NIFTY PRICE INDEX VALUE FORECASTIN USING ARIMA MODEL

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Abstract

The primary aim of employing the ARIMA model for nifty index forecasting is to predict future values through the analysis of historical data.This,econometric approach,the ARIMA model aims to establish a connection between current observed values and their prior values in order to anticipate upcoming trends and events. This model utilizes historical data to analyze and make accurate forecast of future trends. Thereby improving decision making in financial and economic situations.ARIMA model is important to emphasize that the both nifty index and the sensex index often demonstrate correlation with stock prices. Stock prices often align with performance of these two prominent stock market indicies,especially the fluctuations in the nifty 50 index, which composed of 50 selected companies. These indicies,the nifty 50 and sensex ,play a crucial role in the assessing overall stock market performance and have a significant impact on investor sentiment decision making.

Keywords: ARIMA, forecasting, stock market price index, time series, nifty

1. Introduction

The Indian capital market has altered dramatically in the last ten years as a result of different changes. The reforms have had an impact on every section of the Indian capital market, including the primary market, secondary market, derivative market, and mutual funds.

Today, our Indian capital market is one of the most transparent and free of corruption. In recent years, investors have come to believe that market volatility has increased dramatically. The Indian market has improved as a result of contraction in various settlement cycles, pre and post derivative market liberalization, and corporate governance standards, and so on

Stock market volatility and predicting a stock price is a important subject of researcher. in a recent financial markets, speculators, investors and traders have had a worry to predicting the stock market price index. In this ARIMA model can explore more relevant and accurate forecasting index value by removing these difficulties.In this study aim to investigate the application of autogressive integrated moving average (ARIMA) for forecasting weekly stock market price index in nifty for the period from 2013 to 2023. In this study to give a education guidelines to the trader or investor in terms of forecasting and will encourage future academics to use the ARIMA model as a forecasting model.

In this research paper provide a elaborate overview of ARIMA model followed by data description and data collection followed by data analysis and findings obtained. Finally conclude the findings

2. Review of literature

Mistra Vantra (2012)The researcher has scrutinized a form of efficiency that is considered weak, conducting an analysis of data covering a 10-year period from the Indian stock market. The study has delved into a report that challenges the weak form by supporting the idea that the selected return data set lacks randomness. This investigation has brought to light different inconsistencies in market efficiency, providing investors with potentially lucrative trading strategies.

(Ariyo, A.A., Adewumi, A.O. and Ayo, C.K., 2014) The suggested hybrid model consists of two main components: the ARIMA component and the SVMs component. This design enables the model to effectively capture both linear and nonlinear patterns, resulting in enhanced accuracy in overall forecasting. The model introduced here is expected to significantly enhance the predictive capabilities compared to using a single ARIMA model for stock price forecasts. The study highlights that the mere combination of the two most successful individual models doesn't always yield the best outcomes. Hence, the meticulous selection of optimal model parameters holds substantial importance.

The research paper authored by Ariyo, A.A., Adewumi, A.O., and Ayo, C.K. in 2014 extensively explored the process of constructing time series models for the prediction of stock prices using the ARIMA model. The study utilized data from both the New York Stock Exchange (NYSE) and the Nigeria Stock Exchange (NSE) for their investigation. Employing the E views analytical software, they gathered stock data from these two distinct countries. The dataset comprised four key elements: open price, low price, high price, and close price. For the research's scope, the closing price was selected to represent the index's price intended for prediction. This choice was made due to its comprehensive reflection of all the index's activities within a trading day. The outcomes of their analysis unveiled the ARIMA model's potential for short-term prediction. According to this study, ARIMA models can reasonably compete with emerging forecasting techniques when it comes to short-term prediction tasks.

In a study conducted by Vipul (2007), an exploration into the alteration of volatility within the Indian Stock market subsequent to the introduction of derivatives was undertaken. This investigation employed the extreme value measure of volatility. However, it's noteworthy that the Nifty index exhibited a conflicting trend. Specifically, there was an increase in its unconditional GARCH (Generalized Autoregressive Conditional Heteroskedasticity) volatility and persistence, which presented a contradictory pattern compared to the underlying shares.

In their research titled 'Study on Australian Stock Market using ARIMA Model' (Brooks et al., 1999), the authors aimed to determine the potential influence of two macroeconomic variables, GDP and Current Account balance, on Australian stock returns. The investigation spanned a period of four years and involved the analysis of two ordinary indices: the 10-year bond and the 3-year bond future.

