CHAPTER IV
ANALYSIS OF STOCK PRICES DATA WITH ARIMA MODEL

4.1 INTRODUCTION

Stock price prediction will always remain an interesting area for the investors, traders and researchers to explore. It has attracted the interest of researchers to develop better predictive models every now and then. From the subject point of view, stock prices predictions are an important topic of the subjects such as finance and economics. The financial institutions and individual investors need an effective strategy to forecast and take decision based on these forecasts on daily basis. The stock price prediction is regarded as one of the most difficult task to achieve due to complex nature of stock markets [(Pai and Lin, 2005), (Wang et al, 2012), (Wei, 2013)] and investment risk of the stock market. This remains an inspiring aspect for research scholars to evolve with new predictive models or improve the existing ones (Atsalakis et al, 2011).

Till date, various models and techniques had been used to predict stock prices. Among these ARIMA models are the most popular statistical algorithms. As it is often reported in the literature, forecasting can be done on the basis of two different viewpoints, i.e., (i) using statistical techniques, (ii) and using artificial intelligence technique (Wang et al, 2012). ARIMA models are known to be very efficient for forecasting particularly for short-term prediction in the field of financial time series and even the more popular than ANNs techniques in many cases, ((Kyungjoo et al, 2007), (Merh et al, 2010)). Other popular statistical models used in forecasting are regression method, exponential smoothing, generalized autoregressive conditional Heteroscedasticity (GARCH). Few related works that is based on ARIMA models for forecasting financial time series includes (Verma et al, 2015), (Uma Devi et al, 2013), (Kwasi and Kobina, 2014), (Manoj and Edward, 2016), (Abdulah and Bakari, 2014), (Ozaki, 2016), (Adebiyi et al, 2014), (Diem Ngo et al, 2013), (Rangan and Titida, 2006), (Meyler et al, 1998), (Tabachnick and Fidell, 2001).

This chapter presents extensive process of building ARIMA models for short-term stock price prediction. The results obtained from the real-life data establishes the potential strength of ARIMA models to provide stockholders short-term prediction that could support investment decision making processes.

Section 4.1 presents the introduction of the chapter followed by the review of literature in section 4.2. Section 4.3 describes briefly about ARIMA models, whereas section 4.4 presents
general rules laid for non-seasonal Box-Jenkins model identification procedures. Section 4.5 presents the methodology used in this study to carry forward the research and simultaneously section 4.6 illustrates the development processes of the experiments, its results obtained and the interpretation for normal time series stock data, i.e., Sun Pharmaceutical and finally, section 4.7 discusses about the process of the experiments, its results obtained, and interpretation for non-normal time series stock, i.e., Lupin Limited.

4.2 BRIEF OVERVIEW OF SOME RELATED LITERATURE

Ozaki (1977) ascertained that AIC is a powerful tool in identification of different ARIMA models. He used MAICE (minimum AIC estimation) procedure, which selects a model by using Akaike's Information Criterion (AIC) for determining the best ARIMA Models. He obtained that MAICE procedure produces almost results similar to five ARIMA models ((1, d, 0), (2, d, 0), (0, d, 1), (0, d, 2) and (1, d, 1)) of Box-Jenkins.

Rangsan and Titida (2006) developed various ARIMA models for forecasting oil palm prices of Thailand for a period of 5 years from 2000 to 2004. The criteria for choosing best ARIMA model was minimum of mean absolute percentage error (MAPE). They found ARIMA (2,1,0) for the farm price model, ARIMA (1,0,1) for whole sale price, and ARIMA (3,0,0) for pure oil price as the best model in their respective categories. Valenzuela et al (2008) suggested the use of hybrid ARIMA–ANN models for better accuracy than ARMA models which had been prominent by used in linear models of forecasting of time series. They used hybridization of intelligent techniques such as Evolutionary Algorithms, Artificial Neural Networks and Fuzzy systems.

Abdullahi and Bakari (2014) examined the trend or pattern of Nigerian stock market for a period of 1985-2008. They examined the tendency of the Nigerian capital market by applying various ARIMA models. They concluded that ARIMA (2, 1, 2) model performed better on the basis of least MAPE and MAE.

Adebiyi et al (2014) carried out research for prediction of stock prices using ARIMA models on historical stock data collected from Nigeria Stock Exchange and New York Stock Exchange. They found that proposed method of forecasting on short-term basis satisfactorily in comparison to existing techniques for stock price prediction. The results compete
reasonably well with emerging forecasting techniques in short-term prediction with the result obtained from ARIMA models.

**Mondal et al (2014)** analysed 56 time series of Indian stocks from different sectors to determine the accuracy of forecasting methods using ARIMA models. They also mentioned that results obtained in the study were accurate up to 85% of ARIMA models.

**Xiaoguang et al (2014)** analysed the shares of China Merchants Bank for opening prices (04.01.2013 – 18.10.2013) and to predict the next five days (21.10.2013 – 25.10.2013) stock opening price data using ARIMA models-SAS system and concluded it to be very efficient and suitable model for short-term stock predictions.

**Konarasinghe et al (2015)** focused on the forecasting of Sri Lankan share market returns using ARIMA models. The stock price series were tested with partial autocorrelation functions and autocorrelation functions for stationarity of time series. The total market returns, sector returns and individual company returns were forecasted. They have used mean square error, mean absolute deviation, Anderson-Darling test and residual plots for model validation.

**Jadhav et al (2015)** analysed the historical data of six years for Indian stock market using six different models on monthly closing stock indices of Sensex and concluded that ARIMA model helped in predicting fairly accurate values of the future stock indices. Out of the initial six different models, they choose ARIMA (1,0,1) as the best model based on the fact that it satisfies all the conditions for the “goodness of fit unlike the rest”.

**Ngan (2016)** analysed foreign exchange rate actual data for three years from 2013 to 2015 of commercial joint stock banks in Vietnam to forecast foreign exchange rate between Vietnam Dong and United State Dollar (VND/USD) in successive 12 months of 2016 using ARIMA Models. Their results proved ARIMA models, to be most suitable for estimating foreign exchange rate in short-term period.

**Manoj and Edward (2016)** developed and applied ARIMA models on the Indian sectorial stock prices in their sector specific study of 6 sectors namely automobiles, banking, healthcare, information technology, oil & gas and power for daily actual data of 9 years from
February 2007 to April 2015 with 1996 observations to forecast stock prices. They performed sector-specific study for forecasting and suggested that (1, 1, 0) to be the most suitable ARIMA model in comparison to others.

4.3 ARIMA MODEL
Methodology for forecasting of financial time series data known as ARIMA models was introduced in 1970 by Box and Jenkins. Therefore, it is known as Box-Jenkins methodology. The building of ARIMA models for prediction is based on certain set of activities such as (i) identification (ii) estimation (iii) diagnostics checking and (iv) finally forecasting of the results (Ngo et al, 2013). It is one of the leading method used for forecasting in financial time series ((Pai and Lin, 2005), (Devi et al, 2013), (Abdullahi and Bakari, 2014)). ARIMA models have shown efficient capability to generate short-term forecasts. It is treated as one of the best model for short-term prediction (Meyler et al, 1998).

In ARIMA Models future value of the variables is a linear combination of past values and past errors. Mathematically it is represented as:

\[
y_t = \Phi_0 + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \ldots - \theta_q \epsilon_{t-q} \quad (4.1)
\]

where actual values of the data are denoted as \(y_t\), coefficients are denoted as \(\Phi_i\) and \(\theta_j\). The random errors are denoted by \(\epsilon_t\) and degree of auto regressive and moving averages are represented by integer's \(p\) and \(q\). (Ayodele et al, 2014).

4.3.1 Autoregressive (AR) and its Basic Concepts
In autoregressive model the series is regressed on to past values of itself. Therefore, future value of a variable is assumed to be a linear combination of past observation and a random error together with a constant.

An autoregressive (AR) Model of order \(p\), i.e., AR (\(p\)) model can be expressed with the following equations.

\[
y_t = \Phi_0 + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-p} + \epsilon_t \quad (4.2)
\]

Here \(y_t\) and \(\epsilon_t\) are actual values and random errors (or random shock) at time ‘\(t\)’. \(\Phi_i\) (\(i = 1-p\)) are model parameters and ‘\(\phi\)’ is a constant term. The Integer \(p\) is known as the order of the model.
Some of the properties of the autoregressive process when mean, variance and autocorrelation are in stationary AR \((p)\) processes are listed in the following.

**Property 1:** Mean of stationary AR\((p)\) process

\[
\mu = \frac{\phi_0}{\Sigma_{j=1}^{p} \phi_j} \tag{4.3}
\]

**Property 2:** Variance of the stationary AR \((1)\) process

\[
\text{var} \left( y_t \right) = \frac{\sigma^2}{1 - \phi_1^2} \tag{4.4}
\]

**Property 3:** Lag ‘\(h\)’ autocorrelation of a stationary AR \((1)\) process

\[
\rho_h = \phi_1^h \tag{4.5}
\]

**Property 4:** In general for any stationary AR\((p)\) process, the auto covariance at lag \(k > 0\) is given by:

\[
y_k = \phi_1 Y_{k-1} + \phi_2 Y_{k-2} + \cdots + \phi_p Y_{k-p} \tag{4.6}
\]

Similarly the autocorrelation at lag \(k > 0\) can be calculated by

\[
\rho_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} + \cdots + \phi_p \rho_{k-p} \tag{4.7}
\]

Where, \(Y_h = Y_{-h}\) and \(\rho_h = \rho_{-h}\) if \(h < 0\), and \(\rho_0 = 1\)

These equations are known as the **Yule-Walker equations**.

