CO-OPERATIVE UNIVERSITY, SAGAING

DEPARTMENT OF STATISTICS

MASTER OF APPLIED STATISTICS

TIME SERIES ANALYSIS OF FOREIGN EXCHANGE RATE IN CLMV COUNTRIES

EI MOH MOH NYEIN

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This thesis is submitted to the Board of Examiners in partial fulfillment of the requirement for the degree of Master of Applied Statistics.

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ACCEPTANCE

This is to certify that this paper entitled "**Time Series Analysis of Foreign Exchange Rate in CLMV Countries**" submitted as a partial fulfillment towards the degree of Master of Applied Statistics has been accepted by Board of Examiners.

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ABSTRACT

This paper is concerned with the monthly exchange rate between the KHR/USD, LAK/USD, MMK/USD and VND/USD. The objectives of this paper is to investigate the statistical model which models the most appropriate for forecasting of foreign exchange rate in CLMV countries and to forecast the future value of foreign exchange rate in CLMV countries based on fitted models. In the analysis, the suggested model is confirmed by following the Box-Jenkins methodology. In this paper, monthly data of foreign exchange rate in CLMV countries from April 2012 to December 2020 by the International Financial Statistics are studied. After applying Box-Jenkins methodology, the best fitted SARIMA (1, 0, 0) $(2, 1, 0)_{12}$ model in Cambodia, ARIMA (1,2,1) model in Lao, ARIMA (1,1,0) model in Myanmar and ARIMA (0,1,0) model in Vietnam have been obtained. Finally, forecasting has been made for foreign exchange rate in CLMV countries from January 2021 to December 2021. The predicted rate of USD are found that Cambodia will increase from January 2021 to September 2021 and then will decrease from November 2021 to December 2021, Lao will continue to grow the next year, Myanmar will increase the next year and Vietnam will continue to grow the next year. It was found the forecast values fall within the 95% lower and upper limits. Therefore, the ARIMA model is suitable and this model helpful for the government functionaries, monetary policymakers, economists and other stakeholders.

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LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
AR	Autoregressive
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
BIC	Bayesian Information Criterion
CBN	Central Bank of Nigeria
CLMV	Cambodia, Lao, Myanmar and Vietnam
DF	Dickey-Fuller
DSP	Difference Stationary Processes
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GBP	Great Britain Pound
IFS	International Financial Statistics
KHR	Cambodia Riels
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MEAE	Median Absolute Error
MMK	Myanmar, Myanmar Kyat
MPE	Mean Percentage Error
MS	Mean Square
MSE	Mean Squared Error
NBC	Cambodian Central Bank
Lao PDR	Lao People's Democratic Republic
LAK	Lao Kips
PACF	Partial Autocorrelation Function
PP	Phillips-Perrom
PR	Pakistani Rupee
RBI	Reserve Bank of India
RMSE	Root Mean Squared Error

SARIMA	Seasonal Autoregressive Integrated Moving Average
SBV	State Bank of Vietnam
SDR	Special Drawing Right
SE	Standard Error
SS	Sum of Squares
SSE	Error Sum of Squares
SSM	Months Sum of Squares
SST	Total Sum of Squares
SSY	Years Sum of Squares
TSP	Trend Stationary Processes
USD	United States Dollar
VND	Vietnam Dong

CHAPTER 1

INTRODUCTION

Exchange rate is an important variable which influences decisions taken by the participants of the foreign exchange market, namely investors, importers, exporters, bankers, financial institutions, business, tourists and policy makers both in the developing and developed world as well (Dua and Ranjan, 2011).

Due to Globalization, the foreign exchange market has encountered unexpected development over the last few decades. Several economic factors such as inflation, economic growth, interest rates and monetary policies influence the value at which national currencies are traded in international markets. Therefore, the exchange rates play an essential role in controlling dynamics of the foreign exchange market.

Exchange rate is the currency rate of one country indicated in terms of the currency of another country. In the modern world, exchange rates of the most successful countries tend to be fluctuating. This system is specify by the foreign exchange market over supply and demand for that particular currency in relation to the other currencies. In addition, the exchange rate is guided by significant impact of the activities of central banks and other financial institutions.

Variations in the exchange rates have a massive effect, with the consequences for prices, wages, interest rates, production levels, revenue estimates, economic investment and employment opportunities. Forecasting of the exchange rate is the leading events for the practitioners and researchers in the spree of the exchange rate, which is floating (Hu, et al., 1999). The significance of forecasting the exchange rates is that a precise forecast can provide valuable information to allocate of resources, in hedging risk and in policymaking. Foreign exchange is the crucial element that is extensively used on basis for settlement of international transactions and international bills. There is no suspicion that exchange rate has a direct impact on the economic expansion of a country.

Exchange rate volatility involves a significant role in this financial globalisation process. This process effectively, it is very important for the policy makers and various agents to be able to generate accurate forecasts of exchange rates and its anticipated volatilities. So, it would be of great importance to investigate whether established time series models, econometric models or a combination of both models perform equally well for emerging and frontier countries.

1.1 Rationale of the Study

The exchange rate is one of the most important issues in the discussion of world economy (Etuk, et al., 2016). Modern macroeconomics relies hugely on foreign exchange rate dynamics (Medel et al., 2015). Exchange rate modeling and forecasting is important for policy making (Hina & Qayyum, 2015). Forecasting exchange rate is crucial as it has significant impact on the macroeconomic fundamentals such as oil price, interest rate, wage, unemployment and the level of economic growth (Ramzan et al., 2012). Foreign exchange markets are among the most important and the largest financial markets in the world with trading taking place twenty – four hours a day around the globe and trillions of dollars of different currencies transacted each day (Khashei & Bijari, 2011).

The exchange rate serves as an important price factor in the economy (Klein & Shambaugh, 2012). It is a measurement of the price of country's domestic currency relative to a foreign basket of goods or prices (Gourinchas, 1999). It determines the relative prices of domestic and foreign goods, as well as the strength of external sector participation in the international trade (Mohammed & Abdulmuahymin, 2016). In fact, foreign exchange is the component that is widely used on daily basis for settlement of international transactions and international bills (Oleka et al., 2014).

Foreign exchange rates are among the most important prices in international monetary markets (Rahim et al., 2018). The stability of the exchange rate is today a formidable bedrock of all economic activities (Taiwo & Adesola, 2013). The centrality of exchange rates in the formulation of monetary policy derives from the fact that for most countries, the prevailing objective of monetary policy is price stability (Adeoye & Saibu, 2014). Therefore, central banks should pay special attention to exchange rates and the value of their domestic currency (Dilmaghani & Tehranchian, 2015).

Fluctuations in a nation's currency or exchange rate exert changes in domestic production costs (Ngandu, 2008) and also affect the labor market based on channels of appreciation and depreciation of currencies (Nucci & Pozzolo, 2010). A depreciation in the exchange rate increases or promotes the growth of local jobs in the manufacturing and non – manufacturing sectors (Yokoyama et al., 2015). Volatile exchange rates may also increase unemployment through lowering investment in physical capital (Belke & Gros, 2001). Investment may be reduced because higher volatility usually entails increased uncertainty (Nyahokwe & Ncwadi, 2013). Therefore, maintaining exchange rate stability implies controlling a country's level of unemployment (Chimnani et al., 2012) and promoting investment.

Exchange rate is one of the most important prices in an open economy since it affects so many business, investment and policy decisions. Since nations issue its own currencies and there is no common currency worldwide yet, the currencies must be exchanged for the purpose of payments to trading with and investment in other counties. The determination of a foreign exchange rate is closely associated with the existing international monetary system. Governments are using one of the following exchange rate systems. (i) Fixed exchange rate which is fixed by monetary authority, usually pegging to a foreign currency or a group of currencies. (ii) Managed floating meaning that the monetary authority allows free movements of exchange rate, but with the control and intervention to remain within acceptable range. (iii) Free floating meaning that the foreign exchange rate is completely free to move in response to market forces, namely demand and supply of currencies.

The real exchange rate is dependent on the consumer price indices of both home and host countries. It reflects the inflation rates of the countries. Like the consideration of purchasing power of each currency, the foreign rate can also be determined based on the ' interest rate parity'. The higher the interest rate of the home country compared to the host country, the grater the depreciation of the host country currency.

In Cambodia, exchange rates are influenced by tax payments and the purchase of agricultural products. The exchange rate between the U.S. dollar and the Cambodian Khmer Riel is determined by the market. The fluctuation of the exchange rate in the Cambodian economy is due to oversupply or shortage of riel compared to the riel demand. Generally, the demand for riel increases around the new year by the Khmer Calendar, i.e. period of tax payment and the season of crop harvests. Thus, the value of the riel tends to increase. In other periods, on the other hand, its value tends to decrease. In other words, the exchange-value of the riel tends to increase in the first quarter and then gradually decreases over second to the third quarter, and then from the fourth quarter, tends to increase again. To smooth out such exchange fluctuations, the NBC either buys or sells U.S dollars.

Cambodia National Bank's exchange rate strategy is one of the major NBC monetary instruments. The goal is to achieve price solidity and stability. The NBC determines the exchange rate. The NBC Official Exchange Rate Decision Committee, composed of employees from significant subdivisions, such as banking, issuance, foreign exchange board, the international cooperation department, as well as statistics and economic enquiries.

The Bank of the Lao PDR uses the market-based foreign exchange system managed by the Government by setting the daily reference rate for commercial banks and licensed currency exchange bureau to define the exchange rates. Foreign exchange is a foreign country's currency in which comprise of banknotes, coins, check, credit card, debit card, bills of exchange, government bonds, corporate bonds, shares and other payment instruments that are used internationally for payment between countries.

Foreign exchange management is the foreign exchange businesses and transactions management of residents and non-residents of the Lao in accordance with the laws and regulations relating to foreign exchange. The main principles of the foreign exchange management are ensure foreign currency management centrally and uniformly through nationwide, ensure the stability of National currency, ensure the independence of National currency and ensure the mobility of domestic and international settlement. All State income collected in foreign currency must be deposited at the Bank. When it requires to be made payment in domestic, the foreign currency must be sold to the Bank of the Lao in daily exchange rate set by the bank.

Myanmar is well known as a resource rich country in Southeast Asia countries. However, after many decades of isolation under socialism and military rule, Myanmar becomes one of the poorest countries in the region. However, political changes took place in 2010. Myanmar is heading a new era of development and economic growth. A series of reforms in the economy, including monetary, financial and banking reforms were implemented.

The currency of Myanmar, Myanmar Kyat (MMK) was exchanged with foreign currencies at fixed rates, by pegging into Special Drawing Right (SDR). The (official, fixed) exchange rate of MMK per U.S dollar was 5.3990 in 2011-2012 just before the introduction of flexible, managed floating exchange rate system in April 2012. Prior to the new regime, Myanmar had actually multiple exchange rates such as official exchange rate, unofficial (black market rate) exchange rate. The 'trade exchange rate ' existed for the international trade in which importers were required to earn foreign currency from exports officially or, it could buy foreign currency from exporters in case of lacking the necessary exports. The official exchange rate was available only to the public sector, while the market rate was followed by the private sector.

The exchange rate is one of the most essential tools in economic development. In Myanmar, an overvalued exchange rate is currently undermining economic activity. If this situation persists, the country's industrial base will shrink, investors will be discouraged, unemployment will increase, poverty will deepen, more people will leave the country, the divide between rich and poor will increase, and national strength and the people's prosperity will be diminished if not destroyed.

Vietnam is one among the countries seeking such strategy. The export sector has experienced a structural change due to greater integration into the world economy. Besides, one of main tasks of exchange rate tool facilitating trade balance, stays remained despite the fact that the exchange rate regime has been adjusted many times during the last 20 years. In 2015, the exchange rate became a hot issue for Vietnam's economy with regard to concerns about China's devaluation of the Yuan, the rise of the federal fund rate, and the US dollar appreciation opposing many currencies in the world. Due to USD increase, the Vietnam Dong (VND) became more expensive against many foreign currencies, thus, the competitiveness of Vietnamese goods and the trade balance was affected negatively.

Vietnam's foreign exchange market has remained relatively poorly developed despite more than two decades of general reform throughout the economy. Vietnam's exchange rate regime has transformed from a system of multiple exchange rates to a single announced fixed rate, then to the current system of a narrow adjustable band around the official rate, which is itself set on a daily basis and is meant to reflect the interaction of market forces (Nguyen Tran Phuc and Nguyen Duc Tho 2009). The country's exchange rate policy is implemented and managed by its central bank, the State Bank of Vietnam (SBV). The focus of policy in this area has been the nominal and bilateral VND/USD exchange rate. At the time of writing, banks were permitted to quote offer and bid rates which were no lower than 3% below, nor higher than 3% above, the official VND/USD rate.

The structure of a country's exchange rate is one of the factors that affect the survival of the country in the international trade. Exchange rate forecasts consist a fundamental role in nearly all aspects of international financial management. Therefore, exchange rate forecasting is very crucial to assess the benefits and risks attached to the international business environment. High exchange rates have various consequences which include high inflation rates, reduction of exports and slower growth in GDP and increased deficit in the balance of payments. A number of studies and literature that have looked at forecasting exchange rates claim that exchange rates are very difficult to forecast. This makes it difficult to estimate the future value assets and liabilities denominated in foreign currency. This creates uncertainty about the magnitude of profits to be realized from international trade. The importance of forecasting exchange rates in practical aspect is that an accurate forecast can render valuable information to the investors, firms and central banks for use in allocation of assets, in hedging risk and in policy formulation (Tindaon, 2015). Predicting exchange rates is a challenging task to both traders and practitioners in modern financial markets. Statistical and econometric models have been used in the analysis and prediction of foreign exchange rates. Therefore, the modeling and forecasting of the exchange rate in CLMV countries are analyzed in this study.

1.2 Objectives of the Study

The objectives of the study are

(i) to investigate the statistical model which model is the most appropriate for forecasting of foreign exchange rate in CLMV countries

(ii) to forecast the future value of foreign exchange rate in CLMV countries based on fitted models.

1.3 Method of Study

This study is based on time series analysis. The monthly data of foreign exchange rate for the year (2012 to 2020) are obtained from the International Financial Statistics (IFS). Test of stationary is conducted using Augmented Dickey-Fuller (ADF) test. In this study, Box-Jenkins method is used to forecast the exchange rate in CLMV countries. Model identification are made based on autocorrelation (ACF) and partial autocorrelation function (PACF) and auto.arima function from R software. The adequacy of the model is verified by plots of the correlogram of the ACF and PACF for the residuals. Finally, the future value are forecasted using the accuracy of the fitted model.

1.4 Scope and Limitations of the Study

In this study, the analysis is based on secondary data and it was collected from the International Financial Statistics (IFS) over the period of April 2012 to December 2020. Among various time series analysis, Augmented Dickey-Fuller (ADF) unit root test, Box-Jenkins method are used in this study. This study focuses on foreign exchange rate. However, the scope of the study is limited to foreign exchange rate in CLMV countries.

1.5 Organization of the Study

The study is divided into five chapters. Chapter 1 is introduction which is comprised of five sub-headings: rationale of the study, objectives of the study, method of study, scope and limitations of the study and organization of the study. The literature review is presented in Chapter 2. Methodology has been described in Chapter 3. Chapter 4 is data analysis of foreign exchange rate in CLMV countries. And the last Chapter 5 discusses the conclusion based on findings and suggestions.

CHAPTER 2
LITERATURE REVIEW

This chapter reviews both theoretical and empirical literature on the forecasting of foreign exchange rate in CLMV countries.

2.1 Theoretical Review

The focus of theoretical review is on theory rather than on application. The theoretical literature review of foreign exchange rate is as followed.

2.1.1 Definitions of Foreign Exchange Rate

Exchange rate is the value of a particular foreign currency as compared to home currency. Exchange rate can also be termed as the value at which a domestic currency is trading for another country's currency. Exchange rates can either be flexible rate of exchange or fixed rate of exchange. In a fixed exchange rate, the value of the currency is determined by the government, while a flexible exchange rate is market determined and the government does not play role towards the stabilizing the value of the currency.

Exchange rate is among the key factors which in impact imports, balance of payments, exports, production, employment, and foreign exchange reserves. Exchange rates have an important role to play in international trade. Exchange rates influence, exports direct investments, imports, numerous sectors of service like tourism, education, insurance and banking. Since exchange rate are fundamental economy prices, their flexibility and level affect the growth and allocation of resources. Thus, exchange rates fluctuations is one of the main obstacles that developing economies face in the macroeconomic management especially during the periods of economic and financial crisis.

The effects of exchange rate movements are important to firms engaging in international business. It is usual to differentiate three types of currency exposure. The first is translation exposure, also known as accounting exposure. This refers to the impact exchange rate changes can have on a firm value from producing a consolidated set of accounts. That is, when the parent and all subsidiaries accounts are combined for a group report. The second is transaction exposure that is defined as the potential change in the value of a financial position due to changes in the exchange rate between the inception of a contract and the settlement of the contract. The third is operating exposure that is the extent to which an exchange rate change, in combination with price changes, will change a company's future operating cash flow.

2.2 Empirical Review

Newaz (2008) described "Comparing the Performance of Time Series Models for Foreign Exchange Rate". This paper attempted to compare different time series models to forecast exchange rate. Sample data for the paper were taken from September 1985 to June 2006, out of which data till December 2002. All the data were collected from various issues of International Financial Statistics published by International Monetary Fund. It is used Box-Jenkins methodology for building ARIMA model, exponential smoothing, naïve 1 and naïve 2 models. This study shows that ARIMA models provides a better forecasting of exchange rates than exponential smoothing and Naïve models. Comparison of the MAE, MEAE, MAPE, MSE and RMSE shows that the proposed ARIMA model is the best among all these models. The researcher forecasts the exchange rate until 2006 to find out the suitable model. This paper is concluded that the ARIMA model is more appropriate than MAE, MEAE, MAPE, M.S.E. and RMSE models in forecasting short term or long term exchange rates.

Appiah & Adetunde (2011) studied "Forecasting Exchange Rate between the Ghana Cedi and the US Dollar using Time Series Analysis". The purpose of this paper is to evaluate the foreign exchange rate between the Ghana Cedi and the US Dollar and forecast future rates. It is used to ARIMA model was developed using Box and Jenkins method of Time Series Analysis on the monthly data collected from January, 1994 to December 2010. The result showed that the predicted rates were consistent with the depreciating trend of the observed series. ARIMA (1,1,1) model was found as the most suitable model with least Bayesian Information Criterion (BIC) of 9.111, Mean Absolute Percentage Error (MAPE) of 0.915, Root Mean Square Error of 93.873 and high value of R- Square of 1.000. Estimation was done by Ljung-Box test, with (Q 18) = 15.146,16 DF and p-value of 0.514 with no autocorrelation between residuals at different lag times. Finally, a forecast for two-year period from January, 2011 to December, 2012 was calculated which showed a depreciating of the Ghana Cedi against the US Dollar.

Onasanya (2013) described "Forecasting of Foreign Exchange Rate between Naira and US Dollar using Time Domain Model". This research aims to identify a time domain model forecast for Nigeria (naira) and dollar exchange rate. The use of Box

Jenkins approach ARIMA model was applied to a monthly time series data on Nigeria exchange rate for the period January 1994 to December 2011. The result reveals that there is an upward trend and the 2nd difference of the series was stationary. Base on the selection criteria AIC and BIC, the best model that explains the series was found to be ARIMA (1, 2, 1). The diagnosis on such model was confirmed, the error was white noise, presence of no serial correlation and a forecast for period of 12 months terms was made which indicates that the naira will continue to depreciate with these forecasted time period. The policy implication of this research for policy decision makers which makes use of forecasting as a control for economic and financial variables is meant for them to incorporate fiscal policies, monetary and devaluation method to stabilize naira exchange rate and thereby eliminating over dependence on imports.

Osarumwense & Waziri (2013) described "Forecasting Exchange Rate between the Nigeria and US Dollar using ARIMA Models". This paper described the modeling and forecasting time series data of Exchange rate of Nigeria Naira (N) to the USD ($). The Box-Jenkins ARIMA methodology was used for forecasting the monthly data collected from January 1990 to December 2010. The Nigeria Naira to US Dollar Exchange Rate has been increasing from Jan 1990 to Dec 2010. The diagnostic checking has shown that ARIMA (0, 1, 1) is appropriate. A four-year (48 months) forecast was made from January 2011 to December 2014, the result show the Nigeria Naira in steady rate against the USD. These forecasts would be helpful for policy makers to conduct a suitable monetary policy which will in turn achieve its desired objectives and higher economic activity. This may also help the policy makers in extracting useful information about the economic and financial conditions.

Nwankwo (2014) explored "Autoregressive Integrated Moving Average (ARIMA) Model for Exchange Rate (Naira to Dollar)". This objectives study to identify exchange rate model, estimate the model parameters and forecast the future. It is used to the analysis of exchange rate using ARIMA mode within the periods 1982-2011. In this paper, ARIMA (1,0,0) model can provide a better understanding of the underlying system if appropriately parameterized and effort to better understand how exchange rate can be modeled. Therefore, the government should be able to curtail or limit inflation. Increase savings and make more resources available for further productions.