Upon analyzing the data, the study's outcome indicated a conclusive finding. Specifically, the research found that neither GDP nor the current account balance exhibited a substantial impact on Australian stock returns. Despite assessing these macroeconomic variables over a span of four years and across different indices, the researchers concluded that neither GDP nor the current account balance significantly affected the behavior of stock returns within the Australian stock market.

In the study by Krishna Murari (2013) titled 'Volatility Modeling and Forecasting for Banking Stock Returns', the author aimed to predict the short-term volatility of the Indian Banking sector by utilizing the ARIMA model. The focus of the study was on the 12 most liquid and largest capitalized Indian Banking stocks. A substantial dataset of over 3000 observations was employed to model the volatility of returns from these banking stocks, utilizing the Univariate Box-Jenkins or ARIMA model.

In the research conducted by Fatai Adewole Adebayo, Ramysamy Sivasamy, and Dahub Kehinde Shangodoyin (2014) titled 'Forecasting Stock Market Series with ARIMA Model', it was revealed that the ARIMA model holds a prominent position as a widely utilized time series model. This model serves as a valuable tool for investors to predict future trends using historical data. The ARIMA model provides a foundational framework for assessing the forecasting performance across various types of underlying assets.

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In Navaneethan's study (2015) titled "ARIMA modeling to forecast future oil prices," the research aimed to predict future prices of WTI Crude Oil using an ARIMA model. The study spanned a period of 13 years, from 2003 to 2016, which provided a robust dataset for modeling. The model's outcomes effectively projected the future positions of oil prices, extending forecasts for the next twelve months up until October 2017.

The study conducted by Banhi Guha and Gautam Bandyopadhyay (2016), titled "Gold price forecasting using ARIMA model," delved into the process of predicting future gold prices as a means to manage investors' risks. The research centered around employing the ARIMA time series model for gold price prediction.

OBJECTIVES OF THE STUDY

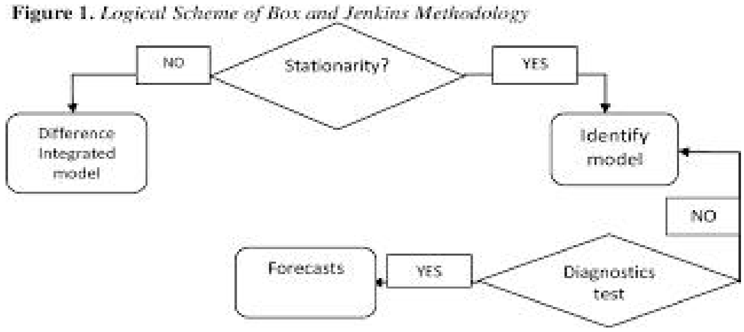
On the basis of literature reviews and gaps identified, the following objectives have been framed:

- To understand the factors that affect index volatility.
- To develop an ARIMA model that can be used to forecast the future price of a NIFTY index.
- To evaluate the accuracy of the ARIMA model by comparing its predictions with actual index value.
- To identify the selected stocks that are most likely to experience high volatility in the future.
- To provide investors with insights into the potential risks and rewards of investing in nifty index.

3. Research Methodology

To forecast the nifty index value in Indian stock market. in this paper applies the ARIMA model are framed by box Jenkins. It also known box Jenkins methodology which consist of some primary steps as identifying, estimating ,diagnosing.

Figure 1. *Logical Scheme of Box and Jenkins Methodology*



The ARIMA model utilizes both AR and MA components. The AR component is utilized to illustrate that the present residuals from previous observation create a linear association. ARIMA (p,d,q) where p denotes the degree of AR model, d denotes the degree of different order and q denotes the degree of MA model. The ARIMA (p, d, q) model takes the following form:

$\Delta dYt = c + \phi p\Delta dYt\text{-}1 + \ldots + \phi p\Delta dYt\text{-}p + \varepsilon\ t + \theta 1\ \varepsilon\ t\text{-}1 + \ldots\ldots + \theta q\varepsilon\ t\text{-}q$

Where ΔdYt indicates a differenced dependent variable at time t, ΔdYt−1, ΔdYt−p indicate the differenced lagged dependent variables, c is a constant, ϕ1, ϕp, θ1, θq indicate model parameters, εt is the residual term and εt−1, εt−q are the previous values of the residual.

