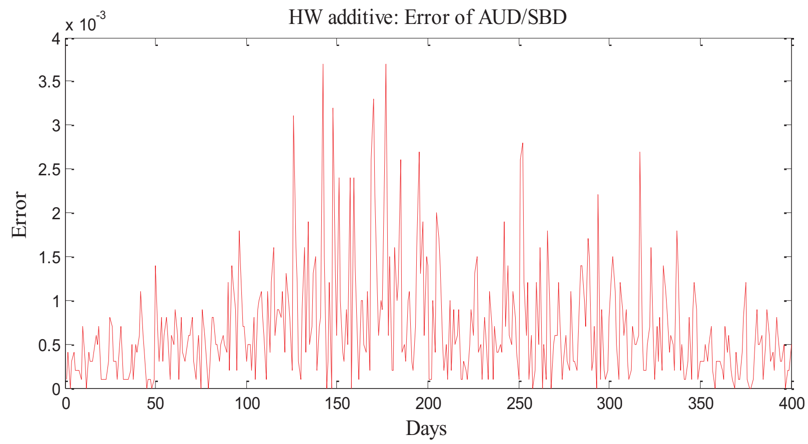


Figure 4.10: Residual for HW additive for testing AUD/SBD.

4.5 Holt–Winter (HW) multiplicative seasonal method

HW multiplicative method is a modification from the exponential smoothing that captures average, trend, and seasonality. Using equation (2.6) in Chapter 2, we carry out the forecast of AUD/SBD for HW multiplicative model. The following sections firstly train the values of alpha, beta and gamma, and these values are then used to forecast the exchange rate of AUD/SBD using the testing sample.

4.5.1 Forecasting HW multiplicative seasonal using the training sample

Table 4.7 presents the result of HW multiplicative seasonal for AUD against Solomon dollar. The model attempts to capture the average, trend and seasonal effect at the end of each period level for multiplicative seasonal. The seasonal effect is set at 5 seasonal cycles which means that only 5 most recent seasonal cycle values are shown in Table 4.7.

Table 4.7: Shows result of HW multiplicative seasonal

Sample: 1 3750
Included observations: 3750
Method: Holt-Winters multiplicative seasonal
Original Series: AUD
Forecasted Series: AUDMULTPLY

Parameters:	Alpha		0.70
	Beta		0.00
	Gamma		0.00
Sum of Squared Residuals			4.16E-02
Root Mean Squared Error			3.33E-03

End of Period Levels:	Mean		0.13
	Trend		-5.15E-05
	Seasonals:	3746	0.99
		3747	1.00
		3748	0.99
		3749	1.00
		3750	0.99

The parameters reported in Table 4.7 are the same for those obtained from the additive seasonal given in Table 4.5 except for the values of SSR and seasonal variations. Similarly, the negative coefficient of the trend component further ascertains the downward trend movement of AUD/SBD exchange rate. Moreover, this coefficient is in the same range as in the other exponential smoothing methods. This further shows the reliability of these time series models in determining the trend component. The seasonal effect oscillates above zero in this result, while in additive method, it alternates around zero. The values indicate very small fluctuation which implies that the influence of seasonal effect on the data is quite low. Also note that the value for its seasonal cycle is about 150 times larger compared to the additive method. The multiplicative factor has really magnified the seasonal effect. The low value of SSR and RMSE imply HW multiplicative model perform better than single and double exponential smoothing for Solomon exchange rate forecasting. The model parameters α, β and γ are estimated using the Eviews software. The values of the trend and the seasonal components favours distance observations as observed in HW additive method given in Table 4.5. Again, the value of $\alpha > 0.5$, which indicates that the estimation for mean favours recent values of observations than past distance ones. This agrees with the single exponential smoothing method. Figure 4.11 shows the actual vs predicted and the residuals for forecasting AUD/SBD exchange rate for HW multiplicative.

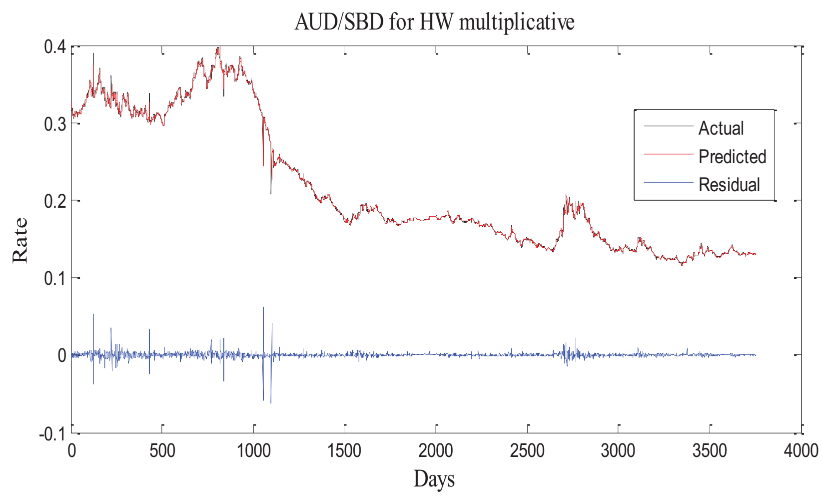


Figure 4.11: Actual vs predicted and residual for training AUD/SBD for HW multiplicative**.**

Figure 4.12 shows the seasonal variation on the recent 5 cycles, it indicates that the AUD/SBD is fluctuated around 9.94×10^{-1}, which might imply that the SBD seems to be stable around this current mean value. The variation is all positive in this model. The amplitude of this cycle is about 150 times that from the additive method, so clearly the multiplicative factor here is 150. The average amplitude for the multiplicative model from mean is around 6.00×10^{-3}.

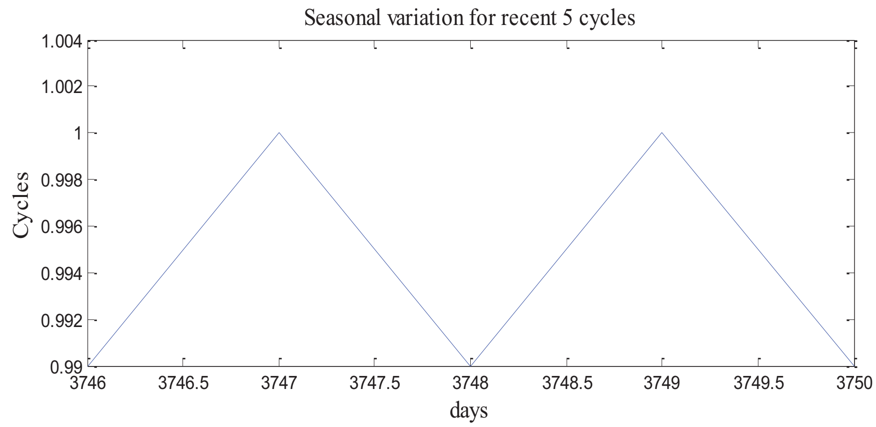


Figure 4.12: Seasonal variation for HW multiplicative for recent 5 cycles

4.5.2 Forecasting HW multiplicative seasonal using the testing sample

We use the training weights from Table 4.7 to get the results in Table 4.8 that will be used for forecasting using the HW multiplicative method. Figures 4.13 and 4.14 shows the actual vs forecasted and the residuals for forecasting AUD/SBD exchange rate for HW multiplicative seasonal.

Table 4.8: Shows result of testing HW multiplicative seasonal

Sample: 1 400
Included observations: 400
Method: Holt-Winters Multiplicative Seasonal
Original Series: AUD
Forecasted Series: AUDMULTIPLY

Parameters:	Alpha		**0.70**
	Beta		**0.00**
	Gamma		**0.00**
Sum of Squared Residuals			3.47E-04
Root Mean Squared Error			9.31E-04

End of Period Levels:	Mean		0.15
	Trend		4.15E-05
	Seasonals:	396	1.00
		397	1.00
		398	1.00
		399	0.99
		400	1.00

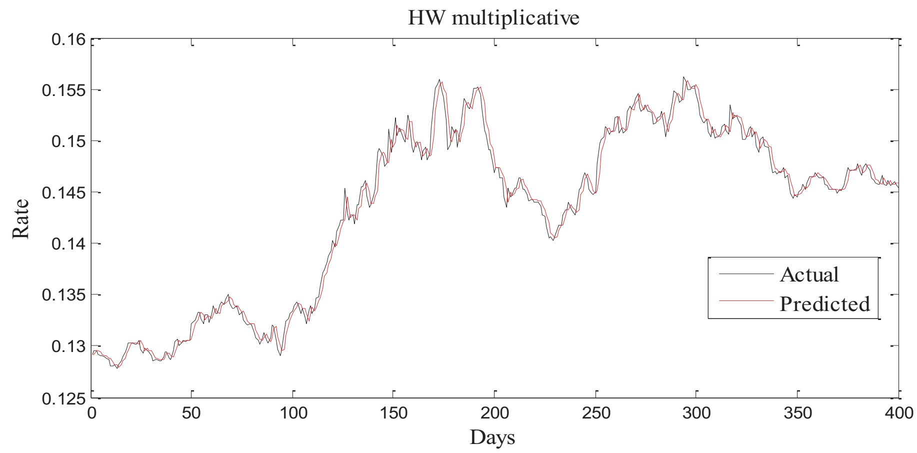


Figure 4.13: Performance of HW multiplicative for AUD/SB using the testing sample.

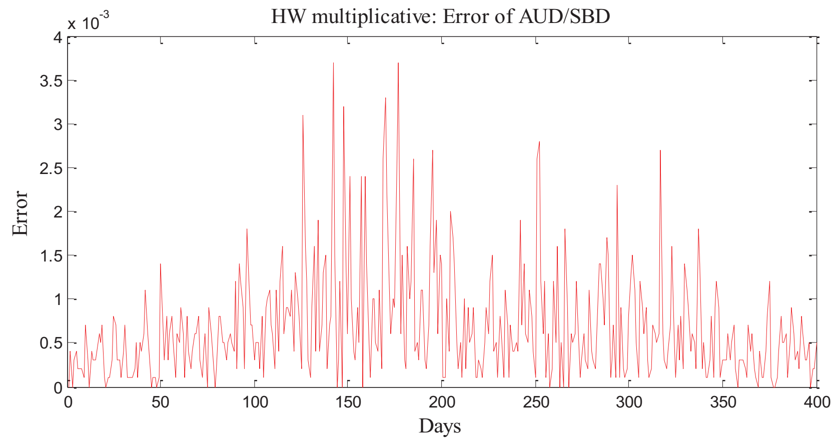


Figure 4.14: Residual for HW multiplicative for testing AUD/SBD.

4.6 Conclusion

This chapter gives the results of forecasting SBD against AUD on various time series models using the weights obtained from the training set. The results indicates that Holt-Winter additive model gives better values of the performance metrics over Holt-Winter multiplicative, double exponential smoothing with trend and single exponential smoothing.

Chapter 5:
Forecasting exchange rates using artificial neural network

5.1 Introduction

In this section, we will discuss the results on forecasting Solomon dollar exchange rates using the proposed ANN model discussed in Section 2.4. The results on the training sample and the testing sample are discussed in Sections 5.2 and 5.3, respectively.

5.2 Results of ANN models for the training sample

Results of performing the residuals analysis for the MLR model presented in Chapter 3, Section 3.6 show that the residuals in forecasting Solomon dollar exchanges against AUD, GBP, EURO and JPY are not normally distributed. It may raise concerns about reliable and consistent forecasting using time series models as the methods depend partly on the properties. Thus it may be worth exploring a forecasting model that can predict the Solomon exchange rates with more reliability and accuracy. In this section, we propose a back propagation artificial neural network model. For the purpose of illustrations, the results for AUD exchange rates are reported in this chapter. The results of the other currencies are presented in Chapter 7 and are also in the appendices 2–4.

The network contains two types of arcs:

1. an arc that connects each input node or neuron to each hidden node,

2. an arc that connects each hidden node to the output node.

The nodes of the input layer are the lags of the exchange rate of the AUD/SBD. The number of nodes in both the input and hidden layers depends on the performance of forecasting the AUD/SBD exchange rates. The results from various error measures presented in Table 5.1 for different numbers of nodes in the input and hidden layers nodes reveal that, ANN (3, 4, 1), the ANN model with three nodes in the input layer and four nodes in the hidden layer, performs better in forecasting the AUD/SBD exchange rates. It has also been seen that ANN (3, 4, 1) performs better for forecasting SBD against the other three currencies (see the results presented in Appendix 5).

