iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 Issue: XI Month of publication: November 2022

DOI: https://doi.org/10.22214/ijraset.2022.47509

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue XI Nov 2022- Available at www.ijraset.com

Arima Model with Box-Cox Transformed Univariate Variable in BSE Sensex

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Abstract: Fluctuation of the stock market's impact on investments of stocks. Sensex prediction plays an important role in the investment of markets. Predicting the stock market is difficult in market scenarios. The present study attempted to predict the stock market due to its complicated features and also compared different Auto-Regressive Integrated Moving Average (ARIMA) models to get the appropriate stock forecasting model using various Box-Cox transformations by using BSE Sensex past daily closing data. The ARIMA Model6 (0 1 0) showed accurate results in calculating the *Mean Absolute Percentage Error* ***(MAPE) and*** *Bayesian Information Criterion* ***(BIC) values, which indicates the potential of using the ARIMA model for accurate stock forecasting.***
Keywords: ARIMA, MAPE, Box-Cox transformation, BSE Sensex,

I. INTRODUCTION

Closing prices or returns on stock prices or closing values of the market as a whole is a kind of time series which in the series analysis is classified under "general random walk". This is a non-stationary time series which means its mean or other statistical properties change over time. The present study is the forecasting of the BSE Sensex index of stock and the daily BSE Sensex index data series. This is daily data series of the BSE Sensex index.

The following is the description of the data set used in the research study.

As per the review collected from various articles, many researchers have investigated volatility time series modeling of the different stock markets, mainly focusing on U.S and Indian stock markets. Some of the researchers have focused on the Indian stock market with ARIMA Model. The foremost drive of the study is to deepen the knowledge about stock market volatility in National Stock Exchange.

Rakesh Gupta (2012) aimed to forecast the volatility of stock markets belonging to the five founder members of the Association of South-East Asian Nations, referred to as the ASEAN-5 by using Asymmetric-PARCH (APARCH) models with two different distributions (Student-t and GED). The result showed that APARCH models with t-distribution usually perform better.

Praveen (2011) investigated BSE SENSEX, BSE 100, BSE 200, BSE 500, CNX NIFTY, CNX 100, CNX 200 and CNX 500 by employing ARCH/GARCH time series models to examine the volatility in the Indian financial market during 2000-14. The study concluded that extreme volatility during the crisis period has affected the volatility in the Indian financial market for a long duration.

Philip Hans Franses & Dick Van Dijk (1996) Forecasting stock market volatility using (nonlinear) GARCH model, as per the finding of the study Q GARCH model is best when the estimation sample does not content extreme observations such as the 1987 stock market crash and the GJR model cannot be recommended for forecasting. In their estimation of volatility they used Within Sample Estimation and Out of Sample estimation and found that the forecasting performance of the GARCH type models appears sensitive to extreme within-sample observations.

Srinivasan et al. (2010) attempted to forecast the volatility (conditional variance) of the SENSEX Index returns using daily data, covering a period from 1st January 1996 to 29th January 2010. The result showed that the symmetric GARCH model do perform better in forecasting conditional variance of the SENSEX Index return rather than the asymmetric GARCH models

Floros (2008) the researcher has investigated the volatility using daily data from two Middle East stock indices viz., the Egyptian CMA index and the Israeli tase-100 index, and has used various models, GARCH, EGARCH, TGARCH, Component GARCH (CGARCH), and Power GARCH (PGARCH).

The study found that the coefficient of the EGARCH model showed a negative and significant value for both indices, indicating the existence of the leverage effect. AGARCH model showed weak transitory leverage effects in the conditional variances and the study showed that increased risk would not necessarily lead to an increase in returns.

II. MATERIAL AND METHODS

The Bombay Stock Exchange (BSE) data were considered for applying the time series models like ARIMA using various Box-Cox transformations in the time series data. The present study is based on the daily closing market index for the Bombay Stock Exchange (BSE). Actively performing BSE Sensex (Aug 2008-Aug 2022) used for forecasting modes. In this study, Statistical software and R- language were used for the forecasting model building.

III. DIAGNOSTIC CHECKING

A. Outliers Checking

An outlier is a value or an observation that is distant from another observation, differs point that differs significantly from other data points Grubbs's test is based on the assumption of normality to check whether the data follows normality or not. This is the foremost step for data should have any outliers.

That is, one should first verify that the data can be reasonably approximated by a normal distribution before applying the Grubbs test.