3.1. Research Design

The Research Design is the strength of character of the research procedure. The research design using in the study is descriptive research which adds shape to our research problem and the research information which is not manipulated. Official daily data of nifty index between 2013-2023 has a total number of 2465 observations which are used to estimate and predict model. It must be noted that the data is divided in to two parts. first part is the in the sample data which covers the period from 2013 from 2023 has a total number of 2465 observation which are used to estimate model, second part is out of sample data which covers the period from 2023 and is used for forecasting.

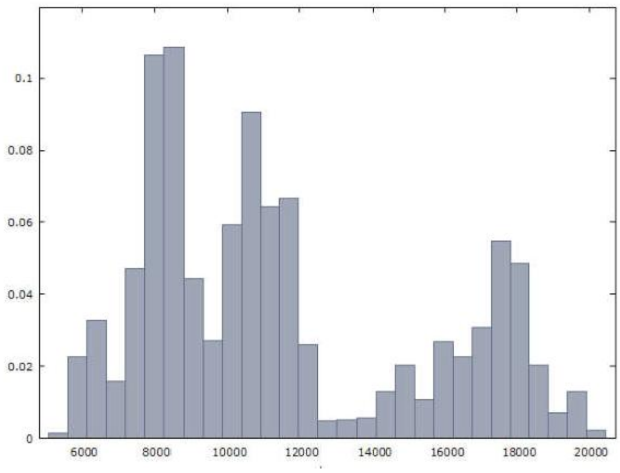
4. Data Description

Official daily value of nifty index of national stock exchange between 2013 and 2023 has a total number of 2465 observation which are used to evaluate and predict the model. It must be noted that the data is divided into two parts, first part cover the sample data which contain the period from 2013 to 2023 and its used for predicting the index value in future. in this data derived from national stock exchange. table 1.display the descriptive statistics of the daily nifty index value for the study selected period. it shows the value of positive skewness 0.63463 which refers to the degree to which the data are asymestric.it has a negative kurtosis (-0.85468),indicating that the distribution has lighter tails than the normal distribution.

Table 1 Descriptive Statistics

Observation	2465
Mean	11485
Median	10607
Minimum	5341.5
Maximum	20192
Standard deviation	3839.80
C.V.	0.33432
Skewness	0.63463
Kurtosis	-0.85468
Jarque-Bera test	240.49

Figure 2. Distribution of the monthly stock market NIFTY price index



4.1. Stationery test

According to the nifty price index series plot between 2013 to 2023 in figure 3, shows that the nifty index value are non stationary at level. As a result non stationery series is used to convert stationery series using lag differencing technique. The plot of nifty index and the differenced nifty value index have been illustrated in figure 3 and figure 4. Figure 3 shows that there is a trend that series. and figure 4 shows that the data are stationery at first differenced.