Table 5.1: ANN result using different lags and hidden layers for training AUD/SBD

Model	RMSE ($\times 10^{-4}$)	MAE ($\times 10^{-4}$)	MAPE ($\times 10^{-3}$)	Bias ($\times 10^{-4}$)	TS	R^2 ($\times 10^{-4}$)
ANN(2,3,1)	32.77	14.92	670.12	3.42	0.23	9984.52
ANN(2,4,1)	32.75	14.93	672.07	4.80	0.32	9984.53
ANN(3,3,1)	33.29	15.46	694.60	-284.80	-18.41	9984.02
ANN(3 ,4, 1)	**32.05**	**14.68**	**660.45**	56.69	3.90	**9985.19**
ANN(3,5,1)	32.14	14.77	664.68	-7.65	-0.52	9985.11
ANN(4,3,1)	32.61	14.99	674.27	-67.66	-4.51	9984.66
ANN(6,3,1)	33.20	15.62	702.05	-17.08	-1.09	9984.10

From Table 5.1, it can be observed that ANN (3, 4, 1) is the preferred model as it has the lowest RMSE, MAE, MAPE, the highest R^2 and the fourth lowest bias with a reasonably smaller value of TS, which is closer to zero. The second preferred model is ANN (3, 5, 1) with the second smallest RMSE, MAE, the third largest MAPE and the second largest R^2 and with decent value for bias. The value for TS for the second model is higher and negative; this may be due to slight over fitting. The least performing model is ANN (3, 3, 1) with the highest value of RMSE and the lowest value of R^2. ANN (2, 3, 1) is interesting to consider, because it has the lowest value of TS and bias, the second smallest value for MAPE and the third smallest value for MAE. This may due to the lesser number of neurons involved in its architectural structure.

We do not analyse beyond models ANN (2, 4, 1), ANN (3, 5, 1) and ANN (5, 1, 1) because these models do not perform better than the multiple linear regressive model with 6 lags (the ANN competing rival). If the number of neurons is kept at 2 in the input layer and we increase the number of neurons in the hidden layers beyond 4 neurons there is no further improvement in fitting observed. Similarly, there is no improvement if the number of neurons in the input layer is kept at 3 and we increase the number of neurons in the hidden layer over 5. Also note that lag 5 of AUD/SBD does not give any better results. Even if we keep 5 neurons in this input layer and try various experiments by adding different numbers of neurons in the hidden layer, still, the outcome is no more satisfactory.

In addition, at lag 4, adding more than 3 neurons in the hidden layer does not produce any improvements beyond the ANN (4, 3, 1) model. Thus, we do not experiment further from three neurons in the hidden layer for lag 4.

Moreover, we do not proceed further beyond ANN (6, 3, 1). This is because adding more than 6 lags of AUD/SBD exchange rates in the input layer and more than 5 neurons in the hidden layer does not give further improvement as compared to the proposed ANN (3, 4, 1) model. From this point on, it appears that the model cannot handle a huge quantity of data beyond 6 lags of AUD/ SBD exchange rates in the input layer and beyond 5 neurons in the hidden layer. This situation is well discussed in the literature (Kamruzzaman & Sarker, 2004) for cases where adding more hidden layers and increasing the number of lags did not improve the performance of ANN. Kamruzzaman and Sarker (2004) point out that increasing the hidden units adds additional parameters, introduces redundancy and deteriorates the performance.

The performance analysis of ANN models was also carried out with various transformation functions such as tangent hyperbolic, cosine, sine, sigmoid and logistic sigmoid, as discussed in Section 2.4.4. It was found that the basic tangent hyperbolic gives the best results and there was no improvement observed for other transformation functions. In addition we put weights on the sigmoid and logistic sigmoid function but still there is no further improvement noted on fitting as well. We, therefore, stick to the basic tangent hyperbolic as our transformation function.

The computational procedure for the proposed ANN model is described below. Figure 5.1 shows the structure of the proposed ANN model with three input nodes: lag 1, lag 2 and lag 3 of AUD/SBD exchange rate; four hidden nodes: H1, H2, H3 and H4; and one output node.

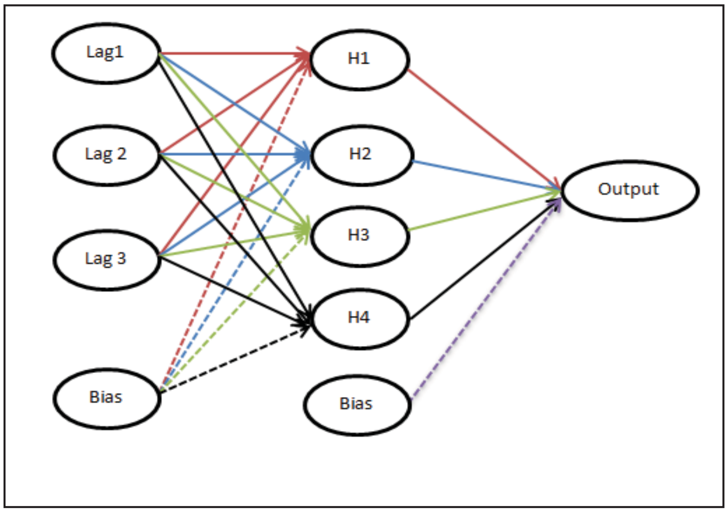


Figure 5.1: Architecture for the proposed ANN (3, 4, 1) model.

Each arc in the network has a weight that governs how much influence the connection in the network has on the forecasting. For example, W_{ij} are the weights that govern the connection between the ith $(i=1,2,3)$ input node and jth $(j=1,2,...,4)$ hidden node, while W_{io} are the weights that govern the connection between jth $(j=1,2,...,4)$ hidden node and the output node o. Each hidden node and output node also has an associated constant or bias term that helps fudge the forecasts to make them more accurate.

The ANN requires variables to be standardized so that they range in value between - 1 and + 1. Each node also has an input and output value. For each input node, the input and output equal the standardized (Z) input value, which is calculated as follows:

$$Z=-1+[2(y_t-y_{\min})/(y_{\max}-y_{\min})];\ t=1,2,...,n \qquad \text{… (5.1)}$$

For each hidden node, the input is the weighted sum of the outputs from all input nodes plus the bias term for the hidden node. The four inputs in hidden node H1, H2, H3 and H4 (refer to Figure 5.1) are:

$$H1(input) = \sum_{i=1}^{3} W_{i1} Z_i + B(H1)$$

$$H2(input) = \sum_{i=1}^{3} W_{i2} Z_i + B(H2)$$

$$H3(input) = \sum_{i=1}^{3} W_{i3} Z_i + B(H3)$$

$$H4(input) = \sum_{i=1}^{3} W_{i4} Z_i + B(H4)$$

where, $Z_i (i = 1, 2, 3)$ are the standardized values of AUD/SBD exchange rate with lag 1, lag 2 and lag 3 respectively, and $B(H1),..., B(H4)$ are the corresponding bias term for each of the four hidden nodes.

The transformation function used in this network model is the tangent hyperbolic "*tanh*" function because as given in (2.23) in Chapter 2 it gives better performance and predictability than equations (2.20)-(2.22) in Chapter 2. For this transformation function in (2.23) in Chapter 2**,** the output is fairly insensitive to the input when the input is either very large or very small. In other words, when a threshold of positive or negative information is reached, going beyond that threshold has little effect on the hidden node's output that is passed on to the output node. Figure 5.2 shows the tangent hyperbolic function that is used to map the exchange rate of AUD/SBD from the input layer to the output layer.

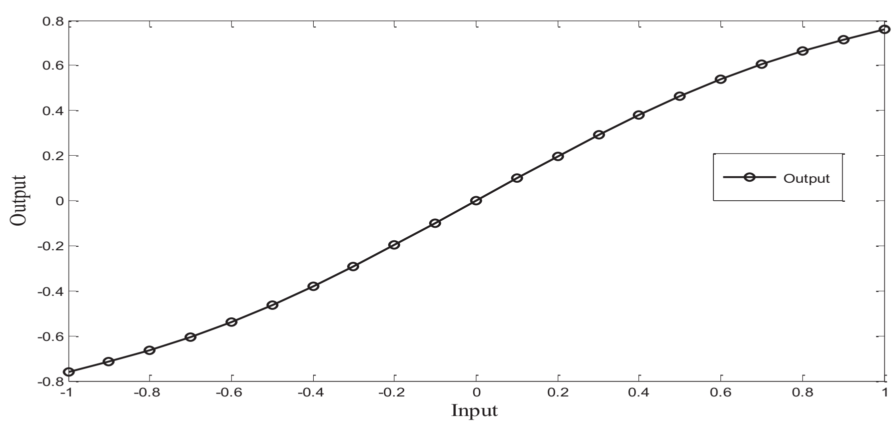


Figure 5.2: Tangent hyperbolic transfer function

The input and output from the output node are given by the weighted sum of the outputs from the hidden nodes plus the output node's bias term. Thus, the input or output to our output node (o) is given by:

$$W_{1o} \times H1(output) + W_{2o} \times H2(output) + W_{3o} \times H3(output) + W_{4o} \times H4(output) + B(output)$$

where $B(output)$ is the bias term in the output node. To make the forecast for the exchange rate for AUD/SBD, we simply take the output from the output node and "unstandardize'' the output using equation (5.1), that is;

$$\hat{y} = smallest\ value + [(y_{\max} - y_{\min})(Z+1)]/2 \qquad \dots (5.2)$$

The computational method developed for solving the proposed ANN model is the Generalized Reduced Gradient algorithm, which is implemented in Excel Evolutionary Solver. The optimum weights and biases that yield the best forecasts are obtained by minimizing SSE given in equation (2.19) in Chapter 2. The results are presented in the last row of Table 7.1 (I) in Chapter 7. Figure 5.3 shows the actual, predicted and residuals for AUD/SBD exchange rates respectively for the training sample

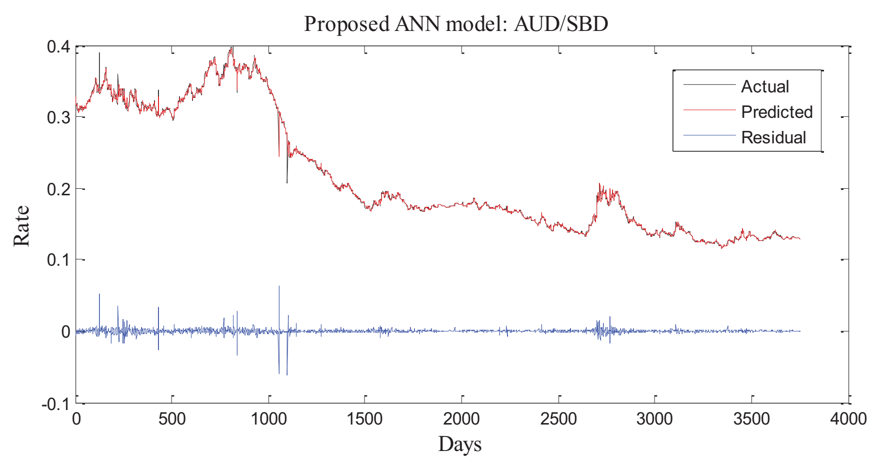


Figure 5.3: Actual, predicted and residuals for the proposed model ANN (3, 4, 1) for training sample.

5.3. Forecasting AUD/SBD using the testing sample

We have used the weights obtained in Section 5.2 from our proposed model given in Table 5.1 to forecast our results given in Table 7.1(a) in Chapter 7. Figure 5.4 show the actual vs forecasted and Figure 5.5 shows the error of the proposed model for AUD/ SBD exchange rate data.