Ayekple et al. (2015) explored "Time Series Analysis of the Exchange Rate of the Ghanaian Cedi to the American Dollar". The objectives of this paper to find the differences between these two models based on the out-of-sample forecast. It is used the Autoregressive Integrated Moving Average (ARIMA) and the Random walk model of predicting the dynamics of the exchange rate (using mid-rate data) of the Ghana cedi to the US dollar over a 10year 2months period from January 2004, to February 2015. The time series models considered the ARIMA model and Random walk model. And then, ARIMA (1, 2, 1) (0, 0, 2) is a suitable model. The exchange rate was estimated for the next 3 years. The exchange rate of the Ghana Cedi to the American Dollar will increase continuously for the year 2016, 2017 and 2018.

Gupta and Kashyap (2015) indicated "Box Jenkins Approach to Forecast Exchange Rate in India". The special objectives of the study are to forecast the exchange rates of Dollar, Yen Euro and GBP in terms of Indian rupee from April 2014 to March 2015 and to purpose a suitable forecasting model to forecast the exchange rates of Dollar, Yen, Euro and GBP. This paper was used the ARIMA model. The month of April 2014, the prediction for USD is 60.66, expected to rise to 61.36 in November 14 and to 61.56 in January 2015 and finally expect to be 61.75 by the end of March 2015. The forecasts for the GBP is 101.22 in August 14 and 102.57 in December 14 and future expected to increase to 102.74 in January 2015 and would probably settle to 103,08 in March 2015. The Euro is expected to be 84.53 in April 14, would probably rise to 85.24 in August 2014 and finally expected to be 86.49 in March 2015. Further analysis of the depicts that Japan Yen expend from 0.60 in April 14 to 0.62 till March 2015. These forecasts will provide government, policy makers, corporate, foreign exchange dealers etc.

Olatunji & Bello (2015) studied "A Suitable Model for the Forecast of Exchange Rate in Nigeria (Nigerian naira versus US dollar)". This objective of this paper is to analysis the modeling and forecasting of time series data the exchange rate Nigeria Naira to the US dollar using the Box Jenkins ARIMA and ARMA methodology for the monthly data collected from January 2000 to December 2012. The ARIMA (1, 1, 2) model is the optimal model for the period forecasted. The forecasts would be helpful for policy makers in Nigeria to foresee ahead of time the exchange rate, and the possible fluctuation intervals of Nigerian naira to the US dollar for future forecasted.

Mohammed & Abdulmuahymin (2016) described "Modeling the Exchange Rate Ability of Nigerian Currency (Naira) with Respect to US Dollar". This research study examined the exchange strength of Nigerian Naira with respect to US Dollar. This paper adopted time series analysis of foreign exchange rate using the ARIMA model from the period 1972 to 2014. The result revealed that the exchange rate of naira to a U.S dollar has been relatively stable from 1972 to 1985, and then a continuous upward trend from 1985 to 2014.The series was slightly stationary after 1st difference and sufficiently stationary after 2nd difference. Base on the selection criteria AIC and SIC, the best model that explains the series was found to be ARIMA (0, 2, 1). The ARIMA was selected as the best model fits the data. The forecast for period of 6 years was made, and this shows that the naira will continue to depreciate on US dollar for the period forecasted.

Ngan (2016) explored " Forecasting Foreign Exchange Rate by using ARIMA Model: A case of VND/USD exchange rate". The purpose of this paper is to evaluate the foreign exchange rate and forecasting future value. This paper uses the ARIMA model from the first day of 2013 to the last day of 2015, the next twelve months of 2016. The results show that ARIMA model is suitable for estimating foreign exchange rate in Vietnam in short-time period. The policy makers should apply ARIMA model in forecasting foreign exchange rate in Vietnam. Specially, in foreign exchange business of the commercial joint stock banks in Vietnam, the financial planners should apply ARIMA model in forecasting as well as care the results of forecasting in measuring foreign exchange rate risk in order to make more benefit for their bank. The forecasting results of our model show that foreign exchange rate VND/USD in 2016 tends to increase. Therefore the managers of the commercial joint stock banks in Vietnam should care about this result and maintain long foreign currency position in foreign exchange business.

Qonita et al. (2017) stated "Prediction of Rupiah against US Dollar by Using ARIMA". This study aims to predict the value of rupiah against US dollar. It is used to ARIMA model from January 4th 2010 until June 24th 2016.This study uses four stages, Including (1) the preparation of the dataset, (2) preprocessing of data, (3) the use of ARIMA models, (4) test accuracy**.** The rupiah against US Dollar Exchange Rate has been increasing from January 4th 2010 until June 24th 2016. The diagnostic checking has shown that ARIMA (2, 1, 2) method has an accuracy rate of 98.74%. Based on the result, the development of the predictive value of the rupiah against the US dollar using ARIMA method was accurate to use. Thus, ARIMA is a feasible method to predict the value of rupiah against the US dollar, where the results of study stated that the rupiah exchange rate against the dollar for 30 days from June 25, 2016 decreased slightly.

Nyoni (2018) described " Modeling and Forecasting Naira/ USD Exchange Rate in Nigeria: a Box Jenkins ARIMA approach". This objective of this paper is to evaluate the model and forecast the Naira / USD exchange rate over the period 1960-2017. The analysis of exchange rate uses the ARIMA model. The optimal model is the ARIMA (1, 1, 1) model. The ADF test further indicates that the residuals of the ARIMA (1, 1, 1) model are stationary and thus bear the characteristics of a white noise process. Forecast actually indicates that the Naira will continue to depreciate. The main policy implication from this study is that the Central Bank of Nigeria (CBN), should devalue the Naira in order to not only restore exchange rate stability but also encourage local manufacturing and promote foreign capital inflows. And then. The predicted Annual Naira / USD exchange rate increasing from over the period 2018 – 2022.

Nyoni and Thanban (2019) explored "An ARIMA Analysis of the Indian Rupee / USD Exchange Rate in India". The main objective of this paper is to predict the India Rupee/ USD exchange rate from 1960 to 2017.The analysis of foreign exchange rate using the Box-Jenkins ARIMA technique. The study presents the ARIMA (0, 1, 6) model, the diagnostic tests further show that this model is quite stable and hence acceptable for forecasting the Indian Rupee / USD exchange rates. The selected optimal model the ARIMA (0, 1, 6) model shows that the Indian Rupee / USD exchange rate will appreciate over the period 2018 – 2022, after which it will depreciate slightly until 2027. The main policy prescription emanating from this study is that the Reserve Bank of India (RBI) should devalue the Rupee, firstly to restore the much needed exchange rate stability, secondly to encourage local manufacturing and thirdly to promote foreign capital inflows. The predicted Indian Rupee / USD exchange rate over the period 2018 to 2027: the annual Indian Rupee / USD exchange rate is expected to fall (appreciate) over the forecasted period.

Oyenuga et al. (2019) described "Modeling the Exchange Rate of the Nigeria Naira to Some Other Major Currencies". The main aim of this paper is to model the exchange rate of Naira against four other major currencies using ARIMA model. The currencies modeled were Dollar, Pounds Sterling, Euro and Swiss Franc. The annual time series data used for the study were extracted from 2018 Central Bank of Nigeria, Statistical Bulletin between 1999 and 2017. The results show that ARIMA (1, 2, 1), ARIMA (2, 2, 1), ARIMA (2, 2, 1) and ARIMA (2, 2, 2) are appropriate for Dollar, Pound, Euro and Swiss Franz respectively based on the minimum SE, Log likelihood and AIC. The residual of the model is white noise. The optimal models are used to make forecasts from 2018 to 2021 which indicate perpetual increase in the exchange rate.

Farhan (2019) explored "Forecasting the Exchange Rates of the Iraqi Dinar against the US Dollar Using the Time Series Model (ARIMA)". This study aims to reach the best model for predicting exchange rates of Iraqi Dinar against the U.S. dollar in the period (2008-2017). For this purpose the following methods have been adopted: time-series analysis is using the Box-Jenkins approach ARIMA model. The time series model using residual and estimated values (ARIMA) (1, 1, 1) proved to be preferable to other models to predict the Iraqi dinar exchange rate against the US dollar during the study. The ARIMA (1, 1, 1) model produced the best forecasts and estimating the exchange rate of any foreign currency. Box and Jenkins model is the most flexible methods in the construction of the time series model, but it needs knowledge and skill to use the model of box and Jenkins, so may find a difference in obtaining the model between users.

Muhammad et al. (2020) described "Forecast Foreign Exchange Rate: The Case of PKR/USD". The main aim of this paper is to forecast the future values of the exchange rate of the USD. Dollar (USD) and Pakistani Rupee (PR). It is used the ARIMA model to forecast the future exchange rates from the first day of April 2014 to 31st March 2019. The results proved that ARIMA (1, 1, 9) is the most suitable model to forecast the exchange rate. The difference between the forecasted values and actual values are less than 1%; therefore, it was found that the ARIMA is robust and this model will be helpful for the government functionaries, monetary policymakers, economists and other stakeholders to identify and forecast the future trend of the exchange rate and make their policies accordingly. The effective forecasted models enable to take timely decisions regarding investments, savings, reserves and businesses, which will lessen the chances of loss due to fluctuation in the exchange rate. The forecasting of next five days is significantly less, which indicates the stability of the exchange rate in the short run from 1st April 2019 to 5th April 2019.

Joshi et al (2020) stated "Modeling Exchange Rate in India-Empirical Analysis Using ARIMA Model". The objective of this study is to analyze the suitability of ARIMA model for forecasting exchange rate in context of India with regard to rupee/dollar, rupee/euro and rupee/yen. The data is collected on monthly basis for exchange rate of rupee verses dollar for the period January 2005 to July 2017 from the Reserve Bank of India (RBI) and is referred to as Model Data in the analysis. The test data is collected on monthly basis from August 2017 to December 2019 for the exchange rate of rupee verses EURO and rupee verses YEN from the website of RBI. It is observed that ARIMA (1, 1, 5) is the most appropriate model for exchange rate forecasting which can be used for forecasting the exchange rates of Indian rupee against the various other currencies.

CHAPTER 3
METHODOLOGY

This chapter examines thoroughly the basic definitions and concepts of time series analysis, fundamental concepts, time series model , test of seasonality**,** test of stationary, correlogram, autocorrelation function (ACF), partial autocorrelation function (PACF**),** Box-Jenkins methodology, autoregressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), autoregressive integrated moving average model(ARIMA), seasonal autoregressive integrated moving average $\mathrm{SARIMA}(\mathrm{p,d,q}) \times (\mathrm{P,D,Q})_S$ model, parameter estimation, diagnostic checking and forecasting.

3.1 Time Series Analysis

A time series is an ordered sequence of observations. Although the ordering is usually through time, particularly in term of some equally spaced time intervals, the ordering may also be taken through other dimension, such as space. Many sets of data appear as time series: monthly price indices, daily closing stock prices, weekly interest rates, quarterly sales and yearly earnings are observed. Time series occur in a variety of fields. Examples of time series abound in such fields as economics, business, engineering, and so on. The list of areas in which time series is observed and studied is endless.

A time series, such as electric signals and voltage, which can be recorded continuously in time, is said to be continuous. A time series, such as interest rates, yields and volume of sales, which are taken only at specific time intervals, is said to be discrete. Discrete time series observed at equal intervals. Even continuous time series provide only digitized values at discrete intervals for computations.

There are various objectives for studying time series. These include the understanding and description of the generation of the generating mechanism, the forecasting of the future values, and optimal control of a system. The fundamental of a time series is that its observations are dependent or correlated, and the order of the observations is dependent or correlated, and the order of the observations is so important. Therefore, statistical procedures and technique that rely on independence assumption are no longer applicable, and different methods are needed. The body of statistical methodology available for analyzing time series is referred to as time series analysis.

The data of the time series can be classified as stationary and non-stationary data according to presence of absence of trend. If there is an upward or a downward trend in data, the time series is stationary. If there is no trends in data, the time series is non-stationary.

Basically time series analysis attempts to understand the underlying context of the data points through the use of a model to forecast future values based on known past values. The main focus of this study is based on MA, AR, ARMA and ARIMA.

3.2 Fundamental Concepts

A time series in general is supposed to be affected by four main components, which can be separated from the observed data. These components are secular trend, seasonal, cyclical and irregular or random components.

Trend refers to the upward or downward movement that characterizes a time series. Thus, trend is a long term movement in a time series. Thus, trend reflects the long-run growth or decline in the time series. For example, series relating to population growth, number of houses in a city etc. show upward trend, whereas downward trend can be observed in series relating to mortality rates, epidemics, etc.

Seasonal variations in a time series are fluctuations within a year during the season. The important factors causing seasonal variations are climate and weather conditions, customs and traditional habits, etc. For example, sales of ice-cream increase in summer, sales of woolen cloths increase in winter. Seasonal variation is an important factor for businessmen, shopkeeper and producers for making proper future plans.

Cycle refers to recurring up or down movements around trend levels. The duration of a cycle extends over longer period of time, usually two or more years measured from peak to peak or trough to trough. Most of the economic and financial time series show some kind of cyclical variation. For example, a business cycle consists of four phases, viz.

Irregular fluctuations component of a time series refers to irregular movements that follow no recognizable or regular pattern. Many irregular fluctuations in a time series are caused by events that cannot be forecasted such as war, strike, earthquake, flood, revolution, etc. There is no defined statistical technique for measuring random fluctuations in a time series.

3.3 Time Series Model

A time series model can be expressed as some combination of these component. Considering the effects of these four components and two different types of models are multiplicative model and additive model.

The multiplicative model is constructed by multiplying four components.

Multiplicative Model: Y(t) = T(t)× S(t)×C(t)× I (t).

The additive model is constructed by adding four components.

Additive Model: $Y(t)$ = T(t) + S(t) + C(t) + I (t)

Where, $Y(t)$ is the observation, $T(t)$ is trend value, $S(t)$ is seasonal variation, $C(t)$ is cyclical variation and $I(t)$ is irregular variation at time t.

Multiplicative model is based on the assumption that the four components of a time series are not necessarily independent and they can affect one another. Additive model: it is assumed that the four components are independent of each other.

In this studies, time series analysis applied in order to forecast the appropriate time series model for the foreign exchange rates in CLMV countries (Cambodia, Lao, Myanmar, and Vietnam). In the classical approach to time series, the analysis usually being by decomposition the time series into four components secular trend, seasonal, cyclical and irregular or random components. By isolating these components and measuring the apparent effect, it is possible to forecast future values of time series.

3.4 Test of Seasonality

In study of seasonality, seasonal variation or each month of the year is usually considered. The following model for the randomized complete block design will be used in testing seasonality in time series.

$$y_{ij} = \mu + \beta_1 + \gamma_j + e_{ij} \qquad ; 1 \leq i \leq n, 1 \leq j \leq k \tag{3.1}$$

Where y_{ij} is a typical value from the overall countries, μ= constant, β_1=a yearly effect, reflecting the fact that the experimental unit fell in the year, γ_j=a monthly effect, reflecting the fact the experimental unit received the month, e_{ij}=a residual component representing all sources of variation other than months and years.

One tests the null hypotheses that the monthly means are all equal or equivalently, which means that there are no differences in monthly effects. To analyze the data, the needed quantities are the total sum of squares (SST), the sum of squares for months (SSM), the sum of squares for years (SSY) and the error sum of square

(SSE). When the sums of squares are divided by the appropriate degree of freedom, one has the mean squares necessary for computing the F statistic. The degrees of freedom are computed as follows;

Total = Month + Years + Error

$$(nk-1) = (k-1) + (n-1) + (n-1)(k-1)$$

Where k = months, n = years

Shock-cut formulas for computing the required sum of squares are as follows

SSM = $\frac{\sum_{i=1}^{n} y_j^2}{k} - C; y_j = \sum_{j=1}^{k} y_{ij}$

SSY = $\frac{\sum_{i=1}^{n} y_i^2}{n} - C; y_i = \sum_{j=1}^{k} y_{ij}$

SSY = $\sum_{i=1}^{n} \sum_{j=1}^{k} y_{ij}^2 - C$

SSE = SST- (SSM+SSY)

Where C = $\frac{y^2}{nk}$;y = $\sum_{i=1}^{n} \sum_{j=1}^{k} y_{ij}$

The results of the calculation for the randomized complete block design are presented in the following analysis of variance (ANOVA) table.

Table 3.1 ANOVA Table for a Two-Way Analysis of Variance

Source	**S.S**	**D.F**	**M.S**	**F-Ratio**
Between Months	SSM	k-1	MSM = SSM/k-1	$F_1 = MSM/MSE$
Between years	SSY	n-1	MSY = SSY/n-1	
Error	SSE	(n-1)(k-1)	MSE = SSE/(n-1)(k-1)	
Total	SST	nk-1		

The computed ratio $F_1$with critical values $K_1 = F_{\alpha,(k-1),(n-1)(k-1)}$ is then compared. If these ratio are equal to or exceed the critical values, reject the null hypothesis**.**

3.5 Test of Stationary

Many financial time series, like exchange rate levels of stock prices appear to be non-stationary. New statistical issues arises when analyzing non-stationary data. Unit root tests are used to detect the presence and form of non-stationarity. This chapter reviews main concepts of non-stationarity of time series and provides a description of some tests for time series stationarity. There are two principal methods of detecting non-stationarity: visual inspection of the time series graph and its correlogram and formal statistical tests of unit roots. This starts with formal testing procedures first.

A non-stationaty time series is called *integrated* if it can be transformed by first differencing once or a very few times into a stationary process. The order of integration is the minimum number of times series needs to be first differenced to yield a stationary series. An integrated of order 1 time series is denoted by I(1). A stationary time series is said to be integrated of order zero, I(0).

Unit root testing is performed for establishing stationary. When performing an economic study, it is often considered that the time series are stationary. However, this may not always be the case. The variables utilized in the models specified are thus tested for stationary using the Augmented Dickey Fuller (ADF) test to ensure regression outcomes that are reliable and on-spurious, indicative of their mean and other significant statistical parameters being constant over time linear regression assumptions.

There are many tests for determining whether a series is stationary or nonstationary. The most popular tests for unit root tests are Dickey-Fuller Test, Augmented Dickey-Fuller Test and Phillips-Perrom (PP) Unit root tests.

3.5.1 Dickey-Fuller Test

There are three variations of the Dickey-Fuller test designed to take account of the role of the constant term and the trend.

(i) Dickey-Fuller Test 1 (No Constant and No Trend)

Consider the AR (1) process

$$y_t = \rho y_{t-1} + u_t \tag{3.2}$$

is stationary when $|\rho| < 1$, but, when $\rho = 1$, it becomes the nonstationary random walk process $y_t = \rho y_{t-1} + u_t$. Hence, one way to test for stationary is to examine the value of ρ. In other words, test whether ρ is equal to one or significantly less than one. Tests for this purpose are known as unit root tests for stationary.

To formalize this procedure a little more, consider again the AR (1) model:

$$y_t = \rho y_{t-1} + u_t$$

where the u_t are independent random errors with zero mean and constant variance ${\sigma_u}^2$. It can test for nonstationary by testing the null hypothsis that $\rho = 1$ against the alternative that $|\rho| < 1$, or simply $\rho<1$. This one-sided (left tail) test is put into a more convenient form by subtracting y_{t-1} from both sides of (3.2) to obtain

$$y_t - y_{t-1} = \rho y_{t-1} - y_{t-1} + u_t$$
$$\Delta y_t = (\rho - 1) y_{t-1} + u_t$$
$$= \gamma\, y_{t-1} + u_t \qquad (3.3)$$

Where $\gamma = (\rho - 1)$ and $\Delta y_t = y_t - y_{t-1}$. Then, the hypotheses can be written in terms of either ρ or γ:

H_0: ρ = 1 ↔ H_0: γ = 0

H_1: ρ < 1 ↔ H_1: γ < 0

The null hypothesis is that the series is nonstationary, If do not reject the null, conclude that is nonstationary process; if reject the null hypothesis that γ = 0, then conclude that the series is stationary.

(ii) Dickey-Fuller Test 2 (with Constant but No Trend)

The second Dickey-Fuller test includes a constant term in the test equation:

$$\Delta y_t = \alpha + \gamma\, y_{t-1} + u_t \qquad (3.4)$$

H_0: ρ = 1 ↔ H_0: γ = 0

H_1: ρ < 1 ↔ H_1: γ < 0

If do not reject the null hypothesis that γ = 0 (ρ = 1), conclude that the series is nonstationary. If reject the null hypothesis that γ = 0, conclude that the series is stationary.

(iii) Dickey-Fuller Test 3 (with Constant and with Trend)

The third Dickey-Fuller test includes a constant and a trend in the test equation:

$$\Delta y_t = \alpha + \gamma\, y_{t-1} + \lambda t + u_t \qquad (3.5)$$

H_0: ρ = 1 ↔ H_0: γ = 0

H_1: ρ < 1 ↔ H_1: γ < 0

If do not reject the null hypothesis that γ = 0 (ρ = 1), conclude that the series is nonstationary. If reject the null hypothesis that γ = 0, conclude that the series is stationary.

