

TREND ANALYSIS AND FORECASTING FOR GOOGLE STOCK PRICE

Submitted in partial fulfillment of the requirements for the award of

Master of Science Degree in Mathematics

By

ANUSUYA A (41630001)



**DEPARTMENT OF MATHEMATICS
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SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with Grade “A” by

NAAC I 12B Status by UGC I Approved by AICTE

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APRIL – 2023



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BONAFIDE CERTIFICATE

This is to certify that this project report is the Bonafide work of ANUSUYA A (41630001) who carried out the project entitled "TREND ANALYSIS AND FORECASTING FOR GOOGLE STOCK PRICE" under our supervision from JANUARY 2023 to APRIL 2023.

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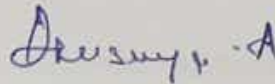
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DECLARATION

I ANUSUYA A (41630001) hereby declare that the project report entitled "TREND ANALYSIS AND FORECASTING FOR GOOGLE STOCK PRICE" done by me under the guidance of Dr Priya Shirley Muller at SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY submitted in partial fulfillment of the requirements for the award of Master of Science Degree in Mathematics

DATE: 26.4.23

PLACE: Chennai



SIGNATURE OF THE CANDIDATE

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ABSTRACT:

The aim of this study is to estimate the future demand for Google's stock price. With the rising industrial demand levels, it is more critical and important than ever to estimate future stock needs so that demands in future can be met. In this work, a forecast was proposed on google stock price prediction model using Auto regressive integrated moving average method (ARIMA) with different possible models to find the best fit of the accuracy. The results have been compared with another model called Exponential smoothing. The work is done using the past 9 years monthly data to forecast till the year 2025.

CONTENTS

CHAPTER 1

INTRODUCTION

1.1 WHAT IS THE STOCK MARKET?	2
-------------------------------	---

1.2 FORECAST	3
--------------	---

1.3 PURPOSE OF FORECASTING	3
----------------------------	---

CHAPTER 2

LITERATURE SURVEY	5
-------------------	---

CHAPTER 3

DATA COLLECTION	8
-----------------	---

CHAPTER 4

METHODOLOGY

4.1 ARIMA	10
-----------	----

4.2 EXPONENTIAL SMOOTHING	12
---------------------------	----

CHAPTER 5

RESULTS AND DISSCUSSION

5.1 SEQUENCE PLOT	14
-------------------	----

5.2 AUTOCORRELATIONS	16
----------------------	----

5.3 PLOT FOR AUTOCORRELATIONS	17
-------------------------------	----

5.4 PARTIAL AUTOCORRELATIONS	18
------------------------------	----

5.5 PLOT FOR PARTIAL AUTOCORRELATIONS	19
---------------------------------------	----

5.6 MAPE	20
----------	----

5.7 RESULTS USING ARIMA	21
-------------------------	----

5.8 FORECAST VALUES	24
5.9 FORECAST PLOT	24
5.10 RESULTS USING EXPONENTIAL SMOOTHING	25
5.11 COMPARISON OF MODELS	26
CHAPTER 6	
CONCLUSION	29
CHAPTER 7	
REFERENCES	31

CHAPTER-1

INTRODUCTION

1.1 WHAT IS THE STOCK MARKET?

The term stock market refers to several exchanges in which shares of publicly held companies are bought and sold.

- Stock markets are venues where buyers and sellers meet to exchange equity shares of public corporations.
- Stock markets are components of a free-market economy because they enable democratized access to investor trading and exchange of capital.
- Stock markets create efficient price discovery and efficient dealing.

Stock prices are driven by corporate earnings or profit expectations. If a trader thinks that the company's earnings are high or will rise further, they will raise the price of the stock. One way for shareholders to get a return on their investment is to buy low stocks and sell them at high prices. If the company performs poorly and the value of the stock declines, the shareholder will lose some or all his investment at the time of sale. Therefore, accurate stock price information is important.

1.2 FORECAST

Forecasting is a process that can predict future events by conducting a study or analysis of past data to find systematic relationships, patterns, and trends. In other words, forecasting itself is a vital part of every business organization and for any significant management decision making.

In future planning, forecasts will become the basis for every company. If a company can predict what will happen in the future, then they can change their current habits and take a position that will be much more developed in the future.