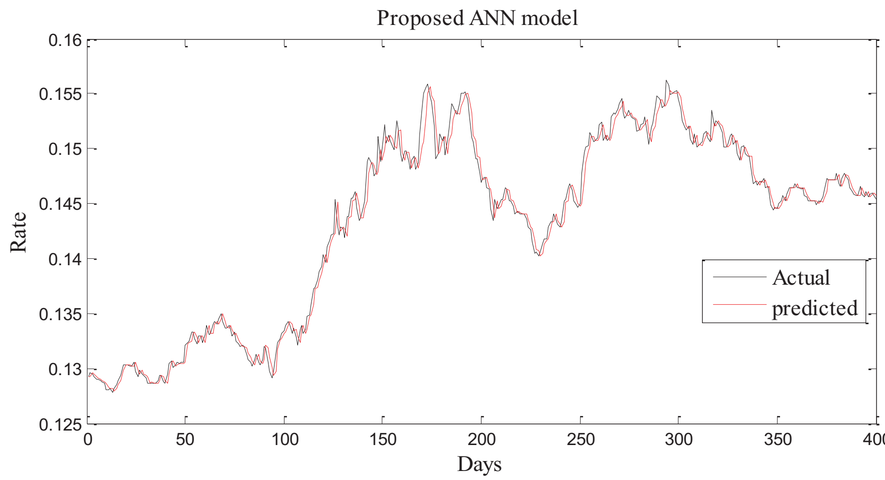


Figure 5.4: Performance of the proposed model ANN (3, 4, 1) using the testing sample.

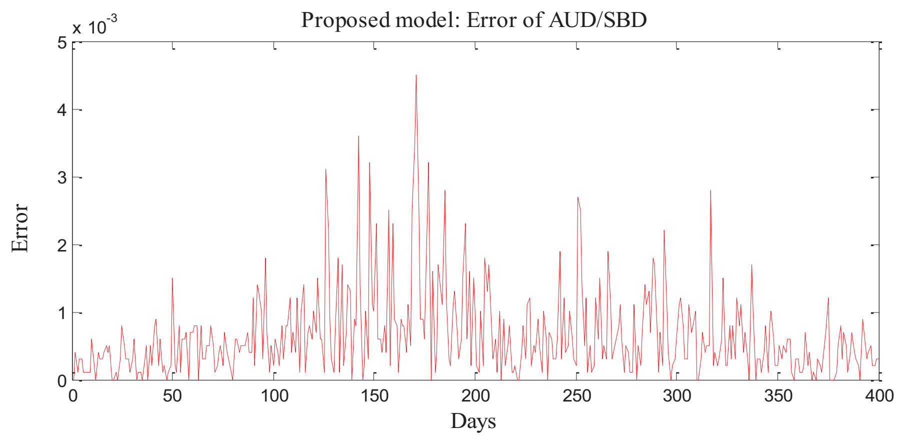


Figure 5.5: Error for testing the proposed model ANN (3, 4, 1).

5.4 Conclusion

This chapter uses the proposed ANN method to forecast SBD against AUD using the weights obtained from the training set. The result indicates that, ANN (3, 4, 1) is the best architecture that gives better values of the performance metrics. The transfer function used in this network is the tangent hyperbolic function because it gives better performance and predictability over other functions that we have experimented.

Chapter 6:
Purchasing power parity result

6.1 Introduction

This chapter presents the results obtained from Eviews for unrestricted and absolute versions of the PPP for Solomon Islands against USA and UK consumer price index (CPI). Their results are given in Sections 6.2 and 6.3 respectively.

6.2 Unrestricted version for Solomon Islands against USA and UK CPI

6.2.1 Solomon Islands against USA CPI

Table 6.1 shows the result of ADF unit root tests for the Solomon Islands exchange rate against the USA CPI. Price differential is not stationary at level but is stationary at first difference and is highly significant at the 1% level. Also other variables are not stationary at level but stationary at first difference and are highly significant. Table 6.2 shows results of unrestricted Johansen co-integration tests for Solomon Islands, USA nominal exchange rate and CPIs.

Normalized co-integrating coefficient equation (standard error in brackets)

$$\underset{}{LNESOUS} = \underset{(21.40)}{65.39} + \underset{(1.92)}{6.95} * LNSOCPI - \underset{(6.56)}{20.81} * LNUSCPI \qquad \ldots (6.1)$$

Table 6.2 shows that there is one co-integrating equation that is significant at the 5% level of confidence. There exists one co-integrating equation between Solomon Islands and USA CPI. Both maximum-Eigen and Trace statistics indicate one co-integration equation and are significant at MacKinnon probability of less than 1%. Equation (6.1) shows the negative sign correctly. All variables are in logarithm and may interpret the coefficient in terms of elasticity. The depreciation of the local dollar will cause an increase in the domestic price and a decrease in the foreign prices. In numerical terms, a 1% increase in the nominal exchange rate is associated with a decrease of 21% of USA prices and an increase of 7% of Solomon Islands prices. This follows the PPP theory. In

Table 6.3 we normalized co-integrating vectors for the Solomon Islands price. This indicates that an increase in local price is caused by the decrease in the value of the local dollar and a decrease in the USA price. This follows PPP theory. The co-integrating vector in Table 6.3 is employed to derive the VECM–model for LNESOUS.

In VECM coefficients in Table 6.4, when DLNESOUS is taken as the dependent variable, VECM has the correct negative sign and is statistically significant at the 1% level. This means that the change in nominal exchange rate is caused by the trend in change in prices of US and Solomon Islands prices. It is very interesting to note that, it will take at least 6% of disequilibrium to be corrected and will take a very long time to be corrected. However, if DLNSOCPI is taken as the dependent variable, VECM has the correct sign and is significant. This implies that the Solomon Islands price is influenced by USA prices and the nominal exchange rate. In Table 6.4 when DLNUSCPI is taken as dependent variable VECM is negative and significant at the 1% level. This implies that the USA price is caused by the nominal exchange rate and Solomon Islands prices. This is contrary to the fact that US price is not caused by Solomon Islands price.

Table 6.1: ADF unit root test for Solomon Islands against USA.

Variables	Level	1st difference	Decision	Integration
Nominal exchange rate LN(SOUS)	-1.97 [0.30]	-19.68*** [<0.01]	Not stationary at level but stationary at 1st difference	I(1)
Domestic price, P^{SOL} LN(SOCPI)	-1.81 [0.38]	-14.32*** [<0.01]	Not stationary at level but stationary at 1st difference	I(1)
Foreign price, P^{US} LN(USCPI)	-0.92 [0.78]	-10.54*** [<0.01]	Not stationary at level but stationary at 1st difference	I(1)
Price differential (P^{SOL} –P^{US}) DLN(SOUSCPI)	-1.59 [0.49]	-14.92*** [<0.01]	Not stationary at level but stationary at 1st difference	I(1)

Null hypothesis: unit root (assume common root process). Asterisks (***) and (**) show significant at the 1% and 5% levels respectively. The p-values are estimated from one-sided standardized normal distribution. Mackinnon probability (1999) is in parentheses [ ].

Table 6.2: Johansen multivariate co-integration test result for Solomon Islands and USA CPI.

Null hypothesis	Alternative hypothesis	Eigen-values	Maximum Eigen statistics $\lambda_{\max}$	0.05 Critical values	Probability
$r = 0$	$r \geq 1$	0.17	46.18***	22.30	<0.01
$r \leq 1$	$r \geq 2$	0.05	12.46	15.89	0.16
$r \leq 2$	$r \geq 3$	0.01	2.85	9.17	0.61
			Trace statistics λ_{trace}		
$r = 0$	$r = 1$	0.17	61.49***	35.19	<0.01
$r \leq 1$	$r = 2$	0.05	15.30	20.26	0.21
$r \leq 2$	$r = 3$	0.01	2.85	9.17	0.61

Asterisk (**) and (**) rejection of null hypothesis at 1% and 5 % level of significance respectively. Probabilities are calculated using MacKinnon-Haug-Michelis (1999) *p*-values.
No deterministic trend (restricted constant).Variables included, LNSOCPI, LNUSCPI and LNESOUS.

Table 6.3: Normalized co-integrating vectors for Solomon Islands and USA prices.

Co-integrating equation	Co-integrating vectors 1
LNSOCPI(-1)	1.00
LNUSCPI(-1)	-2.10
	(0.14)
	[-21.63]
LNESOUS(-1)	-0.16
	(0.06)
	[-2.58]
C	9.31
	(0.52)
	[18.04]

Standard error is in brackets ( ) and t-statistic is in parentheses [ ].

Table 6.4: Vector error correcting estimate or model (VECM) for variables LNESOUS, LNSOCPI and LNUSCPI for Solomon Islands and US prices.

Error Correction	D(LNSOCPI)	D(LNUSCPI)	D(LNESOUS)
D(LNSOCPI (-1))	0.09	0.04	0.18
	(0.06)	(0.02)	(0.15)
	[1.29]	[2.00]	[1.22]
D(LNSOCPI(-2))	-0.02	0.06	0.01
	(0.06)	(0.02)	(0.15)
	[-0.26]	[3.20]	[0.07]
D(LNUSCPI(-1))	0.32	0.55	-0.82
	(0.22)	(0.06)	(0.54)
	[1.43]	[8.74]	[-1.52]
D(LNUSCPI(-2))	-0.53	-0.29	-0.47
	(0.22)	(0.06)	(0.55)
	[-2.31]	[-4.56]	[-0.85]
D(LNESOUS(-1))	-0.01	<-0.01	-0.28
	(0.03)	(0.01)	(0.07)
	[-0.45]	[-0.29]	[-4.34]
D(LNESOUS(-2))	-0.04	-0.01	-0.15
	(0.03)	(0.01)	(0.06)
	[-1.61]	[-1.48]	[-2.26]
VECM	-0.08	-0.01	-0.06
coefficients	(0.01)	(<0.01)	(0.02)
	[-8.20]***	[-2.89]***	[-2.81]***

Asterisk (**) and (***) indicate significance at 5% and 1% respectively. Standard error is in brackets ( ) and t-statistic is in parentheses [ ].

6.2.2 Solomon Islands against UK CPI

Table 6.5 shows results of the ADF unit root test for the Solomon Islands exchange rate against the UK CPI. Price differential is not stationary at level but stationary at first difference and is highly significant at the 1% level. It is interesting to note that CPI for UK is not stationary for both level and first difference format but stationary at their differences, while other variables are not stationary at level but are stationary at first difference and are highly significant.

Normalized co-integrating coefficients equation (standard error in bracket):

$$LNESOUK = 25.71 + 2.30 * LNSOCPI - 7.61 * LNUKCPI \quad \ldots (6.2)$$

(2.15) (0.16) (0.54)

Table 6.6 indicates two co-integrating equations that are significant at the 5% level of confidence. Interestingly, there exist two co-integrating equations between Solomon Islands and UK prices. Both maximum-Eigen and trace statistic indicate two co-integration equations and are significant at Mackinnon probabilities of 1% and 5% respectively. We will consider only one co-integrating equation since the value of maximum-Eigen statistic is not significant at the 1% level of confidence for the two co-integrating equations. Equation (6.2) shows the negative sign correctly. All variables are in logarithm and may interpret the coefficient in terms of elasticity. The depreciation of the local dollar will cause an increase in the domestic price and a decrease in the foreign prices. In numerical terms, a 1% increase in the nominal exchange rate is associated with a decrease of 7.6% of UK prices and an increase of 2.3% of Solomon Islands prices. This again follows the PPP theory. In Table 6.7 we normalized co-integrating vectors for the Solomon Islands price. The signs are opposite sign and indicate that an increase in local price is caused by the decrease in the value of the local dollar and a decrease in the UK price. This follows PPP theory. The co-integrating vector in Table 6.7 is employed to derive the VECM–model for LNESOUK.

In VECM coefficients in Table 6.8, when DLNESOUK is taken as dependent variable, VECM has the correct negative sign and is statistically significant. This means that the change in nominal exchange rate is caused by the trend in changes in UK price and Solomon Islands price. It will take at least 2% of disequilibrium to be corrected and this will take a long time to be corrected. However, when DLNSOCPI is taken as dependent variable, VECM has the correct sign and is significant. This implies that Solomon Islands price is influenced by UK prices and the nominal exchange rate. In Table 6.8, when DLNUKCPI is taken as dependent variable and it is again interesting to note that VECM is negative and significant at 1% level. This means that the UK price is caused by the nominal exchange rate and the local price. This is contrary to the fact that the UK price is not caused by Solomon Islands.

Table 6.5: ADF unit root test for Solomon Islands against UK.

