MH - 1601

Interactive Qualifying Project

Can We Predict a Stock's Price ?

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Abstract

The stock market presents the individual investor with an opportunity to earn money by investing in equities. However the stock market is stacked in favor of the big investment companies. In this project we presented models to rebalance these odds by creating a tool that can be used by individual investors to predict the short-term price of a stock.

Acknowledgement

Special Thanks to Professor Mayer Humi for his help in this project. We started this IQP with little background knowledge in building mathematical models and MATLAB programming. We could not finish this project successfully without his patience and advising and we are grateful for the experience in this project. Thank you, professor.

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Executive Summary

The stock market is generally unpredictable, so predicting the future prices of stocks has been the goal of investors for years. In the long term, it is almost impossible to predict the future price of a stock. In the short term, we have a chance to achieve this goal.

There are other tools from websites that provide future predictions or investment suggestions of stocks. Some of those tools provide investors with inaccurate predictions and do not explain the procedure used for the analysis, in addition, some are too expensive for individual investors to afford. The models we built in this Interactive Qualifying Project, however, are relatively accurate and completely free for all investors. All the data needed to build the models is available in the public domain.. We used Matlab as our main tool to analyze data, apply the models and present our results in graphs. Matlab or its equivalents are widely used software that any investor can use to access our model.

To accomplish our goals, we analyzed the historical data of stocks, involved relevant indices, and built models with various mathematical functions to make a short-term (around 30 days) prediction. First we built a model based only on the historical price of the stock. Then, we built another model that incorporated a relevant index for prediction. We compared these two models for prediction accuracy.

According to our results, we can confidently say that although our models can be developed further by taking into account other factors such as government policy, the models we built can provide investors reliable short-term prediction of stock prices. *However, the use of these models is at the financial risk of the user.*

Introduction

Stock markets were started when countries in the New World began trading with each other. Merchants wanted to establish large businesses, which required substantial amounts of capital that no single merchant could raise alone. As a result, groups of investors pooled their savings and became business partners as well as co-owners. These investors then owned individual shares in their businesses to form joint-stock companies. This exchangeable medium allowed shareholders to conveniently buy, sell and trade their stock with other shareholders and investors.[1]

In the modern stock market, stock is the symbol of an investor's ownership in a company. The investors theoretically own a percentage of everything the company owns or owes. The company's profitability, or lack thereof, determines whether its stock is traded at a higher or lower price. The investor can manipulate the performance of the stock market to make profits.

The principle here is to buy a company's stock at a low price and sell it at a high price, or short-sell the stock before it drops. The difference between trading prices would result in profit to the investor. Logically, you could say that if someone could predict the future stock price, he or she would make a fortune from the stock market. Now we take on this challenge: "Can we predict the stock price?"

Short-term stock market prediction is most reliable during a relatively stable period, when nothing significant happens in the company or in the market. In this case, there won't be a lot of fluctuation in stock prices; and so we can assume the future stock price is related to the past data. Therefore, this type of prediction is more accessible and more accurate. However, it is harder for one to gain a large profit in this stage because of the small changes of the stock prices, which are where the profit comes from.

The main purpose of this project is to help investors make money from the stock market. It is not guaranteed that the stock price will follow our prediction, but we will try to make our prediction as accurate as possible.

Why this is an Interactive Qualifying Project ?

The Interactive Qualifying Project(IQP) is required for every WPI student. It is organized differently from other courses because it is a project for a team working together to achieve a goal. As quoted on the WPI website, 'WPI believes that in order to become the best engineers and scientists they can be, students should have a broad understanding of the cultural and social contexts of those fields, and thus be more effective and socially responsible practitioners and citizens.'[2]

The stock market belongs to the field of social science, and investing is a common societal interest. However, the stock market is highly risky and no one can guarantee that there will always be profit from investment. The objective of this project is to predict the price of stock by using mathematical models and modern tools (Matlab or its equivalent), then provide the best choices for the investors to earn money. Through this 3-term project, we did the research and obtained deeper understanding of the stock market, while at the same time improving our programming and presenting skills. All of these fit within the core intention of the IQP at WPI. Even though this topic is complex and the results we got from this 3-term period are not perfect, we can provide guidance and advice for people who are interested on this project in the future.

Equity and bonds

The concept of stock markets first appeared in the 12th century. It began with the trade of debts among small agricultural communities and banks. Now stock markets have developed and exist in almost every developed and most developing economies, such as in the United States, the United Kingdom, Japan, China, etc.

The basic ideas for the investors in the equity market are buying the stocks at the low prices and selling them when the prices are high, or short-selling stocks before prices drop. The differences between buying and selling price are the profit that is earned.

- **Stocks and equity market**[3]

The **stock** of a corporation shows the equity stake of its owners. It represents the residual assets of the company for the stakeholders. The stakeholders also have the right to trade their stock with others. A **stock market** (**equity market** or **share market)** is the aggregation of buyers and sellers of stocks.

- **Bonds**[4]

Bonds are a type of tradable debt security which are similar to loans. here are several types differentiated by issuing method such as corporate bonds, government bonds and financial bonds. The creditors and debtors of the bonds have a direct debt relationship.

Index[5]

Index is a key term in the stock market. Usually the index can show the trend and performances for some sectors because it is the average price for a group of companies in the same sector. Here are some important indices in the stock market.

1. Dow Jones Industrial Average[6]

The Dow Jones Industrial Average is a stock market index, it was created by Wall Street Journal editor and Dow Jones & Company co-founder Charles Dow. This index was first calculated on May 26, 1896. It is the average stock price of 30 large publicly owned companies based in the United States have traded during a standard trading session in the stock market.

2. Dow Jones Commodity Index of Crude Oil[7]

The Dow Jones Commodity Index of Crude Oil is a weighted average of the crude oil prices, which may be based on the future prices. It is designed to be a representative of the crude oil subset of commodities. This index are often traded on exchanges, allowing investors to gain easier access to the crude oil market without having to enter the futures market. The value of the index fluctuates based on future contracts of the crude oil, and this value can be traded on an exchange in the same way as stock index futures. This index was chosen to make predictions in the petroleum sector.

3. NASDAQ composite[8]

NASDAQ composite was launched in 1971. Similar to the Dow Jones Index, the NASDAQ also shows a trend and summarizes sector performances, but for separate sectors. The **NASDAQ** composite is heavily weighted for the information technology companies. There are many specific subsets of the NASDAQ index, some of which we used in the building of our models.

4. NASDAQ Biotechnology Index [9]

The NASDAQ Biotechnology Index contains securities of NASDAQ-listed companies classified according to the Industry Classification Benchmark as either Biotechnology or Pharmaceuticals which also meet other eligibility criteria. The NASDAQ Biotechnology Index is calculated under a modified capitalization

-weighted methodology. The Index began on November 1, 1993 at a base value of 200.00.

5. NASDAQ-100 Technology Sector Index[10]

The NASDAQ-100 is an index composed of the 100 largest companies on the NASDAQ, excluding financial companies. This index was created with the goal of reducing the influence of the largest stocks and allowing greater diversification with the smaller stocks. The NASDAQ-100 Technology Sector focuses on the major technology companies, such as Apple, Google, etc.

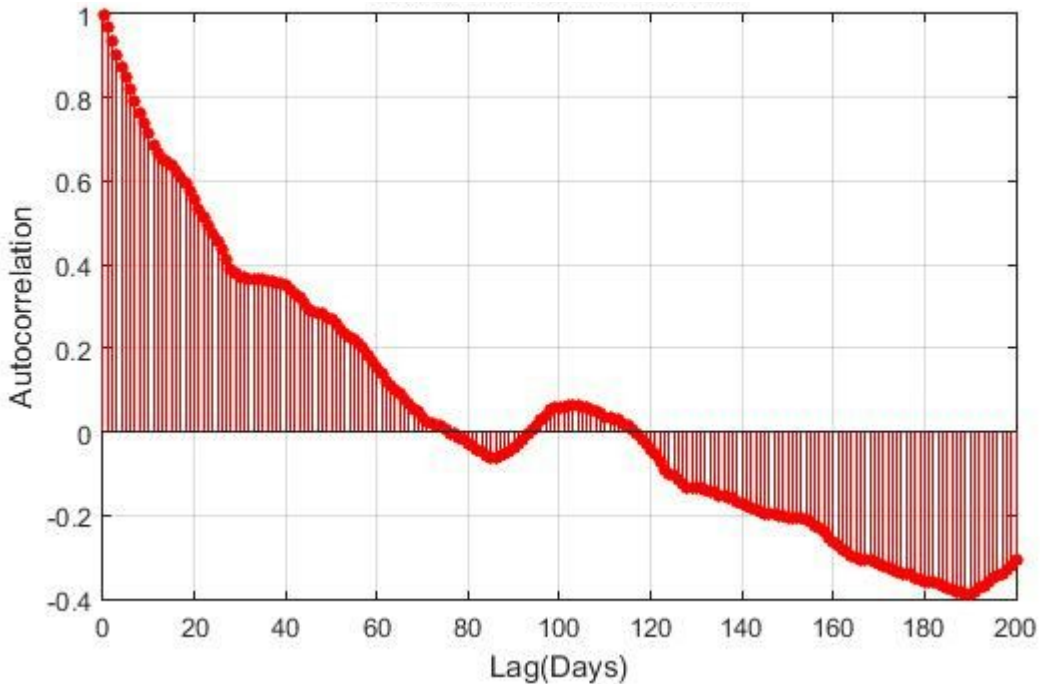
Models

- Model 1

In this project, we tried to predict the future price of a stock without the benefit of background or insider knowledge. As a result, the only way we can predict the future is based on the patterns of the past. Through mathematical modeling, we tried to capture a trend that a stock is following, and then extrapolate this trend into the future. We will follow the construction of both Model 1 and Model 2 with the data from the Tesoro Corporation (TSO). To start, we choose a prediction date in the past to make projections from, so that we can check the accuracy of the projections from the present. For the following plots of TSO, the prediction date is 11/1/15. The first step was to find how long into the past that the trends in the stock are relevant. After all, records for stock prices often consist of years of daily closing prices. We need a way to use the most recent and relevant part. To do this we used the autocorrelation function to narrow down the relevant part before the prediction date. The autocorrelation function finds the number of days before the prediction date in which there is a useful pattern to analyze. We apply an autocorrelation function to the price data using a lag, a measure of how many days in the past to include in the function, large enough to fully capture an expected pattern.

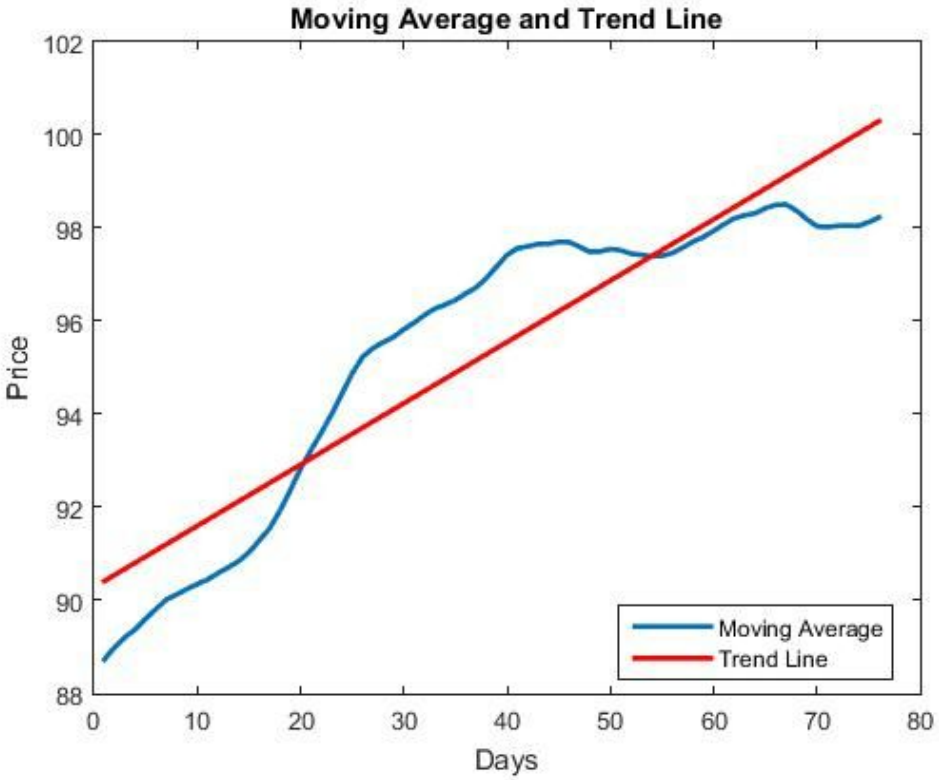
Where the function reaches 0 is the number of days in the past with a relevant pattern. In this case, the function reaches 0 when lag is 74 days, so we can isolate the last 74 days of data before the prediction day to analyze.

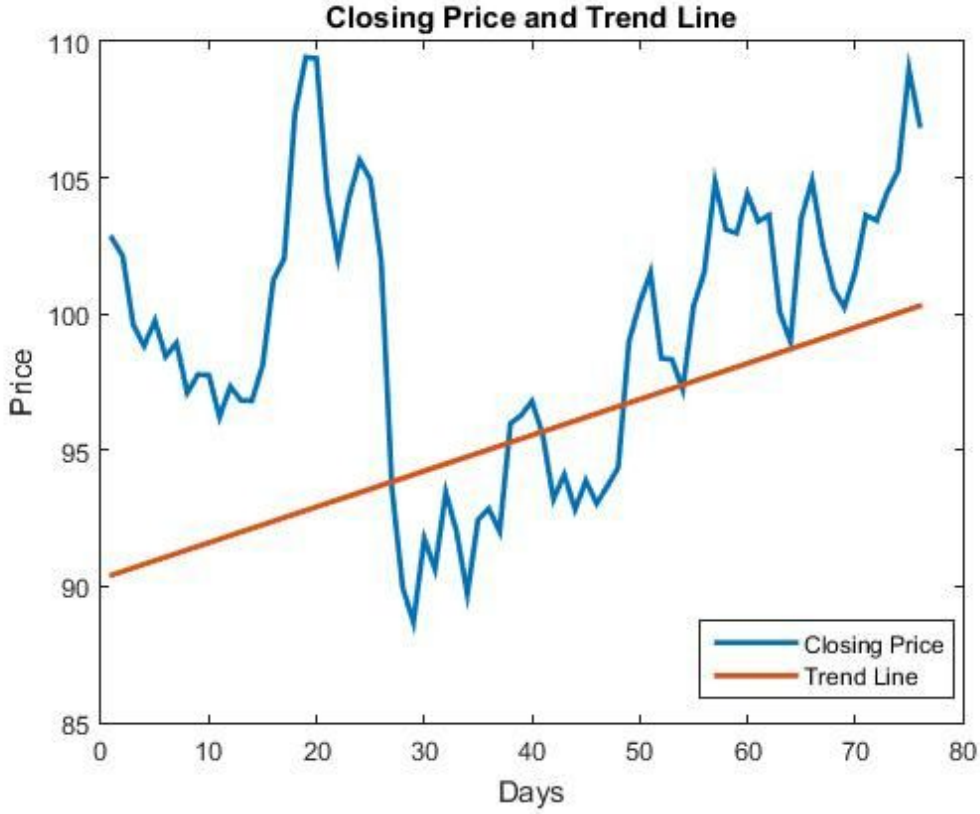
Tesoro Corporation: Autocorrelation Function



Window: 74 Days

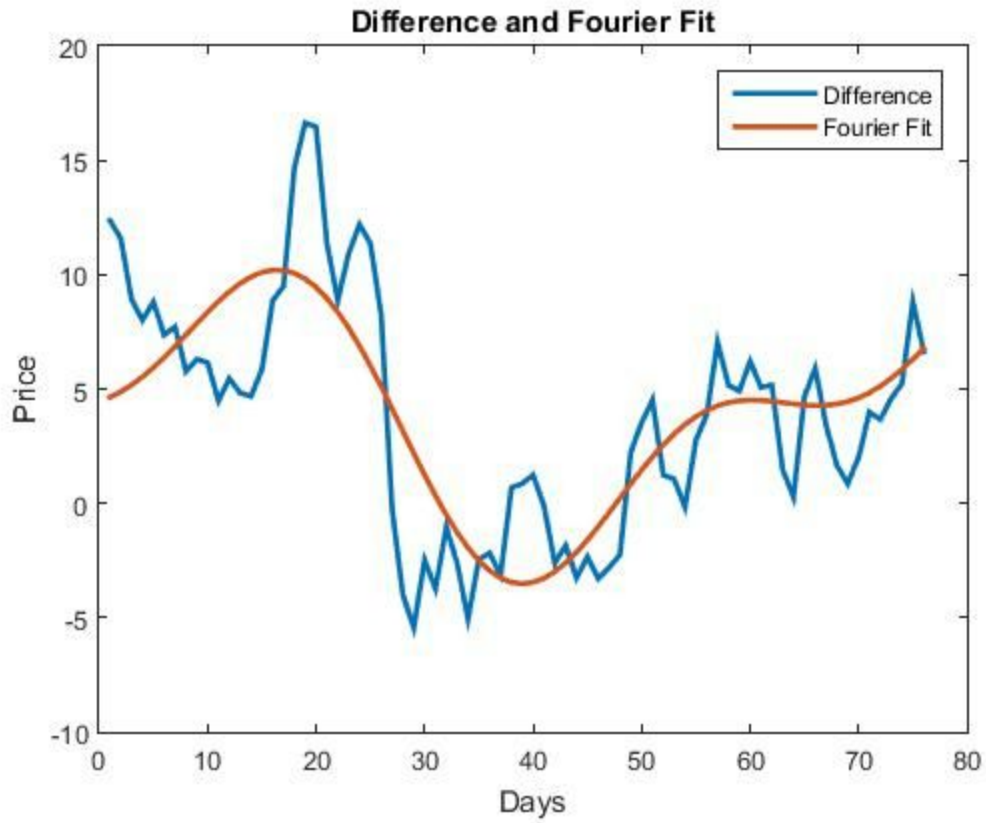
From here, we need to capture the trends that this set of data follows. Often times, the data still fluctuates too much to immediately find a good fit. In order to get a better summary of the noisy data, we use the moving average of this set of data. A moving average takes a series of averages of subsequent subsets of data, which results in a good approximation of a curve. Moving averages can be taken over various sized subsets, known as windows. Choosing this window can affect the final accuracy of the graph, but a generally good window to use is 50 days.


Moving Average and Trend Line
Price
Days
Moving Average
Trend Line
102
100
98
96
94
92
90
88
0
10
20
30
40
50
60
70
80


Closing Price and Trend Line
Price
Days
Closing Price
Trend Line
110
105
100
95
90
85
0
10
20
30
40
50
60
70
80

The first plot here depicts the moving average, as well as a linear fit. The second plot then shows the linear fit with the stock price data for the 74 days. Finding a fit for the moving average is clearly much simpler than for a fit of the closing price, since the moving average is a smoother curve. With the moving average curve, we can easily find a line of fit, which will often be a linear function, although sometimes, the best fit for the moving average will be a polynomial. With this curve fit, we have a function for the general trend of the stock.

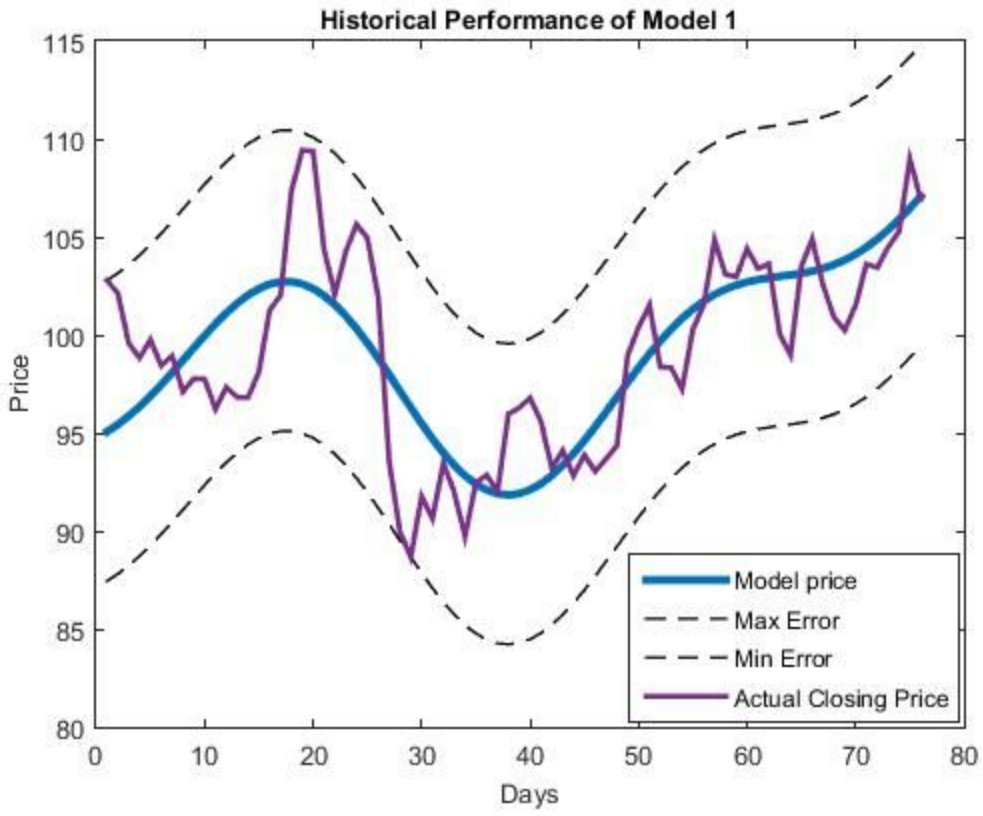
$$Closing\ Price - Moving\ Average\ Trend\ Line = Difference$$



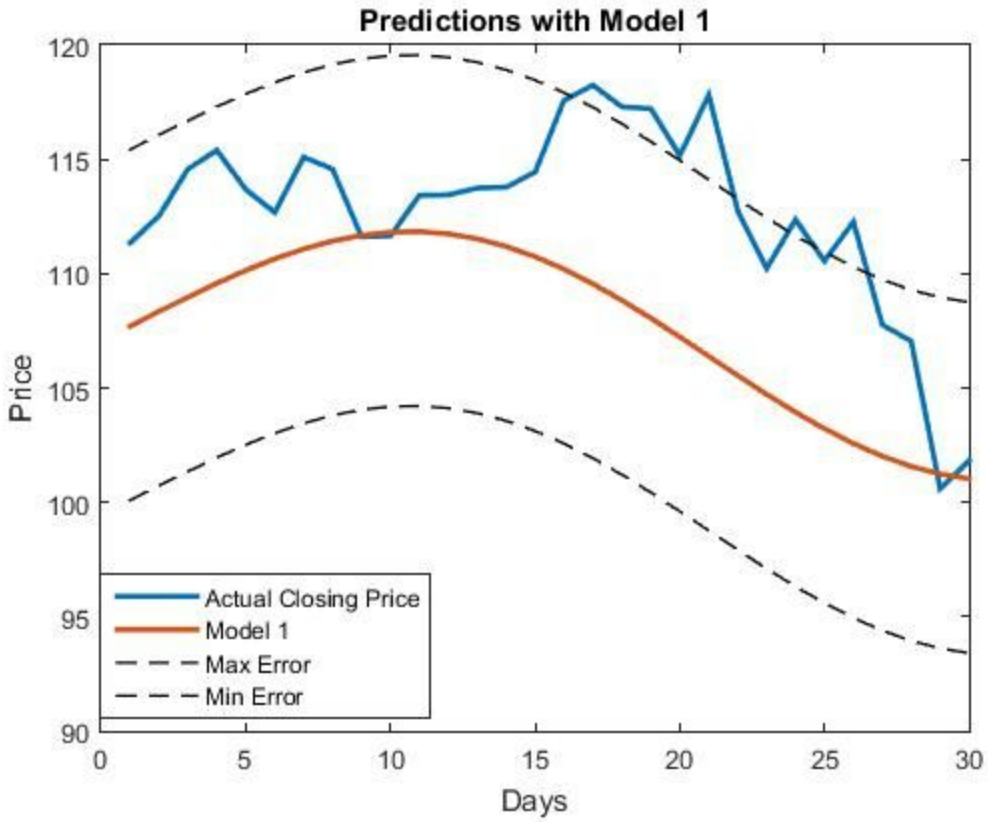
However, predictions with just this trend line are not very accurate, due to the fluctuations present in most stock prices. We must also capture these fluctuations with a mathematical function as well. We want to isolate just the fluctuations, so to do this we subtract the trend line from the price, to get a function with how much the price deviates from the trend. Since doing this isolates the fluctuations, the resulting plot is hard to model with the typical linear or

polynomial functions. As a result, we use a Fourier series to fit the fluctuations as closely as possible. Fourier series can be done to a number of terms, which affects the final fit, we've found that using three terms strikes a good balance between accuracy and convenience. After this, we have two approximations, one for the general trend of the stock price, and another for the fluctuation inherent in the data.

$$Trend\ Line\ +\ Fourier\ Fit\ =\ Model\ 1$$



To complete the first model, we simply add these two approximations together. By simply extending the number of days that the trend line and the Fourier fit calculate for, and then adding them together, we get a prediction for the future based on past data. This is the Model 1 that most of our work is based on.

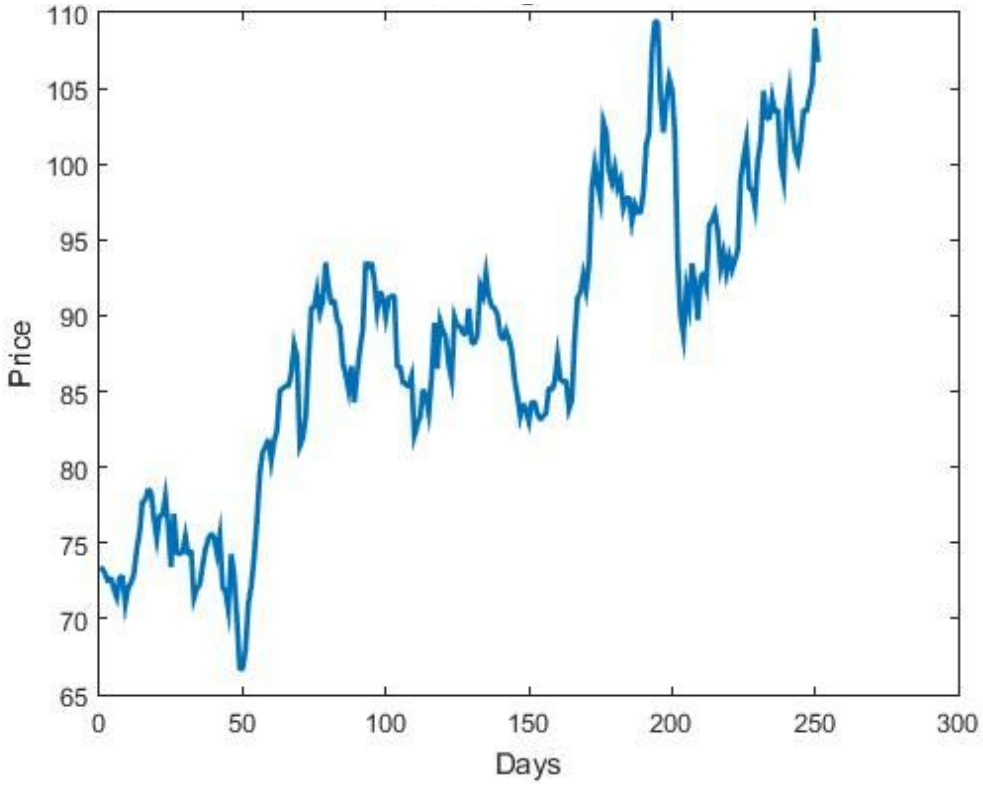

Predictions with Model 1
Price
Days
120
115
110
105
100
95
90
0
5
10
15
20
25
30
Actual Closing Price
Model 1
Max Error
Min Error

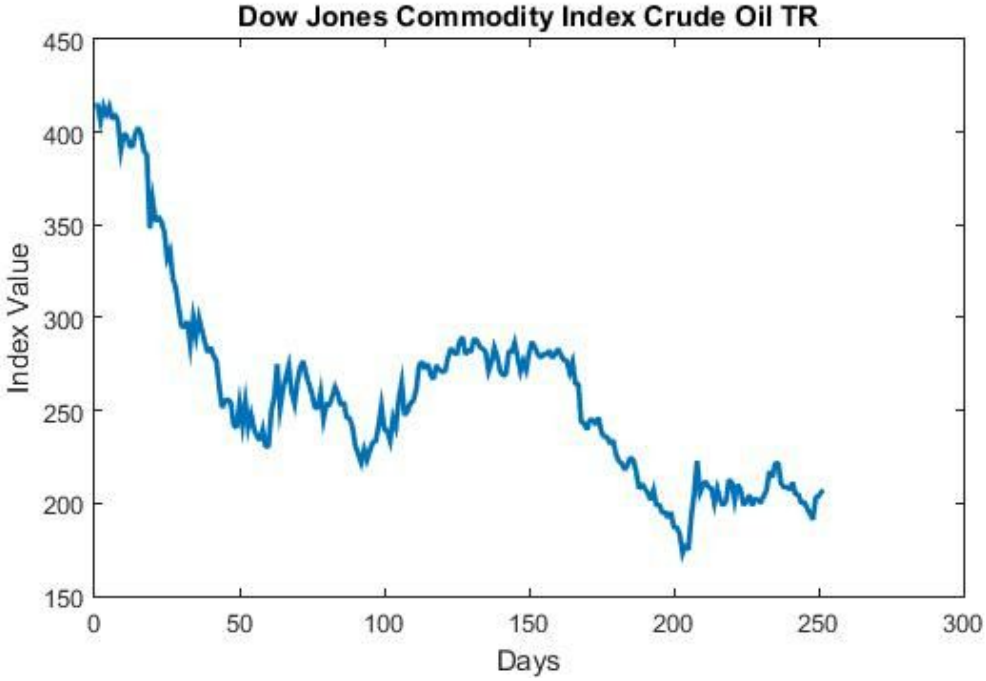
- Model 2

With Model 1, we obtained a prediction using just the historical data for a specific stock. But often times a stock will be influenced by what is happening in the market overall. In order to account for this we need a way to summarize the general market trends. To this end we will use certain indices, such as the Dow Jones or the Nasdaq. These indices capture what is happening in the market at the time. Some indexes, such as the Dow Jones Industrial Average describe what is happening in the entire US economy, while others focus more on specific sectors, such as the Nasdaq Biotechnology Index or the Dow Jones Crude Oil Index. Since there are many indexes with various scope, we need to somehow pick the index most relevant to the stock we are examining.

