Financial Forecasting: An Empirical Study on Box –Jenkins Methodology with reference to the Indian Stock Market

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Abstract

The purpose of this study is to apply the Box-Jenkins methodology to the Indian stock market and forecast the stock prices it is found that the post-sample forecasting the accuracy of ARIMA model is generally better than much simpler time series methods. The ARIMA model, also known as the Box-Jenkins model or methodology, is commonly used in analysis i.e., identification, estimation & diagnostic checking and forecasting. ARIMA Modelling have been done using data of daily closing prices of S&P BSE 500 Index and NIFTY 500 Index. This study would like to compare the application of three forecasting methods for predicting stock prices, the ARIMA time series method, Moving average method and Holt & Winters exponential method. ARIMA(0,1,1) and ARIMA(2,1,2) is considered as the best model based on the fact that it satisfies all the conditions for the Goodness of Fit. The developed stock price predictive model with the ARIMA indeed, the actual and predicted values of the developed stock price predictive model are slightly close. The empirical results obtained reveal the superiority of ARIMA model over simpler time series methods by using MAPE (Mean Absolute Percentage Error).

Keywords: ARIMA model, Box-Jenkins, Time series forecasting, MAPE.

Introduction

Statisticians George Box and Gwilym Jenkins developed a practical approach to build ARIMA model, which best fit to a given time series and also satisfy the parsimony principle. Their concept has fundamental importance on the area of time series analysis and forecasting. The Box-Jenkins methodology does not assume any particular pattern in the historical data of the series to be forecasted. Rather, it uses a three step iterative approach of model identification, parameter estimation and diagnostic checking to determine the best parsimonious model from a general class of ARIMA models This three-step process is repeated several times until a satisfactory model is finally selected. Then this model can be used for forecasting future values of the time series.

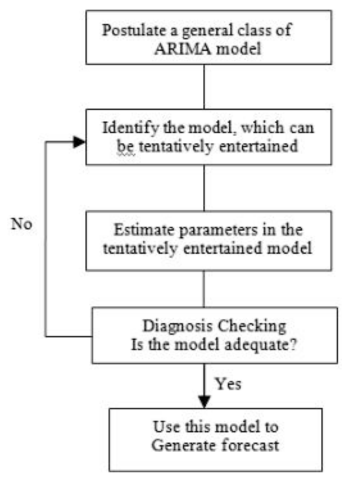
The approach proposed by Box and Jenkins came to be known as the Box-Jenkins methodology to ARIMA models, where the letter `I', between AR and MA, stood for the `Integrated' and reflected the need for differencing to make the series stationary. ARIMA models and the Box-Jenkins methodology became highly popular in the 1970s among academics, in particular when it was shown through empirical studies

(Cooper, 1972; Nelson, 1972; Elliot, 1973;Narasimham et al., 1974; McWhorter, 1975; for a survey see Armstrong, 1978) that they could outperform the large and complex econometric models, popular at that time, in a variety of situations

One of the most popular and frequently used stochastic time series models is the Autoregressive Integrated Moving Average (ARIMA) model. The basic assumption made to implement this model is that the considered time series is linear and follows a particular known statistical distribution, such as the normal distribution. ARIMA model has subclasses of other models, such as the Autoregressive (AR), Moving Average (MA) and Autoregressive Moving Average (ARMA) models. The popularity of the ARIMA model is mainly due to its flexibility to represent several varieties of time series with simplicity as well as the associated Box-Jenkins methodology for optimal model building process. But the severe limitation of these models is the pre-assumed linear form of the associated time series which becomes inadequate in many practical situations. To overcome this drawback, various non-linear stochastic models have been proposed in literature however from implementation point of view these are not so straight-forward and simple as the ARIMA models.

The Box-Jenkins forecast method is schematically shown in Figure 1:

Figure 1: The Box-Jenkins methodology for optimal model selection



Literature Review

Stock market is basically non-linear in nature, prediction of stock market plays important role in stock business. Data mining, GBM, neural network and ARIMA can be effectively used to uncover non-linearity of stock market. The vital idea to successful stock market prediction is achieving best result, also minimize inaccurate forecast stock price. For the past few years forecasting of stock return has been important field of research.