1.3 PURPOSE OF FORECASTING

- In finance, forecasting is used by companies to estimate earnings or other data for subsequent periods.
- Traders and analysts use forecasts in valuation models, to time trades, and to identify trends.
- Forecasts are often predicated on historical data.
- Because the future is uncertain, forecasts must often be revised, and actual results can vary greatly.
- To review the current and past company policies and see how far the influence will be in the future.
- Forecasting is necessary because of the time lag or delay between the time a company policy is set and when the implementation begins.
- Forecasting is the basis of business depreciation in a company so that it can increase the effectiveness of a business plan.

CHAPTER 2

LITERATURE REVIEW

Tan, F, et al. in the article "Development Prospect Analysis of Alphabet" quoted that, the result is that Alphabet has great potential to earn a lot in the future, and people can invest it when the price of the stock is cheaper. On the study of " Stock Price Prediction of "Google" based on Machine Learning" Peng quoted that, on the basis of empirical data, generalized images of classes are formed on the rates of shares of Google and their dynamics, examined the impact of financial market characteristics on these classes, and, based on this, problems of identification and prediction, classification and research of the simulated subject area are solved by studying its model. In "Stock Prediction and Analysis based on RNN Neural Network" Lin, et al. related that, stock price is a time series form of data, the rise and fall of the stock market is related with a variety of good and bad news, showing the state of people's confidence, but there is a certain correlation between the time sequence, so a special type of recurrent neural network (RNN) can be used to model and learn from this time-series related data.

Zhu, et al. in the article "Analysis of Google Trends", focused on the price forecasting model, using two forecasting models to predict the price of Google stock and compare the accuracy, to discuss the fit between different forecasting models and companies, and the impact of forecasting of different lengths of time on the accuracy of the model. Shubakkar in "An Analysis on Tesla's Stock Price Forecasting Using ARIMA Model" stated that, ARIMA model is analyzed for time series prediction, and the results obtained using this model show strong accuracy for short term and daily stock prediction and this engages with other model for predicting stock price.

In "ARIMA and Facebook Prophet Model in Google Stock Price Prediction" where Jin, et al. compared the prediction graphs of models, said that ARIMA model has a better performance in predicting Google's stock price during the pandemic. Moreover, Mohanty in "Stock Price Prediction Using ARIMA Model" stated that this might guide investors in stock market to create profitable investment selections. With the results obtained ARIMA models will compete fairly well with rising prediction techniques in short-run prediction.

Pramod, et al. in his article enhanced that using the market data to predict the share price using machine learning techniques like recurrent neural network named as Long Short-Term Memory, in that process weights are corrected for each data points using stochastic gradient descent.

CHAPTER-3

DATA COLLECTION

Secondary data is suitable for any number of analytics activities. Secondary data refers to data that is collected by someone other than the primary user. Secondary data analysis can save time that would otherwise be spent collecting data and, particularly in the case of quantitative data, can provide larger and higher quality databases that would be unfeasible for any individual researcher to collect on their own.

In this research, secondary data of Google stock price dataset over 9 years has been collected to make the forecast. This data set has 5 columns with all the necessary values such as the opening price of the stock, its closing price of it, its highest in the day, and much more. It has date-wise data of the stock starting from 2015(March) to 2023(March).

CHAPTER 4

METHODOGY

To predict and forecast stock trend using statistical method (ARIMA) and comparing with another technique called exponential smoothing with the statistical tool SPSS (Statistical Package for the Social Sciences) software

4.1 ARIMA

An autoregressive integrated moving average, or ARIMA, is a statistical analysis model that uses time series data to either better understand the data set or to predict future trends.