Variables	Level	1^{st} difference	Decision	Integration
Nominal exchange rate LN(SOUK)	-1.72 [0.42]	-16.45^{***} [<0.01]	Not stationary at level but stationary at 1^{st} difference	I(1)
Domestic price, P^{SOL} LN(SOCPI)	-1.81 [0.38]	-14.32^{***} [<0.01]	Not stationary at level but stationary at 1^{st} difference	I(1)
Foreign price, P^{UK} LN(UKCPI)	1.52 [1.00]	-2.33 [0.16]	Not stationary at level and not stationary at 1^{st} difference	I (??)
Price differential (P^{SOL}-P^{UK}) DLN(SOUKCPI)	-2.04 [0.27]	-15.95 [<0.01]	Not stationary at level but stationary at 1^{st} difference	I(1)

Null hypothesis: unit root (assume common root process). Asterisk (***) and (**) indicate significant at 1% and 5% level respectively. The p-values are estimated from one-sided standardized normal distribution. Mackinnon probability (1999) is in parentheses [ ].

Table 6.6: Johansen multivariate co-integration test result for Solomon Islands and UK, nominal exchange rate and CPIs.

Null hypothesis	Alternative hypothesis	Eigen-values	Maximum Eigen statistics $\lambda_{\max}$	0.05 Critical value	Probability
$r=0$	$r\geq 1$	0.20	55.02^{***}	22.30	<0.01
$r\leq 1$	$r\geq 2$	0.07	17.82^{**}	15.89	0.03
$r\leq 2$	$r\geq 3$	0.03	8.53	9.17	0.07
			Trace statistics λ_{trace}		
$r=0$	$r=1$	0.20	81.37^{***}	35.19	< 0.01
$r=1$	$r=2$	0.07	26.36^{***}	20.26	0.01
$r=2$	$r=3$	0.03	8.53	9.17	0.07

Asterisk (**) and (***) rejection of null hypothesis by 5% and 1% respectively. Probabilities are calculated using MacKinnon-Haug-Michelis (1999) p-values. No deterministic trend (restricted constant).Variables included, LNSOCPI, LNUKCPI and LNESOUK.

Table 6.7: Normalized co-integrating vectors for Solomon Islands and UK prices.

Co-integrating equation	Co-integrating vectors 1
LNSOCPI(-1)	1.00
LNUKCPI(-1)	-2.75
	(0.31)
	[-9.03]
LNESOUK(-1)	-0.46
	(0.10)
	[-4.85]
C	9.00
	(1.21)
	[7.46]

Standard error is in brackets ( ) and t-statistic is in parentheses [ ].

Table 6.8: VECM for variables LNESOUK, LNSOCPI and LNUKCPI for Solomon Islands and UK prices.

Error Correction	D(LNSOCPI)	D(LNUKCPI)	D(LNESOUK)
D(LNSOCPI (-1))	0.10	0.07	0.11
	(0.06)	(0.02)	(0.19)
	[1.50]	[3.33]	[0.58]
D(LNSOCPI (-2))	-0.06	0.02	-0.47
	(0.06)	(0.02)	(0.20)
	[-0.95]	[0.90]	[-2.43]
D(LNUKCPI(-1))	0.38	-0.04	0.62
	(0.19)	(0.07)	(0.58)
	[1.96]	[-0.65]	[1.07]
D(LNUKCPI(-2))	-0.08	-0.09	-0.81
	(0.19)	(0.06)	(0.57)
	[-0.41]	[-1.33]	[-1.42]
D(LNESOUK(-1))	<-0.01	-0.01	-0.05
	(0.02)	(0.01)	(0.06)
	[-0.14]	[-1.45]	[-0.71]
D(LNESOUK(-2))	-0.02	< 0.01	-0.03
	(0.02)	(0.01)	(0.06)
	[-1.13]	[-0.03]	[-0.49]
VECM coefficients	-0.02	-0.01	-0.03
	(<0.01)	(<0.01)	(0.01)
	[-6.60]***	[-3.83]**	[-2.28]***

Asterisk (**) and (***) indicates significance at 5% and 1% respectively Standard error is in brackets () and t-statistic is in parentheses [ ].

6.3. Testing the absolute version – the Symmetry and Proportionality – of the PPP

6.3.1 Solomon Islands against the USA CPI restriction

Tables 6.9 and 6.10 show the results of the Johansen co-integration test for the Solomon Islands and USA nominal exchange rate and CPIs. Table 6.9 shows that there is one co-integrating equation that is significant at the 5% level of confidence. One co-integrating equation exists between Solomon Islands and USA CPI. Both maximum-Eigen and trace statistics indicate one co-integration equation and are significant at MacKinnon probability of less than 1%.

Table 6.10 shows results when applying the likelihood ratio (LR) test to examine the joint symmetry and proportionality restriction. Here we impose the coefficient of LNSOCPI (-1) = 1, LNUSCPI (-1) = -1 and LNESOUS (-1) = -1 as the restriction condition, with no deterministic trend (restricted constant).The Chi-square statistic results using the LR test from Table 6.10 show the null hypothesis the symmetry and proportionality hypothesis is valid for the Solomon Islands country is rejected for the Solomon–USA exchange rate. This implies that the strong version of PPP for Solomon Islands against USA is not valid at the 10 % significance level. This is consistent with Jayaraman and Choong's ealier finding (Jayaraman & Choong, 2014).

Table 6.9: Johansen multivariate unrestricted co-integration test result for Solomon Islands and USA CPI.

Null hypothesis	Alternative hypothesis	Eigen-values	Maximum Eigen statistics $\lambda_{\max}$	0.05 Critical Value	Probability
$r=0$	$r \geq 1$	0.23	65.72***	22.30	<0.01
$r \leq 1$	$r \geq 2$	0.04	11.31	15.89	0.23
$r \leq 2$	$r \geq 3$	0.01	2.94	9.17	0.59
			Trace statistics λ_{trace}		
$r=0$	$r=1$	0.23	79.97***	35.19	<0.01
$r \leq 1$	$r=2$	0.04	14.25	20.26	0.27
$r \leq 2$	$r=3$	0.01	2.94	19.17	0.59

Asterisk (***) and (**) rejection of the null hypothesis at the 1% and 5 % levels of significance respectively. *Probabilities are calculated using MacKinnon-Haug-Michelis (1999) p- values. No deterministic trend (restricted constant). Variables included LNSOCPI, LNUSCPI and LNESOUS.

Table 6.10: Johansen multivariate restricted co-integration test for Solomon Islands and United States: LR-test.

Hypothesized No. of CE(s)	Restricted Log-Likelihood	LR statistic	Degrees of freedom	Probability
$r=1$	2445.17	12.99	2	<0.01
$r=2$	2454.82	*	*	*

*convergences not achieved

6.3.2 Solomon Islands against the UK CPI restriction.

Tables 6.11 and 6.12 show results of the Johansen co-integration test for Solomon Islands and UK nominal exchange rate and CPIs. Table 6.11 shows that there is one co-integrating equation that is significant at the 1% level of confidence. Maximum-Eigen statistics indicate one co-integrating equation at 1% significance while trace statistics indicate two co-integration equations and are significant at Mackinnon probabilities of 1% and 5% respectively. We follow the maximum-Eigen statistic and accept one co-integrating equation between Solomon Islands and UK prices.

Table 6.12 shows results when applying the LR test to examine the joint symmetry and proportionality restriction. Here we impose the coefficient of LNSOCPI (-1) = 1, LNUKCPI (-1) = -1 and LNESOUK (-1) = -1 as the restriction condition. The Chi-square (or LR) statistics results in Table 6.12 show that the null hypothesis that the restrictions are valid is not rejected at the conventional levels of even up to 10%. This implies that for the Solomon Islands–UK exchange rate symmetry and proportionality hypothesis of the PPP is valid. The restrictions for the absolute version of the PPP theory are not supported by the Chi-square statistics in Table 6.12. This implies the exchange rate of Solomon Islands with respect to the UK is not very appropriate for the application of the PPP theory.

Next we are testing the symmetry and proportionality for the Solomon Islands–UK pound exchange rate for error correction. To see the VECM of the restricted version we set the coefficient of LNSOCPI, LNOUKCPI and LNESOUK to (1, -1, -1) respectively as shown in Table 6.13, with no deterministic trend (restricted constant).The result is presented in Table 6.14.

In VECM coefficients in Table 6.14, when DLNESOUS is taken as dependent variable, VECM have the correct negative sign and statistical significance at the 5% level. This means that the change in nominal exchange rate is caused by the trend in change in prices between UK and Solomon Islands, which confirms the PPP theory. It will take less than 1 % of disequilibrium to be corrected and this will take a very long time. Furthermore, if DLNSOCPI is taken as the dependent variable, VECM has the correct sign and is significant at the 1% level. This implies that there is a causal relationship between Solomon Islands price to the nominal exchange rate and UK prices. In Table 6.14 when DLNUKCPI is taken as the dependent variable that VECM is negative and significant at 1 % level. This implies there is a causal relationship between UK price to nominal exchange rate and Solomon Islands price. This is contrary to the fact that UK price is not caused by Solomon Islands price. Interestingly, the coefficients of all the variables are significant, and are causing each other. However, the UK price might be more influenced by its exchange rates; as the UK pound depreciates in value, the UK inflation increases, corroborating the PPP theory since UK is an open economy.

Table 6.11: Johansen multivariate unrestricted co-integration test result for Solomon Islands and UK, nominal exchange rate and CPIs.

Null hypothesis	Alternative hypothesis	Eigen-values	Maximum Eigen statistics $\lambda_{\max}$	0.05 Critical Value	Probability
$r=0$	$r \geq 1$	0.22	60.42***	22.30	<0.01
$r \leq 1$	$r \geq 2$	0.06	15.59	15.89	0.06
$r \leq 2$	$r \geq 3$	0.02	5.31	9.17	0.25
			Trace statistics λ_{trace}		
$r=0$	$r=1$	0.22	81.32***	35.19	<0.01
$r \leq 1$	$r=2$	0.06	20.90*	20.26	0.04
$r \leq 2$	$r=3$	0.02	5.31	9.17	0.25

Asterisk (**) and (***) rejection of null hypothesis by 5% and 1% respectively. Probabilities are calculated using MacKinnon-Haug-Michelis (1999) *p*-values No deterministic trend (restricted constant).Variables included, LNSOCPI, LNUKCPI and LNESOUK.

Table 6.12: Johansen multivariate restricted co-integration test for Solomon Islands and United Kingdom: LR-test.

Hypothesized No. of CE(s)	Restricted Log-Likelihood	LR statistic	Degrees of freedom	Probability
$r=1$	2327.53	2.91	2	0.23
$r=2$	2337.04	*	*	*

Note: *convergences not achieved.

Table 6.13: Normalized co-integration equation after imposing restriction on the coefficient of LNSOCPI (-1); LNUKCPI (-1) and LNESOUK (-1).

Co-integrating equation	Co-integrating vectors 1
LNSOCPI(-1)	1.00
LNUKCPI(-1)	-1.00
LNESOUK(-1)	-1.00
C	0.94 (0.22) [4.24]

Standard error is in brackets ( ) and t-statistic is in parenthesis [ ]

Table 6.14.: VECM for variables LNSOCPI, LNUKCPI and LNESOUK for Solomon Islands and UK prices.

Error Correction	D(LNSOCPI)	D(LNUKCPI)	D(LNESOUK)
D(LNSOCPI (-1))	0.10	0.07	0.11
	(0.07)	(0.02)	(0.19)
	[1.57]	[3.09]	[0.54]
D(LNSOCPI (-2))	-0.05	0.02	-0.48
	(0.07)	(0.02)	(0.20)
	[-0.82]	[0.67]	[-2.44]
D(LNUKCPI(-1))	0.44	-0.05	0.65
	(0.19)	(0.06)	(0.58)
	[2.25]	[-0.73]	[1.13]
D(LNUKCPI(-2))	-0.03	-0.09	-0.80
	(0.19)	(0.06)	(0.57)
	[-0.14]	[-1.46]	[-1.40]
D(LNESOUK(-1))	<0.01	-0.01	-0.04
	(0.02)	(0.01)	(0.06)
	[0.19]	[-1.31]	[-0.61]
	-0.02	<0.01	-0.03
D(LNESOUK(-2))	(0.02)	(0.01)	(0.06)
	[-0.82]	[0.10]	[-0.40]
VECM coefficients	<-0.01	<-0.01	<-0.01
	(<0.01)	(<0.01)	(<0.01)
	[-5.94]***	[-4.35]***	[-2.27]**

Asterisks (**) and (***) indicate 5% and 1% significant levels respectively. $\chi^2 = 2.91$, p=0.23
Standard error is in brackets ( ) and t-statistic is in parentheses [ ].