In order to choose a index, we need to use one that is related to the stock we are examining. This means choosing a more specific index within the industry that the stock is in. From here, we then need to find a measure of how closely the index matches the movement of the stock price. If a stock follows a similar pattern to an index in the past, then it is very likely that they are closely related, and likely that they will follow a similar pattern in the future as well. To do this we find the correlation between a certain index and the stock. Correlation is a measure of how closely one set of data is related to another. The closer the correlation is to 1, the more similar the two sets of data are. The closer the correlation is to 0, the less related the two sets are, and if the correlation is close to -1, then the two sets are opposite, where up and down trends are reversed. Thus we can assume that the closer the correlation between a stock an index, the more the index and by extension the market influences that stock. Thus, we used indices which focused on the industries that our stocks were from. From here, after choosing an index, then we need to actually incorporate it into the model.

Tesoro Corporation YTD Closing Price





Correlation: - 0.7245

As before, we try to predict prices after a certain date, which will be referred to as the prediction date. Using the first model, we build two curves, one for each the stock and the chosen index. The first obstacle to combining the two curves is the fact that the index curve almost always deals with much bigger numbers, usually in the thousands, while the stock price is often below one hundred. In order to combine the two, we need to scale the two sets of data down. To do this we divide the index and the stock data by the respective quantity at the prediction date, that we defined earlier. (In the Tesoro example, this is 11/1/15). This scales down the values both sets of data to around 1, while preserving the trend and shape of the data curve. From here we can start to combine the two curves. The equation would look like this:

$$\frac{Prediction\ from\ Model\ 1\ (stock)}{Price\ at\ Prediction\ Date} \equiv \text{Scaled Stock Model}$$

$$\frac{Prediction\ from\ Model\ 1\ (index)}{Index\ Value\ at\ Prediction\ Date} \equiv \text{Scaled Index Model}$$

We know the the correlation refers to how closely two sets of data are related. So, while combining the two curves, there must be a difference in combining them depending on the correlation value. In order to capture the role of the correlation in the final model we multiply the correlation and the scaled index model. This preserves the assumption that the higher the correlation, the more influential the index and the market are on the stock. This product captures the influence of the index on the stock, and from here we add the influence of the stock itself. Since the highest correlation value is 1, then 1 minus the correlation captures the influence of the stock, since it is the remainder. As a result, the correlation multiplied by the scaled index model added to the remainder multiplied by the stock model gives a final scale model. We will call it the weighted model, since it is the stock including the weight of the index.

$$Correlation \times Scaled\ Index\ Model + (1 - Correlation) \times Scaled\ Stock\ Model = Scaled\ Weighted\ Model$$

Since we were adding two scaled models together, the sum is also scaled, so the values are all close to 1. Since we are trying to predict the stock price, we multiply this scaled weighted model by the scale initially used to make the scaled

stock model. This scales the weighted model up to the price range that the stock will actually be at. This is the final step to creating the second, weighted, model.

$$Price\ at\ Prediction\ Date\ (stock)\ \times Scaled\ Weighted\ Model$$

$$= Final\ Weighted\ Model\ Price$$

Error Margins:

Through the usage of our previous models, we come up with a curve that describes the general trend of the future stock prices. However, it is very unlikely that the prices fit perfectly along the curve. We need to somehow capture a range in which we expect the future price to be within, which we can then use to analyze the accuracy and usefulness of our model.

Looking back at our model, we start by finding the difference between the data and the functions used to fit the data. This happens in two places, when we make the fit of the moving average of the closing prices, and when we use a fourier fit to capture the fluctuations in the data. In both of these situations, since the mathematical fit does not perfectly match the data, there is a difference between the fit and the data. By subtracting the fit from the data, we produce a function that quantifies the difference. This difference shows how far the model is from the fit in the past, and thus how far we can expect it to be in the future.

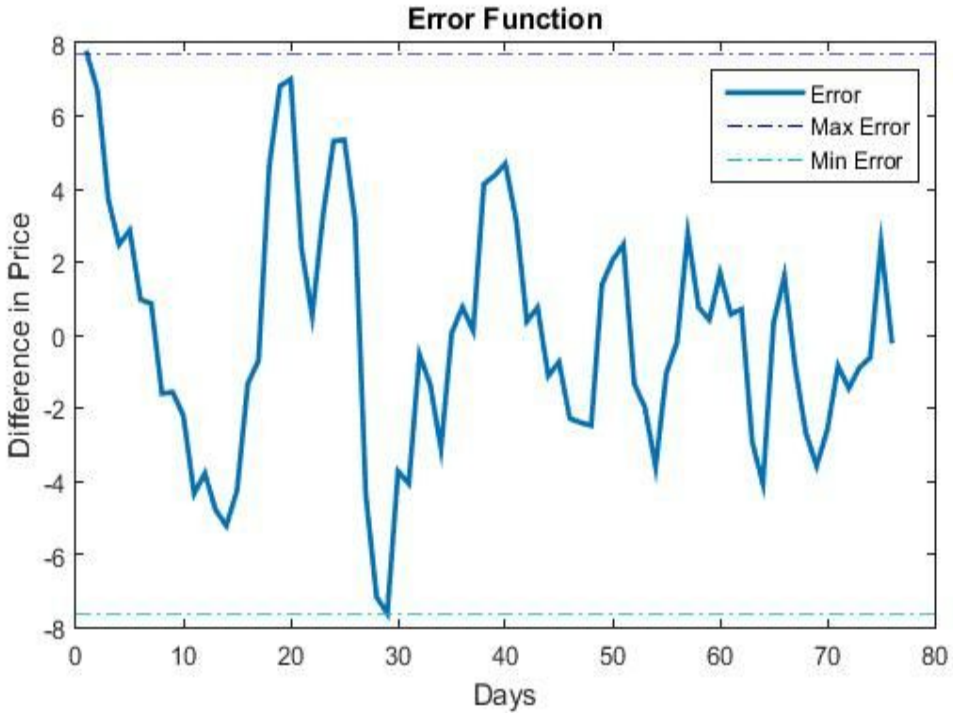
As previously mentioned, there are two places in the model building process where there is a difference between data and fit. The first place, where the fit is taken of the moving average, will be ignored in our error analysis. This is due to the fact that, although the moving average is a good way to smooth the trends of the previous data, it is not the data itself. For the purposes of creating a mathematical baseline to start building our model from, the moving average works well, but is simply too inaccurate for error analysis. This leaves the difference from the fluctuations in the data and the Fourier fit. This also works well since analyzing this difference accounts for the fluctuations in our future model. Our model provides a guideline for where the price will be, and the error analysis based on the

fluctuations accounts for random fluctuations, the range of which will be determined from the difference from the noise and the fit.

While building Model 1, there is a point where we approximate a curve with a Fourier series. This curve is the initial difference between the moving average fit and the stock price. In order to define an error, we find the difference between this curve and the Fourier series. The difference between the curve and the Fourier fit results in an error function, which describes how the price deviates from the model in the past.

$$Closing\ Prices\ -\ Linear\ (Polynomial)\ Fit\ =\ Initial\ Difference$$

$$Initial\ Difference\ -\ Fourier\ Fit\ =\ Error\ Function$$

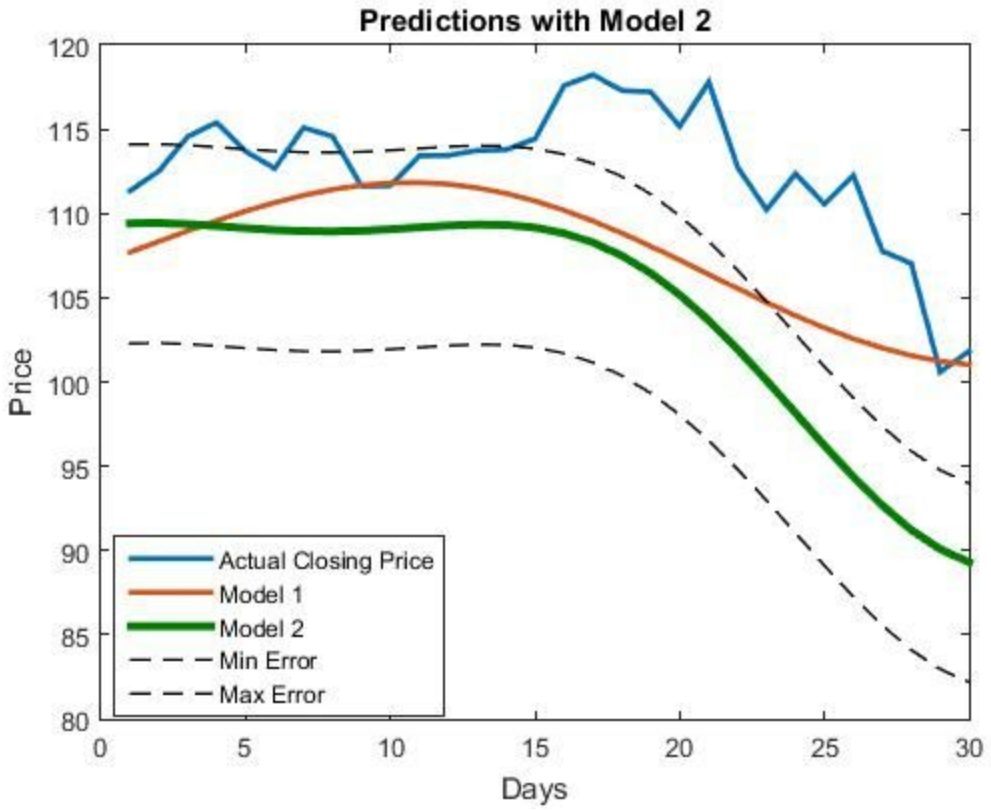


In the Error function, there will be a maximum and a minimum. These represent the amount in which the data was greater than and was less than the model. The maximum and minimum provide a range, where the stock always fluctuated within this range. This provides an overarching margin, for which we expect the stock to fluctuate. Since we expect the stock to behave similarly in the

future as it did in the past, then if the price is outside of this error margin, then we know at that point the model is no longer accurate, since we don't expect the stock to fluctuate further than the maximum and the minimum. Using the maximum and minimum error thus provides an effect margin in which to analyze both the stock and the model itself. Another way to analyze this error is to take the average of the values in the error function. This provides us with a smaller error, but in practice was too constraining to be useful in the price prediction.

$$Max\ of\ Error\ Function\ =\ Upper\ Error\ Bound$$

$$Min\ of\ Error\ Function\ =\ Lower\ Error\ Bound$$



Companies and Other Considerations

Before predicting the stock price, it is important to find good stocks for earning money from investment. Each member in the group chose companies from different sectors in which we are interested.

- Companies from petroleum sector:

Chevron Corporation (CVX)

Chevron Corporation was founded in 1879 and is headquartered in San Ramon, California. The company engages in petroleum, chemicals, and power and energy operations worldwide. Chevron is one of the world's largest oil companies, and its major areas of operations are the West Coast of North America, the U.S. Gulf Coast, Southeast Asia, South Korea, Australia and South Africa. Chevron Corporation is also involved in cash management and debt financing activities, insurance operations, real estate activities, power and energy services, and technology businesses. For the future, Chevron plans to boost oil-and-gas production in 2016 and 2017 as new projects come to fruition.

PHILLIPS 66 (PSX)

Phillips 66 operates as an energy manufacturing and logistics company. It was founded in 1875 and is headquartered in Houston, Texas. It operates through four segments: Midstream, Chemicals, Refining, and Marketing and Specialties (M&S). In general, The company gathers, processes, transports and markets crude oil, natural gas and their products. The Chemicals division also manufactures and markets various chemical products, such as ethylene and some aromatics products.

Phillips has nearly a 3% dividend that is growing, strong cash flow and much less commodity exposure. Warren Buffett recently announced that Berkshire had invested $4.5 billion and acquired almost an 11% position in Phillips 66.

Alon USA Partners (ALDW)

Alon USA operates a petroleum refining and marketing business in the South Central and Southwestern regions of the United States. The company refines crude oil into finished products. Through its wholesale distribution network, ALDW sells products to Alon Energy's retail convenience stores and other third-party distributors. The company has a dividend of $4.16 per share and the yield is 16.61%. It reported a positive average earnings surprise of 41.42% for the trailing four quarters.

Tesoro Corporation (TSO)

Tesoro is an independent refiner and marketer of petroleum products. The company operates six refineries in the western United States with a combined rated crude oil capacity of approximately 845,000 barrels per day. Tesoro's retail-marketing system includes over 2264 branded retail gas stations, some of which are under its own brand name, as well as Shell, Exxon Mobil, ARCO, and USA Gasoline brand.

Valero Energy Corporation (VLO)

Valero Energy Corporation is an international manufacturer and marketer of transportation fuels, petrochemical products and power. The company's asset include 15 petroleum refineries, 11 ethanol plants and a 50-megawatt wind farm. Valero was one of the United States' largest retail operators with retails in the United States, Canada, United Kingdom, and the Caribbean under the Valero, Diamond Shamrock, Shamrock, Ultramar, Beacon, and Texaco brands.

- Companies from pharmaceuticals sector:

Clovis Oncology, Inc. (CLVS)

Clovis Oncology, Inc. is a biopharmaceutical company focused on acquiring, developing and commercializing cancer treatments in the United States, Europe and other international markets.

There are three products in clinical development:

1. Rociletinib (CO-1686), which is in Phase II development for the treatment of non small cell lung cancer.
2. Rucaparib, which is in Phase II and Phase III clinical trials for the treatment of ovarian cancer.
3. Lucitanib, which is in Phase II clinical trials for the treatment of lung cancers.

Gilead Sciences Inc. (GILD)

Gilead Sciences, Inc., a biopharmaceutical company which discovers, develops, and commercializes medicines in areas of unmet medical need in North America, South America, Europe, and the Asia-Pacific.

The company's products include:

1. Stribild, Complera/Eviplera, Atripla, Truvada, Viread, Emtriva, Tybost, and Vitekta for the treatment of HIV infection in adults.
2. Harvoni, Sovaldi, Viread, and Hepsera products for the treatment of liver disease.

Months ago, Gilead Sciences announced positive results from its phase III trial of the F/TAF (emtricitabine and tenofovir alafenamide) combo drug. The trial demonstrates non-inferior efficacy and better safety than Gilead's TDF drug

Truvada. The TAF results are a part of that multipronged strategy, they will ultimately help Gilead maintain its dominance in the HIV market.

ACADIA Pharmaceuticals Inc. (ACAD)

ACADIA Pharmaceuticals Inc. is a biopharmaceutical company focusing on the development and commercialization of small molecule drugs that address unmet medical needs in neurological and central nervous system disorders.

The lead product is NUPLAZID, which completed the Phase III pivotal trials for the treatment of Parkinson's disease psychosis and is in Phase II study for Alzheimer's disease psychosis, and has completed Phase II trial for the treatment of schizophrenia. Acadia also has clinical-stage programs for chronic pain and glaucoma in collaboration with Allergan, Inc.

Acadia has officially submitted a New Drug Application to the FDA for approval of Nuplazid. The FDA has already granted Nuplazid the much-coveted "breakthrough therapy" designation, and considering that patients who have Parkinson's Disease Psychosis currently have no real treatment options, sales estimates for Nuplazid look huge. Currently, analysts are expecting the drug to eventually reach more than $2 billion in peak sales.

uniQure N.V. (QURE)

uniQure N.V. is a biopharmaceutical company developing adeno-associated virus (AAV) based gene therapies through its technology platform for multiple therapeutic areas.

The company offers:

1. Glybera for the treatment of patients with lipoprotein lipase deficiency.
2. AMT-060, a gene therapy that is in Phase I/II clinical trial for the treatment of hemophilia B.
3. S100A1, a preclinical therapeutic for congestive heart failure.

Glybera is the first and currently the only gene therapy product for lipoprotein lipase deficiency, and it's extremely expensive. The European Union estimates that for one patients, the expenditure on treatment with Glybera is about $1.6 million. The next big growth for the company is the genetic therapy for hemophilia B. The expenditure for one patient may be higher than $1 million.

Sarepta Therapeutics, Inc. (SRPT)

Sarepta Therapeutics is a biopharmaceutical company focused on developing innovative RNA-based therapeutics for the treatment of rare and infectious diseases.

The lead product candidate is Eteplirsen, which is in Phase III clinical development stage for the treatment of individuals with Duchenne muscular dystrophy (DMD), a rare genetic muscle-wasting disease.The company is also involved in developing treatments that are in Phase I clinical trials for other diseases, including AVI-7288 for Marburg virus; and AVI-7100 for H1N1 influenza virus.

The company received encouraging news with its new drug application for DMD candidate, Eteplirsen, being accepted for priority review by the FDA. Eteplirsen has received the rare 'pediatric disease' designation from the FDA for DMD. Eteplirsen approval would be a huge boost for the company – it would be able to address about 13% of the total DMD population.

- Companies from Technology Sector:

IPG Photonics

IPG Photonics is a company that manufactures fiber optic lasers. Fiber optic lasers are more efficient and are better at cutting thinner metals than the more ubiquitous CO2 lasers. This is especially useful in the manufacturing of transportation vehicles. Manufacturers today are trying to make vehicles more fuel efficient, and one way to maximize efficiency is to lower weight by using thinner materials. As a result, fiber optic lasers have had increased demand. Tracking the price of IPG Photonics can be a way to see how changing trends in technology affect stock prices.

iRobot

The iRobot Corporation is a company that manufactures robots for commercial and military use. 60% of their products are for commercial use, the most famous of which is the Roomba. iRobot's next commercial robot is meant to mow lawns, and recently the company has also received a 4 million dollar deal with the US Navy, which could lead to further growth. Tracking iRobot is interesting for the future because robotics and automation will become increasingly important in the future, along with the upcoming new product and deals. These could influence the buying decisions of investors, which leads to a change in price. As one of the first high profile robotics companies, iRobot could make an impact in the near future.

Synaptics

Synaptics Inc develops device interfaces, such as touch screens and fingerprint sensors. Especially as touch screens become more ubiquitous in the smartphone age, Synaptics grew quickly earlier in the year and will be relevant still in the near future, as the usage of touch screens increases. However, a recent rival, Fingerprint Cards, has created competition, which has led to a slump in Synaptics' growth. Looking forward, Synaptics will have to deal with stiffer competition now, as their products continue to stay relevant in the future. Observing the effects of a

competitor on a market that was mostly dominated by one company can affect stock prices and predictions.

Cisco Systems

Cisco Systems Inc designs and manufactures a wide variety of networking equipment and software. 85% of the world's internet traffic travels through Cisco's systems. Cisco is influential enough to be a part of the NASDAQ-100 Technology Sector Index, which greatly contributes to the perception of tech stock performance. Cisco has recently announced a partnership with Apple for business users. It will be interesting to see how this will affect both companies, especially since both are in slight slumps. Tracking Cisco's progress will be a good way to observe the effects of such partnerships.

Verizon Communications:

Verizon is a telecommunications company, most well known for being the largest American wireless communications company. Verizon is large enough that it is a component of the Dow Jones Industrial Average, which only accounts for 30 of the largest publicly owned stocks in the United States. Tech stocks have a reputation for being volatile, but Verizon is one of the most stable tech stocks, partially due to its size and establishment. Therefore, tracking Verizon stock price will be a good baseline to compare the stability of prices and predictions of other stocks.

- Companies from Information Technology and Electric Cars Sector:

Tesla (TSLA)

Tesla Motors, Inc. is an American automotive and energy storage company that designs, manufactures, and sells luxury electric cars, electric vehicle components, and battery products. Tesla Motors trades on the NASDAQ stock exchange under the symbol TSLA. Electric cars are very popular today and it could be supported by governments in many countries. In the US, Tesla is the lead manufacturer of electric cars. This sector has a huge potential in the future, so Tesla is in the chosen list.

Toyota (TM)

Toyota Motor Corporation is a Japanese automotive manufacturer. As of July 2014, Toyota was the largest listed company in Japan by market capitalization and by revenue. Toyota is the largest manufacturer of hybrid cars in an already developed industry. It could be the largest competitor of electric cars.

Sumitomo Metal Corporation (SMMYY)

Sumitomo Metal Industries, Ltd. was a steel manufacturer based in Osaka, Japan until it merged with Nippon Steel in 2012 to form Nippon Steel & Sumitomo Metal Corporation, the second largest steel manufacturer in the world as of 2014. At the core of electric cars is the battery, and Sumitomo Metal Industry is the largest raw material provider for the batteries that Tesla uses.

Panasonic (PCRFY)

Same as Sumitomo Metal Corporation, Panasonic also cooperates with Tesla, as a battery manufacturer.Panasonic Corporation, formerly known as Matsushita Electric Industrial Co., Ltd. is a Japanese multinational electronics corporation headquartered in Kadoma, Osaka, Japan. The company was founded in 1918 and has grown to become one of the largest Japanese electronics producers alongside Sony, Hitachi, Toshiba and Canon Inc. In addition to electronics, it offers non-electronic products and services such as home renovation services.

Panasonic is the world's fourth-largest television manufacturer by 2012 market share.

XO Group (XOXO)

XO Group Inc. is a media company that publishes multimedia content for couples who are planning weddings, moving in together, or having a child. The company generates revenue through online advertising, merchandising, registry services, and publishing. The company headquarters are located in New York City, with offices in several locations in the US and in China.

Application of the Models

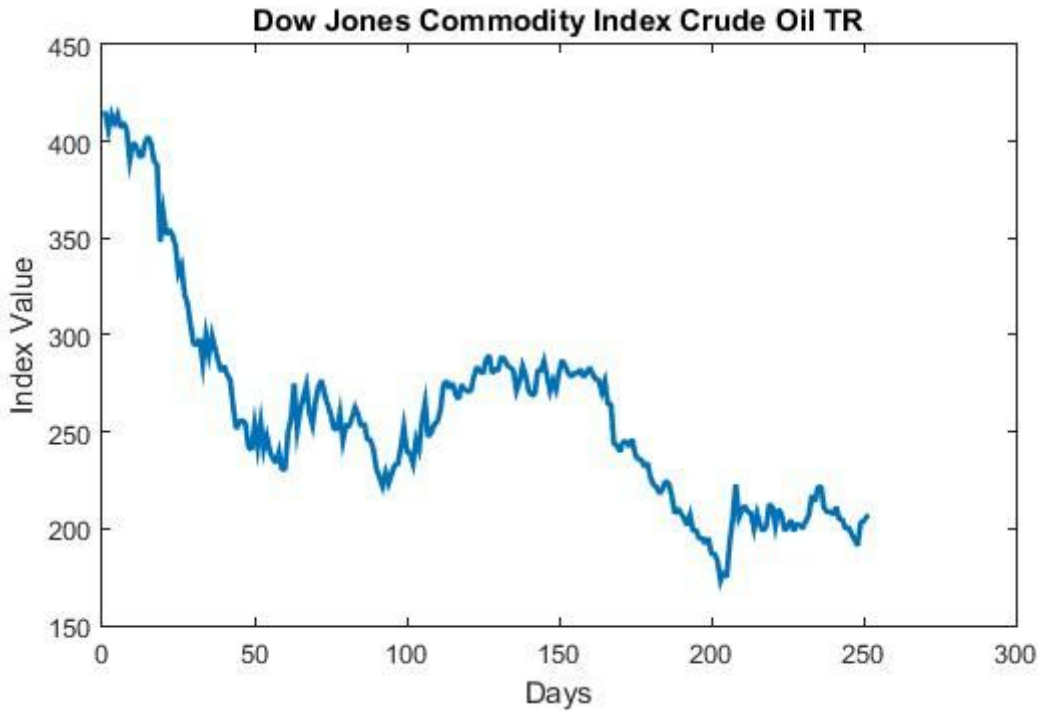
- Petroleum Sector:

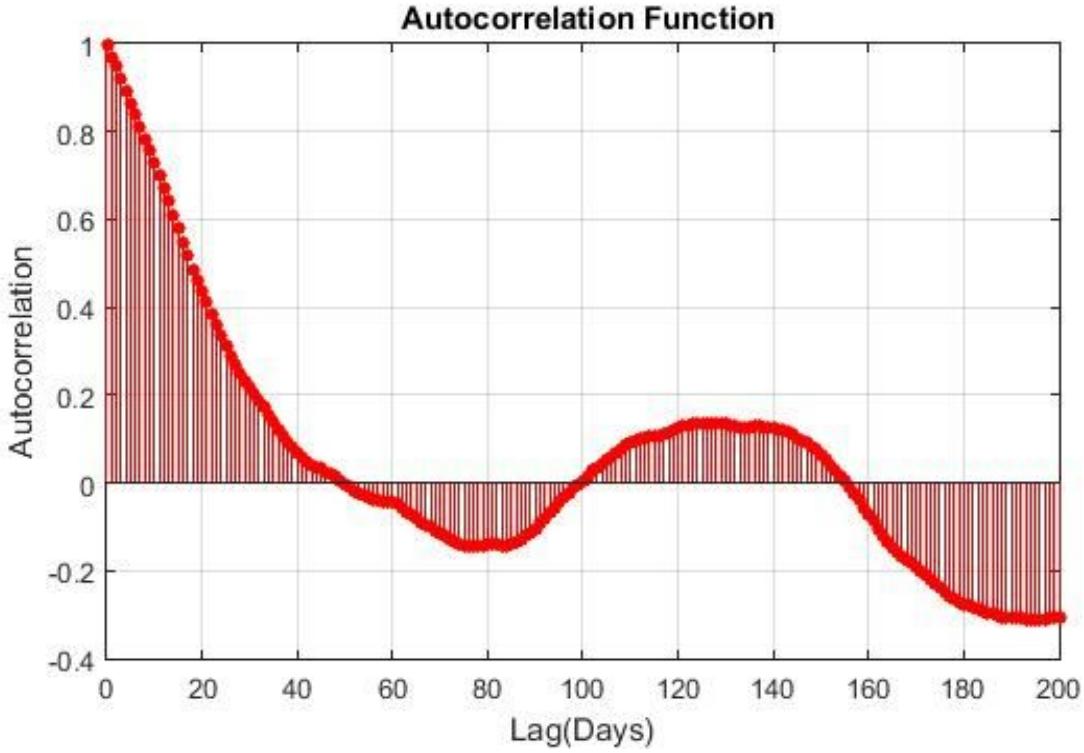
Dow Jones Commodity Index Crude Oil (DJCICL)

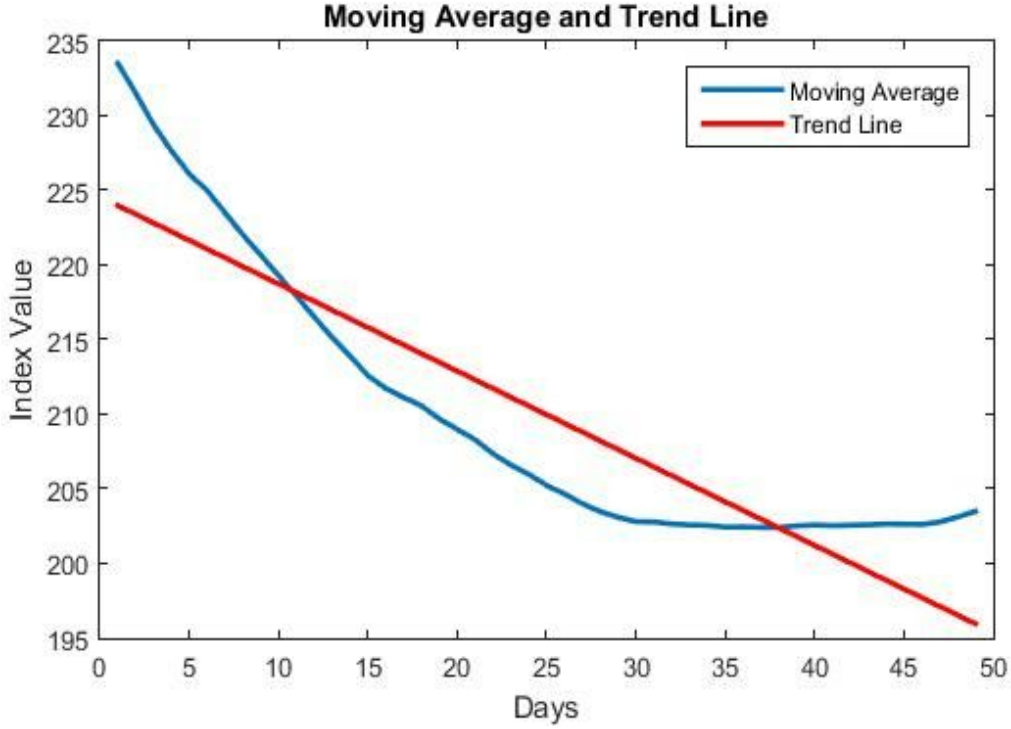
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

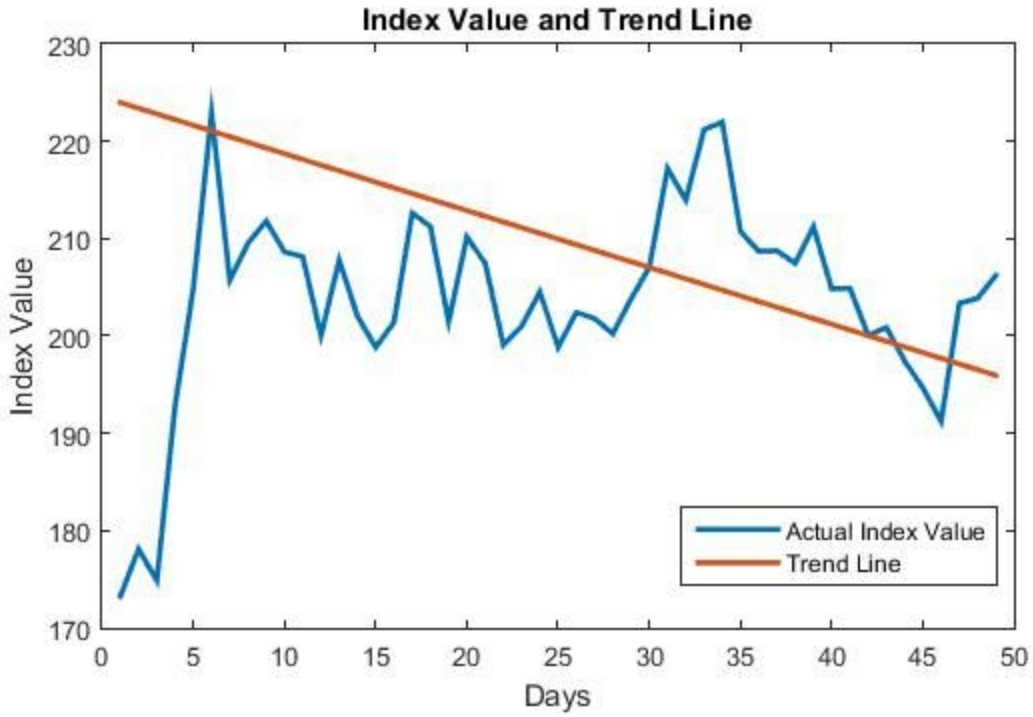
Moving Average Window: 50 Days.