The **ARIMA** model (an acronym for Auto-Regressive Integrated Moving Average), essentially creates a linear equation which describes and forecasts your time series data. This equation is generated through three separate parts which can be described as:

- **AR** — auto-regression: equation terms created based on past data points
- **I** — integration or differencing: accounting for overall “trend” in the data
- **MA** — moving average: equation terms of error or noise based on past data points

The ARIMA model is almost always represented as **ARIMA (p, d, q)** where each of the letters corresponds to one of the three parts described above. These three letters represent parameters that you will have to provide, and are described as follows:

- p determines the number of autoregressive (AR) terms
- d determines the order of differencing
- q determines the number of moving average (MA) terms

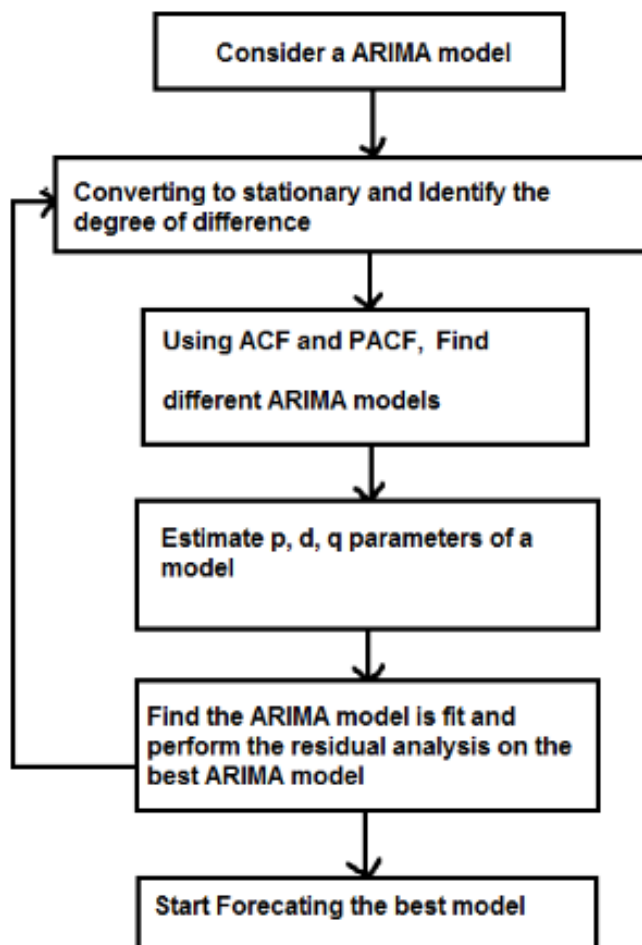


Fig 4.1 Flowchart of ARIMA forecast model

4.2 EXPONENTIAL SMOOTHING

Exponential smoothing is generally used to make short term forecasts, but longer-term forecasts using this technique can be quite unreliable. More recent observations given larger weights by exponential smoothing methods, and the weights decrease exponentially as the observations become more distant. When the parameters describing the time series are changing slowly over time, then these methods are most effective.

SIMPLE METHOD

The simple exponential smoothing (SES) model is usually based on the premise that the level of time series should fluctuate about a constant level or change slowly over the time.

HOLT WINTER'S METHOD

The idea of Holt Winters exponential smoothing is to smooth the original univariate Series (series that consists of single (scalar) observations recorded sequentially over equal time increments.) and to use the smoothed series in forecasting future values of the variable of interest.

Exponential Smoothing assigns exponentially decreasing weights as the observation get older. In other words, recent observations are given relatively more weight in forecasting than the older observations. Holt Winters Algorithms are applied when data is stationary.

CHAPTER 5

RESULTS AND DISSCUSION

5.1 SEQUENCE PLOT

It is an easy way to graphically summarize a data set.

Model Description	
Model Name	MOD_5
Series or Sequence 1	AdjClose
Transformation	None
Non-Seasonal Differencing	1
Seasonal Differencing	0
Length of Seasonal Period	12
Horizontal Axis Labels	Date_
Intervention Onsets	None
Reference Lines	None
Area Below the Curve	Not filled

Applying the model specifications from MOD_5

Table 5.1 Model Description

Case Processing Summary		AdjClose
Series or Sequence Length		96
Number of Missing Values in the Plot	User-Missing	0
	System-Missing	0

