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FORECASTING BSE SENSEX MOVEMENT USING ARIMA MODELLING

Dr. R.K. Sudhamathi*

*Associate Professor,
GRG School of Management Studies,
PSGR Krishnammal College for Women,
Coimbatore, INDIA
Email id: sudhamathi@grgsms.ac.in

ABSTRACT

Forecasting the stock market movement is a challenging task the movement of stock market is influenced by many macroeconomic factors like GDP, inflation, exchange rate, unemployment rate. Beyond the performance of companies and investors sentiments will also influence the movement. The COVID 19 locks down scenario which prevailed all over the world and in India crashed the stock market. On 23rd March 2020 Sensex reached 25,981 points, which was the lowest during the year 2020 when first phase of lockdown was announced in India Global lockdowns, worldwide economic downturn and disruption in demand and supply affected financial markets all over the world. Indian financial market too experienced the same. On 30 May2020 when nationwide lock down was lifted except in the containment zones, the gradual phase of recovery started from there on in the stock market movement. Given the unpredicted situation of stock market movement stock investors are badly losing their money in the stock market. Hence in this article an attempt has been made to forecast the stock market movement using (Auto Regressive Integrated Moving Average (ARIMA) modeling. To forecast the stock market movement BSE Sensex index data for the period from 1st January 2020 to 31st December 2020 has been taken. The data set taken for the study satisfied the ARIMA modeling conditions and provided a good forecast. Such forecasting modeling will enable the investors to make appropriate decision by gauging the stock market movement.

KEYWORDS: *Stock Market Movement, Macro Economic Factors, Sensex, Arima Modeling, Forecasting.*

I INTRODUCTION

Forecasting the stock market movement is a challenging task the movement of stock market is influenced by many macroeconomic factors like GDP, inflation, exchange rate, unemployment rate. Beyond the performance of companies and investors sentiments will also influence the movement. The COVID 19 locks down scenario which prevailed all over the world and in India crashed the stock market. On 23rd March 2020 Sensex reached 25,981 points, which was the lowest during the year 2020 when first phase of lockdown was announced in India.

Global lockdowns, worldwide economic downturn and disruption in demand and supply affected financial markets all over the world. Indian financial market too experienced the same. On 30 May 2020 when nationwide lock down was lifted except in the containment zones, the gradual phase of recovery started from there on in the stock market movement. Given the unpredicted situation of stock market movement stock investors are badly losing their money in the stock market. Hence in this article an attempt has been made to forecast the stock market movement using Auto Regressive Integrated Moving Average (ARIMA) modelling.

II REVIEW OF LITERATURE

Smriti Prasad and Manesh Choubey (2018), on the study titled "Forecasting India"s Total Exports: An Application of Univariate ARIMA Model", forecasted the exports of India based on exports data from 1960 to 2016. ARIMA (0, 1, and 3) was chosen for forecasting 20 years of exports.

Achal Lamat et al. (2015), in the research article titled Modelling and Forecasting of price volatility: An application of GARCH &EGARCH models evaluated the forecasting ability of ARIMA, GARCH and EGARCH models for domestic and international edible oil price indices and international cotton price. The forecasting was done by using the monthly data from April, 1982 to march, 2012. The study results revealed the fact that for domestic and international edible oil prices GARCH model has outperformed ARIMA model in terms of forecasting accuracy. In forecasting cotton prices EGARCH model has outperformed the GARCH and ARIMA models.

Nitin Merh ET. al. (2011) in the research article titled "Next day Stock Market Forecasting: An Application of ANN and ARIMA" attempted to compare the forecast of future index value of sensex (BSE 30) using Artificial Neural Network (ANN) and ARIMA. Sensex (BSE 30) prices from April 16, 2004 to February 25, 2009 have been used for estimation of ANN (4-4-1) and ARIMA (1, 1, and 1) models and prices from February 26, 2009 to April 16, 2009 are predicted and are compared with actual prices to find out residuals and errors. The results showed that the forecasting accuracy obtained for ARIMA (1, 1, and 1) is better than ANN (4-4-1).

Chi-Chen Wang et.al (2011) in the study titled "A comparison of ARIMA forecasting

and heuristic modelling" compared the application of the forecasting methods ARIMA time series model and fuzzy time series by heuristic models on Taiwan export data for the period from Jan 1990 to March 2002. The study concludes that ARIMA modelling can forecast the export amount more accurately than heuristic models. The study also gave the findings that when for prolonged sample period ARIMA modelling provides realistic forecast. If the sample period is shorter, the heuristic models outperform ARIMA models.

