Forecasting the stock market using ARIMA modeling and foresight

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ABSTRACT
In this work, the future prices of the sample companies are predicted using the Box and Jenkins-popularized ARIMA model. The process of methodically discovering, estimating, diagnosing, and forecasting time series is known as ARIMA model construction, and it is driven by empirical evidence. Only stationary time series are suitable for use with the ARIMA model. Because the time series pertaining to the stock market are non-stationary, the underlying stochastic process's properties fluctuate with time. An ARIMA model's AR and MA components only apply to time series that are stationary, in order to forecast the stock market and take into account the stationary time series in this research. Each sample company's model selection must have a foundation, which is demonstrated by determining the ACF, PACF, AIC, and SBC values. The ACF and PACF error plots, which are shown in the images, are crucial. The forecast graph visualization using sample data, which is provided in this chapter for each organization, will be excellent.

Keywords: Stationary, Non-Stationary, Forecast, T-Ratio, ACF, PACF, ACC

1. INTRODUCTION

Making life easier has been a shared human ambition from the beginning of humanity. The general belief in society is that comfort and luxury are brought about by wealth. It follows that the high level of interest in stock market investing is not surprising. Due to its excellent returns, the stock market has been one of the most popular investment options (Josua Tarigan et al., 2021). However, because of its unpredictable nature, investing in the stock market carries certain risk. Financial time series prediction of the stock market is considered a difficult task (Ruchika Kaura et al., 2021). Selecting the industry to invest in, such as the steel, cement, or IT sectors, is another challenge. It might be difficult for investors to choose which stocks, within the same industry sector, to buy and sell at the right time (Dharen Pandey et al., 2021). A common misconception is that an average investor sells the stock too quickly in order to profit and holds onto it too long in order to make up the loss (Xuan Vinh Vo et al., 2021). The investor is caught between safeguarding price appreciation and minimizing additional losses. An increase in stock market knowledge has aided investors in making more informed trading decisions (Asad Ali et al., 2021). On the other hand, information overload is a result of this massive volume of information. Several active efforts have been created to forecast stock tendencies in an effort to mitigate this issue (Augustine Arize et al., 2021).
Dhirubhai Ambani played a major role in enabling Indian investors to make their first-ever stock market entry. Reliance Commercial Corporation was founded by him in 1958 with a fifteen thousand rupee investment. It was involved in the import of polyester yarn. He is regarded as the one who created a truly global multinational organization and rewrote Indian corporate history. His business, Reliance Industries Limited, has expanded and requires funding to continue growing. When Reliance made its initial Initial Public Offer (IPO) in 1977, Dhirubhai was able to persuade middle-class and rural residents that his business would provide significant rewards for investors. This occurred when the general public's knowledge of stock markets was quite low. Even though Reliance was a very profitable company, Ambani rapidly realized that additional growth would require having access to a low-cost source of funding, particularly into allied industries. He chose to use Bombay's budding stock exchange instead of the banking system, igniting an equity cult that would eventually revolutionize India's corporate funding landscape. When Reliance went public in 1977, 58,000 investors purchased shares. Ambani offered