Grubbs's test detects one outlier at a time. Grubbs's test is defined for the hypothesis:

H_0: There are no outliers in the data set, H_a: There is exactly one outlier in the data set

The Grubbs test statistic is defined as

$$G=\frac{\underset{i=1,2,\ldots,n}{Max}|Y_i-\bar{Y}|}{s}$$

B. Data Normality

Normality assumptions were used in the study of model building. In Jarque-Bera normality test was used in this analysis for the normality of the data. The null hypothesis for this is data follows normal distribution; the alternative hypothesis is the data does not follow normality. The data uses the normalized technique for time series indices of BSE indices data.

The Jarque–Bera test is a goodness-of-fit test of whether sample data have skewness and kurtosis matching a normal distribution. The test is named after Carlos Jarque and Anil K. Bera.

The test statistic is always non-negative. If it is far from zero, it signals the data do not have a normal distribution.

$$JB=\frac{n}{6}\left(s^2+\frac{1}{4}\,(k-3)^2\right)$$

where *n* is the number of observations (or degrees of freedom in general); *S* is the sample skewness, k is the sample kurtosis

C. Box Cox Transformation

Generally, transformation plays a lead role in prediction of future values. A Box-Cox transformation is a transformation of non-normal dependent variables into a normal shape. Normality is an important assumption for many statistical techniques; if your data isn't normal, applying a Box-Cox means non-normal to normalize the data.

The following Box-Cox transformation is an exponent, lamda (λ), which varies from -5 to 5, which all values λ are considered and the optimal value for the data selected

$$Y^{(\lambda)}=\begin{cases}Y^{\lambda}-1, & (\lambda\neq 0)\\ \log Y, & (\lambda=0)\end{cases}$$

This test only works for positive data. However, Box and Cox did propose a second formula that can be used for negative y-values

$$Y^{(\lambda)}=\begin{cases}\dfrac{(Y+\lambda_2)^{\lambda_1}-1}{\lambda_1}, & (\lambda\neq 0)\\ \log(Y+\lambda_2), & (\lambda=0)\end{cases}$$

Table1: Various Box Cox transformations

S No	Model	Transformation Model	Lamda (λ)	Transformed data (y)
1	Model-1	$=1/y^3$	-3	$1/y^3$
2	Model-2	$=1/y^2$	-2	$1/y^2$
3	Model-3	=1/y	-1	1/y
4	Model-4	=1/sqrt(y)	-0.5	1/sqrt(y)
5	Model-5	log(y)	0	log(y)
6	Model-6	=sqrt(y)	0.5	sqrt(y)
7	Model-7	y	1	y
8	Model-8	y^2	2	y^2

D. Model Selection and Forecasting

One of the concept in time series modeling is ARIMA, or Auto-Regressive Integrated Moving Average. ARIMA is the combination of two models, the auto-regressive and the moving average models. An auto regressive AR(p) component refers to the use of past values in the regression equation for the series Y. The auto-regressive parameter p specifies the number of lags, or past values, to be used in the model. For example, AR(2) is represented as

$$Y_t=c+\phi_1 y_{t-1}+\phi_2 y_{t-2}+\ldots..+\phi_p y_{t-p}+e_t$$

where φ1, φ2 are parameters for the model. The moving average nature of the model is represented by the "q" value, which is the number of lagged values of the error term. A moving average MA(q) component represents the error of the model as a combination of previous error terms et. The order q determines the number of terms to include in the model

$$Y_t=c+\theta_1 e_{-1}+\theta_2 e_{t-1}+\ldots+\theta q e_{t-q}+e_t$$

Together, with the differencing variable d, which is used to remove the trend and convert a non-stationary time series to a stationary one, these three parameters define the ARIMA model. Thus, ARIMA is specified by three order parameters: (p, d, q)

E. Stationarity Test

One of the imperative assumptions on time series is non stationary relationship. To make sure existence of stationary relationship, the following stationary test and Augmented Dickey–Fuller test (ADF) were employed in the data

$$\Delta\lambda_t = \alpha_0+\alpha_2 t+\sum_{i=1}^{k}\beta\Delta\lambda_{t-1}+\varepsilon_t$$

Where λt denotes the weekly index of the individual stock at time t, β is the coefficient to be estimated, k is the number of lagged terms, t is the trend term, α_2 is the estimated coefficient for the trend, α_0 is the constant and ε is white noise

F. Mean Absolute Percentage Error (MAPE)

It measures this accuracy as a percentage, and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values. A lowest percentage of MAPE is indicates good model for accuracy.

$$\text{MAPE}=\frac{1}{n}\sum_{t=1}^{n}\left|\frac{\text{Actual}-\text{forecast}}{\text{Actual}}\right|$$ Where *n* is the number of fitted points

G. Bayesian Information Criterion (BIC)

The BIC is general approach to model selection that favours more parsimonious models over more complex models (Schwarz, 1978; Raftery, 1995)

$$BIC = -2 * LL + \log(N) * k$$

Where log() has the base-e called the natural logarithm, LL is the log-likelihood of the model, N is the number of examples in the training dataset, and k is the number of parameters in the model. The BIC value is minimized, the model with the lowest BIC is selected.