AN-Sing Chen (1997) in the study titled "Forecasting the S&P 500 index volatility" forecasted S&P 500 cash index volatility using daily data from April 1983 to January 1994 by using mean reversion model, GARCH model, ARIMA model and Naïve model. The study results showed that ARIMA model was informationally superior when compared to other models used in the study in forecasting monthly S&P500 index volatility.

III Objectives of the Study

The objective of the study is to forecast the BSE SENSEX using ARIMA Modelling.

Iv RESEARCH METHODOLOGY

Descriptive research design has been used for the study. To forecast the BSE Sensex, the closing price of BSE Sensex has been taken for the period from 1Janurary 2020 to 31 December 2020 from BSE website. ARIMA modelling has been used for forecasting Sensex. The entire study period data 1 January 2020 to 31 December 2020 has been used for estimation and forecast has been done for the period from 1 January 2021 to 7 January 2021. E-Views software has been used for data analysis.

VARIMA Modelling

The Auto Regressive Integrated Moving Average (ARIMA) model uses time series data to interpret the data and make future forecast. In this study the most popular ARIMA model introduced by Box – Jenkins, 1976 has been used. This model is popular because it adjusts for seasonal and trend factors. ARMA model has two components (1) Autoregressive model (AR) and (2) Moving Averaged (MA).
AR denotes number of past values of the variable included for the forecast and is usually denoted by AR (p). The generalized AR (p) model is:

$$Yt = a0 + b1\ Yt\text{-}1 + \ldots\ldots + bpYt\text{-}p + et \ldots\ldots\ AR\ (p)$$

Note: 1) $b<1$

MA denotes number of present and past error terms that are included to make forecast and is usually denoted by MA (q). The generalized MA (q) model is:

$$Yt = a0 + \delta 1\ et\text{-}1 + \ldots\ldots + \delta q\ et\text{-}q + et \ldots\ldots\ldots\ldots\ldots\ldots MA\ (q)$$

The generalized form of ARMA (p,q) model is

$$Yt = a0 + b1\ Yt\text{-}1 + \delta 1\ et\ \text{-}1 + \ldots\ldots\ldots\ldots\ldots\ldots + bpYt\text{-}p + \delta q\ et\ \text{-}q + et \ldots ARMA\ (p,q)$$

Difference between ARMA and ARIMA integration component. Integration means the level at which data series is stationary and it is denoted by „I" or „d". If the data is stationary at first difference then it is denoted as I(1) or d(1). ARIMA model is generally denoted by ARIMA (p,d,q).
„p" denotes number of lags of past values of the variable
„q" denotes number of times the variable is differenced to become stationary
„q" denotes number of lags of past error term of the variable.
Box-Jenkins ARIMA modeling has four steps: 1. Identify the model 2. Estimate Parameters 3. Diagnostic checking 4. Forecasting.

VI Data Analysis and Interpretation

Tests for Stationary

The first step in forecasting the BSE Sensex is to check for the stationary of the data. The data taken for the study is checked for stationary by using Augmented Dickey Fuller (ADF) Test. The data was stationary at first difference as p-value is less than 0.05. Table-1 shows the results of ADF test.

TABLE -1

Unit Root Test at First Difference

Null Hypothesis: D(CLOSE) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=15)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-17.48966	0.0000
Test critical values:	1% level	-2.574245	
	5% level	-1.942099	
	10% level	-1.615852	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE,2)
Method: Least Squares
Date: 04/20/21 Time: 10:57
Sample (adjusted): 1/03/2020 12/31/2020
Included observations: 250 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CLOSE(-1))	-1.102055	0.063012	-17.48966	0.0000

R-squared	0.551260	Mean dependent var	-1.262040
Adjusted R-squared	0.551260	S.D. dependent var	986.7967
S.E. of regression	661.0357	Akaike info criterion	15.82948
Sum squared resid	1.09E+08	Schwarz criterion	15.84357