Figure 3. The Nifty Price Index Series Plot Between 2013-2023

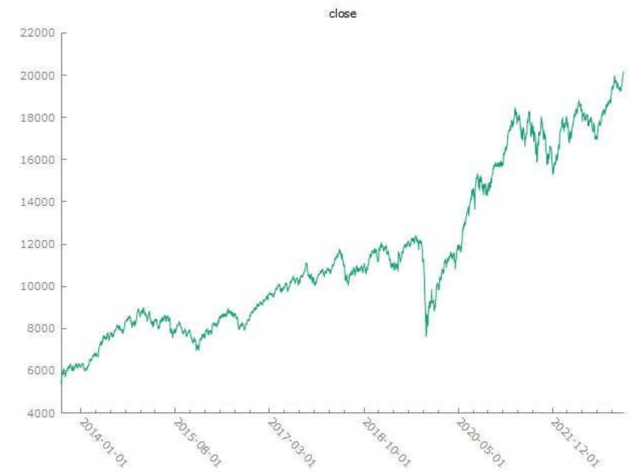
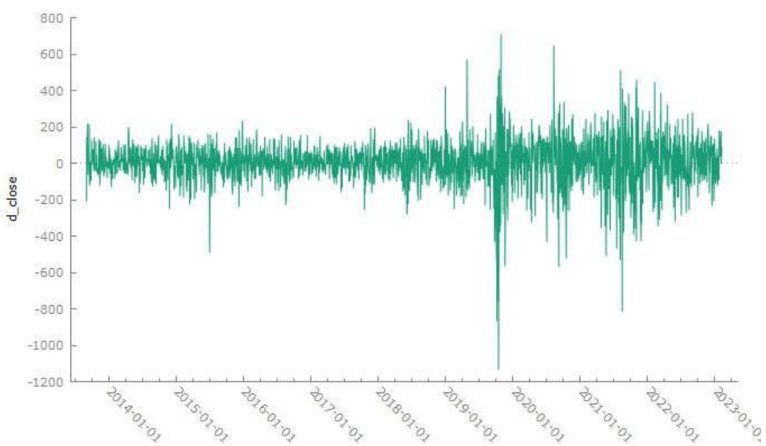
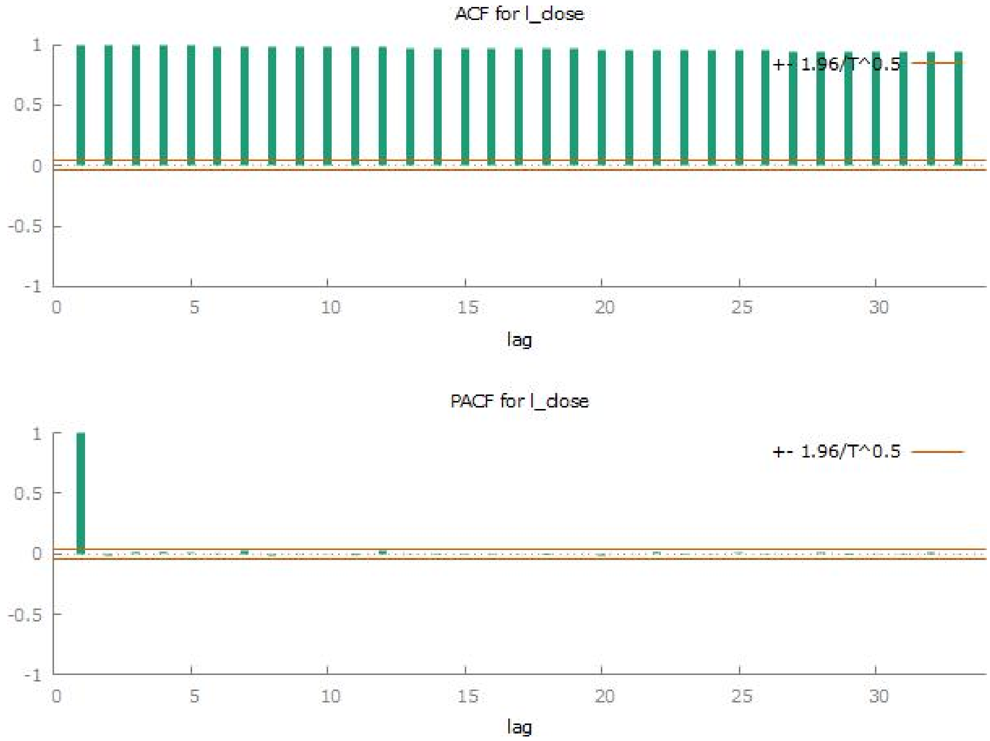


Figure 4. The Differenced Nifty Price Index Series Plot Between 2013-2023



The autocorrelation and auto correlation function graphs of the nifty price index series have been illustrated figure 5. Figure 5 shows that there is partial autocorrelation in the 1st lag. In other lags, there is no autocorrelation since the values are between the significant lines.besideses that the lag 3 and 4,the bar still far from zero and the lags decline quickly, so we conclude that the nifty index time series is not stationery

Figure 5. The Autocorrelation and Partial Autocorrelation Function Graphs of the Nifty Index



Price Series

At the next step augument dickey fuller test at the level was done an the trend and intercept was included for the unit root test. The results of unit root test have been illustrated in table 1. When we look at the p value at level, it seen that the value is 0.9654 (bigger than 0.05).it means the null hypothesis cannot be rejected. We accept that the variables has unit root test.so we have a non stationery variables and we are going to work with ARIMA model(p,d,q).we apply third difference unit root test at third difference is smaller than 0.05.in this case,first difference is going to be enough for identification models

Table 2: The Result of Unit Root Test

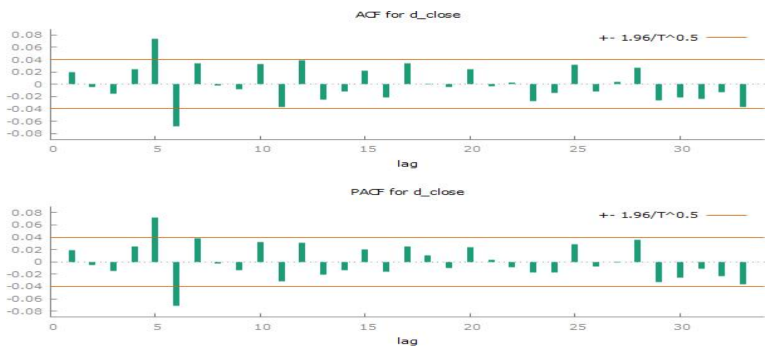
	ADF			
Variable	Level		1st Difference	
SPI	t-Statistic	Probability	t-Statistic	Probability
	-3.372644	0.0591	-11.86094***	0.0000