Autocorrelation Days : 49




Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200


Moving Average and Trend Line
Moving Average
Trend Line
Index Value
Days
235
230
225
220
215
210
205
200
195
0
5
10
15
20
25
30
35
40
45
50


Index Value and Trend Line
Index Value
Days
Actual Index Value
Trend Line
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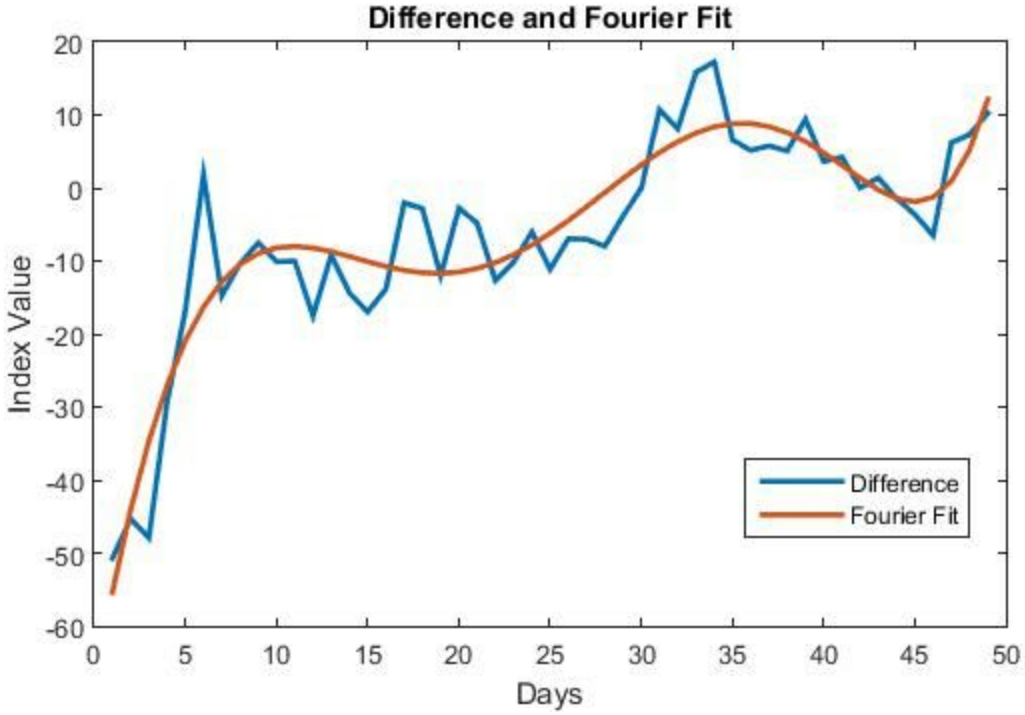
220
210
200
190
180
170
0
5
10
15
20
25
30
35
40
45
50


Difference and Fourier Fit
Index Value
Days
Difference
Fourier Fit
20
10
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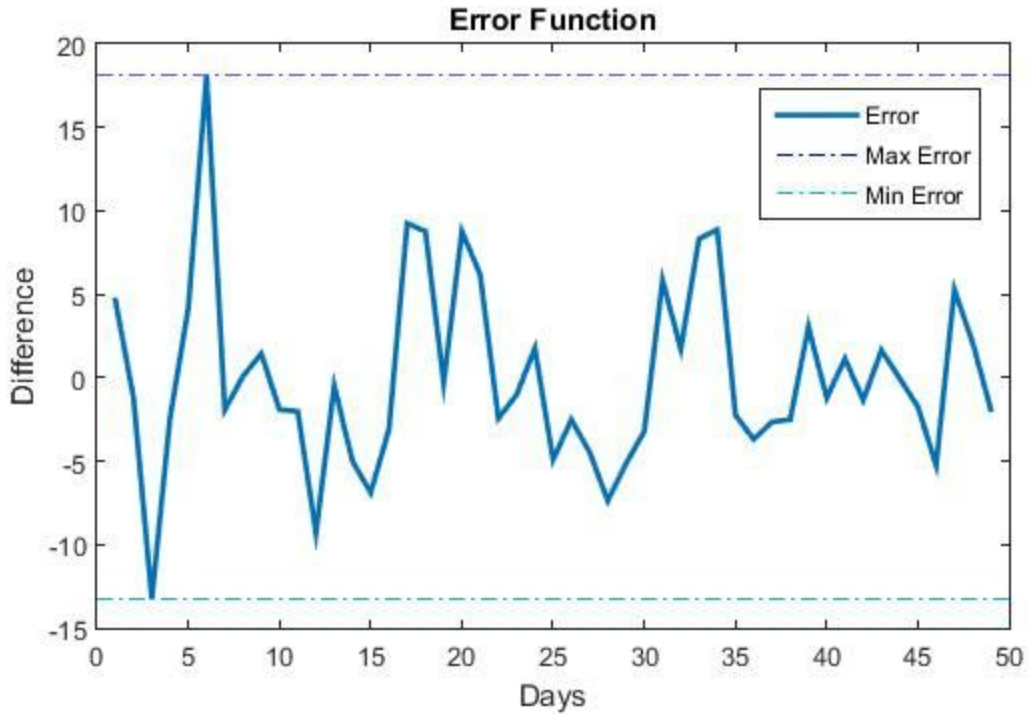
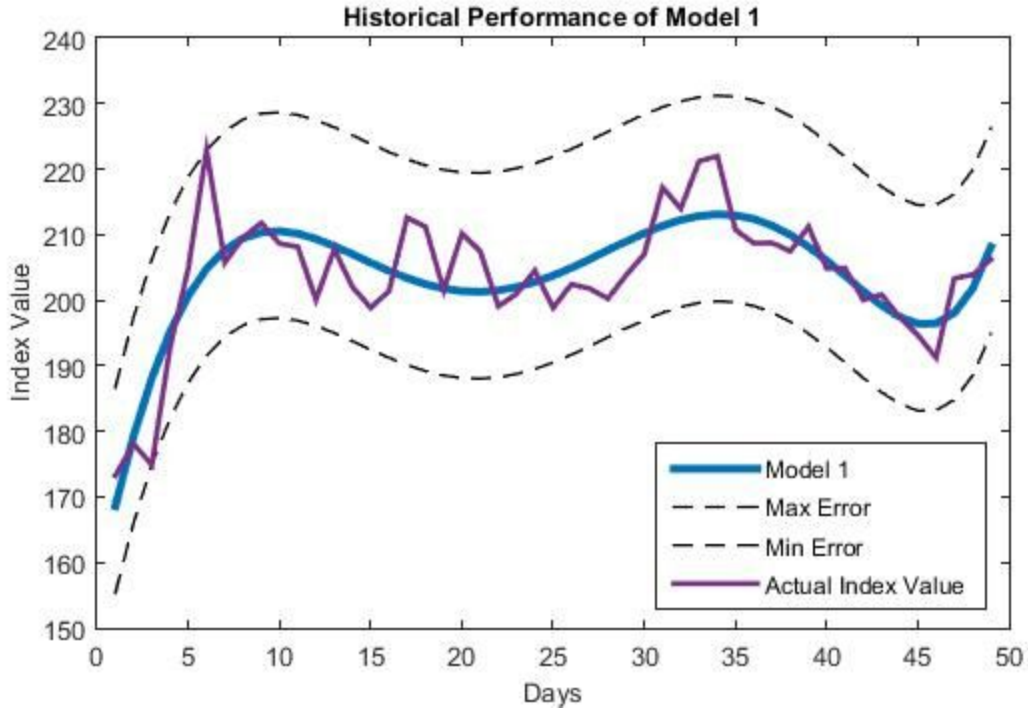
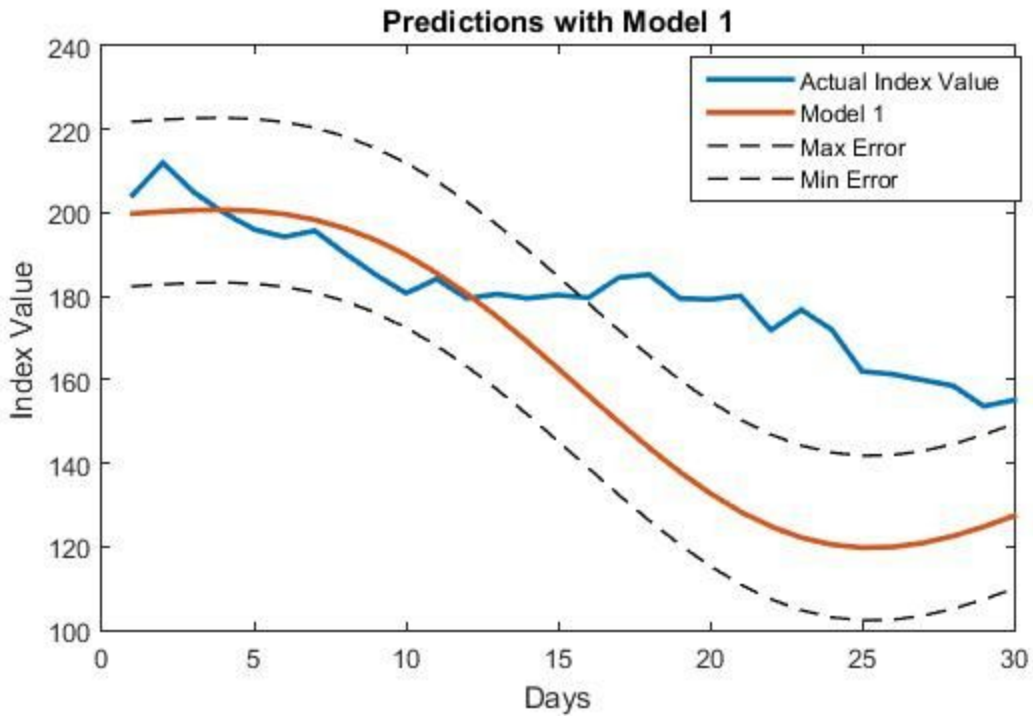
-10
-20
-30
-40
-50
-60
0
5
10
15
20
25
30
35
40
45
50


Error Function
Error
Max Error
Min Error
Difference
Days
20
15
10
5
0
-5
-10
-15
0
5
10
15
20
25
30
35
40
45
50


Historical Performance of Model 1
Model 1
Max Error
Min Error
Actual Index Value
Index Value
Days
240
230
220
210
200
190
180
170
160
150
0
5
10
15
20
25
30
35
40
45
50



Max Error : 10%

Min Error : -9%

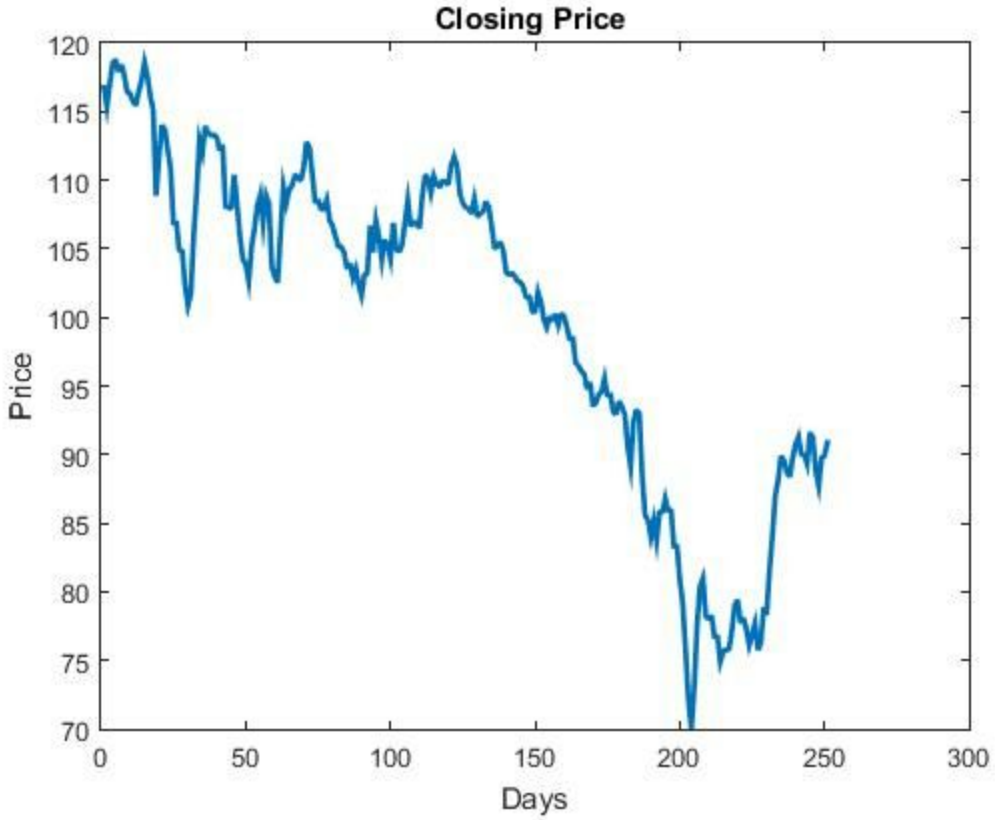
Chevron Corp (NYSE: CVX)

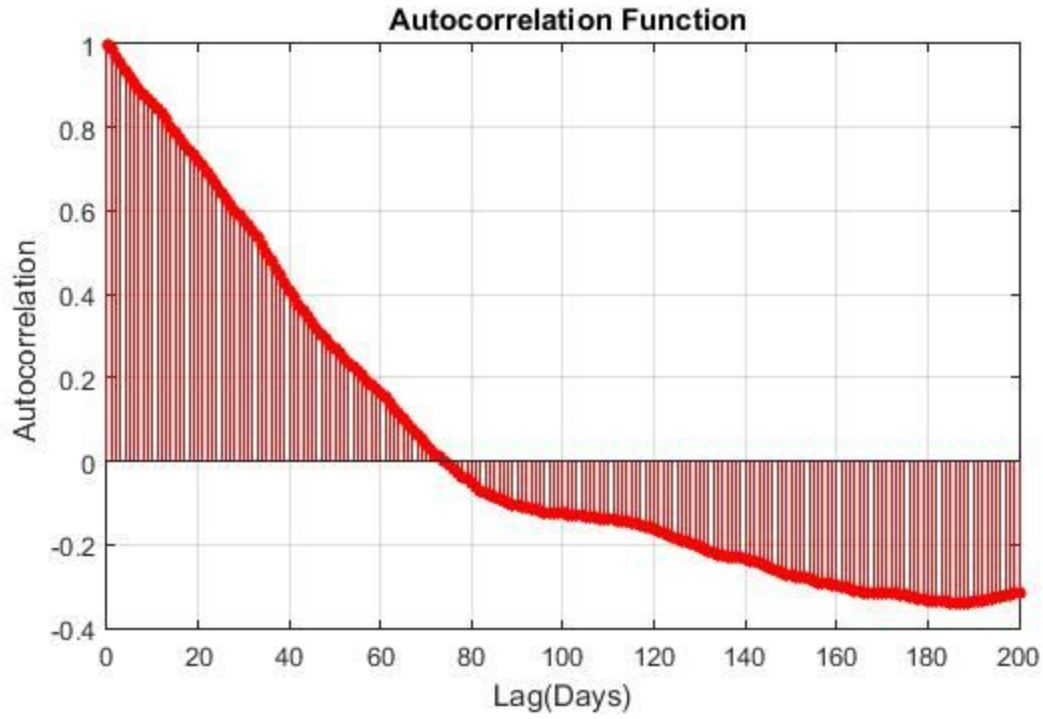
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

Moving Average Window: 50 Days.

Autocorrelation Days : 68

Correlation with the index : 0.7820




Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
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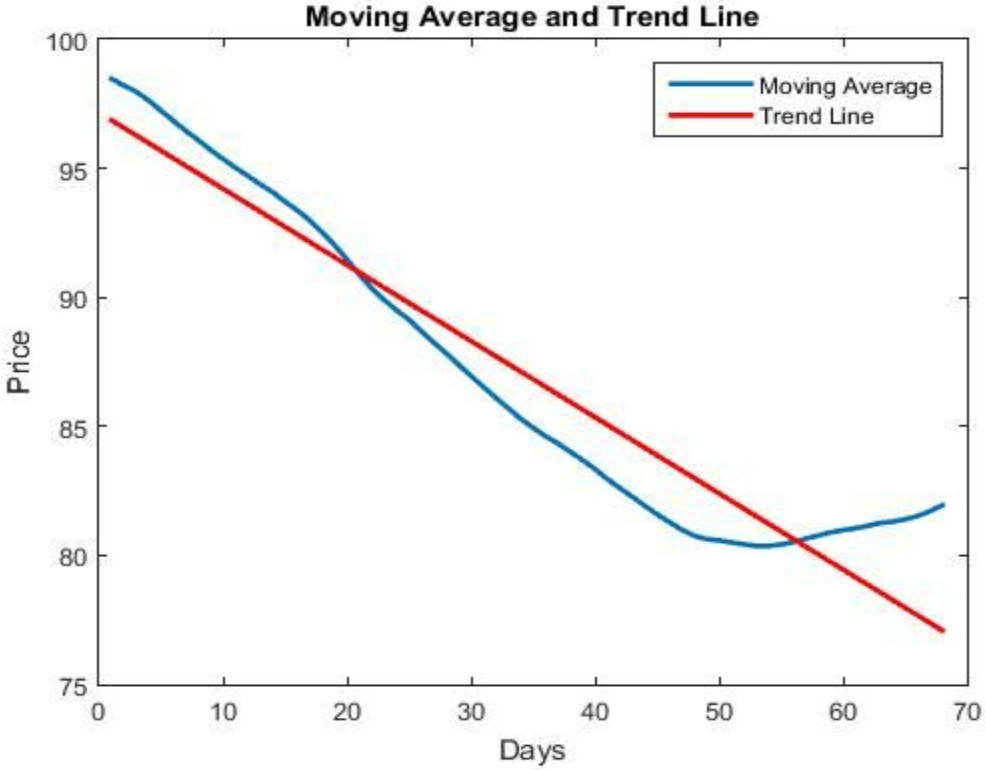
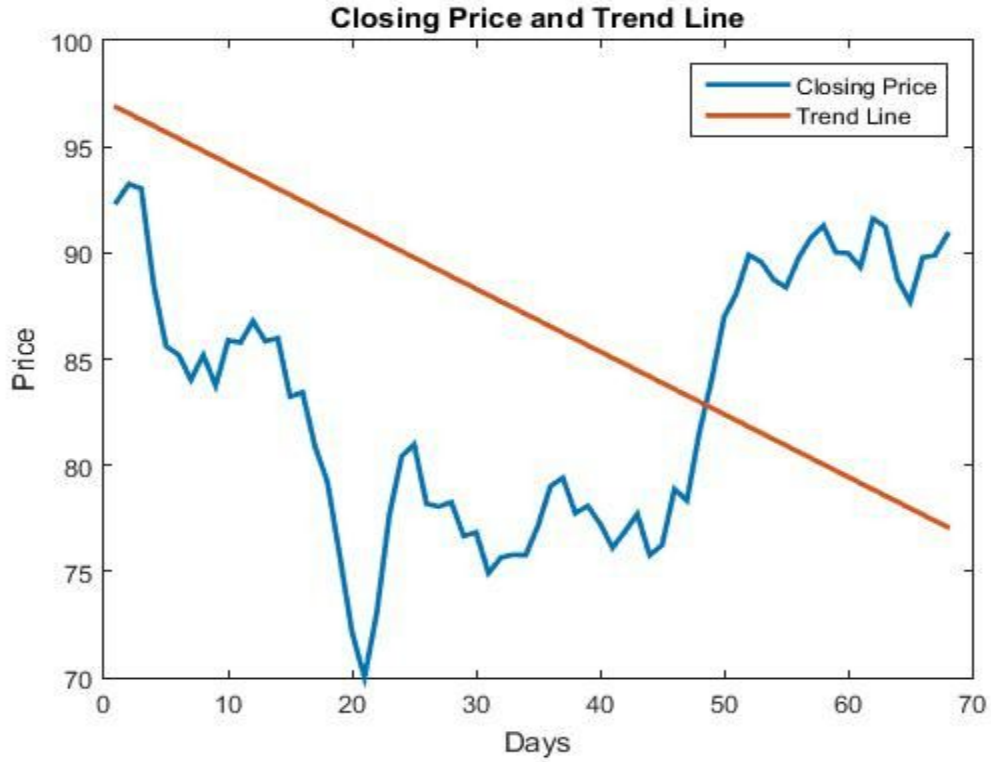
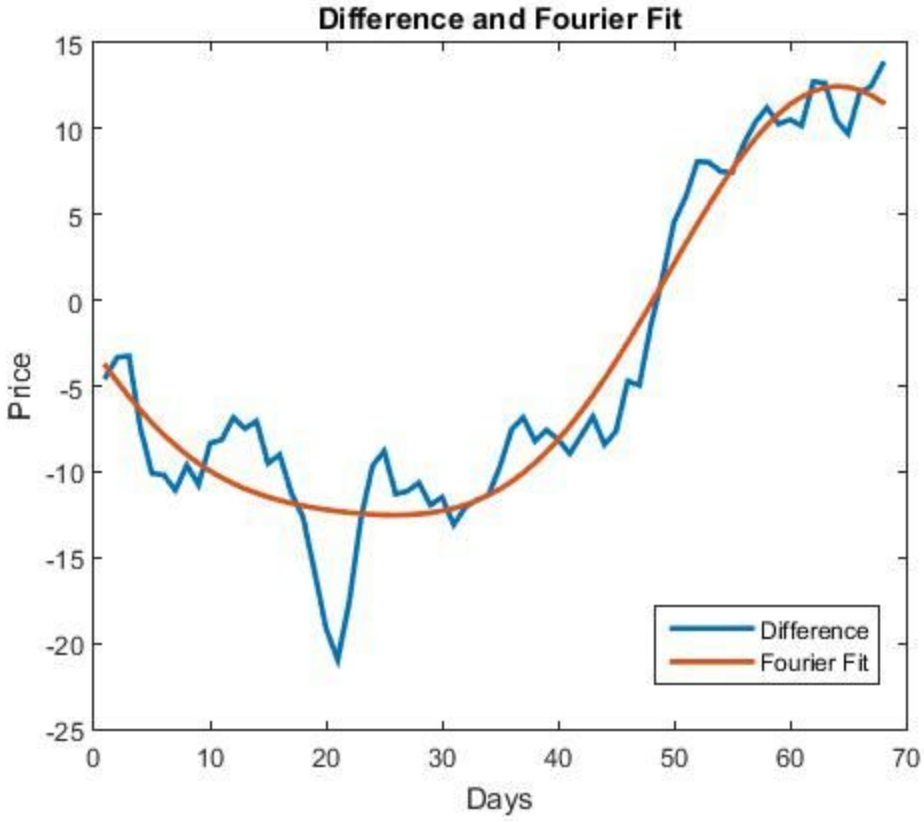
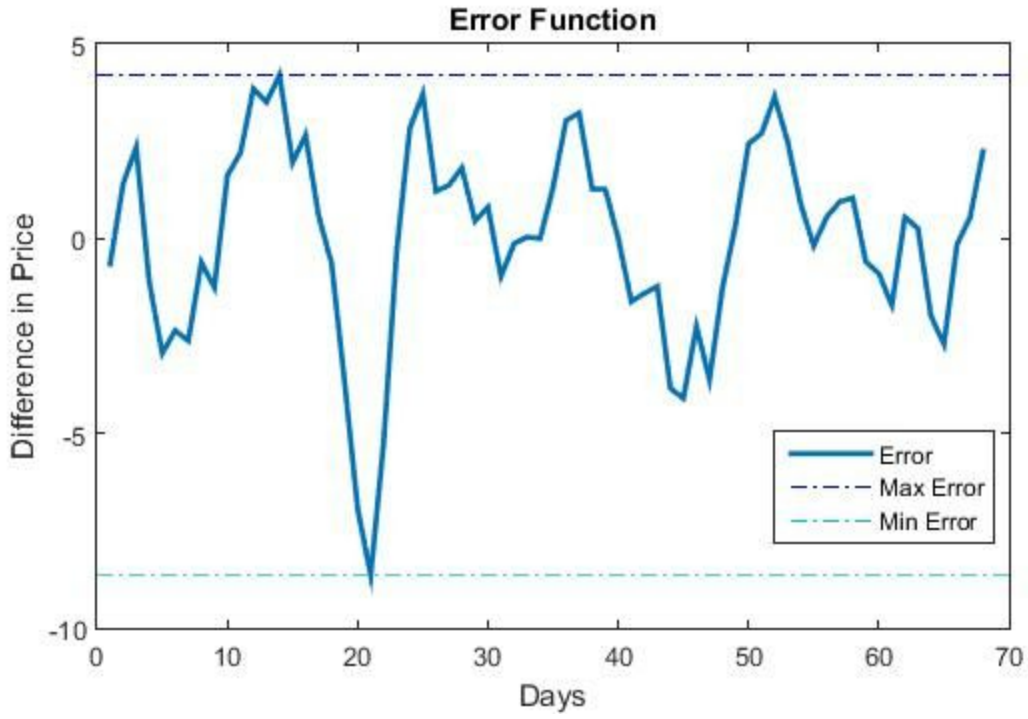
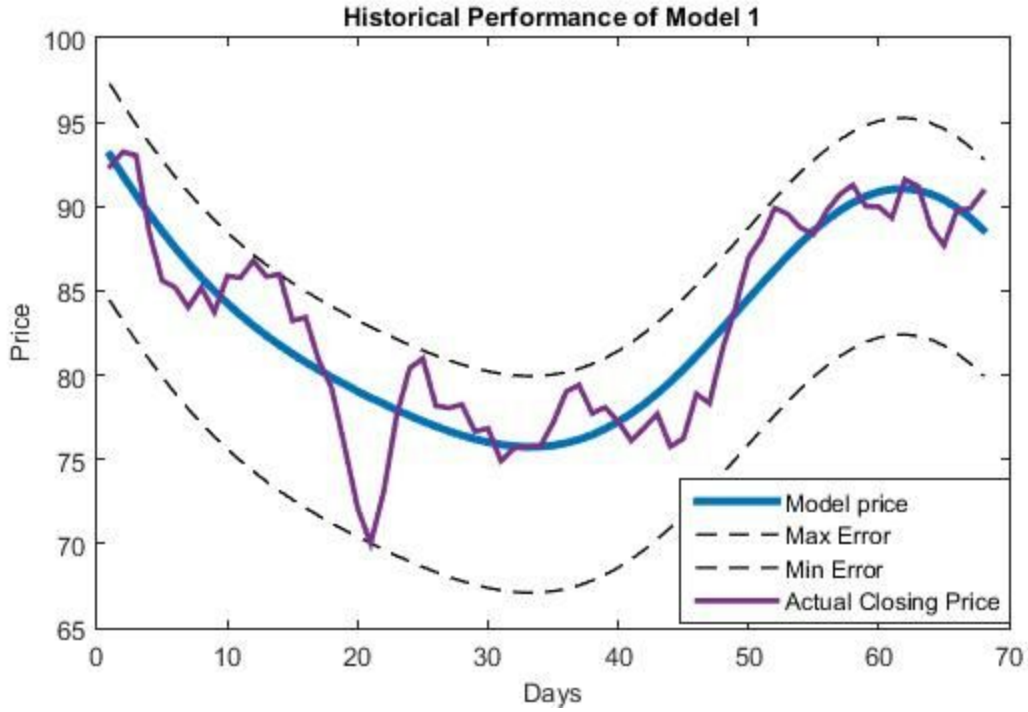
20
40
60
80
100
120
140
160
180
200

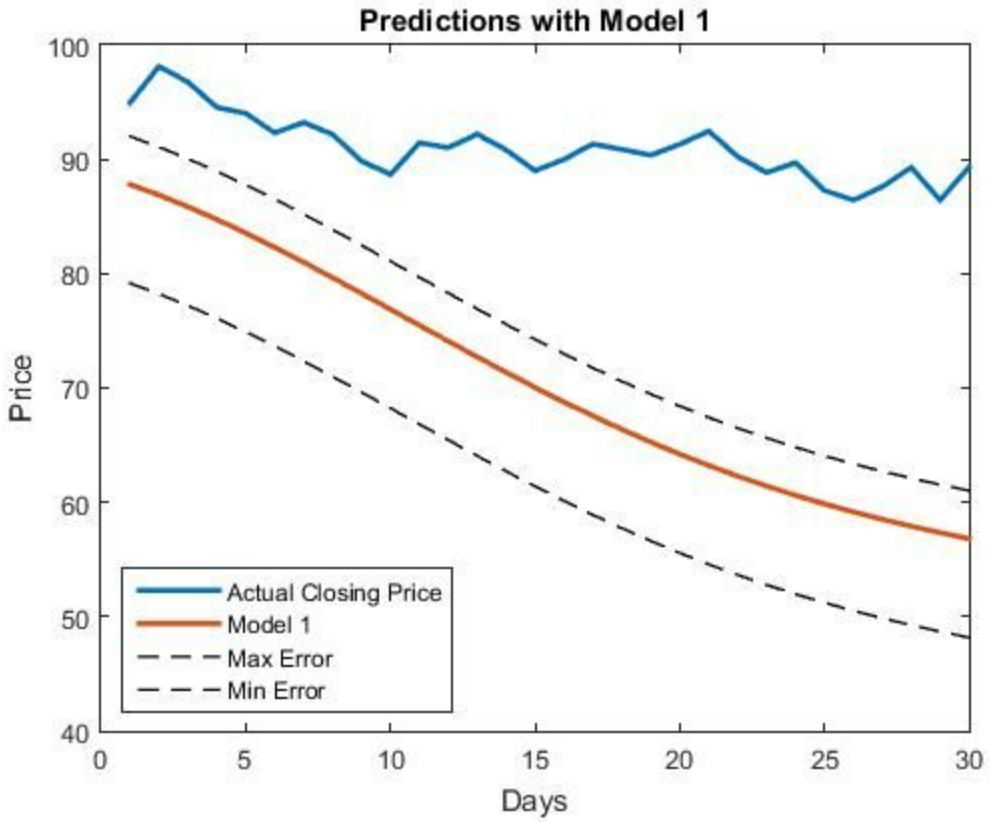

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
100
95
90
85
80
75
0
10
20
30
40
50
60
70


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
100
95
90
85
80
75
70
0
10
20
30
40
50
60
70


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
15
10
5
0
-5
-10
-15
-20
-25
0
10
20
30
40
50
60
70