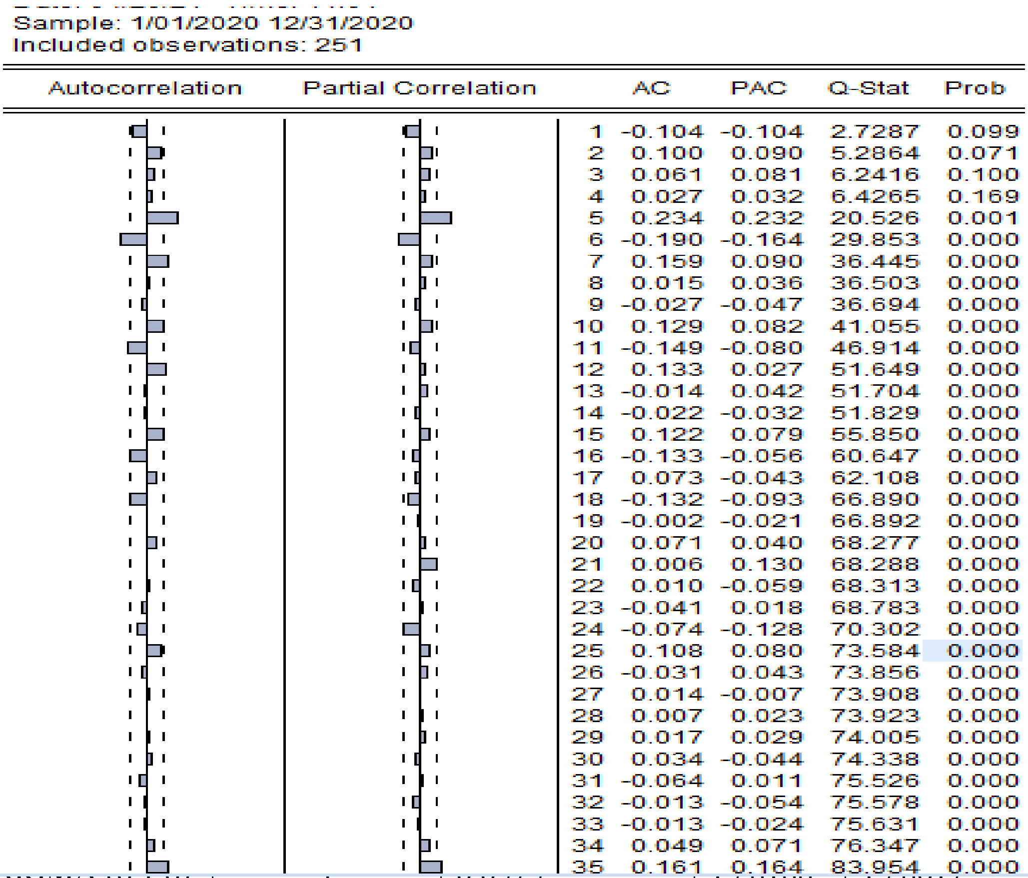
Log likelihood	-1977.686	Hannan-Quinn criter.	15.83515
Durbin-Watson stat	1.980289		

Source: E-Views output

Identification of Model

The data taken for the study is stationary at d (1), hence the series was generated for the same and the correlogram test was performed. Figure -1 shows the correlog ram result which shows that at lag 5,6 and 7the autocorrelation and partial correlation spikes exceeds the standard error. Thus the tentative ARIMA models to be considered for further analysis are ARIMA (5,1, 5), ARIMA (5,1,6), ARIMA (6,1,5) and ARIMA (6,1,6).