3.5.2 The Augmented Dickey-Fuller (ADF) Test

The Augmented Dickey-Fuller test is unit root test for stationary. This test conducted by "augmenting" the preceding three equations of DF test by adding the lagged values of the dependent variable Δy_t. The ADF test here consists of estimating the following regression.

$$\Delta y_t = \alpha + \gamma y_{t-1} + \lambda t + \sum_{i=1}^{m} \beta_i \Delta y_{t-1} + u_t \tag{3.6}$$

Where u_t is a pure white noise error term and where $\Delta y_{t-1} = (y_{t-1} - y_{t-2})$, $\Delta y_{t-2} = (y_{t-2} - y_{t-3})$, etc. The number of difference terms to include is often determined empirically, the idea being to include enough terms so that the error term in eq (3.6) is serially uncorrelated, so that it can obtain an unbiased estimate of γ, the coefficient of lagged y_{t-1}. In ADF test whether $\gamma = 0$ and the ADF test follows the same asymptotic distribution as the DF statistic, so the same critical values can be used.

3.5.3 The Phillips-Perron (PP) Unit Root Tests

An important assumption of the DF test is that the error terms u_t are independently and identically distributed. The ADF test adjusts the DF test to take care of possible serial correlation in the error terms by adding the lagged difference terms of the regressand. Phillips and Perron use nonparametric statistical methods to take care of the serial correlation in the error terms without adding lagged difference terms. Since the asymptotic distribution of the PP test is the same as the ADF test statistic.

3.6 Transforming Nonstationary Time Series to Stationary Time Series

The spurious regression problem may arise from regressing a nonstationary time series on one or more nonstationary time series, so it have to transform nonstationary time series to make them stationary. The transformation methods depends on whether the time series are difference stationary (DSP) or trend stationary (TSP).

(i) Difference-Stationary Processes

If a time series has a unit root, the first differences of such time series are stationary.

Consider a variable y_t that behaves like the random walk model

$$y_t = y_{t-1} + u_t \tag{3.7}$$

This is a nonstationary series with a "stochastic" trend, but it can be rendered stationary by taking the first difference:

$$\Delta y_t = y_t - y_{t-1} = u_t \tag{3.8}$$

The variable y_t is said to be a first difference stationary series.

(ii) Trend-Stationary Processes

A trend stationary process is stationary around the trend line. Hence, the simplest way to make such a time series stationary is to regress it on time and the residuals from this regression will then be stationary.

Consider a model with a constant term, a trend term, and a stationary error term:

$$y_t = \alpha + \delta t + u_t \tag{3.9}$$

The variable y_t is said to be trend stationary because it can be made stationary by removing the effect of the deterministic (constant and trend) components.

3.7 Correlogram

A useful aid in interpreting a set of autocorrelation coefficients is a graph called a correlogram. The correlogram is a important tool for model identification. It is very helpful in identifying which type of Autoregressive Moving Average (ARMA) model gives the best representation of observed time series. For stationary series, the correlogram is compared with the theoretical autocorrelation functions of different Autoregressive Moving Average (ARMA) processes in order to choose the one which is most appropriate.

3.7.1 Autocorrelation Function (ACF)

Autocorrelation refers to the correlation of a time series with its own past and future values. Autocorrelation is also sometimes called 'lagged correlation (or) serial correlation' which refers to the correlation between members of a series of numbers arranged in time. Positive autocorrelation might be considered a specific form of persistence a tendency for a system to remain in the same state from one observation to the next. A graph of the correlation values is called a correlogram. Ideally, to obtain a useful estimate of the autocorrelation function, at least 50 observations are needed. Generally, the estimated autocorrelation would be calculated up to lag no larger than.

The autocorrelation of a series at lag k, meaning the covariance between Z_t and Z_{t+k} is estimated

$$\gamma_k = Cov(Z_t, Z_{t+k}) = E[(Z_t - \mu)(Z_{t+k} - \mu)]$$

The stationary assumption this must be the same for all t. The autocorrelation at lag k, that is the correlation between Z_t and Z_{t+k} ,

$$\rho_k = \frac{E[(Z_t-\mu)(Z_{t+k}-\mu)]}{\sqrt{E[(Z_t-\mu)^2]E[(X_{t+k}-\mu)^2]}} = \frac{\gamma_k}{\sigma_Z^2} \tag{3.10}$$

Since for a stationary process, the variance $\sigma_z^2 = \gamma_0$ is the same at time t as at time t+ k ,

$$\rho_k = \frac{\gamma_k}{\gamma_0}$$

Implying that ρ_0=1, which corresponds with perception.

The stationary and invertible ARMA (p, q) process can be represented as an infinite moving average process:

$$Z_t = \varphi(B)a_t = \sum_{j=0}^{\infty} \varphi_j a_{t\_j}$$

An infinite autoregressive process

$$\pi(B)Z_t = Z_t - \sum_{j=0}^{\infty} \pi_j Z_{t-j} = a_t$$

Where $\varphi(B) = \emptyset^{-1}(b)\theta(B)$ and $(B) = \theta^{-1}(B)\varphi(B)$. The weights $\varphi_j$and π_j are determined from the relations $\emptyset(B)\varphi(B) = \theta(B)$ and $\theta(B)\pi(B) = \emptyset(B)$

$$\varphi_j = \emptyset_1\varphi_{j-1} + \emptyset_2\varphi_{j-2} + \cdots + \emptyset_p\varphi_{j-p} - \theta_j \quad j > 0 \tag{3.11}$$

$$\pi_j = \theta_1\pi_{j-1} + \theta_2\pi_{j-2} + \cdots + \theta_q\pi_{j-q} + \emptyset_j \quad j > 0 \tag{3.12}$$

$$\varphi_0 = 1, \pi_0 = -1 \text{ and } \theta_j = 0 \text{ for } j > q, \emptyset_j = 0 \text{ for } j > p$$

3.7.2 Partial Autocorrelation Function (PACF)

The partial autocorrelation function (PACF) gives the partial correlation of a stationary time series with its own lagged values, regressed the values of the time series at all shorter lags. It contrasts with the autocorrelation function, which does not control for other lags. The ACF is an excellent tool in identifying the order of an MA(q) process, because it is expected to "cut off" after lag *q*. However, in the previous section, the ACF is not useful in the identification of the order of an AR(p) process for which it will most likely have a mixture of exponential decay and damped sinusoid expressions. Hence the process might have an AR structure, fails to provide further information about the order of such structure. For that, define and employ the partial autocorrelation function (PACF) of the time series. But before that, discuss the concept of partial correlation to make the interpretation of the PACF easier.

Consider three random variables *X, Y,* and Z. Then consider simple linear regression of X on Z and Yon Z as

$$\hat{X} = a_1 + b_1 \quad where \ \ b_1 = \frac{cov(Z,X)}{var(Z)}$$

$$\hat{Y} = a_2 + b_2 \quad where \ \ b_2 = \frac{cov(Z,Y)}{var(Z)}$$

Then the errors can be obtained from

$$X^* = X - \hat{X} = X - (a_1 + b_1 Z)$$

$$Y^* = Y - \hat{Y} = Y - (a_2 + b_2 Z)$$

Then the partial correlation between *X* and *Y* after adjusting for Z is defined as the correlation between *X** and Y*; corr(X*, Y*) = corr(X- *X*, *Y*- Y). That is, partial correlation can be seen as the correlation between two variables after being adjusted for a common factor that may be affecting them. The generalization is of course possible by allowing for adjustment for more than just one factor.

The partial autocorrelation function between $y_t$and $y_{t-k}$is the autocorrelation between $y_t$and y_{t-k}after adjusting for $\mathrm{y_{t-1}, y_{t-2}, \cdots, y_{t-k+1}}$. Thus for an AR(p) model the partial autocorrelation function between y_t and y_{t-k} *fork* > *p* should be equal to zero. A more formal definition can be found below.

Consider a stationary time series model $\{y_t\}$ that is not necessarily an AR process. Further consider, for any fixed value of *k*, the Yule-Walker equations for the ACF of an AR(p) process given

$$\rho(j) = \sum_{i=1}^{k} \emptyset_{ik}\rho(j-i)\,,\ \ j = 1,2,\cdots,k \qquad (3.13)$$

$$\rho(1) = \emptyset_{1k} + \emptyset_{2k}\rho(1) + \cdots + \emptyset_{kk}\rho(k-1)$$

$$\rho(2) = \emptyset_{1k}\rho(1) + \emptyset_{2k} + \cdots + \emptyset_{kk}\rho(k-2)$$

$$\vdots$$

$$\rho(k) = \emptyset_{1k}\rho(k-1) + \emptyset_{2k}\rho(k-2) + \cdots + \emptyset_{kk}$$

Matrix notation as

$$\begin{bmatrix} 1 & \rho(1) & \rho(2) & \dots & \rho(k-1) \\ \rho(1) & 1 & \rho(3) & \dots & \rho(k-2) \\ \rho(2) & \rho(1) & 1 & \dots & \rho(k-3) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho(k-1) & \rho(k-2) & \rho(k-3) & \dots & 1 \end{bmatrix} \begin{bmatrix} \emptyset_{1k} \\ \emptyset_{2k} \\ \emptyset_{3k} \\ \vdots \\ \emptyset_{kk} \end{bmatrix} = \begin{bmatrix} \rho(1) \\ \rho(2) \\ \rho(3) \\ \vdots \\ \rho(k) \end{bmatrix}$$

$$P_k \emptyset_k = \rho_k$$

$$P_k = \begin{bmatrix} 1 & \rho(1) & \rho(2) & \dots & \rho(k-1) \\ \rho(1) & 1 & \rho(3) & \dots & \rho(k-2) \\ \rho(2) & \rho(1) & 1 & \dots & \rho(k-3) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho(k-1) & \rho(k-2) & \rho(k-3) & \dots & 1 \end{bmatrix}$$

$$\emptyset_k = \begin{bmatrix} \emptyset_{1k} \\ \emptyset_{2k} \\ \emptyset_{3k} \\ \vdots \\ \emptyset_{kk} \end{bmatrix} \quad \text{and} \quad \rho_k = \begin{bmatrix} \rho(1) \\ \rho(2) \\ \rho(3) \\ \vdots \\ \rho(k) \end{bmatrix}$$

Thus to solve for $\emptyset_k$,

$$\emptyset_k = \mathrm{P}_k^{-1}\rho_k \tag{3.14}$$

For any given *k*, *k* = 1, 2, ... , the last coefficient $\emptyset_{kk}$is called the partial autocorrelation of the process at lag *k*. Note that for an AR(p) process $\emptyset_{kk}$= 0 *fork* > *p*. Hence we say that the PACF cuts off after lag *p* for an AR(p). This suggests that the PACF can be used in identifying the order of an AR process is similar to how the ACF can be used for an MA process.

3.8 Box-Jenkins Methodology

The Box and Jenkins methodology used in analysis and forecasting is widely regarded to be most efficient forecasting technique and is used extensively. It involves the following steps: model identification, model estimation, model diagnostic and forecasting.

Model Identification**:** The foremost step in the process of modeling is to check for the stationary of the time series data. In model identification, the historical data are used to uncertain identify an appropriate Box-Jenkins model. The time plot of the series are looked and compute many important statistics of the data, such as the sample autocorrelation function and the partial autocorrelation function to tentatively choose a model. Parameter estimation consists of finding the best possible estimates for the parameters of the tentatively identified model. These parameters are estimated so that the overall error is reduced. In this stage, methods of estimation such as the method of movements, least-squares estimators and maximum likelihood estimators are considered to estimate the parameters.

The diagnostic checking of model is adequacy. In this last step, various diagnostics such as the method of autocorrelation of the residuals and the Ljung-Box-Piece statistic are used to check the adequacy of the tentatively identification model. If the model is found to be inappropriate, model identification and cycle through the steps until would be returned, ideally, an acceptable model is found. Once a final model is obtained, it can be used to forecast future time series values. The diagnostic statistics and plots of residuals can be used to assess the adequacy of future values to our data.

Box–Jenkins methodology requires that the model to be used in describing and forecasting a time series to be both stationary and invertible. Thus, in order to tentatively identify a Box-Jenkins model, the time series must be determined and forecast is stationary. If it is not, the time series must be transformed into a series of stationary time series values through the process of differencing. A time series is said to be stationary (second-order stationary) if the statistical properties such as the mean (first moment) and the variance (second moment) of the time series are essentially constant through time. From the plot of the time series values, if the observed values of a time series seem to fluctuate with constant variation around a constant mean, then it is reasonable to believe that the time series is stationary, otherwise, it is said to be non-stationary.

3.8.1 Autoregressive (AR) Model

An autoregressive model is simply a linear regression of the current value of the series against one or more prior values of the series. The value of p is called the order of the AR model. AR model can be analyzed with one of various methods, including standard linear least squares techniques.

Stochastic model that can be extremely useful in the representation of certain practically occurring series is the autoregressive model. In the model, the current value of the process is expressed as a finite, linear aggregate of previous values of the process and a shock $\mathrm{a_t}$.

AR (1) process is $x_t = \emptyset x_{t-1} + a_t$

In lag-operator notation, this process is$(1 - \emptyset B)X_t = a_t$ and the characteristic polynomial is $\emptyset(B) = (1 - \emptyset B)$. If $\emptyset(B) = (1 - \emptyset B) = 0$, the only characteristic root is $\beta = \frac{1}{\emptyset}(assuming\ \emptyset \neq 0)$. The AR(1) process is stationary if only if $|\emptyset| < 1$or -1<$\emptyset < 1$.

AR(2) process is $X_t = \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + a_t$

The AR (2) is stationary if only if $\|\alpha_1\| < 1 \quad \|\alpha_2\|$

AR(p) model is written as

$$x_t = \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \cdots \emptyset_p x_{t-p} + a_t \tag{3.15}$$

Where a_t is a white noise sequence with zero mean and some variance σ^2. For assume that $a_t \sim N(o, q)$.

3.8.2 Moving Average (MA) Model

A second type of Box-Jenkins model is called a moving average model. Although these models look very similar to the AR model, the concept behind them is quite different. Moving average parameters relate what happens in period t only to the random errors that occurred in past time periods.

The first order moving average model, denoted by MA (1)

$$x_t = \mu + a_t + \theta_1 a_{t-1}$$

The second order moving average model, denoted by MA (2)

$$x_t = \mu + a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2}$$

A common representation of a moving average model where it depends on a q of its past values is called MA(q) model and represented below

$$x_t = \mu + a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + + \cdots + \theta_q a_{t-q} \quad (3.16)$$

The error terms are assumed to be white noise process with mean zero and variance. A moving average model is conceptually a linear regression of the current value of the series against current and previous white noise error terms. The random shocks at each point are assumed to be mutually independent and to come from the same distribution, typically a normal distribution with location at zero and constant scale.

3.8.3 Autoregressive Moving Average (ARMA) Model

Autoregressive and Moving Average processes can be combined to obtain a very flexible class of univariate processes (proposed by Box and Jenkins), known as ARMA processes.

ARMA(p,q) models have a rich history in the time series literature, but they are not nearly a common in ecology as plain AR(p) models. Both the ACF and PACF are important tools when it is trying to identify the appropriate order of p and q. ARMA (p,q) as a mixture of AR(p) and MA (q) models, such that

$$x_t = \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \cdots + \emptyset_p x_{t-p} + a_t + \theta a_{t-1} + \theta_2 a_{t-2} + \cdots + \theta_q a_{t-q} \quad (3.17)$$

and the a_t are white noise.

Both the AR (p) and MA (q) are special cases of the ARMA model. An ARMA (p, 0) process is the same as an AR (p) process and an ARMA (0, q) process is the same as an MA (q) process. If the available data is stationary, it is better modeled using an ARMA (p, q) model than AR (p) or MA (q) models individually (Chin and Fan, 2005).

This is because an ARMA (p, q) model in such as case uses fewer parameters than the individual models and gives a better representation of the data and this is reffered to as the principle of parsimony (Singh, 2002; Woodward et al., 2011). Adhikari and Agrawal (2013) and Waeto et al., (2017) argued that ARMA(p,q) model is just but a theoretical model which is only used for stationary time series variables. Adhikari and Agrawal (2013) argued that most variables in socio-economic and business are non-stationary thus the ARMA(p,q) model has to be generalized into ARIMA (p,d,q) which caters for the integral process of differencing a non-stationary process to become stationary.

3.8.4 Autoregressive Integrated Moving Average (ARIMA) model

ARIMA model is one method for forecasting time series, it is assumed that past value of the series plus previous error terms contain information for the purpose of forecasting. This model was showed in publish by Box and Jenkins in 1970.

An ARIMA model is labeled as an ARIMA model (p,d,q) where, p is the number of autoregressive terms, d is the number of differences and q is the number of moving averages. The ARIMA model formulation includes four steps:

(i) Identification of the ARIMA (p,d,q) structure. Use autocorrelation function (ACF) and partial autocorrelation function (PACF) to develop the rough function.

(ii) Estimation of the unknown model parameter.

(iii) Diagnostic checks are applied with the object of uncovering possible lack of fit and diagnosing the cause.

(iv) Forecasting from the selection model.

Auto Regressive Integrated Moving Average (ARIMA) models describe the current behavior of variables in terms of linear relationships with their past values. These models are also called Box-Jenkins models on the basis of these authors' pioneering work regarding time-series forecasting techniques. An ARIMA model can be decomposed in two parts. First, it has an Integrated (I) component (d), which represents the amount of differencing to be performed on the series to make it stationary. The second component of an ARIMA consists of an ARMA model for the series rendered stationary through differentiation. The ARMA component is further decomposed into AR and MA components. The autoregressive (AR) component captures the correlation between the current value of the time series and some of its past values. The Moving Average (MA) component represents the duration of the influence of a random (unexplained) shock.

Researchers approve that the estimation of parameters requires a large number of observations. Consequently, there are some limits for using ARIMA model. Nevertheless, once we apply ARIMA model, we reach a high quality in the opposite of the time series models.

If d is a non-negative integer, then (Z_t) is a said to be an ARIMA (p,d,q) process if ($Y_t = (1-B)^d Z_t$) is a causal ARMA (p,q) process. This means that the process (Z_t) satisfies a difference equation of the from

$$\emptyset^*(B)Z_t = \emptyset(B)(1-B)^d Z_t = \theta(B)a_t \qquad \{a_t\} \sim N(0, \delta^2)$$

Where $\emptyset(Z)$ and $\theta(Z)$ are polynomials of degree p and q respectively. Also $\emptyset(Z) \neq 0$ for $|z| \leq 1$ and $\emptyset^*(z)$ has a zero of order d at z = 1, since the corresponding ARMA process is stationary if the roots of $\emptyset(B) = 0$ lie outside the unit circle, and exhibits explosive non-stationary behavior if the roots lie inside the unit circle.

The process (Z_t) is stationary if and only if d = 0, which reduces to an ARMA (p,q) process. The model can be written as

$$\theta(B)\nabla^d Z_t = \theta(B)a_t$$

Or equivalently defined by these two equations

$$\emptyset(B)w_t = \theta(B)a_t$$

$$w_t = \nabla^d Z_t \tag{3.18}$$

These processes can be represented by a stationary, invertible ARIMA process on the difference of the series. For inverting equation (3.18)

$$Z_t = S^d w_t \tag{3.19}$$

Thus

$$Sx_1 = \sum_{h=-\infty}^{t} x_h = (1 + B + B^2 + \cdots)x_1$$

$$= (1-B)^{-1}x_1$$

$$= \nabla^{-1}x_1$$

$$S = (1-B)^{-1} = \nabla^{-1}$$

The operator S^2 is similarly defined as

$$S^2 x_t = Sx_t + Sx_{t-1} + Sx_{t-2} + \cdots$$

$$= \sum_{t=-\infty}^{t} \sum_{h=-\infty}^{t} x_h$$

$$= (1 + 2B + 3B^2 + \cdots)x_t$$

Since the infinite summation operator S = $(1-B)^{-1}$ does not coverage it cannot be used to define the non-stationary ARIMA process. Instead, consider the finite operator S_m, for any positive integer m,

$$S_m = (1 + B + B^2 + \cdots + B^{m-1}) = \frac{1 - B^m}{1 - B}$$

Similary,

$$S_m^{(2)} = \sum_{j=0}^{m-1} \sum_{i=j}^{m-1} B^i$$

$$= (1 + 2B + 3B^2 + \cdots + mB^{m-1})$$

$$= \frac{1 - B^m - mB^m(1-B)}{(1-B)^2}$$

the $(1-B)S_m^{(2)} = S_m - mB^m$, and so on.

Then the relation between X_t and w_t in terms of values back to some origin k< t can be expressed as

$$X_t = \frac{S_{t-k}}{1 - B^{t-k}} w_t = \frac{1}{1 - B^{t-k}} (w_t + w_{t-1} + \cdots + w_{k+1})$$

So that $X_t = w_t + w_{t-1} + \cdots + w_{k+1} + X_k$ can be thought of as sum of a finite number of terms from the stationary process plus an original value of the process X at time k.