Table 5.2 Case Processing Summary

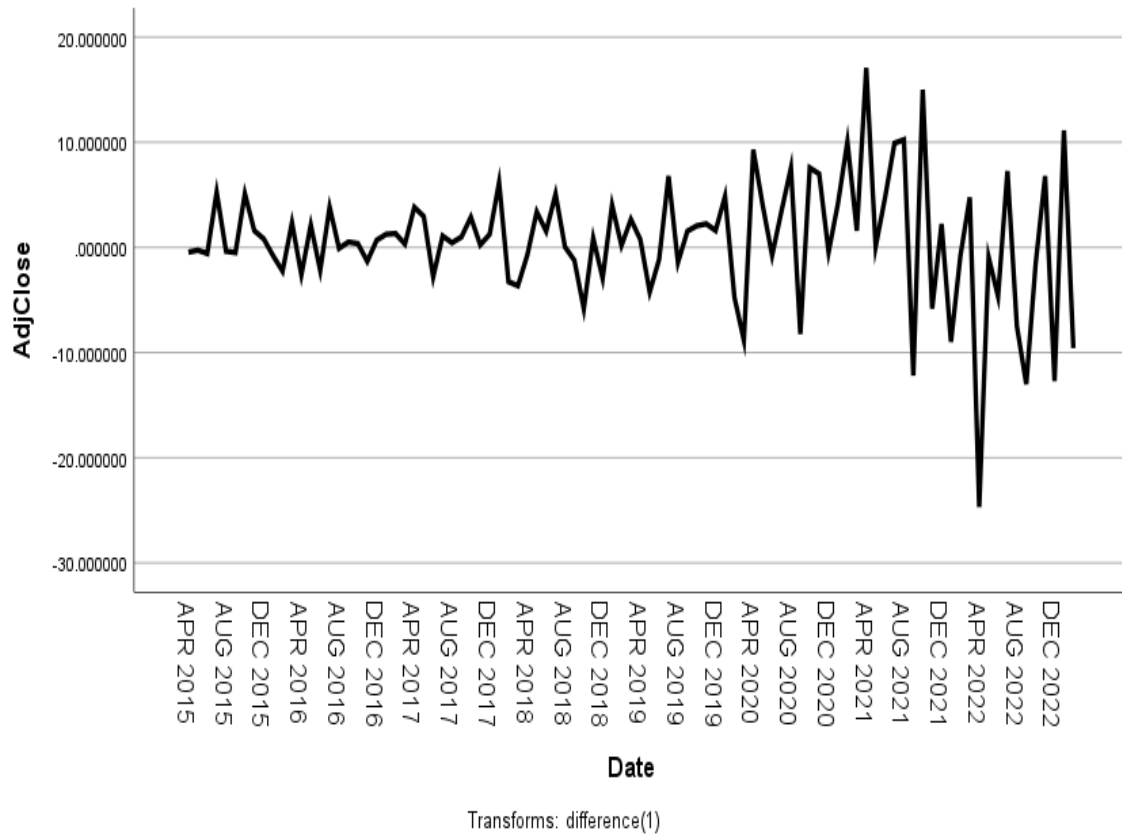


Fig 5.1 Sequence Plot

This plot above is the stationery sequence plot of Google's stock price.

5.2 AUTOCORRELATION

The autocorrelation function is a measure of the correlation between observations of a time series that are separated by k time units.

Autocorrelations					
Series: AdjClose					
Lag	Autocorrelation	Std. Error ^a	Box-Ljung Statistic		
			Value	df	Sig. ^b
1	-.223	.101	4.886	1	.027
2	.148	.100	7.058	2	.029
3	.129	.100	8.736	3	.033
4	.174	.099	11.805	4	.019
5	.044	.099	12.007	5	.035
6	.120	.098	13.487	6	.036
7	-.015	.098	13.511	7	.061
8	.122	.097	15.077	8	.058
9	-.059	.097	15.455	9	.079
10	-.015	.096	15.479	10	.116
11	-.066	.095	15.960	11	.143
12	-.040	.095	16.138	12	.185
13	-.062	.094	16.567	13	.220
14	-.255	.094	23.974	14	.046
15	.162	.093	27.004	15	.029
16	-.121	.093	28.720	16	.026

a. The underlying process assumed is independence (white noise).

b. Based on the asymptotic chi-square approximation.