Figure -1 Correlogram Test



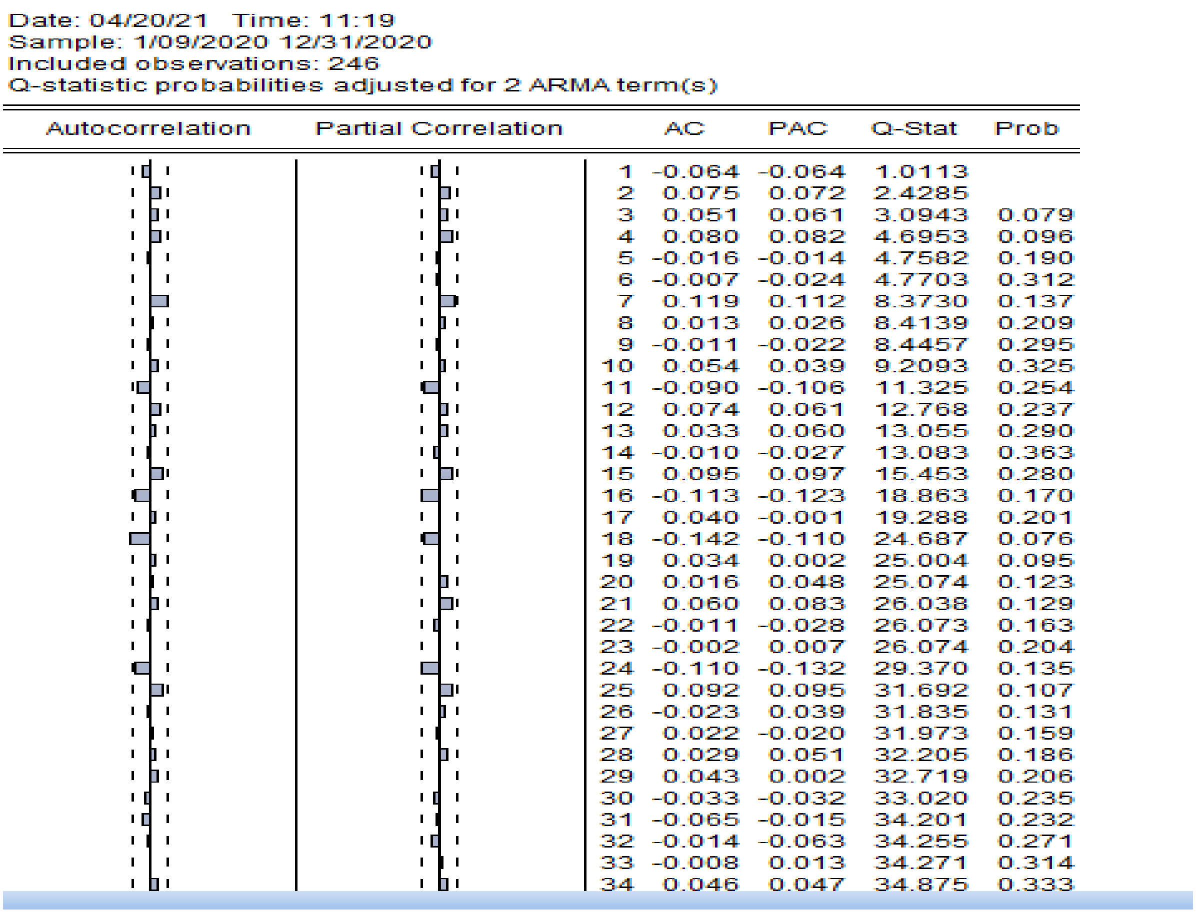
Sample: 1/01/2020 12/31/2020
Included observations: 251

Lag	AC	PAC	Q-Stat	Prob
1	-0.104	-0.104	2.7287	0.099
2	0.100	0.090	5.2864	0.071
3	0.061	0.081	6.2416	0.100
4	0.027	0.032	6.4265	0.169
5	0.234	0.232	20.526	0.001
6	-0.190	-0.164	29.853	0.000
7	0.159	0.090	36.445	0.000
8	0.015	0.036	36.503	0.000
9	-0.027	-0.047	36.694	0.000
10	0.129	0.082	41.055	0.000
11	-0.149	-0.080	46.914	0.000
12	0.133	0.027	51.649	0.000
13	-0.014	0.042	51.704	0.000
14	-0.022	-0.032	51.829	0.000
15	0.122	0.079	55.850	0.000
16	-0.133	-0.056	60.647	0.000
17	0.073	-0.043	62.108	0.000
18	-0.132	-0.093	66.890	0.000
19	-0.002	-0.021	66.892	0.000
20	0.071	0.040	68.277	0.000
21	0.006	0.130	68.288	0.000
22	0.010	-0.059	68.313	0.000
23	-0.041	0.018	68.783	0.000
24	-0.074	-0.128	70.302	0.000
25	0.108	0.080	73.584	0.000
26	-0.031	0.043	73.856	0.000
27	0.014	-0.007	73.908	0.000
28	0.007	0.023	73.923	0.000
29	0.017	0.029	74.005	0.000
30	0.034	-0.044	74.338	0.000
31	-0.064	0.011	75.526	0.000
32	-0.013	-0.054	75.578	0.000
33	-0.013	-0.024	75.631	0.000
34	0.049	0.071	76.347	0.000
35	0.161	0.164	83.954	0.000

Source: Compiled from E-Views output

The ARIMA (5, 1, and 6) model with maximum significance, highest R2 value, lowest AIC and SIC value was selected for the further analysis. For selected model lag significance diagnostic check was performed by using correlogram Q-Statistics. The result of the same is show in Figure- 2.