6.4 Conclusion

This chapter reveals the Eviews results of the unrestricted and absolute versions of the PPP for Solomon Islands against USA and UK consumer price index (CPI). The results indicate the weak form of PPP is supported for Solomon Islands country against both USA dollar and UK sterling pound. The symmetry and proportionality for strong version of PPP were significant for Solomon Islands against UK only and not against US dollar. Using VECM, the Solomon Islands price and nominal exchange rate are caused by the changes in the USA and the UK prices.

Chapter 7: Discussion

In this chapter we carry out a comparison study to discuss whether the proposed ANN model is an efficient and useful tool for forecasting the SBD exchange rate against its major trading currencies. For the purpose of comparison we select four series of exchange rate data:

1. AUD/SBD: SBD exchange rate against AUD
2. GBP/SBD: SBD exchange rate against GBP
3. JPY/SBD: SBD exchange rate against JPY
4. EURO/SBD: SBD exchange rate against EURO

As discussed in Chapters 3–5 the competitive forecasting models that were being considered for the comparison of their performance with the proposed ANN are:

1. Single smoothing
2. Double smoothing
3. HW additive
4. HW multiplicative
5. Multiple linear regression with 6 lags, MLR(6)
6. Proposed ANN (3, 4, 1)

For the comparison of the models we use the testing sample of size 400 to forecast the Solomon Islands exchange rates against AUD, GBP, Yen and EURO. The various error measures are presented in Tables 7.1 (a-d) and in Figures 7.1(a-d). It reveals that the proposed ANN (3, 4, 1) is the preferred model with lowest RMSE, MAE, MAPE and highest R^2, with low values of Bias and TS. The second competing model is the HW additive with the second lowest error values and the second largest R^2 value. The exponential double smoothing on the other hand performs poorly as revealed by most of the performance measures. The proposed ANN (3, 4, 1) model out–performs its competing models. Although it indicates slight bias, this is not significant enough to influence its error performance.

Table 7.1 (a): Error measures for different models for AUD/SBD time series, n=400.

Model	RMSE $(\times 10^{-4})$	MAE $(\times 10^{-4})$	MAPE $(\times 10^{-3})$	Bias $(\times 10^{-3})$	TS	R^2 $(\times 10^{-4})$
Single	10.49	7.14	495.82	97.50	13.65	9845.71
Double	10.60	7.81	541.32	-18.03	- 2.31	9842.43
HW additive	9.31	6.85	473.49	-3.45	**-0.50**	9878.50
HW multiplicative	9.31	6.85	473.51	-3.48	-0.51	9878.50
MLR(6)	9.37	6.94	1480.17	**0.41**	58.98	9876.79
ANN(3,4,1)	**9.23**	**6.56**	**451.79**	29.40	44.80	**9880.62**

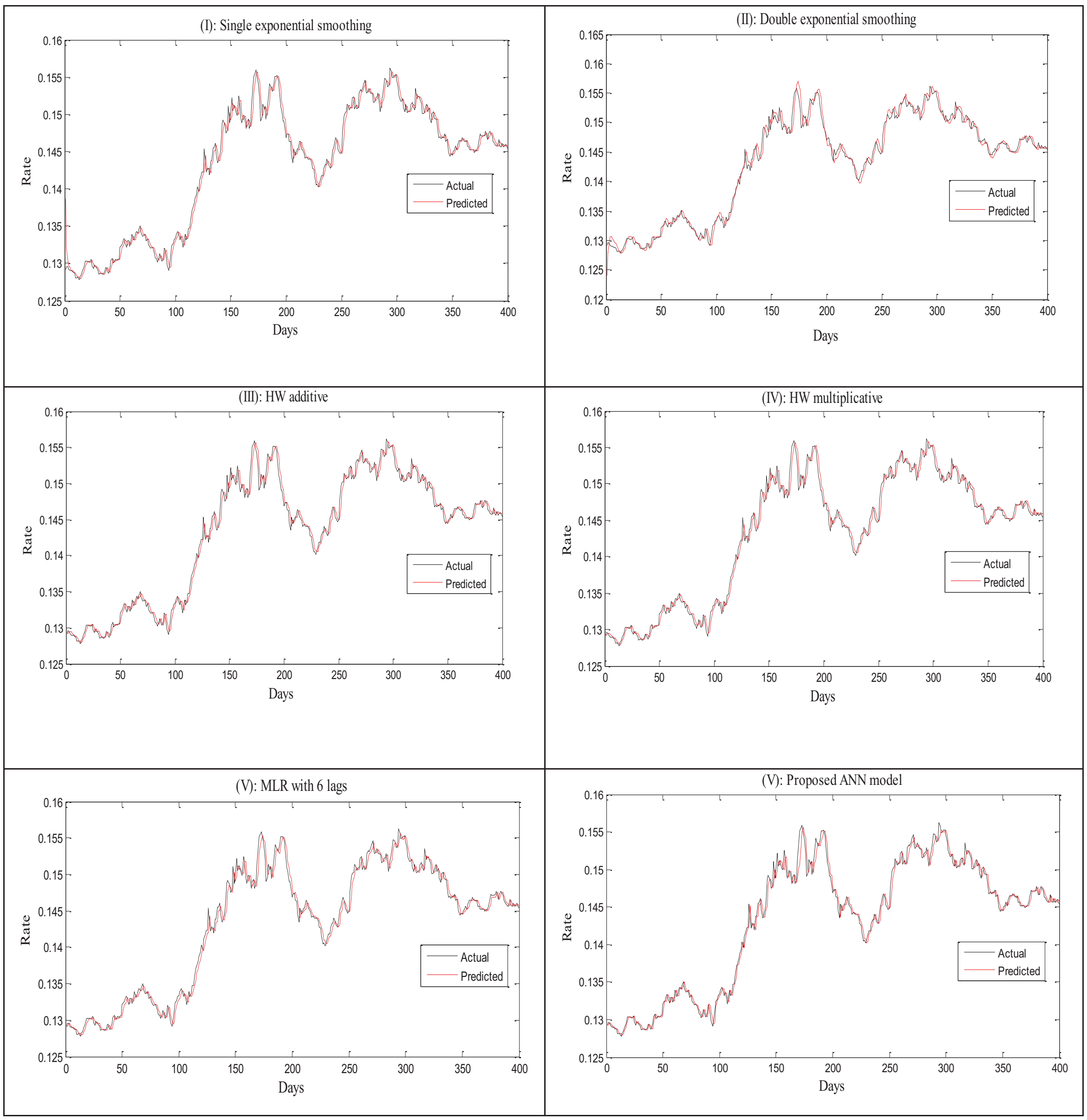


Figure 7.1 (a): Performance of AUD/SBD using testing sample for all the methods.

Table 7.1(b): Error measures for different models for GBP/SBD time series, n=400.

Model	RMSE ($\times 10^{-4}$)	MAE ($\times 10^{-4}$)	MAPE ($\times 10^{-3}$)	Bias ($\times 10^{-3}$)	TS	R^2 ($\times 10^{-4}$)
Single	12.33	5.36	623.00	-0.25	-0.47	8793.68
Double	13.25	6.04	703.96	**-0.20**	- 0.32	8607.26
HW additive	12.33	5.37	624.19	-0.26	-0.50	8792.51
HW multiplicative	12.33	5.36	623.00	-0.25	**-0.47**	8793.68
MLR(7)	12.81	5.87	685.58	-0.96	-1.64	8696.23
ANN(3,4,1)	**11.95**	**5.20**	**603.49**	-4.25	-8.18	**8865.61**

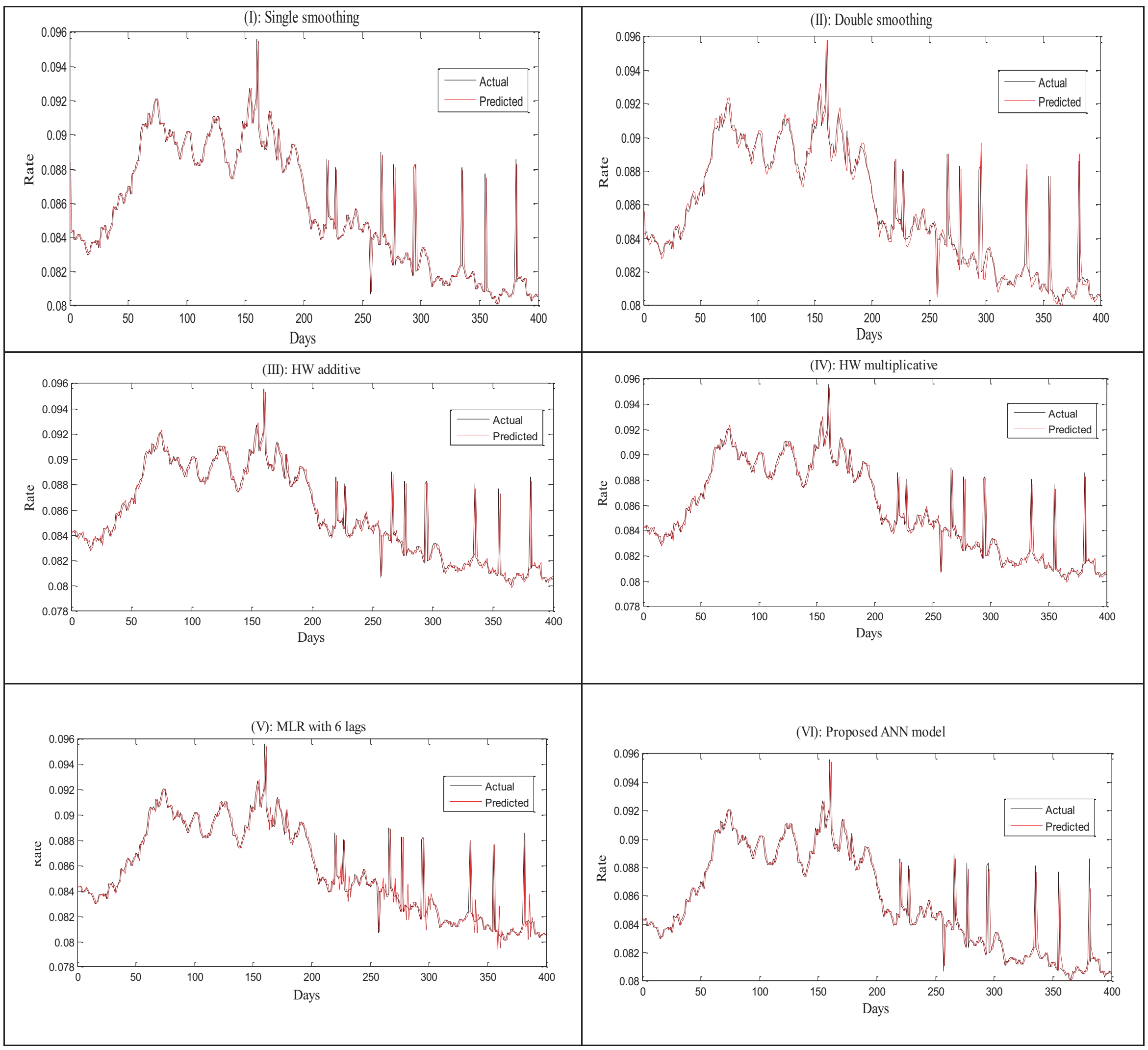


Figure 7.1 (b): Performance of GBP/SBD using testing sample for all the methods.

Table 7.1(c): Error measures for different models for JPY(per 100)/SBD time series, *n*=400.