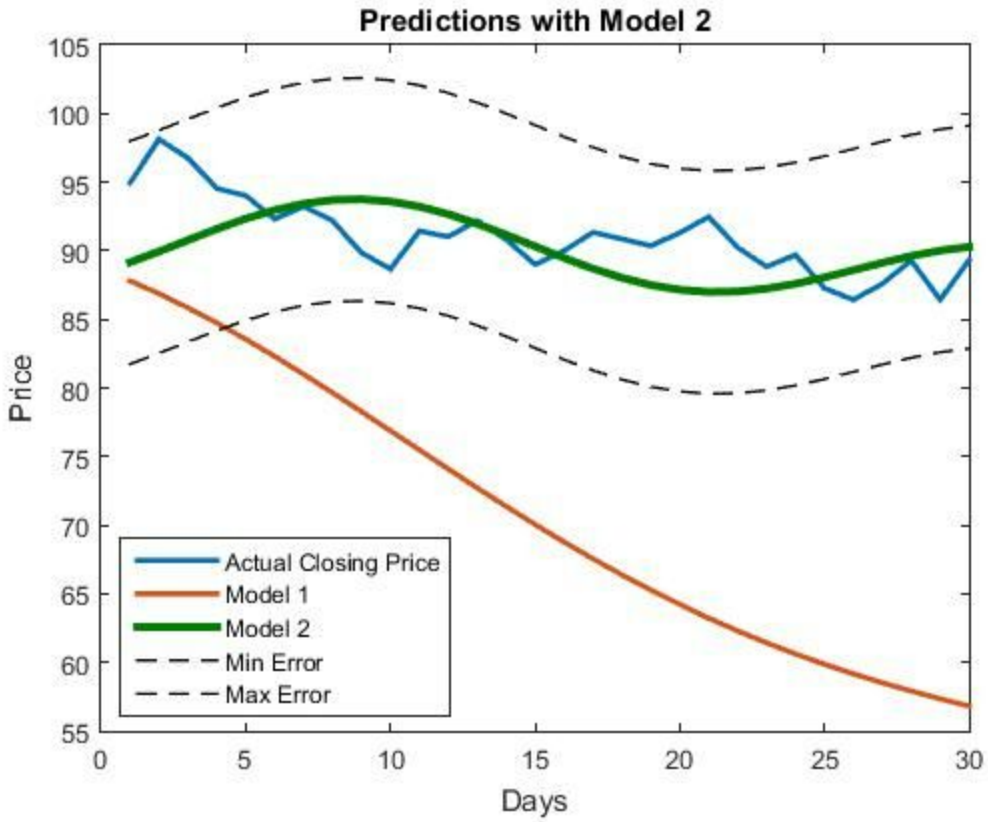

Error Function
Difference in Price
Days
Error
Max Error
Min Error
5
0
-5
-10
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Price
Days
Model price
Max Error
Min Error
Actual Closing Price
100
95
90
85
80
75
70
65
0
10
20
30
40
50
60
70



Max Error : 4.5%

Min Error : -8.5%



Max Error : 10%

Min Error : -8.5%

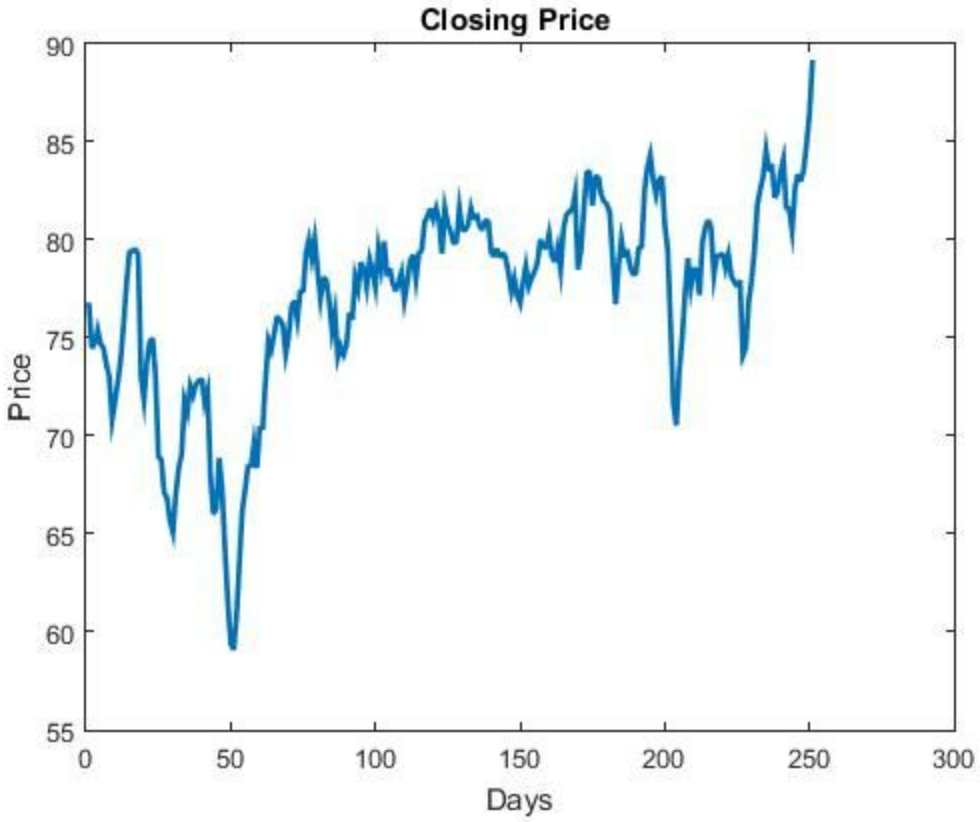
Phillips 66 (NYSE: PSX)

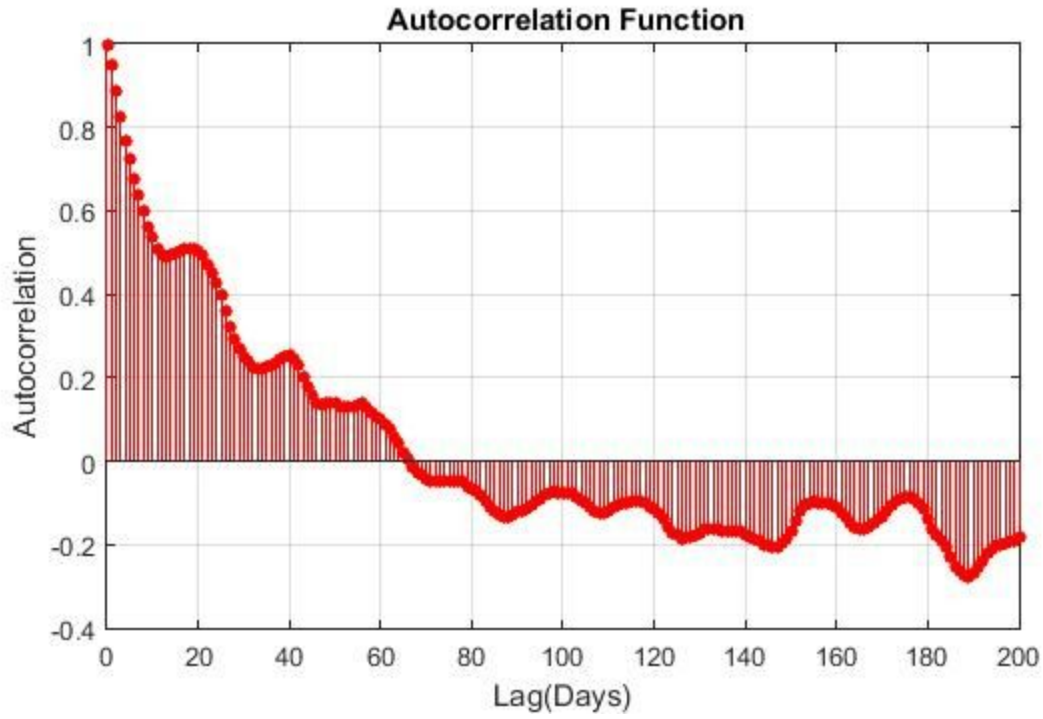
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

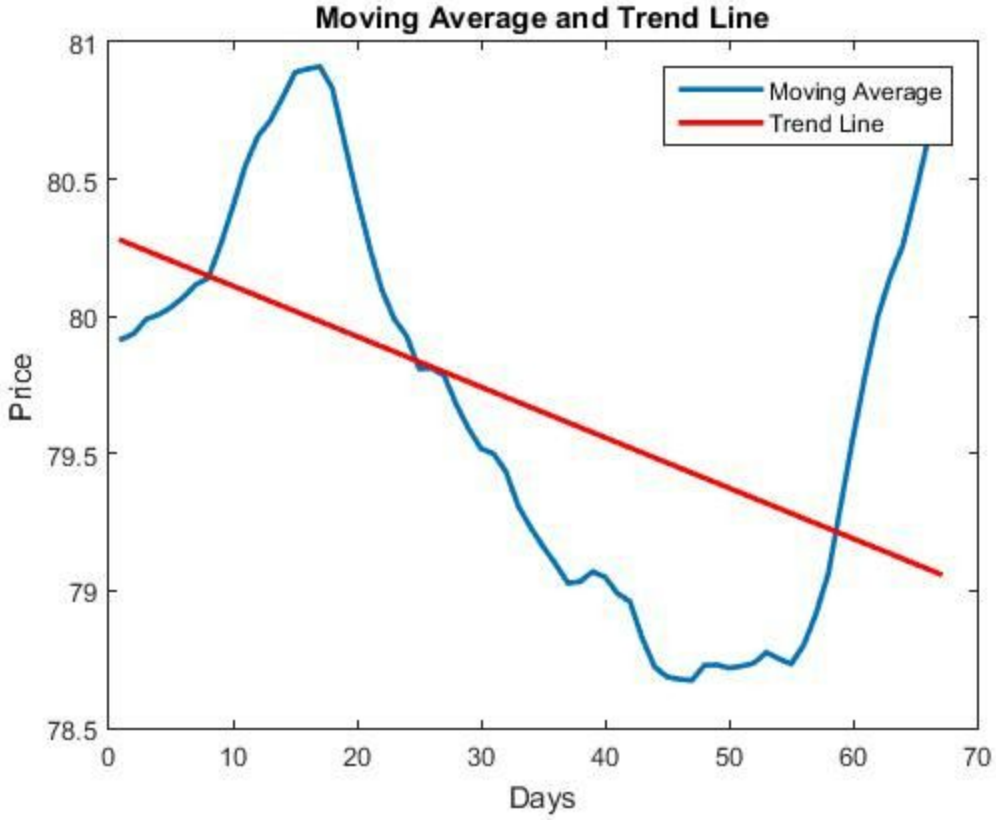
Moving Average Window: 50 Days.

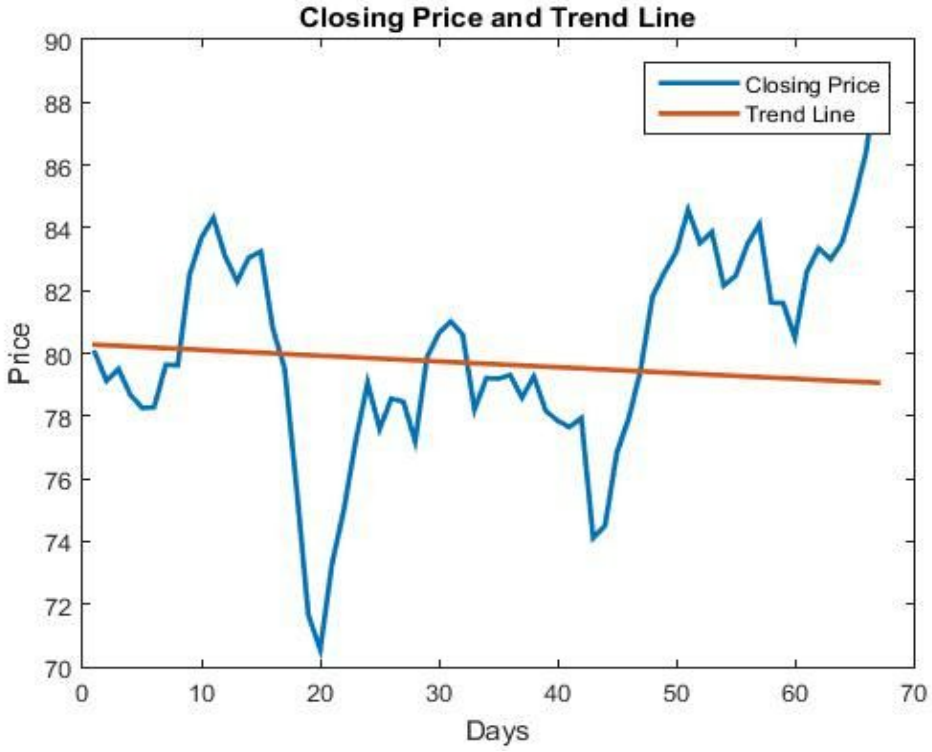
Autocorrelation Days : 67

Correlation with the index : -0.2763




Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200


Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
81
80.5
80
79.5
79
78.5
0
10
20
30
40
50
60
70


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
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86
84
82
80
78
76
74
72
70
0
10
20
30
40
50
60
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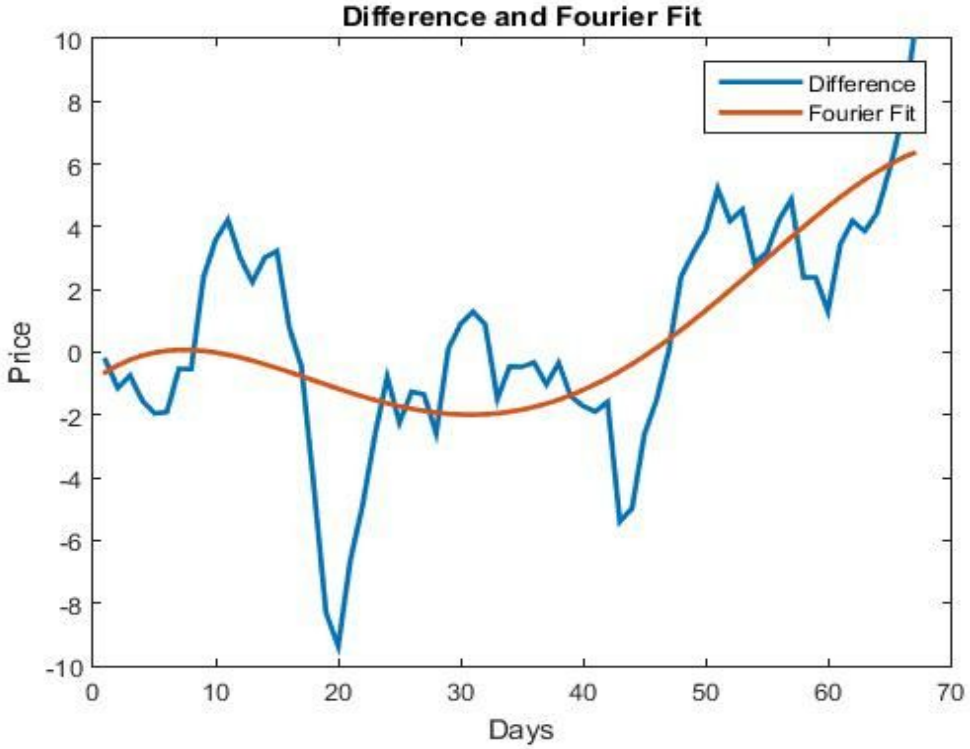
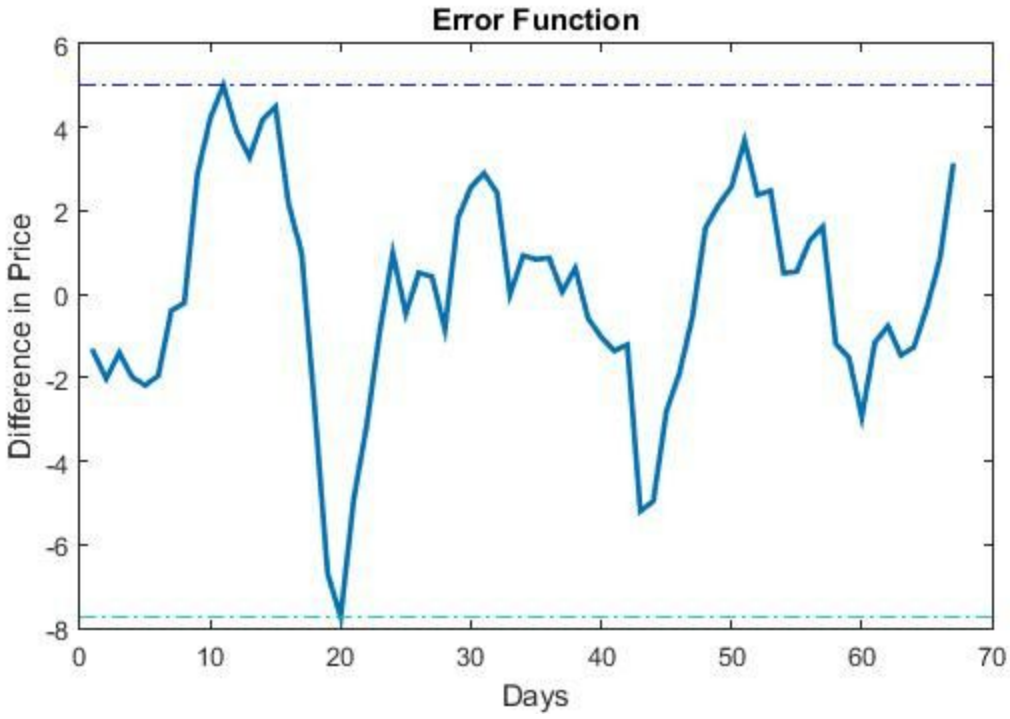

Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
10
8
6
4
2
0
-2
-4
-6
-8
-10
0
10
20
30
40
50
60
70


Error Function
Difference in Price
Days
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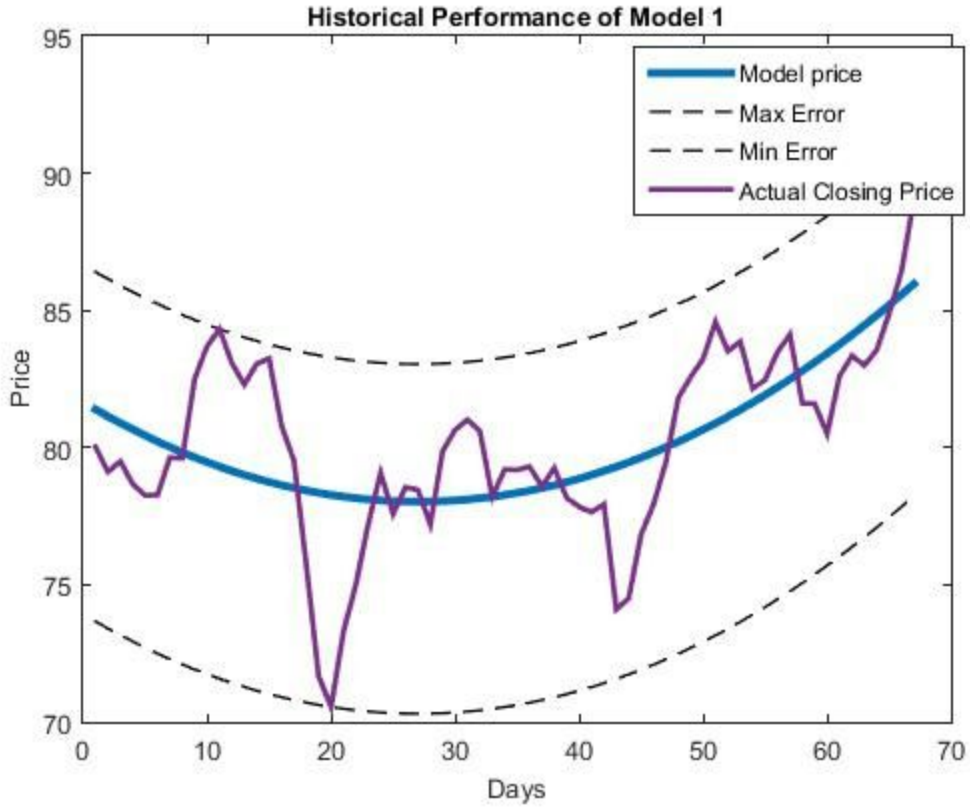
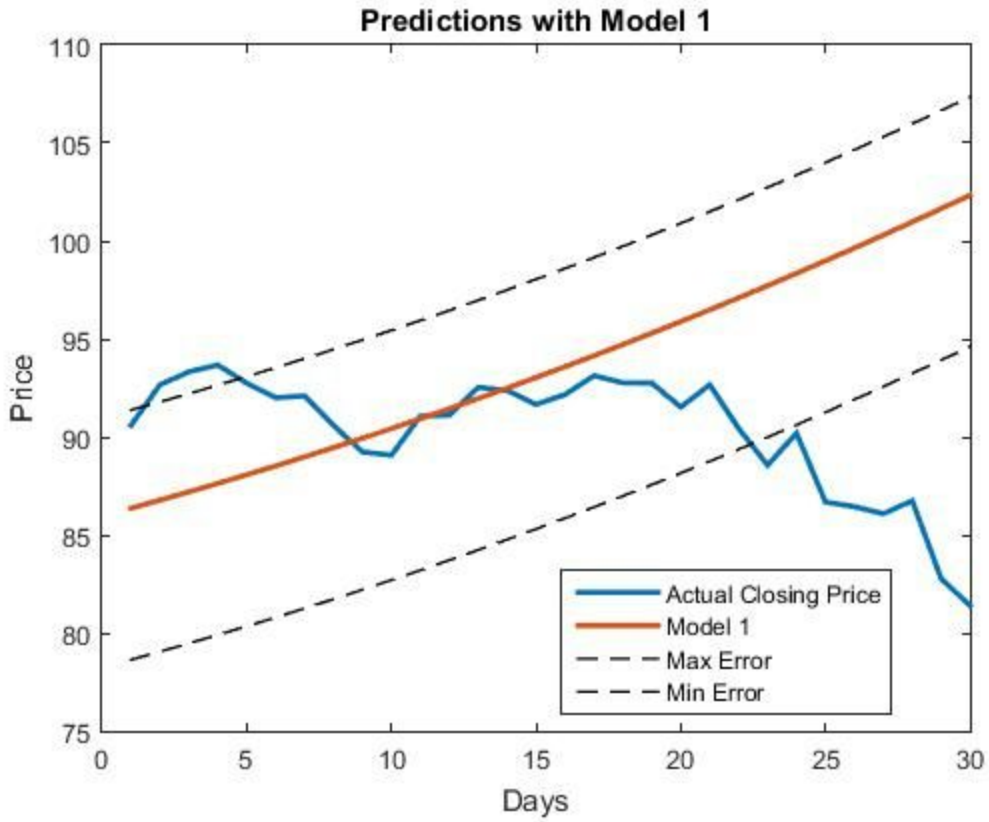
4
2
0
-2
-4
-6
-8
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Price
Days
95
90
85
80
75
70
0
10
20
30
40
50
60
70



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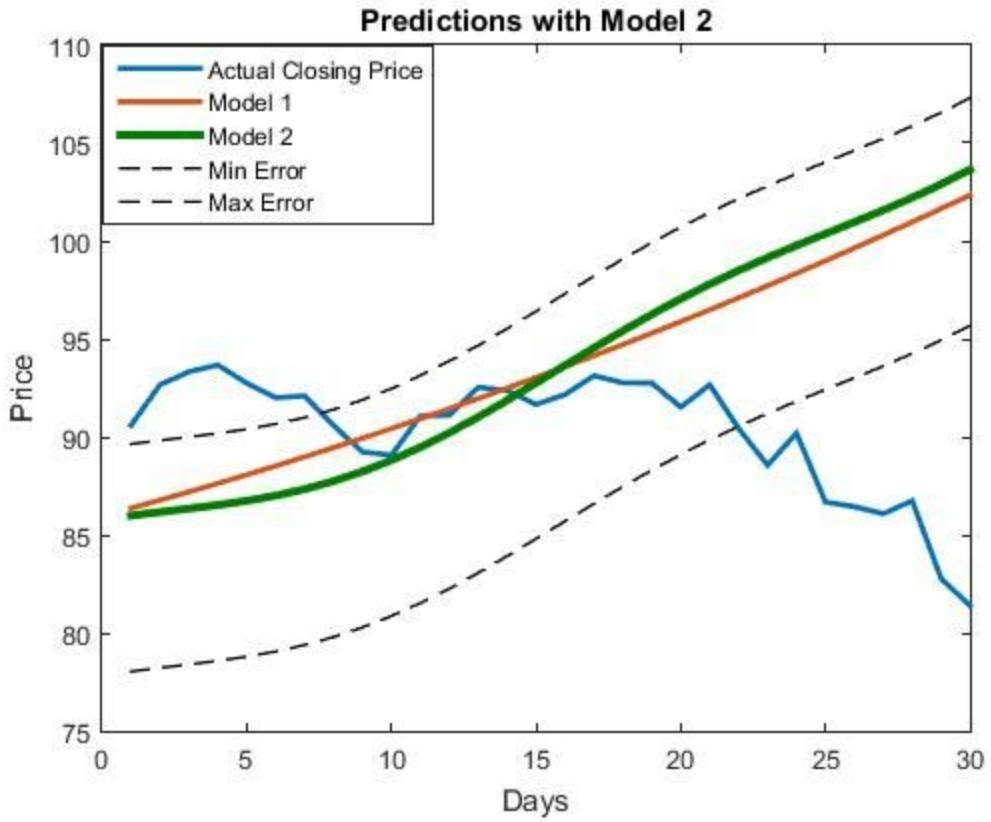
Min Error : -8.5%



Max Error : 5%

Min Error : -8.5%

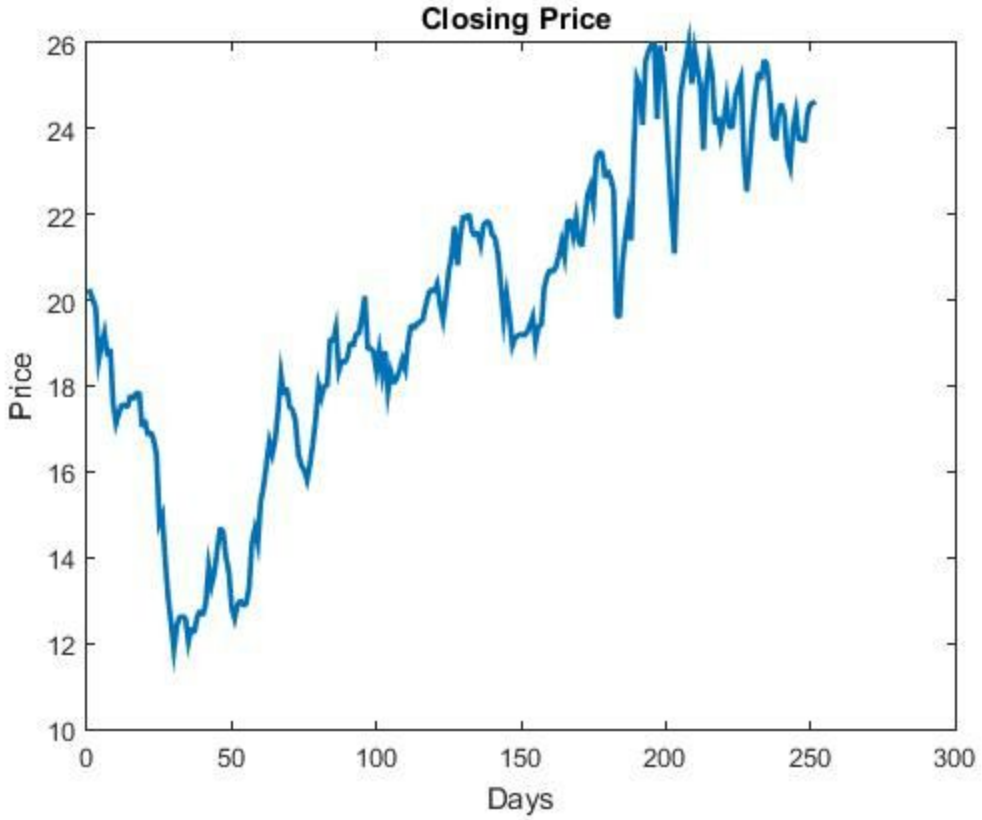
Alon USA Partners LP (NYSE: ALDW)

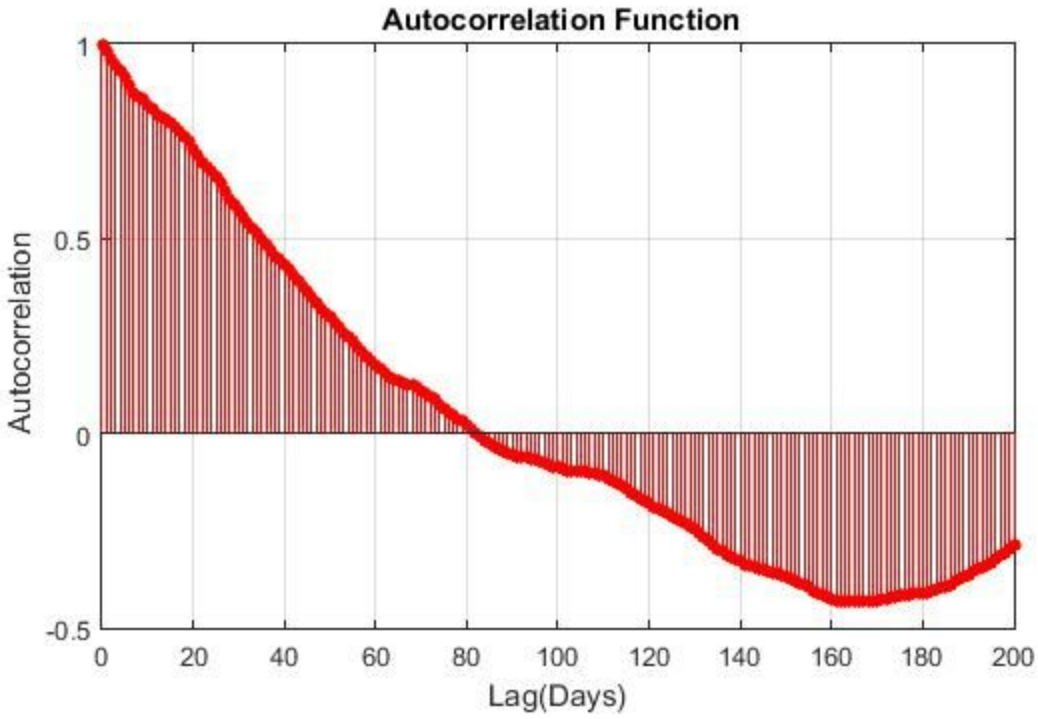
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

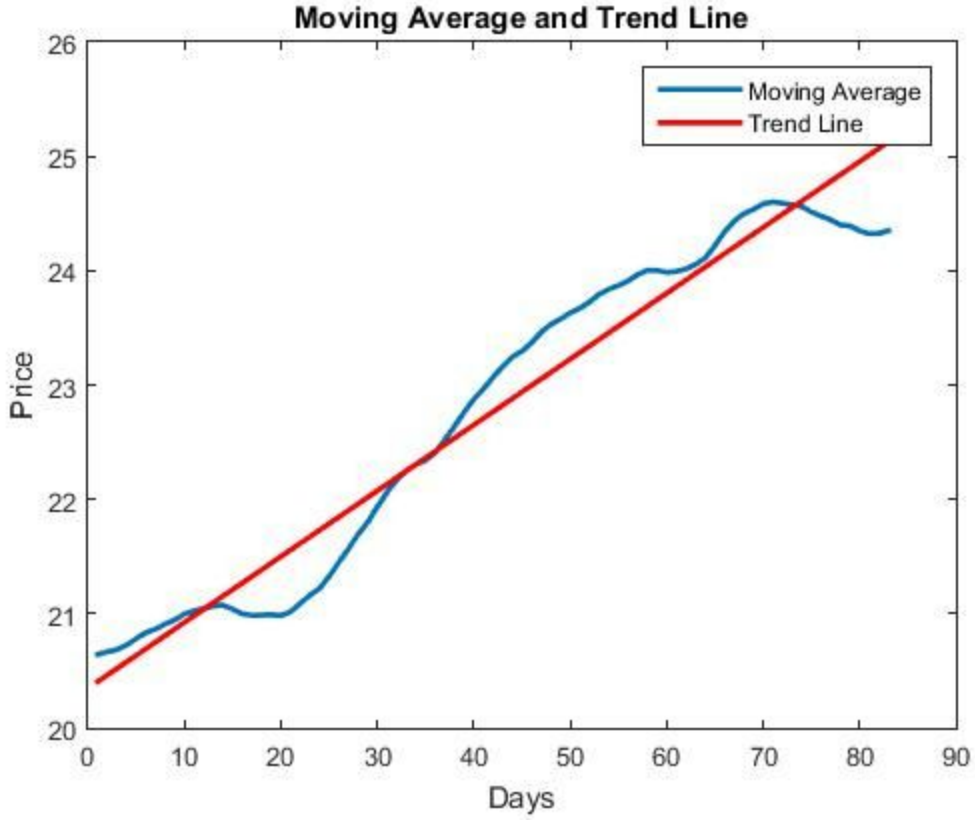
Moving Average Window: 50 Days.