Figure- 2 Correlogram Q-Statistics



Date: 04/20/21 Time: 11:19
Sample: 1/09/2020 12/31/2020
Included observations: 246
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.064	-0.064	1.0113	
		2	0.075	0.072	2.4285	
		3	0.051	0.061	3.0943	0.079
		4	0.080	0.082	4.6953	0.096
		5	-0.016	-0.014	4.7582	0.190
		6	-0.007	-0.024	4.7703	0.312
		7	0.119	0.112	8.3730	0.137
		8	0.013	0.026	8.4139	0.209
		9	-0.011	-0.022	8.4457	0.295
		10	0.054	0.039	9.2093	0.325
		11	-0.090	-0.106	11.325	0.254
		12	0.074	0.061	12.768	0.237
		13	0.033	0.060	13.055	0.290
		14	-0.010	-0.027	13.083	0.363
		15	0.095	0.097	15.453	0.280
		16	-0.113	-0.123	18.863	0.170
		17	0.040	-0.001	19.288	0.201
		18	-0.142	-0.110	24.687	0.076
		19	0.034	0.002	25.004	0.095
		20	0.016	0.048	25.074	0.123
		21	0.060	0.083	26.038	0.129
		22	-0.011	-0.028	26.073	0.163
		23	-0.002	0.007	26.074	0.204
		24	-0.110	-0.132	29.370	0.135
		25	0.092	0.095	31.692	0.107
		26	-0.023	0.039	31.835	0.131
		27	0.022	-0.020	31.973	0.159
		28	0.029	0.051	32.205	0.186
		29	0.043	0.002	32.719	0.206
		30	-0.033	-0.032	33.020	0.235
		31	-0.065	-0.015	34.201	0.232
		32	-0.014	-0.063	34.255	0.271
		33	-0.008	0.013	34.271	0.314
		34	0.046	0.047	34.875	0.333

Source: E-Views output

Figure-2 results reveal that at lag 7, autocorrelation and partial correlation spikes exceeds standard error. Therefore, further two adjusted ARIMA models were identified i.e. ARIMA (5, 7,6) and ARIMA (5,6,7). The parameters were estimated for the adjusted ARIMA and the results are shown in Table-3.

TABLE – 3
Adjusted ARIMA Estimated Parameters

Model	Significance	Adjusted R2	AIC	SIC
ARIMA (5,1,6)	2	0.0669	15.7869	15.8297
AR (5) AR(7) MA(6)	3	0.0777	15.7819	15.8393
AR(5)MA(6)MA(7)	3	0.0782	15.7787	15.835

Source: Compiled from E-Views output

The model ar(5) ma(6) ma(7) which has maximum significance, highest adjusted R2 lowest AIC and SIC values was selected for further diagnostic check. The diagnostic check showed the result that no lags are significant, no autocorrelation and series is homoscedasticity. Therefore, the best model for forecasting is ar(5) ma(6) ma(7) which can be written as follows:

$$Yt = a0+b5Yt\text{-}5+\delta 6et\text{-}6 +\delta 7et\text{-}7 +et$$

$$Yt = 29.35521+0.204282Yt\text{-}5-0.154379et\text{-}6+0.121943et\text{-}7+et.$$

6.4 Forecasting

Figure 3 and 4 shows the graphical representation of forecasted value of the series taken for the study. It could be observed from the Figure 3 that the forecasted line which is in center lies within the standard error lines. This proves that model has provided a good forecast. Figure 4 shows the forecasted value for the series.

