



Comparative Studies of Hybrid ARIMA and Artificial Neural Network (ANN) Techniques for Predicting Exchange Rate in Pakistan

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Abstract

For predicting time series data the ARIMA and ANN provides a good technique in the field of research. Time series data often contain both linear and nonlinear patterns. Therefore, neither ARIMA nor neural networks can be adequate in modeling and predicting time series data. When applying the linear models, most existing studies seem to use the same specification for estimation and forecasting, but the dynamic impact of the concerned variables is ignored. In this study combined the ARIMA and Artificial neural network model by adopting both an equal weighted approach and profit weighted approach to capture both the linear and nonlinear components of the exchange rate, and also developed a hybrid techniques by using models of artificial neural network (ANN) and autoregressive integrated moving average (ARIMA) and their performance were compared to ANN and Hybrid ARIMA models. The Hybrid models are used for forecasting the future exchange rate for dollar, the exports and imports of data. The findings showed that combining both ARIMA and ANN models reap the advantage of linear and nonlinear modeling. The capability of the two models are analyzed based on standard statistical measures such as, mean absolute error (MAE), root mean square error (RMSE), and mean squared error (MSE). Models effectiveness The effectiveness of the models are analyzed for the foreign exchange rate, imports and exports of the data and concluded that hybrid techniques provided the best forecasting results.

Keywords: ARIMA, exchange rate

1. Introduction

The purpose of gathering all this material is to elaborate and discuss the importance of economic hybrid model to predict the falling prices of long and short tends and predict the movements of exchange rates. For that purpose we predict the hybrid techniques by linear regression, multilayer network and predict the macro cycles of certain exchanges, and forecast the market timing ability and predictive power of the model. In model specification we allowed a specific approach and allow for the variations in throughout the predicting tenor and add that stylized facts and after that we combine both the models by taking the profit approach of exchange rate mechanism.

1.1. Hybrid approach in Time Series Forecasting

Hybrid technique actually comes from the following Perspective.

Firstly it is sometimes becomes very difficult to determine whether the data from underlying process is taken from linear or nonlinear sometimes one technique is more effective than the other. Normally large number models are concerned for the accurate and final solution of the projects but the most effective one is selected from all of these due to change in potential influential, uncertainty, and structure and sample factors. By merging different models of study we can actually ease in our work by the little effort.

Secondly, the real world time series are very often pure in linear and nonlinear approach of Study and they both contain linear and nonlinear factors. If we consider this case then neither ARIMA nor ANNs can be adequate in modeling and forecasting the time series process arima can never deal with nonlinear approach whereas neural model network alone cannot deals with both linear and nonlinear approaches.

Thirdly, it is declared universally that no single method is only enough for the problem solving process in every possible situation. It is highly stated that the problems of the real world is very much complex from all the bookish studies and if it is saying that any single perfect model is able for solving all of our routine matters then this is considered absurd.

To test the correctness of ANNs models with mixed results they mostly use ARIMA model for the Solutions. Most of literature showed that if we combine different models and merge in a particular way that they would be able to improve our forecasting's rather than consider the single or individual models that which one is best and how can help us, only due to that reason different models are merged to increase the chance to grasp various models to increase the predicting performance in the projects.

1.2. Conditions for using Hybrid model

Mostly the time series uses the data that consists of linear or nonlinear approaches which is neither the ANNs nor the ARIMA methodologies alone can handle the problem in such cases the combination of linear and nonlinear approach is used for the problem solving activity. If we using the hybrid techniques for predicting forecasting accuracy since M-competition in which the single model perform improved performance, both theoretic and empirical studies tells that merging both methods can be an effective and efficient way to improve the forecasting methods. Whereas In the network neural forecasting research, large variety of schemes and methods are proposed. There are the following conditions in which the hybrid model is suitable.

Firstly, the trades that are necessarily required the trading long term trends reduces the number the reason is that it's not adjust the trading's every period. This method reduces transactions cost and especially when there is a lot of orders placed at one time then there use simple average cross over rule from the models In predicting the exchange rates of the market which will be able to identify the bull and bear macrocycles.