Table 5.3 Values of autocorrelation

5.3 PLOT FOR AUTOCORRELATION

ACF – Autocorrelation Function. This displays how well the present value of the series is related with its past values. Each bar shows the correlation with the present value at a given lag number

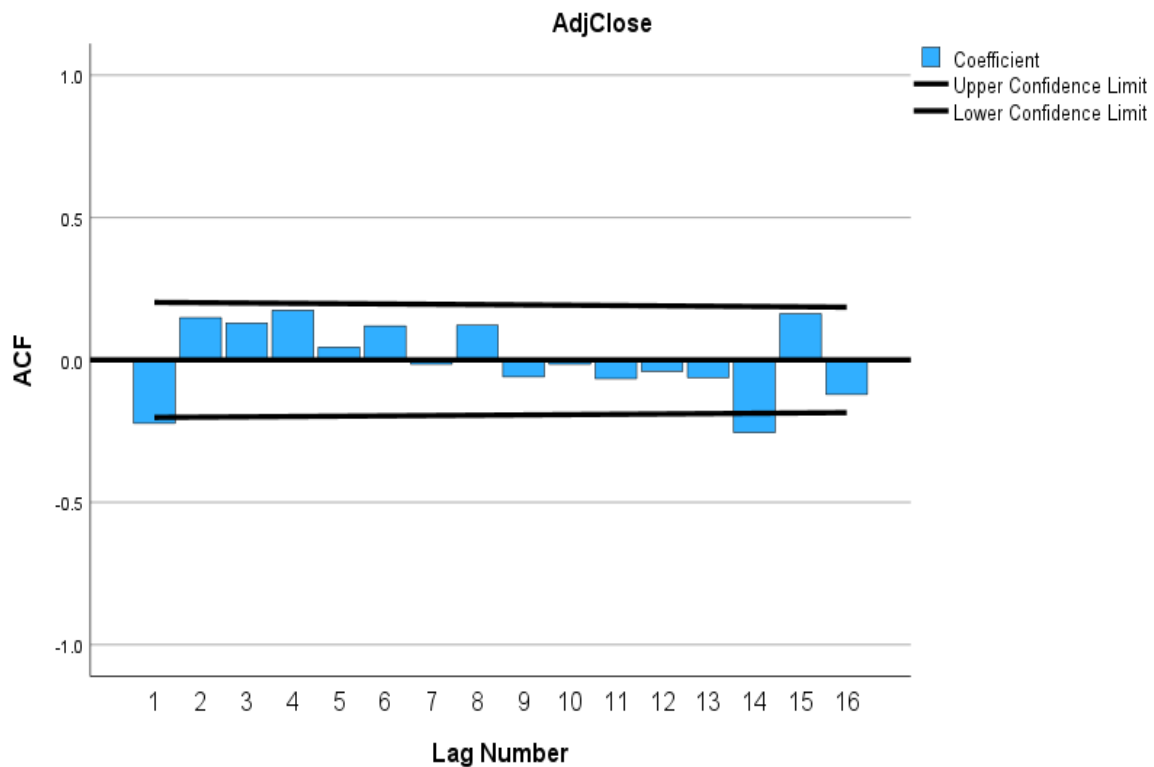


Fig 5.2 ACF Plot

5.4 PARTIAL AUTOCORRELATION

A partial autocorrelation is a summary of the relationship between an observation in a time series with observations at prior time steps with the relationships of intervening observations removed.

Partial Autocorrelations		
Series: AdjClose		
Lag	Partial Autocorrelation	Std. Error
1	-.223	.103
2	.103	.103
3	.194	.103
4	.248	.103
5	.113	.103
6	.086	.103
7	-.066	.103
8	.007	.103
9	-.102	.103
10	-.130	.103
11	-.151	.103
12	-.121	.103
13	-.055	.103
14	-.272	.103
15	.149	.103
16	.128	.103

Table 5.4 Values of partial autocorrelation

5.5 PLOT FOR PARTIAL AUTOCORRELATIONS

PACF – Partial Autocorrelation Function • Unlike the ACF it looks at the correlation of the residuals (the error remaining after removing the variation already explained by the earlier lags) with the current time point. It is a pure measure of correlation as it controls for all correlation values up to that time point.