Model	RMSE ($\times 10^{-4}$)	MAE ($\times 10^{-4}$)	MAPE ($\times 10^{-3}$)	Bias ($\times 10^{-3}$)	TS	R^2 ($\times 10^{-4}$)
Single	12.74	6.36	485.54	9.98	15.69	9726.68
Double	10.13	7.05	532.96	-1.42	- 2.01	9827.18
HW additive	8.53	**5.90**	**442.75**	-6.64	-1.13	9877.38
HW multiplicative	8.53	**5.90**	442.83	-6.77	-1.14	9877.34
MLR(5)	8.74	6.11	459.47	41.42	67.82	9871.00
ANN(3,4,1)	**8.52**	6.00	452.00	**0.68**	**1.13**	**9877.50**

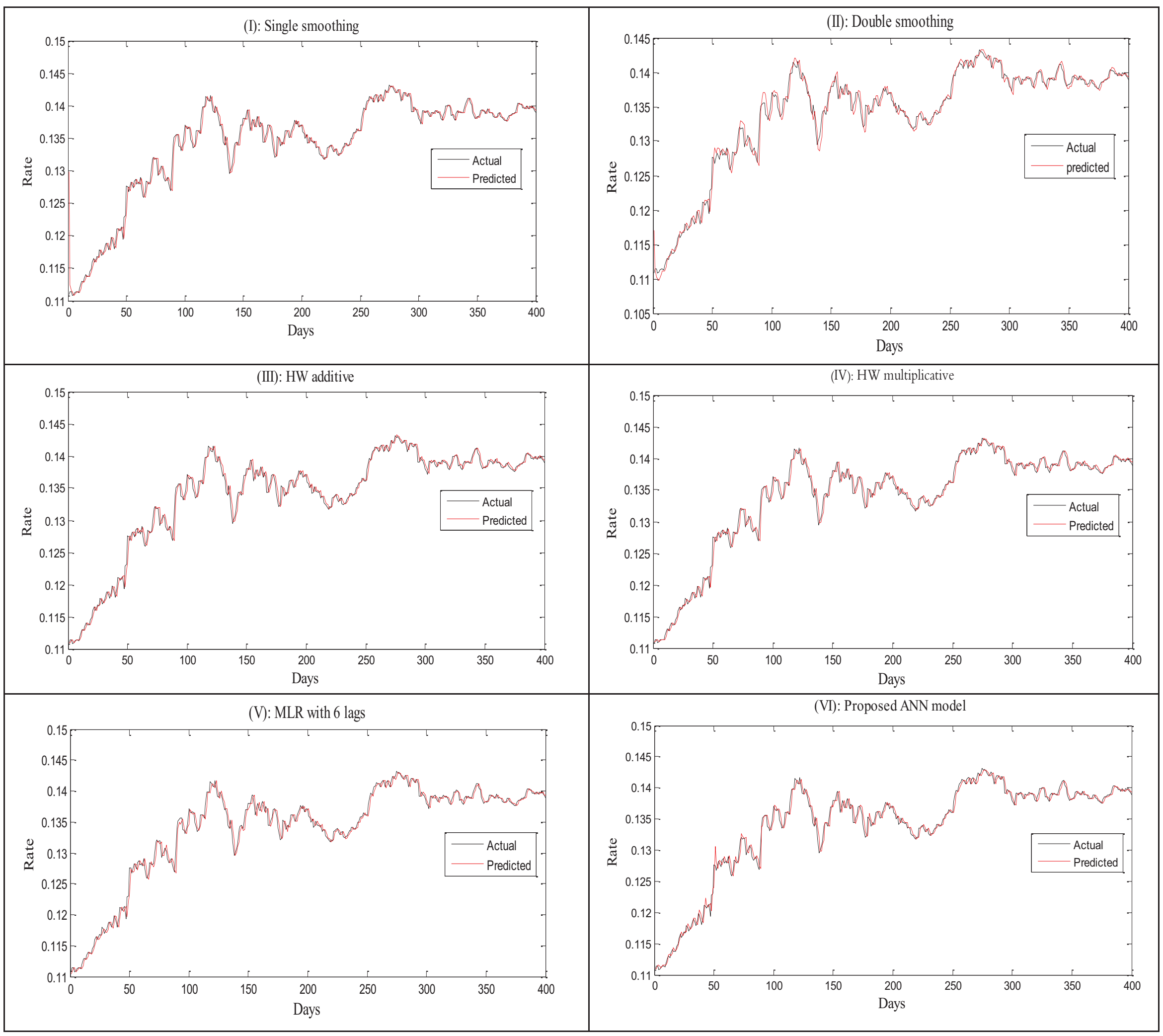


Figure 7.1(c): Performance of JPY(per 100)/SBD using testing sample for all the methods.

Table 7.1(d): Error measures for different models for EURO/SBD time series, n=400.

Model	RMSE $(\times 10^{-4})$	MAE $(\times 10^{-4})$	MAPE $(\times 10^{-3})$	Bias $(\times 10^{-3})$	TS	R^2 $(\times 10^{-4})$
Single	7.26	4.01	394.70	-5.44	-13.56	9249.49
Double	7.63	4.58	451.08	-0.56	- 1.23	9170.68
HW additive	7.20	4.08	401.75	-0.08	-0.19	9261.09
HW multiplicative	7.20	4.09	402.27	-0.08	-0.19	9260.21
MLR(6)	7.39	4.16	410.26	-0.07	**-0.17**	9221.20
ANN(3,4,1)	**6.96**	**3.75**	**369.18**	**-0.02**	-57.95	**9309.42**

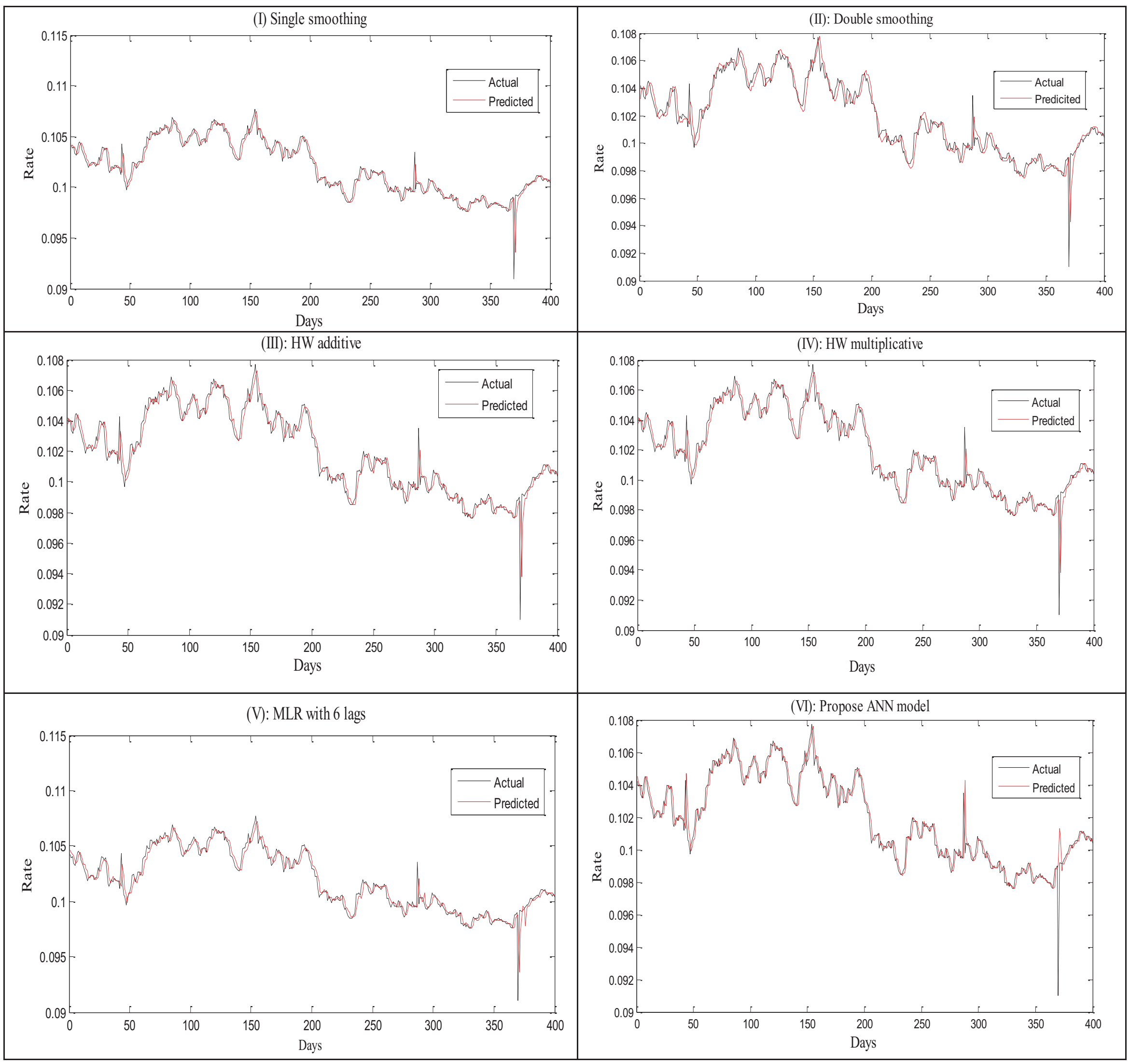


Figure 7.1(d): Performance of EURO/SBD using testing sample for all the methods.

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 & Athanasopoulos, 2014). The results for the naive method along with the proposed method are presented in Table 7.2. The table reveals that the proposed method outperformed the benchmarked method in all of the four exchange rate series. Figure 7.2 shows the actual vs forecasted of the proposed and naive method for the SBD exchange rates against the four currencies.

Table 7.2: Error measures for different exchange rate data for the proposed model and the naive method.

Accuracy measure	AUD/SBD		GBP/SBD		Japanese Yen/SBD		EURO/SBD	
	Naive	ANN	Naive	ANN	Naive	ANN	Naive	ANN
RMSE ($\times10^{-4}$)	164.91	**9.23**	37.61	**11.95**	246.66	**8.52**	36.95	**6.96**
MAE ($\times10^{-4}$)	142.26	**6.56**	31.07	**5.20**	234.33	**6.00**	30.37	**3.75**
MAPE ($\times10^{-3}$)	9603.42	**451.79**	3570.46	**603.49**	17181.46	**452.00**	3030.67	**369.18**

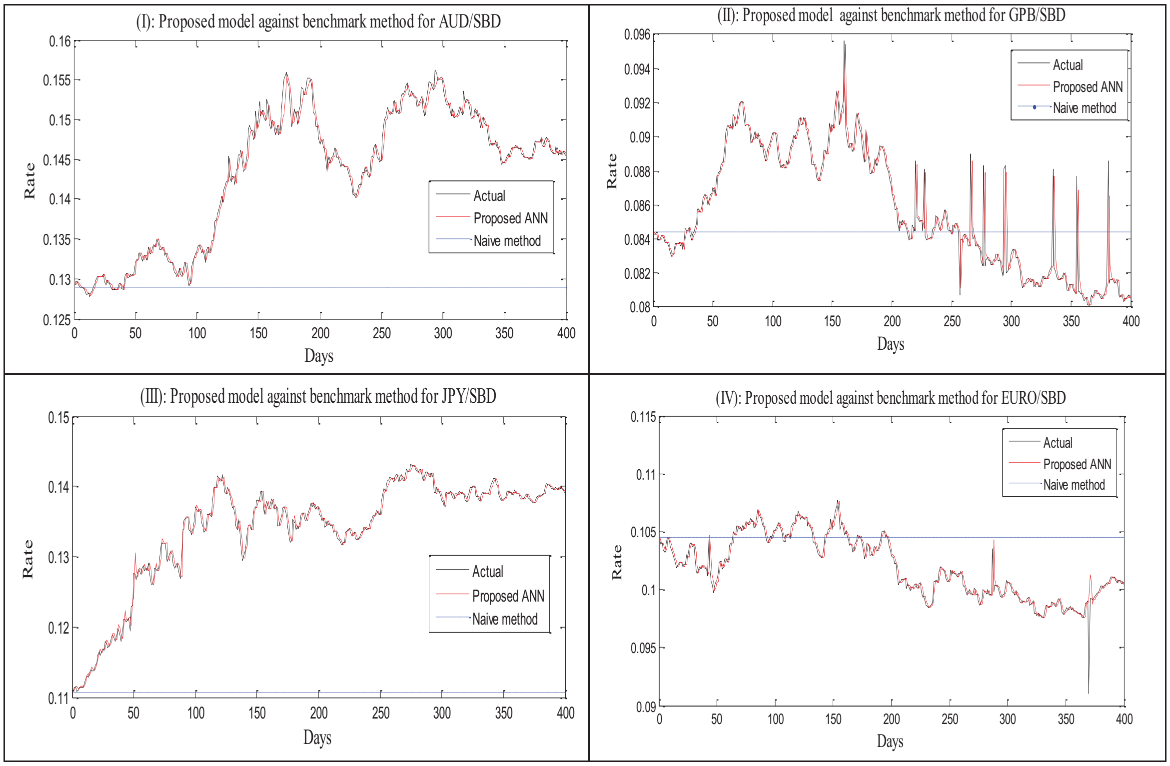


Figure 7.2: Performance of the proposed model against the naive method for SBD exchange rates against AUD, GBP, JPY and Euro.