**Property 5:** On adding ‘\(\sigma^2\)’ to the sum these equations hold true for \(k = 0\) and are equivalent to:

\[
y_0 = \phi_1 y_1 + \phi_2 y_2 + \cdots + \phi_p y_p + \sigma^2 \tag{4.8}
\]

**Property 6:** This property holds true for AR \((2)\) stationary process:

\[
\rho_0 = 1^{p1} = \frac{\phi_1}{1 - \phi_2 \rho_k} = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} \text{ for } k > 1 \tag{4.9}
\]

**Property 7:** The variance of the \(y_i\) in a AR \((2)\) stationary process depicted as:

\[
\text{var} \left( y_i \right) = \frac{1 - \phi_2}{1 + \phi_2} \cdot \frac{\sigma^2}{(1 - \phi_2)^2 - \phi_1^2} \tag{4.10}
\]

### 4.3.2 Moving Average (MA) Models and its Basic Concepts

Moving average (MA) models suggest that the time series can be expressed as a function of previous forecasting errors (or noise) ‘\(e_t\)’. Therefore, MA model’s prediction is based on the errors made in the past, so one can learn from the errors made in the past to improve later predictions. (It means it learns from its own mistake).
A moving average (MA) model of order q, or an MA (q) model can be expressed with the following equation:

\[ y_i = \mu + \epsilon_i + \theta_1 \epsilon_{i-1} + \cdots + \theta_q \epsilon_{i-q} \]  

(4.11)

Here \( y_i \) and \( \epsilon_i \) are actual values and random errors (or random shock) at time ‘i’. The value of ‘y’ at time ‘i+1’ is a linear function of past errors. Mean of the sample data is depicted by the symbol ‘\( \mu \)’. It is assumed that the error terms are independently distributed with a normal distribution having mean = 0 and constant variance = \( \sigma^2 \). \( \Phi_l \) (\( l = 1-p \)) are model parameters and ‘\( \mu \)’ is a constant term. The Integer \( q \) is known as the order of the model.

**Property 1**: The mean of an MA (q) process is \( \mu \).

**Property 2**: The variance of an MA (q) process is defined as:

\[ \text{var} (y_i) = \sigma^2 (1 + \theta_1^2 + \cdots + \theta_q^2) \]  

(4.12)

**Property 3**: The autocorrelation function of an MA (1) process is presented as:

\[ \rho_1 = \frac{\theta_2}{1 + \theta_1^2} \rho_h = 0 \text{ for } h > 1 \]  

(4.13)

**Property 4**: The autocorrelation function of an MA (2) process is presented as:

\[ \rho_2 = \frac{\theta_1 + \theta_1 \theta_2}{1 + \theta_1^2 \theta_2^2} \rho_h = 0 \text{ for } h > 2 \]  

(4.14)

**Property 5**: The autocorrelation function of an MA(q) process is defined as:

\[ \rho_h = \frac{\theta_h + \sum_{j=1}^{q-h} \theta_j \theta_{j+h}}{1 + \sum_{j=1}^{q} \theta_j^2} \]  

(4.15)

for \( h \leq q \) and \( \rho_h = 0 = 0 \) for \( h > q \)

**Property 6**: The PACF of an MA(1) process is presented by the equation as follows:

\[ \pi_k = \frac{-(-\theta_1)^k}{1 + \sum_{i=1}^{k} \theta_1} \pi_{k-k} = \frac{-(-\theta_1)^i}{1 + \sum_{i=1}^{q} \theta_1^2} \pi_k \]  

(4.16)

4.3.3 Autoregressive Moving Average (ARMA) models and its Basic Concepts

A Model which contains all important features of a given time series data is always treated as the best model. Sometimes, autoregressive (AR) model or moving average (MA) model alone does not work out. In such cases a combination of both the models, i.e., autoregressive of order ‘\( p \)’ and moving average of order ‘\( q \)’ is applied to get the desired results. The combination of these two models is known as ARMA model. The mathematical of an ARMA \((p, q)\) model is presented by the following equation.

\[ y_i = \theta_0 + \theta_1 Y_{i-1} + \theta_2 Y_{i-2} + \cdots + \theta_p Y_{k-p} + \epsilon_i + \theta_1 \epsilon_{i-1} + \cdots + \theta_q \epsilon_{i-q} + \]  

\[ \text{Or} \]
\[ y_i = \phi_0 + \sum_{j=1}^{p} \phi_j y_{i-j} + \varepsilon_i + \sum_{j=1}^{q} \theta_j \varepsilon_{i-j} \]  

(4.17)

If a time series \( z_1, \ldots, z_n \) has an ARMA(\( p, q \)) process and zero mean (where \( z_i = y_i - \mu \)), then it can be defined as ARMA(\( p, q \)) by removing the constant term (i.e., \( \phi_0 \)) and saying that \( y_1, \ldots, y_n \) has an ARMA(\( p, q \)) process with mean \( \mu \).

### 4.3.4 Autoregressive Integrated Moving Average (ARIMA) models.

The components of this model are consisting of three parts: an Autoregressive (AR) part, a moving Average (MA) part and ‘I’ the differencing part. This model is particularly referred to as the ARIMA (\( p, d, p \)) model (Box-Jenkins). Here ‘\( p \)’ is the order of the Autoregressive part, ‘\( d \)’ is the order of differencing and ‘\( q \)’ is the order of the moving average part. For instance, an ARIMA (2, 1, 2) model means, that it contains 2 Autoregressive (\( p \)) parameters and 2 moving Average (\( q \)) parameters and it is differenced once to attain the stationarity of the time series data.

If \( d = 0 \), the model becomes ARMA, and is considered as a linear stationary model.

If \( d > 0 \), the model becomes ARIMA and is considered as a linear non-stationary model.

(Refer equation 4.1, page no.82).

If the time series under investigation is non-stationary, it is suggested to take the difference of the series with itself ‘\( d \)’ times to make it stationary. Further, ARMA model is applied on to the differenced part (Abdhuli and Bakari, 2014).

### 4.4 General process of forecasting using ARIMA models as per Box-Jenkins methodology

ARIMA forecasting processes consists of four steps/stages as mentioned below.

(i) Model Identification

(ii) Model Parameter Estimation

(iii) Diagnostic Checking

(iv) Forecasting

Box-Jenkins methodology requires that time series values must be stationary and invertible before one recognizes any pattern in the data and attempt to fit any of the ARIMA model. The graph of autocorrelation function (ACF) reflects about the nature of time series data whether it is stationary or non-stationary over the time. The time series values are considered stationary if the graph of autocorrelation function (ACF) cuts off or dies down very quickly.
On the contrary, it is treated as non-stationary if the graph of autocorrelation function either cuts off or dies down gradually. Some of the examples of the graphs are listed below:

![Graphs showing ACF (PACF) cutting off and dying down extremely slowly](image)

Fig: 4.1 “The ACF (PACF) cuts off fairly quickly versus dies down extremely slowly” (Bowerman, O’connell and Koehler, p. 413)

One can convert the non-stationary time series to stationary time series by calculating the first difference or second or third differences of the original data if the data values are non-seasonal and non-stationary. (Ngo, 2013) as under

The differences of time series data introduced a new variable $Z_t$. The series $Z_t$ will be the first difference of $Y_t$ and is calculated as follows:

First Difference: $Z_t = Y_t - Y_{t-1}$ Where $t = 2, 3, ..., n$   \( (4.18) \)

On finding the first difference if the mean of the time series is not constant than $Z_t$ is recalculated as the difference of the first difference as follows:

Second Difference: $Z_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2})$ where $t = 3, 4, ..., n$  \( (4.19) \)

A series which has been made stationary by applying the appropriate differencing has zero mean and it is considered as a deterministic component of the series. The data is presented as derivation from the mean to concentrate on the random behaviour of the series.

4.4.1 Types of Models or Model Identification

On observing the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of the original time series time series $y_1, y_2, ..., y_n$ or the transformed time series ($z_t$’s), it can be ascertained whether series are stationary or non-stationary and the models to be fitted are called theoretical non-seasonal Box-Jenkins models.

Non-seasonal theoretical Box-Jenkins models are categorized in three categories, i.e., (i) autoregressive (AR) model of order $p$ (ii) moving average (MA) model of order $q$ and (iii) combined autoregressive- moving average (ARMA) model of order $(p, q)$. However, when
the ACF cuts off quickly after lag $q$ and the PACF cuts off quickly after lag $p$, for such a condition there is no theoretical Box-Jenkins model. These conditions are summarized in the table as follows:

**Table 4.1 Theoretical Box-Jenkins model**

<table>
<thead>
<tr>
<th>Model</th>
<th>ACF</th>
<th>PACF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moving average of order $q$</td>
<td>Cuts off after lag $q$</td>
<td>Dies down</td>
</tr>
<tr>
<td>$Z_t = \delta + a t - 01 a t\cdot 1 - 02 a t\cdot 2 - \ldots - 0 q a t\cdot q$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Autoregressive of order $p$</td>
<td>Dies down</td>
<td>Cuts off after lag $q$</td>
</tr>
<tr>
<td>$Z_t = \delta + \phi1 z t\cdot 1 + \phi2 z t\cdot 2 + \ldots + \phi p z t\cdot p + a t$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mixed autoregressive-moving average of order $(p, q)$</td>
<td>Dies down</td>
<td>Dies down</td>
</tr>
<tr>
<td>$Z_t = \delta + \Phi1 z t\cdot 1 + \Phi2 z t\cdot 2 + \ldots + \Phi p z t\cdot p + a t - 01 a t\cdot 1 - 02 a t\cdot 2 - \ldots - 0 q a t\cdot q$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Some of the examples displaying the different behaviours of autocorrelation function and partial autocorrelation function are depicted below

**Fig: 4.2 The ACF and PACF Behaviours (Bowerman, o’connell and Koehler, p. 412)**
It is suggested to follow the subsequent general rules laid out in this text to identify the best model if the ACF or PACF is cutting off more abruptly.