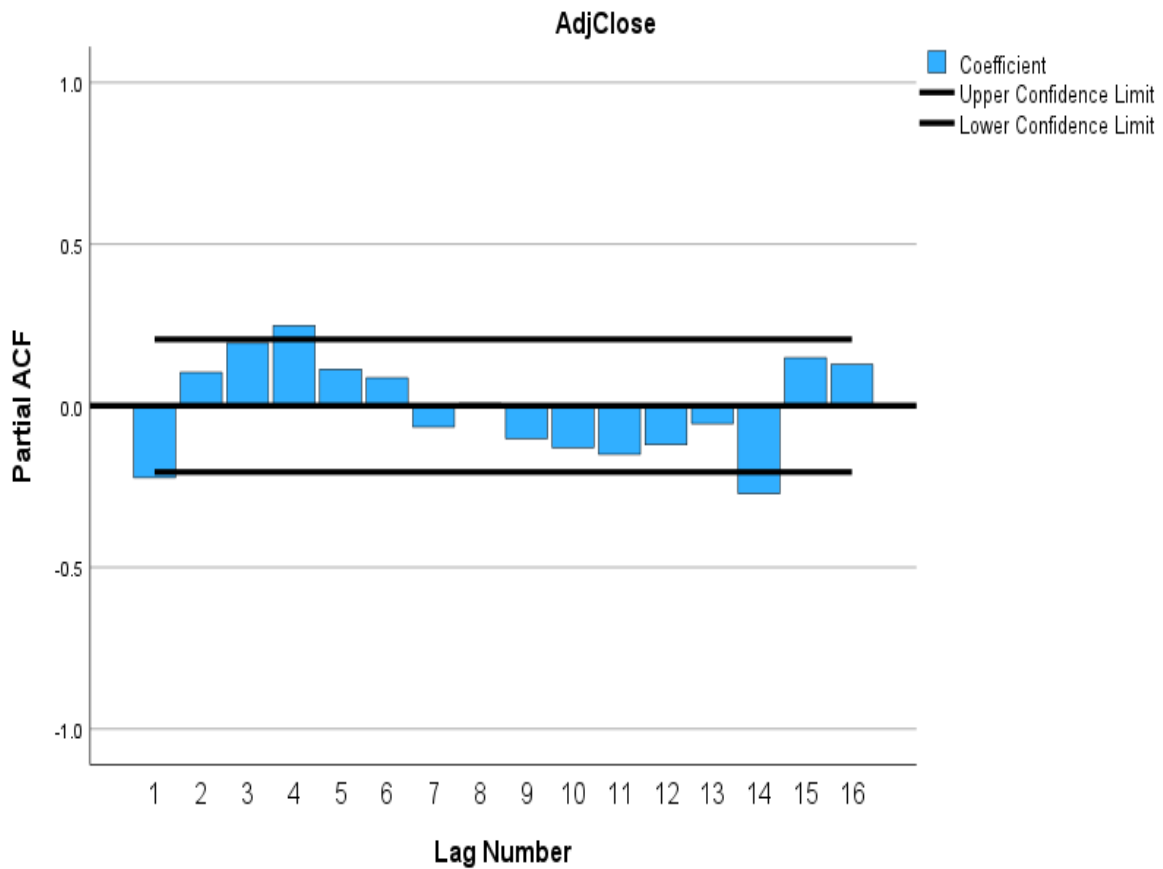


Fig 5.3 PACF Plot

5.6 MAPE

The **mean absolute percentage error (MAPE)**, also known as **mean absolute percentage deviation (MAPD)**, is a measure of prediction accuracy of a forecasting method in statistics. Mean absolute percentage error (MAPE) is a metric that defines the accuracy of a forecasting method. It represents the average of the absolute percentage errors of each entry in a dataset to calculate how accurate the forecasted quantities were in comparison with the actual quantities. MAPE is often effective for analyzing large sets of data and requires the use of dataset values other than zero.

5.7 RESULTS USING ARIMA

Time Series Modeler

ARIMA (p, d, q) The parameter p is the number of autoregressive terms or the number of “lag observations.” It is also called the “lag order,” and it determines the outcome of the model by providing lagged data points.

For p=1, d=1, q=1

Model Description

			Model Type
Model ID	AdjClose	Model_1	ARIMA(1,1,1)(0,0,0)

Table 5.5

Model Statistics

Model	Number of Predictors	Model Fit statistics		Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	Statistics	DF	Sig.	
AdjClose-Model_1	0	.044	5.365	17.514	16	.353	<.001

Table 5.6

R-squared is a measure of how well a linear regression model “fits” a dataset. Also commonly called the coefficient of determination, R-squared is the proportion of the variance in the response variable that can be explained by the predictor variable.