In the general form of the ARIMA model, a constant term is added

$$\emptyset(B)\nabla^d Z_t = \theta_0 + \theta(B)a_t \tag{3.20}$$

$$\emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots \emptyset_p B^p$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots \theta_q B^q$$

$\theta(B)$ is called the autoregressive operator; assumed to be stationary.

$\emptyset(B)\nabla^d$ is called the generalized autoregressive operator; non- stationary operator with d of the roots equal to unity.

$\theta(B)$ is called moving average operator; assumed to be invertible.

In allowing the constant term θ_0 to be nonzero, the ARIMA process is capable of showing deterministic polynomial trend, of degree d. Since

$$E[w_t] = E[\nabla^d Z_t] = \mu_w = \frac{\theta_0}{1 - \emptyset_1 - \emptyset_2 - \cdots - \emptyset_p}$$

For example, when d =1 a nonzero θ_0 allows for estimation of possible deterministic linear trend.

3.8.5 Seasonal Autoregressive Integrated Moving Average, SARIMA$(\mathbf{p}, \mathbf{d}, \mathbf{q}) \times (\mathbf{P}, \mathbf{D}, \mathbf{Q})_s$ Model

The ARIMA model is for non-seasonal and non-stationary data. Box and Jenkins have generalized this model to deal with seasonality. The theoretical justification for modeling univariate time series of traffic flow data as seasonal ARIMA processes is founded in the time series theorem known as the world decomposition. Therefore, it is also necessary to support an assertion that an appropriate seasonal difference will induce stationarity.

The generalized form of SARIMA $(\mathrm{p}, \mathrm{d}, \mathrm{q}) \times (\mathrm{P}, \mathrm{D}, \mathrm{Q})_s$model can be written as:

$$\emptyset_{\mathrm{p}}(\mathrm{B})\Phi_{\mathrm{P}}(\mathrm{B}^{\mathrm{s}})(1-\mathrm{B})^{\mathrm{d}}(1-\mathrm{B}^{\mathrm{s}})^{\mathrm{D}}\mathrm{Z}_{\mathrm{t}} = \theta_0 + \theta_{\mathrm{q}}(\mathrm{B}\,)\Theta_{\mathrm{Q}}(\mathrm{B}^{\mathrm{s}})\mathrm{a}_{\mathrm{t}} \qquad (3.21)$$

Where:

$$\emptyset_{\mathrm{p}}(\mathrm{B}) = 1 - \emptyset_1\mathrm{B} - \emptyset_2\mathrm{B}^2 - \cdots - \emptyset_{\mathrm{p}}\mathrm{B}^{\mathrm{p}}$$

$$\Phi_{\mathrm{P}}(\mathrm{B}^{\mathrm{s}}) = 1 - \Phi_1\mathrm{B}^{\mathrm{s}} - \Phi_2\mathrm{B}^{2\mathrm{s}} - \cdots - \Phi_{\mathrm{p}}\mathrm{B}^{\mathrm{ps}}$$

$$\theta_{\mathrm{q}}(\mathrm{B}) = 1 - \theta_1\mathrm{B} - \theta_2\mathrm{B}^2 - \cdots - \theta_{\mathrm{q}}\mathrm{B}^{\mathrm{q}}$$

$$\Theta_{\mathrm{Q}}(\mathrm{B}^{\mathrm{s}}) = 1 - \Theta_1\mathrm{B}^{\mathrm{s}} - \Theta_2\mathrm{B}^{2\mathrm{s}} - \cdots - \Theta_{\mathrm{Q}}\mathrm{B}^{\mathrm{Qs}}$$

Where;

$\mathrm{p}, \mathrm{d}, and$ q are the order of non-seasonal AR, differencing and MA respectively.

$\mathrm{P}, \mathrm{D}, and$ Q are the order of seasonal AR, differencing and MA respectively.

Z_{t} represents time series data at period t.

B represents backshift operator defined by $\mathrm{BZ}_{\mathrm{t}} = \mathrm{Z}_{\mathrm{t}-1}$.

$(1-\mathrm{B})^{\mathrm{d}}$ represents non-seasonal difference.

$(1-\mathrm{B}^{\mathrm{s}})^{\mathrm{d}}$ represents seasonal difference.

s represent seasonal order (s = 12 for monthly data)

a_{t} represents white noise process at period t. It is identically and normally distributed with mean zero, variance σ^2; and $\mathrm{cov}\,(\mathrm{e}_{\mathrm{t}}, \mathrm{e}_{\mathrm{t}-\mathrm{k}}) = 0 \forall \mathrm{k} \neq 0$, that is, $\{\mathrm{e}_{\mathrm{t}}\} \sim \mathrm{WN}\,(0, \sigma^2)$.

From a practical perspective, fitted seasonal ARIMA models provide linear state transition equations that can be applied recursively to produce single and multiple interval forecasts.

3.8.6 Parameter Estimation

Estimation the parameters in the model most common methods use maximum likelihood estimation. Let N = n + d original observations of a time series. Where d is the degree of differentiating in the ARIMA model. Then the generated series w of n differences $w_1, w_2, \cdots, w_n, w = \nabla^d Z_t$.

Transforms the problem from fitting the parameters $\emptyset$ and θ of the ARIMA model to fitting the same parameters to the in a stationary invertible ARMA (p,q) model, written as

$$a_t = \widetilde{w_t} - \emptyset_1 \widetilde{w_{t-1}} - \emptyset_2 \widetilde{w_{t-2}} - \cdots - \emptyset_p \widetilde{w_{t-p}} + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \cdots + \theta_q a_{t-q}, \quad (3.22)$$

Where $\widetilde{w_t} = w_t - \mu$ with $E[w_t] = \mu$. μ can be estimated by $\overline{w} = \sum_{t-1}^{n} w_t / n$ or if the sample size is not big enough may be includes as an additional parameter o be estimated. Because of the difficulty if starting up the difference equation (3.22) p starting values for the $w's, w_*$ and q starting for the $a's, a_*$ must be given, thus the conditional maximum likelihood estimate.

Assuming that the $a's$ in (3.22) are normally distributed, their probability density is

$$p(a_1, a_2, \cdots a_n) \alpha \sigma_s^{-n} exp\left[-\left(\sum_{t=1}^{n} \frac{a_t^2}{2a_a^2}\right)\right]$$

then the log-likelihood associated with the parameter values the parameter values $(\emptyset, \theta, \sigma_a)$ conditional on the choice of (w_*, a_*) would be

$$l_*(\emptyset, \theta, \sigma_a) = -n \ln(\sigma_a) - \frac{S_*(\emptyset, \theta)}{2\sigma_a^2},$$

The sum of squares function

$$S_*(\emptyset, \theta) = \sum_{t=1}^{n} a_t^2 (\emptyset, \theta / w_*, a_*, w).$$

.

3.8.7 Diagnostic Checking

Time series model building is an iterative process. It establish with model identification and parameter estimation. After parameter estimation, one have to assess model adequacy by checking whether the model assumptions are satisfied. The basic assumption is that the $\{a_t\}$ are white noise. The a_t's are uncorrelated random shocks with zero mean and constant variance. For any estimated model, the residuals a_t's are estimates of these unobserved white noise a_t's. Thus, model diagnostic checking is accomplished through a careful wary analysis of the residual series $\{\widehat{a_t}\}$. Because this residual series is the product of parameter estimation, the model diagnostic checking is usually contained in the estimation phase of a time series package.

(i) To check whether the errors are normally distributed, one can build a histogram of the standardized residuals $\frac{\widehat{a_t}}{\widehat{\sigma_a}}$ an compare it with the standard normal distribution using the chi-square of fit test.

(ii) To check whether the variance is constant, one can examine the plot of residuals.

(iii) To check whether the residuals are approximately white noise,

After tentative model has been fitted to the data, it is important to perform diagnostic checks to test the adequacy of the model. One way to accomplish this is through the analysis of residuals. It has been found that it is effective to measure the overall adequacy of the chosen model by examining a quantity Q known as Box-Pierce statistics (a function of autocorrelations of residuals) whose approximate distribution is chi-square and is computed as follows $Q = n\sum r^2\,(j)$ whose abstract extends from 1 to k with k as the maximum lag considered, n is the number of observations in the series, $\gamma(j)$ is the estimated autocorrelation at lag j:k can be any positive integer and is usually around 20. Q follows chi-square with $(k - m_1)$ degrees of freedom where m1 is the number of parameters estimated in the model. A modified Q statistic is the Ljung-Box statistic which is given by

$$Q = n(n+1)\sum \frac{\gamma^2(j)}{(n-j)} \tag{3.23}$$

The Q statistics is compared to critical value from chi-square distribution. If model is correctly specified, residuals should be uncorrected and Q should be small. A significant value that the chosen model does not fit well. Having chosen a particular ARIMA model and having estimated its parameters, the next step is to check whether the chosen model fit the data reasonably well, as it is possible that another ARIMA model might do the job well.

3.8.8 Forecasting

This section is an excerpt from Box, Jenkins and Reinsel. Forecasting $l, l \geq 1$ time steps into the future when standing at time t will be represented by $Z_{\text{t+1}}$. That is said to be an forecast at origin for lead-time l. The generalized ARIMA process will be represented as an infinite weighted sum of current and previous shocks

$$Z_{t+1} = \sum_{j=0}^{\infty} \varphi_j a_{t+1-j,} \tag{3.24}$$

where φ_0 =1 and the weights may be obtained by

$$\emptyset(B)(1+\varphi_1 B+\varphi_2 B^2+\cdots)=\theta(B).$$

The forecast of $Z_{t+1}$is denoted $\hat{Z}_t(l)$. Suppose the best forecast is

$$\hat{Z}_t(l)=\varphi_l^* a_t+\varphi_{l+1}^* a_{t-1}+\varphi_{l+2}^* a_{t-2}+\cdots$$

where $\varphi_l^*, \varphi_{l+1}^*, \varphi_{l+2}^*+\cdots$ are to be determined. The mean square error of the forecast is

$$E\left[Z_{t+1}-\widehat{Z}_t(l)\right]^2=(1+\varphi_1^2+\cdots+\varphi_{l-1}^2)\sigma_a^2+\sum_{j=0}^{\infty}\left(\varphi_{l+j}-\varphi_{l+j}^2\right)^2\sigma_a^2,$$

which is then minimized by $\varphi_{l+j}^*=\varphi_{l+j}$. Then

$$\begin{aligned}Z_{t+1}&=(a_{t+1}+\varphi_1 a_{t+l-1}+\cdots+\varphi_{l-1}a_{t+1})+(\varphi_1 a_t+\varphi_{l+1}a_{t-1}+\cdots)\\&=e_t(l)+\widehat{Z}_t(l),\end{aligned}$$

where $e_t(l)$ is the error function of the forecast $\widehat{Z}_t(l)$at lead time *l*. Assuming that the $\{a_t\}$are a sequence of independent random variables an thus E$E\left[a_{t+j}\middle|Z_{t,}Z_{t-j,}\cdots\right]=0$ for j > o a few conclusion are made:

1. $\widehat{Z}_t(l)=\varphi_1 a_t+\varphi_{l+1}a_{t-1}+\cdots=E[Z_{t+l}]$.

Thus the minimum mean square error forecast at origin *t*, for lead-time *l*, is the conditional expectation of Z_{t+1} at time t.

2. Since $\left[e_t(l)|Z_{t,}Z_{t-1,}\cdots\right]=0$,

The forecast is unbiased. Also the variance of the forecast error is

$$V(l)=\text{Var}\left(e_t(l)\right)=(1+\varphi_1^2+\varphi_2^2+\cdots+\varphi_{l-1}^2)\sigma_a^2.$$

3. The one-step-ahead forecast error is

$$e_1(l)=Z_{t+1}-\widehat{Z}_t(1)=a_{t+1}$$

In conclusion, denoting $E\left[Z_{t+l}|Z_{t,}t-1,\cdots\right]$ as $[Z_{t+1}]$and $E\left[\mathrm{a}_{t+1}|Z_{t,}Z_{t-1,}\cdots\right]$as $[a_{t+1}]$, the forecast for origin *t* with time *l* is

$$[Z_{t+1}]=\widehat{Z}_t(l)=[a_{t+1}]+\varphi_1 a_{t+l-1}+\cdots,$$

and on form one are used to

$$\begin{aligned}[Z_{t+1}]=\widehat{Z}_t(l)=\emptyset_1[Z_{t+l-1}]+\cdots+\emptyset_{p+d}\left[Z_{t+l-p-q}\right]-\theta_1[a_{t+l-1}]-\cdots-\\\theta_q\left[a_{t+l-q}\right]+[a_{t+l}]\end{aligned}$$

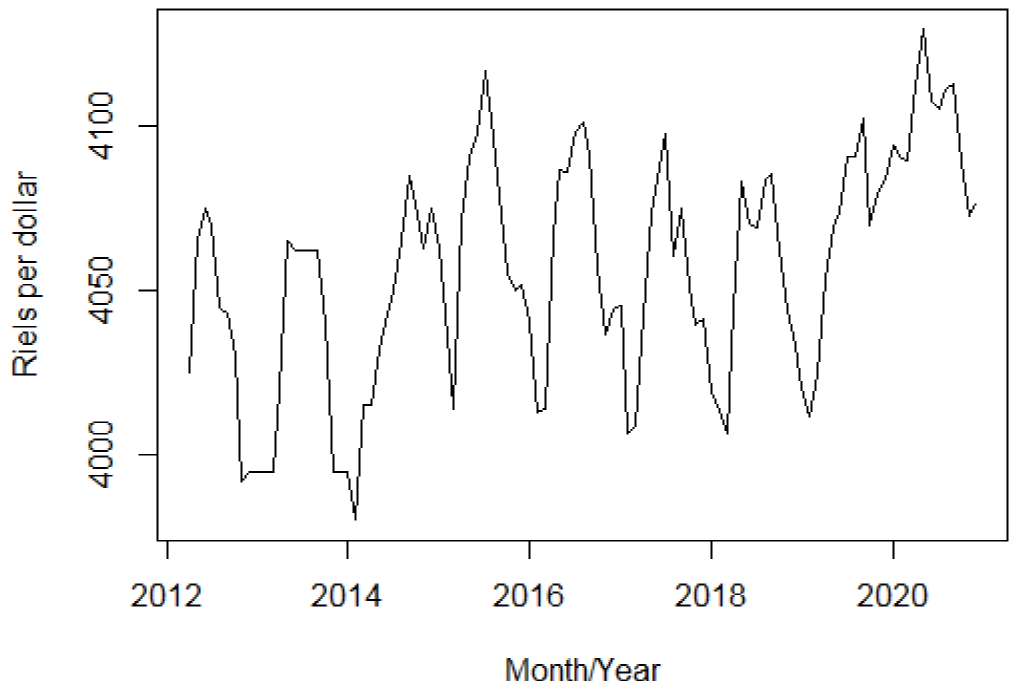
CHAPTER 4

ANALYSIS OF FOREIGN EXCHANGE RATE IN CLMV COUNTRIES

This chapter presents monthly data exchange rate, model identification, estimation of model parameters, model adequacy (diagnostic) checking of estimated models and forecasting in Cambodia, Lao, Myanmar and Vietnam (CLMV) countries.

4.1 Exchange Rate in Cambodia

The exchange rate series Cambodia for the period from April, 2012 to December, 2020 is showed in Figure 4.1. The historical currency exchange rates from April 2012 to December 2020 provided by the International Financial Statistics (IFS) were used.



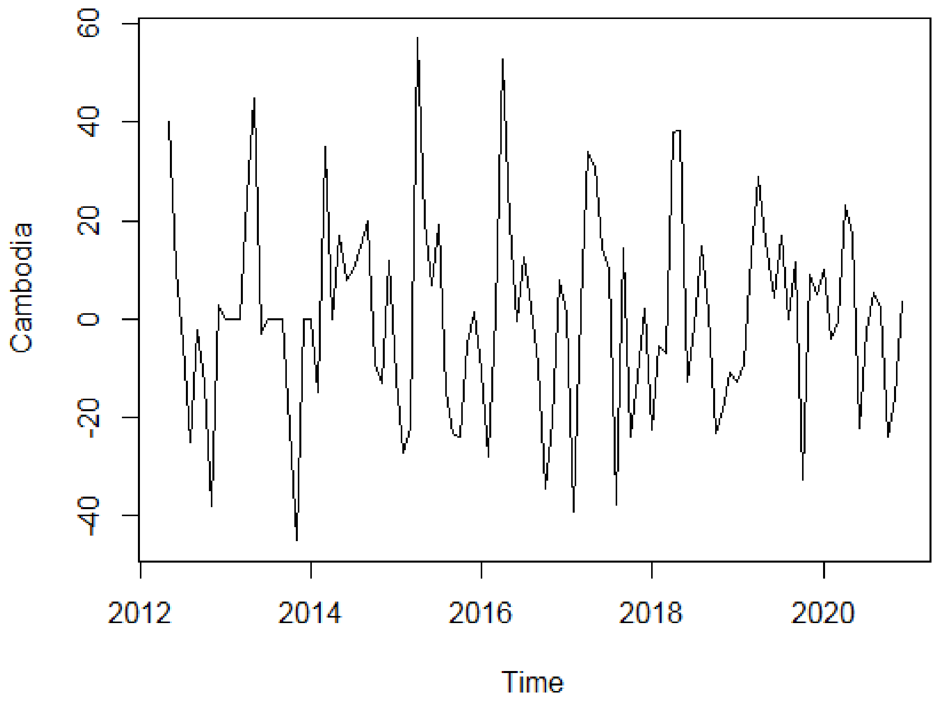
Source: International Financial Statistics (IFS)

Figure 4.1 Monthly Exchange Rate in Cambodia

It is quite obvious there exists seasonality in the exchange rate in Cambodia. The series is a seasonal pattern with peaks and valleys in the same months of the year. Moreover, the seasonal pattern is superimposed on the increasing global trend and it can be said that the series is non-stationary. These series can be reduced to be stationary series by proper transformations.

4.1.1 Model Identification

First stage of ARIMA model building is to identify whether the variable, which is being forecasted, is stationary in time series or not. By stationary it mean, the values of variable over time varies around a constant mean and variance. The time plot of the exchange rate data in figure 4.1 is clearly showed that the data is not stationary (actually, it shows an increasing trend in time series). The ARIMA model cannot be built until this series stationary is made. The first stage is difference of the time series 'd' times to obtain a stationary series in order to have an ARIMA(p,d,q) model with 'd' as the order of differencing used. The best idea is to start difference with lowest order (of first order, d =1) and test the data for unit root problems. So figure 4.2 below is the line plot of the first order differencing exchange rate in Cambodia.



Source: International Financial Statistics (IFS)

Figure 4.2 Exchange Rate Data of First Order Differencing (d = 1)

It can easily be inferred from the above graph that the time series appears to be stationary both its mean and variance. But before moving further, it will be first test the differencing time series data for stationary (unit root problem) using Augmented Dickey-Fuller test.

(i) Test for Stationarity: Augmented Dickey-Fuller (ADF) Test

In this study, the foreign exchange rate in Cambodia is whether stationary or nonstationary to be determined. In order to determine whether the foreign exchange rate contain unit roots, this study employs tests devised by Augmented Dickey-Fuller (ADF). The table 4.1 shows the results of ADF unit root test.