4.4.2 Model Parameter Estimations

“Stationarity is the first condition of a Box-Jenkins model. It should be invertible also. Invertible means recent observations are more heavily weighted than more remote observations; the parameters ($\emptyset_1$, $\emptyset_2$, …, $\emptyset_p$, $\theta_1$, $\theta_2$, …, $\theta_q$) used in the model decline from the most recent observations down to the further past observations”. (Bowerman et al, 2010).

The t-values and approximate p-values test the following hypothesis.

“Let $\theta$ be any particular parameter in a Box-Jenkins model.

$H_0 : \theta = 0$ versus $H_1 : \theta \neq 0$

We can reject null hypothesis $H_0$ if and only if either of the following conditions holds:

1. $|t| > t_{\alpha/2}^{(n-n_p)}$ where $n_p$ is the number of parameters in the model.
2. $p - value < \alpha$  

(Bowerman et al, 2010)

If the null hypothesis is rejected at the smaller significant level $\alpha$, it indicates very strongly that the observed parameter is very important for the model. To decide the best model we compare the results based on Akaike’s Information Criterion (AIC), and Schwarz’s Bayesian Criterion (SBC) etc. The best model has smaller standard errors.

4.4.3 DIAGNOSTICS CHECKING

The key role of diagnostic checking is to ascertain the adequacy of the ARIMA models fitted to the data. A model is adequate if it extracts all the relevant information from the data. The unexplained part of the data, i.e., residual should be very small. The parts of the data which are not explained by the model should be as small as possible and residuals should not have systematic or predictable patterns.

As per Box-Jenkins methodology diagnostics testing includes all essential statistical properties of the error terms, i.e., normality and weak white noise assumptions.

Residual of an estimated model should demonstrate white noise behaviour. If this assumption is not true then there is a scope to extract some more important information from modelling process. Two methods used for diagnostic checking are mentioned below.

- Graphical method:
  (i) Plots of residuals to check the systematic pattern.
(ii) Use the SACF and SPACF (relate to identification step) of the residuals.

By examining the autocorrelations and partial autocorrelation graphs of the residuals adequacy of the models can be ascertained. If the spikes are exceeding two standard errors, it is an indication of an adequate model.

- Testing method: Autocorrelation Tests (Q-test)

To test the adequacy of an overall model, the null and alternative hypotheses are:

$H_0$: The model is adequate or the model does not exhibit lack of fit.

$H_a$: The model is inadequate or the model exhibit lack of fit.

Test statistics to test $H_0$ is given as under:

The Ljung–Box Statistic: 

\[
Q = n (n + 2) \sum_{k=1}^{m} \frac{r_k^2}{n-k}
\]  

(4.22)

Where

- $n =$ length of time series or number of observations used to fit ARIMA models.
- $r$ = estimated auto correlation of the residual series of lag ‘$k$’.
- $m =$ number of lags being tested.
- $d =$ degree of non-seasonal differencing used to transform the original time series value into stationary. If it is included in the building of ARIMA model than ‘$n$’ of equation (4.22) will be replaced by $n'$ where $n'=n-d$. (Bowerman, O’Connell and Koehler, p. 459).
- $\alpha =$ Significance level

Critical Region: The Box-Ljung test rejects the null hypothesis if

\[
Q > \chi^2_{(1-\alpha,h)}
\]

Where $\chi^2_{(1-\alpha,h)}$ is the chi-square distribution table value with $h$ degree of freedom and $h = m-p-q$. One can also use level of significance or $p$-values calculated for a given value of $\chi^2$ to test $H_0$.

If the $p$-value is greater than $\alpha$ it can be recommended that the model is adequate.

Weakness of Q-test:

Q-test is only asymptotically valid. In case of small and medium size samples it may perform poorly. Diagnostic test based on autocorrelation test can only diagnose and reveal the under parameterized model but will not reveal the over parameterized model. Modifications have been incorporated in the literature for Ljung-Box test are available in the form of McLeod-Li test, Monti’s test, etc.

4.4.4 Forecasting Stock Prices of Select Indian Companies-An Empirical Evidence
This section deals with the brief interpretation of time series data of 25 BSE Sensex companies of Indian stock market. The data under consideration is taken from Yahoo India finance for a period of 2 years from 20.01.2014 - 20.01.2016. All 25 stocks are analysed for normality test. In this research, we have taken 2 companies from pharmaceutical sector for the detailed analysis (due to space constraints). It contains both types of distribution, i.e., normal distribution and non-normal distribution. The stocks of Lupin Limited follow non-normal distribution while stocks of Sun Pharmaceuticals follow normal distribution. With the help of Jarque Bera test statistic, we accept the normality hypothesis for Sun Pharmaceutical and reject the normality hypothesis for Lupin Limited.

In all 500 observations are used for fitting various ARIMA models and rest 23 observations are used to test the data. The data is comprised of four variables, namely: open price, low price, high price and close price respectively. In the research, open price of the data represents the price of the index to be forecasted. Open price for the forecast is selected because in stock market everyone is interested to know about the ups and downs of the prices of the next day with respect to the prices of the previous day.

In this segment the data will be examined to check for the most appropriate class of ARIMA processes by selecting the order of non-seasonal models applied. During forecasting processes certain errors are committed. These forecasting errors are the difference between the actual value and the forecast value for the corresponding period. These can be calculated as \( E_t = A_t - F_t \) where ‘E’ is the forecast error at period ‘t’, ‘A’ is the actual value at period ‘t’ and ‘F’ is the forecast for period ‘t’. Some of the measures of forecasting accuracy used for the analysis are listed below.

<table>
<thead>
<tr>
<th>Table 4.2: Measures of error for forecasting accuracy</th>
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<tbody>
<tr>
<td>Mean absolute error (MAE)</td>
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<tr>
<td>Mean absolute percentage error (MAPE)</td>
</tr>
<tr>
<td>Percent Mean Absolute error Deviation (PMAD)</td>
</tr>
<tr>
<td>Mean squared Error (MSE)</td>
</tr>
<tr>
<td>Root Mean squared Error (RMSE)</td>
</tr>
</tbody>
</table>
To validate the forecast, the data is divided into two parts. The first part of the data is used for fitting ARIMA models and the other part of the data is used for judging the goodness of fit statistics for the different models.

The method used in the study to develop ARIMA models for stock price prediction is explained in detail underneath:

(i) To check the basic nature of the data, whether it is stationary or not, the graphical analysis is done with software, Microsoft Excel.

(ii) To check the presence of unit root in the data, Augmented Dickey Fuller test is applied.

(iii) The data under consideration is found non-stationary and it is made stationary by taking first difference and second difference of the series simultaneously.

(iv) ARIMA models are fitted taking \( p = [0,1,2] \), \( q = [0,1,2] \) and \( d= [0,1,2] \), where \( p + q \) is less than or equal to 3. This is how 12 ARIMA models are tested on the time series data.

(v) Interpretation of goodness of fit statistics and graphical analysis is done by analysing behaviours (spikes) of ACF and PACF to identify the best ARIMA model autocorrelogram (ACF) and partial-autocorrelogram (PACF) graphs to identify the best fit ARIMA model.

(vi) To determine the best ARIMA model among various fitted models, the following criterions were used in this study for each stock data:

(i) **Degree of freedom:**

   In statistics, the number of degrees of freedom is the number of values in the final calculation of a statistic that are free to vary. The number of independent ways by which a dynamic system can move, without violating any constraint imposed on it, is called number of degrees of freedom

(ii) **The sum of squares due to error:**

   “This statistic measures the total deviation of the response values from the fit to the response values. It is also called the summed square of residuals and is usually labelled as \( SSE \).

   \[
   SSE = \sum_{i=1}^{n} w_i(y_i - \hat{y}_i)^2 \tag{4.23}
   \]

   SSE value closer to 0 indicates that the model has a smaller random error component, and the fit will be more useful for prediction”.

(iii) **Mean Square Error**

“MSE is the mean square error or the residual mean square. Mathematically it is represented as:

\[
MSE = \frac{SSE}{v}
\]  

(4.24)

MSE value closer to 0 indicates a fit that is more useful for prediction”.


(iv) **Root Mean Squared Error**

“RMSE is also known as the fit standard error and the standard error of the regression. It is an estimate of the standard deviation of the random component in the data, and is defined as:

\[
RMSE = s = \sqrt{MSE}
\]  

(4.25)

Where MSE is the mean square error or the residual mean square

Value of SSE closer to 0 indicates a fit that is more useful for prediction”.


(v) **White Noise Variance and its processes**

“White noise the sequence \(\{\varepsilon_t\}\), consisting of independent (or uncorrelated) random variables with mean 0 and variance \(\sigma^2\) is called white noise. It is a second order stationary series with \(\varepsilon_0 = \sigma^2\) and \(\varepsilon_k = 0, k \neq 0\).

Covariance stationary processes for time series, \(y_t\) are as follows:

1. \(E(y_t) = \mu\) for all \(t\)
2. \(Var(y_t) = \sigma^2\) for all \(t, \sigma^2 < \infty\)
3. \(Cov(y_t, y_{t+\tau}) = \gamma(\tau)\) for all \(t\) and \(\tau\).

