

**Sensitivity Analysis of Change of Currency
Exchange ARIMA Modeling Parameters between
(0,1,1) and (1,1,0) Depending on Economic Policies**

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ABSTRACT

This thesis contains a literature survey of exchange rates, and forecasting exchange rates by using ARIMA models. The thesis shows that the best forecasting ARIMA parameters are changing in time, looking like the characteristics of the time series is changing randomly. A search of forecasting parameters within AR and MA orders 1 to 5 indicated that (1,1,1) is successful in forecasting the five-day ahead values. This study tested the sensitivity of the change of best-forecasting model parameters between AR ($p=1, d=1, q=0$) and MA ($p=0, d=1, q=1$) characters by using the financial policy decision dates as a predictor. The test is evaluated on GBP=X time series using the Federal Bank Federal Fund Rate decision dates.

The test results indicate that the statistical value of sensitivity for 26 FFR decision dates is almost 5% shifted on the decision dates, indicating that the FFR decisions had a considerable structural effect on the dynamics of the market.

Keywords: exchange rate, forecasting exchange rate, time series, auto regressive integrated moving average (ARIMA).

ÖZ

Bu tez, ARIMA modeli kullanarak döviz kurlarının tahmini konusunda bir literatür taraması ve ARIMA modelinin döviz kur tahmini amaçlı kullanımını içermektedir. Tez, en iyi tahmin sağlayan ARIMA parametrelerinin zaman içinde zaman serisinin özelliklerine bağıntılı olarak rastgele görünümde değiştiğini göstermektedir. AR ve MA dereceleri 1 ile 5 arasındaki tahmin parametreleri tarandığında, (1,1,1) 'in beş günlük değerlerin tahmininde başarılı olduğunu da göstermiştir. Bu çalışmada finansal politika değişimin bir öngörücü olarak kullanıldığında en iyi tahmin sağlayan parametrelerin AR ($p = 1, d = 1, q = 0$) ve MA ($p = 0, d = 1, q = 1$) karakterleri arasındaki değişimin duyarlılığı test edilmiştir. Test, U.S. Federal Bankası Federal Fon Oranı karar tarihleri kullanılarak GBP = X zaman serisinde uygulanmıştır.

Test sonuçları, 26 FFR karar tarihine ilişkin duyarlılığın istatistiksel değerinin, karar tarihlerinde neredeyse %5 oranında değiştiğini ve FFR kararlarının pazarın dinamikleri üzerinde önemli bir yapısal etkiye sahip olduğunu göstermektedir.

Anahtar Kelimeler: döviz kuru, tahmini döviz kuru, zaman serileri, otomatik regresif entegre hareketli ortalama (ARIMA).

DEDICATION

This thesis is dedicated to those who shared with me the ups and downs of life, its happy and sad moments.

To my Grandfather, may God Bless your Soul, and May God Keep my Grandmother.

To whom that their favors cannot be counted. No words can satisfy what they really deserve, may God make you more prosperous, my parents.

To my heart beats, my Brothers and Sister, Rand, Rasan and Reber.

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LIST OF SYMBOLS AND ABBREVIATIONS

$n_{A/AD}$	In the algorithm, number of A in AD
$n_{A/AR}$	In the algorithm, number of A in AR
$n_{A/BD}$	In the algorithm, number of A in BD
$n_{A/BR}$	In the algorithm, number of A in BR
n_{DR}	In the algorithm, number of days between RD and DD
n_{DR}	In the algorithm, number of days between BD - DD, as well as between AD – DD also between BR - RD; and AR - RD
n_{DRm}	In the algorithm, number of days after and before DD, and RD
A	In the algorithm, ARIMA (1, 1, 0) has less 5-Day-forecasting error than ARIMA (0, 1, 1)
ACF	Autocorrelation Function
AD	In the algorithm, forecasting day after the decision day
ANN	Artificial Neural Network
AR	Auto Regressive
AR	In the algorithm, forecasting day after the random day
ARCH	Autoregressive Conditional Heteroskedasticity
ARFIMA	Autoregressive Fractionally Integrated Moving
BD	In the algorithm, forecasting day before the decision day
BETI	Bucharest Exchange Trading Index
BP	Back Propagation

BR	In the algorithm, forecasting day before the random day
CAPM	Capital Asset Pricing Model
CN	Condition Negative
COV	Covariance
CP	Condition Positive
CRISP-DM	Cross-industry Standard Process for Data Mining
DD	In the algorithm, a decision day
DLS-SVM	Dynamic Least-Squares Support-Vector Machines
EURO	European Currency
EX_t	Mean of X_t
FCM	Fuzzy-C-Means
FF	Federal Fund
FFR	Federal Fund Rate
FN	False Negatives
FP	False Positives
FRB	Federal Reserve Bank
GBP	Great British Pound
GPL	General Public License
INR	Indian Rupe
ISO	International Standards Organization
LME	London Metal Exchange

LS-SVM	Least-Squares Support-Vector Machines
M	In the algorithm, ARIMA (0, 1, 1) has less 5-day-forecasting error than ARIMA (1, 1, 0)
MA	Moving Average
MACD	Moving Average Convergence Divergence
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSD	Mean Squared Deviation
NAR	Nonlinear Autoregressive Neural Network
NER	Nominal Exchange Rate
NMA	Non-Linear Moving Average
NN	Neural Network
PACF	Partial Autocorrelation Function
PCN	Predicted Condition Negative
PCP	Predicted Condition Positive
RBF	Radial Basis Function
RD	In the algorithm, n_R days before a DD.
RER	Real Exchange Rate
RMSE	Root Mean Squared Error
RON	Romanian New Leu Currency

RSI	Relative Strength Index
SANN	Seasonal Artificial Neural Network
SBP	Standard Back Propagation
SCG	Scaled Conjugate Gradient
SDMA	Six Days Moving Average
SVM	Support Vector Machine
TLNN	Time Lagged Neural Network
TN	True Negatives
TNR	True Negative Rate
TP	True Positives
TPR	True Positive Rate
TS	Time Series
TSK	Takagi-Sugeno-Kang
USD	United State Dollar
VND	Vietnamese Dong Currency
X_t	Random Variable
YEN	Japanese Currency

Chapter 1

INTRODUCTION

1.1 Exchange Rates

Exchange of currency between countries is a necessity to accomplish international trade. International standards for currency codes, ISO 4217, recognizes more than 250 regional and national currencies worldwide due to the fact that every country or nation has their own valid currency. The exchange rate, is described as the value that a certain currency has against other valid currencies at a certain point in time, for instance, the rate, of a US dollar against the Euro [1].

Beker in 2006, stated that the exchange rate is decided first by the sort of exchange that a certain country follows which requires a multifaceted process of decision making arranged by the economic policy makers [2]. Such a process takes into consideration both the advantages and disadvantages of the rate of exchange of a certain system whether to be fixed or flexible. Beker also studied other variables and factors that might influence the rate of exchange depending on different approaches whether they are old or modern [2]. Lien has defined the exchange rate as amount of national currency units to pay for one unit of foreign currency [3].

As we have mentioned above, we can define the exchange rate as regard to the value or price of a certain currency against another currency. Thus, Yang in 2014, and the

Central Bank of Nigeria in 2016, have distinguished four types of exchange rates: Fixed Rate, Flexible Rate, Real Rate, and Nominal Rate [4] [5].

Fixed exchange rate is also known as “pegged exchange rate”. According to this type of exchange rate, the value of the currency of a regime is fixed against the value of another currency included among the a basket of other currencies or against another measurable value like the value of gold, for instance, in this system of currency exchange, a country’s central bank is usually in charge of fixing that rate by the use of certain restrictive procedures in selling and buying its currency at a fixed price, so that it can keep its ‘pegged ration’. In this way the bank maintains a constant value of its currency in relation to the reference to which it is pegged.

Flexible exchange-rate system is a monetary system where the law of supply and demand decides the value of a country’s currency. Along with purely fixed and purely flexible rate systems, there are other varied approaches between these two, which have different implications that allow the currency of a country to involve in foreign exchange markets [1].

Real exchange rate (RER) is the actual exchange ratio of the charge of foreign goods in relation to the charge of local goods. To formulate it mathematically, the actual exchange rate is the percentage of a foreign charge level and the local charge level, multiplied by the nominal exchange rate.

Nominal exchange rate (NER) is the comparative price of a local currency in relation to a foreign currency. For example, if the USD/EURO exchange is equal to 1.13, it

means that to buy one unit of the European currency it takes 1.13 dollars (or on the other hand, to buy one dollar, 0.88 euros are needed).

1.2 Exchange Rate and Time Series

Foreign exchange takes a large space in the debate of the world economy. When an exchange rate is exercised between two currencies, the value of each currency is specified against each other. Lien in 2009, defines exchange rate as “*the number of national currency units that require payment for the purchase of one unit of foreign currency, or the number of currency units required to purchase one unit of foreign currency*” [3]. At the same time the rate of a foreign nation currency is decided in relation to the local currency of the home country. In most of the economies of the developed countries the economic growth of a nation is decided by the value of its currency regarding the other moneys or currencies [6] [7].

Rate of exchange is a very sensitive economic variable that influences the decisions taken by investors, exporters, importers, financial institutions, bankers, tourists, business and policymakers both in the development and advanced world [8]. Dua claimed that decision makers can foresee the future of a country’s finance and economy by predicting the right time of exchange as it gives them useful information on what to buy and what to sell and how to draw their economic policy. However, one cannot often predict the exchange rates accurately [9].

Mishkin stated at 2007 that following factors as have influence on the exchange rates on the long run: (i) Relative Price Levels, (ii) Trade Barriers, (iii) Preferences for Domestic Versus Foreign Goods, and (iv) Productivity [10].

The international markets have witnessed a great shift in this regard when the euro currency appeared in 1999 as a new challenger to the USD to face the United States economy. The USD is still the most powerful currency worldwide and has a great influence in business and trade especially in the international oil trade as well as preserving the value of other currencies [11].