For $p=4$, $d=1$, $q=1$

Model Description

			Model Type
Model ID	AdjClose	Model_1	ARIMA(4,1,1)(0,0,0)

Table 5.7

Model Statistics

Model	Number of Predictors	Model Fit statistics		Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	Statistics	DF	Sig.	
AdjClose-Model_1	0	.077	5.386	11.451	13	.573	<.001

Table 5.8

The value for R-squared can range from 0 to 1. A value of 0 indicates that the response variable cannot be explained by the predictor variable at all. A value of 1 indicates that the response variable can be perfectly explained without error by the predictor variable

For $p=14$, $d=1$, $q=1$

Model Description

			Model Type
Model ID	AdjClose	Model_1	ARIMA(14,1,1) (0,0,0)

Table 5.9

Model Statistics

Model	Number of Predictors	Model Fit statistics		Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	Statistics	DF	Sig.	
AdjClose-Model_1	0	.250	4.714	3.719	3	.293	<.001

Table 5.10

In general, the larger the R-squared value, the more precisely the predictor variables are able to predict the value of the response variable. In scientific studies, the R-squared may need to be above 0.95 for a regression model to be considered reliable. In other domains, an R-squared of just 0.3 may be sufficient if there is extreme variability in the dataset.

For p=14, d=1, q=14

Model Description

			Model Type
Model ID	AdjClose	Model_1	ARIMA(14,1,14) (0,0,0)

Table 5.11

Model Statistics

Model	Number of Predictors	Model Fit statistics		Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	Statistics	DF	Sig.	
AdjClose-Model_1	0	.390	4.114	.	0	.	<.001

Table 5.12

From the above four models, it is estimated that ARIMA (14,1,14) having the least MAPE error has the best fit of accuracy. Using this model, the forecast till the year 2025 has been calculated.

5.8 FORECAST VALUES

		Forecast									
Model		Mar 2023	Apr 2023	May 2023	Jun 2023	Jul 2023	Aug 2023	Sep 2023	Oct 2023	Nov 2023	Dec 2023
AdjClose-Model_1	Forecast	98.001515	104.381214	110.628292	107.707751	121.149600	123.003612	133.693564	139.459751	157.658684	163.114819
	UCL	110.059500	119.727587	128.581867	126.991260	146.120136	151.482597	167.592482	178.170147	204.984685	213.884264
	LCL	86.961447	90.558003	94.621757	90.706014	99.521400	98.737826	105.211421	107.421126	119.033121	121.958754
		Jan 2024	Feb 2024	Mar 2024	Apr 2024	May 2024	Jun 2024	Jul 2024	Aug 2024	Sep 2024	Oct 2024
		185.057862	189.966772	193.255833	206.568929	216.602946	218.422931	229.403044	238.804598	234.975784	247.497658
		244.896594	251.769295	256.906540	275.155540	288.520521	290.906035	305.494528	318.303295	313.619470	331.661936
		136.905521	140.293830	142.221838	151.665884	159.033393	160.394467	168.480125	175.200074	172.122980	180.449647
		Nov 2024	Dec 2024	Jan 2025	Feb 2025	Mar 2025					
		233.306651	229.170118	224.502279	230.324549	214.771519					
		314.474075	310.061468	304.749399	314.197043	294.268507					
		168.948911	165.225221	161.235154	164.461659	152.565539					