Notes: *** 1 percent level

4.2. Model identification

At the next step is model identification. We check the correlogram to determine p for AR component and q for a MA component of ARIMA model. To found p and q values, we are going to use the auto correlation and partial auto correlation functions.ACF and PACF may suggest to derive the possible models. The autocorrelation and partial autocorrelation graphs have been illustrated in figure 6

Figure 6. The Autocorrelation and Partial Autocorrelation Function Graphs in First Difference



In the table 3 shows that the tentative ARIMA (p,d,q) test results for various parameters.Adjusted R squared,AIC,SC,HQC values and parameter significance are all crucial criteria for selecting models.in general ,the larger coefficient of determination and adjusted R squared,and the smaller the AIC,HQC,and SC values,better ARIMA (p,d,q) model.so the possible models are going to be following.

Table 3: Statistical Results of the Tentative ARIMA models.

Nifty index	Arima 101	ARIMA 202	ARIAM 313	ARIMA 413
Adj R2	0.99041	0.99042	0.999055	0.999056
AIC	30573.05	30575.47	30517.33	30517.03
SBC	30596.29	30610.33	30563.81	30569.32
HQC	30581	30588.14	30534.22	30536.03
P Value	0.321	0.333	0.0162	0.126

Tables 4 indicate the estimated results for the chosen ARIMA (4,1,3) model and diagnostic tests, respectively.

Table 4: Estimation Results of the ARIMA (4,1,3) Model

Mean dependent var	5.942208	S.D. dependent var	118.9213
Mean of innovations	−0.000413	S.D. of innovations	117.9142
R-squared	0.999056	Adjusted R-squared	0.999054
Log-likelihood	−15249.52	Akaike criterion	30517.03
Schwarz criterion	30569.32	Hannan-Quinn	30536.03

	Coefficient	*Std. Error*	*Z*	*p-value*	
Const	5.94168	2.38259	2.494	0.0126	**
phi_1	−1.64762	0.127632	−12.91	<0.0001	***
phi_2	−1.16871	0.180662	−6.469	<0.0001	***
phi_3	−0.228436	0.0998748	−2.287	0.0222	**
phi_4	−0.0545660	0.0270315	−2.019	0.0435	**
theta_1	1.67910	0.128565	13.06	<0.0001	***
theta_2	1.21249	0.191655	6.326	<0.0001	***
theta_3	0.220003	0.117213	1.877	0.0605	*

C has a coefficient value of 5.94168,and z-statistic is equal to 2.494 with p-value 0.126.AR (4) co efficient is estimated to be −0.0545660 and z statistic is equal to −2.019 with p-value 0.0435.on the other hand,MA (3) has a coefficient value of 0.220003 and z statistic is equal to 1.877 with p-value 0.0605.

Table 5: Diagnostic Tests Result of the ARIMA (4,1,3) Mode

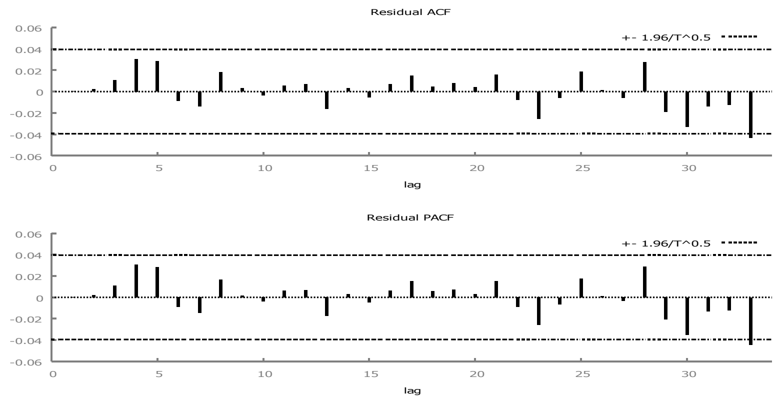
Diagnostic Test:			
Breusch-Godfrey Serial Correlation LM Test:			
F-Statistic	1.033	Prob. F	0.3016
0bs R squared	0.998	Prob. chi Square	0.7491
Heteroskedasticity Test			
F-statistic	0.563024	Prob. F(9,136)	1.8253
Obs*R-squared	0.196720	Prob. Chi-Square(9)	1.8125
Scaled explained SS	6.411169	Prob. Chi-Square(9)	0.6574
Normality Test			
Jarque Bera	2.404921	Probability	0.378128
Ramsey RESET Test			
	Value	Probabilty	
t-statistic	2.27059	0.0233	
F-statistic	3.77390	0.0233	