Indian middle-class wage earners the prospect of rapid wealth accumulation via the stock market. However, he was no shady character. Genuine value could be found in Reliance shares, and some who were lucky enough to invest in the business early on went on to become billionaires. Sports stadiums served as the venue for annual general meetings, where shareholders would lavish praise and sometimes even veneration upon Ambani. The impact of globalization has been enormously transformative. Infosys, an IT company, had significant growth following the liberalization of the Indian economy in the 1990s. The business announced its IPO in 1993. Infosys employs more than 50,000 people and generates over $2 billion in revenue annually. In 2006, Infosys became the first Indian business to list on the NASDAQ.The best investment for a high return is in the stock market, as demonstrated by these two variables. Therefore, the research's subject of choice is stock market prediction. John B. Williams [1938] is credited with creating the idea of investment value and is the one who also provided a formula for figuring out the intrinsic value of companies. But in their seminal work "Security Analysis," B. Graham and D. Dood [1962] popularized the idea of intrinsic value. Numerous scholars have proposed that the theory of intrinsic worth be developed further. Fundamentalists predict stock values using corporate data and the state of the industry's economy. is a significant study that ran from 1927 to 1960. According to Elton et al. (1986), the state of the economy as a whole accounts for between 25% and 50% of the fluctuations in a company's yearly earnings. Numerous measurements are utilized, including statistics on new highs and lows and relative strength measures by Jones et al.,(1977). Technical analysis methods can be broadly divided into two categories: charts and mechanical trading strategies by Jones et al.,(1977). According to Aditya Sharma et al. (2021), security researchers typically employ both fundamental and technical analysis. Ball et al. (1968) looked at the price fluctuations of businesses that reported both "good" and "bad" earnings. In a different study, Joy et al. [1977] examined how stock price is affected by quarterly earnings reporting. The price-earning ratio's informative content was tested by Basu [1977]. Eleven trading days apart, Aharony et all., [1980] looked at every dividend and earnings announcement made during the same quarter. According to Kalay et all., [1985] research, unconditional positive excess returns follow every dividend announcement. This was further supported by the research of Eades, Hess, and Kim (1985). Kim (1991(a,b) and 1992) discovered indications of heightened information production on the days of dividend announcements, leading to higher trading volumes and elevated price fluctuations. Mukesh et all., [1995] examined the process of price creation on the day of the dividend announcement using daily closing prices and transaction data. Stock values quickly changed in response to the release of fresh information regarding the stocks (Sudhanshu Pani et al., 2021). However, there was some evidence refuting the semi-strong type of EMI from the research done by Joy and Jones [1979]. Most likely, Ramachandran [1985] was the first to look into how the stock price behaved when a bonus issue was announced. Using a sample of forty bonus issue announcements spread over six years, he applied the conventional methodology for event studies. His research yielded conflicting results regarding market efficiency. A study by Subramanian [1989] looked at how economic developments affected stock values. Obaidullah (1990) used weekly returns for a sample of 33 businesses that reported their half-early earnings for the period ending in September 1989. Obaidullah [1992] also looked into how pricing changes in response to bonuses announced. He started by looking into a sample of 75 supplementary issues that were released between 1987 and 1989. Srinivasan [1993] looked into how well the market processed the information in right issue announcements; he discovered that the market was largely semi-strongly efficient. Kanokkarn et all., 2021 proposed the highly efficient if security prices accurately represent all pertinent information, including that which is not yet publicly accessible, in addition to published information. Examining the utilization of and profit from insider trading constitutes a second sort of study approach under the strong form of efficiency. It is concluded by Jeffe (1974) and Joseph E. Finnerty (1976) that insiders do engage in trading and profit excessively. According to Kon and Jen (1979) and Givoly et al. (1985), certain managers can be differentiated from others based on their aptitude for choosing profitable investments. This does not align with a robust type of efficiency. Evidence of business insiders obtaining risk-adjusted excess returns has been discovered by Seyhun (1986), Benesh and Pari (1987), and Peers (1992). Security analysts' recommenced stock performance serves as a barometer for robust market efficiency. The economic worth of the suggestions made in the "Heard on the Street" articles for both short-term and long-term investors was investigated by Bauman et al. in 1995. Security analysts' investment advice was found to be more beneficial for long-term investors than for short-term ones. About 4,000 stock returns predicted by 35 different firms of stock brokers and internal analysts of a major UK investment institution were examined by Dimson and Marsh [1984]. Extra return can be obtained over time if portfolios are constructed based on year-end low Price/Sales (P/S) and Market Value / Book Value (MV/BV) Ratios, according to an empirical study conducted by Karan [1996] using ISE data covering the period of December 31, 1988 - March 31, 1995. By Ball et al.,(1968) examined the price movements of companies that experienced ‘good’ earnings report as well as ‘bad’ earning report. Ozmen [1992] conducted a first investigation on anomalies in ISE utilizing the January 1998 through February 1992 compound index. In contrast to this outcome, the aforementioned study reports that Monday was the second-highest return day in absolute terms after Friday, suggesting that ISE experienced the same negative Monday effect as numerous overseas capital markets. On the other hand, according to worldwide results, Friday (%0.67) was the day of the week with the highest return, and Thursday (% - 0.14) had the lowest return (Ozmen 1992). The rest of this article as follows: Building and Determining the Model was discussed in Section 2. ACC using the ARIMA model was discussed in Section 3. ARIMA mode for M&M was discussed in Section 4. the Result and Discussion are discussed in Section 5. K. Kalaiarasi, (2019) suggested Optimization of fuzzy inventory model for EOQ using Lagrangian method, Malaya Journal of Matematik 7(3):497-501 (2019). K. Kalaiarasi, **(2022)**, suggested Applying Hessian Matrix Techniques to obtain the efficient optimal order quantity using Fuzzy parameters.

2. Building and Determining the Model

In the early 1970s, George Box and Gwilym Jenkins made the Autoregressive Integrated Moving Average (ARIMA) widely known. Later, in 1994, Box, Jenkins, and Reinsell made improvements to it. If the time series is stationary, the ARIMA model can be utilized. When data is stationary, it indicates that there is neither increase nor decline. That is, throughout the time period, the data must be horizontal. Time plots are typically useful for evaluating stationary. We say a time series is stationary in the mean if it is plotted and there is no indication that the mean has changed over the series' duration. If the plotted series shows no appreciable change in variance over time, we say that the series is stationary in the variance.