Ayodele Ariyo Adebiyi, Aderemi Oluyinka Adewumi and Charles Korede Ayo(2010) examines the forecasting performance of ARIMA and artificial neural networks model with published stock data obtained from New York Stock Exchange. The empirical results obtained reveal the superiority of neural networks model over ARIMA model. The findings further resolve and clarify contradictory opinions reported in literature over the superiority of neural networks and ARIMA model and vice versa.

Hsien-Lun Wong,Yi-Hsien Tu and Chi-chen Wang(2010) used ARIMA model and vector ARMA model with fuzzy time series method for forecasting. Fuzzy time series method especially heuristic model performs better forecasting ability in short-term period prediction. The ARIMA model creates small forecasting errors in longer experiment time period. In this paper, the author investigates whether the length of the interval will influence the forecasting ability of the models or not.

Mayank kumar B Patel and Sunil R Yalamalle(2014) aims at using of Artificial Neural Network techniques to predict the stock price of companies listed under LIX15 index of National Stock Exchange (NSE). The results from the model will be used for comparison with the real data to ascertain the accuracy of the model.

Preethi and santhi(2012) surveys recent literature in the area of Neural Network, Data Mining, Hidden Markov Model and Neuro-Fuzzy system used to predict the stock market fluctuation. Neural Networks and Neuro-Fuzzy systems are identified to be the leading machine learning techniques in stock market index prediction area. NN and Markov Model can be used exclusively in the finance markets and forecasting of stock price. In this paper, they propose a forecasting method to provide better an accuracy rather traditional method.

Rene D. Estember and Michael John R. Marana (2016) examined the potential of the Geometric Brownian Motion (GBM) method as an accurate and effective forecasting method compared to the Artificial Neural Network (ANN) method. The number of days the volatility and drift are moved were also determined and this was used to perform the forecast of stock prices of holding companies registered with the Philippine Stock Exchange and also compared to the ANN method. it also indicates that the GBM method is more effective than the ANN method in forecasting stock prices of these sample holding companies.

Nitin Merh, Vinod P. Saxena and Kamal Raj Pardasani (2010) an attempt is made to develop hybrid models of three layer feed forward back propagation ANN and ARIMA for forecasting the future index value and trend of Indian stock market viz. SENSEX, BSE IT, BSE Oil & Gas, BSE 100 and S& P CNX Nifty. Simulation results of hybrid models are compared with results of ANN based models and ARIMA based models.

R.K. and Pawar D.D(2010) used to predicated the stock rate because it is a challenging and daunting task to find out which is more effective and accurate method so that a buy or sell signal can be generated for given stocks. Predicting stock index with traditional time series analysis has proven to be difficult an artificial neural network may be suitable for the task. Neural network has the ability to extract useful information from large set of data. In this paper the author also presented a literature review on application of artificial neural network in stock market Index prediction.

Jing Tao Yao and chew Lim tan(2011) explained artificial neural networks for classification, prediction and recognition. Neural network training is an art. Trading based on neural network outputs, or trading strategy is also an art. Authors discuss a seven-step neural network prediction model building approach in this article. Pre and post data processing/analysis skills, data sampling, training criteria and model recommendation have been showed.

M. suresh Babu, N. Geethanjali and B. Sathyanarayana (2011) examined the data mining techniques are able to uncover the hidden pattern, predict future trends and behaviors in financial market. Pattern matching techniques is found to be descriptive in time series analysis. In this paper, author applied ant algorithm to accommodate a flexible and dynamic pattern-matching task in time series analysis. Apart from segment size the ant to sub-time-series size affects the system performance. In this paper, the ratio was set to 1 and also the ratio reduced to obtain a better result.

David Enke and Suraphan Thawornwong (2005) explained machine learning for data mining to evaluate the predictive relationship of numerous financial and economic variables. Neural network model used for estimation and classification are then examined for their ability to provide an effective forecast of future values. A cross-validation technique was used to improve the generalization ability of several models. The trading strategies guided by classification models generate higher risk-adjusted profits than the buy-and-hold strategy as well as guided by the level-estimation based forecast of the neural network and regression models. The author decides to deploy the forecast the stock dividends, transaction costs and individual-tax brackets to replicate the realistic investment practices.