Ribeiro proposed that anticipating the value and fluctuation of the exchange rate of a country is the most important component in the process of decision making managerially and financially. Many countries worldwide adopt the theory of forecasting exchange rate with different models that produce different results [12]. In other words, a country's exchange rate is an important indicator to that country's economy because if the exchange rates are not stable, the economy of that country will be badly affected on the long run especially when it comes to the dollar's exchange rate which decides the power of a country's economy. Thus, all countries need to have a good forecasting tool to be able to cope with exchange rates fluctuations and stability and consequently to have a control in their economy [13].

It is vital to know that forecasting any currency's rate of exchange is a process that requires observation, search, and analysis. Search has to take place in terms of time series, on collected observations carefully to analyze them using an appropriate mathematical model, which can follow the movement of primary data. Once the model follows the movements correctly, it can be used to forecast future happenings. This approach is mainly of benefit when enough information is not available about the statistical model or prototype that the consecutive observations will use or follow or when there is no efficient and adequate model that can offer explanations.

Time series forecasting has important applications in different areas where appropriate decisions have been taken with good results. Researchers have made potential efforts during the past several decades in order to develop and improve appropriate time series forecasting models [14].

Alam in 2012, designed a model by which he would be able to compare three various learning algorithms: SBP, SCG and BP with the use of Bayesian Regularization neural network models [8]. The most important aim of the study is to carry out a foreign currency exchange forecasting model by means of using historical data. The model also aims at introducing an accurate forecast of exchange rate that can give a better understanding for the movements of exchange rate. ANN model used inputs, four hidden layers and an output unit in order to forecast the exchange rate. The new model as anticipated has come up with good results as the prediction of data generated by the Resilient Back propagation based model was obviously appropriate for forecasting currency exchange rate USD, EURO and YEN against the Indian Rupee.

Korkmaz in 2013, focused on test an idea that countries produce and export goods that have a benefit in producing energy and importing the goods that they are necessity. And that currency was the instrument employed in this deal or business. Therefore, the association between the rate of exchange and economic development has been checked by conducting “*panel data analysis*”. The researcher used the annual data in the period of 2002-2011, which was collected from nine randomly selected European countries. By analyzing data statistically, research has shown that there is an association between the rate of exchange and economic development. The

study has come up with the result that there is interconnection between exchange rate and economic development in the nine European countries under study [15].

The importance of the real exchange strategies in stimulating economic advancement was identified by Martin in 2018. A solid RER strategy can significantly help meet this externality and other market disappointments. The subsequent improvement of these areas prompts generally speaking faster economic development. The effect of RER strategies is enhanced when they are supplemented by customary industrial arrangements that increase the flexibility of the total supply to the RER. *“Among the instruments required to actualize a steady and solid RER are involvements in the exchange foreign market and regulation of capital flows”* [16].

In a thesis, Yarmukhamedov in 2007, carried out an empirical study investigating the influence of ‘exchange rate fluctuations’ on export and import trade in Sweden discussing some of the methodological problems faced by previous similar studies critically [17].

1.3 Work Related to ARIMA Model

Babu in 2015, conducted research attempting to tackle problems of globalization that have positively influenced the scope for exchange market in India. The study aimed at the exchange rate movement of Indian INR against the USD, GBP, EUR and Japanese YEN using three currency forecasting models: ARIMA, Neural Network and Fuzzy. The paper has indicated that in the Indian exchange market the ARIMA model achieved better results than the other models in spite of the fact that previous studies have shown that earlier, studies have approved that NN models were more

successful than ARIMA model and Fuzzy Neuron model achieved better results than the NN model [18].

Fawumi in 2015, conducted forecasting research for economic reasons in order to analyze difficulties encountered by users such as those problems related the experience of users, the tremendous numbers of databases. This thesis aimed at finding solutions to such problems. The study was designed so that an interactive web based time series software can be easily used by end users. The software was designed to match with distinctive features of end users, together with a target software that can be efficiently used to manage, analyze and transform time series. The language used in this thesis was *R Language* which is the language that helps users in the “*analysis of time series, decomposition and filtering, analysis of seasonality, analysis of nonlinear time series, dynamic regression models and other time series operations*” [19].

Olayiwola in 2016, designed a model of prediction for copper spot prices in which he employed data from the London Metal Exchange (LME) [20]. The thesis aimed at exploring the use of the decision tree data mining model and ARIMA as a forecast tool for time series quantities. This study has also used some other methods in order to be able to forecast copper prices with mixed results because of the high volatility inherent in the price of the metal in the global markets over any period (TS) as the problem of the study states. The study has made use of the CRISP-DM methodology in developing a decision tree model for the prediction of copper spot prices using time series data of LME monthly copper prices from January 1970 to January 2012. The results of the study have shown that the decision tree model was more precise

than the ARIMA model which makes the former more reliable if used unreal world situations.

Ngan in 2016, carried out a study investigating exchange rates in the “foreign exchange business of commercial joint stock banks in Vietnam” [21]. The study has designed a model of forecasting that could examine the applied ability of ARIMA model in case of foreign rate of exchange between United State Dollar and Vietnam Dong. The forecasting model of the study has revealed that foreign exchange rate VND/USD in 2016 tends to raise. It has also found out that foreign exchange rate fluctuations and currency status have effects on the profit and loss in foreign exchange business. Accordingly, when a foreign exchange rate increased, one commercial joint stock bank obtained profit in foreign exchange trade, if this commercial joint stock bank was able to maintain a foreign currency for a relatively long time and contrariwise. The predicting results of this paper have also shown that foreign rate of exchange VND/USD increased constantly. Thus the study recommended that the superiors of the “commercial joint stock banks” in Vietnam should take this result into consideration and they have to do their utmost care in maintaining a long foreign currency position in foreign exchange trade.

Mocaj in 2017, investigated the TS of USD/ALL exchange rate [22]. They obtained the data of USD/ALL for the years 2000-2015, on a monthly frequency basis, from the Bank of Albania. They used three types of forecasting methods of times series: ARIMA, NAR and the proposed hybrid method of (ARIMA, NAR and ARIMA-ANN) in order to get the most efficient and well-developed predicting precision. As regard to the preciseness of forecasting and fitting, the experimental analysis proves

that hybrid model has provided the best results as it rendered exceptional results which were much better than ARIMA and ANN. Such good results mean that combining a linear and non-linear model can produce accurate results, which makes it effective and useful for exchange rate series forecasting.

Petrica in 2016, opted to utilize a more complicated method introduced by Box and Jenkins (1970) grounded on the earlier conduct of the variable being demonstrated/predicted the quantitative method in business and finance has been extensively used during the last few years due to the fact that both markets and financial establishments have interactively made use of available data and information. The paper examined the confinement of “*autoregressive integrated moving average (ARIMA) models in financial and monetary economics using the behavior of BET Index and EUR/RON exchange rates, respectively*”. This paper is distinguished by its analysis of the financial time series that led to the discovery of fat-tails (large deficits or profits are coming at a higher likelihood than the ordinary distribution would recommend) and the unpredictable way of grouping, these experimental properties that cannot be dealt with by incorporated ARMA models in spite of the restriction of these models [23].

1.4 Work Related to Sensitivity of Exchange Rate

Fernald in 2017, in their study on exchange rate sensitivity tried to answer the question whether the dollar has become more sensitive to interest rates and whether the USD has become more sensitive to unexpected changes in the course of monetary policy [24]. It has been found that the association between sensitivity and interest rate partial and the economic effects seemed to be moderate. The results of this study has also shown that the dollar was more sensitive to unanticipated changes in near-

term policy rates. However, when both the news about near-terms rates and the news about path of policy are released at the same time the evidence became too weak.

Asphage in 2014, conducted a study in order to find out the sensitivity of stock prices to unanticipated changes in exchange rates at Swedish companies [25]. To arrive at the aims of their study they try to find answers to the following study questions: the way in which the Swedish companies are responsive to the exchange rate? And how the response is different from one sector to another and the size of the organization or company. The thesis has employed asset pricing theories and models including the CAPM and Fama-French three-factor model making use of the multiple linear regression analysis. Finally, it has been found out that there was “sensitivity towards the exchange rate in portfolios of Swedish stocks”.

Beckmann in 2017, wrote a paper reviewing the current theoretical and empirical studies on how the oil prices and exchange rates are related to each other [26]. They started with reviewing theoretical transmission channels, which dealt with bi-directional causality. On the other hand, the empirical studies, which were reviewed, focused on either explaining or forecasting one variable with the other. The study concluded that the evidence varies considerably due to the nature of the sample, country choice and empirical method. However, there were some common outlines such as (i) there were strong relationship between exchange rates and oil prices which were often seen over the long-run; and (ii) as on the short-run, either exchange rates or oil prices were likely good forecaster of the other variable, but the effects were strongly time-varying. The paper has identified some vital ways for future

research in the field like the possibility of studying predictability over different periods of time and choosing optimum samples for forecasting.

Shareef in 2013, explained econometric TS models for modeling and forecasting evolution have shown a close in the prices of major international stock markets. These are London, New York, Shanghai and Tokyo stock market. The data set of time series contains the trading days from 1st January 2008 to 31st December 2012 i.e. (5years). After pre-processing the data to replace missing values using the interpolation method and converting all closing prices to the US dollar, it uses the ARMA framework, which was used to design the data set time series. It has been found that the model can be used to fit data in the estimation period. The Root Mean Square Error (RMSE) is used to find the estimation order of the parameter in the ARMA form, which is the correct values. The forecasting process was built on the ARMA model to predict the future value of the data indicators in 2010-2012 on the New York, London, Tokyo and Shanghai stock exchange. The idea of forecasting this work is to predict the closing price two days ago based on the closing price of the previous two years every two days. Forecasting is very significant in economic and industrial TS analysis and in sailing and purchasing. The funds were invested in these stock markets, and it shows that investing in the London stock market was the best investment [27].

It is too difficult to predict financial changes and developments due to the inherent complications of the financial system itself. The period used in estimating the stock price is usually five years to be able to collect series of data for prices. This work aims at using certain methods and practices of intelligence and mathematical

equations and procedures that constitute and develop a model that is able to forecast the price estimates in the future and make an index for further predictions. Not only that but the system has to be able to determine all the stages of “k-means clustering with majority vote” that can tell which method or technique is the best to predict the future prices. The suggested method makes use of a combination of useful methods so that the most accurate prediction can be achieved. The following methods of prediction are used in this proposed model to predict future prices as well as providing historical data: Radial Basis Function (RBF) with self-regulation map, K-Nearest Neighbor and Autoregressive Fractionally Integrated Moving (ARFIMA), are applied in predicting the future price of the stock index on its historical price information. However, the best forecasting method is the “*voting by majority after k-means clustering*”. The experiment was carried out by using data got from the London stock of exchange, which contained previous closing prices of the stock index. The results confirmed that the suggested method was the best for forecasting future prices [28].