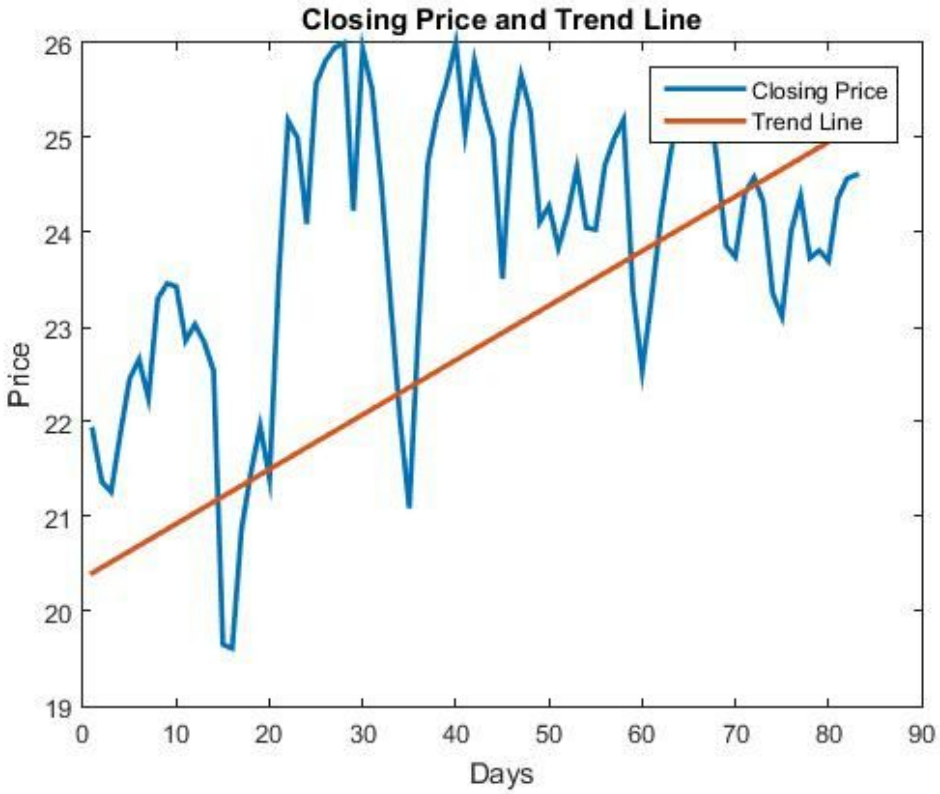
Autocorrelation Days : 83

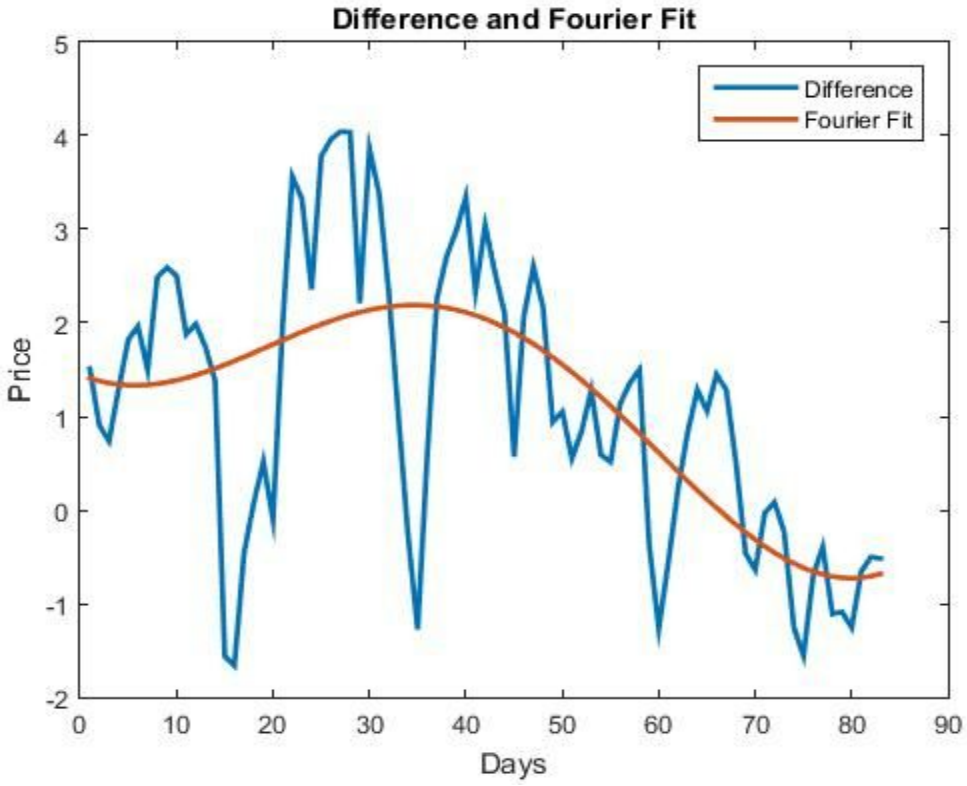
Correlation with the index : -0.4977

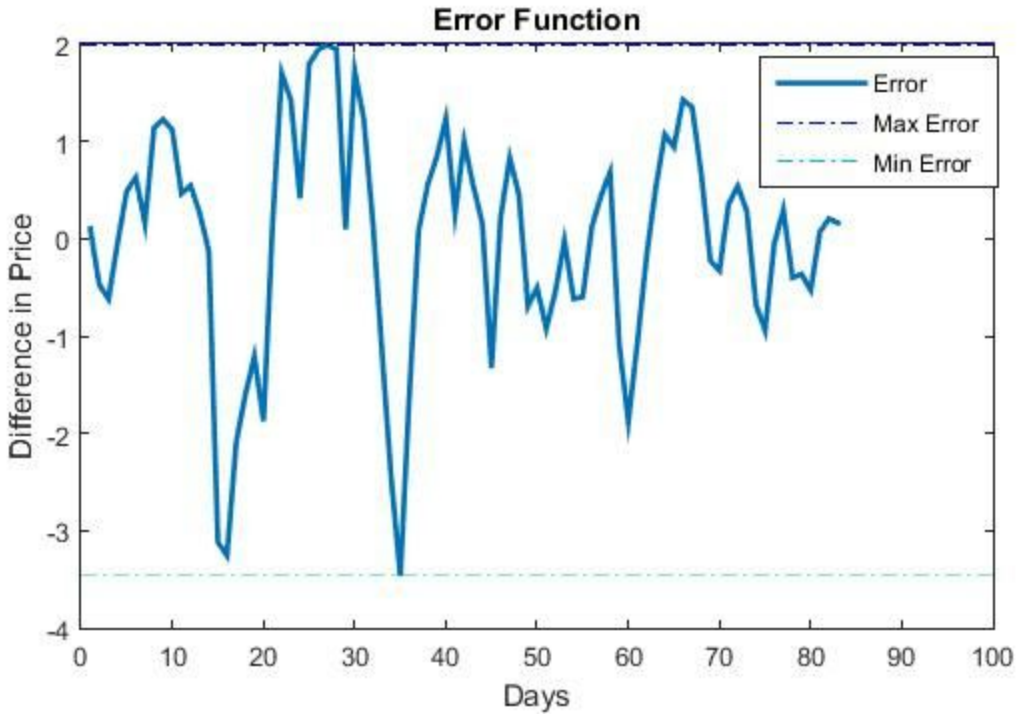


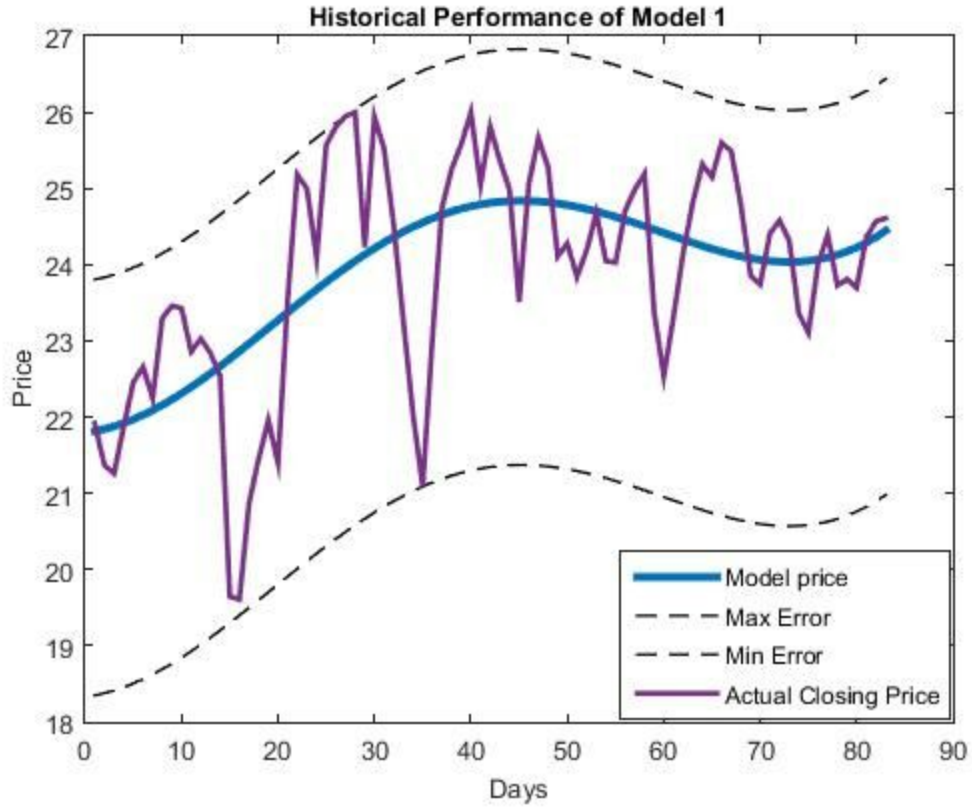

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.5
0
-0.5
0
20
40
60
80
100
120
140
160
180
200

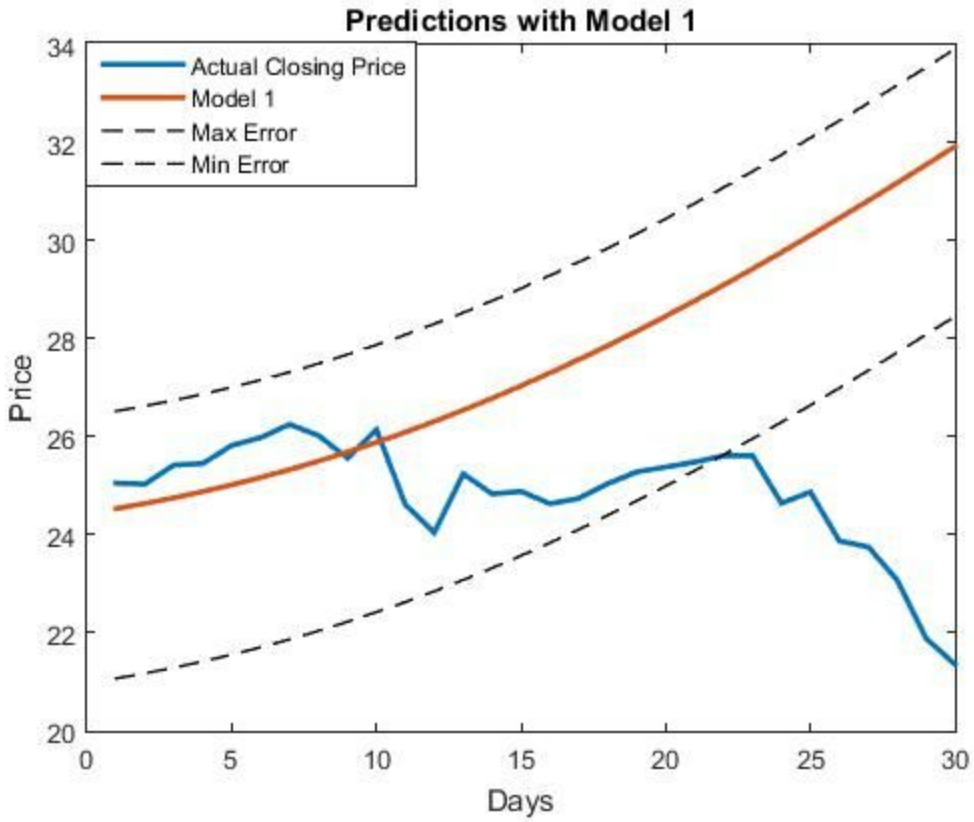

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
26
25
24
23
22
21
20
0
10
20
30
40
50
60
70
80
90


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
26
25
24
23
22
21
20
19
0
10
20
30
40
50
60
70
80
90


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
5
4
3
2
1
0
-1
-2
0
10
20
30
40
50
60
70
80
90

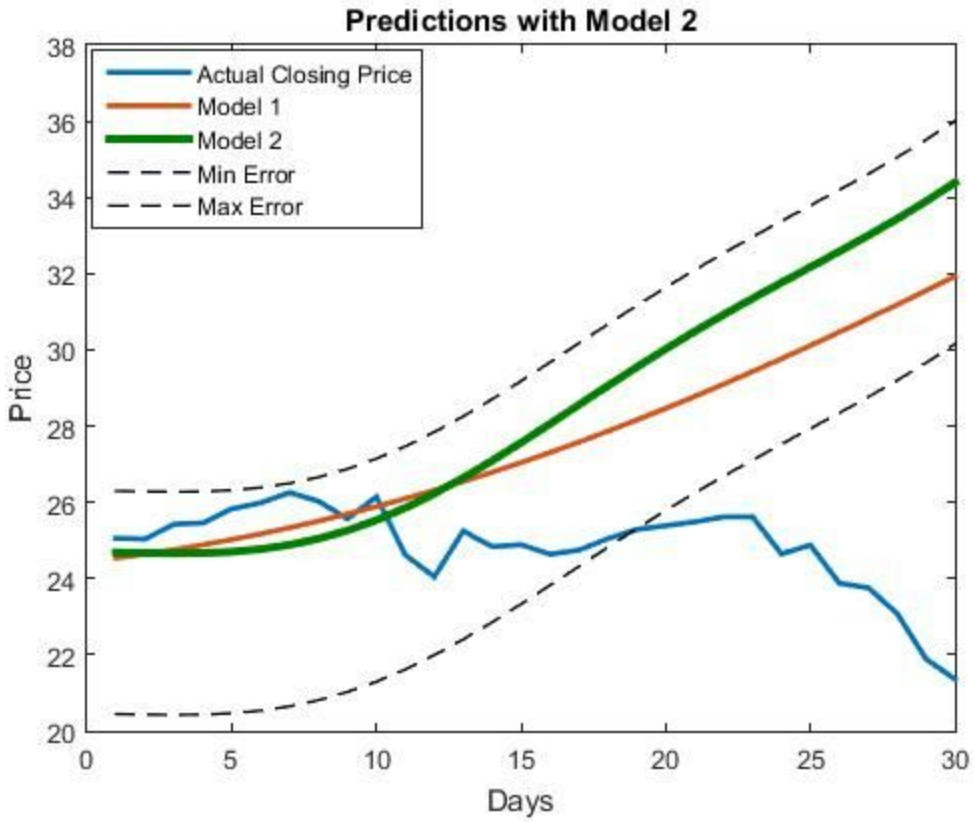

Error Function
Error
Max Error
Min Error
Difference in Price
Days
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90
100


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Price
Days
27
26
25
24
23
22
21
20
19
18
0
10
20
30
40
50
60
70
80
90



Max Error : 8%

Min Error : -12%



Max Error : 7.5%

Min Error : -15%

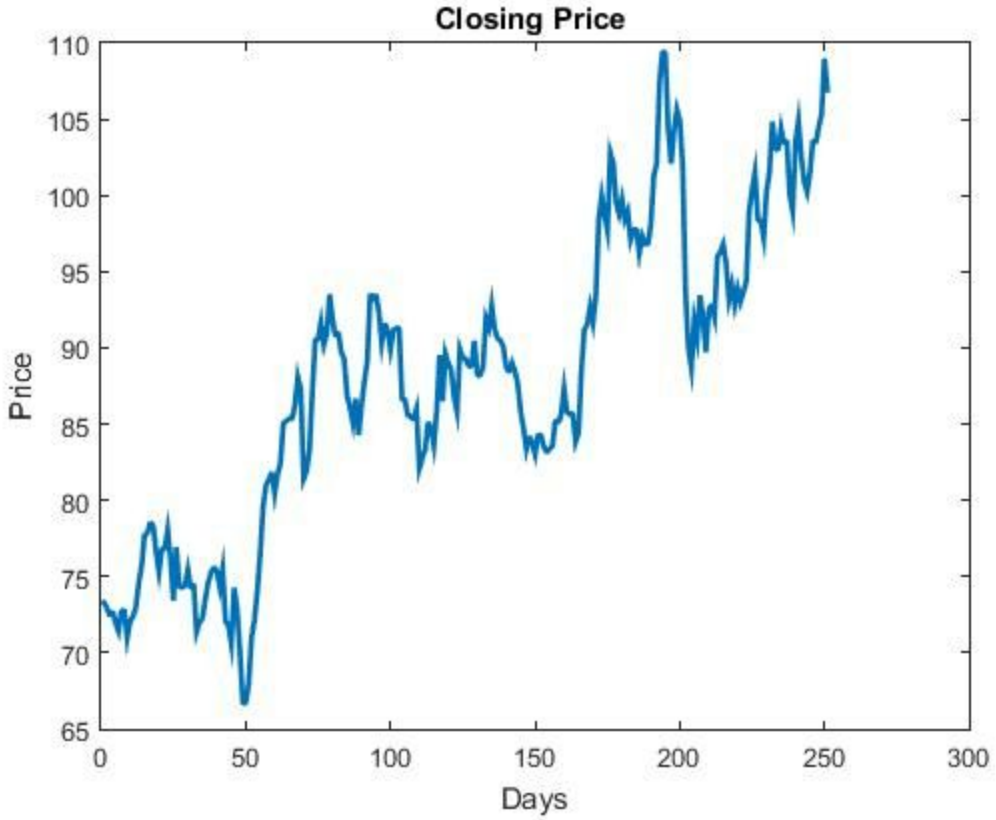
Tesoro Corporation (NYSE: TSO)

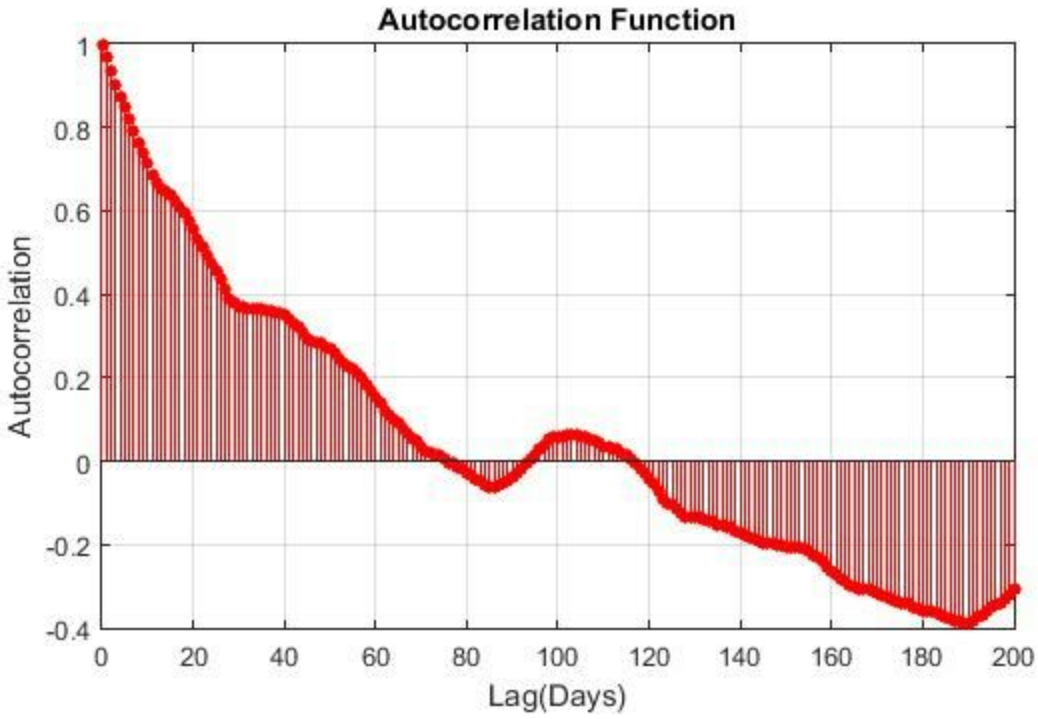
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

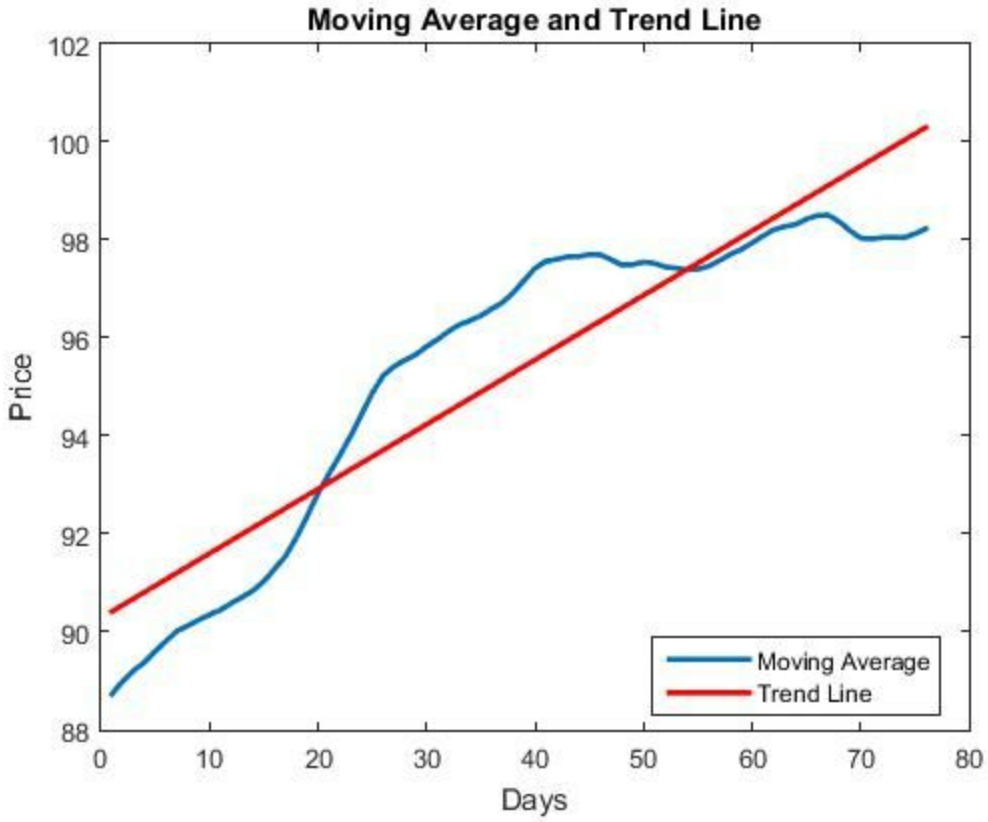
Moving Average Window: 50 Days.