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This rule of study is very prominent as a market participant and considers best indicator for the market trends, by using this rule we can easily allocate the bull and the bear market and easily filter and identify the trade orders and at last it can trade at a high frequency if anybody feel to reduce the noise by trading cycles (Ling et al., 2015)

The investors sometimes becomes very aggressive about the profit and further loss or protection of price. There are several theories and studies that describes and partially answers, the most of them are refers to the market frameworks as utility curves or consumptions and the changes and sometimes cause a great loss in the productivity and decision making process.

1.3. Auto-Regressive Integrated Moving Average (ARIMA)

It is an important area of forecasting in which the previous observations of the same variables are collected, observed and define the related relationship of the variables. The model is then used to extrapolate the time series into the future. This modeling approach is particularly useful when little knowledge is available on the underlying data generating process or when there is no satisfactory explanatory model that relates the prediction variable to other explanatory variables. Much effort has been devoted over the past several decades to the development and improvement of time series forecasting models. One of the most important and widely used time series model is the AutoRegressive Integrated Moving Average (ARIMA) model. The popularity of ARIMA model is due to its statistical properties as well as the well-known Box Jenkin's Methodology in the model building process. Bulk amount of volunteer's are presented in their research in the development of several past decades for the predicting and forecasting the time series. ARIMA model is one of the most repetitively used models. It is popular due to its most of the explanatory and statistical features. But there are some limitations in this mode that it can take only the linear from the model it cannot capture the data that is in the form of nonlinear. One of its complex problems is that it can take unknown random process and face to face interactions with the market such that unexpected factors affect the variables. (Merh et al., 2008; Ali, 2018)

1.4. Artificial Neural Network (ANN)

Most of the studies stated that mostly economic variables are non-stationary dimensions or naturally nonlinear in parameters. Nonlinear models are mostly used to 12 obtain the nonlinear parameters. In these models it's not possible to draw any standard formula for the parameters (Clement &Hendry., 2002; Malik, 2019; Khalild, 2022). Merh et al. (2010) showed that in recent years ANN has become a popular modeling tool. Complex real world problems in which non-linearity is often present can be successfully modeled using this technique. Due to its quality of nonlinearity ANN became very popular because this type of methodology easily handled the nonlinear pattern. With this there is no need to require the certain model the major feature of this is nonlinear modeling flexibility so there is no need to specify the particular form of model. This Kind of Approach is followed where is no theoretical guidance is available for the referred data processing's. They had suggested that two or more computational models can be synergic ally combined to give a better approach for prediction problems each model's unique capability can be used to model different patterns of data. The advantages of the relatively easy-to-tune ARIMA models and the computational power of ANN have been combined to give the time series prediction for the hybrid ARIMA and ANN techniques. The past studies showed that the combination of ANN and ARIMA are much better than individual model and the results are more substantial when dealing with nonstationary series, and it gives better forecasting results then use the models separately.

1.5. Foreign Exchange rate

The world's widest market is the Foreign Exchange and it plays very important role in accuracy forecasting and international investments and the rate of exchange also become very essential for success. Whatever it deals with the effect of economic activity, foreign trade the distribution of health across the cities and also very important for the governmental and monetary policies so decision maker has interest for the forecast in the modeling. There are also several models proposed for that study from the recently last five decades in the literature of forecast exchange rates because the foreign exchange having highly noticed and non stationary which used the classical methods incompetents. So that he has to follow the more advanced techniques recently nonlinear ANN proved to be effective for the time series prediction (Priyadarshini 2014; Subhanni et al., 2022; Ali, 2022). Gencay (1999) argued that exchange rate is one of the most important policy variables in an open economy as it affects the macroeconomic variables like, trade, capital flows, FDI, inflation, international reserve, GDP and remittances, etc.