Thanon proposed a method to improve the accuracy of forecasting by combining several forecasting methods including technical analysis using TSK Fuzzy model. The proposed method is tested on London stock exchange to prove that it improves performance compared to the technical forecasts. The rules were obtained using clustering algorithm FCM. Prediction accuracy is improved to 94.7% in predicting two days ahead closing prices [29].

Critical review of previous studies shows that ARIMA models have been employed successfully in linear time series forecasting. This study is targeting to discover the

ARIMA model in a different perspective by testing the dependence of ARIMA model parameters on several economic and political factors, such as the change of financial policies of the main actors in the exchange market. The literature survey indicated that the kind of relations has not been collected interest among the researchers. In this respect, this study is a candidate of the frontier research to determine the connection between the sharp changes of the ARIMA model parameters of the exchange rates as a result of economic events.

1.5 Problem Statement

ARIMA model is a successful method in the forecasting of exchange rates. Determination of the model parameters (p, d, q) is an important factor in reducing the forecasting error of ARIMA based forecasting. This study is focused on testing the dependence of the ARIMA parameters on the financial policy decisions. GBP/USD exchange rates are almost independent to the actions of speculative actors since both GBP and USD are used as reference value in import and export of the other countries.

It is natural to expect a considerable influence of the financial decisions of US Federal Bank Federal Fund Rates return (US-FB-FFR) directly on the GBP/USD exchange rates. This study claims further effects of this kind of influential decisions not only on the value of exchange rates, but also on the dynamics of the market, which shall appear on the ARIMA model as the change of parameters, or even a change of the complete structural character such as from AR to MA, or from MA to AR.

The available GBP/USD exchange rate data and available 26 (FB-FFR) decision dates give us an opportunity to test this thesis in a simple methodology, by the sensitivity and specificity analysis of the parameters on the FFR decision dates.

1.6 Organization and Structure of the Thesis

Chapter 1 is introduction and literature review. The remaining parts of this thesis are organized as follows. Chapter 2 addresses the theories of times series architectural that provide the reader with brief details. It also gives details about the concepts of ARIMA elements. Chapter 3 presents the conceptual design and the related aspects and assumptions related to the building and implementation of the ARIMA model for forecasting exchange rates five days ahead. The Federal Bank Rate (FFR) data set, and the sensitivity and specificity tests of ARIMA parameters are displayed in Chapter 4. Chapter 5 is the conclusion of the study.

Chapter 2

TIME SERIES AND ARIMA MODEL

2.1 Definition and Application of Time Series

TS modeling and forecasting is of a great significance to many practical areas. Generally, a TS is successive groups of data points that are usually calculated over consecutive period's time. Adhikari defined time series mathematically as “a set of vectors: X_t , $t= 0, 1, 2, \dots$, where t represents the time elapsed. The variable X_t is treated as a random variable”. According to this definition the calculations which are derived from an event in a time series are ordered chronically in a good manner [14].

According to Mondal in 2014, a TS is “*a set of well-defined data items collected at successive points at uniform time intervals*”. It is worth mentioning that statistics considers time series analysis as a very important area in the discipline as it analyzes groups of data, and studies their features in order to predict their future values [30].

Falk in 2012, admit that there must be various reasons that make us to record and analyze the data of a time series. One of these reasons is the desire of researchers and specialists to get profound understanding on how data are generated which allows them to predict future values or to have full control of the system. It is important to realize that time series are characterized by the following properties: they are independent when they are generated, they scatter over periods of time, they are

frequently decided by tendency and they function in recurring mechanisms that is cyclic in nature. Conversely, the analysis of time series involves certain and specialized methods that are labeled as time series analysis [31].

2.1.1 Components of a Time Series

Shumway in 2016, and Stoffer in 2011, distinguish four major components of TS, which are “seasonal variations, trend, cyclic variation and irregular or random variations”. The researchers above also provided the following useful and brief description for each of these series [32] [33].

- a. Seasonal variations: In trade and marketing there are certain seasons in the year when certain economic activities become active for one reason or another. Similar things take place with time series as they show consistent fluctuations at certain months or a quarter every year. That is called, in this context, seasonal variations. For example, we can see retail sales go up every year in December which are interpreted in terms of TS as “fluctuations within a year during the season”. The reasons that led to this phenomenon, seasonal variations, include climate and weather as well as cultural factors like a community and a nation’s customs and traditional habits. Accordingly, Seasonal variation is a vital factor that should be taken into consideration for making proper future plans.
- b. Trend: When the time series tend either to increase, decrease or stays at it a longer duration of time is over is called a trend. It is also called Secular Trend. Accordingly, we can conclude that a trend is a long-standing movement in a time series.
- c. Cyclical variation: This is known as the changes that take place in a time series on the medium term due to certain environments, which also reoccur in cycles.

The duration of a cycle takes two or more years. It is important to state that most of the time series that are of economic and financial nature display one or more type of cyclical difference in a way or another.

- d. Irregular or random variations: These sorts of variations occur in a time series as a result of unforeseen effects that inconsistent and also do not reoccur according to a specific pattern. These variations usually take place as result of war, strike, earthquake, flood, revolution, etc. It is not possible to measure these kinds of fluctuations statistically in a time series.

Ihaka in 2005, distinguished between the n-dimensional random variables and what he calls a stochastic process. Considering the random variables, the time series can only really “observed at a finite number of times, and the underlying sequence of random variables (X_1, X_2, \dots, X_n) is just an n-dimensional random variable”. As with so called stochastic process “it is convenient to allow the number of observations to be infinite. In that case $\{X_t, t = 1, 2, \dots\}$ ”. All n-dimensional distributions need to be taken into consideration if we have to identify its statistical properties. Accordingly, a stochastic process is considered motionless, i.e. “stationary”, if its statistical characteristics remain same with time [34].

2.1.2 Concept of Stationary

Stationary TS is a time series data set in which statistical properties such as the mean, variance and autocorrelation are not changing by time. A non-stationary series is a time series with statistical properties changing over time. Many forecasting tools, including ARIMA, does not work properly if the data set is non-stationary. It is necessary to transform non-stationary TS either to a weak stationary, or to a strict

stationary form to use these tools properly. We can distinguish between two kinds of stationary which namely are strong or strict stationary and weak stationary [35].

Vaart in 2013, provides formal tests of stationary including the Augmented Dickey-Fuller test, which is a very popular test. It comes in the following statements [36]:

1. “The time series X_t is strictly stationary if the distribution (on \mathbb{R}^{h+1}) of the vector (X_t, X_{t+1}, X_{t+h}) is independent of t , for every $h \in \mathbb{N}$.”
2. “The time series X_t is stationary (or more precisely second order stationary) if EX_t , EX_{t+h} and X_t exist and are finite and do not depend on t , for every $h \in \mathbb{N}$.”

It is worth confirming at this point that the weak stationary is adequate and satisfactory to meet the objectives of this study because it is characterized by the property that the mean, variance and auto-covariance structure remain consistent over time [35]. This means that the series are flat, have no actual trend, their variance is steady and stable, have no seasonal fluctuations or autocorrelation.

2.2 Time Series Forecasting Methods

ARIMA is not the only forecasting method for TS processes. For example, ARIMA model is compared to some non-linear stochastic models, such as NMA, ARCH, Neural network forecasting models: TLNN and SANN, and SVM based forecasting models: LS-SVM and DLS-SVM, on six TS data sets, for five performance measures including MAE, RMSE with almost equally comparable performances [14].

2.3 Introduction to ARIMA Modeling

The word (ARIMA) is an abbreviation for Auto Regressive Integrated Moving Average model. ARIMA models are usually used for stationary “time series forecasting”. According to this model, if one starts with a non-stationary time series, he/she has to difference the time series until obtaining a stationary TS. If the user difference the time series d times to obtain a stationary series, then he /she has got an ARIMA (p, d, q) model, where d is the order of differencing [37].

Zhang in 2003, thinks of ARMA model as a significant method to study TS. In fact, the theory behind (ARIMA) time series model was presented by Box and Jenkins (1976) who recorded the systematic procedure for applying the technique in their landmark book. The ARIMA model is well known for its statistical characteristics together with the well-known Box-Jenkins methodology used in the building process of the model [38]. According to Adhikari an ARMA (p, q) model is a result of mixing AR (p) and MA (q) models and is suitable for time series modeling. In an AR (p) model “the future value of a variable is supposed to be a linear combination of p past observations and a random error together with a constant term” [14].

It is worth mentioning, as put by Nugroho in 2014, that ARIMA and Box-Jenkins forecasting usually refer to the same set of techniques. However, ARIMA modeling is considered as a complex model because it employs several time series procedures. The users of this model need to be well known about the details of its procedures before they become certain of the success of forecasting [39].

It is believed that ARMA models are not efficient upon application to describe non-stationary TS, which often face problems in practice. That is the cause of why ARIMA modeling has been suggested instead of ARMA in spite of the fact that ARIMA is a copy of ARMA as well as the case of non-stationary. Box-Jenkins has specified four stages for ARIMA model selection as stated by Ababio in 2012. They include [40]:

1. Deciding (p, d, q) values.
2. Estimation of the parameters of the model.
3. Making sure if the suggested model is fit to the data, if it is not then choose another model.
4. Finally, choose the model that best serves your objectives.

2.3.1 The Stages of ARIMA Algorithm

ARIMA is an acronym stands for Auto-Regressive Integrated Moving Average and is identified by these three order parameters: (p, d, q). The practice of fitting an ARIMA model is sometimes called the Box-Jenkins method. The analysis carried out by PROC ARIMA is made up of three separate stages, matching the stages explained by Box and Jenkins in 1976 as seen in Figure 1. The Identify, Estimate, and Forecast statements implement these three stages as briefly detailed as follows [41]:

1. Identification stage: This stage involves specifying response series and identifying appropriate ARIMA models for it. The identify statement recognizes the time series that must be employed in afterward statements. It is also possible that time series at this stage will be differenced, and the following correlation might also take place: “*computes autocorrelations, inverse autocorrelations, partial autocorrelations, and cross correlations*”.