Abdulsalam sulaiman olaniyi, adewole, kayoed s, Jimoh R.G(2010) examined the moving average [MA] method to uncover the patterns, relationship and to extract values of variables from the database to predict the future values of other variables through the use of time series data. The advantage of the MA method is a device for reducing fluctuations and obtaining trends with a fair degree of accuracy. This techniques proven numeric forecasting method using regression analysis with the input of financial information obtained from the daily activity equities published by Nigerian stock exchange.

Kuang Yu Huang, Chuen-Jiuan Jane(2009) used the moving average autoregressive exogenous (ARX) prediction model is combined with grey system theory and rough set theory to create an automatic stock market forecasting and portfolio selection mechanism. Financial data were collected automatically every quarter and are input to an ARX prediction model for forecast the future trends. Clustered using a K means clustering algorithm and then supplied to a RS classification module which selects appropriate investment stocks by a decision-making rules. The advantages are combining different forecasting techniques to improve the efficiency and accuracy of automatic prediction. Efficacies of the fusion models are evaluated by comparing the forecasting accuracy of the ARX model with GM (1, 1) model. The hybrid model provides a highly accurate forecasting performance.

Assaleh et al. (2011) utilize two prediction models for forecasting securities' prices of two leading stocks in Dubai Financial Market (DFM). These stocks are: Emaar Properties (EMAAR) and Dubai Islamic Bank (DIB).EMAAR is the leading real estate developer in the Middle East and DIB is the world's first fully fledged Islamic bank. These stocks were chosen because they have sufficient historical data, actively traded, and each represents a different sector in the UAE economy. The study uses daily closing prices over the period from April 2000 to March 2006 (a total of 2176 data points).They use Artificial Neural Networks (ANN) and Polynomial Classifiers (PC) as modeling techniques to predict stock prices from historical price data. This was the first time to apply PC to be used in stock prices

Research Methodology

This study used published stock data of S&P BSE 500 Index and NIFTY 500 Index from Indian stock market on ARIMA model developed which includes 6450 daily closing observations for the period from Feb.1st 1999 till Dec.30th 2016 of S&P BSE 500 Index and Sep.17th 2007 till Dec.30th 2016 of NIFTY NSE 500 Index. The data used in this research work were historical daily stock prices. The stock data consists of open price, low price, high price, close price, and volume traded. The open price is the opening price of the index (PoI) at the start of the trading day, the low price represents the minimum PoI during the trading day, the high price represents the maximum PoI during the trading day, and the closing price indicates the PoI when the market closes. In this research the closing price is chosen to represent the PoI to be modeled and predicted. This is because the closing price reflects all the activities of the index of the day.The figure 2&3 are showing the historical stock prices trend of the S&P BSE 500 Index and NIFTY 500 Index for the study period. The S&P BSE 500 index is designed to be a broad representation of the Indian market. Consisting of the top 500 companies listed at BSE Ltd., the index covers all 20 major industries in the Indian economy. S&P BSE 500 index represents nearly 93% of the total market capitalization on BSE. The NIFTY 500 Index is India's first broad-based stock market index of the Indian stock market. The NIFTY 500 represents about 96% of total market capitalization and about 93% of the total turnover on the National Stock Exchange of India (NSE).

Moving average model

$$F_{t+1} = \frac{(A_t + A_{t-1} + A_{t-2} + \dots\dots\dots + A_{t-n+1})}{n}$$

A_t = Data at time t
F_{t+1} = Forecast value at time t+1
n = Number of data

Holt and winters exponential model

$$S_t = \alpha \frac{A_t}{I_{t-L}} + [(1-\alpha)(S_{t-1} + T_{t-1})]$$

$$T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$$

$$I_t = \gamma \frac{A_t}{S_t} + (1-\gamma)\, I_{t-L}$$

$$F_{t+p} = (S_t + T_t\, p)\, I_{t-L+P}$$

S_t = Smoothing value
α = Constant of smoothing value ($0 < \alpha < 1$)
A_t = Actual value at time t
β = Constant of trend value ($0 < \beta < 1$)
T_t = Trend parameter at time t
γ = Constant of seasonal value ($0 < \gamma < 1$)
I_t = Seasonal parameter at time t
p = Number of forecasting
L = Lead time
F_{t+p} = Forecasting value at time p

Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA approach was first popularized by Box and Jenkins, and ARIMA models are often referred to as Box-Jenkins models. The general transfer function model employed by the ARIMA procedure was discussed by Box and Tiao (1975). When an ARIMA model includes other time series as input variables, the model is sometimes referred to as an ARIMAX model. The ARIMA procedure analyzes and forecasts equally spaced univariate time series data, transfer function data, and intervention data using the Auto Regressive Integrated Moving-Average (ARIMA) model. An ARIMA model predicts a value in a response time series as a linear combination of its own past values, past errors (also called shocks or innovations), and current and past values of other time series. In ARIMA models a non-stationary time series is made stationary by applying finite differencing of the data points.

The ARIMA(p,d,q) model using lag polynomials is given below :

$$\varphi(L)(1-L)^d\, y_t = \theta(L)\varepsilon_t \text{, i.e.}$$

$$(1- \textstyle\sum_{i=1}^{p} \varphi_i L^i)\, (1-L)^d\, y_t = (\, 1 + \sum_{j=1}^{q} \theta_j\, L^j\,)\, \varepsilon_t$$

Here, p, d and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. The integer d controls the level of differencing. Generally d=1 is enough in most cases. When d=0, then it reduces to an ARMA(p,q) model. An ARIMA(p,0,0) is nothing but the AR(p) model and ARIMA(0,0,q) is the MA(q) model. ARIMA(0,1,0), i.e. yt = yt +εt-1 is a special one and known as the Random Walk model. It is widely used for non-stationary data, like economic and stock price series.

ARIMA Modeling

The analysis performed by ARIMA is divided into three stages, corresponding to the stages described by Box and Jenkins (1976).

1. Identification stage
2. Estimation and diagnostic checking stage
3. Forecasting stage

1. **Identification stage:** In order to forecast stock prices of S&P BSE 500 index and NIFTY 500 index, ARIMA model have been applied. Table1 reports the statistical description for daily observations of S&P BSE 500 and NIFTY 500 stock Index during the period of 1999-2016 that contains; mean, median, max, min, skewness, kurtosis, standard Error and Shapiro-wilk results.

Table 1. Descriptive Statistics

Statistical Indicators	S&P BSE 500	NIFTY 500	Statistical Indicators	S&P BSE 500	NIFTY 500
Average	5143.059	4612.095	Minimum	792.180	1966.850
Standard Deviation	3273.261	1180.288	Maximum	12074.350	7345.550
Skew	0.303	0.413	Probability	0.00000	0.00000
Kurtosis	-1.070	0.206	No. of observations	4464	1987
Median	5349.620	4440.000	Variance	10714234.75	1393080.36
Standard Error	0.037	0.055	Shapiro-Wilk test	0.919235	0.922194

Correlogram Analysis

A correlogram is used to determine whether a particular series is stationary or nonstationary. Usually, a stationary time series will give an autocorrelation function (ACF) and partial autocorrelation function(PACF) that decay rapidly from its initial value of unity at zero lag. In the case of nonstationary time series, the ACF dies out gradually over time. The correlogram of the time series of S&P BSE 500 index and NIFTY 500 index was observed to be nonstationary as the ACF dies down extremely slowly. Differencing is used to make this non stationary time series become stationary. The value of difference (d) is determined by the number of times the differencing is performed on the time series.

Augmented Dickey-Fuller test

The present study employs the Augmented Dickey Fuller test to examine whether the time series properties are stationary or not. The results are present that all series are nonstationary at 1 percent, 5 percent and 10 percent level of significance i.e.,there are unit roots in the time serie. The main result based on this test is that; ADF test is statistically not significant at all level of significance.This indicates to accept null hypothesis and reject that the stock prices are stationery. That all confirms the existence of autocorrelation. Hence the null hypotheses of ADF test are accepted and concluded that the time series data are nonstationary at level.

