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ARIMA Model in Forecasting Stock Returns – A Study With Reference To BSE Sensex

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Abstract-Although accurate stock price prediction is difficult, the autoregressive integrated moving average (ARIMA) model has proven to be reliable in a variety of linear and non-linear time series forecasting methods. With a market capitalization of around 2, 61, 80,305.91 crores, the Bombay stock exchange is India's largest stock exchange. The goal of this study is to find the best ARIMA model for forecasting the BSE Sensex price index. In order to find the best ARIMA model for forecasting the stock market index, the researchers utilised a three-step iterative quantitative approach.The study found that the ARIMA (1,1,0) model is the most stable and appropriate model for forecasting India's stock price index for the subsequent year.

***Key Words*-ARIMA model, time series plots, Stock Index**

1. INTRODUCTION

The stock market is a marketplace that allows for the seamless exchange of corporate stock purchases and sales. Every Stock Exchange has its own value for the Stock Index. The index is the average value derived by adding up the prices of various equities. This aids in the representation of the entire stock market as well as the forecasting of market movement over time. The stock market can have a significant impact on individuals and the economy as a whole. As a result, effectively predicting stock trends can reduce the risk of loss while increasing profit.

The ARIMA model is a short-term prediction model and a time series model with high precision. The basic idea of the model is that some time series are a set of random variables that depend on time, but the changes of the entire time series have certain rules, which can be approximated by the corresponding mathematical model. Through the analysis of the mathematical model, it can understand the structure and characteristics of time series more fundamentally and achieve the optimal prediction in the sense of minimum variance.

The ARIMA model, a time series prediction method, was proposed by Box and Jenkins in the 1970s. The model consists of AR, I, and MA. Here AR represents the Autoregressive model, I represent the Integration indicating the order of single integer, and MA represents the Moving Average model. In general, a stationary sequence can establish a metrology model. The unit root test is used to judge the stationarity of the sequence. As for a non-stationary sequence, it should be converted to a stationary sequence with difference operation. The number of corresponding difference is called as the order of single integer. The ARIMA (p, D, q) model is essentially a combination of differential operation and ARMA (p, q) model [3, 4]. A non-stationary I (D) process is one that can be made stationary by taking D differences. The process is often called difference-stationary or unit root processes. A series that can be modeled as a stationary ARMA (p,q) process after being differenced D times is denoted by ARIMA (p,D,q) . The form of the ARIMA (p,D,q) model is

$$\Delta^D y_t = c + \phi_1 \Delta^D y_{t-1} + \ldots + \phi_p \Delta^D y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \quad (1)$$

Where ΔDyt denotes a D-th differenced series, and εt is an uncorrelated process with mean zero. In lag operator notation, Liyt=yt−i. The ARIMA (p,D,q) model can be written as$\phi*(L)yt=\phi(L)(1-L)Dyt=c+\theta(L)\varepsilon t$.Here, ϕ∗(L) is an unstable AR operator polynomial with exactly D unit roots. Someone can factorthis polynomial as ϕ(L)(1−L)D, where ϕ(L)=(1−ϕ1L−……−ϕpLp) is a stable degree p AR lag operatorpolynomial. Similarly, θ(L)=(1+θ1L+…+θqLq) is an invertible degree q MA lag operator polynomial.When two out of the three terms in ARIMA(p,D,q) are zeros, the model may be referred to, basedon the non-zero parameter, dropping "AR", "I" or "MA" from the acronym describing the model. Forexample, ARIMA (1,0,0) is AR (1), ARIMA (0,1,0) is I (1), and ARIMA (0,0,1) is MA (1).

2. REVIEW OF LITERATURE

Uma Devi and et.al[2] explains the seasonal trend and flow is the highlight of the stock market. Eventually investors as well as the stock broking company will also observe and capture the variations, as constant growth of the index. This will help new investor as well as existing ones to make a strategic decision. It can be achieved by experience and the constant observation by the investors. In order to overcome the above said issues, ARIMA algorithm has been suggested in three steps, Step 1: Model identification , Step 2: Model estimation and Step 3: Forecasting.

AyodeleAdebiyi, A and et.al[1] , Uma Devi, B and et.al [2] Pai, P and et.al[3] Wang, J.J and et.al [4] and Wei, L.Y[5] authors explains to execute in financial forecasting due to complex nature of stock market Stock price prediction is regarded as one of the most difficult task.

Atsalakis, G.S and et.al[6] explained in this paper as to catch hold of any forecasting method is the desire of many investors which would give assurance of easy profit and minimize investment risk from the stock market. For researchers to develop gradually new predictive models remains a motivating factor.