1.6. Objective

The objectives of the study are

- To develop the models for forecasting the average monthly US dollar exchange rate by using ANN and ARIMA models.
- To compare the results of predicted values to actual values 16
- To evaluate the performance of models by calculating MAPE, AAE and RMSE.
- To compare the results between models based techniques of Hybrid ARIMA and ANN models.

2. Review of Literature

Pramanik et al (2010) stated that in controlling flood damage advance time step stream flow forecasting is gained very importance. During the past few decades, in stream flow forecasting artificial neural network (ANN) techniques had been considerably used and proved to be better forecasting ability than other forecasting method such as general transfer function and multiple regression techniques. They used discrete wavelet transformation functions to preprocess the time series of the flow data into wavelet coefficients of different frequency bands. The coefficients of effective wavelet and the decomposed wavelet coefficients of all frequency bands were selected from the correlation analysis of the observed flow data.

Maknickiene&Maknickas (2012) used neural network forecasting as human like experts predictions. The ANN experts could be successfully used same characteristics compatibility and reliability of opinion. Expert's procedure adapted to the neural networks can enhance the quality of predicting and profit suitably. The proposed trading model, allowed to achieve up to 4 % profit in testing period for EUR/USD cross ratios. By using the Delphi method investigation of trading model for historical data shows a stable profit progress and the calculation of the similarity of predicting of LSTM based recurrent neural networks. The method of Delphi upgrades the prediction boundaries. Hence, the Ann expert's opinion allowed abolitions of completely wrong predictions.

Morrison & Labonte (2013) further argue that subsequent to a depreciation of an importer's currency, thereby raising the cost of imports, the foreign exporter might reduce his local currency export price in order to stabilize the prices in the importing country. However, this policy is a long strategy that is aimed at maintaining market share. However, markup exchange rates are industry specific and rely on the demand curve that the exporter experiences in a given country. Similar to these findings and deductions, they suggested that exchange rate movements due to policies can be passed through to goods and services trade prices. Alternatively, the price can be absorbed in producers' profit mark ups and margins.

Zaki (2014) used ARIMA and ANN techniques for Crime forecasting. He used hybrid approach for the for the four crime category that are Break and Enter Non Dwelling, Non-Domestic Violence Related Assault and Steal from Retail Store and Steal from Person. And the crime series was predicted by using 216-month observations. Specially, the results from the hybrid techniques yield a good modeling structure and able of expressing the nonlinear structure of the complicated time series and thus provide more accurate predictions. The four case studies from the hybrid models are 92.78%, 91.08%, 94.13% and 93.62, respectively, in model application which was satisfactory. Forecasted crime data from the hybrid techniques were analyzed with those from the ARIMA and neural network using the performance measures. And the result showed that hybrid model provides a better accuracy over the neural network and ARIMA models for crime series prediction.

As &Sk (2015) examined the behavior (JPY), (GBP), Indian Rupee (INR) against the (USD), they examined the currencies traded in Indian foreign exchange markets by using techniques of Neural Network, ARIMA and Fuzzy neuron. For the analysis Daily RBI reference exchange rates from January 2010-April 2015 were used. For the exchange rate predictability of Rupee against USD, GBP, Yen and Euro using classical time series method (ARIMA) and complex nonlinear methods such as Fuzzy neurons and Neural Network were used. The finding showed that market in India ARIMA model did better than those of however earlier literature showed that ANN performs better than ARIMA model and fuzzy model.

Khandelwal et al. (2015) developed the time series by using DWT (Discrete Wavelet Transform) suggested DWT techniques for prediction by separating a time series data set into nonlinear and linear components and analyzed time series data sets into linear and non-linear components. Both models were used to forecasting and individually recognized the reconstructed linear and nonlinear parts, respectively. They suggested the unique ability of, ANN, ARIMA, and DWT to improve the forecasting precision.

3. Materials and Methods

3.1. Introduction to Time Series Analysis and some basic concepts

Data obtained from observations collected sequentially over time are extremely common, In business phenomena such as weekly interest rates, daily closing stock prices, monthly prices indices, yearly sales figure are observed. The purpose of time series analysis is generally twofold: to understand or model the stochastic mechanism that gives rise to an observed series and to predict or forecast the future values of a series based on history of that series and possibly other related series or factors. A somewhat unique feature of time series and their models is that we usually cannot assume that the observations arise independently from a common population.