Estimation and diagnostic checking stage

In order to construct the best ARIMA model for S&P BSE 500 and Nifty 500 index, the autoregressive (p) and moving average(q) parameters have to be effectively determined for an effective model. Table 3 shows the different parameters p and q in the ARIMA model. ARIMA (0, 1, 1) is considered the best for S&P BSE 500 index and ARIMA (2,1,2) is considered the best for NIFTY 500 index is as shown in Table 2 and Table 3.

Table 2 : ARIMA (0,1,1) estimation output with close prices of S&P BSE 500 Index

parameters	*Coefficient*	*Std. Error*	z	*p-value*
const	2.25073	1.25614	1.792	0.0732
AR(1)	0.113393	0.0148458	7.638	<0.0001

Mean dependent var	2.248810	S.D. dependent var	74.86002
Mean of innovations	0.000359	S.D. of innovations	74.37148
Log-likelihood	−25564.12	Akaike criterion (AIC)	51134.24
Schwarz criterion	51153.45	Hannan-Quinn	51141.01

Table 3 : ARIMA (2,1,2) estimation output with close prices of Nifty 500 Index

parameters	*Coefficient*	*Std. Error*	z	*p-value*
const	1.59801	1.41445	1.130	0.2586
AR(1)	1.19122	0.0925221	12.87	<0.0001
AR(2)	−0.759814	0.101019	−7.521	<0.0001
MR(1)	−1.10509	0.104358	−10.59	<0.0001
MR(2)	0.692736	0.112597	6.152	<0.0001

Mean dependent var	1.606826	S.D. dependent var	62.37728
Mean of innovations	0.007381	S.D. of innovations	61.81107
Log-likelihood	−11002.92	Akaike criterion (AIC)	22017.85
Schwarz criterion	22051.41	Hannan-Quinn	22030.18

Table 4:Statistical results of different ARIMA parameters for S&P 500 index and NIFTY 500 index

ARIMA	S&P BSE 500 index		NIFTY 500 index	
	AIC	Mean of innovation	AIC	Mean of innovation
(1,0,0)	51215.16	1.0743	22064.82	0.6064
(1,0,1)	51158.89	0.8467	22042.97	0.4724
(2,0,0)	51158.90	0.8256	22043.00	0.4725
(0,0,1)	78903.08	-0.5784	31129.33	-0.0697
(0,0,2)	73512.27	-0.8330	29034.40	-0.1800
(1,1,0)	51134.33	0.0003	22023.12	-0.0022
(0,1,0)	51189.67	-0.0000	22044.99	0.0000
(0,1,1)	**51134.24**	**0.0003**	22023.62	-0.0012
(1,1,2)	51138.08	0.0007	22026.61	-0.0022
(2,1,0)	51136.19	-0.0006	22025.11	-0.0023
(2,1,2)	51137.41	0.0004	**22017.85**	**0.0073**
(1,1,1)	51136.15	0.0004	22025.11	-0.0021

The optimal model order is chosen by the number of model parameters, which minimizes either Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC).In the process of diagnosis it is verified whether the residual or error generated if white noise or not. The autocorrelations specifying Q*-value, P-value (significance) at different degrees of freedom having a lag of maximum 200 are shown in the table (Table 5). To determine whether the time series is white noise or not, the Ljung-Box Q* statistic is compared with the chi-square distribution with (h-m) degrees of freedom. Here h is the number of lags and m is the number of parameters. Table 5 clearly demonstrates that the Q* statistic has same distribution as chi-square with (h-m) degrees of freedom. Plots and the autocorrelations generated indicated that the model fits well.