Figure 3 Forecasted Series with Standard Error

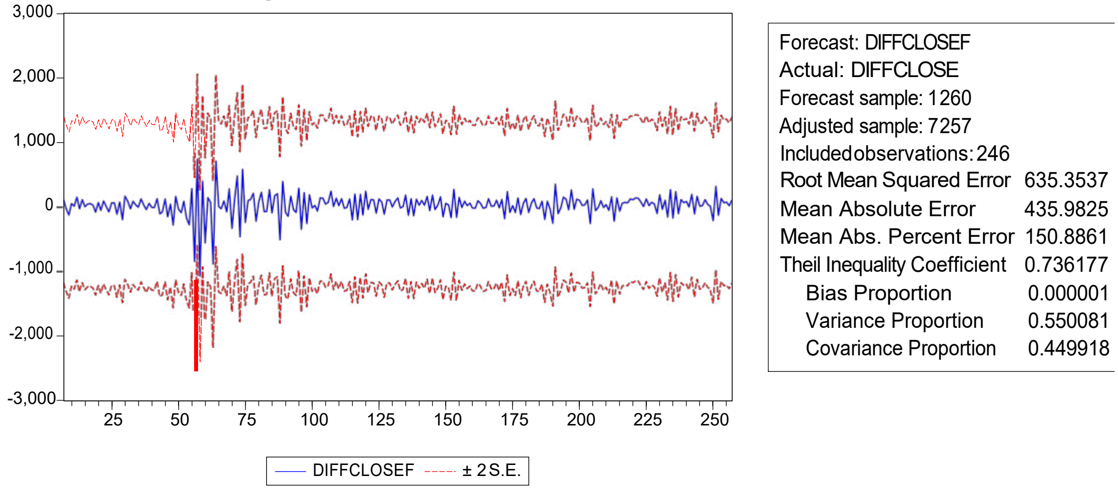
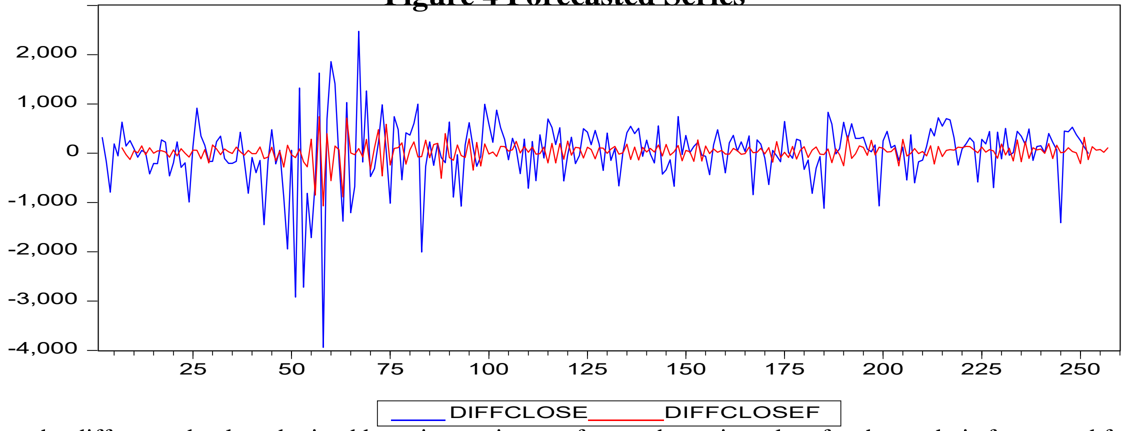


Figure 4 Forecasted Series



Using the differenced value obtained by using e-views software the series taken for the study is forecasted for further 5 days by using the equation Y^t+1 = ΔY^t + Yt-1 + et and shown in Table- 4 .

TABLE-4

Forecasted Value of BSE Sensex

Day	ΔY^t	Yt-1	Forecasted Value (Y^t+i)	Actual BSE Sensex Value
01 Jan 2021	133.7003	47751.33	47885.03	47,868.98
04 Jan 2021	64.80808	47885.03	47949.84	47,868.98
05 Jan 2021	79.41463	47949.84	48029.25	48,437.78
06 Jan 2021	23.09253	48029.25	48052.35	48,174.06
07 Jan 2021	110.9387	48052.35	48163.28	48,093.32

Source: Compiled using E-Views output

It could be observed from Table-4 that the forecasted value and actual BSE Sensex value is almost similar and the difference is due to error term. Therefore ar(5) ma(6) ma(7) provides good forecast.

VII CONCLUSION

In this article an attempt has been made to forecast BSE Sensex movement using ARIMA modelling. To forecast the movement BSE Sensex data was taken for the period from

1 January2020 to 31st December 2020. Box Jenkins, method was used for the analysis. Analysis iteration showed ar(5) ma(6) ma(7) as a best fit model for forecasting. Forecast done by using the best fit model showed that almost the forecasted value was same as actual BSE Sensex value. Thus ARIMA modelling is one of the best model that can be used for forecasting the stock market future movement.

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