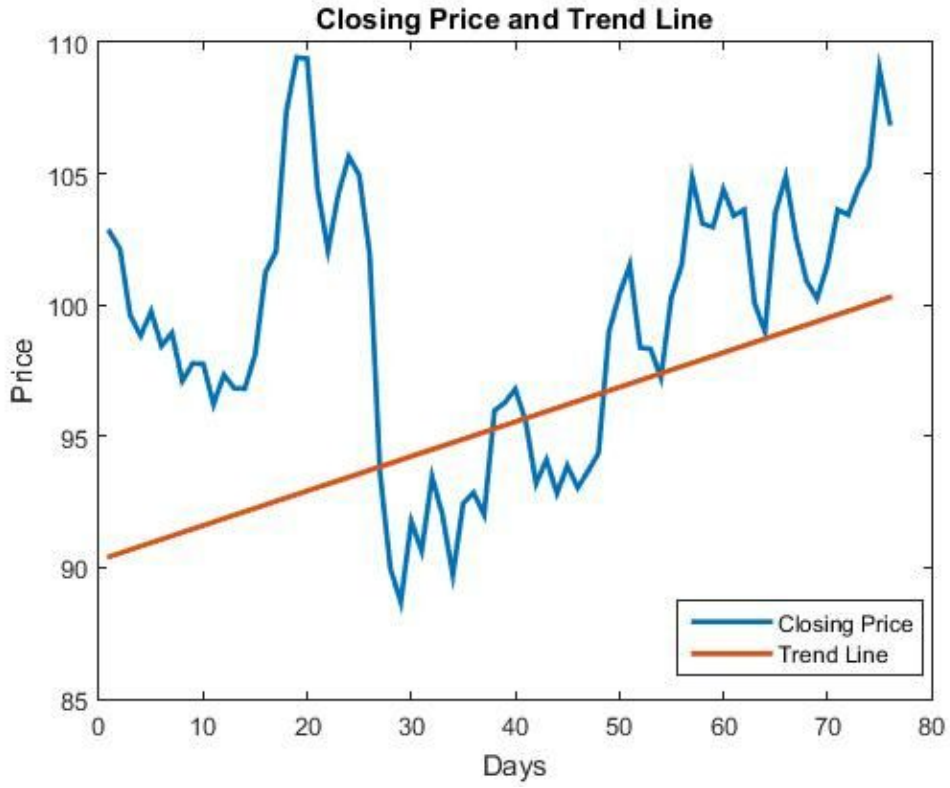
Autocorrelation Days : 76

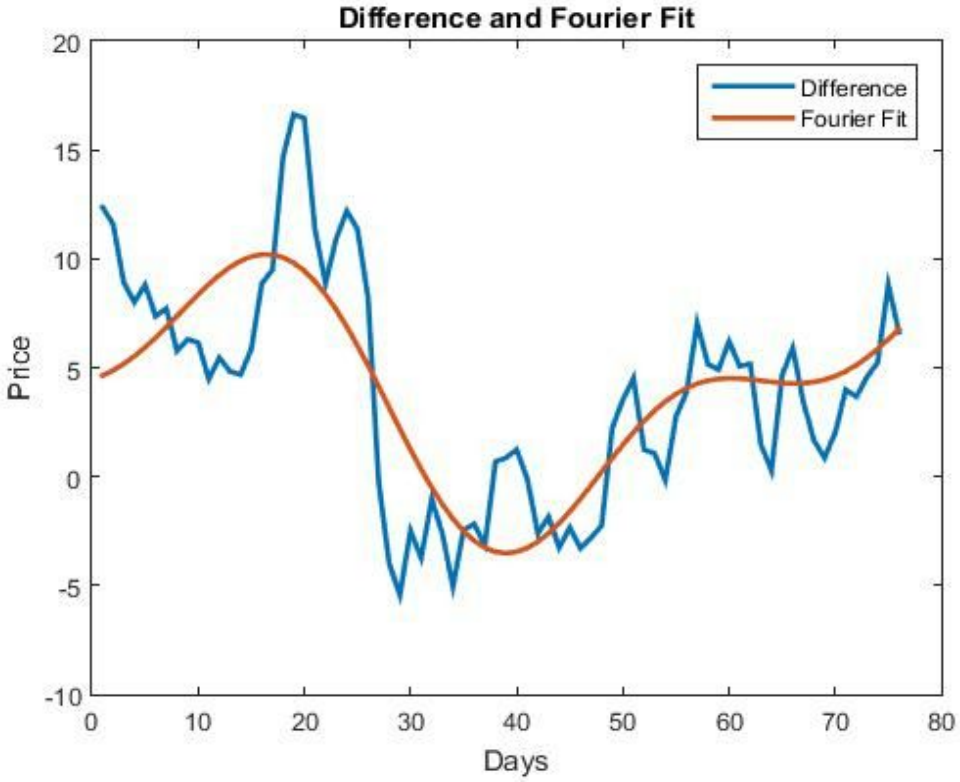
Correlation with the index : -0.7245

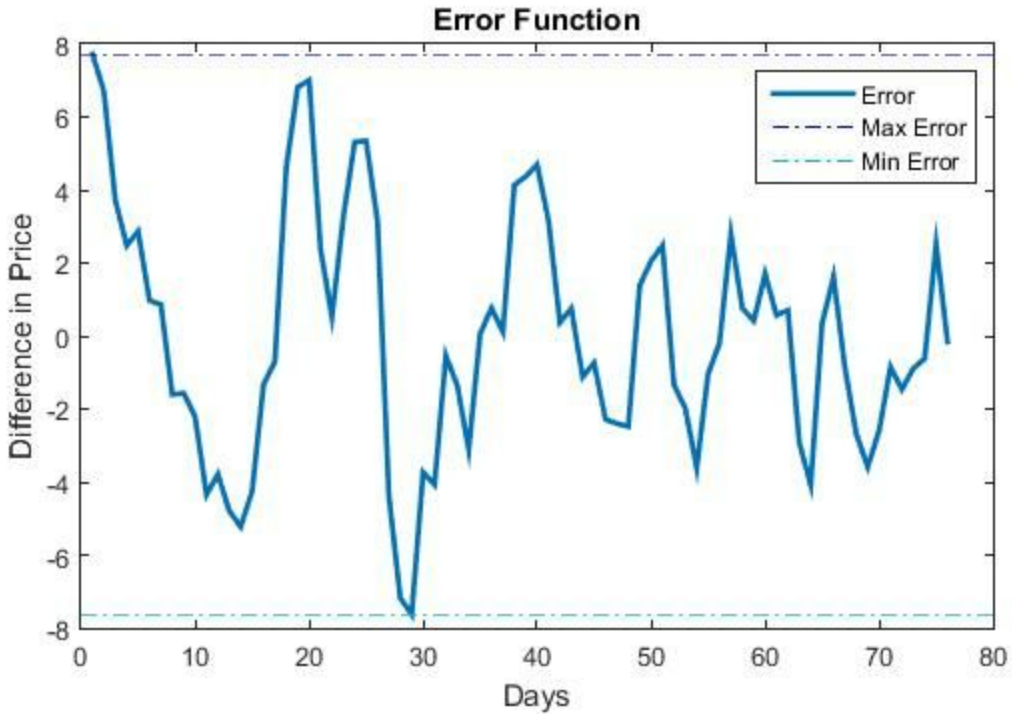


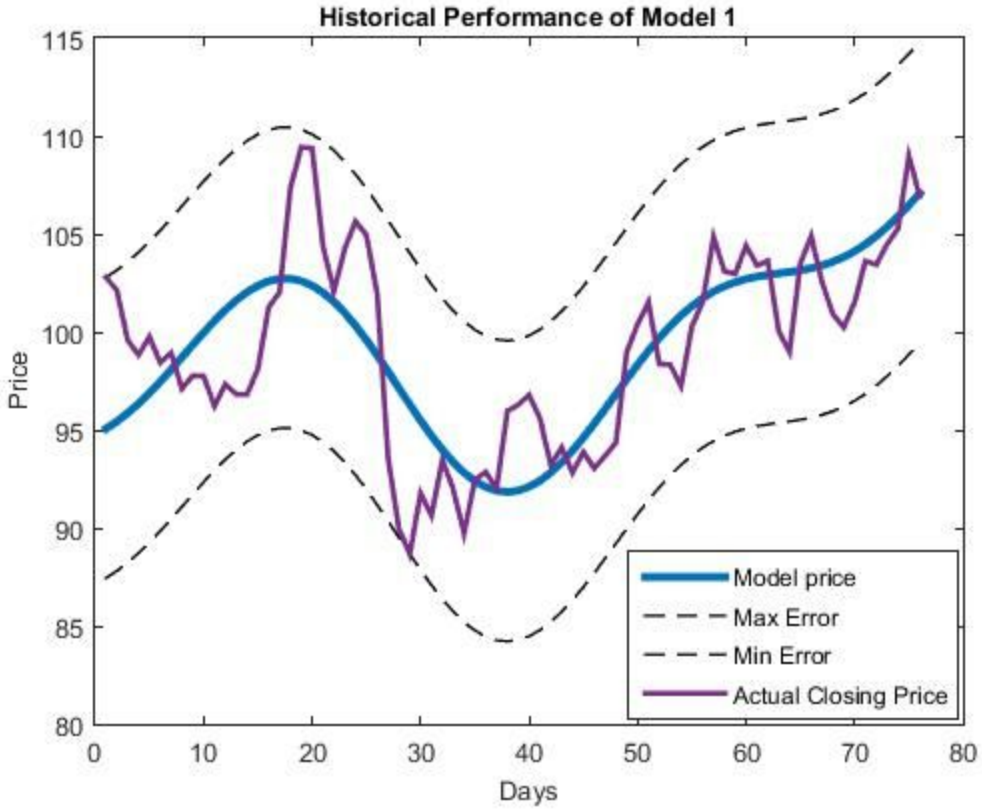

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

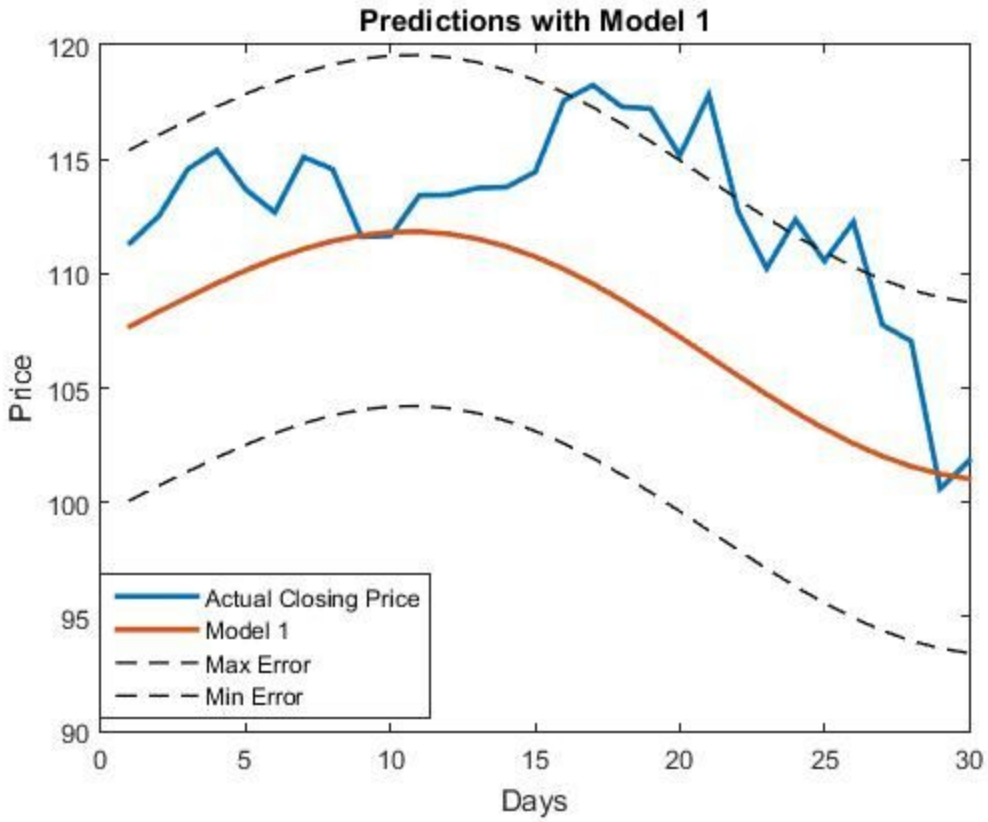

Moving Average and Trend Line
Price
Days
Moving Average
Trend Line
102
100
98
96
94
92
90
88
0
10
20
30
40
50
60
70
80


Closing Price and Trend Line
Price
Days
Closing Price
Trend Line
110
105
100
95
90
85
0
10
20
30
40
50
60
70
80


Difference and Fourier Fit
Price
Days
Difference
Fourier Fit
20
15
10
5
0
-5
-10
0
10
20
30
40
50
60
70
80

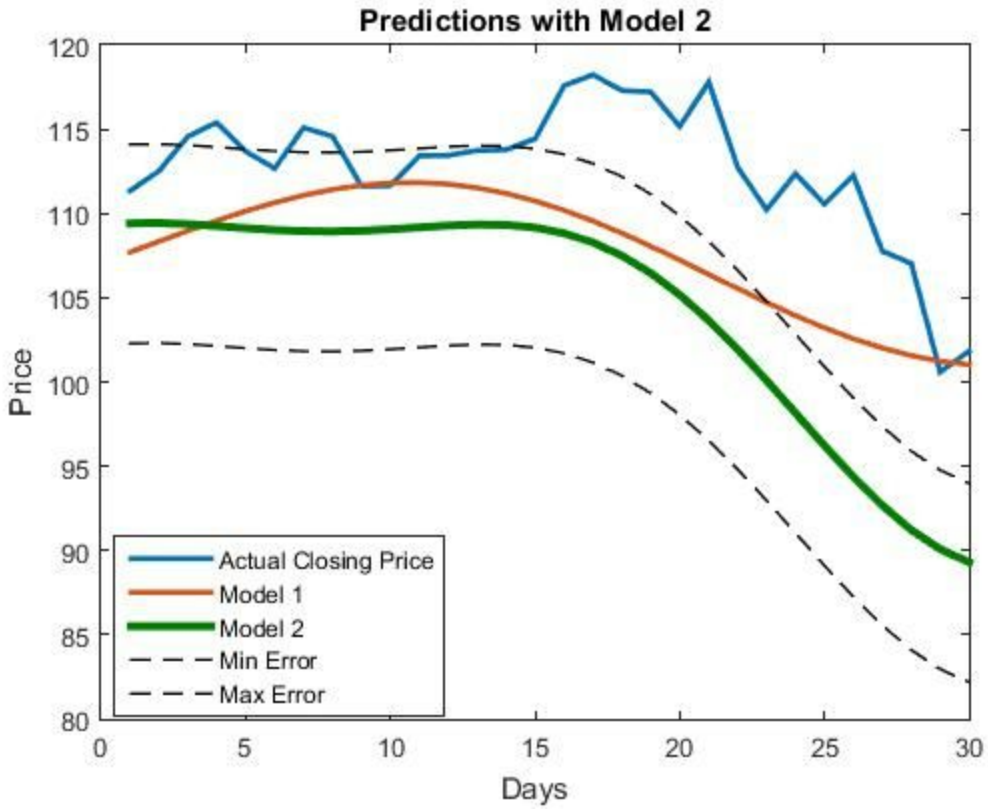

Error Function
Error
Max Error
Min Error
Difference in Price
Days
8
6
4
2
0
-2
-4
-6
-8
0
10
20
30
40
50
60
70
80


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Price
Days
115
110
105
100
95
90
85
80
0
10
20
30
40
50
60
70
80



Max Error : 7%

Min Error : -7%



Max Error :4%

Min Error : -7%

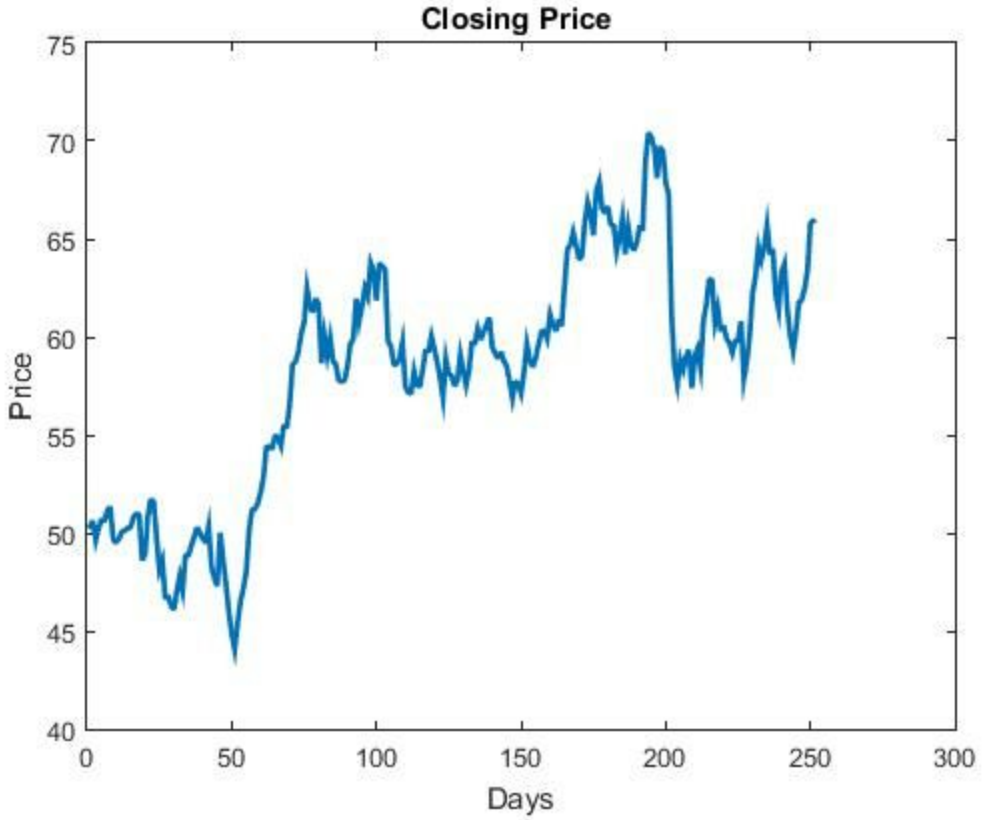
Valero Energy Corp (NYSE: VLO)

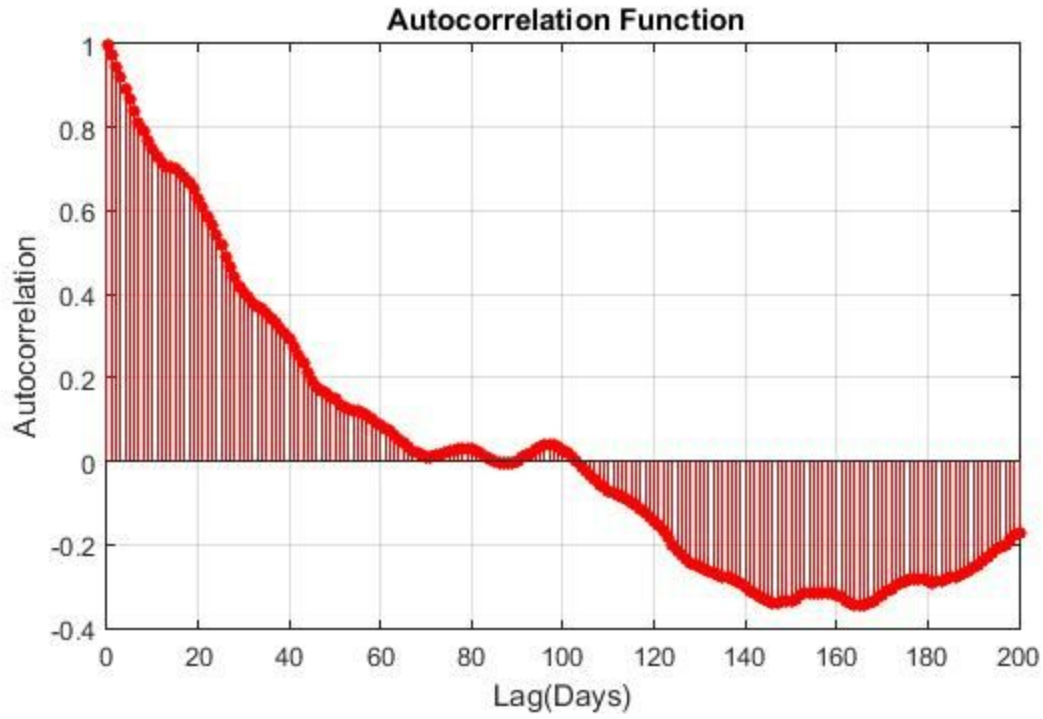
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

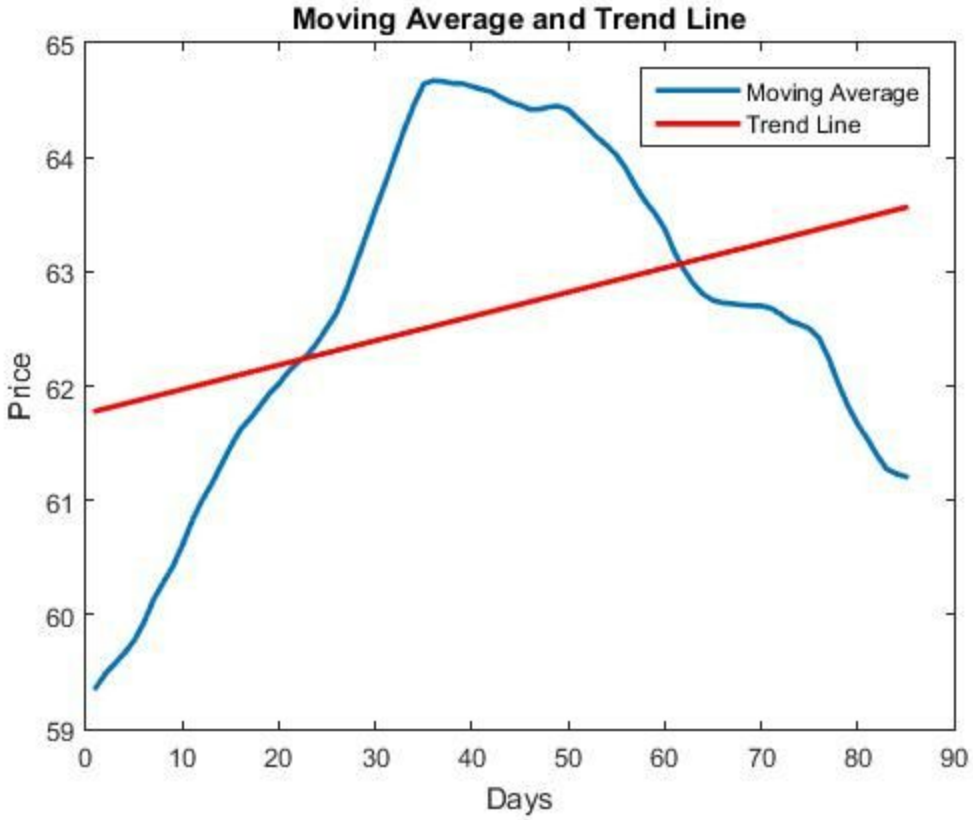
Moving Average Window: 50 Days.

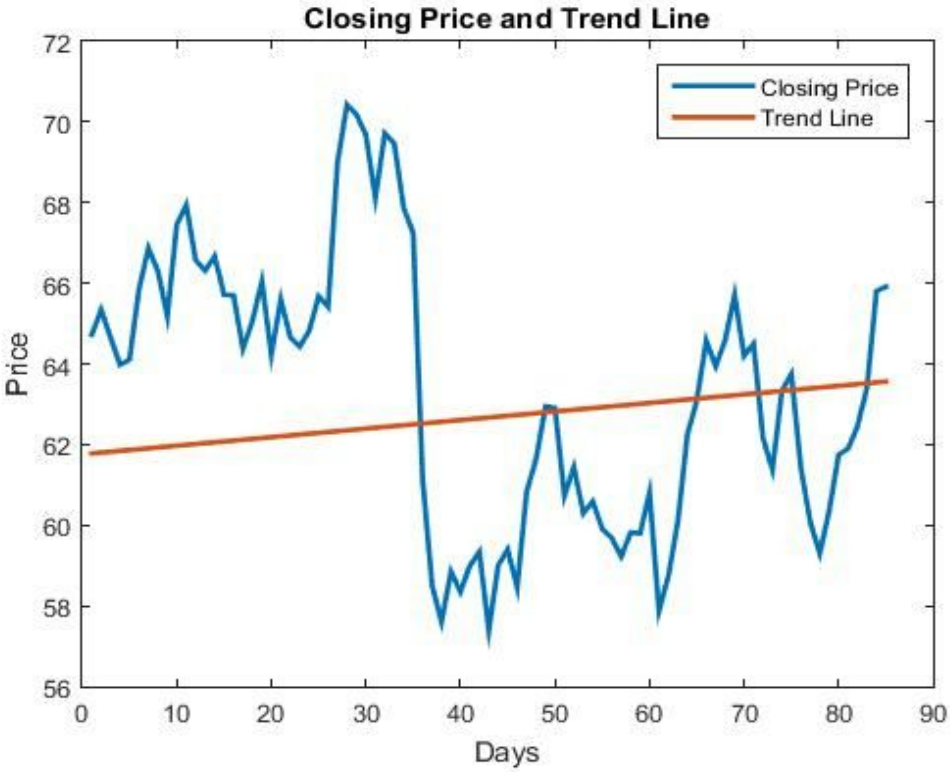
Autocorrelation Days : 85

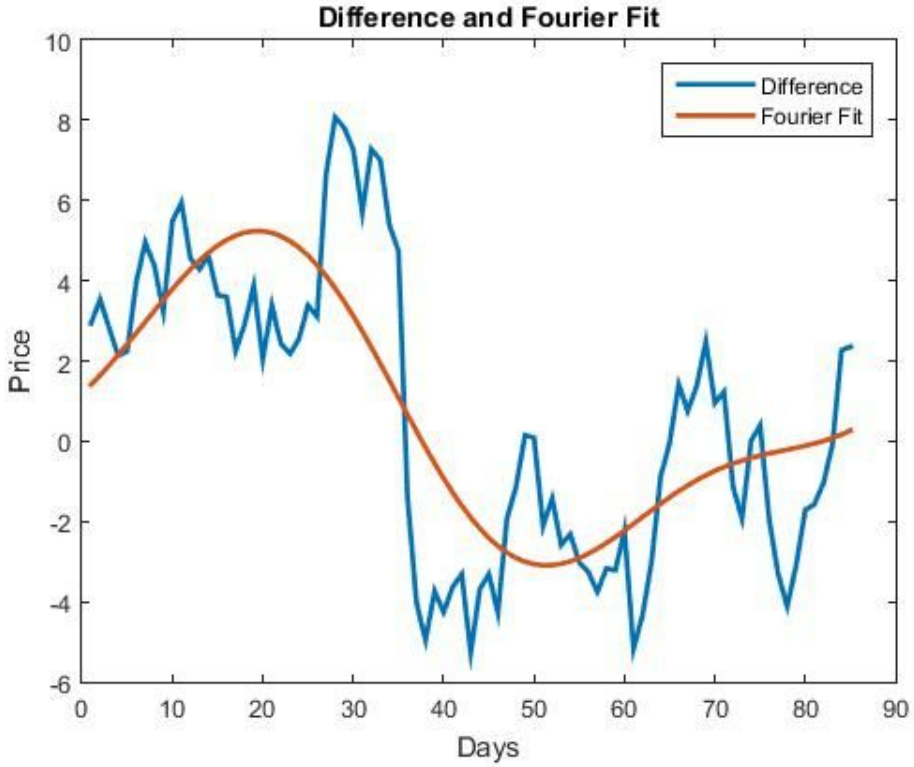
Correlation with the index : -0.6179

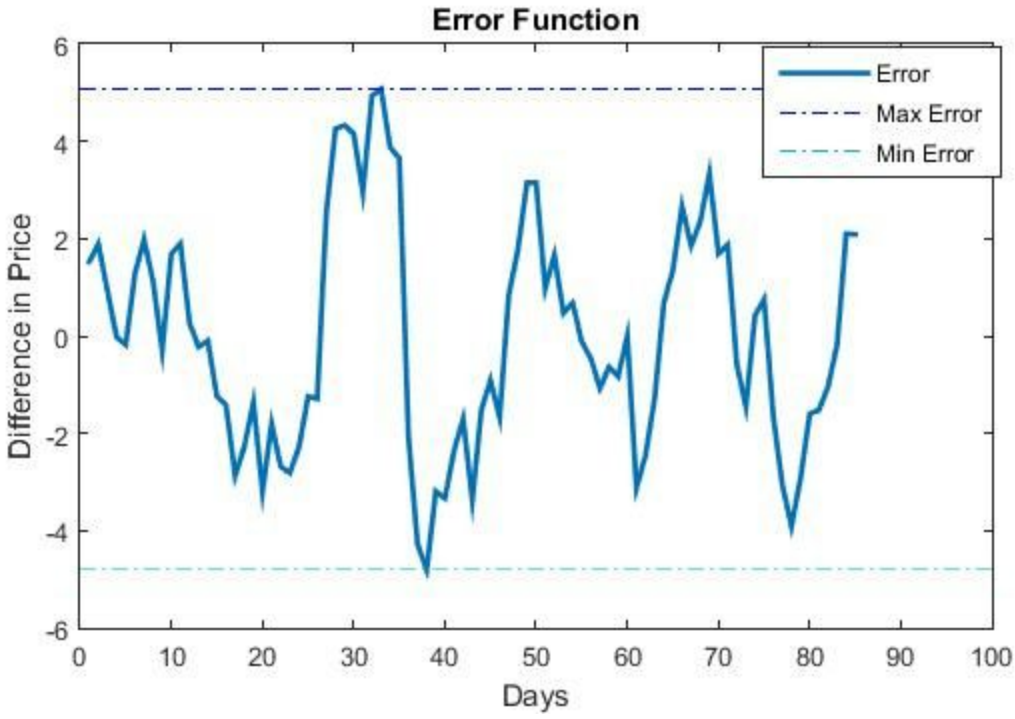


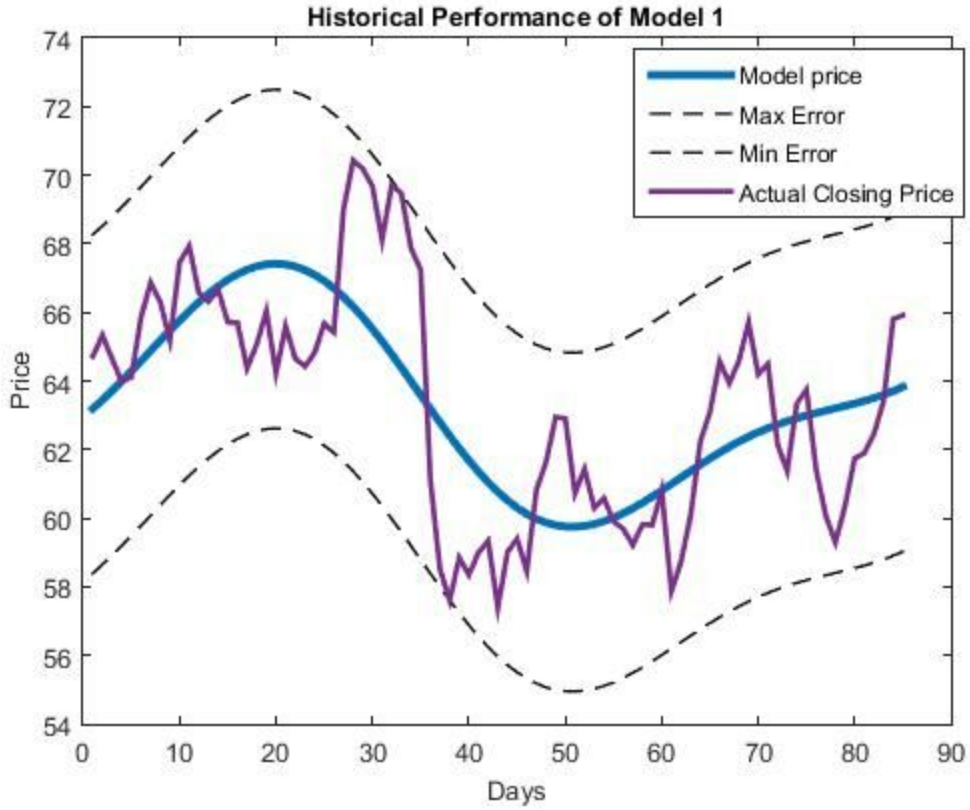

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

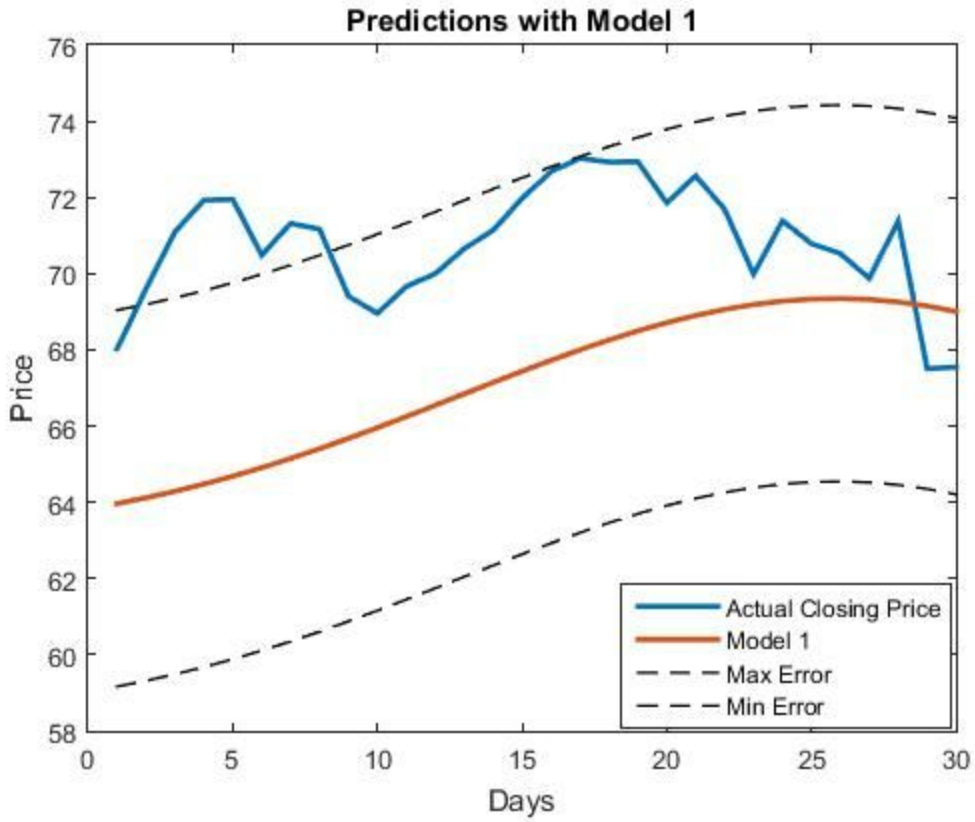

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
65
64
63
62
61
60
59
0
10
20
30
40
50
60
70
80
90


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
72
70
68
66
64
62
60
58
56
0
10
20
30
40
50
60
70
80
90


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
10
8
6
4
2
0
-2
-4
-6
0
10
20
30
40
50
60
70
80
90

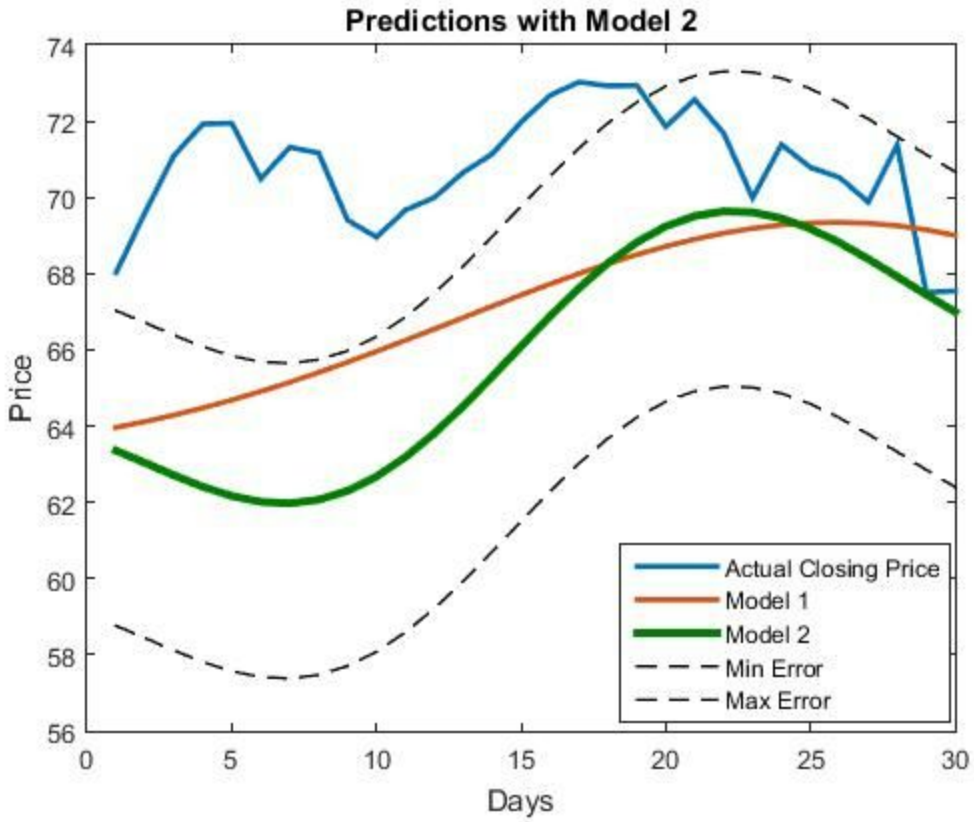

Error Function
Error
Max Error
Min Error
Difference in Price
Days
6
4
2
0
-2
-4
-6
0
10
20
30
40
50
60
70
80
90
100