Table 5. Ljung-Box test for the Verification of White Noise

INDEX	(h-m) degree of freedom	LB-statistics Q^*	p-value	Is Series White Noise
S&P BSE 500	(200-2)=198	398.474	0.1938	YES
NIFTY 500	(200-2)=198	212.905	1.1910e	YES

Forecasting stage:

In forecasting stage, the best model selected can be expressed as follows: $Y_t = \phi_1 Y_{t-1} + \theta_0 + \varepsilon_t,$ where $\varepsilon_t = Y_t - \widehat{Y_t}$ is the difference between the actual value and the forecast value of the series

Table 6.sample of empirical results of ARIMA(0,1,1) of S&P BSE 500 Index and ARIMA(2,1,2) of NIFTY 500

	S&P BSE 500 index			NIFTY 500 index		
Sample period	Actual value	Predicted value	Forecast error	Actual value	Predicted value	Forecast error
2-Jan-17	11072.57	11049.1	0.00212	7002.5	6990.79	0.001672
3-Jan-17	11119.59	11051.3	0.006141	7028.75	6991.76	0.005263
4-Jan-17	11119.08	11053.6	0.005889	7030.75	6987.77	0.006113
5-Jan-17	11236.35	11055.8	0.016068	7106.9	6983.17	0.01741
6-Jan-17	11199.51	11058.1	0.012626	7083.1	6981.65	0.014323
9-Jan-17	11203.16	11060.3	0.012752	7085.15	6984.23	0.014244
10-Jan-17	11274.73	11062.6	0.018815	7132.2	6989.37	0.020026
11-Jan-17	11402.48	11064.8	0.029615	7214.15	6994.44	0.030455
12-Jan-17	11429.21	11067.1	0.031683	7231.85	6997.49	0.032407
13-Jan-17	11423.49	11069.3	0.031005	7228.3	6998.17	0.031837
16-Jan-17	11456.66	11071.6	0.03361	7247.95	6997.58	0.034544
17-Jan-17	11448.45	11073.8	0.032725	7243.65	6997.26	0.034015
18-Jan-17	11490.75	11076.1	0.036086	7269	6998.24	0.037249
19-Jan-17	11518.8	11078.3	0.038242	7287.75	7000.57	0.039406
20-Jan-17	11388.54	11080.6	0.027039	7202.75	7003.49	0.027664
23-Jan-17	11449.08	11082.8	0.031992	7242.55	7006.12	0.032645
24-Jan-17	11564.65	11085.1	0.041467	7315.25	7007.94	0.04201
25-Jan-17	11716.17	11087.3	0.053675	7417.7	7009.02	0.055095
27-Jan-17	11783.09	11089.6	0.058855	7455.15	7009.83	0.059733
30-Jan-17	11773.74	11091.8	0.05792	7452.15	7010.88	0.059214
31-Jan-17	11659.94	11094.1	0.048529	7379.3	7012.43	0.049716
1-Feb-17	11873.72	11096.3	0.065474	7516.05	7014.39	0.066745
2-Feb-17	11924.46	11098.6	0.069258	7547.1	7016.45	0.070312
3-Feb-17	11959.4	11100.8	0.071793	7569.9	7018.32	0.072865
6-Feb-17	12051.26	11103.1	0.078677	7628.1	7019.90	0.079732
7-Feb-17	12014.51	11105.3	0.075676	7603.2	7021.27	0.076538
8-Feb-17	12032.03	11107.6	0.076831	7614.75	7022.60	0.077764
9-Feb-17	12049.23	11109.8	0.077966	7623.6	7024.07	0.078641
10-Feb-17	12053.91	11112.1	0.078133	7631.25	7025.70	0.079351
13-Feb-17	12048.6	11114.3	0.077544	7626.95	7027.45	0.078603

This study experimented with different parameters of autoregressive (p) and moving average (q) in order to determine the best model that will give best forecast as indicated in Table 6.ARIMA (0,1,1) is considered the best for S&P BSE 500 index and ARIMA(2,1,2) is considered the best NIFTY 500 index is as shown in Table 2&3; hence it was selected as the best models based on the criteria listed in the previous section. The actual stock price and predicted values are presented in Table 6, while Figure 4&5 gives the graph of predicted price against actual stock price to see the performance of the ARIMA model selected. However, the forecast error is slightly low and impressive as the predicted values are close to the actual values and move in the direction of the forecast values in many instances as shown in Figure 2, which depicts the correlation of the level of accuracy. The forecast error is determined by