(source: http://www.statslab.cam.ac.uk/~rrw1/timeseries/t.pdf)

(vi) **Mean Absolute Percentage Error (MAPE):**

“MAPE is a measure to calculate, how much a dependent series varies from its model-predicted level. It is independent of the units used and can therefore be used to compare series with different units.
It expresses the accuracy as a percentage of the error and is easier to understand than any other statistics. MAPE can be calculated by the following equation.

\[
\frac{1}{n} \sum \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100 \quad (y_t \neq 0)
\]

where \(y_t\) equals the actual value, \(\hat{y}_t\) equals the fitted value, and \(n\) equals the number of observations. (Source: http://support.minitab.com/en-us/minitab/17/topic-library/modeling-statistics/time-series/time-series-models/what-are-mape-mad-and-msd/)

(vii) Final Prediction Error

“Akaike's Final Prediction Error (FPE) criterion provides a measure of model quality by simulating the situation where the model is tested on a different data set. As per Akaike's theory, the most accurate model has the smallest FPE. Mathematically it is defined as follows:

\[
FPE (P) = \sigma^2 (p) \left(1 + \frac{p+1}{N}\right) \left(1 - \frac{p+1}{N}\right)^{-1}
\]

It is an estimate of the one step ahead prediction error variance model of order \(p\), where \(\sigma^2(p)\) is the estimated residual variance of the model and \(N\) is the number of observations.

OR

If you use the same data set for both model estimation and validation, the fit always improves as you increase the model order and, therefore, the flexibility of the model structure. Akaike's Final Prediction Error (FPE) is defined by the following equation:

\[
FPE = \det \left( \frac{1}{N} \sum_{t=1}^{N} e(t, \theta_N) \left( e(t, \theta_N) \right)^T \left( 1 + \frac{d/N}{1 - d/N} \right) \right)
\]

where:

\(N\) is the number of values in the estimation data set.
\(e(t)\) is a \(ny\)-by-1 vector of prediction errors.
\(\theta_N\) represents the estimated parameters and \(d\) is the number of estimated parameters.

If number of parameters exceeds the number of samples, FPE is not computed when model estimation is performed (model. Report FPE is empty). The FPE command returns NaN”. (source: //in.mathworks.com/help/ident/ref/fpe.html

(viii) Akaike Information criterion
“AIC is a measure of the relative quality of statistical models for a given set of data. It estimates the quality of each model, relative to each of the other models. Hence, AIC provides a means for model selection.

The new procedure of order determination developed by Akaike (1972 and 1973), is a promising one. Akaike's Information Criterion (AIC) is defined as follows:

\[ \text{AIC} = (-2) \log_e (\text{maximum likelihood}) + 2 \times \text{(number of free parameters)} \]

AIC measures both the fit of a model and the unreliability of a model. Akaike (1973) introduced the MAICE (minimum AIC estimation) procedure which selects the model whose structure with its associated parameter values gives the minimum of AIC.

AIC and BIC hold the same interpretation in terms of model comparison. That is, the larger difference in either AIC or BIC indicates stronger evidence for one model over the other (the lower the better)”.

(source:https://en.wikipedia.org/wiki/Akaike_information_criterion)

(ix) **Correction of Akaike’s Information criterion**

“AICc is AIC with a correction for finite sample sizes. The formula for AICc depends upon the statistical model. Assuming that the model is univariate, linear, and has normally distributed residuals (conditional upon regressors), the formula for AICc can be defined as follows:

\[ \text{AICc} = \text{AIC} + \frac{2k(k+1)}{n-k-1} \]  

where \( n \) denotes the sample size and \( k \) denotes the number of parameters”.(source-https://en.wikipedia.org/wiki/Akaike_information_criterion)

(x) **Schwarz Bayesian information Criterion**

“Bayesian information criterion (BIC) or Schwarz (SBC, SBIC) is a criterion for model selection among a finite set of models; the model with the lowest BIC is preferred. It is based, in part, on the likelihood function and it is closely related to the Akaike information criterion (AIC).

When fitting models, it is possible to increase the likelihood by adding parameters, but it may result in over-fitting. Both BIC and AIC resolve this problem by introducing a penalty term for the number of parameters in the model; the penalty term is larger in BIC than in AIC”. (source-https://en.wikipedia.org/wiki/Bayesian_information_criterion)
4.5 DEVELOPMENT PROCESSES AND RESULTS OF ARIMA MODELS

In the subsequent section, actual experimental process to build various ARIMA models is carried out by using software Microsoft Excel and software XLStat. Various experiments are conducted by applying different ARIMA models and results are calculated on the basis of goodness of fit statistics and other accuracy measures as stated above. The graphical representation of the stock prices of Sun Pharmaceutical following normal distribution is illustrated below.

4.5 EXPERIMENTAL PROCESS AND RESULTS OF SUN PHARMACEUTICAL (NORMAL DISTRIBUTION)

4.6.1 Graphical Analysis

Fig 4.3 Graph of opening price of Sun Pharmaceutical stock at BSE
Table 4.3: Augmented Dickey-Fuller Statistics

<table>
<thead>
<tr>
<th></th>
<th>Original</th>
<th>First Difference</th>
<th>Second Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tau (Observed value)</td>
<td>-2.164</td>
<td>-7.991</td>
<td>-13.443</td>
</tr>
<tr>
<td>Tau (Critical value)</td>
<td>-0.907</td>
<td>-0.907</td>
<td>-0.907</td>
</tr>
<tr>
<td>p-value (one-tailed)</td>
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<td>&lt; 0.0001</td>
<td>&lt; 0.0001</td>
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<tr>
<td>Alpha</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
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</table>

Table 4.4: Various statistics of ARIMA models at First Difference for opening price of Sun Pharmaceutical stock at BSE

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<td>150181.9</td>
<td>188472.8</td>
<td>149673.4</td>
<td>149565</td>
<td>149573.8</td>
<td>149529.5</td>
<td>149596.1</td>
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<tr>
<td>MSE</td>
<td>568.3658</td>
<td>2389.134</td>
<td>302.177</td>
<td>379.2209</td>
<td>301.1538</td>
<td>301.1187</td>
<td>300.9532</td>
<td>300.8643</td>
<td>300.9982</td>
</tr>
<tr>
<td>RMSE</td>
<td>23.84042</td>
<td>48.87877</td>
<td>17.38324</td>
<td>19.47359</td>
<td>17.35378</td>
<td>17.35277</td>
<td>17.348</td>
<td>17.34544</td>
<td>17.3493</td>
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<tr>
<td>WN Variance</td>
<td>568.3658</td>
<td>2389.134</td>
<td>302.177</td>
<td>379.2209</td>
<td>301.1538</td>
<td>301.1187</td>
<td>300.9532</td>
<td>300.8643</td>
<td>300.9982</td>
</tr>
<tr>
<td>MAPE(Diff)</td>
<td>99.80871</td>
<td>239.597</td>
<td>208.8889</td>
<td>210.873</td>
<td>199.8472</td>
<td>199.5004</td>
<td>199.1988</td>
<td>200.2772</td>
<td>199.3024</td>
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<tr>
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<td>115.111</td>
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<td>4253.212</td>
<td>4253.143</td>
<td>4252.788</td>
<td>4252.765</td>
<td>4252.765</td>
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<td>4259.143</td>
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<td>4260.9</td>
</tr>
<tr>
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<td>4259.26</td>
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<td>4262.91</td>
<td>4260.846</td>
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<td>4260.982</td>
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<th>(2,2,2)</th>
<th>(2,2,0)</th>
<th>(0,2,2)</th>
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</thead>
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<tr>
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<td>835999.6</td>
<td>487188.9</td>
<td>341204.3</td>
<td>217577.5</td>
<td>189161.8</td>
<td>762418.2</td>
</tr>
<tr>
<td>MSE</td>
<td>5556.046</td>
<td>2627.45</td>
<td>1688.888</td>
<td>984.22</td>
<td>689.3017</td>
<td>439.5506</td>
<td>382.145</td>
<td>1540.239</td>
</tr>
<tr>
<td>WN Variance</td>
<td>5556.046</td>
<td>2627.45</td>
<td>1688.888</td>
<td>984.22</td>
<td>689.3017</td>
<td>439.5506</td>
<td>382.145</td>
<td>1540.239</td>
</tr>
<tr>
<td>MAPE(Diff)</td>
<td>190.6844</td>
<td>2653.282</td>
<td>10859.3</td>
<td>17791.13</td>
<td>29278.78</td>
<td>25881.24</td>
<td>27066.65</td>
<td>2723.486</td>
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<tr>
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<td>325.0355</td>
<td>306.4595</td>
<td>210.1273</td>
<td>208.3362</td>
<td>506.2749</td>
</tr>
<tr>
<td>-</td>
<td>5303.011</td>
<td>5089.709</td>
<td>4823.951</td>
<td>4649.223</td>
<td>4436.932</td>
<td>4369.274</td>
<td>5039.705</td>
<td>4564.772</td>
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</table>
Table 4.5: ARIMA models at Second Difference for opening price of Sun Pharmaceutical stock at BSE

<table>
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<th>Model</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. deviation</th>
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</thead>
<tbody>
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<td>(0,1,0)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(1,1,0)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(0,1,1)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(2,1,0)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(0,1,2)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(1,1,1)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
</tbody>
</table>

Table 4.6: Descriptive Statistics of opening price of Sun Pharmaceutical stock at BSE