3.2. Stationarity

The basis of time series analysis is stationarity. The time series is said to be stationary if the mean, the variance and the auto covariance (at various lags) does not change regardless of what is the point measure, i.e. it fixed over time. Moreover, the time series $\{y_t\}$ is said to be strictly stationary if the joint distribution of y_{t_1}, \dots, y_{t_k} is identical to that of $y_{t_1+h}, \dots, y_{t_k+h}$, for all choice of t_1, \dots, t_k and all choice of time lag h . Where k is an any positive integer and t_1, \dots, t_k is a collection of k positive integers. In other words, strict stationarity requires that the joint distribution of y_{t_1}, \dots, y_{t_k} is constant under time shift. A weaker version of stationarity is often assumed. A time series $\{y_t\}$ is weakly stationary if both the mean of y_t and the covariance between y_t and y_{t+s} are time-invariant, where s is an arbitrary integer. More specifically is weakly stationary if: (a) $E(y_t) = \mu$, which is a constant, for all t . (b) $Cov(y_t, y_{t+s}) = \gamma(s)$, which only depends on all time t and lag s . However in weak stationarity, we suppose that the first two moments of y_t are finite. if y_t is strictly stationary and its first two moments are finite, then y_t is also weakly stationary, from the definitions, but the converse is not true in general.

3.3. Non-stationary

Data points are often non-stationary or have means, variances and covariance that change over time. Non stationary data can be in the form of trends, cycles, random walks or combinations of the three. Non-stationary data, as a rule, are unpredictable and cannot be modelled or forecasted. The results obtained by using non-stationary time series may be spurious in that they may indicate a relationship between two variables where one does not exist. In order to receive consistent, reliable results, the non-stationary data needs to be transformed into stationary data. In contrast to the non-stationary process that has a variable variance and a mean does not remain near, or returns to a long run mean over time, the stationary process reverts around a constant long-term mean and has constant variance independent of time. Non-stationary time series can be converted into stationary series.

3.4. Homogeneous non-stationary time series

In practice, many of the time series to work with non-stationary. Fortunately, many nonstationary time series process can be transformed by differencing the series one or more time. Such kind of time series is known as homogeneous non-stationary series or integrated process.

3.5. Tests of Stationarity

As in time series analysis, it is important to distinguish whether the series under consideration is stationary or not, many statistical techniques are available, the brief descriptions of some methods are given below.

3.6. Graphical Analysis

The first and simplest type of test one can apply to check for stationary is to actually plot the time series and look for evidence of trend in mean, variance, autocorrelation and seasonality, if any such patterns are present than these are signs of non-stationary and different mechanisms exist to turn the series into a stationary one.

3.7. Correlogram test

One of the most useful descriptive tools in time series analysis is to generate the correlogram plot which is simple a plot of the serial correlations versus the lag k called auto-correlogram for $k = 0, 1, \dots, M$, where M is usually much less than the sample size n . It is characteristics for non-stationary series to have a very slowly decreasing ACF, while a faster decline than is registered in the case of stationary series. It is also helpful to plot partial autocorrelations versus the lag k called partial auto-correlogram for $k=0,1,2 \dots M$, where M is usually much less than the sample size n . PACF is helpful in determining how many times a series have to be differenced to make it stationary. The number of lags to which PACF is significant shows the number of time a series have to be differenced to make it stationary.