$$\text{Forecast Error (FE)} = \frac{(Actual - predicted)}{Actual}$$

The Box –jenkins methodology used ARIMA model to calculate the errors between the actual close price and the predicted close price generated by all the model. In this study mean square percent error (MSPE) have been used for each method of forecasting and each stock index. The table 7 shows results to find the best model from three models for forecasting of stock prices in Indian stock market is ARIMA. Figure 4 & 5 displays the comparison between the actual close of S&P BSE 500 Index and NIFTY 500 index forecasted close price generated by the ARIMA model discussed above during Jan 2, 2017 to Feb 13, 2017.

Table 7 MAPE from Three forecasting model of the result

Index	MAPE value(%)		
	Moving Average	**Holt and Winters exponential**	**ARIMA**
S&P BSE 500	95.44	9.14612	4.327354
NIFTY 500	95.4384	5.536832	4.418632

Figure 2: Historical stock prices trend of S&P BSE 500 index for Feb.1st 1999 to Dec.30 2016

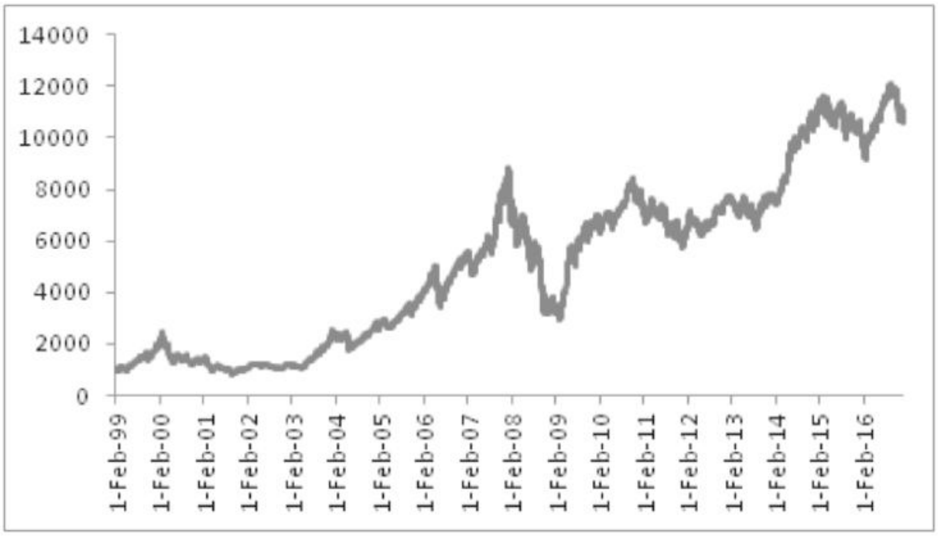


Figure 3: Historical stock prices trend of NIFTY 500 index for Sep.17th 2007 to Dec.30 2016

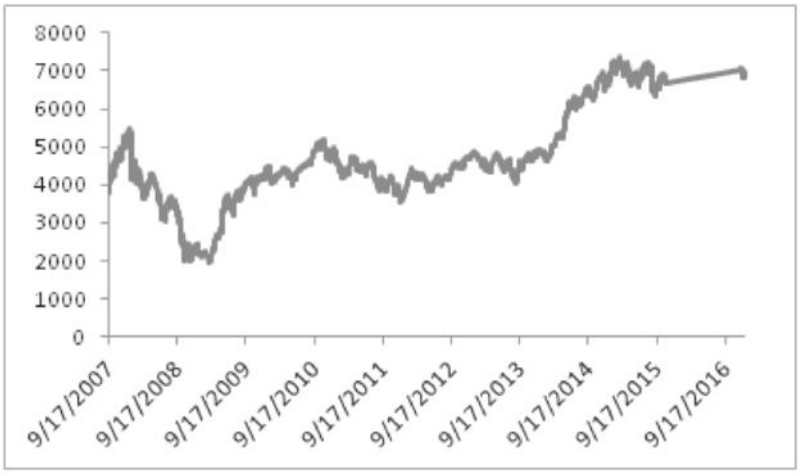


Figure 4: Graph of actual stock price versus predicted values for S&P BSE 500 index using ARIMA.