Table 4.1 The Results of Unit Root Test for Foreign Exchange Rate in Cambodia

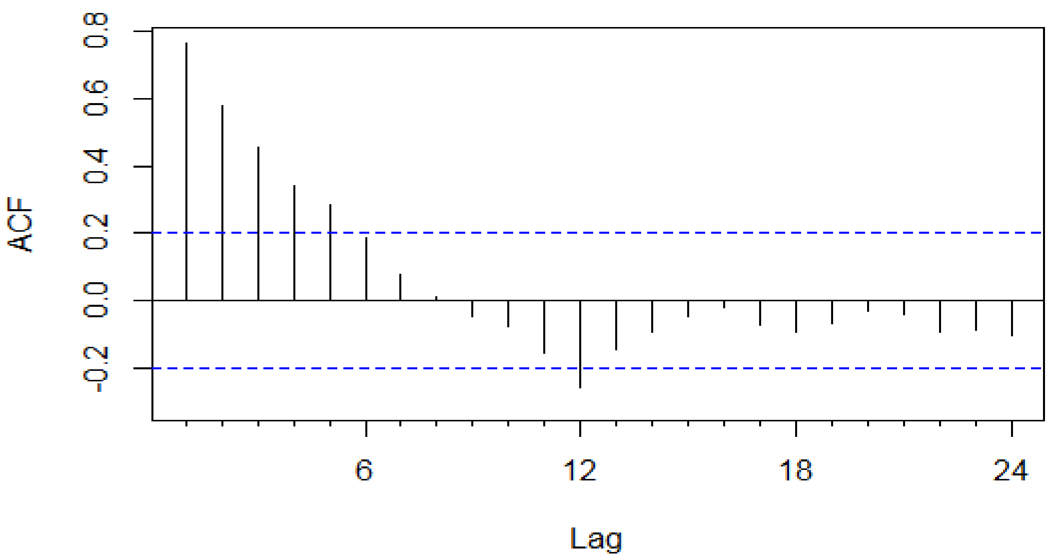
	Dickey-Fuller	Lag order	p-value
Level	-2.8493	7	0.2245
First Difference	-6.4151	7	0.01

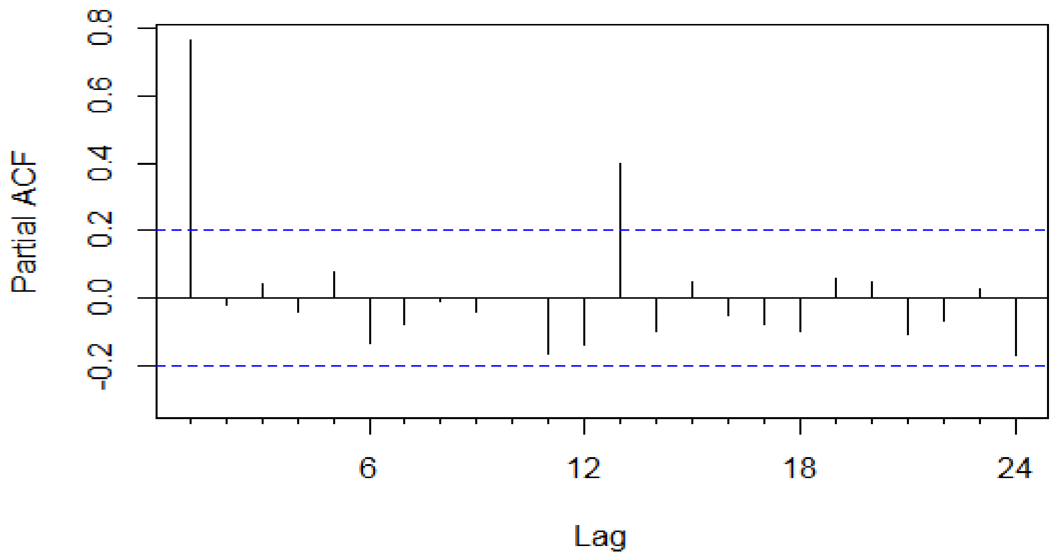
Source: International Financial Statistics (IFS)

According to the above table, the foreign exchange rate is not stationary at the 5% level of significance. The ADF test statistic is -2.8493 with associated significance of 0.2245 which is greater than 0.05. Thus, the null hypothesis is failed to reject and conclude that the time series data is not stationary at the level. Therefore, to make the variable stationary was difference once and the result of ADF presented above table shows that at 5 % level of significance, foreign exchange rate is found to be stationary at first difference and it can also conclude that foreign exchange rate in Cambodia is stationary with integrated of order 1.

(ii) Correlogram and Partial Correlogram

The Figure 4.3 below represents the plot of correlogram (auto-correlation function, ACF) for lags 1 to 24 of the seasonal first order difference time series of the exchange rate in Cambodia.





Source: International Financial Statistics (IFS)

Figure 4.3 ACF and PACF for Seasonal First Difference Series of Monthly Exchange Rate Series in Cambodia

In the plots of the seasonally difference data, there are spikes in the PACF at lags 12 and 24, but nothing at seasonal lags in the ACF. This may be suggestive of a seasonal AR(2) term. In the non-seasonal lags, there are three significant spikes in the PACF, suggesting a possible AR(1) term. The pattern in the ACF is not indicative of any simple model. Consequently, this initial analysis suggests that a possible model for these data is an ARIMA$(1,0,0)(2,1,0)_{12}$. In addition, when calculating after using auto.arima function from R software, ARIMA$(1,0,0)(2,1,0)_{12}$ was found to be the most suitable model.

4.1.2 Parameter Estimation for Multiplicative Seasonal ARIMA $(\mathbf{1,0,0})(\mathbf{2,1,0})_{\mathbf{12}}$ Model

Using multiplicative seasonal ARIMA $(1,0,0)(2,1,0)_{12}$ model, the estimated parameters with their statistics were shown in Table 4.2.

Table 4.2 Estimated Parameters and Model Statistics for Seasonal ARIMA $(1,0,0)(2,1,0)_{12}$ Model of Exchange Rate in Cambodia

	Estimate	SE	t
Constant	0.633	0.369	1.7154
ar1	0.8175	0.0593	13.7858
sar1	-0.6405	0.1038	-6.1705
sar2	-0.2862	0.1174	-2.4378

Source: International Financial Statistics (IFS)

The theoretical form of the SARIMA $(1,0,0)(2,1,0)_{12}$ model is given by

$$(1 - \emptyset_1 B)(1 - \Phi_1 B^{12} - \Phi_2 B^{24})(1 - B^{12})\mathrm{y_t} = a_t$$

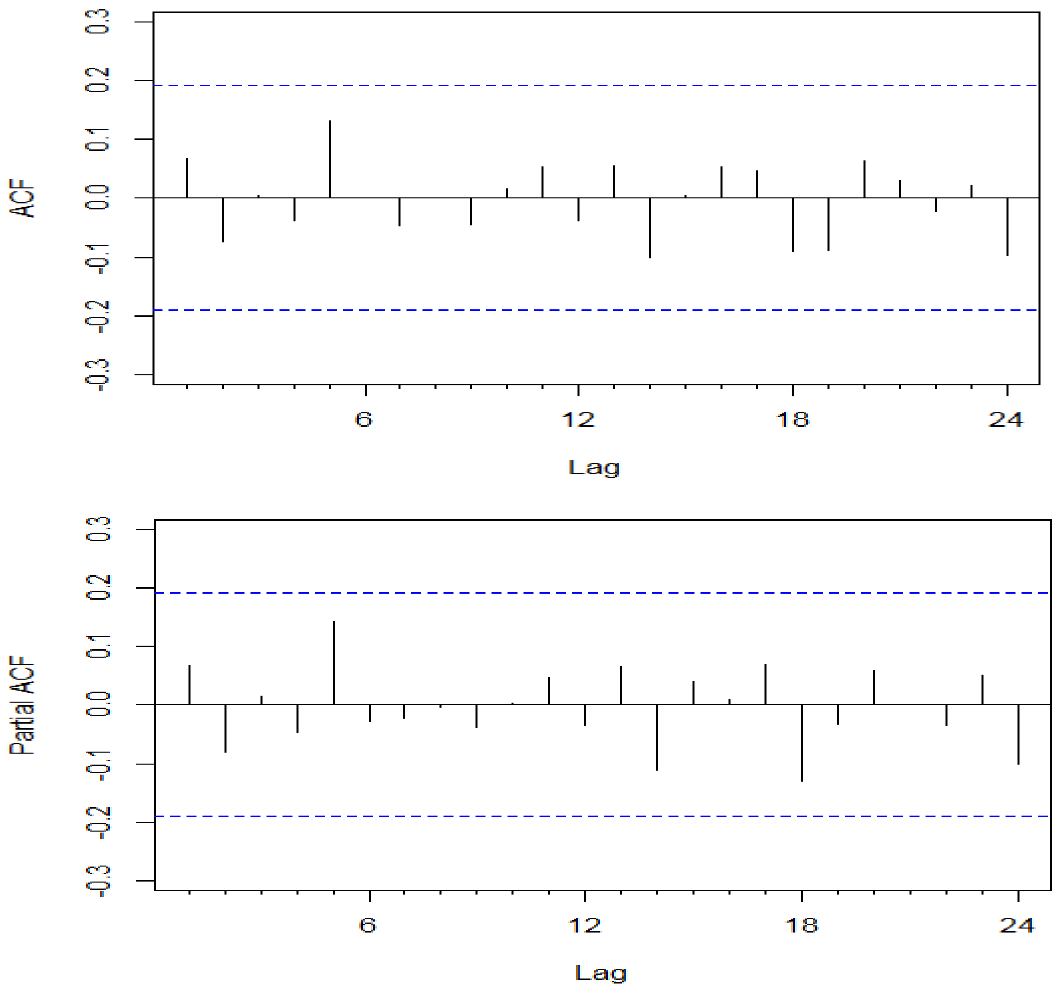
and the estimated model is

$$(1 - 0.8175B)(1 + 0.6405B^{12} - 0.2862B^{24})(1 - B^{12})\mathrm{y_t} = a_t$$

The estimates of autoregressive and the seasonal autoregressive parameters are labeled $\emptyset_1$, Φ_1 and Φ_2, which are 0.8175, -0.6405, and -0.2862, respectively. Based on 95% confidence level, it can be concluded that all the coefficients of the ARIMA (1, 0, 0) (2, 1, 0)$_{12}$ model are significantly different from zero as shown in Table 4.2.

4.1.3 Model Adequacy (Diagnostic) Checking of Estimated Models

To check model adequacy, the Figure 4.4 shows the residual ACF and PACF of the modified model.



Source: International Financial Statistics (IFS)

Figure 4.4 Estimated ACF and PACF of Residual Values for Seasonal ARIMA(1,0,0)(2,1,0)$_{12}$ Model of Exchange Rate in Cambodia

Values of the residual ACF of seasonal ARIMA $(1,0,0)(2,1,0)_{12}$ are all small and no patterns. And, the values of residual PACF of modified model lie inside the confidence limits. This suggested that this model is adequate. Hence, the autocorrelation of $\hat{a}_t$can be taken as significant different from zero.

4.1.4 Forecasting for Monthly Exchange Rate Series in Cambodia

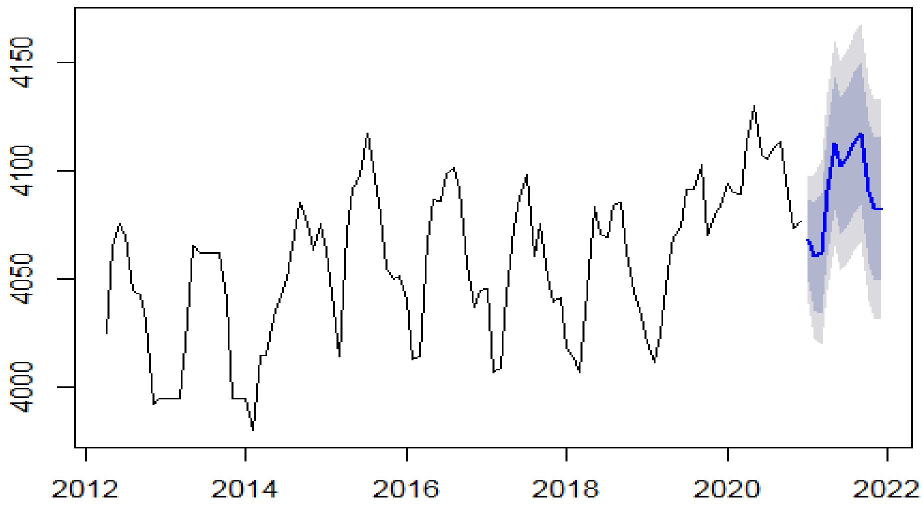
After the empirical examination the most appropriate models for exchange rate in Cambodia were determined. The best fitting model for exchange rate from January 2021 to December 2021 were examined for their forecast performance. The results of forecast by using seasonal ARIMA $(1,0,0)(2,1,0)_{12}$ for exchange rate in Cambodia were shown in Table 4.3 and Figure 4.5.

Table 4.3 Results of Forecast by Using Seasonal ARIMA$(1,0,0)(2,1,0)_{12}$ Model for Exchange Rate in Cambodia

Month-Year	Forecast	Lo 95	Hi 95
Jan - 2021	4067.751	4038.552	4096.949
Feb - 2021	4060.342	4022.629	4098.056
Mar - 2021	4061.778	4019.315	4104.241
Apr - 2021	4090.389	4045.028	4135.749
May- 2021	4112.527	4065.328	4159.725
Jun - 2021	4102.095	4053.707	4150.482
Jul - 2021	4106.529	4057.362	4155.695
Aug - 2021	4112.438	4062.758	4162.118
Sep - 2021	4117.366	4067.346	4167.386
Oct - 2021	4090.399	4040.153	4140.646
Nov - 2021	4082.345	4031.948	4132.742
Dec - 2021	4082.066	4031.568	4132.563

Source: International Financial Statistics (IFS)

The forecast values from January 2021 to December 2021 are shown together with their 95% lower and upper confidence limits. According to Table 4.3, the forecast values from January 2021 to December 2021 fall within 95% lower and upper confidence limits. The forecasting the exchange rate in Cambodia will increase from January 2021 to September 2021 and then will decrease from November 2021 to December 2021.



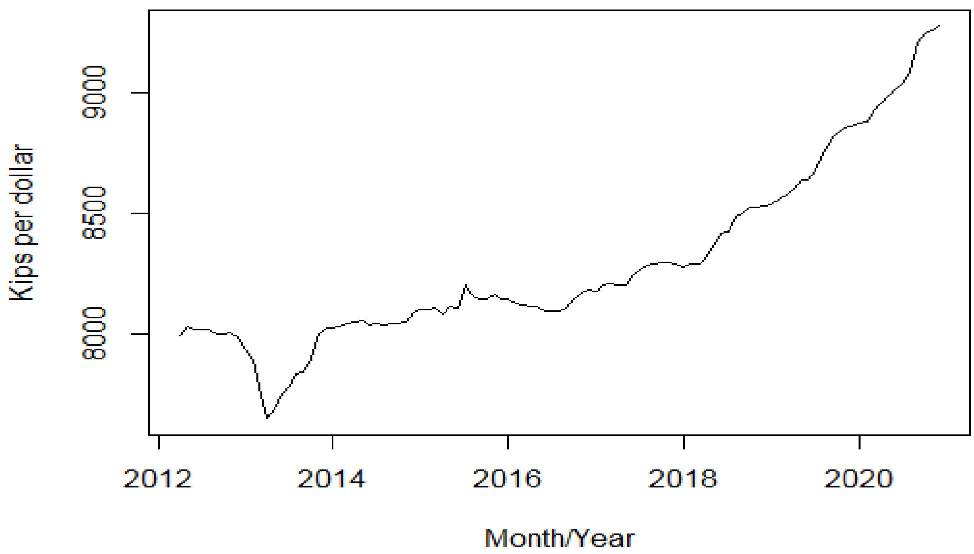
Source: International Financial Statistics (IFS)

Figure 4.5 Forecast Values for Exchange Rate in Cambodia

According to Figure 4.5, the forecasted trend of the exchange rate in Cambodia will increase from January 2021 to September 2021 and them will decrease from November 2021 to December 2021.

4.2 Exchange Rate in Lao

The exchange rate series of Lao for the period from April, 2012 to December, 2020 is shows in Figure 4.6. The historical currency exchange rates from April 2012 to December 2020 provided by the International Financial Statistics (IFS) were used.



Source: International Financial Statistics (IFS)

Figure 4.6 Monthly Exchange Rate in Lao

According to the figure 4.6, Lao's foreign exchange rate has been steadily rising from 7994.00 LAK/USD to 8005.00 LAK/USD in April 2012 to November 2012. Then exchange rates are decreasing from 7985.00 LAK/USD to 7897.00 LAK/USD in December 2012 to October 2013. Then Lao foreign exchange rates are increasing from 8000.00 LAK/USD to 8200.00 LAK/USD in December 2013 to July 2015. A Lao foreign exchange rate has been decreasing from 8165.00 LAK/USD to 8177.40 LAK/USD in August 2015 to January 2017. After, Lao foreign exchange rate is against increasing from 8201.00 LAK/USD to 9258.00 LAK/USD in February 2017 to December 2020. It is quite evident from the graph that there is an upward trend.

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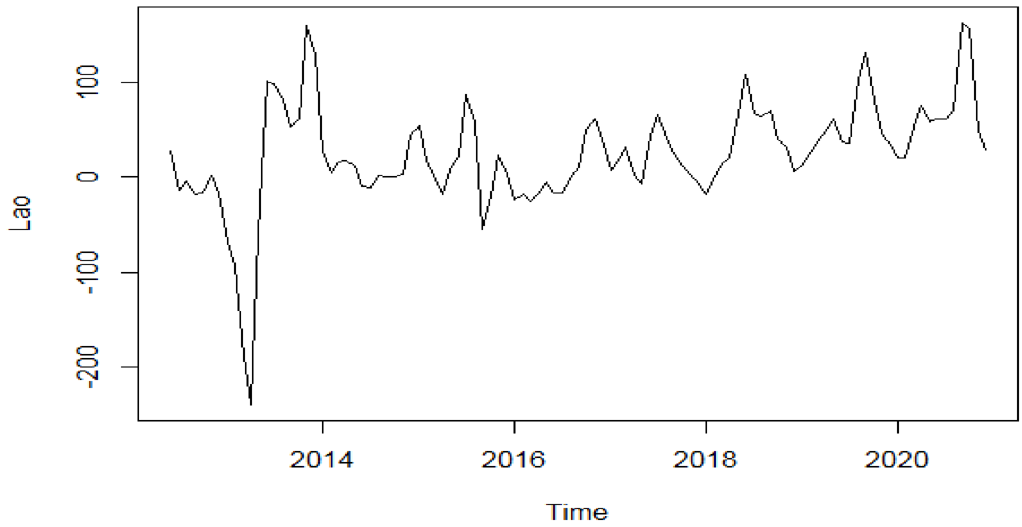
4.2.1 Model Identification

First stage of ARIMA model building is to identify whether the variable, which is being forecasted, is stationary in time series or not. By stationary we mean, the values of variable over time varies around a constant mean and variance. The time plot of the exchange rate data in figure 4.6 above clearly shows that the data is not stationary (actually, it shows an increasing trend in time series). The ARIMA model cannot be built until this series stationary is made. The first stage is differencing of the time series 'd' times to obtain a stationary series in order to have an ARIMA(p,d,q) model with 'd' as the order of differencing used. The best idea is to start the differencing with lowest order (of first order, d =1) and test the data for unit root problems. However, time series of first order differencing are not stationary. Therefore, Figure 4.7 below is the line plot of the second order differencing exchange rate data in Lao.



Source: International Financial Statistics (IFS)

Figure 4.7 Exchange Rate Data of Second Order Differencing (d = 2)

It can easily be inferred from the above graph that the time series appears to be stationary both in its mean and variance. But before moving further, we will first test the difference time series data for stationary (unit root problem) using Augmented Dickey-Fuller test.

(i) Test for Stationarity: Augmented Dickey-Fuller (ADF) Test

In this study, the foreign exchange rate in Lao is whether stationary or nonstationary to be determined. In order to determine whether the foreign exchange rate contain unit roots, this study employs tests devised by Augmented Dickey-Fuller (ADF). The table 4.4 shows the results of ADF unit root test.