3.8. Autocorrelation Function(ACF)

The most important tools for study dependence is the sample autocorrelation function. The correlation coefficient between any two variables random X, Y , which measures the strength of linear dependence between X, Y , always takes values between -1 and 1 . If we assuming stationarity, and we want to estimate autocorrelation function for a set of lags $K = 1,2, \dots$. The simplest way to do this is to compute the sample correlation ρ between the pairs k units apart in time. Note that the concept of correlation expanding in the case of stationary time series to become the autocorrelation function. The correlation coefficient between and is called the lag- k autocorrelation of and denoted by the symbol γ_k , which under the assumption of weak stationary and defined as:

$$\gamma_k = \frac{\sum_{t=1}^{n-k} (Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^n (Y_t - \bar{Y})^2}$$

Where $\gamma_k = \text{Cov}(Y_t, Y_{t+k})$

3.9. Partial Autocorrelation Function (PACF)

The correlation coefficient between two random variables Y_t and Y_{t-k} after removing the impact of the intervening, $Y_{t-1}, Y_{t-2}, \dots, Y_{t-k+1}$ called (PACF) at lag k and denoted by ϕ_{kk}

3.10. Unit root tests

The stationarity tests described in the above section make use of subjective visual inspection of plots and Correlogram. Although the properties of sample Correlogram are useful tool for detecting the presence of unit root or non-stationary, but the method is necessarily imprecise. Because unit root process might have the same shaped ACF as a near unit root process and what may appear as unit root process to one observer may appear as a stationary process to the other. This ambiguity in visual inspection necessitates a formal testing procedure. A more recent series of tests were developed to help with determining stationarity. These tests also known as unit root tests and stationarity tests are based for the most part on formal statistical tests and the difference between them lies in the stringency of the assumptions they use as well as in the form of the null and alternative hypotheses they adopt.

3.11. ARIMA Models

Time series models use the past movements of variables in order to predict their future values. Unlike structural models that relate a main variable to a set of other variables, the time series model is not based on economic theory. However, in term of forecasting, the reliability of the estimated equation should be based on out-of-sample performance (Zhang et.al 2001).

The model is generally referred to as an ARIMA(p,d,q) model where parameters p, d , and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. ARIMA models form an important part of the Box-Jenkins approach to time-series modeling. In an ARIMA model the future values of a variable is assumed to be a linear function of several past observations and random errors. That is, the underlying process that generates the time series with the mean μ has the form (Khashei&Bijari, 2011)

3.12. Steps for building an ARIMA model

3.12.1. Model Identification

The choice of a particular mathematical model based on some statistical measures that characterize the model for another, and the experience derived from studies and research.

3.12.2. Model Estimation

After the nomination of one or more appropriate models to describe the viewing time series of data, we estimate parameters of the model using one of estimation methods.

3.13. Model Diagnostic

It includes the residuals analysis to see how close the calculated values from the nominated model with observations, and measuring of the validity of the assumptions of the model. In the case of passing the model for these tests, we adopt it as the final model, which is used to estimate future predictions, but in the case of non-passing, we return to the first step for the appointment of a new model.

3.14. Predicting

The final model is used to generate future predictions and then calculate the prediction errors that occurred.

3.14.1. The artificial neural network (ANN) model

Artificial neural network are nonlinear mapping structures based on the functions of human brain. They are powerful tools for modeling especially when the underlying data relationship is unknown. Ann can identify the nonlinear relationship. Recently, computational intelligence systems and among them artificial neural networks (ANN), which in fact are model free dynamics, has been used widely for approximation functions and forecasting. The model is characterized by a network of three layers of simple processing units connected by acyclic links (Figure 1). The relationship between the output and the inputs has the following mathematical representation (Khashei&Bijari., 2010).

An artificial neuron network (ANN) is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes based on that input and output. The relationship between the output and the inputs ($y(t-1), \dots, y(t-p)$) Has the following mathematical representation (Kim and Vald)

$$y_t = w_0 + \sum_{j=1}^q w_j \cdot g(w_{(0,j)} + \sum_{i=1}^p w_{(i,j)} \cdot y_{(t-i)})$$

3.14.2. Activation Function

A function used to transform the activation level of neuron (weighted sum of inputs) to an output signal. Mathematical model of neuron is expressed as. (3.2) Where y_i is output of neuron i , w_{ij} is the weight from neuron j to neuron i , x_j is the output of neuron j , θ_i is the threshold for neuron i , and g is the activation function define as Although this is simple model describe neuron is as binary processing unit McCulloch and Pitts (1949). defines for the transfer function. Many different transfer functions are available to neural network model. The most common transfer function is the logistic sigmoid function, which is given by the following equation: Where i is the index on the inputs to the neuron, x_i is the input to the neuron, w_i is the weighting factor attached to that input, and w_0 is the bias to the neuron.