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Price
Days
74
72
70
68
66
64
62
60
58
56
54
0
10
20
30
40
50
60
70
80
90



Max Error :8%

Min Error : -8%



Max Error :6%

Min Error : -8.5%

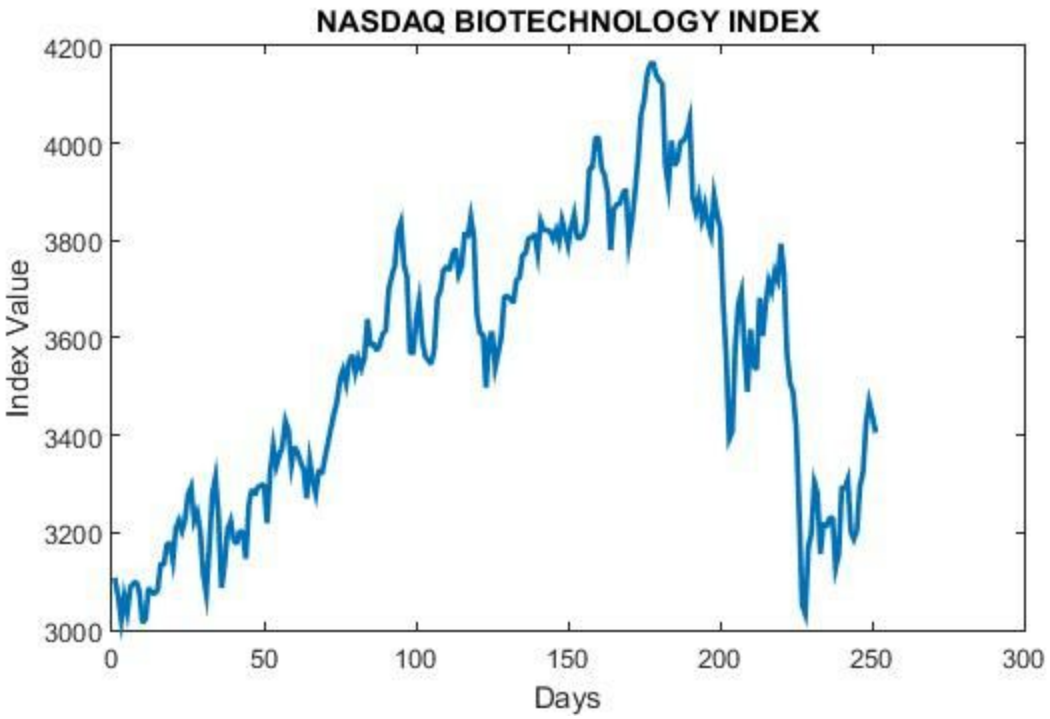
- Pharmaceutical Sector:

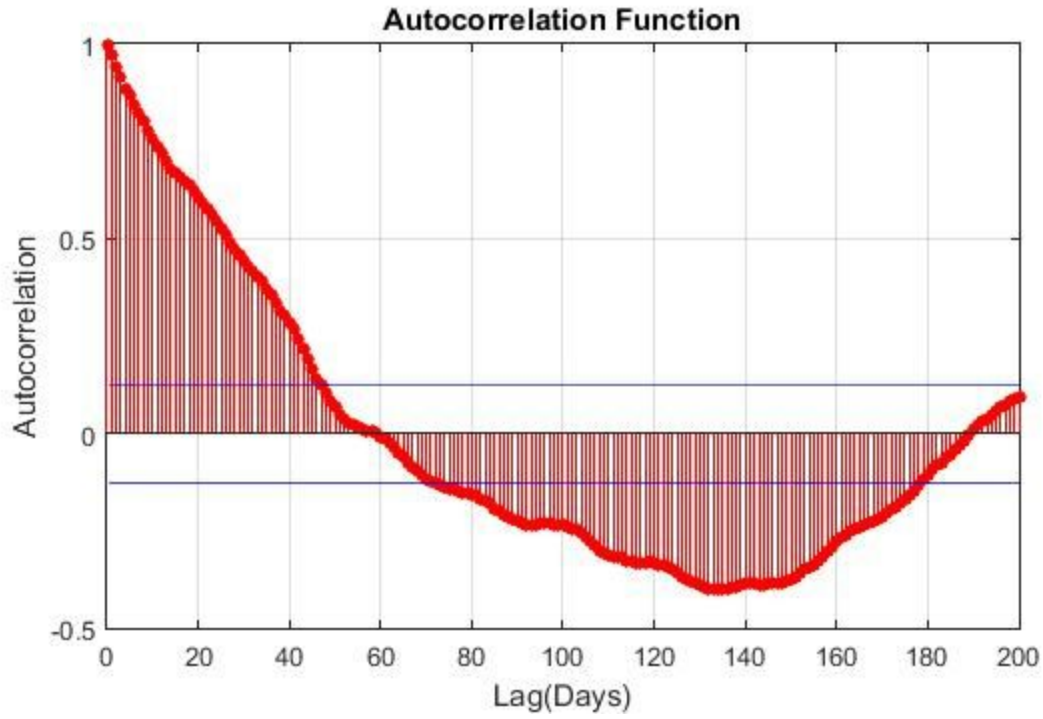
NASDAQ Biotechnology Index (NBI)

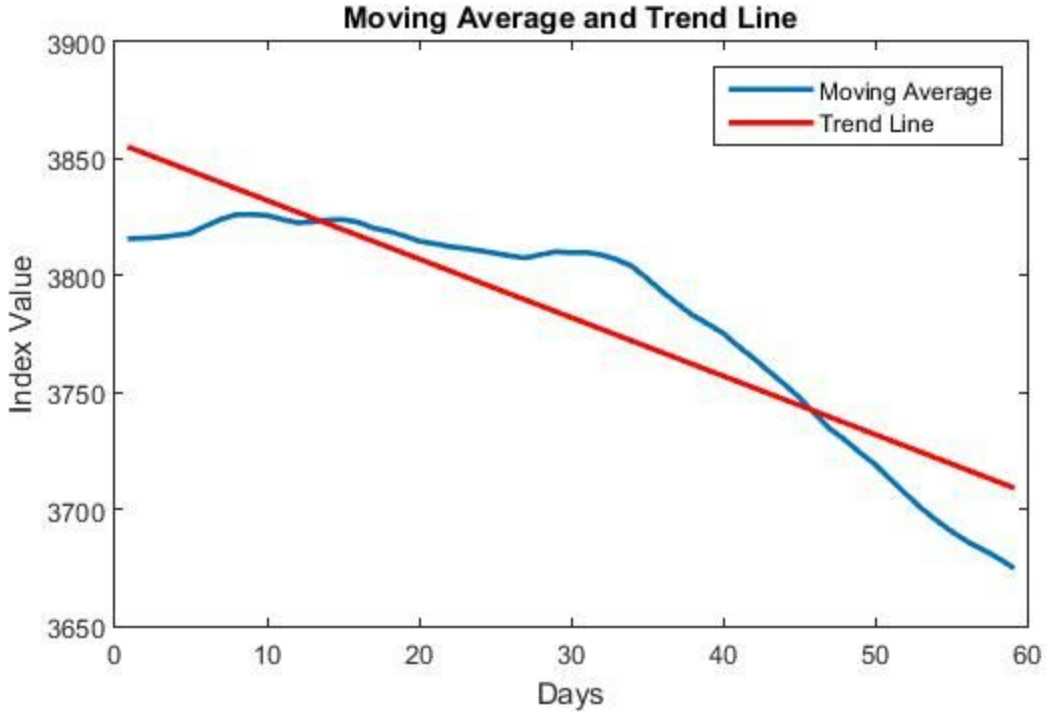
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

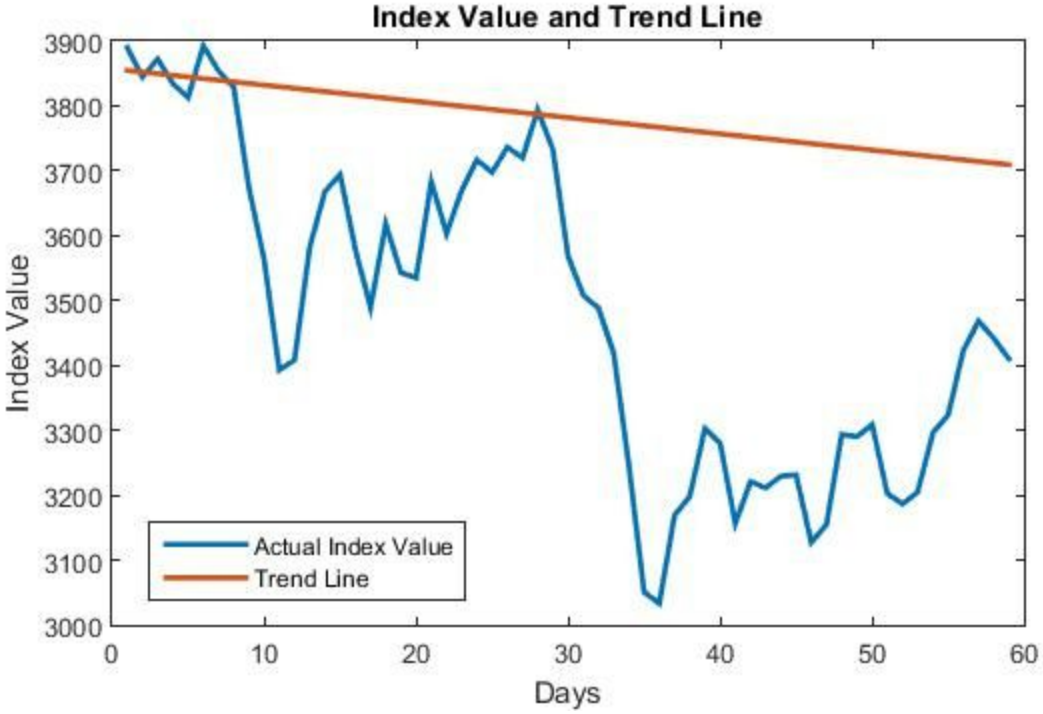
Moving Average Window: 100 Days.

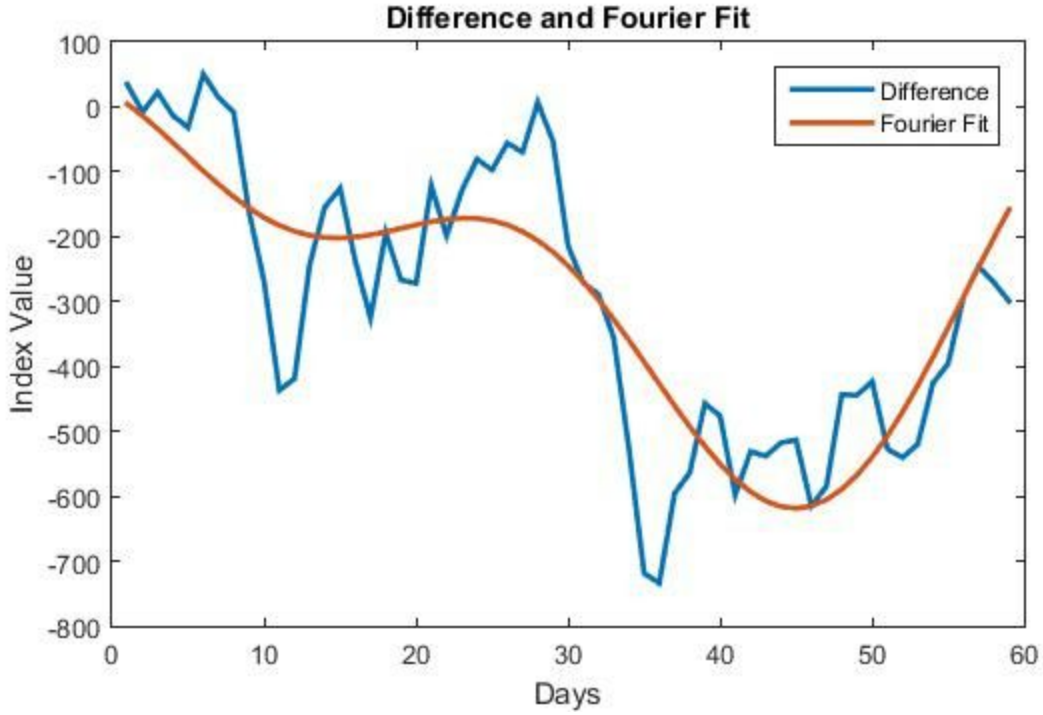
Autocorrelation Days : 59

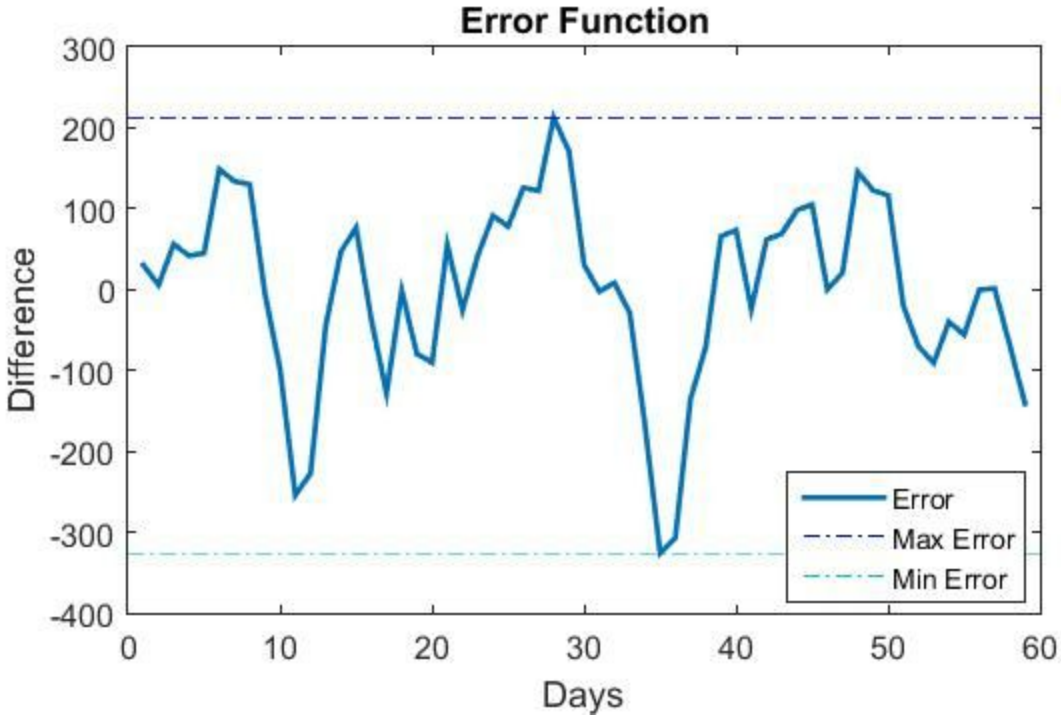


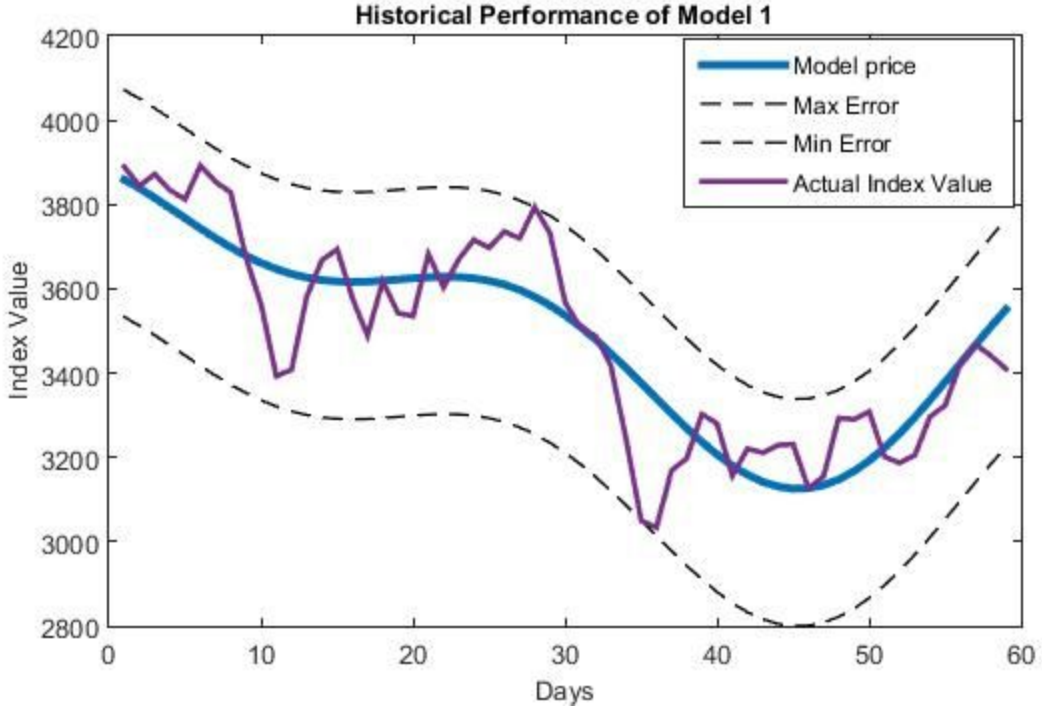

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.5
0
-0.5
0
20
40
60
80
100
120
140
160
180
200

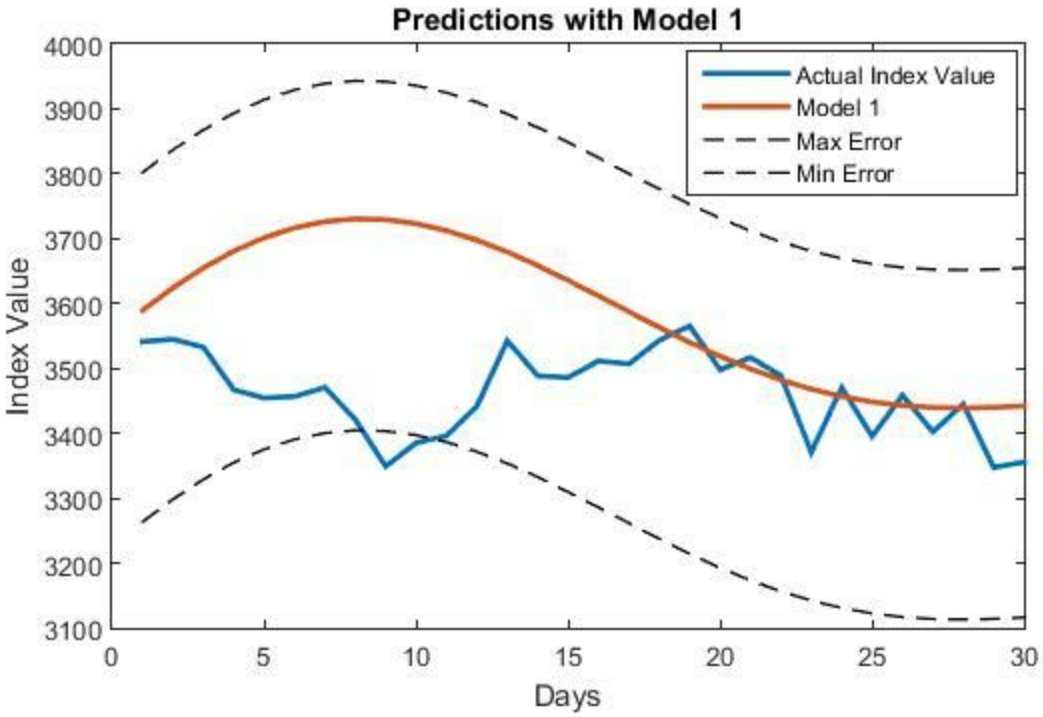

Moving Average and Trend Line
Moving Average
Trend Line
Index Value
Days
3900
3850
3800
3750
3700
3650
0
10
20
30
40
50
60


Index Value and Trend Line
Index Value
Days
Actual Index Value
Trend Line
3900
3800
3700
3600
3500
3400
3300
3200
3100
3000
0
10
20
30
40
50
60


Difference and Fourier Fit
Index Value
Days
Difference
Fourier Fit
100
0
-100
-200
-300
-400
-500
-600
-700
-800
0
10
20
30
40
50
60


Error Function
Difference
Days
Error
Max Error
Min Error
300
200
100
0
-100
-200
-300
-400
0
10
20
30
40
50
60


Historical Performance of Model 1
Index Value
Days
Model price
Max Error
Min Error
Actual Index Value
4200
4000
3800
3600
3400
3200
3000
2800
0
10
20
30
40
50
60



Max Error : 5.6%

Min Error : -9.7%

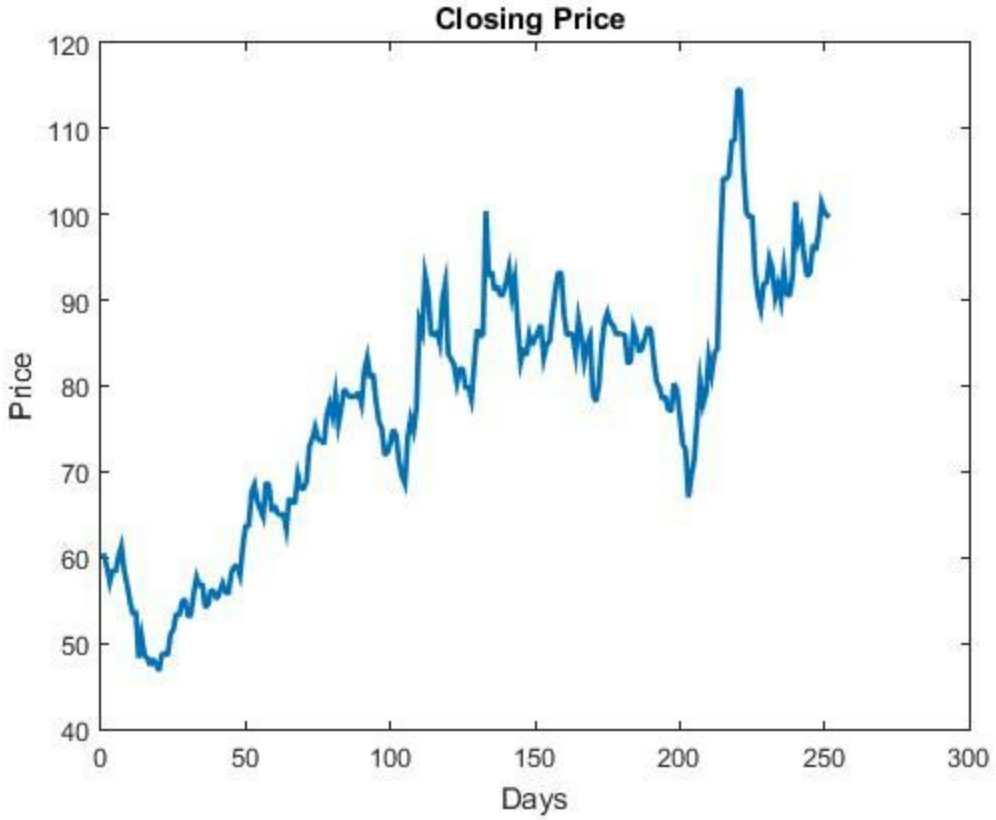
Clovis Oncology, Inc. (NASDAQ: CLVS)

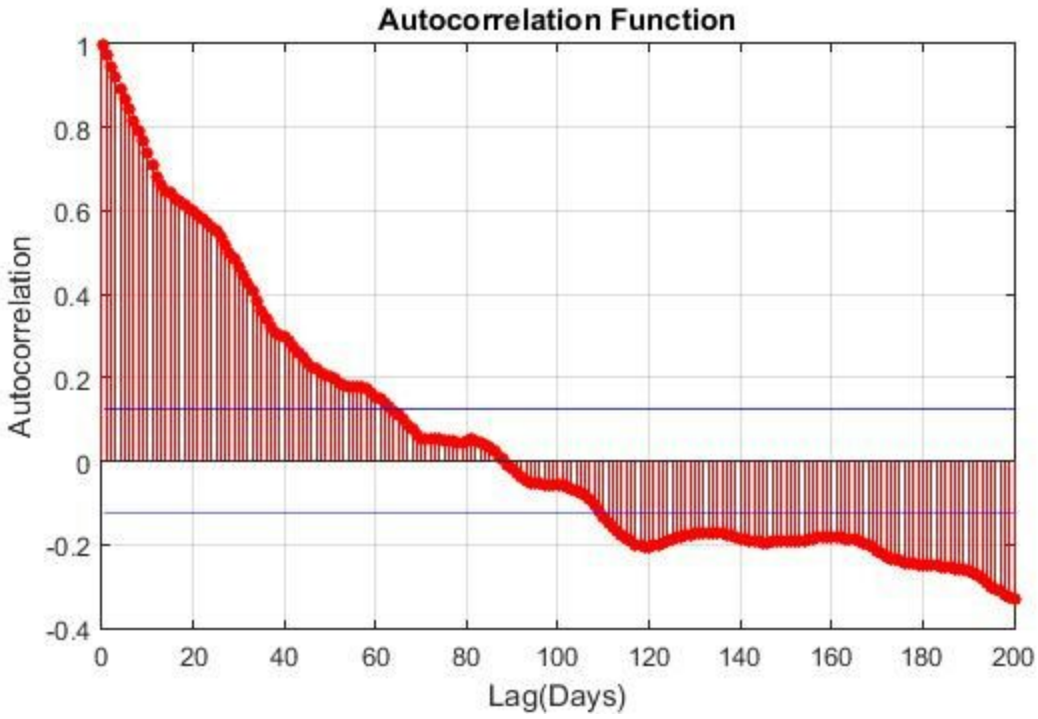
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

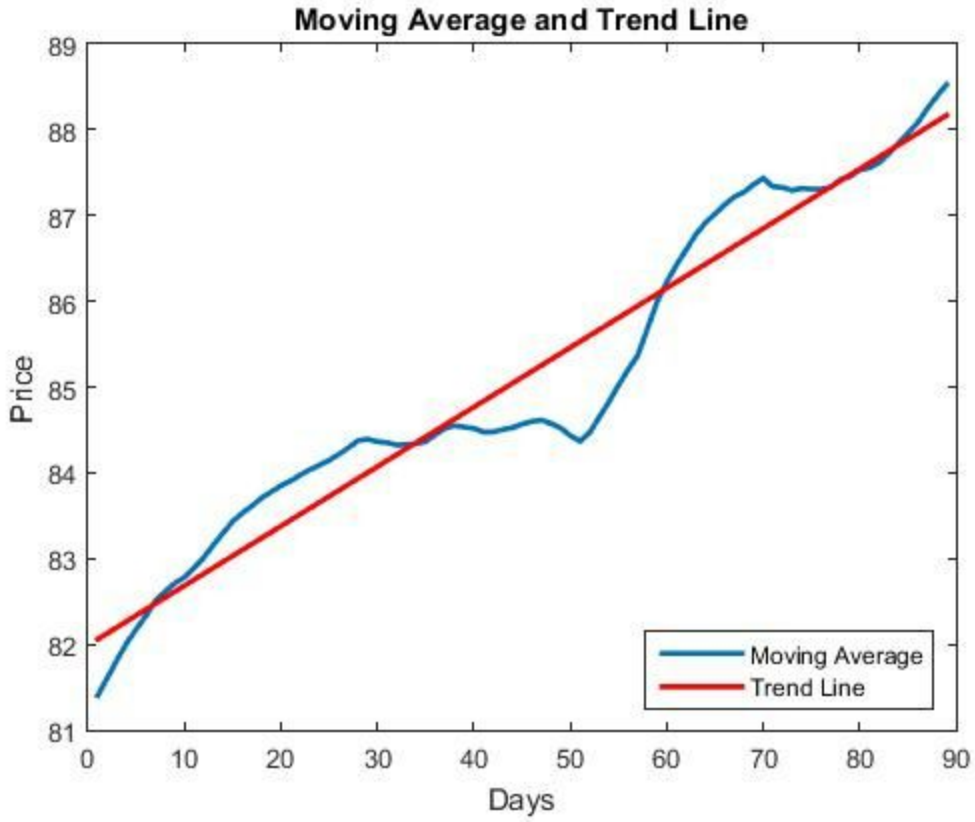
Moving Average Window: 50 Days.