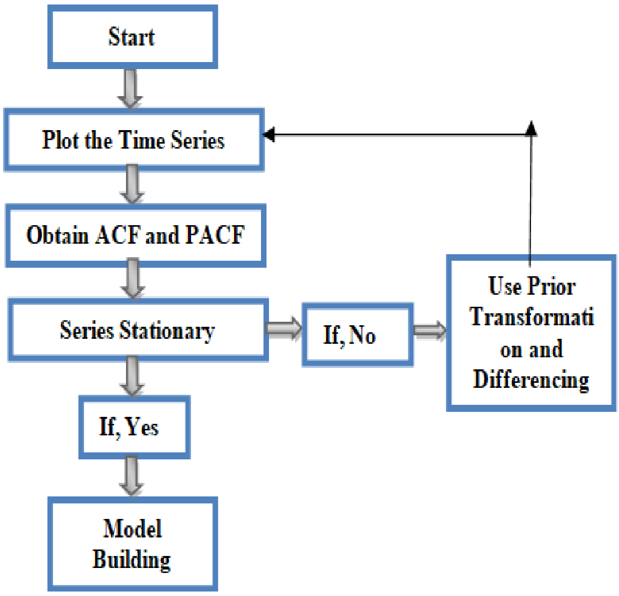

Figure 1. Model Building Process for Non-stationary Series

While non-stationary series' autocorrelation differs significantly from zero at multiple lags, stationary series' autocorrelation approaches zero rather rapidly. A time series plot's visual representation suffices to describe whether data is stationary or non-stationary. By differencing the data once or twice to the maximum, stationary can be achieved.

In some instances, we obtain the stationary series by transforming the data. The transformation of the given data can be square root, reciprocal, or logarithmic. The time series that are stationary and non-stationary are shown in Figures 2 and 3. The majority of time series exhibit non-stationary. A technique for eliminating non-stationary is the differencing method.

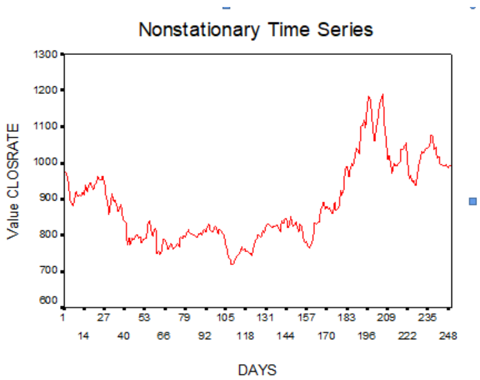

Figure 2. Non-stationary Time Series

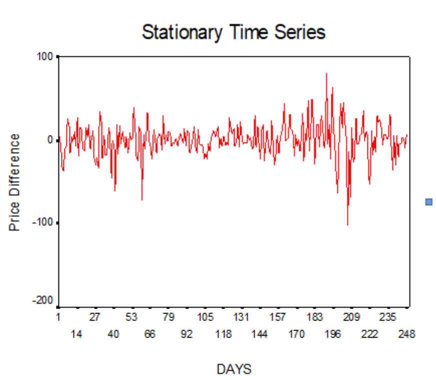

Figure 3. Stationary Time Series

Figure 4 summarizes the Box – Jenkins time series modeling approach.For lag (k), the Autocorrelation function (ACF) is given by

$$r_k = \frac{\sum_{t=k+1}^{n} (\lambda_t - \bar{\lambda})(\lambda_{t-k} - \lambda)}{\sum_{t=1}^{n} (\lambda_t - \bar{\lambda})^2}$$

λ - is the time series mean with 'n' observations located?

The correlation between the series and itself, lagging by period k, is represented by the autocorrelation function at lag (k) for the observed time series. When the number of observations is high enough $n \geq 50$, the sampling distribution of the autocorrelation coefficient of white noise data can be roughly represented by a normal curve with mean zero and standard error $(1/\sqrt{n})$.

Here, $t = \frac{ACF(k)}{Std.Error(k)}$ is a normal variate and ACF(k) is substantially different from zero at 5% level of significance if the magnitu-tude of t is greater than 1.96, is used to assess the significance of the ACF (k), or whether the ACF(k) is significantly distinct from zero.