<table>
<thead>
<tr>
<th>Model</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0,1,0)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(1,1,0)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(0,1,1)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(2,1,0)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(0,1,2)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
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<tr>
<td>(1,1,1)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
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<tr>
<td>(2,1,2)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
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<tr>
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<tr>
<td>(1,1,2)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(2,1,1)</td>
<td>-77.300</td>
<td>99.650</td>
<td>-0.331</td>
<td>17.366</td>
</tr>
<tr>
<td>(0,2,0)</td>
<td>-104.500</td>
<td>109.000</td>
<td>-0.016</td>
<td>23.824</td>
</tr>
<tr>
<td>(1,2,0)</td>
<td>-104.500</td>
<td>109.000</td>
<td>-0.016</td>
<td>23.824</td>
</tr>
<tr>
<td>(0,2,1)</td>
<td>-104.500</td>
<td>109.000</td>
<td>-0.016</td>
<td>23.824</td>
</tr>
<tr>
<td>(1,2,1)</td>
<td>-104.500</td>
<td>109.000</td>
<td>-0.016</td>
<td>23.824</td>
</tr>
<tr>
<td>(2,2,1)</td>
<td>-104.500</td>
<td>109.000</td>
<td>-0.016</td>
<td>23.824</td>
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<tr>
<td>(1,2,2)</td>
<td>-104.500</td>
<td>109.000</td>
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<td>(2,2,2)</td>
<td>-104.500</td>
<td>109.000</td>
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<td>(2,2,0)</td>
<td>-104.500</td>
<td>109.000</td>
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<td>(0,2,2)</td>
<td>-104.500</td>
<td>109.000</td>
<td>-0.016</td>
<td>23.824</td>
</tr>
</tbody>
</table>

ARIMA-1D(0,1,0)

ARIMA (open first difference)

Residuals

ARIMA-1D(0,1,0)
Fig 4.6: The correlogram of Sun Pharmaceutical Stock Price At \( p=0 \) \( d=1 \) \( q=0 \)
Fig 4.7: The correlogram of Sun Pharmaceutical Stock Price At $[p=1 \ d=1 \ q=0]$
Fig 4.8: The correlogram of Sun Pharmaceutical Stock Price At [p=0, d=1, q=1]
Fig 4.9: The correlogram of Sun Pharmaceutical Stock Price At \( p=2 \ d=1 \ q=0 \)
Fig 4.10: The correlogram of Sun Pharmaceutical Stock Price At $\{p=0 \ d=1 \ q=2\}$
Fig 4.11: The correlogram of Sun Pharmaceutical Stock Price At $[p=1\ d=1\ q=1]$
Fig 4.12: The correlogram of Sun Pharmaceutical Stock Price At \[ p=0 \text{ d}=2 \text{ q}=0 \]

ARIMA-2D(0,2,0)

ARIMA-2D(1,2,0)

ARIMA-2D(0,2,0)

ARIMA-2D(0,2,0)
Fig 4.13: The correlogram of Sun Pharmaceutical Stock Price At \( p=1 \ d=2 \ q=0 \)
Fig 4.14: The correlogram of Sun Pharmaceutical Stock Price At [ p=0 d=2 q=1]

ARIMA-2D(0,2,1)

ARIMA-2D(0,2,1)

ARIMA-2D(0,2,1)

ARIMA-2D(0,2,1)
Fig 4.15: The correlogram of Sun Pharmaceutical Stock Price At $\{p=1 \ d=2 \ q=1\}$
Fig 4.16: The correlogram of Sun Pharmaceutical Stock Price At \[ p=2 \ d=2 \ q=1 \]
Fig 4.17: The correlogram of Sun Pharmaceutical Stock Price At \([ p=1 \ d=2 \ q=2]\)

4.6.2 Illustration and interpretation of the experimental results of Sun Pharmaceutical

Table 4.7: ARIMA Models at First Difference for opening price of Sun Pharmaceutical stock at BSE

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<tr>
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<td>118740.</td>
<td>150181.</td>
<td>188472.</td>
<td>149673.</td>
<td>149573.</td>
<td>149529.</td>
<td>149596.</td>
<td></td>
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<td>8</td>
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<td>7</td>
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<td>MSE</td>
<td>5556.04</td>
<td>6</td>
<td>2627.45</td>
<td>1688.88</td>
<td>984.22</td>
<td>689.301</td>
<td>439.550</td>
<td>382.145</td>
<td>1540.23</td>
</tr>
<tr>
<td>WN variance</td>
<td>5556.04</td>
<td>6</td>
<td>2627.45</td>
<td>1688.88</td>
<td>984.22</td>
<td>689.301</td>
<td>439.550</td>
<td>382.145</td>
<td>1540.23</td>
</tr>
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<td>4</td>
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<td>10859.3</td>
<td>17791.1</td>
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<td>1</td>
<td>5089.70</td>
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<td>4649.22</td>
<td>4436.93</td>
<td>4369.27</td>
<td>5039.70</td>
<td>4564.77</td>
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<td>2638.08</td>
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<td>988.204</td>
<td>694.894</td>
<td>441.330</td>
<td>385.245</td>
<td>1552.73</td>
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<td>5307.01</td>
<td>5</td>
<td>5093.70</td>
<td>4829.95</td>
<td>4657.22</td>
<td>4444.93</td>
<td>4379.27</td>
<td>5045.70</td>
<td>4570.77</td>
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Table 4.8: ARIMA Models at Second Difference for opening price of Sun Pharmaceutical stock at BSE
Analysis of results of time series data of Sun Pharmaceutical (for normal distribution) at first difference based on the statistics of goodness of fit / accuracy using ARIMA models:

i) Some of Squares due to Error
Different ARIMA models are compared for SSE values. It is found that ARIMA (1,1,2) has the lowest SSE value 149529.50 in comparison to ARIMA (0,1,0) having SSE value 282477.80, ARIMA (1,1,0) having value 1187400, ARIMA (0,1,1) having value 150181.90, ARIMA (2,1,0) having value 188472.80 and ARIMA (0,1,2) having value 149673.40, ARIMA (1,1,1) having value 149656, ARIMA (2,1,2) having value 149573.80 and ARIMA (2,1,1) having value 149596.10 respectively.

ii) Mean Squared Error
MSE values of different ARIMA models are compared. It is observed that ARIMA (1,1,2) has the lowest MSE value 300.86 in comparison to ARIMA (0,1,0) having value 569.36, ARIMA (1,1,0) having value 2389.13, ARIMA (0,1,1) having value 302.17, ARIMA (2,1,0) having value 379.22, ARIMA (0,1,2) having value 301.15, ARIMA (1,1,1) having value 301.11, ARIMA (2,1,2) having value 300.95 and ARIMA (2,1,1) having value 300.99 respectively.

iii) Root Mean Squared Error
Different ARIMA models are compared for RMSE values. It is found that ARIMA (1,1,2) has lowest RMSE value 17.34 in comparison to ARIMA (0,1,0) having value 23.84, ARIMA (1,1,0) having value 48.87, ARIMA (0,1,1) having value 17.38, ARIMA (2,1,0) having value 19.47, ARIMA (0,1,2) having value 17.35, ARIMA (1,1,1) having value 17.35, ARIMA (2,1,2) having value 17.34 and ARIMA (2,1,1) having value 17.34 respectively.
iv) **White Noise Variance**

WN variance values are analysed for different ARIMA models. It is observed that ARIMA (1,1,2) has **lowest WN variance value 300.86** in comparison to ARIMA (0,1,0) having value 569.36, ARIMA (1,1,0) having value 2389.13, ARIMA (0,1,1) having value 302.17, ARIMA (2,1,0) having value 379.22 and ARIMA (0,1,2) having value 301.15, ARIMA (1,1,1) having value 301.11, ARIMA (2,1,2) having value 300.95 and ARIMA (2,1,1) having value 300.99 respectively.

v) **Mean Absolute Percentage Error**

Different ARIMA models are compared for MAPE values. It is found that ARIMA (0,1,1) has **lowest MAPE value 104.47** in comparison to ARIMA (0,1,0) having value 472.24, ARIMA (1,1,0) having value 424.92, ARIMA (2,1,0) having value 266.64, ARIMA (0,1,2) having value 115.11, ARIMA (1,1,1) having value 115.37, ARIMA (2,1,2) having value 113.62, ARIMA (1,1,2) having value 124.23 and ARIMA (2,1,1) having value 114.18 respectively.

vi) **Final Prediction Error**

FPE values are analysed for different ARIMA models. It is observed that ARIMA (0,1,2) has **lowest FPE value 301.15** in comparison to ARIMA (0,1,0) having value 568.36, ARIMA (1,1,0) having value 2398.76, ARIMA (0,1,1) having value 302.17, ARIMA (2,1,0) having value 382.28, ARIMA (1,1,1) having value 302.33, ARIMA (2,1,2) having value 303.38, ARIMA (1,1,2) having value 302.07 and ARIMA (2,1,1) having value 303.43 respectively.

vii) **Akaike Information Criterion**

Different ARIMA models are compared for AIC value. It is found that ARIMA (0,1,1) has **lowest AIC value 4259.09** in comparison to ARIMA (1,1,0) having value 5280.76, ARIMA (2,1,0) having value 4368.21, ARIMA (0,1,2) having value 4259.21 ARIMA (1,1,1) having value 4259.14, ARIMA (2,1,2) having value 4262.78, ARIMA (1,1,2) having value 4260.76 and ARIMA (2,1,1) having value 4260.90 respectively.

viii) **Correction of AIC**

AICC value are analysed for different ARIMA models. It is observed that ARIMA (0,1,1) has **lowest AICC value 4259.03** in comparison to ARIMA (1,1,0) having value 5280.78, ARIMA (2,1,0) having value 4368.26, ARIMA (0,1,2) having value 4259.26 ARIMA (1,1,1)
 ix)  **Schwarz Bayesian Information Criterion**  
Different ARIMA models are compared for SBC value. It is found that ARIMA (0,1,1) has **lowest SBC value 4267.42** in comparison to ARIMA (1,1,0) having value 5289.17, ARIMA (2,1,0) having value 4380.84, ARIMA (0,1,2) having value 4271.83, ARIMA (1,1,1) having value 4271.76, ARIMA (2,1,2) having value 4283.83, ARIMA (1,1,2) having value 4277.59 and ARIMA (2,1,1) having value 4277.73 respectively.