3.14.3. Hybrid ARIMA and ANN models

Some researchers suggests hybrid approach to time series forecasting using both ARIMA and ANN models that is,

$$y_t = L_t + N_t$$

Where y_t denotes original time series, L_t denotes the linear component and N_t denotes the nonlinear

component. Linear component is estimated by ARIMA model and residuals obtained from the ARIMA model $e_t = y_t - \hat{L}_t$. Where \hat{L}_t is the forecast value for time t from the estimated relationship (1). By modeling residuals using ANNs, nonlinear relationships can be discovered (Zhang, 2003). With n input nodes, the ANN model for the residuals will be

$$e_t = (e_{t-1}, e_{t-2}, \dots, e_{t-n}) +$$

4. Results and Discussions

4.1. Model Building with ARIMA Process for Exchange Rate

The following Steps involved in ARIMA modelling

- ❖ Identification
- ❖ Estimation
- ❖ Diagnostic checking
- ❖ Forecaste

Table 1: Descriptive Statistic for Exchange Rate

Name of statistics	Exchange Rate	After One Differencing
Minimum value	11.43	-13.51
1st.Q	17.96	-0.3025
Median	32.94	0
S.D	48.71956	2.194506
Mean	56.53	0.172
3rd.Q	92	0.6998
Maximum value	177.3	16.33

Table 1 provides descriptive statistics of Exchange Rate of Pakistan used for examining performance of three different models such as ARIMA ANN and hybrid model. The Minimum value of exchange rate is 11.43 and Maximum value is 177.3 A number of ARIMA models were developed using the Exchange Rate. The datasets from 1960 to 2017 were used for model development. The ARIMA model development is described briefly for Exchange Rate. The data showed that the mean working series is 56.53 with standard deviation 48.71956 taking 685 observations under consideration. Methods of Checking Stationary

4.2. Methods of Checking Stationary

- ❖ Graphical method (Time series Plot)
- ❖ ACF and PACF
- ❖ Box and Pierce Q statistic
- ❖ Ljung Box Statistic
- ❖ Augmented Dickey Fuller test

Graphical method

Graph for Exchange Rate

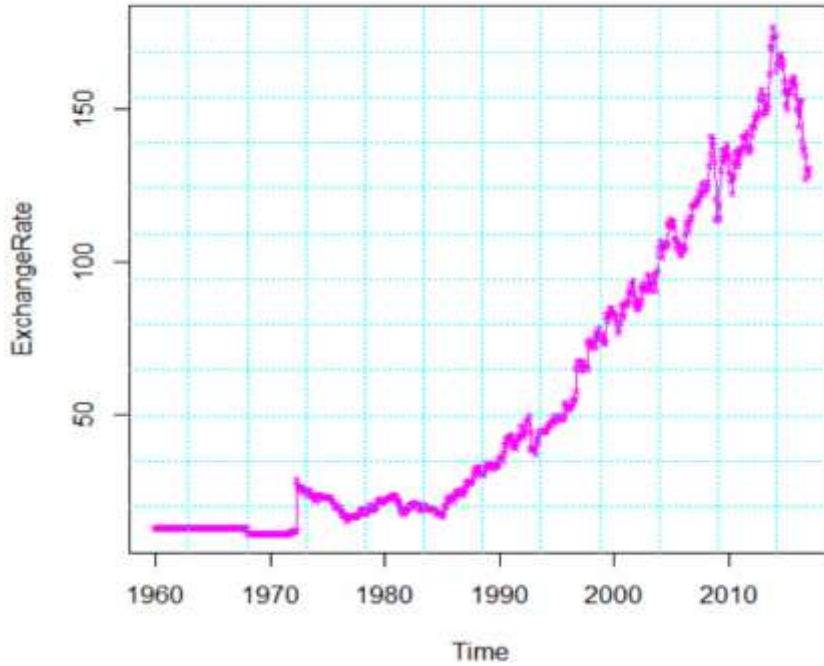


Figure 1: Monthly Exchange Rate Time series 1960 to 2017

Figure 1 evaluates the time series plot of different years for Exchange Rate. From identification it is evaluated that process is not stationary