Also stationary tests can be carried out in order to decide whether differencing is required. One or more ARIMA models that could match data are advised in the output of the identify statement analysis. The models provide options that give the user chances to test the stationary.

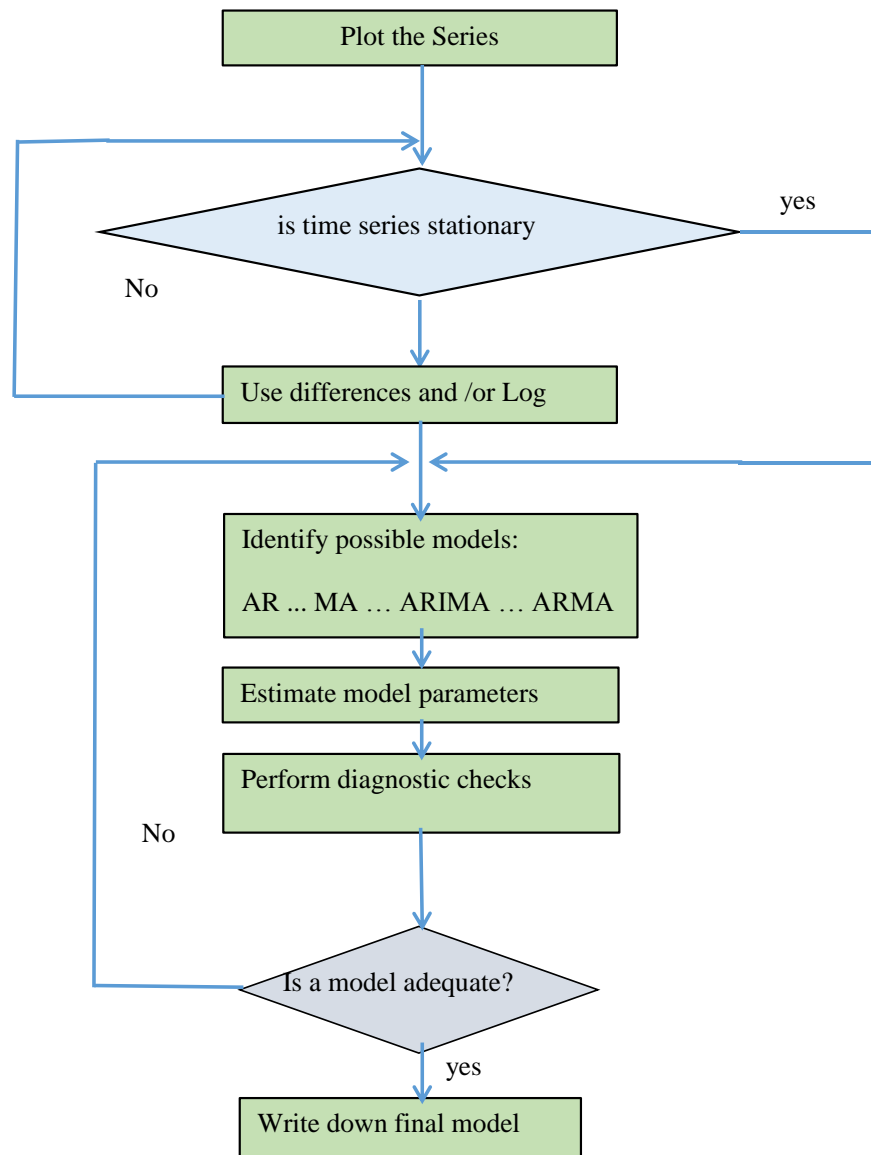


Figure 1: Flowchart of Box and Jenkin, Source: Shrivastav 2012 [42]

2. Estimation and Diagnostic checking stage: The aim of this stage is to identify the ARIMA model that matches the variable identified in the previous identify statement, and to find out the approximate parameters of that model. This stage also provides diagnostic statistics that helps the user to decide on how much the model is competent. This stage includes also tests for parameter estimates ‘significance tests in order to find out if there were any unnecessary terms. The Goodness-of-fit statistics is another test included in this stage which gives the user an opportunity to compare this model to other models. On the hand, the ‘ *white noise residuals tests*’ are used to find out if the outstanding series contain extra information that a more complicated model can use. If the diagnostic tests diagnose certain problems with the model, the user can opt to another model, thus the user has to repeat the “estimation and diagnostic checking stage”.
3. Forecasting stage: This stage involves forecasting time series values for the future and yielding confidence periods for these forecasts from the ARIMA model produced by the preceding estimate stage.

It is important to mention that these autoregressive models are established on the notion that the present value of the series X_t can be interpreted as a function of P past values X_{t1} , X_{t2} , and X_{t3} ; where P decides the number of steps occurred in the past required to predict the present value.

2.4 Structural of ARIMA Parameters

It is possible to combine Autoregressive (AR) and moving average (MA) models together to produce new models labeled ARMA models. ARMA models are usually employed by using the lag operator notation.

ARIMA model has three main structural parameters, denoted by ARIMA (p, d, q), where p is the parameter that determines the order of the autoregressive part, d is the differencing order that makes TS stationary, and q sets the order of moving average process. A model without differencing (d = 0) is usually called an ARMA (p, q) model. Differencing is a method to convert a non-stationary series into a stationary-series. The model used in this study is an ARIMA (2, 1, 0) model, which is the simplest possible integrated model, with auto-regressive order 2 and moving-average having order 0 [43].

The Box-Jenkins methodology does not adopt any specific decoration in the historical data of the series to be forecasted. In fact, it utilizes an approach that consists with the following three reiterated steps: “model identification, parameter estimation and diagnostic checking and forecasting stage” to decide upon choosing the optimal model from a general class of ARIMA models. The user has to repeat these steps several times until an appropriate matching model is ultimately chosen, which can be effectively employed for predicting the values of the time series in the future. The schematically methodology of Box-Jenkins Model shown in Figure 2 As provided by [14] [44].

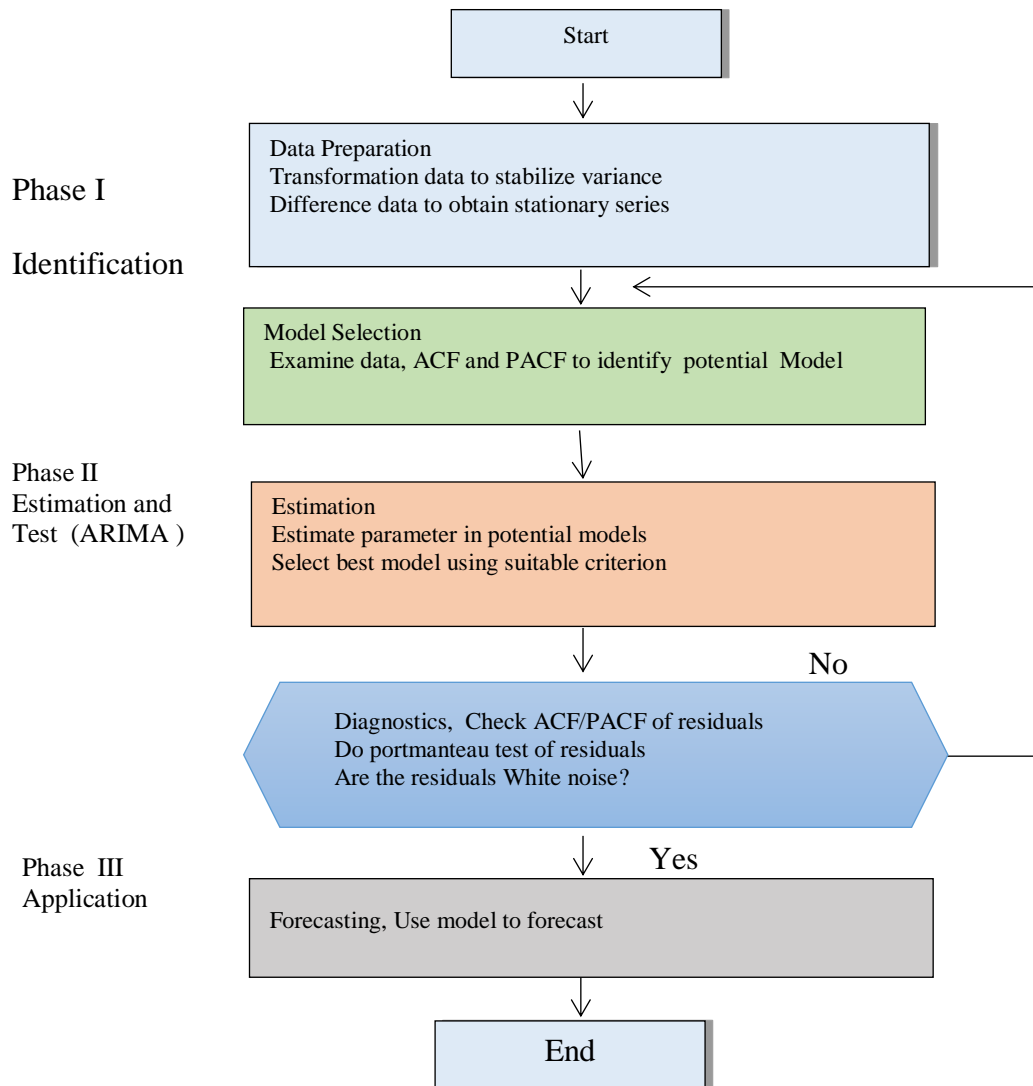


Figure 2: The Box-Jenkins Methodology, Source: Junior 2014 [44]

2.5 About the Programming Environment

R is a system, which is commonly used for computational purposes and statistical graphics uses. It is composed of a language and a runtime device with graphics, debugger and access to definite system functions. It is also able to run programs stored in script files. The R design has been significantly influenced by two languages, namely: Becker, Chambers and Wilks' S and Sussman's Scheme. The resulting language has the same appearance as S, whereas the basic implementation and semantics are taken from Scheme. Core R is a language that the computer interprets, which allows the following functions to take place: branching, looping and standard programming that uses functions. It is worth mentioning that users use R language for writing most of the functions. For efficiency, procedures can be written in C, C ++ or FORTRAN as well. R distribution covers functions that can be used for greater numbers of statistical operations including "linear and generalized models, nonlinear regression models, time series analysis, classical and non-parametric classical tests, clustering and smoothing". There are a variety of their important functions that flexibly allows the user to draw different graphics and various data presentations. In addition to that, there are other modules like "add-on packages", for different certain useful purposes [45].