**Analysis of results of time series data of Sun Pharmaceutical (for normal distribution) at second difference based on the statistics of goodness of fit / accuracy using ARIMA model:**

i)  **Some of Squares due to Error**  
Different ARIMA models are compared for SSE values. It is found that ARIMA (2,2,2) has **lowest SSE value 189161.8** in comparison to ARIMA (0,2,0) having value 2750243, ARIMA (1,2,0) having value 1300588, ARIMA (0,2,1) having value 835999.60, ARIMA (1,2,1) having value 487188.90, ARIMA (2,2,1) having value 341204.30, ARIMA (1,2,2) having value 217577.50, ARIMA (2,2,0) having value 762418.20 and ARIMA (0,2,2) having value 282999 respectively.

ii)  **Mean Squared Error**  
MSE value is analysed for different ARIMA models. It is observed that ARIMA (2,2,2) has **lowest MSE value 382.145** in comparison to ARIMA (0,2,0) having value 5556.04, ARIMA (1,2,0) having value 2627.45, ARIMA (0,2,1) having value 1688.88, ARIMA (1,2,1) having value 984.22, ARIMA (2,2,1) having value 689.30, ARIMA (1,2,2) having value 439.55, ARIMA (2,2,0) having value 1540.23 and ARIMA (0,2,2) having value 571.71 respectively.

iii)  **Root Mean Squared Error**  
Different ARIMA models are compared for RMSE value. It is found that ARIMA (2,2,2) has **lowest RMSE value 19.54** in comparison to ARIMA (0,2,0) having value 74.53, ARIMA (1,2,0) having value 51.25, ARIMA (0,2,1) having value 41.09, ARIMA (1,2,1) having value 31.37, ARIMA (2,2,1) having value 26.25, ARIMA (1,2,2) having value 20.96, ARIMA (2,2,0) having value 39.24 and ARIMA (0,2,2) having value 23.91 respectively.
iv) **White Noise Variance**
WN variance value is compared for different ARIMA models. It is observed that ARIMA (2,2,2) has **lowest WN variance value 382.145** in comparison to ARIMA (0,2,0) having value 5556.04, ARIMA (1,2,0) having value 2627.45, ARIMA (0,2,1) having value 1688.88, ARIMA (1,2,1) having value 984.22, ARIMA (2,2,1) having value 689.30, ARIMA (1,2,2) having value 439.55, ARIMA (2,2,0) having value 1540.23 and ARIMA (0,2,2) having value 571.71 respectively.

v) **Mean Absolute Percentage Error**
Different ARIMA models are compared for MAPE value. It is found that ARIMA (0,2,2) has **lowest MAPE value 101.88** in comparison to ARIMA (0,2,0) having value 1122.04, ARIMA (1,2,0) having value 531.63, ARIMA (0,2,1) having value 424.03, ARIMA (1,2,1) having value 325.03, ARIMA (2,2,1) having value 306.45, ARIMA (1,2,2) having value 210.12, ARIMA (2,2,2) having value 208.33 and ARIMA (2,2,0) having value 506.27 respectively.

vi) **Final Prediction Error**
FPE value is analyzed for different ARIMA models. It is observed that ARIMA (2,2,2) has **lowest FPE value 385.24** in comparison to ARIMA (0,2,0) having value 5556.04, ARIMA (1,2,0) having value 2638.08, ARIMA (0,2,1) having value 1688.88, ARIMA (1,2,1) having value 988.20, ARIMA (2,2,1) having value 694.89, ARIMA (1,2,2) having value 441.33, ARIMA (2,2,0) having value 1552.73 and ARIMA (0,2,2) having value 571.71 respectively.

vii) **Akaike Information Criterion**
Different ARIMA models are compared for AIC value. It is found that ARIMA (2,2,2) has **lowest AIC value 4379.274** in comparison to ARIMA (1,2,0) having value 5307.01, ARIMA (0,2,1) having value 5093.70, ARIMA (1,2,1) having value 4829.95, ARIMA (2,2,1) having value 4657.22, ARIMA (1,2,2) having value 4444.93, ARIMA (2,2,0) having value 5045.70 and ARIMA (0,2,2) having value 4570.77 respectively.

viii) **Correction of AIC**
AICC value is analysed for different ARIMA models. It is observed that ARIMA (2,2,2) has **lowest AICC value 4379.39** in comparison to ARIMA (1,2,0) having value 5307.03,
ARIMA (0,2,1) having value 5093.70, ARIMA (1,2,1) having value 4830.00, ARIMA (2,2,1) having value 4657.30, ARIMA (1,2,2) having value 4445.01, ARIMA (2,2,0) having value 5045.75 and ARIMA (0,2,2) having value 4570.80 respectively.

ix) **Schwarz Bayesian Information Criterion**
Different ARIMA models are compared for SBC value. It is found that **ARIMA (2,2,2)** has lowest SBC value **4400.29** in comparison to ARIMA (1,2,0) having value 5315.42, ARIMA (0,2,1) having value 5102.11, ARIMA (1,2,1) having value 4842.56, ARIMA (2,2,1) having value 4674.04, ARIMA (1,2,2) having value 4461.75, ARIMA (2,2,0) having value 5058.31 and ARIMA (0,2,2) having value 4583.38 respectively.

**Comparison between first and second difference results of analysed ARIMA models:**
All statistics of goodness of fitness are compared for first and second difference of time series data detailed as under:

i) **Some of Squares due to Error**
SSE value is compared for both the orders. It is found that SSE value obtained from first differencing **(149529.50)** is lowest for **ARIMA model (1,1,2)** in comparison to SSE value for second differencing **(189161.80)** of ARIMA model (2,2,2). Thus, **ARIMA model (1,1,2)** is considered best model for prediction of stock prices amongst 18 models of ARIMA on the basis of SSE analysis.

ii) **Mean Squared Error**
On comparison of the orders of differencing, it is found that MSE value obtained on first differencing **(300.86)** was lowest for **ARIMA model (1,1,2)** in comparison to MSE value obtained on second differencing **(382.14)** of ARIMA model (2,2,2). Thus, **ARIMA model (1,1,2)** is considered best model for prediction of stock prices amongst 18 ARIMA models on the basis of MSE analysis.

iii) **Root Mean Squared Error**
RMSE value is compared for both the orders and it is found that RMSE value obtained from first differencing **(17.34)** was lowest for ARIMA model (1,1,2) in comparison to RMSE value for second differencing **(19.54)** of ARIMA model (2,2,2). Thus, **ARIMA model (1,1,2)** is
considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of RMSE analysis.

iv) **White Noise Variance**
On comparison of the orders of differencing, it is found that WN variance value obtained on first differencing (300.86) was lowest for ARIMA model (1,1,2) in comparison to WN variance value for second differencing (382.14) of ARIMA model (2,2,2). Thus, ARIMA model (1,1,2) is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of WN analysis.

v) **Mean Absolute Percentage Error**
MAPE value is compared for both the orders and it is found that MAPE value obtained from second differencing (101.88) was lowest for ARIMA model (0,2,2) in comparison to MAPE value for first differencing (104.48) of ARIMA model (0,1,1). Thus, ARIMA model (0,2,2) is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of MAPE analysis.

vi) **Final Prediction Error**
On comparison of the orders of differencing, it is found that FPE value obtained on first differencing (301.15) was lowest for ARIMA model (0,1,2) in comparison to FPE value for second differencing (385.24) of ARIMA model (2,2,2). Thus, ARIMA model (0,1,2) is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of FPE analysis.

vii) **Akaike Information Criterion**
AIC value is compared for both the orders and it is found that AIC value obtained from first differencing (4259.00) was lowest for ARIMA model (0,1,1) in comparison to AIC value for second differencing (4379.27) of ARIMA model (2,2,2). Thus, ARIMA model (0,1,1) is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of AIC analysis.

viii) **Correction of AIC**
On comparison of the orders of differencing, it is found that AICC value obtained on first differencing (4259.03) was lowest for ARIMA model (0,1,1) in comparison to AICC value
for second differencing(4379.39) of ARIMA model (2,2,2). Thus, **ARIMA model (0,1,1)** is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of AICC analysis.

ix) **Schwarz Bayesian Information Criterion**

SBC value is compared for both the orders and it is found that SBC value obtained from first differencing (4267.42) is lowest for **ARIMA model (0,1,1)** in comparison to SBC value for second differencing (4400.29) of ARIMA model (2,2,2). Thus, **ARIMA model (0,1,1)** is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of SBC analysis.

**Appraisal of experiment:**

Out of eighteen applied models, the best fit model is selected for the final analysis on the basis of maximum number of votes for lowest value of each statistics for goodness of fit. ARIMA (1,1,2) at first difference earned five votes having lowest value of each for SSE, MSE, RMSE, White Noise and -2 log like respectively in comparison to four votes of ARIMA model (0,0,1). Thus, **ARIMA (1, 1, 2)** came out to be the best model amongst different ARIMA models.