The degree of link between Y_t and Y_t – k is measured using partial autocorrelation after the influence of other time lags at 1, 2, 3, 4,.. k – 1 is eliminated. With standard error $(1/\sqrt{n})$, the estimated partial autocorrelation is normally distributed and roughly independent. The ACF and PACF coefficients at various lags can be used to identify the seasonality of the time series. There will be a noticeable autocorrelation at seasonal lag multiples. A monthly seasonal data set may exhibit a significant amount of autocorrelation at lags of 12, 24, etc. Since there is no seasonality in the time series taken into consideration for this research project, it is not covered in detail. The Autoregressive Moving Average Model (ARMA), a valuable class of time series models, can be created by combining the auto regression (AR) and moving average (MA) models in an efficient manner. When the series remains steady, the Model can be applied. By permitting differencing (d) for the data, the ARMA model can be expanded to non-stationary time series, resulting in the ARIMA model and the parameters are as follows: I: d = degree of difference, AR: p = Auto regressive component, and MA: q = Moving Average part.

Table 1: Parameter p and q theoretical selection

Process	ACF	PACF
AR (1)	When something decays exponentially, it starts on the negative side $\phi_1 < 0$ and changes signs on the positive side if $\phi_1 > 0$	peak at lag 1 and then drop off at zero Positive $\phi_1 > 0$ and negative $\phi(1) < 0$ spikes are possible.
AR (p)	Dither exponential decay or damped sine wave. The exact pattern is established by the strength and indications of ϕ_p, $p = 1,2,..k$	Increases to p at lag 1 and then stops at zero
MA(1)	Peak at one lag time, then cease suddenly at zero. Positive $\phi_1 < 0$ and negative $\phi_1 > 0$ spikes are possible.	If ϕ_1 is more than zero, exponential decay starts on the negative side and switches signs

		if ϕ_1 is less than zero.
MA(q)	Increases at lag 1 to q before cutting off at zero	Either exponential decay or damped sine waves. The sizes and indications of $\phi_i, i=1,2...q$ each component define the exact pattern.

The general ARIMA model without constant term is represented as

$$\left(1-\sum_{i=1}^{p}\phi_i B^i\right)(1-B)^d Y(t)=\left(1-\sum_{i=1}^{p}\phi_i B^i\right)e(t)$$

The moving average and auto-regression parameters p and q have the following restrictions on their permissible values.

for p = 1, $-1 < \phi_1 < 1$

for p = 2 , $-1 < \phi_2 < 1$, $\phi_2 + \phi_1 < 1$, $\phi_2 - \phi_1 < 1$,

for q = 1, $-1 < \theta_1 < 1$

for q = 2 , $-1 < \theta_2 < 1$, $\theta_2 + \theta_1 < 1$, $\theta_2 - \theta_1 < 1$,

More complex requirements apply to p greater than three and q less than three. There are several ARIMA models available for forecasting and time series fitting. Nonetheless, the model selection guidelines are provided below. Check the ACF and PACF when the stationary has been reached. In the event that there is no significant Auto correlation following lag (q), the MA (q) model might be suitable. In the event where lag p yields no significant PACF, an AR (p) model might be suitable. A particular set of data in a time series study may be represented by one or more suitable models. Often, it's simple to make the right decision. The literature for model selection has suggested a number of criteria for model assumption, including

The Information Criterion of Akaike

The Bayesian Information Standard

The final prediction error of Schwartz's Bayesian Criterion

Using a Corner Table

The lowest value of AIC or SBC gives the best model for fitting the Time Series.

$$AIC(m) = n(1 + \log 2\pi) + \left(e^{\sigma^2}\right)^n + 2m$$

3. ACC using the ARIMA model

Figure (3) shows the daily closing stock price graph of Associated Cement Company (ACC) for the period of 9 January 2008 to 3 November 2008. The graph makes it clear that the time series is not stationary. As a result, the first difference is computed, and Figure (6) provides the appropriate graph. The time series now become motionless. The ARIMA Model has been determined by taking into account this sample data. The figure (7) provides the ACF. Table (5) displays the coefficients, T-Ratio, Standard Error, and Log Likelihood. The time series lacks seasonality and pattern, as indicated by the ACF. Figure (11) displays the plot of the price, forecast, and 95% upper and lower control lines. In Figure (12), the residual ACF and PACF plots are displayed. Since the residual plot of this series is comparable to that of white noise, it fits in nicely as $(1 - \phi_1 B)(1 - B) Y_t = e_t$, , $Y_t = 1.1156166\, Y_{t-1} - 0.1156166 Y_{t-2} + e_t$