Table 5.13 Forecast values

5.9 FORECAST PLOT

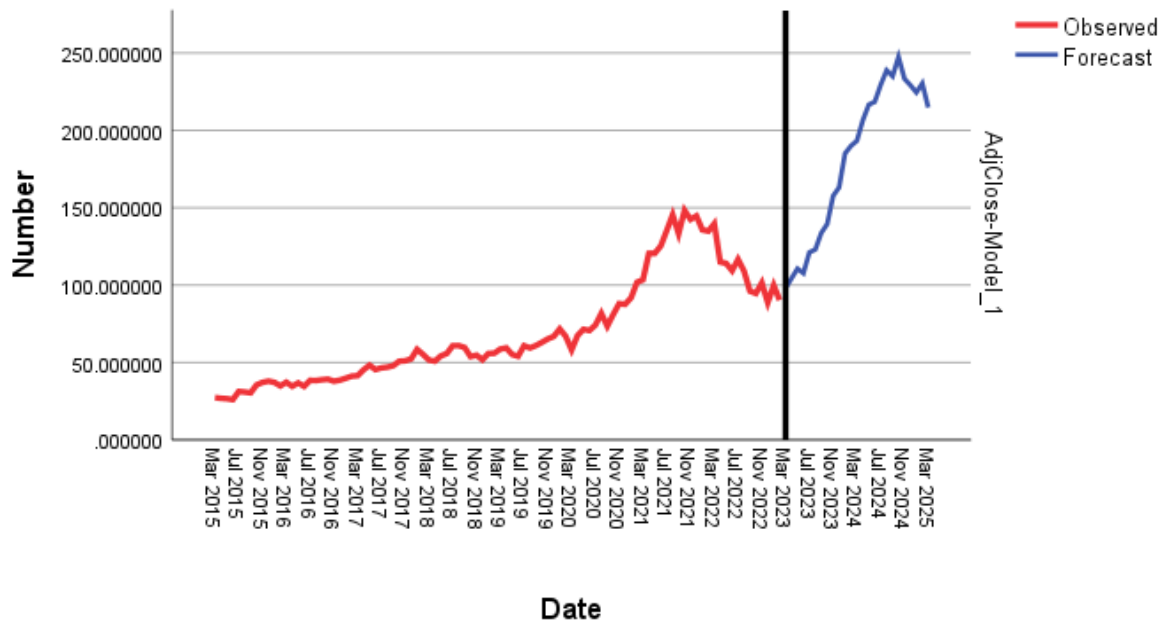


Fig 5.4 Forecast Plot

The time series has a specific direction in which the data is moving in. The above picture is of a series of data having an upwards facing trend.

5.10 RESULTS USING EXPONENTIAL SMOOTHING

SIMPLE METHOD

Simple exponential smoothing estimates only the level component. Think of the level component as the typical value or average. This method updates the level component for each observation

Model Description

Model Type			
Model ID	AdjClose	Model_1	Simple

Table 5.14

Model Statistics

Model	Number of Predictors	Model Fit statistics		Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	Statistics	DF	Sig.	
AdjClose-Model_1	0	-.007	5.464	17.371	17	.430	<.001

Table 5.15

HOLT'S LINEAR TREND

This method is used for forecasting the time series when the data has both linear trend and seasonal pattern. Winter's smoothing technique allows us to include seasonality while making the prediction along with the trend.

Model Description

			Model Type
Model ID	AdjClose	Model_1	Holt

Table 5.16

Model Statistics

Model	Number of Predictors	Model Fit statistics		Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	Statistics	DF	Sig.	
AdjClose-Model_1	0	.598	5.337	18.413	16	.300	<.001

Table 5.17

5.11 COMPARISON OF MODELS

MODEL	MAPE
ARIMA (1,1,1)	5.365
ARIMA (4,1,1)	5.386
ARIMA (14,1,1)	4.714
ARIMA (14,1,14)	4.114
EXPONENTIAL SMOOTHING (SIMPLE)	5.464
EXPONENTIAL SMOOTHING (HOLT'S LINEAR)	5.337

Maximum absolute percentage error - The largest forecast error, expressed as a percentage. It works best if there are no extremes to the data. Smaller values indicate better fit.

So, it's estimated that ARIMA (14,1,14) have the least MAPE error comparing with other ARIMA models and the Exponential Smoothing. It's found that this model has the best fit of accuracy of all models. Therefore, forecasting the ARIMA (14,1,14) gives the forecast values (Table 5.13) and the forecast plot (Fig 5.4) is determined using the values.

CHAPTER 6

CONCLUSION

Forecasting the future and performances of every stock industry would help investors accumulate wealth during prosperous periods and reduce liabilities during turbulent moments. In this context, the future demand for Google's stock price has been estimated here using Auto Regressive Integrated Moving Average method. The trend has been analyzed and the forecasting has been done till the year 2025. Comparing ARIMA with Exponential Smoothing, it is determined that the results of ARIMA gives the best fit of accuracy for the prediction of forecast values.

CHAPTER 7

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