Mitra, S.K[7] , Atsalakis, G.S and et.al[8] , Mohamed, M.M[9] authors asserted as in the past years, to predict stock prices several models and techniques had been developed. One of them is: an artificial neural networks (ANNs) model due to its ability to learn patterns from data and infer solution from unknown data are very popular. Few related works on ANNs model are given in their literature for stock price prediction.

Wang, J.J and et.al[4] defined in recent time, to improve stock price predictive models by exploiting the unique strength hybrid approaches have also been engaged. ANNs is from artificial intelligence perspectives. From statistical models perspective ARIMA models have been derived. Generally, from two perspectives: statistical and artificial intelligence techniques the prediction can be done it is reported in their literature.

Merh, N and et.al[10] , Sterba, J and et.al[11] and Javier, C and et.al[12] defined as in financial time series forecasting, ARIMA models are known to be robust and efficient, especially for short-term prediction than the popular ANNs techniques. In fields of Economics and Finance they have been extensively used. Other statistical models like: regression method, exponential smoothing, generalized autoregressive and conditional heteroskedasticity (GARCH) are also discussed.

3. RESEARCH METHODOLOGY

This study is an empirical approach to forecast the index prices of Bombay stock exchange of India. Monthly share prices of BSE SENSEX, from January 2000 to December 2020 are taken for study purposes. A total of 252 observations were usedto forecast the prices of the index for the time period January 2021 to February2022Using the E views12 software.initially the trend projections of the index is analysed and the the time series is tested for non -normality. Stationarity of the time series data is analysed using the Augmented dicker fuller unit root test . Since the data is non stationary at their level the returns are difference at first order and then the ACF and the PACF of the differenced data is plotted to determine the ARIMA(p,D,q) order. To further test if the selected ARIMA model is the best fit, ACF residual test and plots are calculated, in addition to this Portmanteau test is used to test the adequacy of the model.

4. OBJECTIVES OF THE STUDY

- To analyze the best fit ARIMA (p,D,q) model for the BSE Sensex
- To compare the accuracy of the forecast prices with actuals for the next time period.

5. AN ARIMA (P, D, Q) MODEL FOR BSE SENSEX

To determine the ARIMA (p, d, q) order for the selected markets a test of stationarity has to be applied for the time series data. From figure 1 it is noticed that there is general increasing trend in the BSE, which showed a decreasing initially after which it showed an increasing trend with no clear seasonal pattern. The random fluctuations in the data are roughly increased in size over time. This is referred to non-stationary in the variance of the data and must be corrected.. ACF plot is useful for identifying non-stationary time series. For a stationary time series, the ACF will drop to zero relatively quickly, while the ACF of non-stationary data decreases slowly. Also, for non-stationary data, the value of r1 is often large and positive.Hence to remove the trend and seasonality the data is differenced at I(1). The ACF plots and PACF plots at their level and at Diff 1 is given in table 2.

Figure 1: Time Series Plots Of Bse Sensex, Since January 2000 To December 2020

Source: Researchers output from E views 12

Table 1: ACF AND PACF of BSESENSEX at Their Level and Diff 1

Date: 10/20/21 Time: 15:14
Sample (adjusted): 2000M02 2021M07
Included observations: 258 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.010	-0.010	0.0258	0.872
		2	-0.013	-0.013	0.0705	0.965
		3	0.068	0.068	1.3014	0.729
		4	-0.018	-0.017	1.3876	0.846
		5	-0.056	-0.055	2.2297	0.817
		6	0.037	0.031	2.5923	0.858
		7	0.097	0.099	5.0942	0.648
		8	-0.035	-0.026	5.4290	0.711
		9	-0.106	-0.114	8.4443	0.490
		10	0.083	0.068	10.303	0.414
		11	-0.096	-0.086	12.815	0.306
		12	-0.165	-0.151	20.274	0.062
		13	0.071	0.048	21.660	0.061
		14	-0.102	-0.111	24.536	0.039
		15	-0.003	0.031	24.539	0.056
		16	-0.022	-0.032	24.676	0.076
		17	0.024	0.009	24.837	0.098
		18	0.003	0.027	24.840	0.129
		19	0.011	0.041	24.874	0.165
		20	-0.019	-0.061	24.980	0.202
		21	0.008	0.008	24.998	0.247
		22	-0.045	-0.027	25.576	0.270
		23	-0.036	-0.092	25.940	0.304
		24	0.114	0.126	29.696	0.195