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IV. RESULTS AND DISCUSSIONS

Table1: Descriptive Statistics of BSE Sensex indices

BSE Index	Descriptive Statistics
Mean	45603.37
Standard Error	297.00
Median	41543.45
Standard Deviation	9354.47
Kurtosis	-1.39
Skewness	0.19
Range	35784.35
Minimum	25981.24
Maximum	61765.59
Count	992

From the above table, the mean value of BSE Sensex is 45603.37, the Standard Deviations of index is 9354.47. The skewness and 0.19 and -1.39 respectively, it means the distribution is longer than the right. The fig1 shows there is an increasing trend of BSE Sensex over the time period.

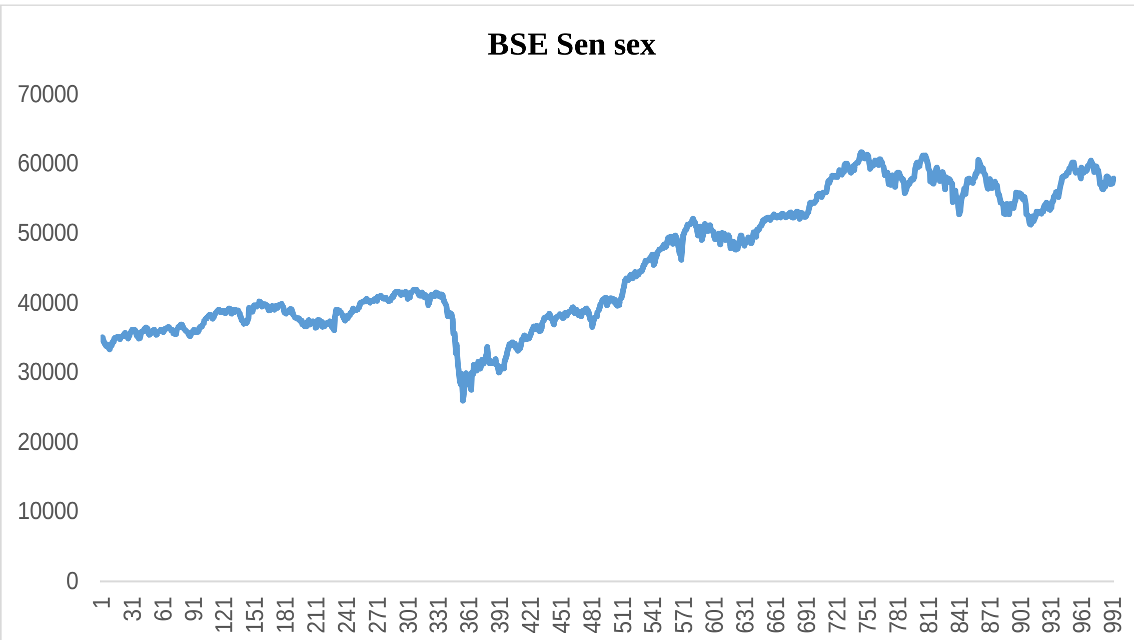

Fig1: pattern of BSE Sensex data (2019 to 2022)

Table2: Diagnostic test of BSE Sensex

S No	Test	Test name	Value	p-value
1	Outlier test	Grubbs's test	3.4628	0.0753
2	Normality test	Jarque-Bera test	86.851	0.000

The next step, after the descriptive statistics, is going to check the data validity. In view of time series data foremost step is to check the outlier and normality of distributions. The appropriate method of outliers is Grubbs's test, the value is given by 3.4628, and the p-value is 0.0753 which is accepted at 0.05 level and concludes that H_0 is the highest value and is not an outlier. The normality test of BSE Sensex is Jarque –Bera 86.851, p-value is 0.000 which indicates do not reject the null hypothesis and the data is not normally distributed in the time series. Then we use the Box-Cox transformations for BSE Sensex data

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Table3: Stationarity test of BSE Sensex

S No	ADF test	p-value	Difference	Stationarity
1	-2.0499	0.55772	Zero difference	Non Stationarity
2	-9.0314	0.0100**	First difference	Stationarity

Note ** Significant at 0.01 level

The Dickey-Fuller test returns a p-value of 0.01, resulting in the rejection of the null hypothesis and accepting the alternate hypothesis, it means the data is stationary. It is quite common in Sensex data. By taking the difference between BSE Sensex, we are essentially stationarizing the time series. Though not all stock returns are stationary, in many experiments regarding financial analysis, many assume it is.