Similarly, results of other five stocks where time series data is normally distributed is observed and it is found that ARIMA (1,1,1,) model is best fit for Coal India, Hero Motor Corp and Reliance Industries. ARIMA (0,1,1) model for Gail and ARIMA (0,1,2) model for NTPC gave best results amongst different ARIMA models for stock prices of select companies under consideration.
4.7 Experimental Process and Results of Lupin Limited (Non-Normal Distribution)

4.7.1 Graphical Analysis:

Figure 4.18 Graph of opening price of Lupin stock at BSE

Figure 4.19: Graph of First Difference of opening price of Lupin stock at BSE

Figure 4.20: Graph of Second Difference of opening price of Lupin stock at BSE
Table 4.9: Dickey-Fuller Statistics

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<tr>
<th>Dickey-Fuller test</th>
<th>Original</th>
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<th>Second Difference</th>
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<tr>
<td>Tau (Observed value)</td>
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<td>-7.956</td>
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<td>Tau (Critical value)</td>
<td>-0.907</td>
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<td>p-value (one-tailed)</td>
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Table 4.10: Various statistics of ARIMA models at First Difference for opening price of Lupin Limited

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<td>374520.</td>
<td>500994.</td>
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<td>753.561</td>
<td>1008.03</td>
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<td>753.561</td>
<td>1008.03</td>
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<td>752.720</td>
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Table 4.11: ARIMA Model at Second Difference for opening price of Lupin Limited

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Table 4.12: Descriptive Statistics of opening price of Lupin stock at BSE
Fig 4.21: The correlogram of LUPIN Stock Price At \( p=0 \ d=1 \ q=0 \)
Fig 4.22: The correlogram of LUPIN Stock Price At \( p=1 \ d=1 \ q=0 \)
Fig 4.23: The correlogram of LUPIN Stock Price At \( p=0 \ d=1 \ q=1 \)
Fig 4.24: The correlogram of LUPIN Stock Price At \( p=2 \ d=1 \ q=0 \)
**Fig 4.25: The correlogram of LUPIN Stock Price At [ p=0 d=1 q=2]**
Fig 4.26: The correlogram of LUPIN Stock Price At \( p=1, d=1, q=1 \)
Fig 4.27: The correlogram of LUPIN Stock Price At [p=0 d=2 q=0]
ARIMA-2D(1,2,0)

**Fig 4.28:** The correlogram of LUPIN Stock Price At \( p=1 \ d=2 \ q=0 \)
ARIMA-2D(0,2,1)

ARIMA-2D(0,2,1)

ARIMA-2D(0,2,1)

ARIMA-2D(0,2,1)

ARIMA-2D(0,2,1)

ARIMA-2D(0,2,1)

Fig 4.29: The correlogram of LUPIN Stock Price At \( p=0 \ d=2 \ q=1 \)
ARIMA-2D(1,2,1)

ARIMA-2D(1,2,1)

ARIMA-2D(1,2,1)

ARIMA-2D(1,2,1)

Fig 4.30: The correlogram of LUPIN Stock Price At [ p=1 d=2 q=1]
**Fig 4.31: The correlogram of LUPIN Stock Price At \( p=2 \) \( d=2 \) \( q=1 \)**
Fig 4.32: The correlogram of LUPIN Stock Price At $p=1 \ d=2 \ q=2$
4.7.2 Illustration and interpretation of the experimental results of Lupin limited

Table 4.13: ARIMA Model at first Difference for opening price of *Lupin limited* stock at BSE

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<tr>
<th>Model</th>
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<td>555177</td>
<td>374520</td>
<td>500995</td>
<td>374112</td>
<td>374116</td>
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<td>MSE</td>
<td>1455.49</td>
<td>1117.06</td>
<td>753.561</td>
<td>1008.04</td>
<td>752.74</td>
<td>752.748</td>
<td>752.721</td>
<td>752.757</td>
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<tr>
<td>RMSE</td>
<td>38.1509</td>
<td>33.4224</td>
<td>27.4511</td>
<td>31.7496</td>
<td>27.4361</td>
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<td>WN Variance</td>
<td>1455.49</td>
<td>1117.06</td>
<td>753.561</td>
<td>1008.04</td>
<td>752.74</td>
<td>752.748</td>
<td>752.721</td>
<td>752.757</td>
<td>1123.52</td>
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<tr>
<td>MAPE(Diff)</td>
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<td>167.404</td>
<td>221.548</td>
<td>163.216</td>
<td>163.299</td>
<td>163.042</td>
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<tr>
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<td>4848.03</td>
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<td>753.561</td>
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<td>752.74</td>
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<td>4854.03</td>
<td>4714.56</td>
<td>4714.56</td>
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Table 4.14 ARIMA Model at Second Difference for opening price of LUPIN stock at BSE

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<td>503348</td>
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<td>6244.15</td>
<td>4330.26</td>
<td>2442.51</td>
<td>1925.18</td>
<td>1123.52</td>
<td>1463.91</td>
<td>4245.12</td>
<td>1016.87</td>
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<td>79.0199</td>
<td>65.8047</td>
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<td>43.8769</td>
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<td>2442.51</td>
<td>1925.18</td>
<td>1123.52</td>
<td>1463.91</td>
<td>4245.12</td>
<td>1016.87</td>
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<td>MAPE(Diff)</td>
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<td>5048.88</td>
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Analysis of results of time series data of Lupin Limited (for non-normal distribution) at first difference based on the statistics of goodness of fit / accuracy using ARIMA models:

i) Some of Squares due to Error

Different ARIMA models are compared for SSE values and it is observed that ARIMA (2,1,1) has lowest value SSE 374102.10 in comparison to ARIMA (0,1,0) having value 723377.50, ARIMA (1,1,0) having value 555176.70, ARIMA (0,1,1) having value 374520, ARIMA (2,1,0) having value 500994.50 and ARIMA (0,1,2) having value 374111.60, ARIMA (1,1,1) having value 374115.80, ARIMA (2,1,2) having value 374120 and ARIMA (1,1,2) having value 556139.70 respectively.

ii) Mean Squared Error

MSE value are analyzed for different ARIMA models and it is observed that ARIMA (2,1,1) has lowest value MSE (752.72) in comparison to ARIMA (0,1,0) having value 1455.48, ARIMA (1,1,0) having value 1117.05, ARIMA (0,1,1) having value 753.56, ARIMA (2,1,0) having value 1008.37 and ARIMA (0,1,2) having value 752.73, ARIMA (1,1,1) having value 752.74, ARIMA (2,1,2) having value 752.75 and ARIMA (1,1,2) having value 1123.51 respectively.

iii) Root Mean Squared Error

Different ARIMA models are compared for RMSE value and it is found that ARIMA (2,1,1) has lowest value RMSE 27.43 in comparison to ARIMA (0,1,0) having value 38.15, ARIMA (1,1,0) having value 33.42, ARIMA (0,1,1) having value 27.45, ARIMA (2,1,0) having value 31.74 and ARIMA (0,1,2) having value 27.43, ARIMA (1,1,1) having value 27.43, ARIMA (2,1,2) having value 27.43 and ARIMA (1,1,2) having value 33.51 respectively.

iv) White Noise Variance

WN Variance value are analyzed for different ARIMA models and it is observed that ARIMA (2,1,1) has lowest value WN Variance (752.72) in comparison to ARIMA (0,1,0) having value 1455.48, ARIMA (1,1,0) having value 1117.05, ARIMA (0,1,1) having value 753.56, ARIMA (2,1,0) having value 1008.37 and ARIMA (0,1,2) having value 752.73, ARIMA (1,1,1) having value 752.74, ARIMA (2,1,2) having value 752.75 and ARIMA (1,1,2) having value 1123.51 respectively.
v) Mean Absolute Percentage Error
Different ARIMA models are compared for MAPE value and it is found that ARIMA (0,1,1) has lowest MAPE value 107.06 in comparison to ARIMA (0,1,0) having value 328.06, ARIMA (1,1,0) having value 267.31, ARIMA (2,1,0) having value 245.55 and ARIMA (0,1,2) having value 109.25, ARIMA (1,1,1) having value 109.34, ARIMA (2,1,2) having value 109.65, ARIMA (1,1,2) having value 176.80 and ARIMA (2,1,1) having value 108.98 respectively.

vi) Final Prediction Error (FPE)
FPE values are analyzed for different ARIMA models and it is observed that ARIMA (0,1,2) has lowest FPE value 752.73 in comparison to ARIMA (0,1,0) having value 1455.48, ARIMA (1,1,0) having value 1121.56, ARIMA (0,1,1) having value 753.56, ARIMA (2,1,0) having value 1016.83, ARIMA (1,1,1) having value 755.78, ARIMA (2,1,2) having value 758.83, ARIMA (1,1,2) having value 1028.06 and ARIMA (2,1,1) having value 758.80 respectively.

vii) Akaike Information Criterion
Different ARIMA models are compared for AIC value and it is found that ARIMA (0,1,1) has lowest AIC value 4713.16 in comparison to ARIMA (1,1,0) having value 4902.85, ARIMA (2,1,0) having value 4854.02, ARIMA (0,1,2) having value 4714.55 ARIMA (1,1,1) having value 4714.56, ARIMA (2,1,2) having value 4718.55, ARIMA (1,1,2) having value 4909.53 and ARIMA (2,1,1) having value 4716.55 respectively.

viii) Correction of AIC
AICC values are analyzed for different ARIMA models and it is observed that ARIMA (0,1,1) has lowest AICC value 4713.19 in comparison to ARIMA (1,1,0) having value 4902.88, ARIMA (2,1,0) having value 4854.07, ARIMA (0,1,2) having value 4714.60 ARIMA (1,1,1) having value 4714.60, ARIMA (2,1,2) having value 4718.67, ARIMA (1,1,2) having value 4909.61 and ARIMA (2,1,1) having value 4716.63 respectively.

ix) Schwarz Bayesian Information Criterion
Different ARIMA are compared to SBC values and it is found that ARIMA (0,1,1) has lowest SBC value 4721.58 in comparison to ARIMA (1,1,0) having value 4911.27, ARIMA (2,1,0) having value 4866.65, ARIMA (0,1,2) having value 4727.18, ARIMA (1,1,1) having
Analysis of results of time series data of Lupin Limited (for non-normal distribution) at second difference based on the statistics of goodness of fit / accuracy using ARIMA model.