Date: 10/20/21 Time: 15:13
Sample: 2000M01 2021M07
Included observations: 259

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.978	0.978	250.74	0.000
		2	0.957	-0.004	491.55	0.000
		3	0.936	-0.006	722.68	0.000
		4	0.916	0.028	945.11	0.000
		5	0.896	-0.027	1158.6	0.000
		6	0.876	0.008	1363.8	0.000
		7	0.858	0.030	1561.5	0.000
		8	0.838	-0.065	1750.7	0.000
		9	0.821	0.063	1933.1	0.000
		10	0.809	0.100	2110.6	0.000
		11	0.797	-0.001	2283.6	0.000
		12	0.785	0.010	2452.2	0.000
		13	0.776	0.057	2617.4	0.000
		14	0.768	0.023	2780.0	0.000
		15	0.762	0.075	2941.0	0.000
		16	0.756	-0.025	3100.0	0.000
		17	0.753	0.080	3258.5	0.000
		18	0.743	-0.169	3413.1	0.000
		19	0.730	-0.049	3563.1	0.000
		20	0.716	-0.019	3708.0	0.000
		21	0.702	-0.009	3848.1	0.000
		22	0.689	0.013	3983.6	0.000
		23	0.678	0.055	4115.1	0.000
		24	0.667	0.014	4243.2	0.000

The ACF and the PACF table given above highlights that the series are not stationary at their level, but they are stationary after first differencing. Hence the null hypothesis of no serial correlation can be rejected after first differencing. Hence the series are stationary. Further the results of the unit root test too confirms that the series are not stationary at their levels instead they are stationary after first order differencing. From table 2 ,It can be seen that ADF=1.179which is greater than the critical value of the significance level of 0.01, 0.05 and 0.1, that is to say, the original returns sequence of the selected indices is non-stationary. The time series plot given in figure 2 explains that the original sequence is exponential. Further, the first-order difference is performed on all the selected indices. The results of the ADF test for the sequence are given in Table: 2. It can be seen that ADF=-16.127which is less than the three critical values of the test level. That is to say, the differencing sequence of the selected indices and the first-order difference is a stationary series, and the significance test of the stationarity is passed. It can be seen that the original returns series of the BSE is a first-order single-order sequence that is I(1).

Table 2: ADF test results of the BSESENSEX at their level and first order

Null Hypothesis: BSESENSEX has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=15)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.175910	0.9980
Test critical values:	1% level	-3.455585	
	5% level	-2.872542	
	10% level	-2.572707	

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

Null Hypothesis: D(BSESENSEX) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=15)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.12746	0.0000
Test critical values:	1% level	-3.455685	
	5% level	-2.872586	
	10% level	-2.572730	

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

Source: Researchers output from E views 12

6.MODEL IDENTIFICATION

The autocorrelation and partial autocorrelation function graphs of the returns series after first order differencing given in table 1 identifies the order for AR and MA sequence.

Lags 4, 9 and 11 are statistically significant for BSE SENSEX, The ACF and the PACF PLOTS of the time series show a similar pattern that is they both decline rapidly; hence the model is not AR Or MA but an ARIMA model. Table 3 lists the test results of ARMA (p, q) for different parameters. Adjusted R-squared, AIC value, BIC value and HQ are all important criteria for selecting models. The AIC criterion and the BIC criterion are mainly used for ranking, and select the optimal model. Generally, the smaller the AIC , BIC AND HQ value, The corresponding ARMA (p,q) model is superior. Finally the selected model for BSE SENSEX is (1,1,0).

Table 3:ARMA(p,q) for BSE SENSEX for different parameters

No.	AR Order (P)	MA Order (Q)	Sum of Squares	Pseudo R-Squared	Percent Change From Last
0	0	0	3.094463	0	0
1	1	0	0.205355	93.36	-93.36
2	2	1	0.204144	93.4	-0.59
3	4	3	0.206231	93.34	1.02
4	6	5	0.206049	93.34	-0.09
5	8	7	0.20757	93.29	0.74

The r square value generates a statistic that acts like the R-Squared value in multiple regression. A value near zero indicates a poorly fitting model, while a value near one indicates a well fitting model. The r square for the given series is 93.36 which indicated that the model is fit. The mean squared error, or MSE, is calculated as the average of the squared forecast error values. Squaring the forecast error values forces them to be positive; it also has the effect of putting more weight on large errors. The error values are in squared units of the predicted values. A mean squared error of zero indicates perfect fit, or no error. MSE for the selected model (1,0) is 0.00081 which is closer to zero, hence this explains that the model is perfectly appropriate. Similarly the RMSE value closer to aero explains no error in the selected model. The RMSE for the selected ARMA (1,0) is 0.0286. Hence ARMA(1,0) is perfectly appropriate in forecasting the series.