Graph for After One Differencing Exchange Rate

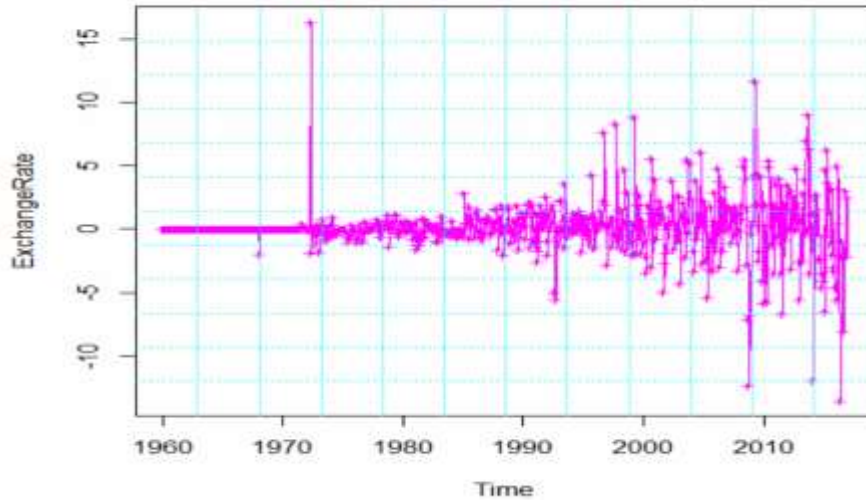


Figure 2: Exchange Rate time series after differencing Figure

2 evaluates the time series plot of different years for Exchange Rate. From identification it is evaluated that process is stationary after one differencing

4.3. Mathematical methods

Box and Pierce Q statistic (process is stationary) (process is not stationary and difference is needed)

Table 2: P value of Box and Pierce Q test

$\chi^2 = 680.49$	df = 1	p-value = 2.2e-16
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2.2e-16 < 0.05 p-value less than 0.05 so do not accept and the process is not stationary

Table 3: P value of Box and Pierce Q test after differencing

$\chi^2 = 1.6232$	df = 1	p-value = 0.2027
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0.2027 > 0.05 P- values greater than 0.05 so accept and the process is stationary after one differencing. Box and Pierce Q test shows that exchange rate of Pakistan is stationary after one differencing

Ljung Box Statistic (process is stationary) (process is not stationary and difference is needed)

Table 4: P value of Ljung Box Statistic

$\chi^2 = 683.47$	df = 1	p-value = 2.2e-16
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0.2027 > 0.05 here the values greater than P- values so accept and the process is stationary after one differencing. Box and Pierce Q test shows that exchange rate of Pakistan is stationary after one differencing

Table 5: P value of Ljung Box Statistic after differencing

$\chi^2 = 1.6303,$	df = 1	p-value = 0.2017
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In Ljung box the P- values 0.2017 greater than 0.05 so accept and the process is stationary.

Augmented Dickey Fuller unit root test (difference is needed to make process stationary) (process is stationary and no need to difference the data

Table 6: Dickey Fuller unit root test after one differencing

Dickey-Fuller = - 10.023,	p-value = 0.01
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Here the value 0.01 less than 0.05 hence do not reject and process is stationary and there is no need to difference the data. ACF, PACF, Box and Pierce test, Ljung box test, Augmented Dickey Fuller all revealed that original exchange rate time series is not stationary and we need to difference the series and after one differencing exchange rate series is become stationary.

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