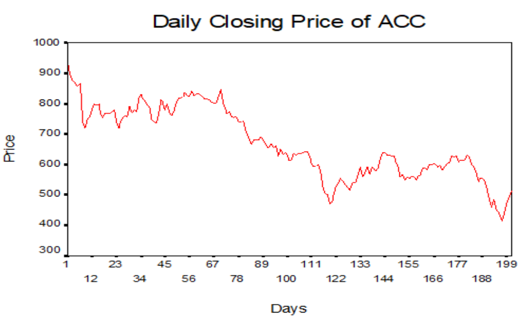

Figure 5. Graph of Daily Closing Price of ACC

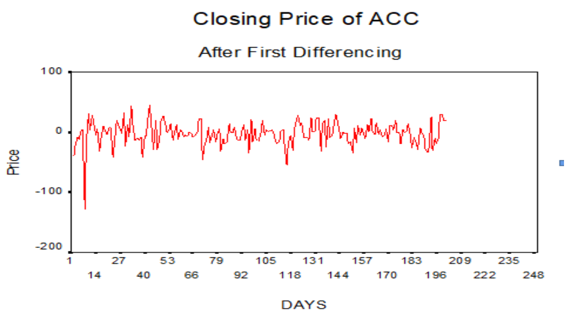

Figure 6. After Differencing Graph of Daily Closing Price

Figure (11) shows the plot of Price, Forecast, Upper and Lower Control Limit at 95% Confidence Level.

Table 2. Autocorrelations : Daily Closing Rate of ACC

Lag	Corr.	Err.	-1 -.75 -.5 -.25 0 .25 .5 .75 1	Box-Ljung	Prob.
1	0.113	0.070	.@**.	2.608	.106
2	-.026	0.070	.*@ .	2.743	.254
3	-.002	0.070	.*.	2.744	.433
4	-.097	0.070	.**@ .	4.693	.320
5	-.049	0.069	.*@ .	5.195	.393
6	0.059	0.069	.@*.	5.911	.433
7	0.016	0.069	.*.	5.962	.544
8	0.051	0.069	.@*.	6.511	.590
9	0.021	0.069	.*.	6.600	.679
10	-.064	0.069	.*@.	7.469	.681
11	-.029	0.068	.*@.	7.644	.745
12	-.032	0.068	.*@ .	7.867	.795
13	-.096	0.068	.**@ .	9.842	.707
14	-.036	0.068	.*@ .	10.125	.753
15	0.089	0.068	.@**.	11.852	.690
16	-.003	0.067	.*.	11.854	.754
17	-.024	0.067	.*.	11.984	.801
18	-.004	0.067	.*.	11.989	.848
19	-.002	0.067	.*.	11.989	.886
20	-.004	0.067	.*.	11.992	.916
21	0.019	0.067	.*.	12.725	.941
22	-.053	0.066	.*@.	12.725	.941
23	-.005	0.066	.*.	12.732	.958
24	-.002	0.066	.*.	12.732	.970
25	-.095	0.066	.**@.	14.816	.946
26	-.073	0.066	.*@.	16.060	.935
27	-.043	0.065	.*@.	16.485	.943
28	0.018	0.065	.*.	16.565	.957
29	-.028	0.065	.*@ .	16.745	.966
30	-.026	0.065	.*@.	16.906	.974
31	0.006	0.065	.*.	16.913	.981
32	0.031	0.064	.@*.	17.147	.985
33	0.042	0.064	.@*.	17.564	.987
34	-.003	0.064	.*.	17.565	.991
35	-.038	0.064	.*@.	17.914	.993
36	0.135	0.064	.@***	22.414	.963
37	0.077	0.064	.@**.	23.900	.953
38	-.012	0.063	.*.	23.938	.963
39	0.127	0.063	.@***	28.005	.905
40	-.021	0.063	.*.	28.121	.921

Table 3. Partial Autocorrelations : Daily Closing Rate of ACC

Partial Autocorrelations: Daily Closing Rate of ACC

Transformations: difference (1), Pr-Aut- Stand.

Lag	Corr.	Err.	-1 -.75 -.5 -.25 0 .25 .5 .75 1
1	0.113	.071	.@**.
2	-.039	.071	. *@ .
3	0.006	.071	. * .
4	-.100	.071	.**@ .
5	-.027	.071	. *@ .
6	0.062	.071	.@* .
7	0.000	.071	. * .
8	0.046	.071	.@* .
9	0.001	.071	. * .
10	-.055	.071	. *@ .
11	-.009	.071	. * .
12	-.027	.071	. *@ .
13	-.086	.071	.**@ .
14	-.033	.071	. *@ .
15	0.085	.071	.@**.
16	-.025	.071	. *@ .
17	-.033	.071	. *@ .
18	-.005	.071	. * .
19	0.025	.071	. * .
20	0.003	.071	. * .
21	0.011	.071	. * .
22	-.061	.071	. *@ .
23	-.005	.071	. * .
24	-.010	.071	. * .
25	-.089	.071	.**@ .
26	-.074	.071	. *@ .
27	-.049	.071	. *@ .
28	0.045	.071	.@* .
29	-.052	.071	. *@ .
30	-.048	.071	. *@ .
31	0.010	.071	. * .
32	0.044	.071	.@* .
33	0.048	.071	.@* .
34	-.024	.071	. * .
35	-.051	.071	. *@ .
36	0.148	.071	.@***
37	0.065	.071	.@* .
38	-.045	.071	. *@ .
39	0.097	.071	.@**.
40	-.031	.071	.*@ .