Model	AIC	BIC	HQ	SSE	MSE	RMSE
ARMA(1,0)	-2.5889	-2.544	-2.555	0.2053553	0.0008181487	0.0286033

Source: Researchers output from E views 12

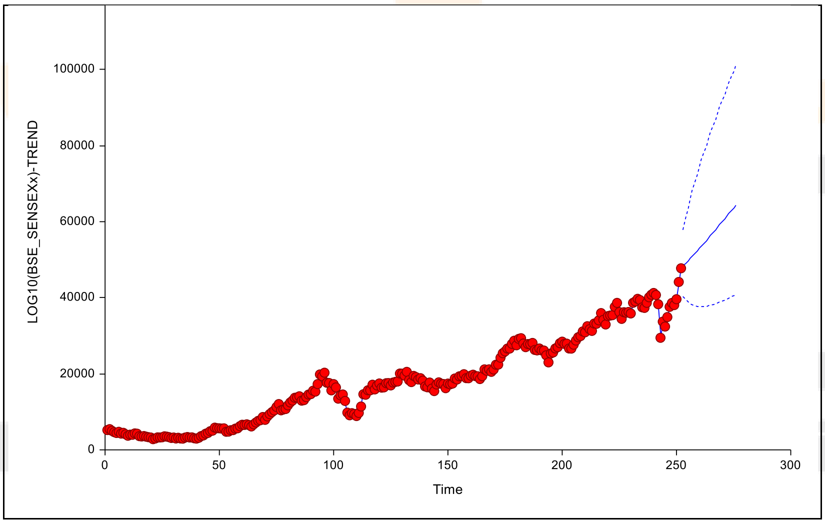
7. FORECAST AND DATA PLOT FOR BSE SENSEX

The forecast and data plots for the series are given in table 4 and figure 2 for the years 2021 and 2022. The table also highlights the upper and the lower prediction limits for the series. These limits explain the accuracy of the model used to forecast the future values. The forecast values lie between the predictability limits given in the table and the actual values are closer to the forecasted values. Hence the model is a best fit.

Table 4: Actual and forecast values of BSE SENSEX for the year 2021 and 2022

Date	Forecast	Actual values	Lower 95% Limit	Upper 95% Limit
Jan-21	48388.66	46285.77	40438.624	57901.64
Feb-21	49029.95	49099.99	39498.944	60860.767
Mar-21	49675.28	49509.15	38862.02	63497.307
Apr-21	50324.75	48782.36	38416.745	65923.863
May-21	50978.44	51937.44	38106.323	68198.689
Jun-21	51636.45	52482.71	37897.158	70356.798
Jul-21	52298.87	52586.84	37767.472	72421.349
Aug-21	52965.79	57552.39	37702.225	74408.722
Sep-21	53637.3	59126.36	37690.538	76331.094
Oct-21	54313.51	59306.93	37724.257	78197.88
Nov-21	54994.5	57064.87	37797.097	80016.586
Dec-21	55680.37	58253.82	37904.101	81793.35
Jan-22	56371.22	58014.17	38041.284	83533.299
Feb-22	57067.14	56247.28	38205.396	85240.79
Mar-22	57768.23		38393.744	86919.584
Apr-22	58474.59		38604.076	88572.963
May-22	59186.31		38834.49	90203.83
Jun-22	59903.5		39083.36	91814.772
Jul-22	60626.26		39349.293	93408.115
Aug-22	61354.68		39631.081	94985.963
Sep-22	62088.86		39927.674	96550.237
Oct-22	62828.91		40238.155	98102.693
Nov-22	63574.92		40561.717	99644.948
Dec-22	64327		40897.647	101178.499

Figure:2 Data Plot of BSE Sensex For 2021 and 2022



8. ACF OF RESIDUALS

The plot shows the autocorrelation function of the residuals. The autocorrelation function is a measure of the correlation between the observations of a time series that are separated by k time units (yt and yt–k). Autocorrelation function of the residuals is used to determine whether the model meets the assumptions that the residuals are independent. If the assumption is not met, the model may not fit the data. If no significant correlations are present, then the residuals are independent. The ACF of the residuals and the ACF residuals plot is given in Table 5 and figure 3. The ACF residuals table explains that there are no significant correlations found in the series up to 48 lags since the ACF values are lesser than 0.12598. hence we reject the null hypothesis that residuals are uncorrelated. If the residuals are white noise, these autocorrelations should all be non-significant. If significance is found in these autocorrelations, the model should be changed. Hence the residuals are non significant and they are independent.