Ihaka and Gentleman from the department of Statistics at the University of Auckland, New Zealand, were the first scholars who wrote the R language whose name is taken from the initials of those two persons. Martin Maechler was able in 1995 to convince Ross and Robert to use the General Public License (GPL) to make R a free software. That was a big event in the history of the discipline as it became possible to have free access to the language by anyone who wants to make use of it. Later in 1996 a public mailing list was introduced under the name of R-help and R-devel lists followed by forming the R Core Group in 1997, which included individuals associated with S and S-Plus. Nowadays, the core group has control over the source code for R and it is the only group who has the authority to check and make changes to the main R source tree. Lastly the R version 1.0.0 was distributed in 2000 for the public [46].

2.6 Conclusion for ARIMA Model

Mondal in 2014, summarized the ARIMA model as follows: It is a broadly used model that can envisage linear time series data. The ARIMA models are frequently labeled as Box-Jenkins models. It is used for the types of data that are non-stationary. Box and Jenkins have adopted this model and made it known to deal with seasonality. They called it the “Seasonal ARIMA (SARIMA) model“. This model makes use of the seasonal differencing of proper order in order to get rid of the non-stationery from the series. The first order that the seasonal difference model performs is “it points out the difference between an observation and the corresponding observation from the preceding year” [30].

It is worth mentioning that a good number of literatures has been written on the comparison between ARIMA models and ANN in forecasting using time series data. Most of those studies considered data as bases for comparisons whereas other studies made use of economic data. The accuracy of forecasts obtained by matching time series models to time series data, for example, stock price indices, received a great attention by many statisticians and economists. One of the areas that statisticians and economists focused on is the accuracy of forecasts in relation to time series models and how these models fit to the concerned variables [47]. One of the successful models is the Box-Jenkins “Autoregressive Integrated Moving Average” (ARIMA) which proved to be efficient in rendering accurate forecasts to certain extents for future happenings in different instances and situations. However, not all the predictions suggested by the model were always accurate enough in all the cases due to the fact that “the forecasts converge to the mean of the series” after three or four forecast values. Okasha in 2013, also suggested the Artificial Neural Networks (ANN) as a good alternative to the Box-Jenkins approach, especially when the data is nonlinear and for predicting different future values [47].

Chapter 3

GBP/USD TIME SERIES AND FORECASTING BY ARIMA

3.1 Definition of Sensitivity

According to the National Information Center on Health Services Research and Health Care Technology (NICHSR) of USA, the diagnostics tests are evaluated using the following statistical terms which are used in scoring the performance of a prediction [48].

A *true positive* test result is a test result that detects the disease is present. A *true negative* test result is one that does not detect the disease is absent. A *false positive* test result is one that detects the disease is absent. A *false negative* test result is one that does not detect a marker when the disease is present [48].

The output of a prediction may be used to determine the sample cases to be in a target category or not. If the prediction pointed the case is in the target class, it is called *identified* to be in class. Else, if the prediction pointed the case is not in the target category, it is called *rejected* to be in class. *Identified* set of samples are also called *predicted condition positive* (PCP) and *rejected* samples build the set of *predicted condition negative* (PCN) [49].

For example, let total 100 patients be tested by blood screen test (BST) as explained in Wikipedia for cancer diagnosis [49]. Let's say BST *identified* 20 patients to be positive, which means patients have cancer. That means, it *rejected* the remaining 80 patients since BST test predicted them negative, meaning that cancer not diagnosed. Now in other terms, from total population of 100, BST has *predicted condition positive* (PCP) = 20, and *predicted condition negative* (PCN) =80.

Assume that patients also taken an endoscopic diagnosis test (EDT) to specify their actual condition. From all 100, EDT identified only 16 patients' positive, which is expressed by statistical term *condition positive*. That means the remaining 84 patients are not cancer, or statistically there are 84 patients in the set of *condition negative*.

Now, knowing who is cancer by EDT test, we can check how successful BST diagnosed cancer. From 20 patients which are identified by BST, 14 of them are found cancer by EDT. In statistical terms, they are *correctly identified* cases, *hits*, or *True Positives* (TP) of the BST test. The remaining 6 patients of 20 BST identified cases are *incorrectly identified*, or *false alarm* cases since EDT has negative result for them. In statistics they form *type-I errors*. In machine learning they are called *False Positives* (FP).

The BST test rejected 80 patients diagnosing that they are not cancer. From these 80 patients, two of them diagnosed cancer positively by EDT test. These two cases are *incorrectly rejected* patients, or *missed* cases. In machine learning terminology, they are called *False Negatives*, (FN). Remaining 78 patients are *correctly rejected* cases, or in machine learning they are *True Negatives* (TN) cases as seen in Table 1.

Table 1: Confusion Matrix of the Example

	Cancer confirmed by endoscopic diagnosis test (EDT)		
	in-Category, positive	not-in-Category, negative	
BST Identified, predicted positive	True Positive TP=14	False Positive FP=6	Pred. Cond. Pos PCP=20
BST Rejected, predicted negative	False Negative FN=2	True Negative TN=78	Pred. Cond. Pos PCN=80
	Condition Positive CP=16	Condition Negative CN=84	Total Pop.=100
	Sensitivity TP/CP=87.5%	Specificity TN/CN = 92.9%	

In statistics, sensitivity, in other terms recall, or hit rate, and in machine learning the term true positive rate (TPR) are all pointing the same ratio, the ratio of correctly predicted cases in the total predicted cases. Now for our example we find out.

$$\text{sensitivity} = \frac{\text{hits}}{\text{hits} + \text{misses}} = \text{TPR} = \frac{TP}{TP + FN} = \frac{14}{14 + 2} = 87.5\%$$

A dual measure for the cases rejected to be in the class is called in statistics specificity, also selectivity or in machine learning true negative rate (TNR). Which is the ratio of correctly rejected cases in all condition negatives.

$$\text{specificity} = \text{TNR} = \frac{TN}{TN + FP} = \frac{78}{78 + 6} = 92.9\%$$

3.2 Source of Exchange Rate Time Series

In this study, the time series data set for USD/GBP exchange rates are accessed through the finance.Yahoo data base by using the web interfacing function available in R CRAN repository using pdfetchYAHOO function of pdfetch library.

```
library(knitr)
library(pdfetch)
# if file not available in the folder,
# get it from yahoo and save it into workfolder
re=try(load("RR/GBP.RDATA"))
if(re[1]!='GBP'){
  GBP = pdfetch_YAHOO('GBP=X', interval="1d" )
  save(file="RR/GBP.RDATA", list="GBP")}
rm(re) # removes tryCatch result
```

Which gets a time series data for over 10 years either from the folder RR, or from YAHOO. The head and foot of this data are in Table 2:

Table 2: Head of Raw GBP=X Data Set

Period	GBP=X.p	GBP=X.h	GBP=X.l	GBP=X.c
2007/01/01 12:00:00 AM	0.5104	0.5107	0.5091	0.5091
2007/01/02 12:00:00 AM	0.5091	0.5093	0.5065	0.5067
2007/01/03 12:00:00 AM	0.5067	0.5131	0.5062	0.5122
2007/01/04 12:00:00 AM	0.5124	0.5153	0.5119	0.5147
2007/01/05 12:00:00 AM	0.5146	0.5189	0.5119	0.5179
2007/01/08 12:00:00 AM	0.5182	0.5189	0.5154	0.5154

The number of vectors in the downloaded time series raw data is 3240, starting from date 2007-01-01 and ending on 2019-05-30. Raw data has four columns for each work day of US, mainly for *opening* (GBP=X.p), *highest* (GBP=X.h), *lowest*

(GBP=X.l),, and *closing* (GBP=X.c), exchange rate values of the transactions in that day as seen in Table 2.

3.3 Filling Missing Values of TS Data Set

For a more precise analysis, previous studies indicate that the missing days shall be interpolated to complete the data set for each day [27]. This process is achieved using `na.approx()` function in `zoo` library.

```
GC[,2]=na.approx(GC[,1])
```

Table 3: Closing Values in Raw and Interpolated Data

Period	Clo	Cli
2007/01/01 12:00:00 AM	0.5091	0.5091
2007/01/02 12:00:00 AM	0.5067	0.5067
2007/01/03 12:00:00 AM	0.5122	0.5122
2007/01/04 12:00:00 AM	0.5147	0.5147
2007/01/05 12:00:00 AM	0.5179	0.5179
2007/01/06 12:00:00 AM	NA	0.5171
2007/01/07 12:00:00 AM	NA	0.5162
2007/01/08 12:00:00 AM	0.5154	0.5154
2007/01/09 12:00:00 AM	0.5157	0.5157
2007/01/10 12:00:00 AM	0.5175	0.5175

As seen in Table 3, the closing rates, Clo, for 2007-01-06 in the raw data is NA, which stands for Not Available. For these missing values, a value is interpolated using the previous and later available values. After filling the missing days into Cli, the length of the data set expands from 3240 to 4533.

3.4 Visual Inspection of TS Data

The overall plot of a TS data is easily obtained by `plot` function as seen in Figure 3.