Table 4.4 The Results of Unit Root Test for Foreign Exchange Rate in Lao

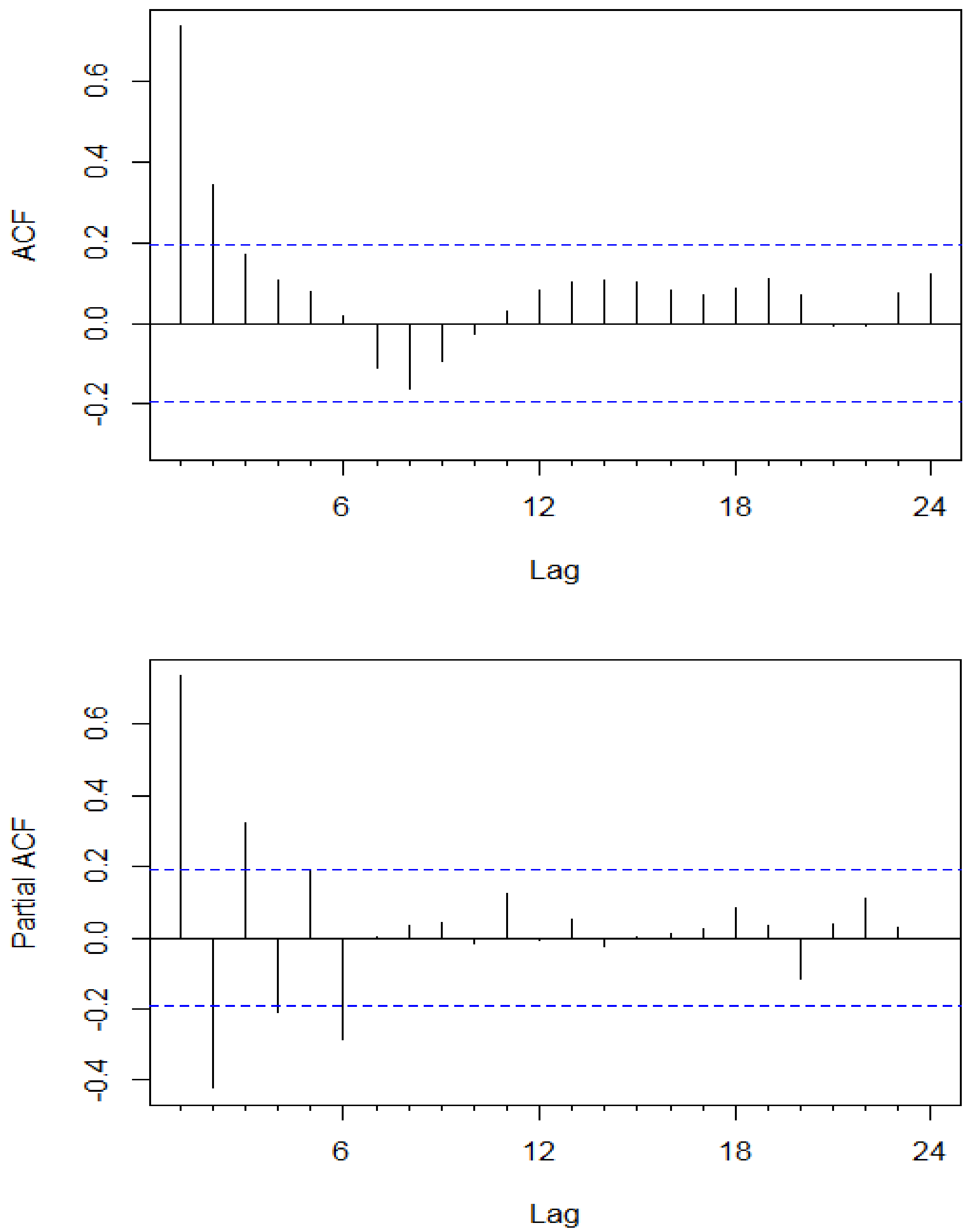
	Dickey-Fuller	**Lag order**	**p-value**
Level	1.4904	11	0.99
First Difference	-3.2351	11	0.08576
Second Difference	-3.6827	11	0.02918

Source: International Financial Statistics (IFS)

According to the above table, the foreign exchange rate is not stationary at level and first difference, in Lao. The ADF test statistic are -3.2351 and -3.6827 with associated significance of 0.99 and 0.08576 which is greater than 0.05. Thus, the null hypothesis is failed to reject and conclude that the time series data is not stationary at the level and first difference. Therefore, to make the variable stationary was second difference and the result of ADF presented above table shows that at 5 % level of significance, foreign exchange rate is not found to be stationary at second difference. And then, foreign exchange rate is found to be stationary at second difference, in Lao.

(ii) Correlogram and Partial Correlogram

The Figure 4.8 below represents the plot of correlogram (auto-correlation function, ACF) for lags 1 to 24 of the second order difference time series of the exchange rate in Lao.



Source: International Financial Statistics (IFS)

Figure 4.8 ACF and PACF of Second Differenced Series by Lag

The above correlogram infers that the auto-correlation at lag 1 is spike after second differencing, moving average order is the q =1 and partial auto-correlations at lag 1 is spike, autoregressive order is the p =1. Hence, the ARIMA (1,2,1) model would be appropriate for the series. In addition, when calculating after using auto.arima function from R software, ARIMA (1,2,1) was found to be the most suitable model.

4.2.2 Estimation of Model Parameters

The results of the estimated models are displayed in Table 4.5.

Table 4.5 Parameter Estimates for ARIMA (1, 2, 1) Model

Model Fit Statistics			
AIC	**AICS**	**BIC**	
998.3	998.54	1006.21	
Coefficients	**Estimate**	**Standard Error**	**t-value**
ar1	0.4217	0.0984	4.2856
ma1	-0.9603	0.0313	-30.6805

Source: International Financial Statistics (IFS)

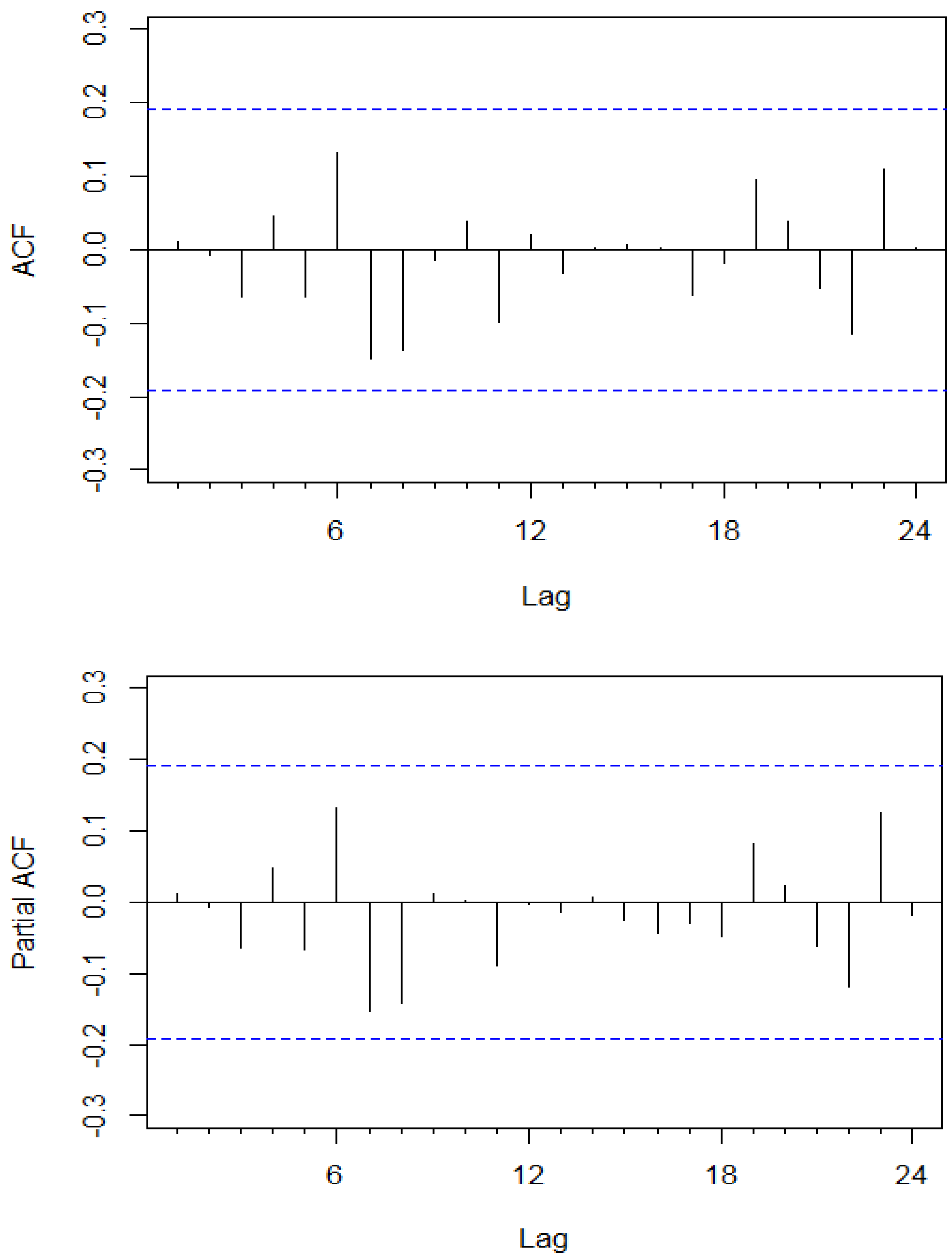
The following estimated model was obtained

$$\hat{y}_t = \emptyset_1 y_{t-1} - \theta_1 a_{t-1}$$
$$= 0.4217 y_{t-1} + 0.9603 a_{t-1}$$

Both coefficients of the AR (1) and MA (1) components are statistically significant. The coefficient of the AR (1) component is positive while the coefficient of the MA (1) component is negative as conventionally expected. The AR (1) coefficient is 0.4217 and is thus close to one, implying that the series returns to its mean slowly. The MA (1) coefficient is -0.9603 and represents the fraction of last period's shock that is still felt in the current period. While these results are not similar to any previous study done in Lao, they are indeed consistent with the findings of Appiah & Adetunde (2011) who found that an ARIMA (1, 2, 1) model was the optimal exchange rate forecasting model for Lao.

4.2.3 Model Adequacy (Diagnostic) Checking of Estimated Models

To investigate further whether there are any correlations between successive forecast errors, we will plot the correlogram (ACF) and partial correlogram (PACF) of the forecast errors. Following Figure 4.9 represents ACF and PACF of the forecast errors:



Source: International Financial Statistics (IFS)

Figure 4.9 Estimated ACF and PACF of Residuals – ARIMA (1,2,1)

It is clearly evident from the ACF plot above that none of the autocorrelation coefficients between lag 1 and 24 are breaching the significant limits i.e. all the ACF values are well within the significant bounds.

Similarly ACFs, all the PACFs or partial autocorrelation coefficients of residuals of fitted ARIMA for lag 1 to lag 24 are within the significant limits. This means ACF and PACF concluded that there is no non-zero autocorrelations in the forecast residuals (or standard errors) at lag 1 to 24 in the fitted ARIMA(1,2,1) model.

4.2.4 Forecasting

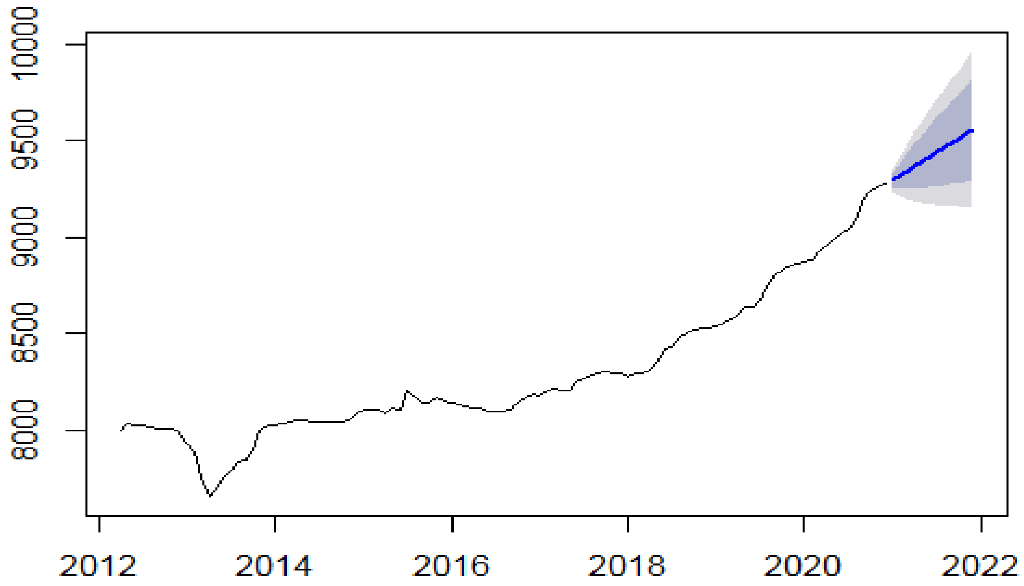
After the empirical examination the most appropriate models for exchange rate in Lao were determined. The best fitting model for exchange rate from January 2021 to December 2021 were examined for their forecast performance. The results of forecast by using ARIMA for exchange rate in Lao were shown in Table 4.6 and Figure 4.10.

Table 4.6 Results of Forecast by Using ARIMA (1,2,1) Model for Exchange Rate in Lao

Month-Year	Forecast	Lo 95	Hi 95
Jan-2021	9294.836	9236.092	9353.58
Feb-2021	9317.711	9213.689	9421.733
Mar-2021	9341.446	9197.424	9485.467
Apr-2021	9365.543	9185.68	9545.406
May-2021	9389.794	9177.11	9602.477
Jun-2021	9414.108	9170.754	9657.463
Jul-2021	9438.45	9165.954	9710.946
Aug-2021	9462.804	9162.263	9763.344
Sep-2021	9487.162	9259.369	9814.955
Oct-2021	9511.522	9157.051	9865.994
Nov-2021	9535.883	9155.149	9916.618
Dec-2021	9560.245	9153.544	9966.946

Source: International Financial Statistics (IFS)

The forecast values from January 2021 to December 2021 are shown together with their 95% lower and upper confident limits. According to Table 4.6, the forecast values from January 2021 to December 2021 fall within 95% lower and upper confidence limits. The forecasting the exchange rate in Lao will increase.



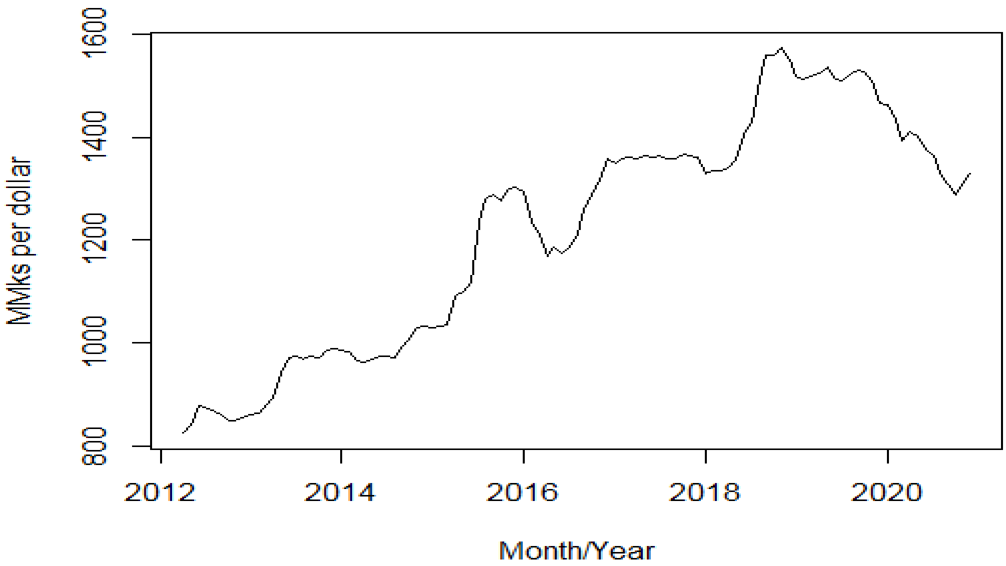
Source: International Financial Statistics (IFS)

Figure 4.10 Forecast Values for Exchange Rate in Lao

According to Figure 4.10, the forecasted trend of the exchange rate in Lao will continue to grow the next year.

4.3 Exchange Rate in Myanmar

The exchange rate series of Myanmar for the period from April, 2012 to December, 2020 is shown in Figure 4.11. The historical currency exchange rates from April 2012 to December 2020 provided by the International Financial Statistics (IFS) were used.



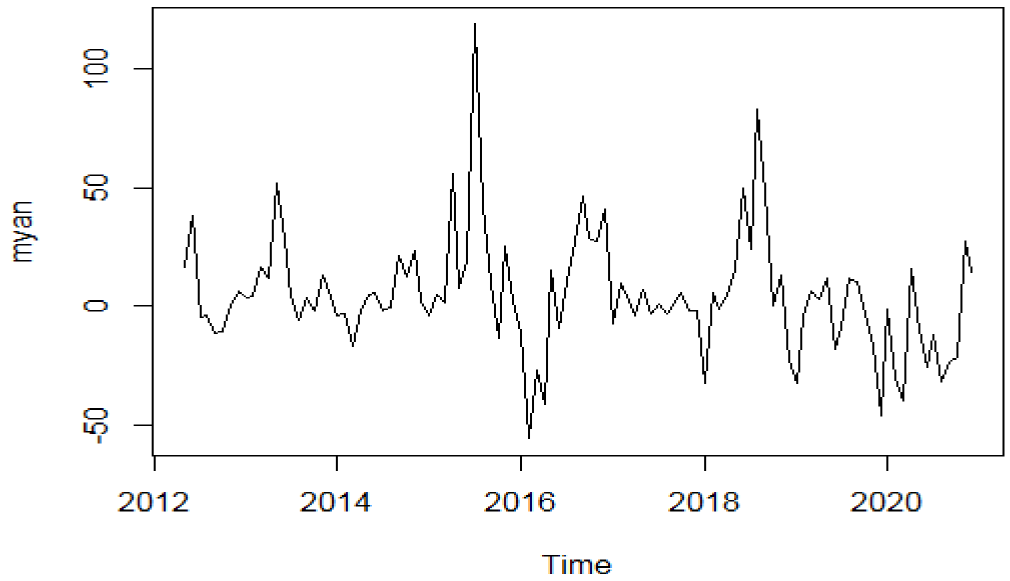
Source: International Financial Statistics (IFS)

Figure 4.11 Monthly Exchange Rate in Myanmar

Exchange rate is one of the most important prices in an open economy since it affects so many business, investment and policy decisions. Myanmar foreign exchange rate has been steadily rose from 824.0 MMK/USD to 1362 MMK/USD in April 2012 to December 2017. Then exchange rates increased from 1330.0 MMK/USD to 1550.0 MMK/USD in January 2018 to December 2018. Then Myanmar foreign exchange rates declined from 1518.0 MMK/USD to 1329 MMK/USD in January 2019 to December 2020. It is quite evident from the graph that there is an upward trend.

4.3.1 Model Identification

First stage of ARIMA model building is to identify whether the variable, which is being forecasted, is stationary in time series or not. By stationary it mean, the values of variable over time varies around a constant mean and variance. The time plot of the exchange rate data in figure 4.11 above clearly shows that the data is not stationary (actually, it shows an increasing trend in time series). The ARIMA model cannot be built until this series stationary is made. The first stage is difference of the time series ‘d’ times to obtain a stationary series in order to have an ARIMA(p,d,q) model with ‘d’ as the order of differencing used. The best idea is to start the differencing with lowest order (of first order, d = 1) and test the data for unit root problems. So figure 4.12 below is the line plot of the first order difference exchange rate in Myanmar.



Source: International Financial Statistics (IFS)

Figure 4.12 Exchange Rate Data of First Order Differencing (d = 1)

It can easily be inferred from the above graph that the time series appears to be stationary both in its mean and variance. But before moving further, it will be first test the difference time series data for stationary (unit root problem) using Augmented Dickey-Fuller test.

(i) Test for Stationarity: Augmented Dickey-Fuller (ADF) Test

In this study, the foreign exchange rate is whether stationary or nonstationary to be determined in Myanmar. In order to determine whether the foreign exchange rate contain unit roots, this study employs tests devised by Augmented Dickey-Fuller (ADF). The table 4.7 shows the results of ADF unit root test.

Table 4.7 The Results of Unit Root Test for Foreign Exchange Rate in Myanmar

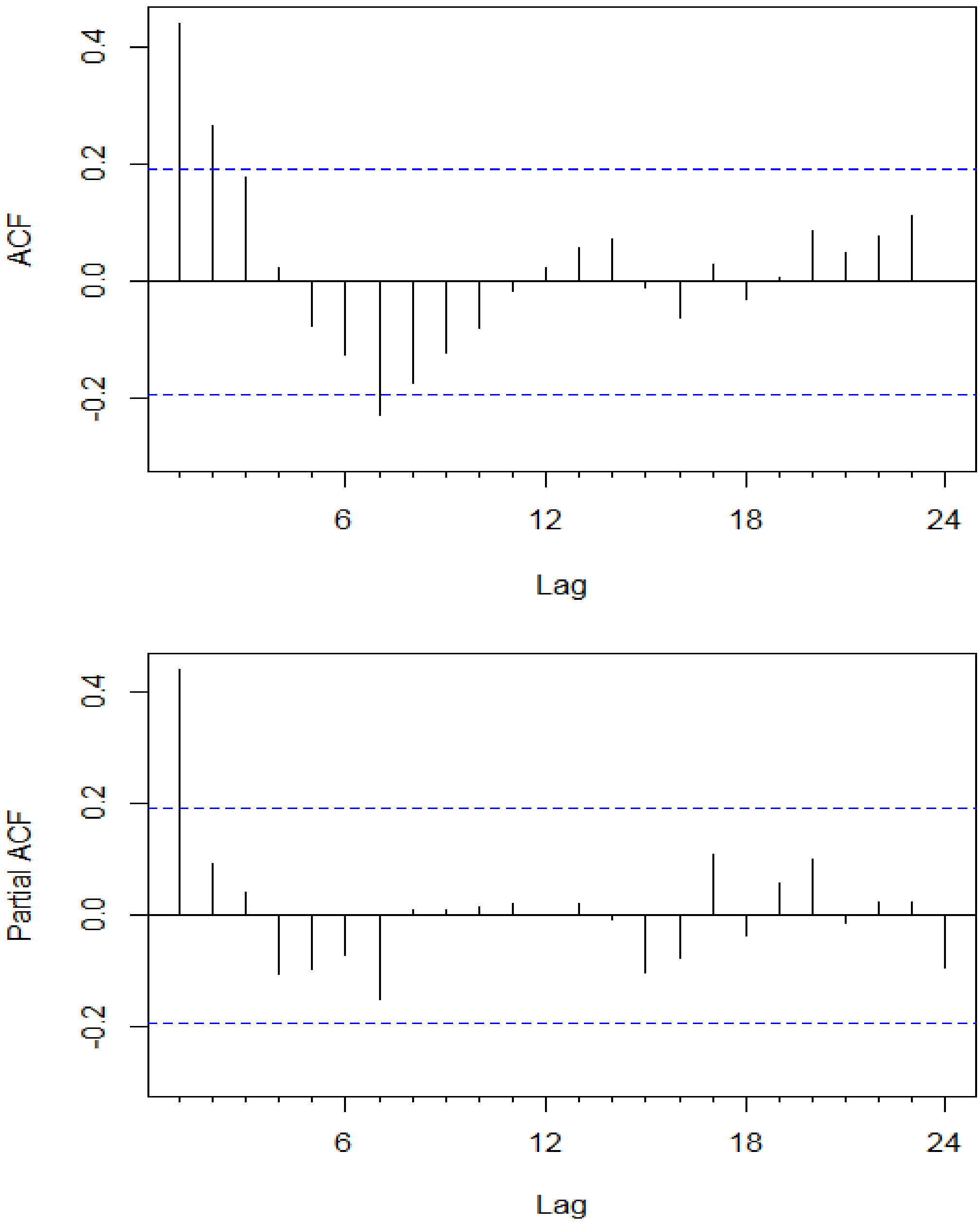
	Dickey-Fuller	Lag order	p-value
Level	-1.7417	4	0.6838
First Difference	-4.4505	4	0.01

Source: International Financial Statistics (IFS)

According to the above table, the foreign exchange rate is not stationary at the level. The ADF test statistic is -1.7417 with associated significance of 0.6838 which is greater than 0.05. Thus, the null hypothesis is failed to reject and conclude that the time series data is not stationary at the level. Therefore, to make the variable stationary was difference once and the result of ADF presented above table shows that at 5 % level of significance, foreign exchange rate is found to be stationary at first difference and it can also conclude that foreign exchange rate is stationary with integrated of order 1 in Myanmar.