Finally, to discuss about the purchasing power parity, we have found that there is a long-run relationship between Solomon Islands nominal exchange rates and the price differential against USA and UK prices. The weak form of the PPP theory is supported for Solomon Islands against both the US dollar, and the UK pound Sterling. The strong form of the PPP theory–the symmetry and proportionality hypothesis– is supported for the Solomon against the UK currency. The strong version is not supported for the USA. It is also noted that it will take a very long time for the disequilibrium to be corrected for both USA and UK prices as the value of α is less than 1%. This finding confirms the result obtain by Jayaraman and Choong (2014) for Solomon Islands against USA, using symmetry and proportional log likelihood testing. Using the VECM, we have found that Solomon Islands price and nominal exchange rate are caused by changes in USA prices and UK prices. The prices in a small open economy, with pegged exchange rate regimes, such as Solomon Islands are greatly determined by the international prices. The nominal exchange rate neutrality hypothesis is supported by this study, though it is only in the long-run. The real exchange rate is determined by the PPP for both pegged and floating exchange regimes, but it takes considerably long time, to reach the stable PPP real exchange rates, and alignment with international prices in the pegged exchange regime of Solomon Islands. However, it is interesting to note that in the Solomon Islands case, though it is a pegged exchange regime, even the changes in the nominal exchange rates are Granger caused by the long-term trends in co-integrating vector including the price level changes in the foreign countries and in Solomon Islands, as revealed in the error correction models.

Chapter 8: Conclusions

In this thesis, we propose an ANN model for forecasting Solomon exchange rates against four major trading currencies. The result this study reports is that the ANN (3, 4, 1) produces least values of RMSE, MAE, and MAPE and the highest value of R^2. The model does not produce over fitting as indicated by the very low value of bias and low value of tracking signal. 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, MAE and MAPE over the benchmarked method for all the currencies. These empirical findings strongly indicate that ANN is an efficient tool for forecasting the Solomon exchange rates more accurately.

In the literature, it is seen that scholars relied on various approaches in forecasting. Some of them prefer structural framework specifying economic characteristics while other believed on statistical modeling. The current work took the middle path and hence very unique. One has to note that artificial intelligence has been extremely important tool for the prediction when individual expectation is considered to be modelled. Under flexible rate regime particularly, the nominal exchange rate is highly influenced by individual expectation and the artificial intelligence happens to be the powerful tools as there is no alternative to model individual expectation. Despite, Solomon exchange rate is under the flexible regime artificial intelligence is expected to produce best forecasting because it requires fewer assumptions. Since there is no standard forecasting method or technique used in forecasting the Solomon exchange rate, we therefore, recommend ANN method as an alternative tool for forecasting SBD against its major trading currencies.

Further, after carrying out the research on the purchasing power parity, the results reveal that the changes in SBD/USD and SBD/UK pound are influenced by the long term trends in the price differential of Solomon Islands and the US and UK respectively. The symmetry and proportionality of the strong version of PPP were found to be very significant for Solomon Islands against UK price only and not against the US dollar. The price levels in an open small pegged exchange regime such as Solomon Islands are greatly determined by international prices, and interestingly, even the nominal exchange rates are determined by price differentials in the long-run.

In future research, we can experiment on different sets of training and testing samples and find out which combination yields better forecasts. Further, other hybrids of neural network with the proposed ANN model can be experimented on to see if there is any further improvement. For the purchasing power parity theory, we can use the CPI of Solomon Islands against its other major trading currencies such as AUD, JPY, EURO and NZD.

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Appendices

Appendix 1: Questionnaire and responses from our CBSI correspondent (Mr. Ali Homelo)

1. *Is forecasting exchange rate a problem (challenge) in Solomon Islands? Its Accuracy and reliability.*

   Exchange rate forecasting is always a challenge as far as CBSI exchange rate calculations is concerned. As Administrators of our exchange rate regime in the country, forecasting our exchange rate for the next 3 to four months is always a challenge. One of the fundamental issues is on technical capacity to fully establish a local technical model where we can fully forecast where our dollar would lie in the next week, months or so. Forecasting our exchange rate especially our CBSI mid-rate is only done along with the USD forecast sourced from our external sources. Since our basket is heavily weighted in USD, the USD forecast from external sources can form the basis to forecast where our mid-rate would be; however, forecasting our mid-rate and SBD against other currencies remains a challenge. (We rely heavily on external exchange rate forecasts). With continuous changes and reviews made to the exchange rate regime it is paramount that a proper forecasting modelling tool is established to help forecast our exchange rate according to the economic circumstances and monetary policy decisions of the country. While exchange rate policy is one fundamental tool for our monetary policy its transmission or pass through effect to our consumers is always lagging and not effective enough to stimulate economic activities and fundamentals.

   Generally speaking Exchange rate forecasting remains a challenge for CBSI given the different exchange rate policy review adopted during the past years. The bank has in the past fixed the dollar to USD and later intervened to set the rates accordingly to its policy goals, later a review to set the rate against the basket (pegged to the basket) was again introduced, allowing the rate to fluctuate within an approved band. Whilst we have forecasts for the major trading currencies from our external currency forecasts reports and Bloomberg sources, we can rely only our forecasts based on the USD Forecast as per our exchange rate regime. Depending on the exchange rate regime we adopted our forecast is based on USD forecast against major currency from our external sources.

2. *What method of exchange rate forecasting do you employ? How many periods/days ahead do you usually forecast?*

   In terms of forecasting methodology, no standard forecasting methodology was developed though our forecast basically relied on FX4cast.com currency report of major currencies. The Fx4cast report forecasted USD and major currencies on monthly basis, quarterly basis, 6–monthly basis and annual basis. Our forecast of the rate on an ad hoc basis would be based on the fundamental observation along the lines of the economic fundamentals of the country and forecasts based on the USD forecast. However, there is not much activity in the forecasting of the exchange rates. Our rates are calculated daily and any changes to the impact of the rates along with the economy will be reviewed according to the monetary policy goals of the bank. In the meantime little activity has been done on regular forecasting of the exchange rates. We rely very much on the external sources forecasts of USD against other major trading currencies.

3. *How do you calculate the exchange rate? Exchange rate regime and basket of currencies*.

   I may not exactly outline the formula for the calculation of the SBD against USD and all other rates. However, the basket of invoiced currencies was given allocated weights adding up to 1. The major currencies in the basket are USD, AUD, NZD, JPY and GBP. USD and AUD have the most portion of the weight: both add up to around 80% while the balance is shared by the other remaining currencies. An index of the weights is calculated and exchange rates for these currencies against USD are sourced from our external sources and used to determine the movement in the basket. The basket movement basically determines the daily rate in SBD/USD. Our dollar is pegged to the basket of invoiced currencies.

Appendix 2: Great Britain pound results

2.1. *Results of training GBP/SBD multiple linear regressions*

Method: Least Squares
Sample (adjusted): 8 3756
Included observations: 3749 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.21E-05	5.07E-05	1.225242	0.2206
GBP(-1)	0.992048	0.016306	60.83764	0.0000
GBP(-2)	-0.017543	0.022863	-0.767316	0.4429
GBP(-3)	0.017762	0.022368	0.794087	0.4272
GBP(-4)	-0.201829	0.022124	-9.122691	0.0000
GBP(-5)	0.289628	0.022367	12.94912	0.0000
GBP(-6)	-0.153444	0.022861	-6.712166	0.0000
GBP(-7)	0.072535	0.016298	4.450571	0.0000

R-squared	0.998923	Mean dependent var	0.091430
Adjusted R-squared	**0.998921**	S.D. dependent var	0.023859
S.E. of regression	0.000784	Akaike info criterion	-11.46323
Sum squared resid	0.002297	Schwarz criterion	**-11.44994**
Log likelihood	21495.83	Hannan-Quinn criter.	-11.45851
F-statistic	495874.1	Durbin-Watson stat	1.998829
Prob(F-statistic)	0.000000		

Forecasted Equation: $\hat{y}_t = 6.21\times10^{-5} + 0.99y_{t-1} + ... + 0.07y_{t-7}$

2.2. *Results of training time series methods for GBP/SBD*

Sample: 1 3750
Included observations: 3750
Method: Single Exponential
Original Series: GBP
Forecast Series: GBPSINGLE

Parameters:	Alpha	0.9640
Sum of Squared Residuals		0.002965
Root Mean Squared Error		0.000889
End of Period Levels:	Mean	0.084397

Sample: 1 3750
Included observations: 3750
Method: Double Exponential
Original Series: GBP
Forecast Series: GBPDOUBLE

Parameters:	Alpha	0.5100
Sum of Squared Residuals		0.003245
Root Mean Squared Error		0.000930
End of Period Levels:	Mean	0.084357
	Trend	-0.000115

Sample: 1 3750			
Included observations: 3750			
Method: Holt-Winters Additive Seasonal			
Original Series: GBP			
Forecast Series: GBPADDITIVE			
Parameters:	Alpha		0.9700
	Beta		0.0000
	Gamma		0.0000
Sum of Squared Residuals			0.002433
Root Mean Squared Error			0.000806
End of Period Levels:	Mean		0.084412
	Trend		-1.18E-05
	Seasonals:	3746	-1.26E-05
		3747	3.15E-05
		3748	1.84E-06
		3749	-4.92E-06
		3750	-1.58E-05

Sample: 1 3750			
Included observations: 3750			
Method: Holt-Winters Multiplicative Seasonal			
Original Series: GBP			
Forecast Series: GBPMULTIPLY			
Parameters:	Alpha		0.9700
	Beta		0.0000
	Gamma		0.0000
Sum of Squared Residuals			0.002434
Root Mean Squared Error			0.000806
End of Period Levels:	Mean		0.084404
	Trend		-1.18E-05
	Seasonals:	3746	0.999782
		3747	1.000177
		3748	1.000086
		3749	1.000038
		3750	0.999917

2.3. *Results of time series model for testing GBP/SBD*

Sample: 1 400
Included observations: 400
Method: Single Exponential
Original Series: GBP
Forecast Series: GBPSINGLE

Parameters:	Alpha	**0.96**
Sum of Squared Residuals		6.32E-04
Root Mean Squared Error		1.26E-03
End of Period Levels:	Mean	0.08

Sample: 1 400
Included observations: 400
Method: Double Exponential
Original Series: GBP
Forecast Series: GBPDOUBLE

Parameters:	Alpha	**0.51**
Sum of Squared Residuals		0.70
Root Mean Squared Error		1.33E-03
End of Period Levels:	Mean	0.08
	Trend	2.35E-05

Sample: 1 400
Included observations:
400
Method: Holt-Winters
Additive Seasonal
Original Series: GBP
Forecast Series:
GBPADDITIVE

Parameters:	Alpha	**0.97**
	Beta	**0.00**
	Gamma	**0.00**
Sum of Squared Residuals		6.09E-04
Root Mean Squared Error		1.23E-03

End of period levels:	Mean	0.08	
	Trend		-9.06E-06
	Seasonals:	396	-1.26E-05
		397	-4.61E-05
		398	-8.70E-05
		399	-5.79E-05
		400	0.000204

Sample: 1 400
Included observations: 400
Method: Holt-Winters Multiplicative Seasonal
Original Series: GBP
Forecast Series: GBPMULTIPLY

Parameters:	Alpha		**0.97**
	Beta		**0.00**
	Gamma		**0.00**
Sum of Squared Residuals			6.08E-04
Root Mean Squared Error			1.23E-03

End of Period Levels:	Mean		0.08
	Trend		-9.06E-06
	Seasonals:	396	0.999904
		397	0.999468
		398	0.998949
		399	0.999302
		400	1.002376