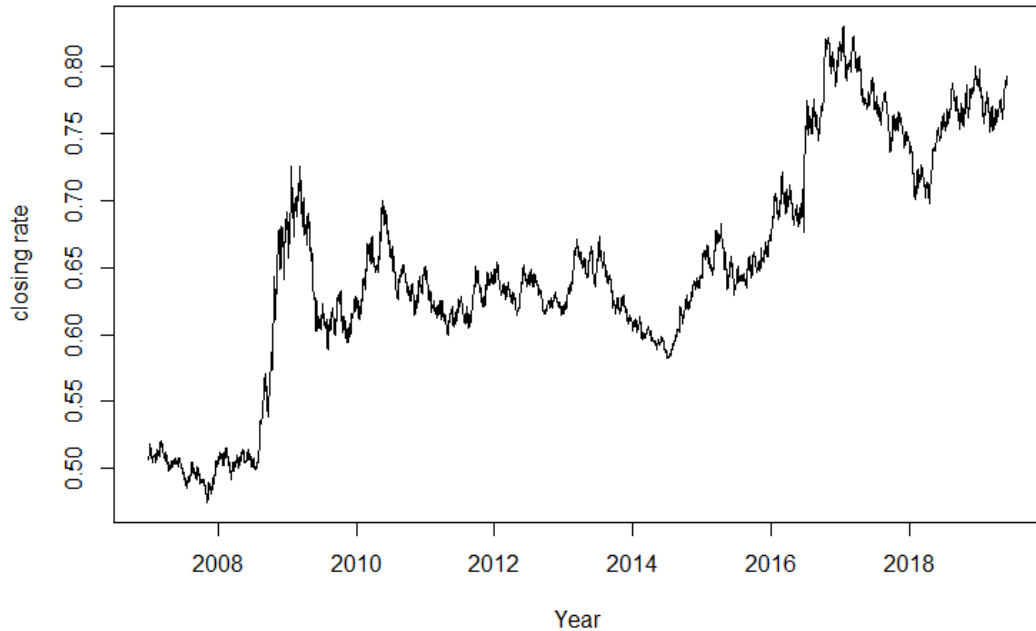


Figure 3: Plot of Overall TS Data Set

Data is apparently non-stationary, since the mean value is changing over the time, and it needs processing to convert it to a stationary TS data. Therefore, it is necessary to use differencing of order $d=1$.

For better inspection, some parts of data may be plot for one year periods, as seen in Figure 4.

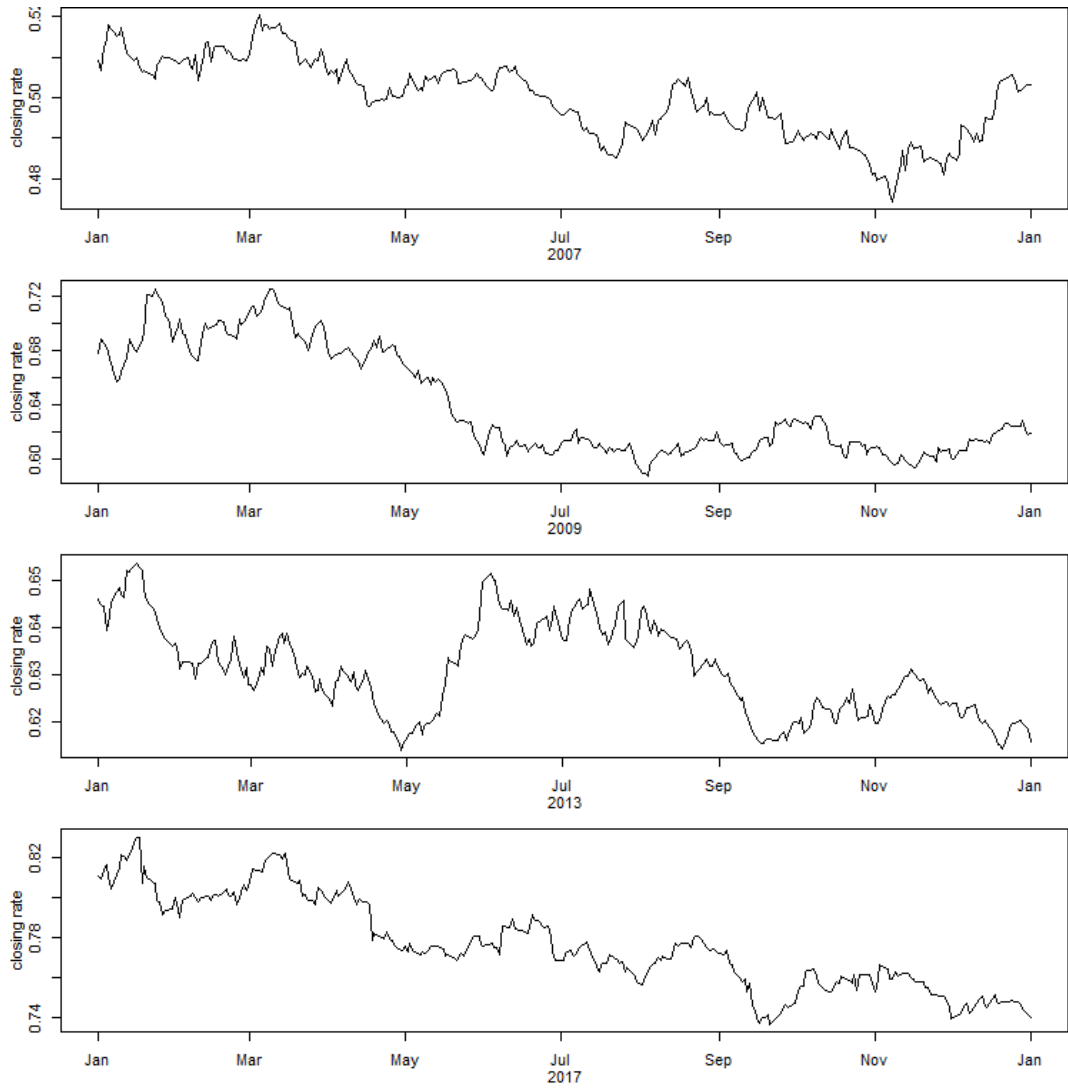


Figure 4: Sample Plot of TS Data Set for Years

Chapter 4

ARIMA PARAMETER SENSITIVITY TO ECONOMIC POLICIES

4.1 Financial Policy Data

Without any objection, the most significant financial decisions that effects the USD/GBP exchange rates are Federal Reserve Bank (FRB), Federal Fund (FF) interest rate and maturity decisions.

The following dates are compiled from data sets published on Federal Reserve Bank historical data (H15 series) web pages by Wikipedia [50]. Economists study this data in following periods:

- (1) (1979-2008): FF interest increased from 11% to 12%.
- (2) (Dec 2008 to Dec 2015): constant FFI period.
- (3) (2011): Twist to rise in Discount Rates.
- (4) (Sep 2012 to December 2013): Quantitative Easing Period.
- (5) (Dec 2015, ongoing): FF interest rate hike.

Table 4: Dates of FR Bank Federal Fund Rate Decisions

Ddate	FFR	FFRa	DiscR	Votes
2018-12-19	2.25	2.5	3	10-0
2018-09-26	2	2.25	2.75	9-0
2018-06-13	1.75	2	2.5	8-0
2018-03-21	1.5	1.75	2.25	8-0
2017-12-13	1.25	1.45	2	7-2
2017-06-14	1	1.25	1.75	8-1
2017-03-15	0.75	1	1.5	9-1
2016-12-14	0.5	0.75	1.25	10-0
2015-12-16	0.25	0.5	1	10-0
2011-06-22	0	0.25	0.75	10-0
2008-12-16	0	0.25	0.5	10-0
2008-10-29	1	1	1.25	10-0
2008-09-08	1.5	1.5	1.75	-
2008-04-30	2	2	2.25	8-2
2008-03-18	2.25	2.25	2.5	8-2
2008-03-16	3	3	3.25	10-0
2008-01-30	3	3	3.5	9-1
2008-01-22	3.5	3.5	4	8-1
2007-12-11	4.25	4.25	4.75	9-1
2007-10-31	4.5	4.5	5	9-1
2007-09-18	4.75	4.75	5.25	10-0
2007-08-16	5.25	5.25	5.75	10-0
2007-08-07	5.25	5.25	6.25	10-0
2007-06-28	5.25	5.25	6.25	10-0
2007-05-09	5.25	5.25	6.25	10-0
2007-03-21	5.25	5.25	6.25	10-0
2007-01-31	5.25	5.25	6.25	11-0

At Table 4, `Ddate` denotes the decision date, `FFR` is the Federal Fund interest Rate decided on this date, `FFRa` is the upper-bound of `FFR`, `DiscR` is the discount rates, and finally `votes` state the support of committee members in decision. A plot of this data set is shown in Figure 5.

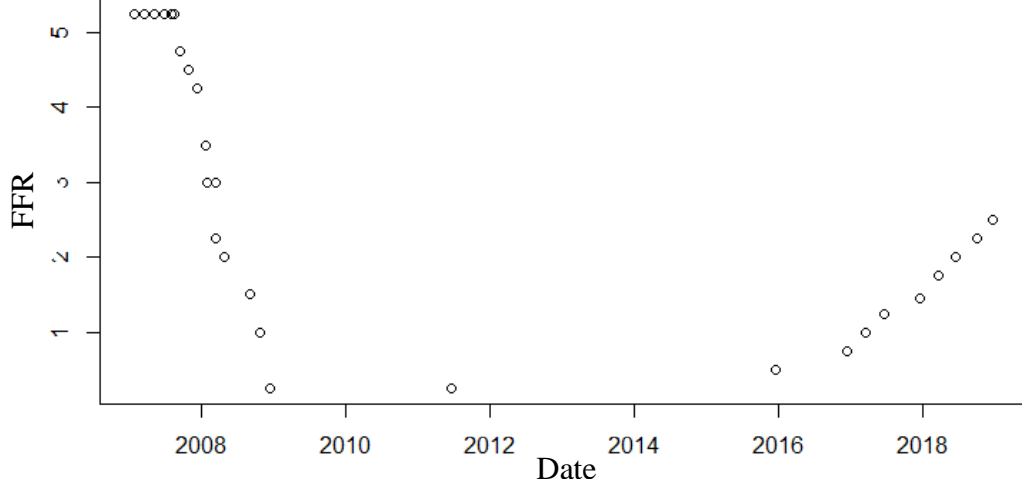


Figure 5: Plot of Federal Reserve Bank, Federal Fund Rates Data

With the decision dates in this data set, this study targets to compare optimum ARIMA parameters (p, d, q) that minimize forecasting error before and after the decision dates, to determine a sensitivity of the parameters on the decision dates.