(ii) Correlogram and Partial Correlogram

The Figure 4.13 below represents the plot of correlogram (auto-correlation function, ACF) for lags 1 to 24 of the first order difference time series of the exchange rate in Myanmar.



Source: International Financial Statistics (IFS)

Figure 4.13 ACF and PACF of First Differenced Series by Lag

According to Figure 4.13, the moving average order is q = 2 because Acf is spike at lag1 and lag2 after the first difference is made and according to Pacf, the autoregressive order is p = 1 because lag1 is spike. Therefore, the appropriate model can be assumed to be ARIMA (1,1,2). In addition, when calculating after using auto.arima function from R software, ARIMA (1,1,0) was found to be the most suitable model.

4.3.2 Estimation of Model Parameters

The results from the estimated models are therefore displayed in Table 4.8.

Table 4.8 Parameter Estimates for ARIMA (1, 1, 0) Model

Model Fit Statistics			
AIC	**AICS**	**BIC**	
945.32	945.44	950.61	
Coefficients	**Estimate**	**Standard Error**	**t-value**
ar1	0.4577	0.0867	5.2791

Source: International Financial Statistics (IFS)

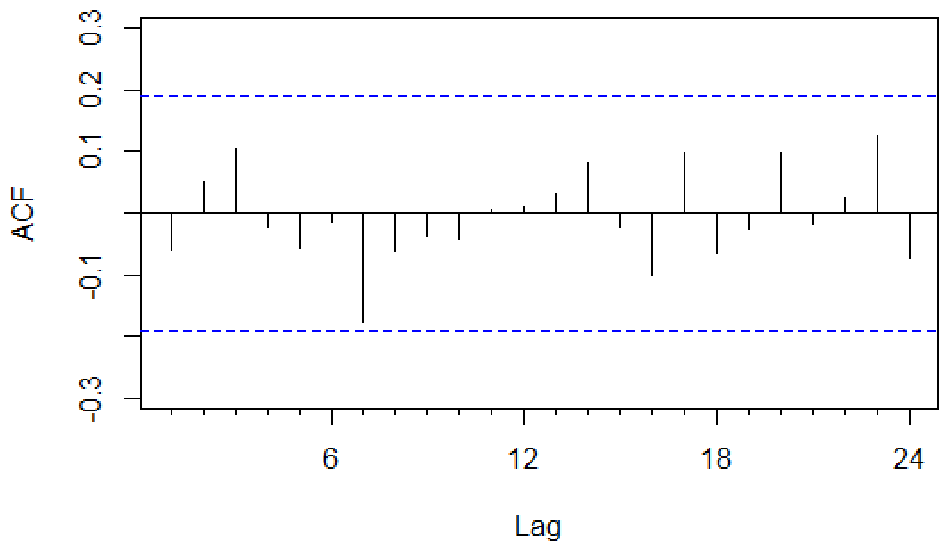
The following estimated model was obtained

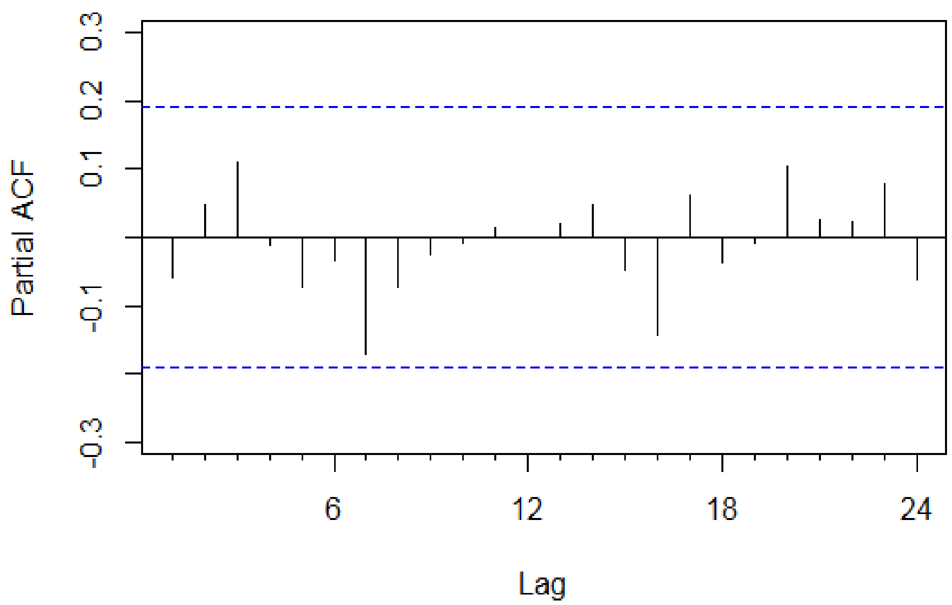
$$\hat{y}_t = \emptyset_1 y_{t-1}$$
$$= 0.4577 y_{t-1}$$

Based on the parameters as reported in table 4.8 above, the estimate of the ar1 coefficient ($\emptyset_1$) of 0.4577 is found to be statistically significant since it test statistic of t-value of 5.2791 is greater than 2 in absolute terms, and is therefore maintained in the model. The estimated $\emptyset_1$ coefficient again strictly conforms to the bounds of parameter stationary since its value of 0.4577 lies between -1 and 1.

4.3.3 Model Adequacy (Diagnostic) Checking of Estimated Models

To investigate further whether there are any correlations between successive forecast errors, we will plot the correlogram (ACF) and partial correlogram (PACF) of the forecast errors. Following Figure 4.14 represents ACF and PACF of the forecast errors:





Source: International Financial Statistics (IFS)

Figure 4.14 Estimated ACF and PACF of Residuals – ARIMA (1,1,0)

Similarly ACFs, all the PACFs or partial autocorrelation coefficients of residuals of fitted ARIMA for lag 1 to lag 24 are within the significant limits. This means ACF and PACF concluded that there is no non-zero autocorrelations in the forecast residuals (or standard errors) at lag 1 to 24 in the fitted ARIMA (1,1,0) model.

4.3.4 Forecasting

After the empirical examination the most appropriate models for exchange rate in Myanmar were determined. The best fitting model for exchange rate from January 2021 to December 2021 were examined for their forecast performance. The results of forecast by using ARIMA for exchange rate in Myanmar were shown in Table 4.9 and Figure 4.15.

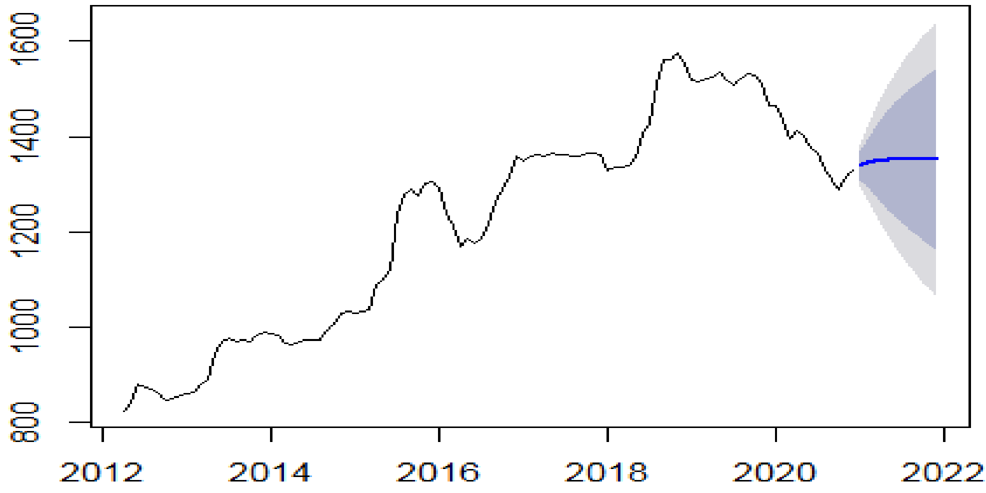
Table 4.9 Results of Forecast by Using ARIMA (1,1,0) Model for Exchange Rate in Myanmar

Month-Year	Forecast value	Lo 95	Hi 95
Jan-2021	1335.692	1291.732	1379.651
Feb-2021	1338.709	1260.999	1416.419
Mar-2021	1340.090	1233.269	1446.910
Apr-2021	1340.722	1208.744	1472.700
May-2021	1341.011	1186.970	1495.052
Jun-2021	1341.144	1167.419	1514.869

Month-Year	Forecast value	Lo 95	Hi 95
Jul-2021	1341.205	1149.640	1532.769
Aug-2021	1341.232	1133.281	1549.183
Sep-2021	1341.245	1118.077	1564.413
Oct-2021	1341.251	1103.826	1578.676
Nov-2021	1341.253	1090.375	1592.132
Dec-2021	1341.255	1077.605	1604.904

Source: International Financial Statistics (IFS)

The forecast values from January 2021 to December 2021 are shown together with their 95% lower and upper confidence limits. According to Table 4.9, the forecast values from January 2021 to December 2021 fall within 95% lower and upper confidence limits. The forecasting the exchange rate in Myanmar will increase.



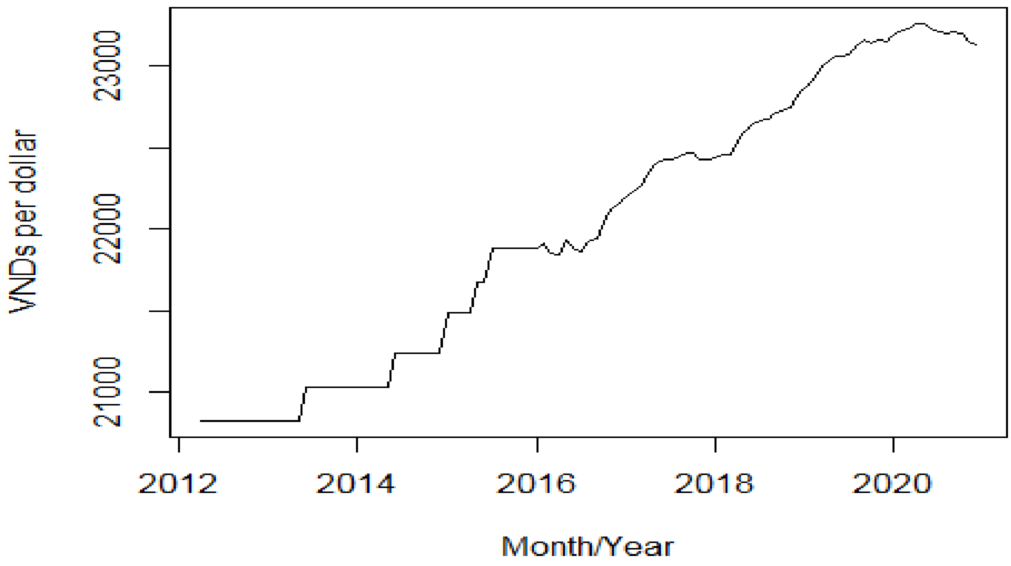
Source: International Financial Statistics (IFS)

Figure 4.15 Forecast Values for Exchange Rate in Myanmar

According to Figure 4.15, the forecasted trend of the exchange rate in Myanmar will continue to grow the next year.

4.4 Exchange Rate in Vietnam

The exchange rate series of Vietnam for the period from April, 2012 to December, 2020 is shown in Figure 4.16. The historical currency exchange rates from April, 2012 to December, 2020 provided by the International Financial Statistics (IFS) were used. It is quite evident from the graph that there is an upward trend.



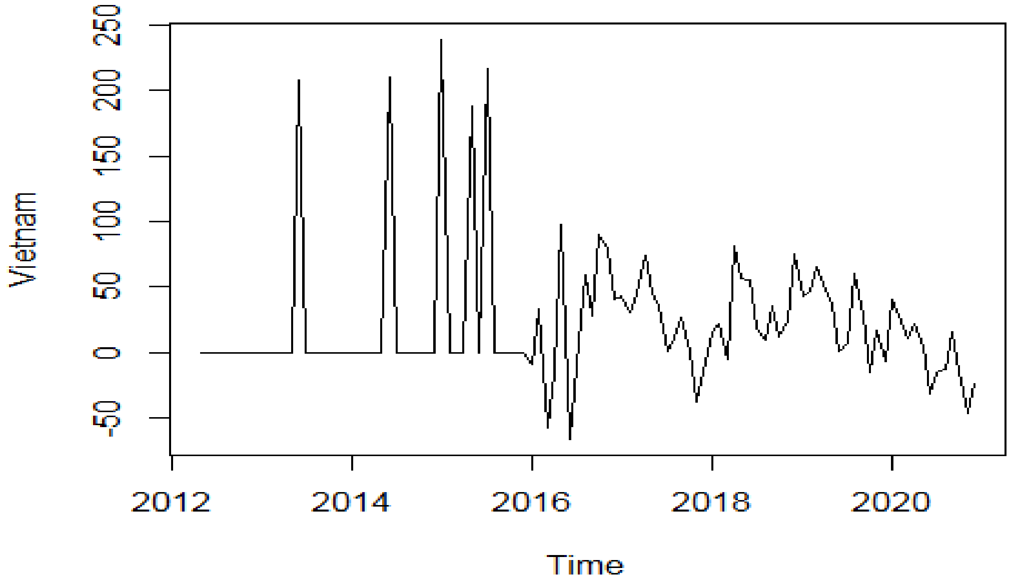
Source: International Financial Statistics (IFS)

Figure 4.16 Monthly Exchange Rate in Vietnam

Exchange rate VND/USD, is raising the rate from 20828 VND/USD to 21,890 VND/USD in April 2012 to December 2015, the Bank also decided to widen the exchange rate. Exchange rate again is decreasing from 21881 VND/USD to 21862 VND/USD in January 2016 to July 2016. And then, foreign exchange rate increases from 21921 VND/USD to 23215 VND/USD in August 2016 to September 2020. Further, Foreign exchange rates have slightly fallen from 23201 VND/USD to 23131 VND/USD in October 2020 to December 2020. It is quite evident from the graph that there is an upward trend.

4.4.1 Model Identification

First stage of ARIMA model building is to identify whether the variable, which is being forecasted, is stationary in time series or not. By stationary it mean, the values of variable over time varies around a constant mean and variance. The time plot of the exchange rate data in figure 4.16 above clearly shows that the data is not stationary (actually, it shows an increasing trend in time series). The ARIMA model cannot be built until this series stationary is made. The first stage is difference of the time series 'd' times to obtain a stationary series in order to have an ARIMA(p,d,q) model with 'd' as the order of differencing used. Caution to be taken in differencing as over differencing will tend to increase in the standard deviation, rather than a reduction. The best idea is to start differencing with lowest order (of first order, d =1) and test the data for unit root problems. So figure 4.17 below is the line plot of the first order difference exchange rate in Vietnam.



Source: International Financial Statistics (IFS)

Figure 4.17 Exchange Rate Data of First Order Differencing (d=1)

It can easily be inferred from the above graph that the time series appears to be stationary both in its mean and variance. But before moving further, it will be first test the difference time series data for stationary (unit root problem) using Augmented Dickey-Fuller test.

(i) Test for Stationarity: Augmented Dickey-Fuller (ADF) Test

In this study, the foreign exchange rate is whether stationary or nonstationary to be determined in Vietnam. In order to determine whether the foreign exchange rate contain unit roots, this study employs tests devised by Augmented Dickey-Fuller (ADF). The table 4.10 shows the results of ADF unit root test.

Table 4.10 The Results of Unit Root Test for Foreign Exchange Rate in Vietnam

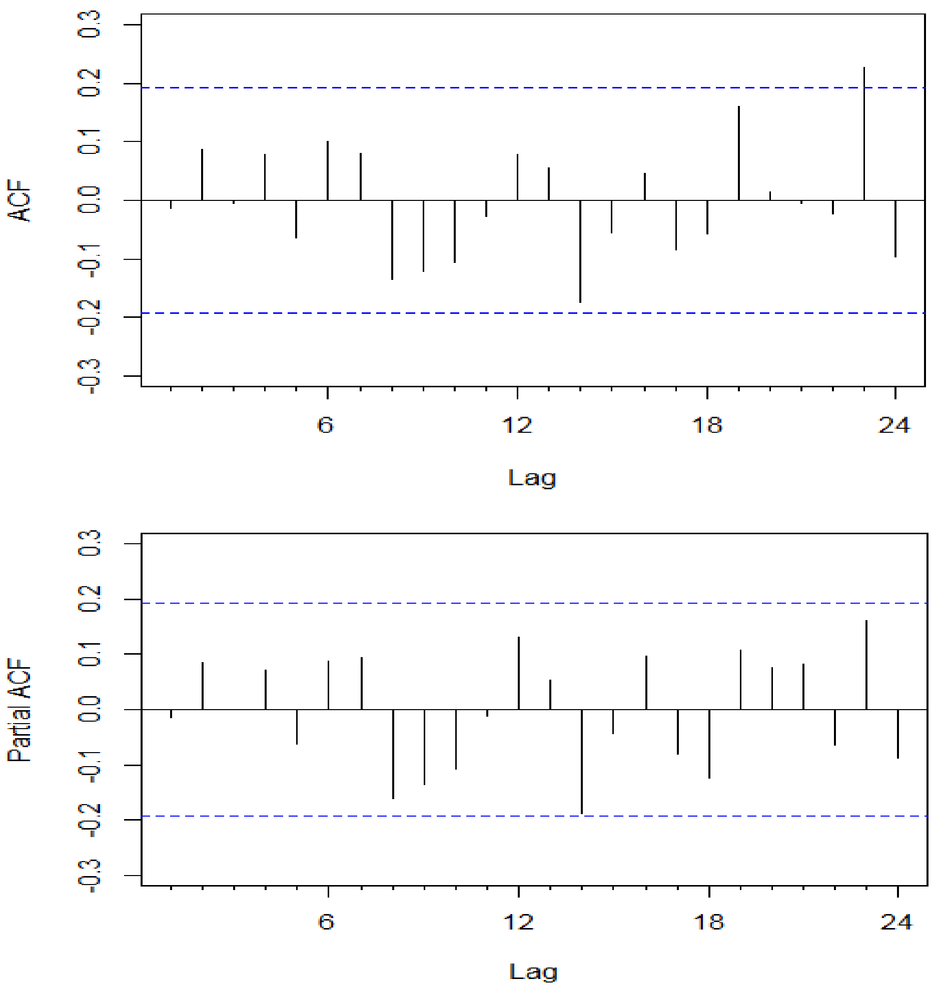
	Dickey-Fuller	Lag order	p-value
Level	-2.3975	4	0.4118
First Difference	-4.0755	4	0.01

Source: International Financial Statistics (IFS)

According to the above table, the foreign exchange rate is not stationary at the level. The ADF test statistic is -2.3975 with associated significance of 0.4118 which is greater than 0.05. Thus, the null hypothesis is failed to reject and conclude that the time series data is not stationary at the level. Therefore, to make the variable stationary was difference once and the result of ADF presented above table shows that at 5 % level of significance, foreign exchange rate is found to be stationary at first difference and it can also conclude that foreign exchange rate is stationary with integrated of order 1 in Vietnam.