Appendix 3: Japanese yen results

3.1. *Results of training JPY/SBD multiple linear regressions*

Dependent Variable: JPY
Method: Least Squares
Sample (adjusted): 6 3756
Included observations: 3751 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000159	0.000114	1.398331	0.1621
JPY(-1)	0.895883	0.016157	55.44904	0.0000
JPY(-2)	0.118863	0.021657	5.488450	0.0000
JPY(-3)	-0.011587	0.021743	-0.532915	0.5941
JPY(-4)	-0.153801	0.021639	-7.107494	0.0000
JPY(-5)	0.149337	0.016127	9.260254	0.0000

R-squared	0.998356	Mean dependent var	0.163662
Adjusted R-squared	**0.998354**	S.D. dependent var	0.051054
S.E. of regression	0.002071	Akaike info criterion	-9.519770
Sum squared resid	0.016066	Schwarz criterion	**-9.509805**
Log likelihood	17860.33	Hannan-Quinn criter.	-9.516226
F-statistic	454945.3	Durbin-Watson stat	2.000550
Prob(F-statistic)	0.000000		

Forecasted Equation: $\hat{y}_t = 1.59\times10^{-4} + 0.90y_{t-1} + ... + 0.15y_{t-5}$

3.2. *Results of training time series methods for JPY/SBD*

Sample: 1 3750
Included observations: 3750
Method: Single Exponential
Original Series: JPY
Forecast Series: JPYSINGLE

Parameters:	Alpha	0.9180
Sum of Squared Residuals		0.022446
Root Mean Squared Error		0.002447
End of Period Levels:	Mean	0.110628

Sample: 1 3750
Included observations: 3750
Method: Double Exponential
Original Series: JPY
Forecast Series: JPYDOUBLE

Parameters:	Alpha	0.4640
Sum of Squared Residuals		0.019653
Root Mean Squared Error		0.002289
End of Period Levels:	Mean	0.110855
	Trend	9.93E-05

Sample: 1 3750
Included observations: 3750
Method: Holt-Winters Additive Seasonal
Original Series: JPY
Forecast Series: JPYADDITIVE

Parameters:	Alpha			0.9000
	Beta			0.0000
	Gamma			0.0000
Sum of Squared Residuals				0.016451
Root Mean Squared Error				0.002095
End of Period Levels:		Mean		0.110666
		Trend		-4.36E-05
		Seasonals:	3746	3.43E-05
			3747	6.17E-05
			3748	3.68E-05
			3749	-0.000103
			3750	-3.02E-05

Sample: 1 3750
Included observations: 3750
Method: Holt-Winters Multiplicative Seasonal
Original Series: JPY
Forecast Series: JPYMULTIPLY

Parameters:	Alpha			0.9000
	Beta			0.0000
	Gamma			0.0000
Sum of Squared Residuals				0.016446
Root Mean Squared Error				0.002094
End of Period Levels:		Mean		0.110647
		Trend		-4.36E-05
		Seasonals:	3746	1.000127
			3747	1.000272
			3748	1.000219
			3749	0.999500
			3750	0.999883

3.3. *Results of times series model for testing JPY/SBD*

Sample: 1 400
Included observations: 400
Method: Single Exponential
Original Series: JPY
Forecast Series: JPYSINGLE

Parameters: Alpha		**0.9180**
Sum of Squared Residuals		0.000649
Root Mean Squared Error		0.001274
End of Period		
Levels:	Mean	0.138934

Sample: 1 400
Included observations: 400
Method: Double Exponential
Original Series: JPY
Forecast Series: JPYDOUBLE

Parameters:	Alpha	**0.4640**
Sum of Squared Residuals		0.000410
Root Mean Squared Error		0.001013
End of Period		
Levels:	Mean	0.139007
	Trend	-0.000177

Sample: 1 400
Included observations: 400
Method: Holt-Winters Additive Seasonal
Original Series: JPY
Forecast Series: JPYADDITIVE

Parameters:	Alpha			**0.9000**
	Beta			**0.0000**
	Gamma			**0.0000**
Sum of Squared Residuals				0.000291
Root Mean Squared Error				0.000853
End of Period Levels:	Mean			0.138986
	Trend			7.17E-05
	Seasonals:		3746	1.20E-05
			3747	6.40E-05
			3748	1.48E-05
			3749	-5.70E-05
			3750	-3.37E-05

Sample: 1 400
Included observations: 400
Method: Holt-Winters Multiplicative Seasonal
Original Series: JPY
Forecast Series: JPYMULTIPLY

Parameters:	Alpha		**0.9000**
	Beta		**0.0000**
	Gamma		**0.0000**
Sum of Squared Residuals			0.000291
Root Mean Squared Error			0.000853
End of Period Levels:	Mean		0.138974
	Trend		7.17E-05
	Seasonals:	396	1.000028
		397	1.000454
		398	1.000090
		399	0.999575
		400	0.999853

Appendix 4: EURO results

4.1. Results of training EURO/SBD multiple linear regressions

Dependent Variable: EURO
Method: Least Squares
Sample (adjusted): 7 3756
Included observations: 3750 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.06E-05	9.81E-05	0.719754	0.4717
EURO(-1)	0.651047	0.016071	40.51102	0.0000
EURO(-2)	0.219006	0.019268	11.36612	0.0000
EURO(-3)	0.043565	0.019569	2.226244	0.0261
EURO(-4)	-0.065699	0.019569	-3.357322	0.0008
EURO(-5)	-0.031179	0.019266	-1.618342	0.1057
EURO(-6)	0.182375	0.016066	11.35181	0.0000

R-squared	0.998116	Mean dependent var	0.130065
Adjusted R-squared	**0.998113**	S.D. dependent var	0.046501
S.E. of regression	0.002020	Akaike info criterion	-9.569529
Sum squared resid	0.015274	Schwarz criterion	**-9.557901**
Log likelihood	17949.87	Hannan-Quinn criter.	-9.565394
F-statistic	330487.8	Durbin-Watson stat	1.994846
Prob(F-statistic)	0.000000		

Forecasted Equation: $\hat{y}_t = 7.06 \times 10^{-5} + 0.65 y_{t-1} + ... + 0.18 y_{t-6}$

4.2. *Results of training time series methods for EURO/SBD*

Sample: 1 3750
Included observations: 3750
Method: Single Exponential
Original Series: EURO
Forecast Series: EUROSINGLE

Parameters: Alpha		0.6740
Sum of Squared Residuals		0.016810
Root Mean Squared Error		0.002117
End of Period Levels:	Mean	0.104513

Sample: 1 3750
Included observations: 3750
Method: Double Exponential
Original Series: EURO
Forecast Series: EURODOUBLE

Parameters: Alpha		0.3032
Sum of Squared Residuals		0.019146
Root Mean Squared Error		0.002260
End of Period Levels:	Mean	0.104522
	Trend	-0.000178

Sample: 1 3750
Included observations: 3750
Method: Holt-Winters Additive Seasonal
Original Series: EURO
Forecast Series: EUROADDITIVE

Parameters:	Alpha		0.6500
	Beta		0.0000
	Gamma		0.0000
Sum of Squared Residuals			0.015878
Root Mean Squared Error			0.002058

End of Period Levels:	Mean		0.104512
	Trend		-2.37E-05
	Seasonals:	3746	5.27E-05
		3747	-2.99E-05
		3748	1.73E-06
		3749	-3.78E-05
		3750	1.33E-05

Sample: 1 3750
Included observations: 3750
Method: Holt-Winters Multiplicative Seasonal
Original Series: EURO
Forecast Series: EUROMULTIPLY

Parameters:	Alpha		0.6500
	Beta		0.0000
	Gamma		0.0000
Sum of Squared Residuals			0.015890
Root Mean Squared Error			0.002058

End of Period Levels:	Mean		0.104494
	Trend		-2.37E-05
	Seasonals:	3746	1.000313
		3747	0.999440
		3748	1.000084
		3749	0.999841
		3750	1.000323

4.3. *Results of testing time series model for EURO/SBD*

Sample: 1 400
Included observations: 400
Method: Single Exponential
Original Series: EURO
Forecast Series: EUROSINGLE

Parameters: Alpha		**0.6740**
Sum of Squared Residuals		0.000211
Root Mean Squared Error		0.000726
End of Period		
Levels:	Mean	0.100484

Sample: 1 400
Included observations: 400
Method: Double Exponential
Original Series: EURO
Forecast Series: EURODOUBLE

Parameters: Alpha		**0.3032**
Sum of Squared Residuals		0.000233
Root Mean Squared Error		0.000763
End of Period		
Levels:	Mean	0.100509
	Trend	-4.15E-05

Sample: 1 400
Included observations: 400
Method: Holt-Winters Additive Seasonal
Original Series: EURO
Forecast Series: EUROADDITIVE

Parameters:	Alpha		**0.6500**
	Beta		**0.0000**
	Gamma		**0.0000**
Sum of Squared Residuals			0.000207
Root Mean Squared Error			0.000720
End of Period Levels:	Mean		0.100554
	Trend		-7.90E-06
	Seasonals:	396	8.45E-06
		397	3.76E-05
		398	3.67E-05
		399	4.09E-05
		400	-0.000124

Sample: 1 400
Included observations: 400
Method: Holt-Winters Multiplicative Seasonal
Original Series: EURO
Forecast Series: EUROMULTIPLY

Parameters:	Alpha			**0.6500**
	Beta			**0.0000**
	Gamma			**0.0000**
Sum of Squared Residuals				0.000208
Root Mean Squared Error				0.000720
End of Period Levels:		Mean		0.100555
		Trend		-7.90E-06
		Seasonals:	396	1.000091
			397	1.000388
			398	1.000369
			399	1.000409
			400	0.998744

Appendix 5: Training results of the proposed model for other exchange rate series

Table 5.1: *ANN result for training different lags and hidden layers (GBP/SBD)*

Model	RMSE ($\times 10^{-4}$)	MAE ($\times 10^{-4}$)	MAPE ($\times 10^{-3}$)	Bias ($\times 10^{-4}$)	TS	R^2 ($\times 10^{-4}$)
ANN(2,3,1)	8.05	4.00	435.00	3.01	0.75	9988.63
ANN(2,4,1)	8.04	4.00	434.58	-1.35	-0.34	9988.64
ANN(3,3,1)	8.04	4.00	434.78	**0.01**	**0.01**	9988.65
ANN(3 ,4, 1)	**8.01**	**4.02**	**436.45**	-0.75	-0.19	**9988.72**
ANN(3,5,1)	8.04	4.00	435.17	-2.52	-0.63	9988.63
ANN(4,3,1)	8.05	4.01	535.56	0.34	0.08	9988.62

Table 5.2: *ANN result for training different lags and hidden layers (JPY/SBD)*

Model	RMSE ($\times 10^{-4}$)	MAE ($\times 10^{-4}$)	MAPE ($\times 10^{-3}$)	Bias ($\times 10^{-4}$)	TS	R^2 ($\times 10^{-4}$)
ANN(2,3,1)	20.92	9.43	541.03	**-1.01**	**-0.11**	9983.34
ANN(2,4,1)	20.87	9.44	543.10	6.69	0.71	9983.27
ANN(3,3,1)	20.86	9.44	542.99	24.29	2.57	9983.28
ANN(3 ,4, 1)	**20.27**	**9.44**	**541.59**	4.85	0.51	**9984.21**
ANN(3,5,1)	20.61	9.47	545.44	-4.52	-0.48	9983.68
ANN(4,3,1)	20.96	9.49	546.31	-66.24	-6.78	9983.13

Table 5.3: *ANN result for training different lags and hidden layers (EURO/SBD)*

Model	RMSE ($\times 10^{-4}$)	MAE ($\times 10^{-4}$)	MAPE ($\times 10^{-3}$)	Bias ($\times 10^{-4}$)	TS	R^2 ($\times 10^{-4}$)
ANN(2,3,1)	20.71	8.02	612.79	**0.03**	**<0.01**	9980.16
ANN(2,4,1)	20.69	8.00	612.45	0.99	0.12	9980.21
ANN(3,3,1)	20.61	8.15	612.98	0.23	0.03	9980.35
ANN(3 ,4, 1)	**19.02**	**7.44**	**573.24**	-2.55	-0.01	**9983.27**
ANN(3,5,1)	19.06	7.44	572.72	0.34	0.05	9983.19
ANN(4,3,1)	20.62	8.16	622.77	0.22	0.03	9980.34