Likelihood ratio	0.02384	0.0231

The diagnostic tests in Table 5 show that there is no heteroskedasticity where p-value (0.6982) is greater than 5%. Moreover, LM Test (p-values 0.6574) reveals that the model has no serial correlation. Finally, the Ramsey RESET test confirms the stability of the chosen model because the p-value (0.0231) is greater than the threshold of 5%.

At the next step, the autocorrelation and partial autocorrelation function graphs of the residual series and squared residuals were checked. The graphs have been illustrated in Figure 7 On the graph of series' residuals indicates that the bar at lag 0 to lag 35 at the graph of white noise process is located below the significant line. According to the graph, the p-value for lag 0 to lag 37 are greater than 0.05. So, it means we cannot reject Null Hypothesis (Residuals are white noise). These results imply that the residuals are white noise, which indicates that the model is valid

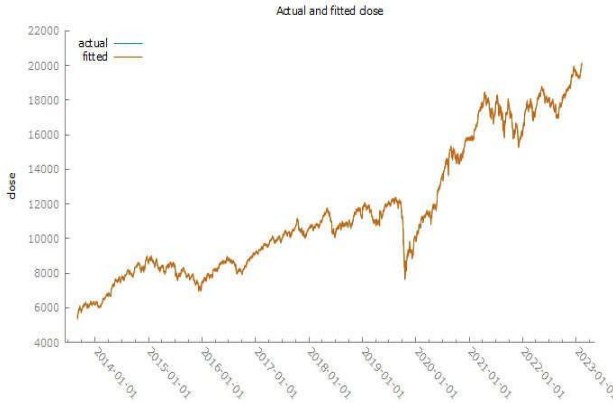
Figure 7 The Autocorrelation and Partial Autocorrelation Function Graphs for Residuals

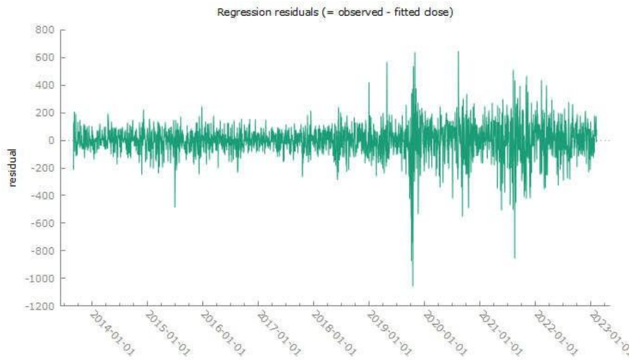


4.3. Data Forecasting

After ensuring that the residuals are white noise and ARIMA process is (covariance) stationary and invertible, so we can forecast with this ARIMA (4,1,3) model. ARIMA (4,1,3) model is used to forecast the stock market price index from 2022 to 2023. The static forecast has been chosen because of better performance than the dynamic one. Table 5 shows the ARIMA (4,1,3) static forecast statistical performance measures showing that the statistic forecast has lower RMSE, MAR, and MAPE values. Additionally, since ARIMA (4,1,3) is the only model with significant coefficients and passed all diagnostic tests, no other models were considered.

Figure 9 &10 shows that the real values of the Nifty index closely follow the forecasted value, indicating that the developed model can accurately predict the stock market price index





5. Conclusion

In this study aims to investigate the application of autogressive integrated moving averages (ARIMA) for predicting the nifty index value for the period from 2013 to 2023.applying the box Jenkins analysis the finding revealed that the nifty index value can be determined using arima approach. As compared to all other tentative models,the research shows that the ARIMA (4,1,3)and the results indicated that the predicted valuesare similar to the actual value, minimizing predicting errors. Generally,the stock market price in nifty explode the upward trend over the predicted period

The results of the study can set an example for researchers and practitioners working in the stock market and can be a guide for economic decision units and investors in the stock market. The number of indicators in the obtained data set can be increased and it is predicted that in future studies, hourly, weekly and monthly data can be added to increase the amount of data and to obtain results with higher accuracy

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