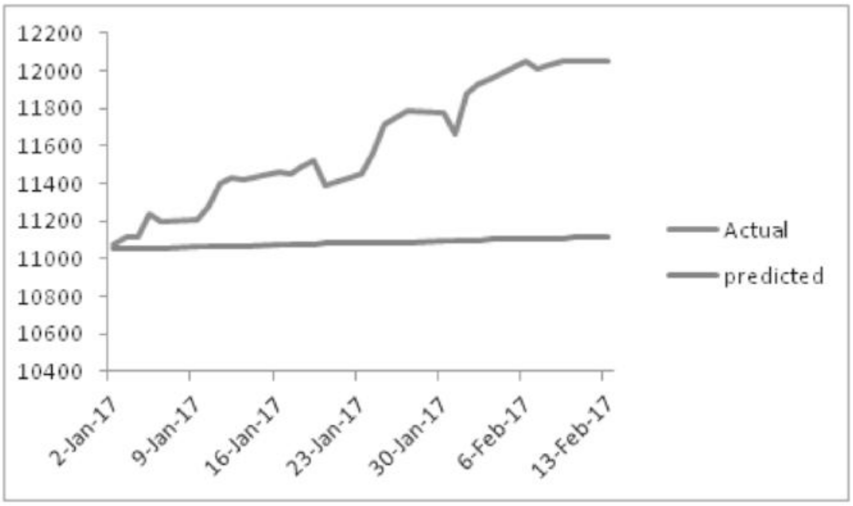
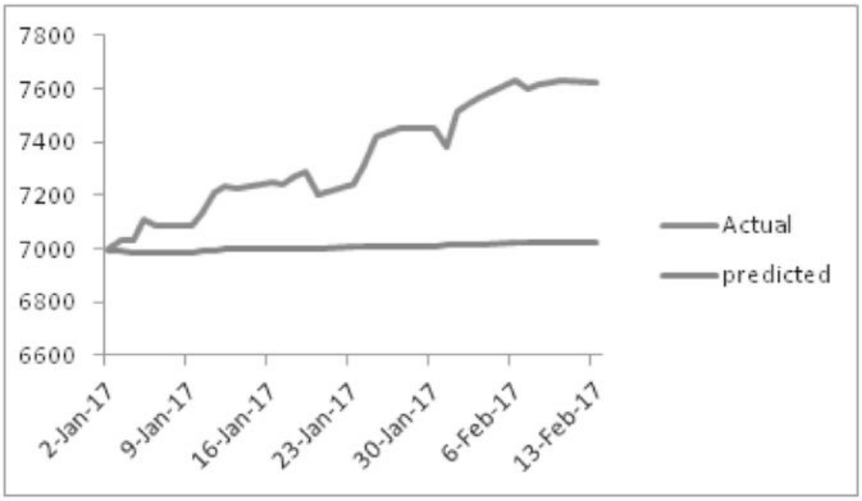


Figure 5 : Graph of actual stock price versus predicted values for NIFTY 500 index using ARIMA



Conclusion

In the current research an attempt was made to study whether ARIMA model achieves better results than moving average and Holt & winters exponential methods. The box-jenkins methodology applied ARIMA model to forecast the stock prices for S&P BSE 500 Index and NIFTY 500 Index The analysis of the performance of the Indian stock market with respect to time presents us a suitable time series ARIMA model (0,1,1) and (2,1,2) which helps us in predicting the approximate values of the future. The developed stock price predictive model with the ARIMA indeed, the actual and predicted values of the developed stock price predictive model are slightly close. ARIMA(0,1,1) and ARIMA(2,1,2) as the best model based on the fact that it satisfies all the conditions for the Goodness of Fit. In this study three models were used to apply into two stock market indices in order to find suitable forecasting model which get better error more than currently model . The results showed that the ARIMA model get the best MAPE (Mean Absolute Percentage Error) which is the measurement of this study.

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