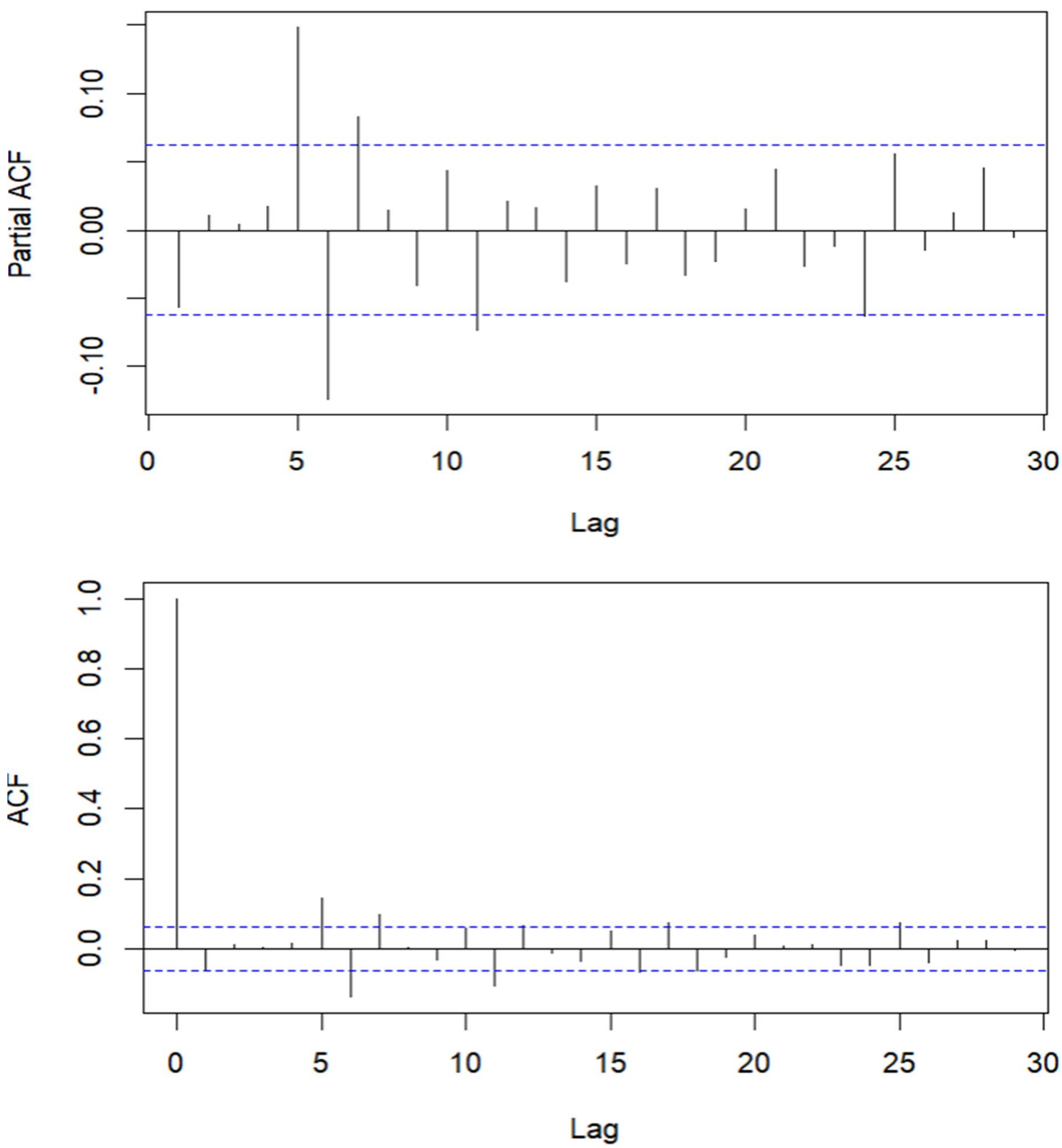

Fig1: ACF and PACF functions of BSE Sensex

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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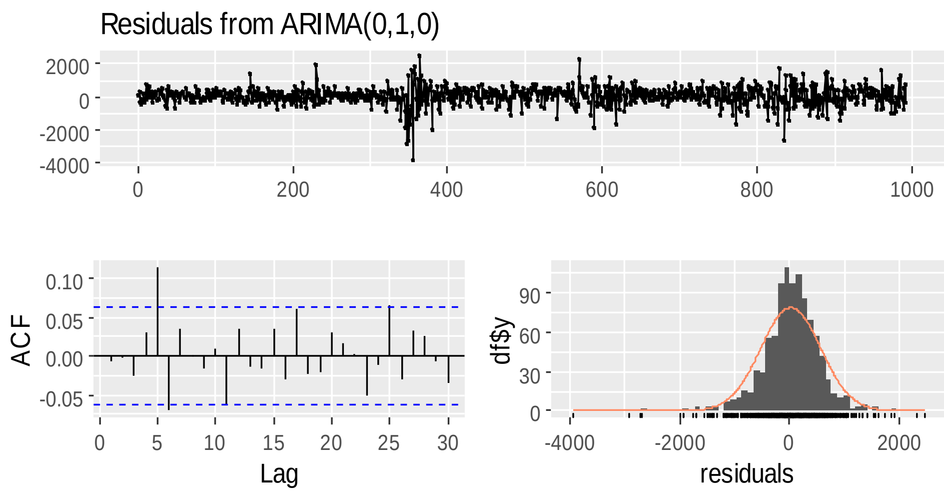
ACF stands for Auto-Correlation Function. ACF gives us values of any auto-correlation with its lagged values. In essence, it tells us how the present value in the series is related in terms with its past values. ACF will help us determine the number, or order, of moving-average (MA) coefficients in our ARIMA model.

PACF stands for Partial Auto-Correlation Function. Instead of finding correlations of present with lags like ACF, it finds correlation of the residuals with the next lag value. If there is any hidden information in the residual which can be modelled by the next lag, we might get a good correlation and we will keep that next lag as a feature while modelling. PACF helps us identify the number of auto-regression (AR) coefficients in our ARIMA model.



The method used in this current study to develop ARIMA models for BSE Sensex explained in below table. The tool used for performance is R-language five emerging stock indices daily data were used in this model. In this study the closing index is chosen to represent the index to be predicted. To determine the fitting best ARIMA model among the several combinations performed, the following criteria used in this modelling

1) Relatively small of Bayesian Information Criterion (BIC)
2) Relatively high of the R-Square
3) Relatively low MAPE value