Plot Symbols: Autocorrelations * Two Standard Error Limits.

Total cases: 250 Computable first lags after differencing: 199

Table 4. Variables in the Model

	DF	Adj. Sum of Squares	Residual Variance
Residuals	198	75570.676	381.64440

Table 5. Variables in the Model

	B	SEB	T-RATIO	APPROX. PROB.
AR1	0.1156166	0.0708017	1.6329634	0.10406590
DAYS	-2.1381374	1.5609543	-1.3697630	0.17231226

Table 6 . AIC - SBC

	AIC : 1759.118 SBC : 1763.416	AIC : 1758.486 SBC : 1765.083	AIC : 1760.211 SBC : 1700.106
1	AIC : 1758.8 SBC : 1769.9	AIC : 1760.012 SBC : 1769.907	AIC : 1762.0 SBC : 1775193
2	AIC : 1760.125 SBC : 1770.019	AIC : 1762.0 SBC : 1775.196	AIC : 1759.118 SBC : 1763.416

Results	
Number of Residuals	200
Standard error	19.535721
Log likelihood	-877.24329
AIC	1758.4866
SBC	1765.0832

Table 7. Analysis if Variance

	DF	Adj. Sum of Squares	Residual Variance
Residuals	198	75570.676	381.64440

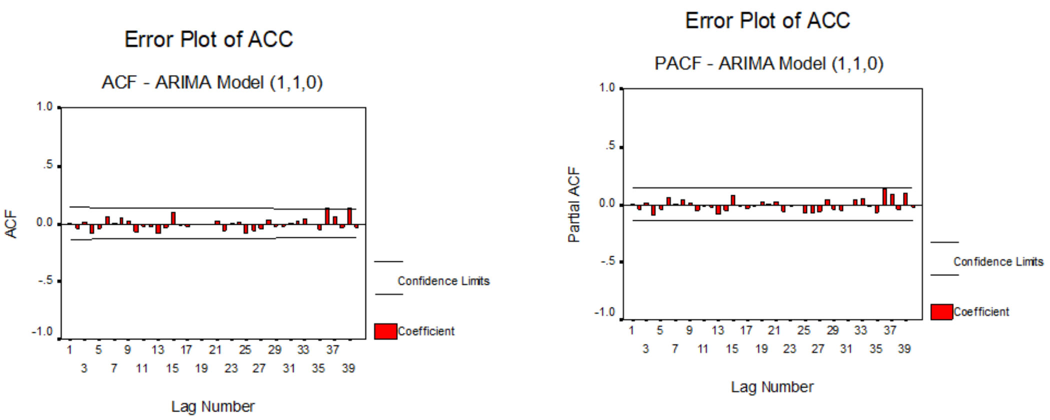

Figure 7. Error Plot of ACC – PACF

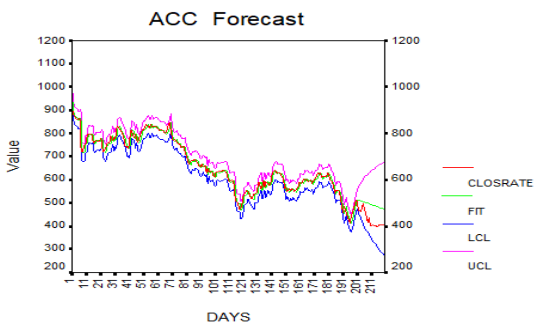

Figure 8. ACC Forecast

4. ARIMA mode for M&M

Figure 9 displays the time series plot of the closing stock price for Mahendra & Mahendra. Consideration is given to sample data during the time frame spanning from January 9, 2008, to December 3, 2008. Since the series is not stationary, the first difference is computed, and Figure (10) provides the relevant curve. Figures (11) and (12) provide for the time series. Table (6) presents a tabulation of the AIC and SBC values. ACF, PACF, and the lowest AIC or SBC value are used to choose the fitting model, which is (2, 1, 1). White noise is evident in the error plot presented in Figures (11) and (12).