4.2 Proposed Procedure to get Sensitivity and Specificity.

This study proposes to get the sensitivity of ARIMA parameters on financial decision by the following procedure:

- 1) For i .th decision date d_{di} determine n_R days earlier day d_{ri} , The test targets to determine the difference in ARIMA parameters for optimum forecasting of next five days comparing n_{DR} days after and before d_{ri} against n_{DR} days after and before d_{di} .
- 2) For each d_{di} and d_{ri} , construct n_{TS} days time series T_{bdi} , T_{bri} , T_{adi} , and T_{ari} , where, index b and a denotes n_{DR} days before and after the date d_{di} or d_{ri} .
- 3) For each time series, determine the best fitting ARIMA (p, d, q) model, using $(p, d, q) = \{(0,1,1), (1,1,0)\}$, by forecasting rates of next five days, and determining the mean forecasting error to select the optimum parameters among $(0,1,1)$ or $(1,1,0)$.

- 4) Calculate the sensitivity and selectivity of d_{di} on getting different parameters for d_{di} and d_{ri} .

4.3 ARIMA Parameters and Forecasting

ARIMA parameters (p, d, q) are the order of auto-regressive terms, p ; the order of differencing, d , and the order of moving average terms, q . They are significant parameters in performance of forecasting. In this study, our aim is to test the effect of the change of financial policy on these three parameters.

The function `Arima()` in the library `forecast` returns a class of fitted model coefficients for a given set of training TS, and parameters (p, d, q) . In the same library, the function `forecast()` returns the forecasted values \hat{x}_k for the requested amount of future time steps. The k step ahead absolute forecasting error $e_{f,k}$ is calculated by:

$$e_{f,k} = x_k - \hat{x}_k$$

For a more realistic forecasting error, this study takes the mean of $e_{f,k}$ for five days

$$\bar{e}_k = \frac{1}{5} \sum_{k=1}^5 |e_{f,k}|$$

4.3.1 Forecasting Example

For example, with the first decision date in the decision table, $d_d=2018-12-19$, counting $n_R = 30$ days before d_d the date of random day is $d_r=2018-11-19$. $n_{DR} = 3$ days after the decision date is $d_a=2018-12-22$. Consequently, the training TS dataset T_{da} starts from 2018-12-05 and ends on 2018-12-22 both inclusive. The fitting model parameters `fit` and the forecasted exchange rates `fc` are obtained by calling

```

fit = Arima(GC$cli[sDD+na],
            order=c(1,1,0), include.drift = T)
fc = forecast(fit,h=nF)

```

Where `GC$cli[sDD+na]` is the time sequence for training TS, T_{db} . Here, `include.drift=T` provides removal of drift from TS to reduce the non-stationary behavior of training TS. Parameters of ARIMA are specified by `order=c(1,1,0)` which sets $p = 1$, $d = 1$, and $q = 0$, setting model to *AR1* type. The plot in Figure 6, which shows forecasted values for five days is obtained by plot function using `fc`.

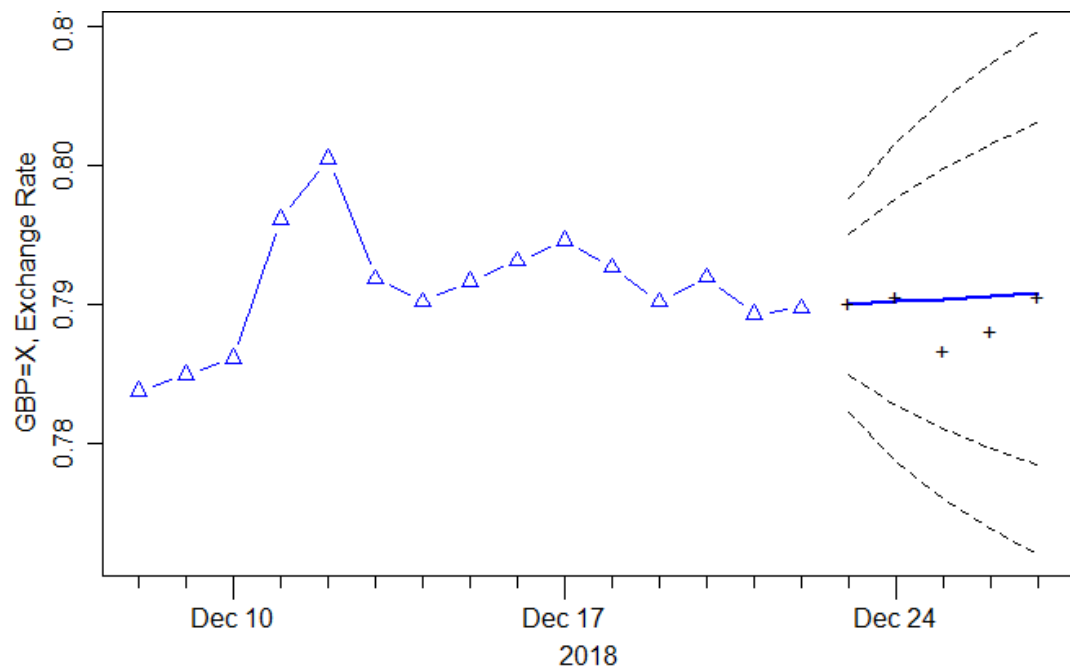


Figure 6: Forecast of Five Days for T_{adi}

For this example, the mean error is calculated by:

```
ef = GC$cli[sFD+na]-as.numeric(fc$mean)
efm = mean(abs(ef))
```

Which gives $e_f = 0, 0, -0.004, -0.002, 0$ for five days, and $\bar{e}_f = 0.001$.

4.4 Search of Parameters for Minimum Forecast Error

The proposed algorithm given in section 4.2 searches the best 5-days-ahead forecasting model parameters among the ar1 and ma1 options, $\{(1,1,0), (0,1,1)\}$, using the minimum number of days n_{DRM} which does not give any singularity or non-stationary errors with ARIMA procedure for the length of the training TS.

4.5 Test for “Ar1 Occurs More Frequently Before Decision Days”

For this test,

- 1) Values for n_{DRM}, n_R, n_{TSM} are decided.
- 2) For each DD , the n_R day before that DD is determined as RD .
- 3) For each day $n_{DR} \in [1 \dots n_{DRM}]$ days before and after both DD and RD , arima(0,1,1) and arima(1,1,0) are applied with $n_{TS} = 18$ day training TS data for determine each day is A or M .
- 4) A in BD ; A in AD ; A in BR ; and A in AR are counted to classify DD and RD for TP, FP, FN, TN groups.
 - 4.i) For DD s, if $n_{A/AD} > n_{A/BD}$ (that means DD identified increase of A correctly) increment TP ; else, (DD missed to reject increase of A ,) increment FN .

4.ii) For RD s, if $n_{A/AR} > n_{A/BR}$ (that means RD rejected increase of A falsely) increment FP ; else, (DD rejected increase of A correctly,) increment TN .

5) Sensitivity (TPR), and specificity (TNR) rates are calculated by

$$TPR = \frac{TP}{TP+FN}; \text{ and } TNR = \frac{TN}{TN+FP}.$$

4.5.1 An Example on Small Set of ARIMA Results

In this example, ARIMA results provide the following best parameter sets with three DD (plus three RD) and $n_{DRM} = 4$ days as shown in Table 5.

Table 5: Best Parameter Sets with Three DD Plus Three RD and n_{DRM}

row	BD_4	BD_3	BD_2	BD_1	$DD RD$	AD_1	AD_2	AD_3	AD_4
1	A	A	M	M	DD	M	A	A	A
2	M	A	A	A	RD	A	M	A	A
3	M	A	M	M	DD	A	M	M	M
4	A	M	A	M	RD	M	M	A	M
5	M	M	M	A	DD	A	A	M	M
6	A	M	A	M	RD	M	A	A	A

Explanation of procedure applied on example:

i. Initialize array of confusion matrix

$$CM = (TP, FN, FP, TN) = (0, 0, 0, 0).$$

ii. For row-1, 2 of BD s are A , and 3 of AD s are A , $\Rightarrow n_{A/AD} = 3$, and $n_{A/BD} = 2$, \Rightarrow

$$n_{A/AD} > n_{A/BD} \text{ identified correctly; } \Rightarrow \text{increment } TP, \Rightarrow CM = (1, 0, 0, 0).$$

iii. For row-2, $n_{A/BR} = 3$, $n_{A/AR} = 3$, $\Rightarrow n_{A/AR} > n_{A/BR}$ rejected correctly; \Rightarrow

$$\text{increment } TN, \Rightarrow CM = (1, 0, 0, 1)$$

iv. For row-3, $n_{A/BD} = 1$, $n_{A/AD} = 1$, $\Rightarrow n_{A/AD} > n_{A/BD}$ identified incorrectly; \Rightarrow

$$\text{increment } FN, \Rightarrow CM = (1, 1, 0, 1)$$

- v. For row-4, $n_{A/BR} = 2$, $n_{A/AR} = 1$, $\Rightarrow n_{A/AR} > n_{A/BR}$ rejected correctly; \Rightarrow increment TN , $\Rightarrow CM=(1,1,0,2)$
- vi. For row-5, $n_{A/BD} = 1$, $n_{A/AD} = 2$, $\Rightarrow n_{A/AD} > n_{A/BD}$ identified correctly; \Rightarrow increment TN , $\Rightarrow CM=(2,1,0,2)$
- vii. For row-6, $n_{A/BR} = 2$, $n_{A/AR} = 2$, $\Rightarrow n_{A/AR} > n_{A/BR}$ rejected correctly; \Rightarrow increment TN , $\Rightarrow CM=(2,1,0,3)$
- viii. sensitivity: $TPR = \frac{TP}{TP+FN} = 2/3 = 66\%$;
specificity: $TNR = \frac{TN}{TN+FP} = 3/3 = 100\%$.

4.6 Coding the Sensitivity Procedure

The proposed test algorithm which is given in Section 4.2 has been expressed in R code by the following functions:

`AMe(TS, TSF, ordx)` returns the 5-days mean forecasting error of the ARIMA with parameters `ordx`, by training the fitted coefficients with `TS`, and then comparing its forecasting errors with `TSF`.

`Acnt(TS, DD, nDRM=10, nR=30, nTS=15)` returns the counts of `ABR`, `AAR`, `ABD`, `AAD` by comparing the errors returned from `AMe()` calls.