i) Some of Squares due to Error
Different ARIMA models are compared for SSE value and it is found that ARIMA (2,2,2) has lowest value SSE value 503348.20 in comparison to ARIMA (0,2,0) having value 7108483, ARIMA (1,2,0) having value 3090853, ARIMA (0,2,1) having value 2143479, ARIMA (1,2,1) having value 1209045, ARIMA (2,2,1) having value 953964.80, ARIMA (1,2,2) having value 556139.70, ARIMA (2,2,0) having value 2101332 and ARIMA (0,2,2) having value 724635 respectively.

ii) Mean Squared Error
MSE values are analyzed for different ARIMA models and it is observed that ARIMA (2,2,2) has lowest MSE (1016.86) in comparison to ARIMA (0,2,0) having value 14360.57, ARIMA (1,2,0) having value 6244.16, ARIMA (0,2,1) having value 4330.26, ARIMA (1,2,1) having value 2442.51, ARIMA (2,2,1) having value 1925.18, ARIMA (1,2,2) having value 1123.51, ARIMA (2,2,0) having value 4245.11 and ARIMA (0,2,2) having value 1463.91 respectively.

iii) Root Mean Squared Error
Different ARIMA models are compared for RMSE value and it is found that ARIMA (2,2,2) has lowest RMSE value 31.88 in comparison to ARIMA (0,2,0) having value 119.83, ARIMA (1,2,0) having value 79.01, ARIMA (0,2,1) having value 65.80, ARIMA (1,2,1) having value 49.42, ARIMA (2,2,1) having value 43.87, ARIMA (1,2,2) having value 33.51, ARIMA (2,2,0) having value 65.15 and ARIMA (0,2,2) having value 38.26 respectively.

iv) White Noise Variance
WN Variance value is analyzed for different ARIMA models and it is observed that ARIMA (2,2,2) has lowest WN Variance value 1016.86 in comparison to ARIMA (0,2,0) having value 14360.57, ARIMA (1,2,0) having value 6244.16, ARIMA (0,2,1) having value 14727.18, ARIMA (2,1,2) having value 4739.59, ARIMA (1,1,2) having value 4926.35 and ARIMA (2,1,1) having value 4733.38 respectively.
4330.26, ARIMA (1,2,1) having value 2442.51, ARIMA (2,2,1) having value 1925.18,
ARIMA (1,2,2) having value 1123.51, ARIMA (2,2,0) having value 4245.11 and ARIMA
(0,2,2) having value 1463.91 respectively.

v) Mean Absolute Percentage Error
Different ARIMA models are compared for MAPE values and it is found that ARIMA
(0,2,2) has lowest MAPE value 106.01 in comparison to ARIMA (0,2,0) having value
843.82, ARIMA (1,2,0) having value 566.90, ARIMA (0,2,1) having value 377.60, ARIMA
(1,2,1) having value 287.56, ARIMA (2,2,1) having value 235.01, ARIMA (1,2,2) having
value 176.80, ARIMA (2,2,2) having value 203.92 and ARIMA (2,2,0) having value 521.35
respectively.

vi) Final Prediction Error
FPE values are analyzed for different ARIMA models and it is observed that ARIMA
(2,2,2) has lowest FPE value 1025.11 in comparison to ARIMA (0,2,0) having value
14360.57, ARIMA (1,2,0) having value 6269.42, ARIMA (0,2,1) having value 4330.26, ARIMA
(1,2,1) having value 2452.40, ARIMA (2,2,1) having value 1940.80, ARIMA (1,2,2) having
value 1128.06, ARIMA (2,2,0) having value 4279.55 and ARIMA (0,2,2) having value 1463.91
respectively.

vii) Akaike Information Criterion (AIC)
Different ARIMA models are compared for AIC values and it is found that ARIMA
(2,2,2) has lowest AIC value of 4863.27 in comparison to ARIMA (1,2,0) having value
5735.58, ARIMA (0,2,1) having value 5559.78, ARIMA (1,2,1) having value 5279.92, ARIMA
(2,2,1) having value 5165.33, ARIMA (1,2,2) having value 4909531, ARIMA (2,2,0) having
value 5547.34 and ARIMA (0,2,2) having value 5036.26 respectively.

viii) Correction of AIC
AICC values are analyzed for different ARIMA models and it is observed that ARIMA
(2,2,2) has lowest AICC value 4863.39 in comparison to ARIMA (1,2,0) having value
5735.60, ARIMA (0,2,1) having value 5559.80, ARIMA (1,2,1) having value 5279.97, ARIMA
(2,2,1) having value 5165.41, ARIMA (1,2,2) having value 4909.61, ARIMA (2,2,0) having
value 5547.39 and ARIMA (0,2,2) having value 5036.31 respectively.
ix) Schwarz Bayesian Information Criterion

Different ARIMA models are compared for SBC values and it is found that ARIMA (2,2,2) has lowest SBC value 4884.29 in comparison to ARIMA (1,2,0) having value 5743.99, ARIMA (0,2,1) having value 5568.18, ARIMA (1,2,1) having value 5292.53, ARIMA (2,2,1) having value 5182.15, ARIMA (1,2,2) having value 4926.35, ARIMA (2,2,0) having value 5559.95 and ARIMA (0,2,2) having value 5048.88 respectively.

Comparison between first and second difference of analyzed ARIMA models:

i) Some of Squares due to Error

SSE value is compared for both the orders and it is found that SSE value obtained from first differencing (374102.10) was lowest for ARIMA model (2,1,1) in comparison to SSE value from second differencing (503348.20) of ARIMA model (2,2,2). Thus ARIMA model (2,1,1) is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of SSE analysis.

ii) Mean Squared Error

On comparison of the orders of differencing, it is found that MSE value obtained on first differencing (752.72) was lowest for ARIMA model (2,1,1) in comparison to MSE value from second differencing (1016.85) of ARIMA model (2,2,2). Thus ARIMA model (2,1,1) is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of MSE analysis.

iii) Root Mean Squared Error

RMSE value is compared for both the orders and it is found that RMSE value obtained from first differencing (27.43) was lowest for ARIMA model (2,1,1) in comparison to RMSE value from second differencing (31.88) of ARIMA model (2,2,2). Thus ARIMA model (2,1,1) is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of RMSE analysis.

iv) White Noise Variance

On comparison of the orders of differencing, it is found that WN Variance value obtained on first differencing (752.72) was lowest for ARIMA model (2,1,1) in comparison to WN value from second differencing (1016.86) of ARIMA model (2,2,2). Thus ARIMA model (2,1,1) is
considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of WN analysis.

v) **Mean Absolute Percentage Error**
MAPE value is compared for both the orders and it is found that MAPE value obtained from first differencing (106.01) was lowest for ARIMA model \((0,2,2)\) in comparison to MAPE value from second differencing (107.06) of ARIMA model \((0,1,1)\). Thus **ARIMA model \((0,2,2)\)** is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of MAPE analysis.

vi) **Final Prediction Error**
On comparison of the orders of differencing, it is found that FPE value obtained on first differencing (752.73) was **lowest for ARIMA model \((0,1,2)\)** in comparison to FPE value from second differencing (1025.11) of ARIMA model \((2,2,2)\). Thus **ARIMA model \((0,1,2)\)** is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of FPE analysis.

vii) **Akaike Information Criterion**
AIC value is compared for both the orders and it is found that AIC value obtained from first differencing (4713.16) was **lowest for ARIMA model \((0,1,1)\)** in comparison to AIC value from second differencing (4863.27) of ARIMA model \((2,2,2)\). Thus **ARIMA model \((0,1,1)\)** is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of AIC analysis.

viii) **Correction of AIC**
On comparison of the orders of differencing, it is found that AICC value obtained on first differencing (4713.19) was **lowest for ARIMA model \((0,1,1)\)** in comparison to AICC value from second differencing (4863.39) of ARIMA model \((2,2,2)\). Thus **ARIMA model \((0,1,1)\)** is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of AICC analysis.

ix) **Schwarz Bayesian Information Criterion**
SBC value is compared for both the orders and it is found that SBC value obtained from first differencing (4721.58) was **lowest for ARIMA model \((0,1,1)\)** in comparison to SBC value
from second differencing (4884.29) of ARIMA model (2,2,2). Thus ARIMA model (0,1,1) is considered best model for prediction of stock prices amongst 18 different models of ARIMA on the basis of SBC analysis.

Appraisal of experiment:
On the considered time series stock prices data, eighteen ARIMA models are applied and the best fit model is selected on the basis of maximum number of votes for lowest value of each statistics for goodness of fit for final analysis. ARIMA model (2,1,1) at first differencing earned five votes for lowest value of each for SSE, MSE, RMSE, White Noise and -2 log like in comparison to four votes obtained by ARIMA model (0,1,1). Thus ARIMA Model (2,1,1) resulted best method amongst different methods of ARIMA Model. Similarly, results of other 18 stocks in which time series data was not normally distributed were observed and it was found that ARIMA Model (1,1,1) for Adani Port, Bajaj Autos, Cipla, Tata Steel, TCS, ARIMA Model (0,1,2) for Axis Bank, Bharti Airtel, Dr. Reddy, HDFC Bank, HDFC Finance, Lupin Limited, Maruti Suzuki, ONGC, Power Grid, State Bank of India, Wipro, ARIMA Model (2,1,0) for ICIC Bank, ARIMA Model (2,2,1) for Infosys and ARIMA Model (0,2,1) for L&T is resulted as the best method amongst different methods of ARIMA models for stock prices of companies under consideration.