The model fitted is:$(1 - \phi 1 \text{ B} - \phi 2 \text{ B2}) (1 - \text{B}) \lambda \text{t} = (1 - \theta_1 \text{B}) \text{ et}$, Where, Bn λ (t)= Y(t) – n ,

simplifying we get , $[1- (1+ \phi1)\text{B} + (\phi1 - \phi2)\text{B2} + \phi2\text{B3}] \lambda (\text{t}) = \text{e(t)} - \text{e(t)} \theta_1 - 1$,

Substituting the values of $\phi1$,$\phi2$ and θ_1

λ (t) = 2.2205353 Y(t) – 1 – 1.5134632 λ (t) – 2 + 0.2929279 λ (t) – 3 + e(t) – 0.9976704 e(t) – 1

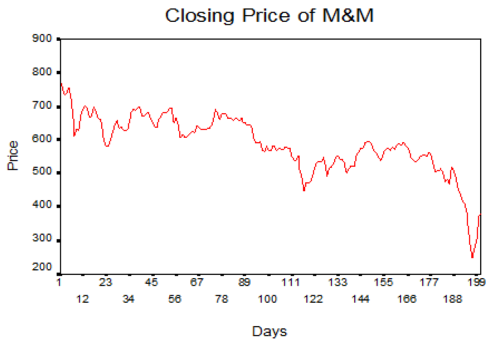

Figure 9. Closing Price of M&M

Figure 10. Closing Price of M&M - After First Differencing

Table 8. Autocorrelations – Daily Closing Rate of M&M

Autocorrelations: Daily Closing Rate of M&M

Transformations: difference (1), Auto- Stand.

Lag	Corr.	Err.	-1 -.75 -.5 -.25 0 .25 .5 .75 1	Box-Ljung	Prob.
1	.255	.070	.@**.	3.173	.000
2	.056	.070	.@* .	13.813	.001
3	-.117	.070	.**@.	16.613	.001
4	-.093	.070	.**@.	18.412	.001
5	-.127	.069	.***@	21.775	.001
6	-.077	.069	.**@.	23.013	.001
7	-.009	.069	.*.	23.032	.002
8	-.053	.069	.*@.	23.629	.003
9	-.114	.069	.**@	26.375	.002
10	-.097	.069	.**@	28.369	.002
11	.033	.068	.@*.	28.599	.003
12	.040	.068	.@*.	28.949	.004
13	.107	.068	.@**.	31.412	.003
14	.005	.068	.*.	31.418	.005
15	.075	.068	.@*.	32.646	.005
16	.050	.067	.@*.	33.196	.007
17	.028	.067	.@* .	33.374	.010
18	.019	.067	.*.	33.453	.015
19	-.079	.067	.**@.	34.835	.015
20	-.108	.067	.**@.	37.466	.010
21	.005	.067	.*.	37.471	.015
22	.033	.066	.@*.	37.720	.020
23	.040	.066	.@*.	38.084	.025
24	.028	.066	.@*.	38.261	.033
25	.020	.066	.*.	38.354	.043
26	.021	.066	.*.	38.452	.055
27	-.083	.065	.**@.	40.045	.051
28	-.047	.065	.*@.	40.559	.059
29	-.075	.065	.**@ .	41.898	.057
30	-.025	.065	.*@.	42.052	.071
31	-.053	.065	.*@.	42.722	.078
32	-.034	.064	.*@.	42.996	.093
33	-.007	.064	.*.	43.007	.114
34	-.019	.064	.*.	43.092	.136

35	-.046	.064	.*@.	43.608	.151
36	.059	.064	.@*.	44.473	.157
37	.037	.064	.@*.	44.815	.177
38	.010	.063	.*.	44.842	.207
39	.093	.063	.@**.	47.003	.177
40	.014	.063	.*.	47.051	.206

Plot Symbols: Autocorrelations * Two Standard Error Limits.
Total cases: 251 Computable first lags after differencing: 199

Table 9 Partial Autocorrelations – Daily Closing Rate of M&M
Transformations: difference (1), Pr-Aut- Stand.

Lag	Corr.	Err.	-1 -.75 -.5 -.25 0 .25 .5 .75 1
1	0.255	.071	.@**.**
2	-.010	.071	.*.
3	-.138	.071	.***@ .
4	-.033	.071	.*@.
5	-.093	.071	.**@.
6	-.038	.071	.*@.
7	0.014	.071	.*.
8	-.086	.071	.**@.
9	-.118	.071	.**@.
10	-.058	.071	.*@ .
11	0.057	.071	.@*.
12	-.012	.071	.*.
13	0.059	.071	.@*.
14	-.069	.071	.*@ .
15	0.070	.071	.@*.
16	0.048	.071	.@*.
17	0.001	.071	.*.
18	0.021	.071	.*.
19	-.094	.071	.**@.
20	-.059	.071	.*@.
21	0.107	.071	.@**.
22	0.022	.071	.*.
23	0.007	.071	.*.
24	0.006	.071	.*.
25	0.019	.071	.*.
26	0.033	.071	.@*.
27	-.077	.071	.**@.
28	-.041	.071	. *@.
29	-.084	.071	.**@.
30	0.004	.071	.*.
31	-.037	.071	. *@.
32	-.032	.071	.*@.
33	-.017	.071	.*.
34	-.061	.071	.*@.
35	-.040	.071	.*@.
36	0.069	.071	.@*.
37	-.044	.071	.*@.
38	-.048	.071	.*@.