Table3: Model Performance of BSE Sensex

Model	Transformation Model	ARIMA Model	R-Square	MAPE	BIC-value
Model1	$=1/y^3$	ARIMA (0 0 1)	0.998	0.785	12.403
Model 2	$=1/y^2$	ARIMA (0 1 0)	0.487	0.943	42.56
Model 3	=1/y	ARIMA (0 0 1)	0.741	0.784	36.52
Model 4	=1/sqrt(y)	ARIMA (0 0 0)	0.998	0.739	13.56
Model 5	log(y)	ARIMA (1 0 0)	0.978	0.367	24.56
Model 6	=sqrt(y)	ARIMA (0 1 0)	0.998	0.064	0.258
Model 7	y	ARIMA (0 1 0)	0.958	0.071	14.52
Model 8	y^2	ARIMA (0 1 0)	0.956	1.720	35.65

The result of BSE Sensex, applied various type of Box-Cox transformations and used best ARIMA models. From the Model6 the R-square is 0.997, MAPE is 0.064 and BIC value is 0.258, which means higher R-value, lower MAPE and BIC values for the above Model6. Conclude that Model6 which is the Box-Cox transformation of SQRT(y) is the best appropriate model of BSE Sensex data.

V. CONCLUSIONS

Difficult to the building of forecasting models mostly in time series data. Mainly in stock market data very oscillates over time. Forecasting with Auto ARIMA models provides a prediction based on historical data, in which data has been tested stationary and employed first-order differences to remove white noise problems. In this study, Auto ARIMA estimated BIC, MAPE, and R-Square which yielded a more accurate forecast over the time period and performance of the models. Thus, the study shows that the ARIMA model outperforms in forecasting BSE Sensex indices in terms of forecasting accuracy and in generating upcoming indexes.

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