Using these functions, the sensitivity and specificity of change of ARIMA parameters (1,1,0) and (0,1,1) are obtained, and plot in Figure 7, where, circles show the sensitivity, and crossed circles shows the specificity of the change of parameters from AR to MA depending on the 26 FFR decision days. In the figure, x is n_{DRM} , the number of days after and before `DD`, and `RD` in the test.

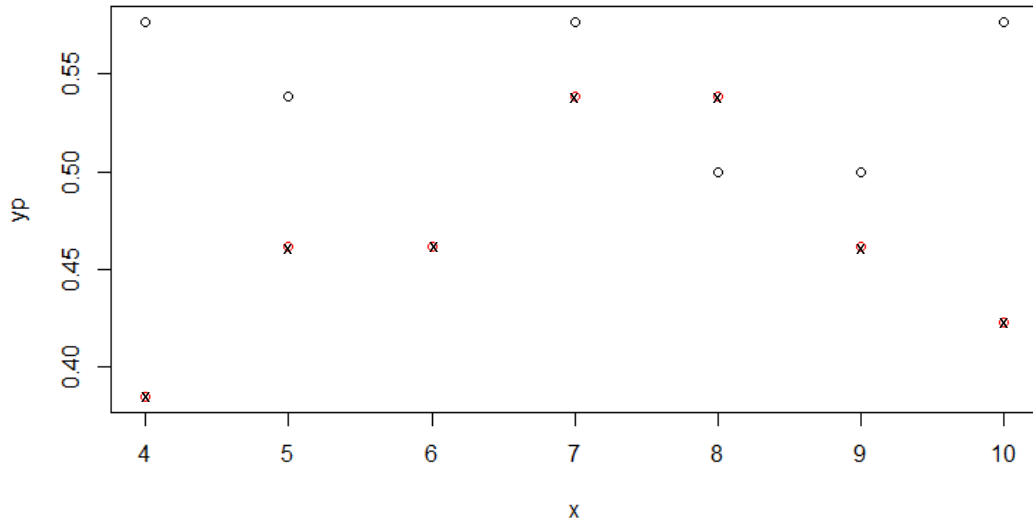


Figure 7: Sensitivity and Specificity of ARIMA Parameters of USD/GBP Exchange Rate Forecasting Models

4.7 Conclusion

The results of the analysis shows that there is a sensitivity and specificity of ARIMA parameters of USD/GBP exchange rate forecasting models on the Federal Reserve Bank federal fund investment rate decision dates in the direction to change the parameters from auto-regressive to moving average. Even if the sensitivity is not dominant, it apparently remains over 50% in all tests while the test-days after and before the decision day are in the range of 4 to 10.

Chapter 5

CONCLUSION

ARIMA is one of the strongest forecasting method for TS data streams such as exchange rates, and stock market prices. This thesis has focused on investigation of usage of ARIMA, and proposed sensitivity and specificity tests to determine the extent of the structural changes in the market by decisions of an important financial actor in GBP/USD exchange rate markets.

The sensitivity and specificity tests in Chapter 4 indicated that the market changes its ARIMA structural parameters sharply by some hidden variables along with the FFR decisions. According to the tests based on 26 FFR decision dates, the ARIMA model statistically swaps between AR1 and MA1 modes compared to the one month earlier date. The test is carried on the hypothesis that for the FFR decision dates, the ARIMA parameters of best forecasting models before the decision date are less in AR structure compared to the after the decision date. The test results gave that sensitivity is almost 55%, which is 5% over the neutral value of sensitivity. On the other side, the specificity of the test is almost at the neutral value (50%).

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APPENDIX

Appendix A: Program Codes

A.1 R Codes of the modeling and forecasting

Library `lubridate` provides manipulation of dates, and construction of arrays of dates.

Library function `date` picks the date of the first entry from `dfrc`, the Federal Bank Decision frame.

```
library(lubridate)
DD= date(dfrc$ddate[1]); na=3; nb=3; nR=30; nTS=17; nF=5
sDD= seq(from=DD-nTS, to=DD, by='days')
sFD= seq(from=DD+1, to=DD+nF, by='days')
```

After running these sentences, `DD` keeps the date of first decision, `sDD` contains a sequence of 17 days from the day `DD-17` to the day `DD`, and `sFD` contains a sequence of 5 days from `DD` to `DD+5`.

The fitting model parameters `fit` and the forecasted exchange rates `fc` are obtained by calling the function `ARIMA`.

```
fit = Arima(GC$cli[sDD+na], order=c(1,1,0), include.drift = T)
```

where `GC$cli[sDD+na]` is the time sequence for training TS, T_{db} . Here, `include.drift=T` provides removal of drift from TS to reduce the non-stationary behavior of training TS. Parameters of ARIMA are specified by `order=c(1,1,0)`.

For the forecasting of next five days after the training time series, the libraries `forecast` and `stats` are necessary. The function `forecast` provides a class that contains forecasted values, together with their confidence intervals.

```
fc=forecast(fit,h=5)
ef =GC$cli[sFD+na]-as.numeric(fc$mean)[[1]]
```

Plot of forecast is possible by the `plot` and `lines` functions,

```
plot(fc,15,type='b',xaxt='n', col='blue'
      , pch=2, shaded=FALSE, main=' '
      , ylab='GBP=X, Exchange Rate', xlab=year(DD))
lines(GC$cli[sFD+na], type='p',pch='+')
```

where, plot draws the training time series, forecasted mean values, and confidence intervals for the next five days, and, lines adds the actual values for the forecasted days.

The mean error is calculated by

```
ef = GC$cli[sFD+na]-as.numeric(fc$mean)
efm = mean(abs(ef))
```

A.2 R Codes of the Sensitivity Analysis

The proposed algorithm is expressed in R code by three functions:

- 1) `AME(TS, TSF, ordx)` that returns the 5-days mean forecasting error of the ARIMA with parameters `ordx`, by training the fitted coefficients with `TS`, and then comparing its forecasting errors with `TSF`.

```
AME= function(TS,TSF,ordx){
## AMe returns 5-day ahead forecasting error.
fitpara = Arima(TS, order=ordx,include.drift=T)
forecst = forecast(fitpara,h=length(TSF))
ef = TSF - as.numeric(forecst$mean )
erm = mean(abs(ef)); erm}
```

- 2) `Acnt(TS, DD, nDRM=10, nR=30, nTS=15)` returns the counts of ``ABR``, ``AAR``, ``ABD``, ``AAD`` by comparing the errors returned from `AME()` calls.

```
Acnt = function(TS, DD, nDRM, nR, nTS, nF){
## Returns counts of ABR,AAR,ABD,AAD.
#####
SDD = seq(from=DD-nTS, to=DD, by='days')
sFD = seq(from=DD+1, to=DD+nF, by='days')
MA1=c(0,1,1); AR1=c(1,1,0)
# Confusion array
# for each DD, find errors for AR, MR, AD, MD and decide
# A or M, count each day A, and M to find
# how many A, and how many M
ABR=0; AAR=0; ABD=0; AAD=0; # they count A in BR, AR, BD, AD.
for(i in 1:nDRM){
# Autoregres Before Random Day
eA=AME(zoo(TS[sDD-nR-i]), zoo(TS[sFD-nR-i]), AR1 )
# MovingAver Before Random Day
eM=AME(zoo(TS[sDD-nR-i]), zoo(TS[sFD-nR-i]), MA1 )
if(eA>eM) ABR=ABR+1
# Autoregres After Random Day
eA=AME(zoo(TS[sDD-nR+i]), zoo(TS[sFD-nR+i]), AR1 )
# MovingAver After Random Day
eM=AME(zoo(TS[sDD-nR+i]), zoo(TS[sFD-nR+i]), MA1 )
if(eA>eM) AAR=AAR+1
# Autoregres Before Decision Day
eA=AME(zoo(TS[sDD-i]), zoo(TS[sFD-i]), AR1 )
# MovingAver Before Decision Day
```

```

    eM=AMe(zoo(TS[sDD-i]), zoo(TS[sFD-i]), MA1 )
    if(eA>eM) ABD=ABD+1
    # Autoregres After Decision Day
    eA=AMe(zoo(TS[sDD+i]), zoo(TS[sFD+i]), AR1 )
    # MovingAver After Decision Day
    eM=AMe(zoo(TS[sDD+i]), zoo(TS[sFD+i]), MA1 )
    if(eA>eM) AAD=AAD+1
  }
  c(ABR, AAR, ABD, AAD)
}

```

3) The confusion table of each case is obtained by the code

```

ConfTbl = function(TS, DDS, nDRM, nR, nTS, nF){
  CM = c(0,0,0,0)
  names(CM)=c("TP", "FN", "FP", "TN") ;
  for(id in 1:length(DDS)){
    AY=Acnt(TS=GC$c1i, DDS[id], nDRM, nR, nTS, nF)
    names(AY)=c("ABR", "AAR", "ABD", "AAD")
    if(AY["ABD"]<=AY["AAD"]) CM["TP"] = CM["TP"]+1
    else CM["FN"] = CM["FN"]+1
    if(AY["ABR"]<=AY["AAR"]) CM["FP"] = CM["FP"]+1
    else CM["TN"] = CM["TN"]+1
  }
  TPR=CM["TP"]/(CM["TP"]+CM["FN"]);
  TNR=CM["TN"]/(CM["TN"]+CM["FP"]);
  list("CM"=CM, "TPR_TNR"=c(TPR, TNR))
}

```

The confusion table `ct` is calculated for six different periods (from 4 days to 10 days)

for each FFR decision date.

```

x=c(); yp=x; yn=x
for (i in 4:10){
  ct= ConfTbl(TS=GC$c1i, DDS=date(dfrc$ddate[1:26])
              , nDRM=i, nR=30, nTS=17, nF=5)
  x=c(x, i);
  yp=c(yp, ct$TPR_TNR[[1]]); yn=c(yn, ct$TPR_TNR[[2]])
}

```

Finally, the obtained array of TPR and TNR values which were stored in `yp`,

displayed on a plot.

```

{plot(x,yp,ylim=range(yp,yn))
  lines(x,yn,type='p',col='red')}

```