Plot Symbols: Autocorrelations * Two Standard Error Limits.
Total cases: 251 Computable first lags after differencing: 199

Table 10. M&M - Parameters (2, 1, 1)

	DF	Adj. Sum of Squares	Residual Variance
Residuals	198	62888.828	317.49576

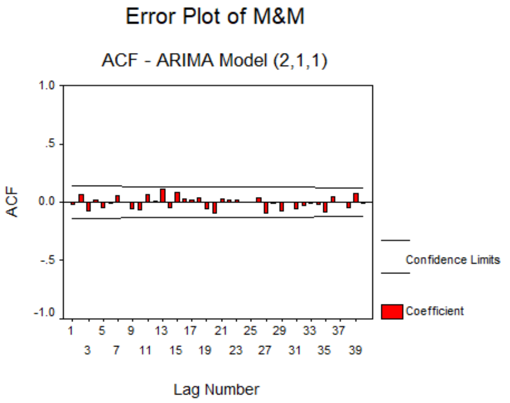

Figure 11. Error Plot of M&M

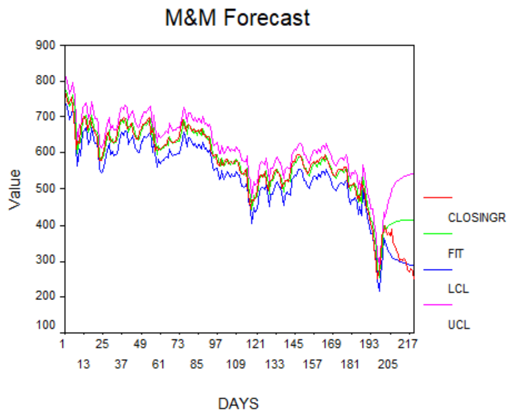

Figure 13. M&M Forecast

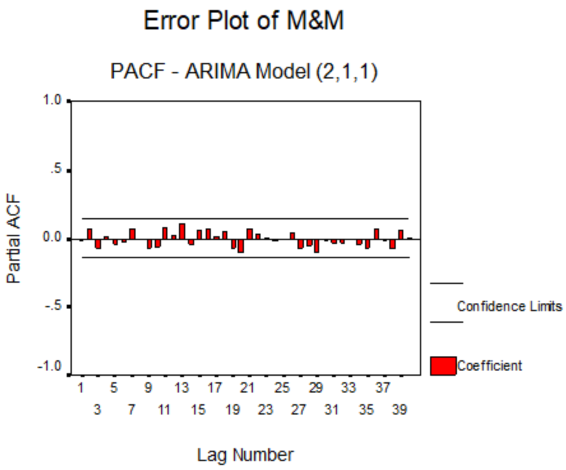

Figure 12. Error Plot of M&M (PACF)

Table 11. Model Selection for M&M

q\p	0	1	2
0	AIC : 1740.629 SBC : 1743.928	AIC : 1729.214 SBC : 1735.811	AIC : 1731.219 SBC : 1741.116
1	AIC : 1730.496 SBC : 1737.093	AIC: 1731.224 SBC : 1741.119	AIC : 1725.746 SBC : 1738.934
2	AIC : 1729..831 SBC: 1739.726	AIC : 1730.700 SBC : 1743.894	AIC : 1728.865 SBC : 1745.357

Table 12. Variables in the Model

	B	SEB	T-RATIO	APPROX. PROB.
AR1	1.2205353	0.06902807	17.681725	0.00000000
AR2	-.2929279	0.06857520	-4.271630	0.00003024
MA1	0.9976704	0.11449815	8.713420	0.00000000
DAYS	1.3908019	26709109	-5.207220	0.00000048

5. CONCLUSION

In this chapter, the future prices of the sample companies are predicted using the Box and Jenkins-popularized ARIMA model. Comprehensive explanations of ARIMA's systematic representation and model identification are provided. In order to make it easier to understand how the properties of the underlying stochastic process vary over time, stationery and nonsationary time series are shown graphically. It is explained how to transform differencing (d) to obtain stationary time series. Crucial are the ACF and PACF error charts, which are displayed in the pictures. Based on the AIC and SBC values, each company's p, d, and q values are established. Estimated parameters have been tabulated for each stock. The following six corporations had their ARIMA models created: ACC, M&M, TATA MOTORS, IOB, TVS MOTORS, and GRASIM; ARIMA model and the range of parameter such as: (1,1,0), (2,1,1), (0,1,1),(2,1,2), (0,1,1) and (0,1,0). In figures (9), (10), (11), (12), and (13), the actual stock closing price and the forecast price with control limits are compared.

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