(ii) Correlogram and Partial Correlogram

The Figure 4.18 below represents the plot of correlogram (auto-correlation function, ACF) for lags 1 to 24 of the second order difference time series of the exchange rate in Vietnam.



Source: International Financial Statistics (IFS)

Figure 4.18 ACF and PACF of First Differencing Series by Lag

The ACF and PACF plots show one significant spike in each. Although these lone significant spikes are in the last few lags, one of the twenty four lags (or 0.05%) appearing significant at a 95% confidence interval is within probabilistic expectations.

These lone significant spikes are therefore ignored. The appropriate model is an ARIMA (0,1,0) model. In addition, when calculating after using auto.arima function from R software, ARIMA (0,1,0) was found to be the most suitable model.

4.4.2 Estimation of Model Parameters

The results from the estimated models are displayed in Table 4.11.

Table 4.11 Parameter Estimates for ARIMA (0, 1, 0) model

Model Fit Statistics			
AIC	**AICS**	**BIC**	
1119.35	1119.47	1124.64	
Coefficients	**Estimate**	**Standard Error**	**t-value**
Constant	22.1442	5.0588	4.3774

Source: International Financial Statistics (IFS)

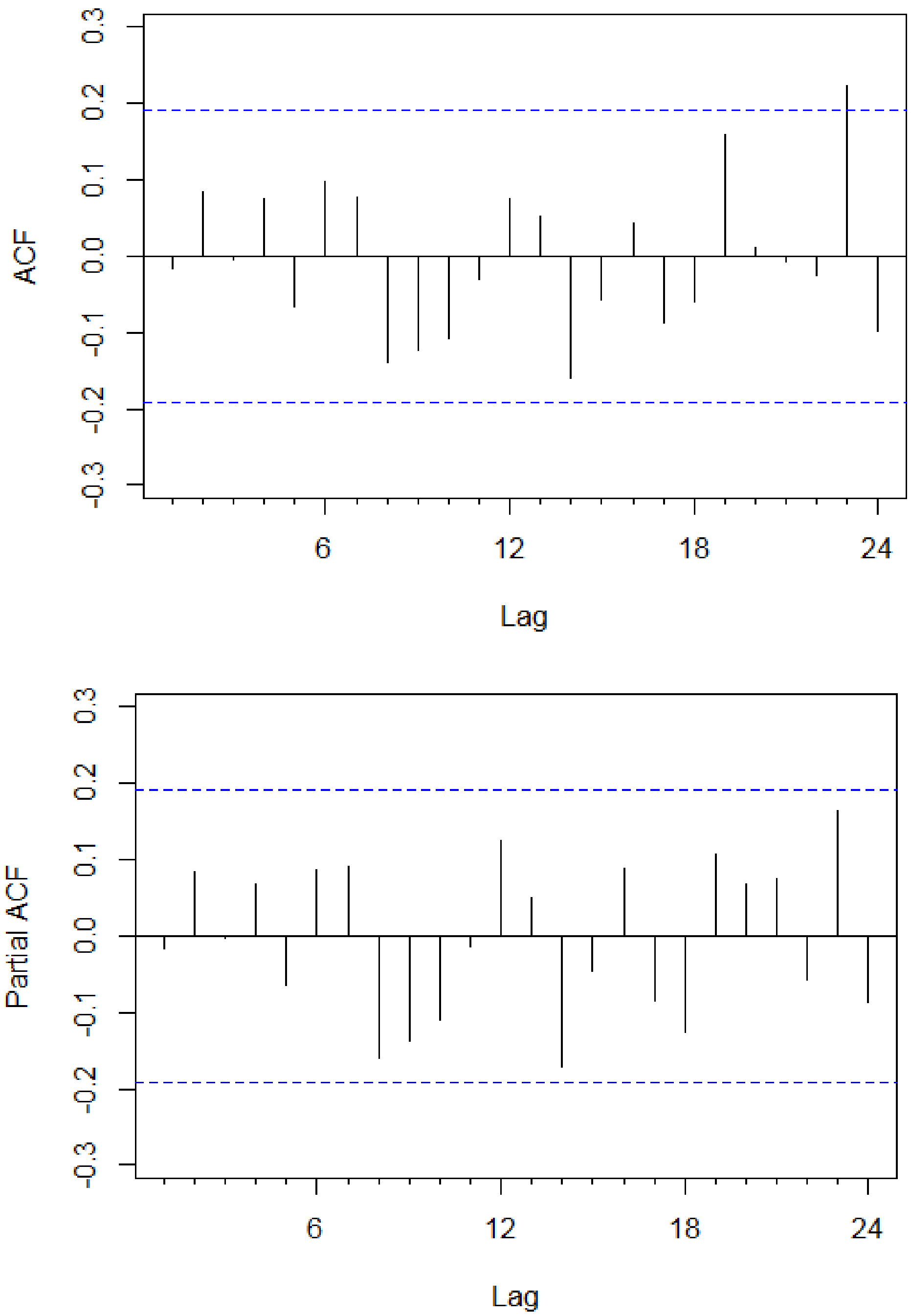
The following estimated model was obtained

$$\hat{y}_t = 22.1442 + y_{t-1}$$

ARIMA(0,1,0) is the random walk model. The 1 in (0,1,0) implies that the model does not have an average, but rather the level of the process changes over times. The process level estimated as the most recent value is the forecast. The number of parameters to be estimated is 0.

4.4.3 Model Adequacy (Diagnostic) Checking of Estimated Models

To investigate further whether there are any correlations between successive forecast errors, we will plot the correlogram (ACF) and partial correlogram (PACF) of the forecast errors. Following Figure 4.19 represents ACF and PACF of the forecast errors:



Source: International Financial Statistics (IFS)

Figure 4.19 Estimated ACF and PACF of Residuals, ARIMA (0,1,0)

Similarly ACFs, all the PACFs or partial autocorrelation coefficients of residuals of fitted ARIMA for lag 1 to lag 24 are within the significant limits. This means ACF and PACF concluded that there is no non-zero autocorrelations in the forecast residuals (or standard errors) at lag 1 to 24 in the fitted ARIMA (0,1,0) model.

4.4.4 Forecasting

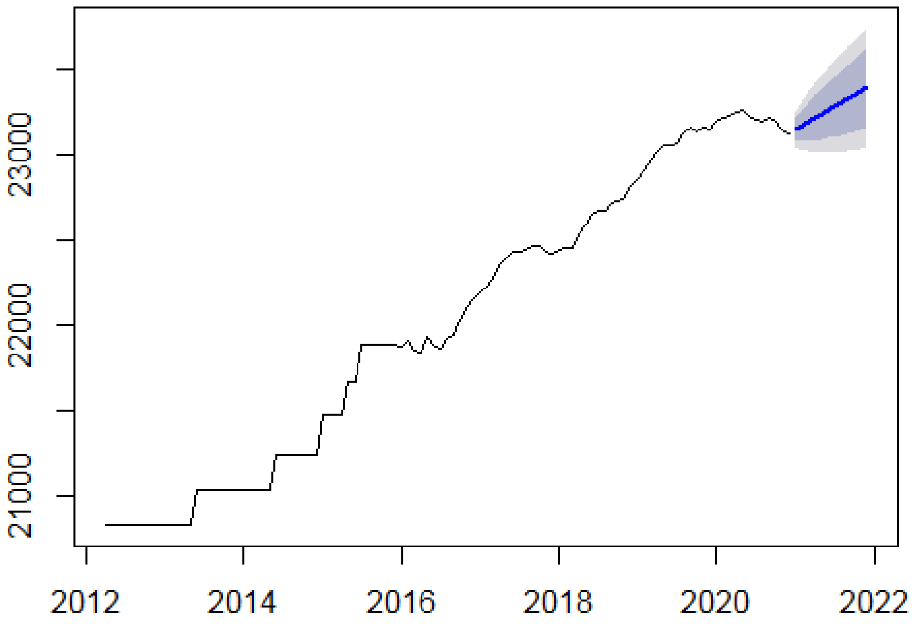
After the empirical examination the most appropriate models for exchange rate in Myanmar were determined. The best fitting model for exchange rate from January 2021 to December 2021 were examined for their forecast performance. The results of forecast by using ARIMA for exchange rate in Vietnam were shown in Table 4.12 and Figure 4.20.

Table 4.12 Results of Forecast by Using ARIMA (0,1,0) Model for Exchange Rate in Vietnam

Month-Year	Forecast	Lo 95	Hi 95
Jan-2021	23153.14	23051.46	23254.83
Feb-2021	23175.29	23031.49	23319.09
Mar-2021	23197.43	23021.31	23373.55
Apr-2021	23219.58	23016.21	23422.94
May-2021	23241.72	23014.35	23469.09
Jun-2021	23263.87	23014.79	23512.94
Jul-2021	23286.01	23016.98	23555.04
Aug-2021	23308.15	23020.55	23595.76
Sep-2021	23330.3	23025.25	23635.35
Oct-2021	23352.44	23030.89	23674
Nov-2021	23374.59	23037.34	23711.83
Dec-2021	23396.73	23044.49	23748.97

Source: International Financial Statistics (IFS)

The forecast values from January 2021 to December 2021 are shown together with their 95% lower and upper confidence limits. According to Table 4.12, the forecast values from January 2021 to December 2021 fall within 95% lower and upper confidence limits. The forecasting the exchange rate in Vietnam will increase.



Source: International Financial Statistics (IFS)

Figure 4.20 Forecast Values for Exchange Rate in Vietnam

According to Figure 4.20, the forecasted trend of the exchange rate in Vietnam will continue to grow the next year.

CHAPTRE 5
CONCLUSION

This chapter focuses on the conclusion of the thesis to findings, suggestions and recommendations and needs for further study.

5.1 Findings

This study attempts to select the best fit model on foreign exchange rate in CLMV countries. Monthly data from the year 2012 to 2020 are obtained from International Financial Statistics (IFS). Test of seasonality is conducted to the monthly values of the CLMV countries by using ACF and PACF. According to the results of seasonality, the seasonal effects are found in the Cambodia data series. Unit root test is performed by using Augmented Dickey-Fuller s (ADF) test. The results of the unit root tests show that the level values of the all data series are not stationary. However, first differenced series of Cambodia, Myanmar and Vietnam are stationary and second differenced series of Lao is stationary. Thus, Box-Jenkins seasonal ARIMA model and ARIMA are used to forecast foreign exchange rate of CLMV countries.

The ARIMA model is for non-seasonal and non-stationary data. Box and Jenkins have generalized this model to deal with seasonality called seasonal ARIMA. Following the Box and Jenkins methodology, the time series modeling involves transformation of the data to achieve stationarity, followed by identification of appropriate models, estimation of model parameters, diagnostic checking of the model assumption and forecast future values.

In addition, the Box-Jenkins Method was utilized in modeling and forecasting the foreign exchange rate series of CLMV countries. The seasonal ARIMA $(1,1,0)(2,1,0)_{12}$ for Cambodia, the ARIMA (1,2,1) for Lao, the ARIMA (1,1,2) for Myanmar and the ARIMA (0,1,0) for Vietnam were found to be the most suitable models for foreign exchange rate and the diagnostic checks satisfied these models. These models were found to be adequate for the observed data series. Therefore, these models were used to compute the forecast values. It is necessary to evaluate the forecasting accuracy of the model because accurate predictions should provide foreign exchange markets and the government with useful information for competitiveness analysis and strategy formulation.

Based on the best fitted models, monthly exchange rate series in CLMV countries are forecasted for future periods of 2021. The forecast values form January 2021 to December 2021 were obtained together with their 95% lower and upper confidence limits. It was found that the forecast values fall within their 95% lower and upper limits. Therefore, the forecast value obtained by using fitting model was generally considered to be reliable. The forecast values can be applied in a variety of future planning purposes which are important for the foreign exchange market development in CLMV countries.

Therefore, the conclusion of this research is that for the next year, the foreign exchange rate of Cambodia, will increase from January to September and then will decrease from November to December 2021. In Lao, the forecasted trend of the exchange rate will continue to grow the next year. The forecasted trend of the exchange rate in Myanmar will slightly increase the next year. In Vietnam, the forecasted trend of the exchange rate will continue to grow the next year.

5.2 Suggestions and Recommendations

Based on the discussion of the results and conclusions drawn from the study, the following recommendations are considering:

Firstly, it is recommended for the future researchers to forecast the KHR/USD, LAK/USD, MMK/USD and VND/USD in the short and long run both. Moreover, other exchange rates forecasted with different data sets are suggested. Therefore, it was found that the ARIMA is appropriate and this model will be helpful for the government functionaries, monetary policymakers, economists and other stakeholders. Given the analysis and forecasts of this study, the recommendation is that policy makers in Cambodia ought to devalue the Riels in order to restore and maintain exchange rate stability. The effective forecasted models facilitate to take timely decisions regarding investments, savings, reserves and businesses, which will lessen the chances of loss due to fluctuation in the exchange rate.

Secondly, the results can be obtained by studying the most important variables that affect the value of the exchange rate. It uses statistical models to predict future exchange rates. Historical data should be considered for more accurate results in predicting the future. The data used in the analysis are more accurate and benefit the results of studies and research.

Finally, the time series model using residual and estimated values (ARIMA) proved that these models were prepared to maintain the exchange rate during the study. Box and Jenkins model is the most flexible methods in the construction of the time series model.

5.3 Needs for Further Study

Further research should focus on comparison of forecasting performances of models such as GARCH and exponential smoothing to the forecasting performance of an ARIMA model. When forecasting foreign exchange rate of CLMV countries, different time periods or different observational frequencies could be interest and could give better forecasting results. One of the critiques of the efficient market hypothesis is that there appears to be seasonality in the stock market. Therefore, if evidence for seasonality can be found in stock market data, a seasonal ARIMA model, or SARIMA, should be tested to forecast the time series to examine if better out-of-sample forecasting can be achieved compared to the results of this study.

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APPENDIX (A)

Year/ Monthly	Foreign Exchange Rate			
	Cambodia	Lao	Myanmar	Vietnam
2012 M4	4025	7994	824	20828
2012 M5	4065	8035	840.5	20828
2012 M6	4075	8022	878.5	20828
2012 M7	4070	8021.18	874	20828
2012 M8	4045	8018.43	870	20828
2012 M9	4043	8003	858.5	20828
2012 M10	4030	8002	848	20828
2012 M11	3992	8005	848.5	20828
2012 M12	3995	7985	855	20828
2013 M1	3995	7937	858.5	20828
2013 M2	3995	7891	863	20828
2013 M3	3995	7749	879.5	20828
2013 M4	4020	7651	891	20828
2013 M5	4065	7688	943	20828
2013 M6	4062	7753	971	21036
2013 M7	4062	7787	975	21036
2013 M8	4062	7835	969	21036
2013 M9	4062	7840	972.5	21036
2013 M10	4040	7897	971	21036
2013 M11	3995	8000	984	21036
2013 M12	3995	8025	988	21036
2014 M1	3995	8027	984.5	21036
2014 M2	3980	8030	981.5	21036
2014 M3	4015	8043	965	21036
2014 M4	4015	8048	963	21036
2014 M5	4032	8055	968	21036
2014 M6	4040	8039	974	21246
2014 M7	4050	8044	972.5	21246
2014 M8	4065	8041	972	21246
2014 M9	4085	8045	993	21246
2014 M10	4076	8042	1005.5	21246
2014 M11	4063	8048	1029	21246
2014 M12	4075	8086	1031.5	21246
2015 M1	4063	8103	1028	21485
2015 M2	4036	8103	1033	21485
2015 M3	4014	8105	1034.5	21485
2015 M4	4071	8085	1090.5	21485
2015 M5	4091	8113	1098	21673

Year/ Monthly	Foreign Exchange Rate			
	Cambodia	Lao	Myanmar	Vietnam
2015 M6	4098	8108	1117.5	21673
2015 M7	4117	8200	1236	21890
2015 M8	4102	8165	1279	21890
2015 M9	4079	8145	1289	21890
2015 M10	4055	8145	1276	21890
2015 M11	4050	8168	1301.5	21890
2015 M12	4051.5	8148	1304	21890
2016 M1	4041	8144	1293	21881
2016 M2	4013	8130	1237.5	21914
2016 M3	4014	8119	1211	21857
2016 M4	4067	8112	1170	21842
2016 M5	4086.5	8114	1185.5	21939
2016 M6	4086	8095	1176	21873
2016 M7	4098.5	8097	1186.5	21862
2016 M8	4101	8094	1214	21921
2016 M9	4091.5	8108	1260.5	21949
2016 M10	4057	8144	1289	22039
2016 M11	4036.5	8170	1316.5	22118
2016 M12	4044.5	8184	1357.5	22159
2017 M1	4045.5	8177.4	1350	22202
2017M2	4006.5	8201	1360	22232
2017 M3	4008.5	8209	1362	22276
2017 M4	4042.5	8203	1358	22350
2017 M5	4073.5	8203	1365	22396
2017 M6	4088	8246	1362	22431
2017 M7	4098	8269	1363	22432
2017 M8	4060.5	8288	1360	22443
2017 M9	4075	8293	1360	22470
20117 M10	4051	8300	1366	22471
2017 M11	4039.5	8296	1364	22433
2017 M12	4041.5	8293	1362	22425
2018 M1	4019	8278	1330	22441
2018 M2	4013.5	8290	1336	22463
2018 M3	4006.5	8293	1335	22458
2018 M4	4044.5	8310	1340	22539
2018 M5	4083	8360	1355	22595
2018 M6	4070.5	8419	1405	22650
2018 M7	4069	8427	1429	22669
2018 M8	4084	8484	1512	22678
2018 M9	4085.5	8497	1560	22714

Year/ Monthly	Foreign Exchange Rate			
	Cambodia	**Lao**	**Myanmar**	**Vietnam**
2018 M10	4062.5	8524	1560	22726
2018 M11	4044	8528	1573	22750
2018 M12	4033	8530	1550	22825
2019 M1	4020.5	8540	1518	22868
2019 M2	4011.5	8555	1513.8	22915
2019 M3	4024.5	8578	1520.1	22980
2019 M4	4053.5	8604	1523.4	23028
2019 M5	4069.5	8639	1535.2	23065
2019 M6	4074	8641	1517.5	23066
2019 M7	4091	8675	1509.2	23073
2019 M8	4091	8744	1521.3	23133
2019 M9	4102.5	8806	1531.6	23161
2019 M10	4070	8826	1528.3	23145
2019 M11	4079	8852	1511.6	23162
2019 M12	4084	8861	1465.5	23155
2020 M1	4094	8872	1464.2	23196
2020 M2	4090	8881	1434.3	23224
2020 M3	4089.5	8925	1394.9	23235
2020 M4	4112.5	8957	1410.9	23257
2020 M5	4129.5	8984	1401	23261
2020 M6	4107.5	9019	1375.3	23229
2020 M7	4105.5	9046	1363.7	23213
2020 M8	4111	9089	1331.9	23200
2020 M9	4113	9209	1308.5	23215
2020 M10	4089	9245	1287.4	23201
2020 M11	4073	9258	1314.7	23155
2020 M12	4076.5	9274	1329.1	23131

APPENDIX (B)

For Cambodia

```
> fit1=auto.arima(yt,D=1)
> summary(fit1)
```

Series: yt

ARIMA(1,0,0)(2,1,0)$_{12}$ with drift

Coefficients:

	ar1	sar1	sar2	drift
	0.8175	-0.6405	-0.2862	0.633
s.e.	0.0593	0.1038	0.1174	0.369

sigma^2 estimated as 221.9: log likelihood = -383.9

AIC = 777.79 AICc = 778.48 BIC = 790.46

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.4982649	13.7154	10.45482	0.01161528	0.2576846	0.514716

	ACF1
Training set	0.06700196

For Lao

```
> fit3=auto.arima(yt)
> summary(fit3)
```

Series: yt

ARIMA(1,2,1)

Coefficients:

	ar1	ma1
	0.4217	-0.9603
s.e.	0.0984	0.0313

sigma^2 estimated as 898.3: log likelihood = -496.15

AIC = 998.3 AICc = 998.54 BIC = 1006.21

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	2.641425	29.39537	19.44256	0.03051896	0.2364875	0.1073371

	ACF1
Training set	0.01030495

For Myanmar

> fit3=auto.arima(yt)

> summary(fit3)

Series: yt

ARIMA(1,1,0)

Coefficients:

	ar1
	0.4577
s.e.	0.0867

sigma^2 estimated as 503: log likelihood = -470.66

AIC = 945.32   AICc = 945.44   BIC = 950.61

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	2.6617	22.21403	15.15278	0.2476794	1.234827	0.1332194

	ACF1
Training set	-0.05980449

For Vietnam

> fit3=auto.arima(yt)

> summary(fit3)

Series: yt

ARIMA(0,1,0) with drift

Coefficients:

	drift
	22.1442
s.e.	5.0588

sigma^2 estimated as 2692: log likelihood=-557.68

AIC=1119.35   AICc=1119.47   BIC=1124.64

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.1981509	51.38406	33.70474	0.0008016176	0.154014	0.1092213

	ACF1
Training set	-0.01613069