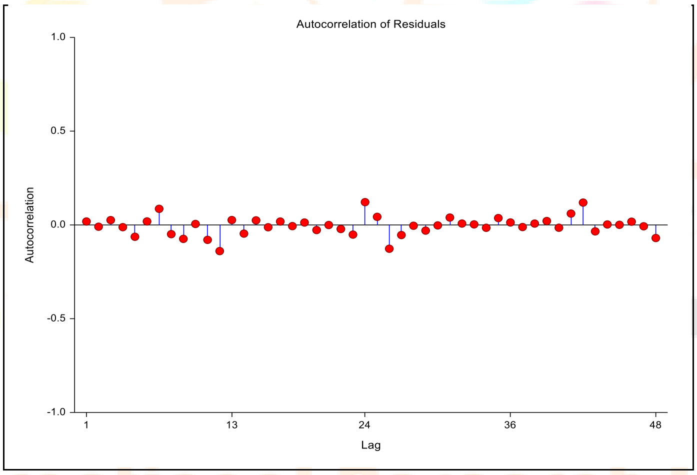
Table5: ACF Residuals

Lag	Correlation	Lag	Correlation	Lag	Correlation	Lag	Correlation
1	0.018357	13	0.025977	25	0.043022	37	-0.01131
2	-0.009574	14	-0.046374	26	-0.12706	38	0.007123
3	0.025601	15	0.024283	27	-0.054	39	0.02069
4	-0.011944	16	-0.01239	28	-0.0045	40	-0.01504
5	-0.063219	17	0.018106	29	-0.03033	41	0.060427
6	0.018667	18	-0.00639	30	-0.0026	42	0.119092
7	0.085823	19	0.012807	31	0.039303	43	-0.03446
8	-0.049234	20	-0.027355	32	0.007295	44	0.002468
9	-0.074366	21	-0.000539	33	0.002864	45	0.000568
10	0.005069	22	-0.021808	34	-0.01537	46	0.017191
11	-0.079662	23	-0.051609	35	0.036464	47	-0.00727
12	-0.13951	24	0.121469	36	0.013108	48	-0.06989

Significant if |Correlation| > 0.125988

In the ACF residuals plot, the mean of the residuals are close to zero and there is no significant correlation in the residual series. Hence the model is an appropriate fit and valid.

Figure 3: ACFPlot of Residuals



9. PORTMANTEAU TEST- TESTING FOR ADEQUACY

Portmanteau tests are available for testing for autocorrelation in the residuals of a model: it tests whether any of a group of autocorrelations of the residual time series are different from zero. The Portmanteau Test (sometimes called the Box-Pierce-Ljung statistic) is used to determine if there is any pattern left in the residuals that may be modeled. This is accomplished by testing the significance of the autocorrelations up to a certain lag. For lags m > 1, the Monte-Carlo version of Box and Pierce test and the asymptotic chi-square suggests that the model is adequate.

TABLE 6: Portmanteau Test- Testing For Adequacy

Lag	DF	Portmanteau Test Value	Prob Level	Decision (0.05)
2	1	0.11	0.740824	Adequate Model
3	2	0.28	0.870277	Adequate Model
4	3	0.31	0.95724	Adequate Model
5	4	1.35	0.85277	Adequate Model
6	5	1.44	0.91977	Adequate Model
7	6	3.37	0.761785	Adequate Model
8	7	4	0.779631	Adequate Model
9	8	5.46	0.707688	Adequate Model
10	9	5.46	0.792056	Adequate Model
11	10	7.15	0.711185	Adequate Model
12	11	12.34	0.338557	Adequate Model

13	12	12.52	0.404731	Adequate Model
14	13	13.1	0.440102	Adequate Model
15	14	13.26	0.506204	Adequate Model
16	15	13.3	0.579054	Adequate Model
17	16	13.39	0.644029	Adequate Model
18	17	13.4	0.708918	Adequate Model
19	18	13.45	0.764388	Adequate Model
20	19	13.65	0.803528	Adequate Model
21	20	13.65	0.847639	Adequate Model
22	21	13.79	0.878636	Adequate Model
23	22	14.53	0.881608	Adequate Model
24	23	18.67	0.720079	Adequate Model
25	24	19.19	0.741562	Adequate Model

10. CONCLUSION

The main objective of this study was to determine the optimal ARIMA model for forecasting the Stock price index. The findings of the study reveal that the ARIMA (1,1,0) model is stable and the most suitable model to forecast the stock price index of BSE SENSEX from January 2021 to February 2022. Investors should thus be able to utilise the model for accurate stock price prediction and generating sustainable profits on stock investments. In general, bse Sensexshowed an upwards trend over the forecasted period.

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