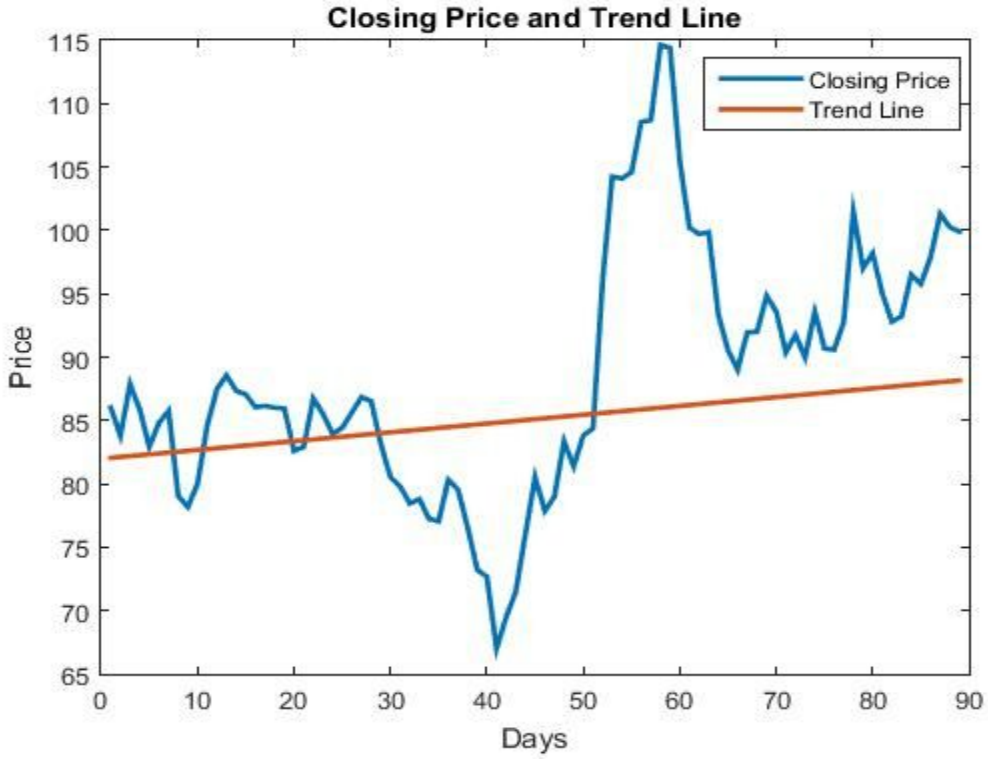
Autocorrelation Days : 89

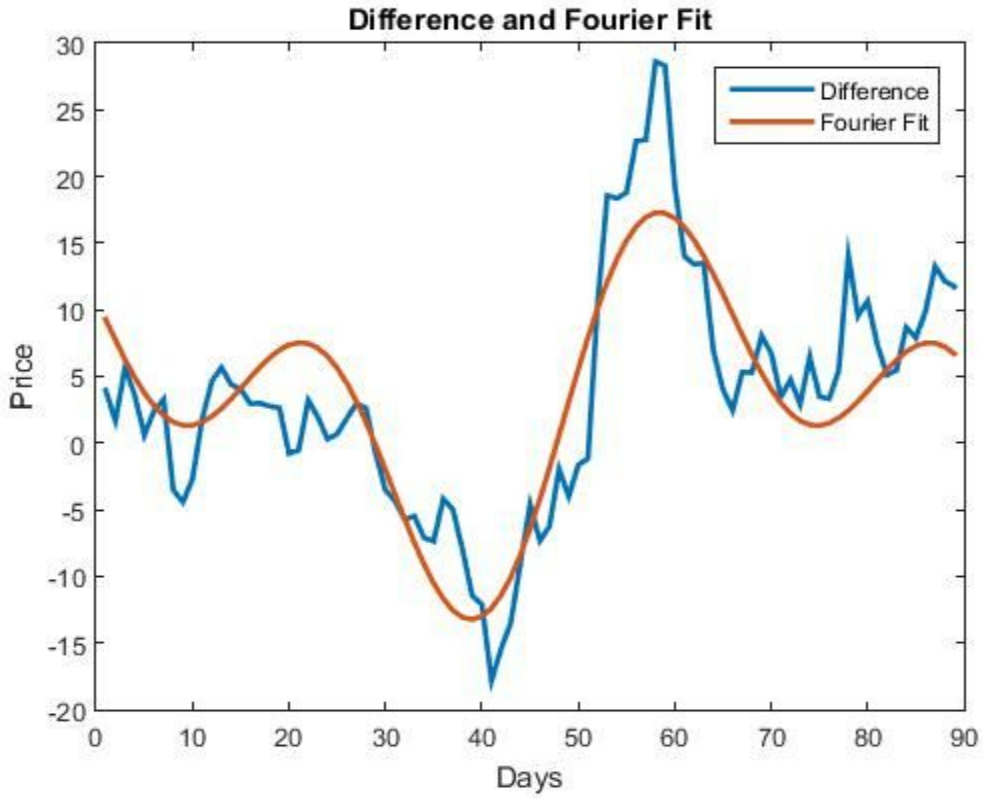
Correlation with the index : 0.5749

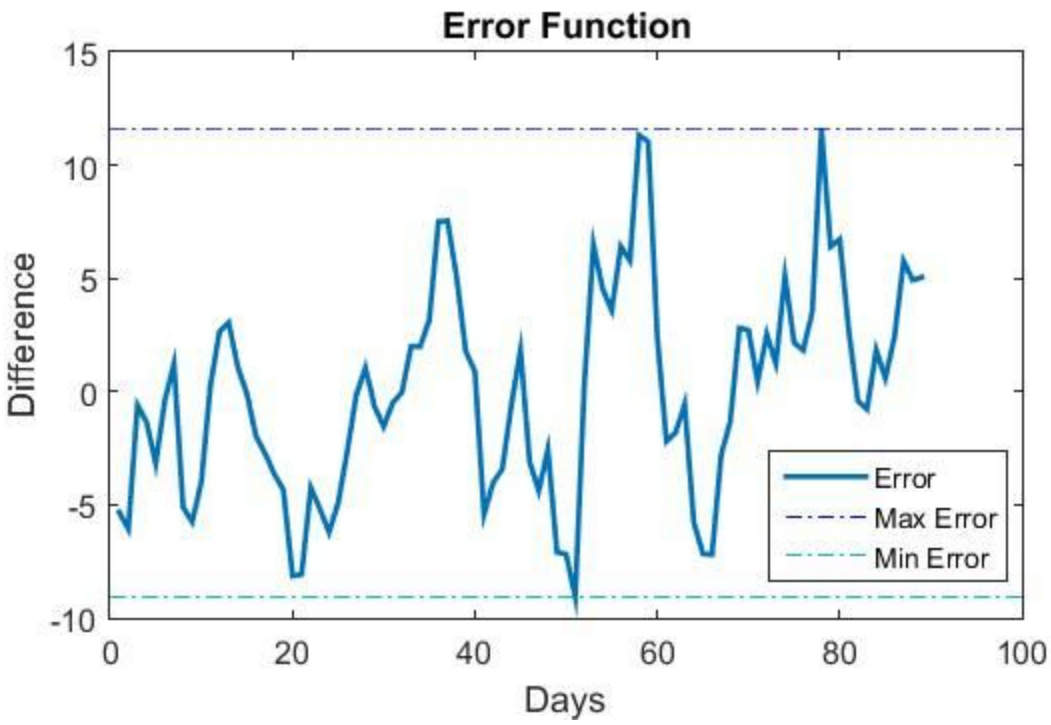


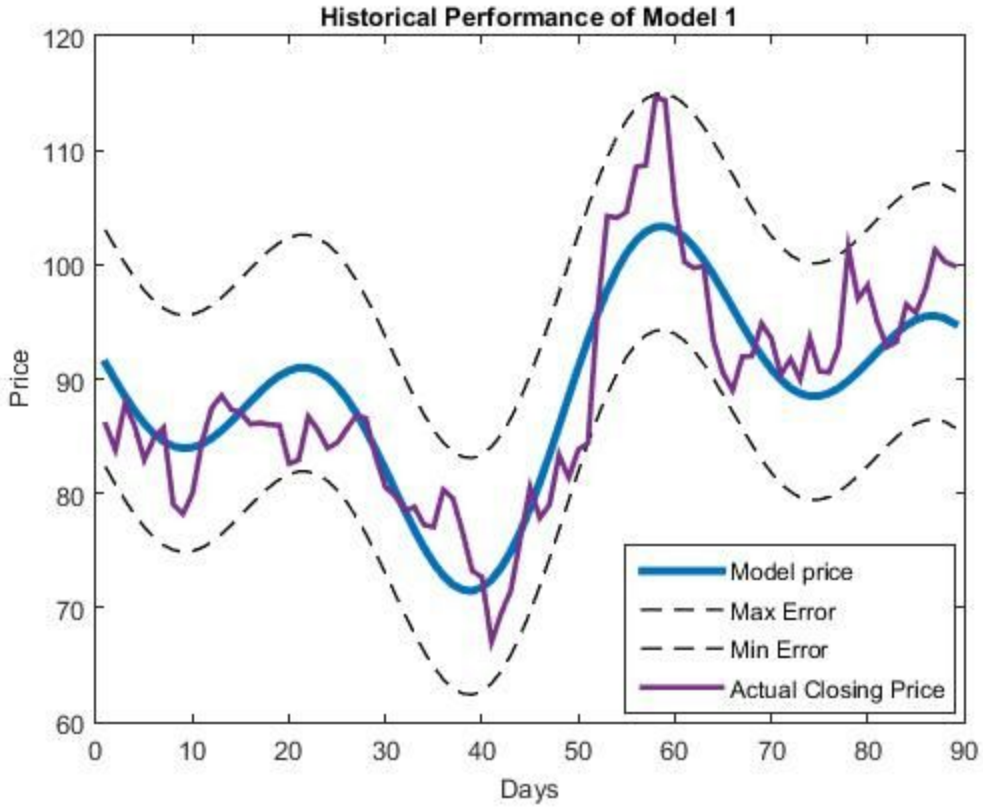

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

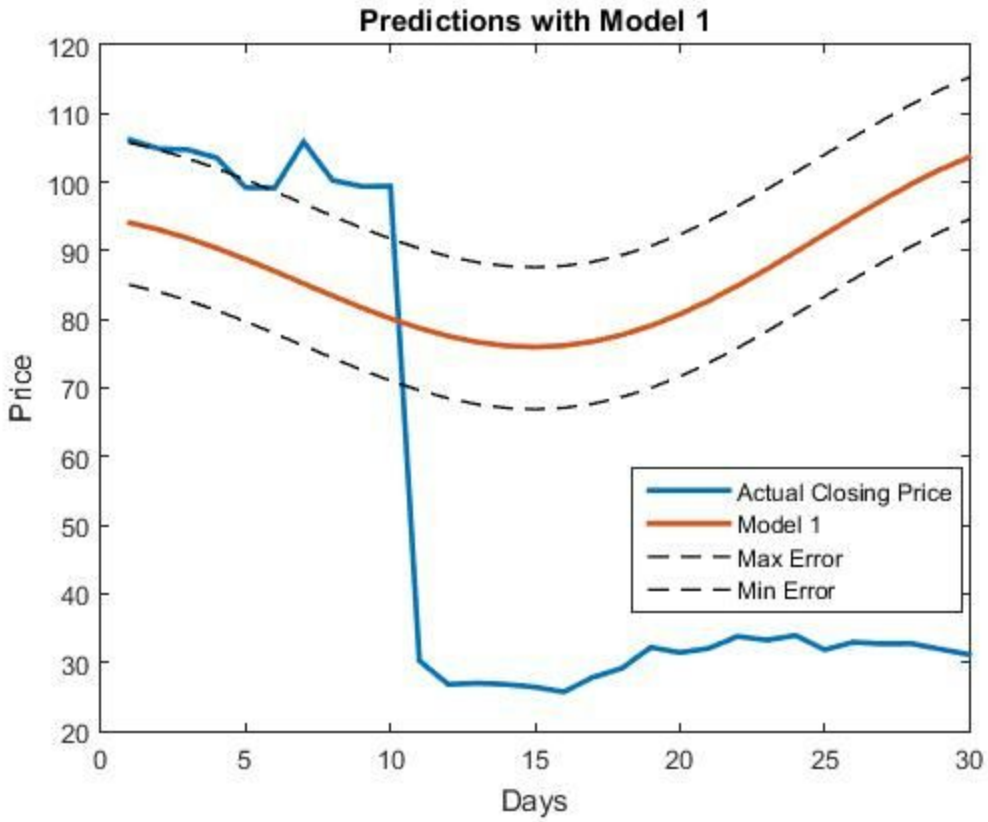

Moving Average and Trend Line
Price
Days
Moving Average
Trend Line
89
88
87
86
85
84
83
82
81
0
10
20
30
40
50
60
70
80
90


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
115
110
105
100
95
90
85
80
75
70
65
0
10
20
30
40
50
60
70
80
90


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
30
25
20
15
10
5
0
-5
-10
-15
-20
0
10
20
30
40
50
60
70
80
90

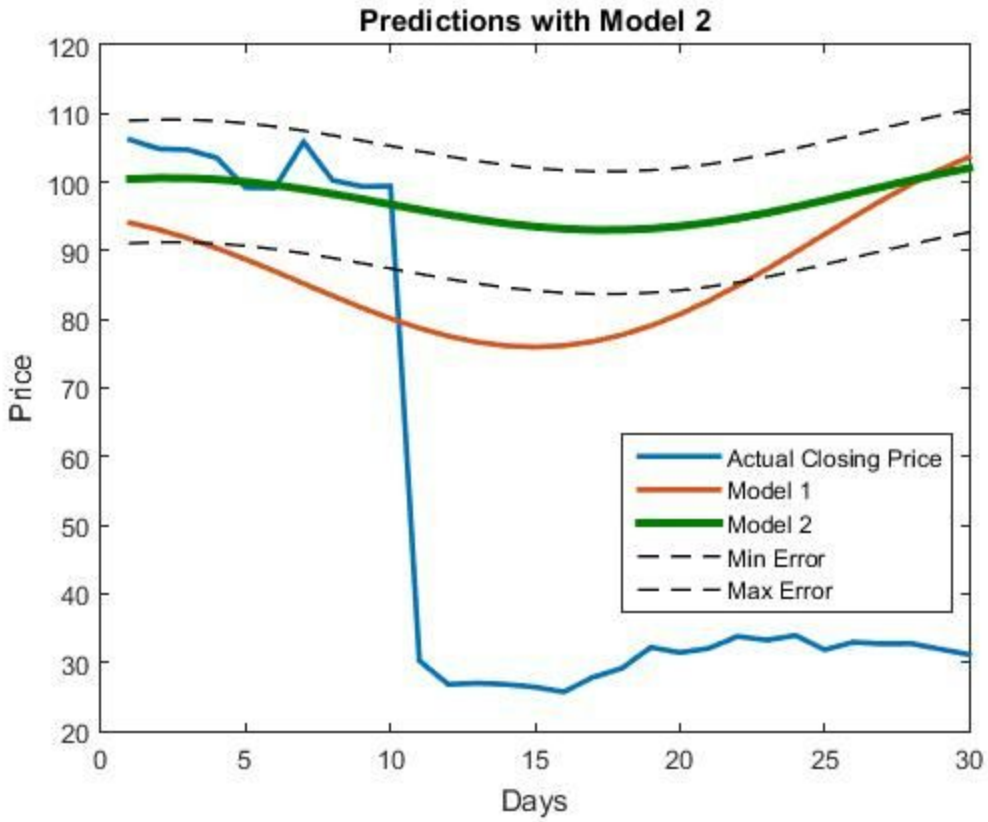

Error Function
Difference
Days
Error
Max Error
Min Error
15
10
5
0
-5
-10
0
20
40
60
80
100


Historical Performance of Model 1
Price
Days
Model price
Max Error
Min Error
Actual Closing Price
120
110
100
90
80
70
60
0
10
20
30
40
50
60
70
80
90



Max Error : 10.5%

Min Error : -8.4%



Max Error : 9.0%

Min Error : -10.0%

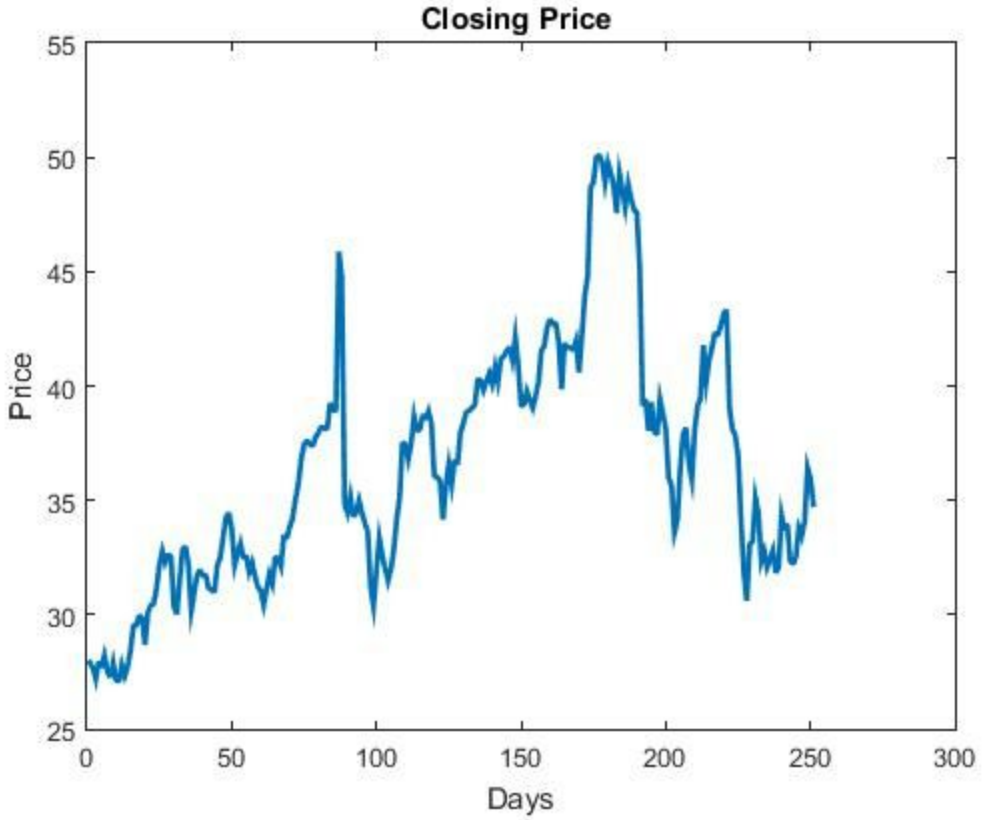
ACADIA Pharmaceuticals (NASDAQ: ACAD)

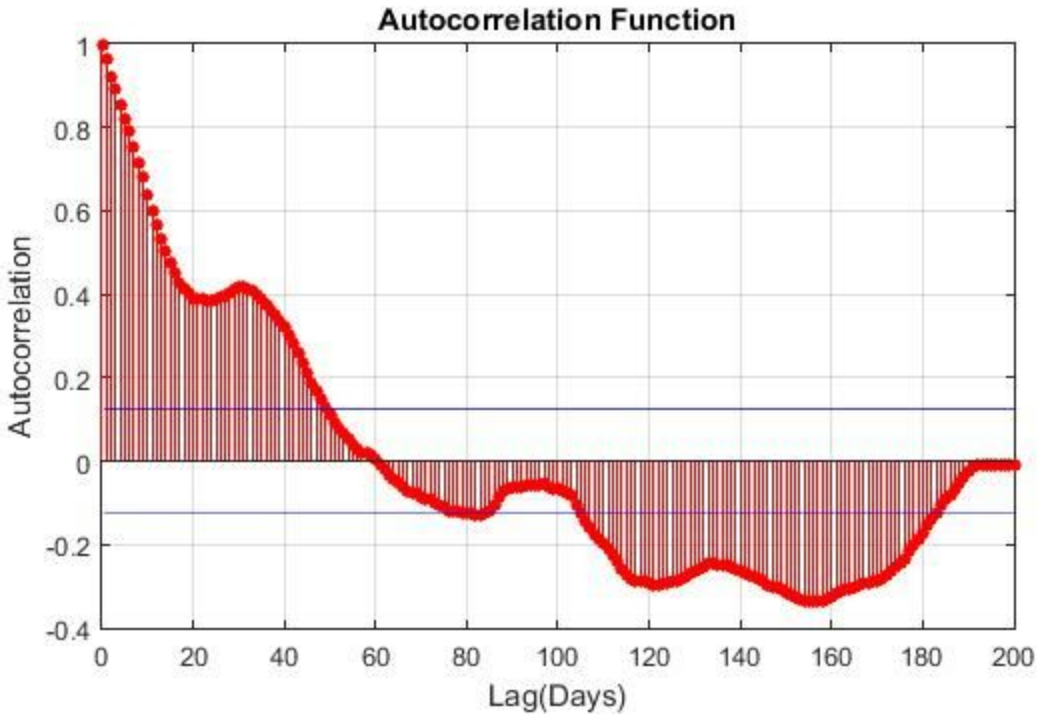
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

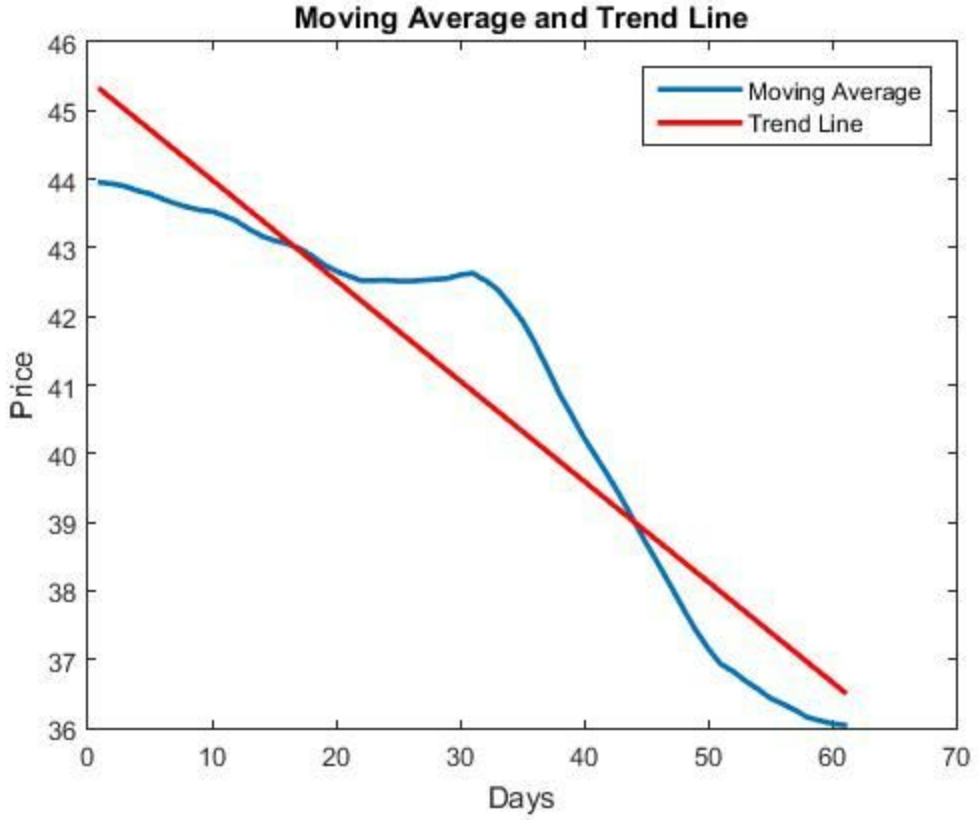
Moving Average Window: 50 Days.

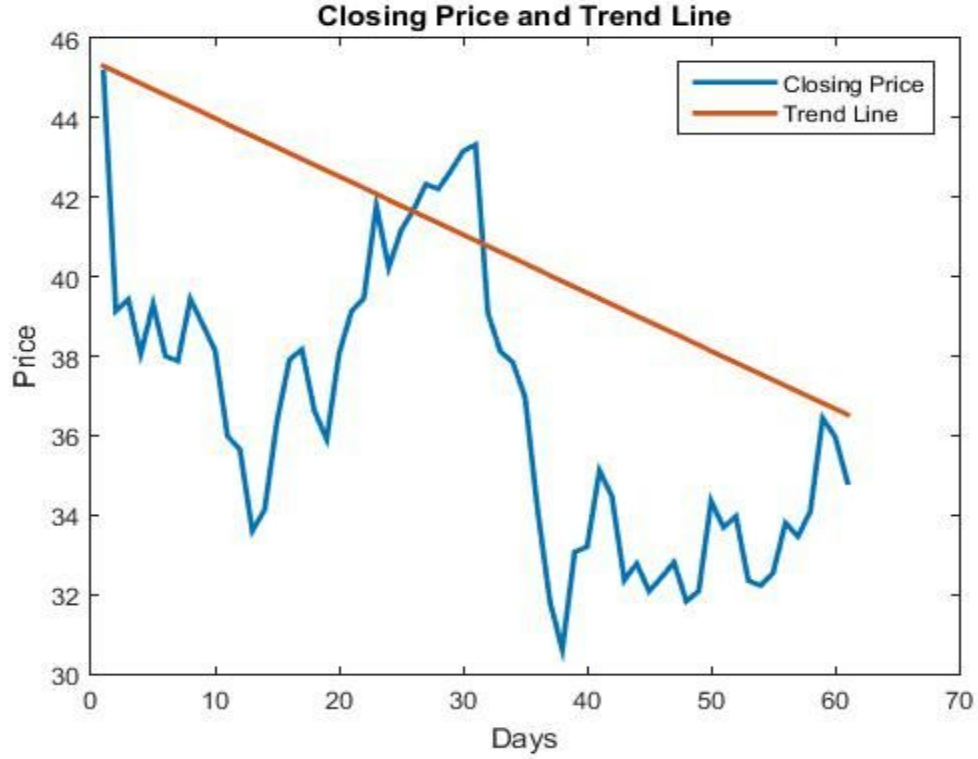
Autocorrelation Days : 61

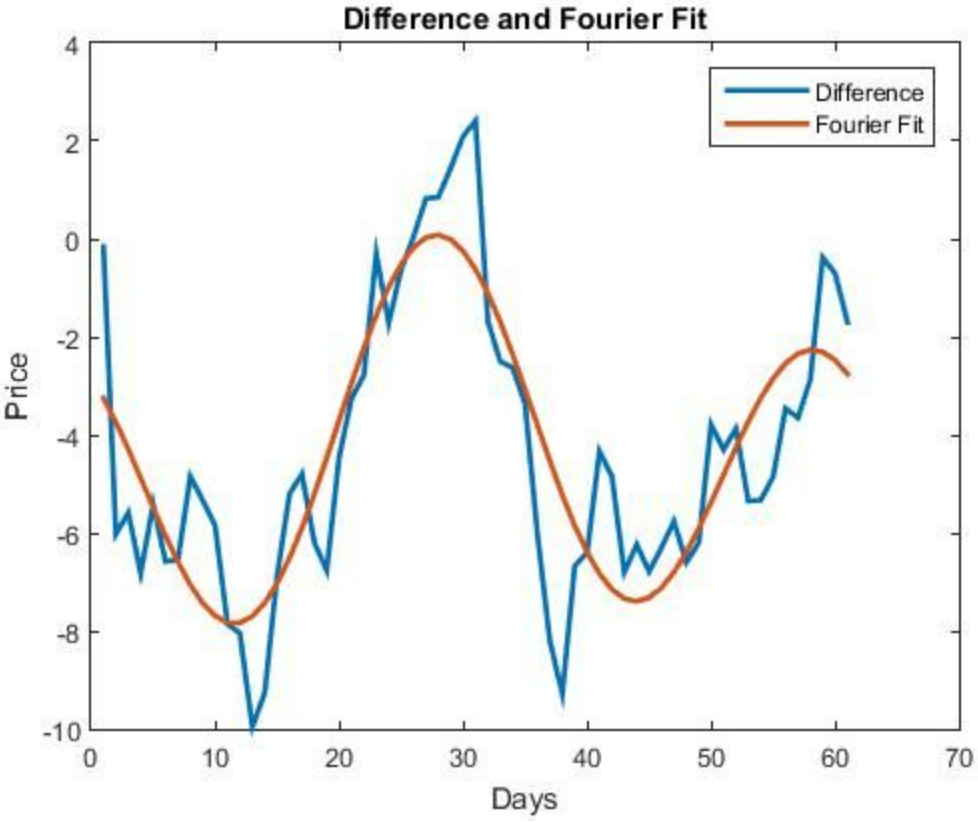
Correlation with the index : 0.8916

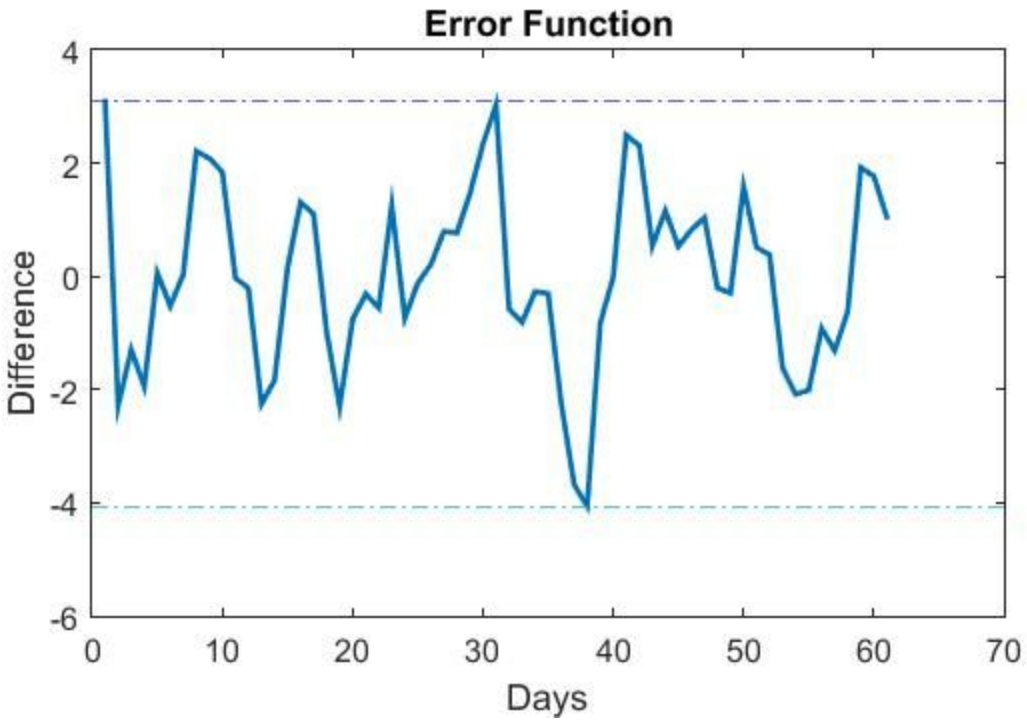


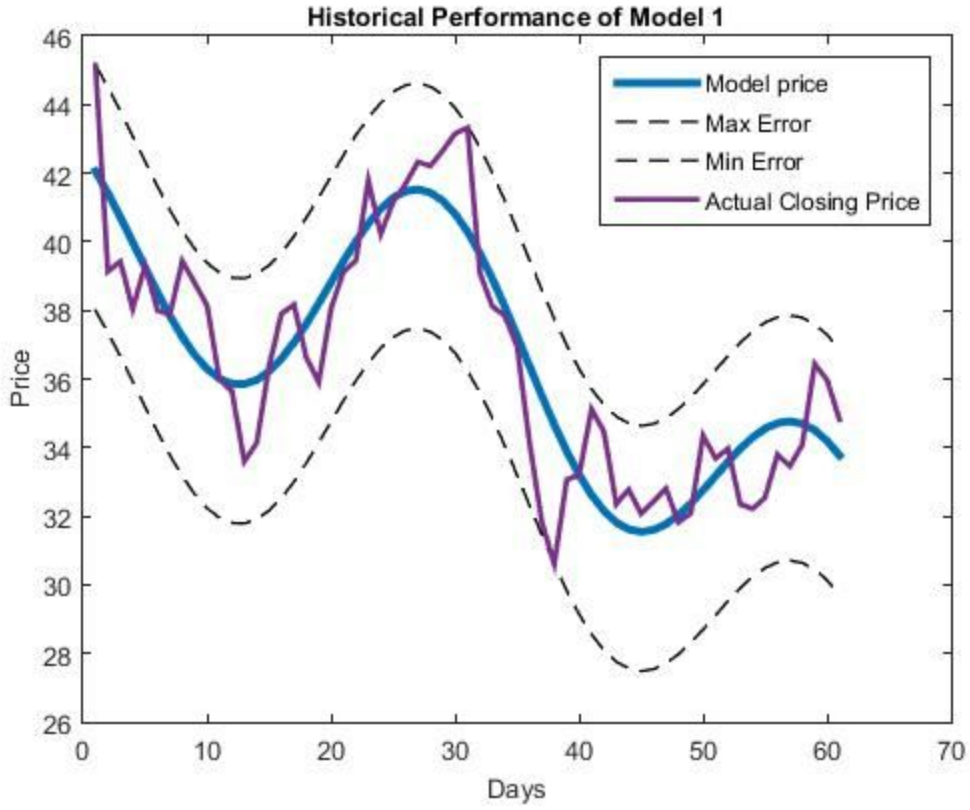

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

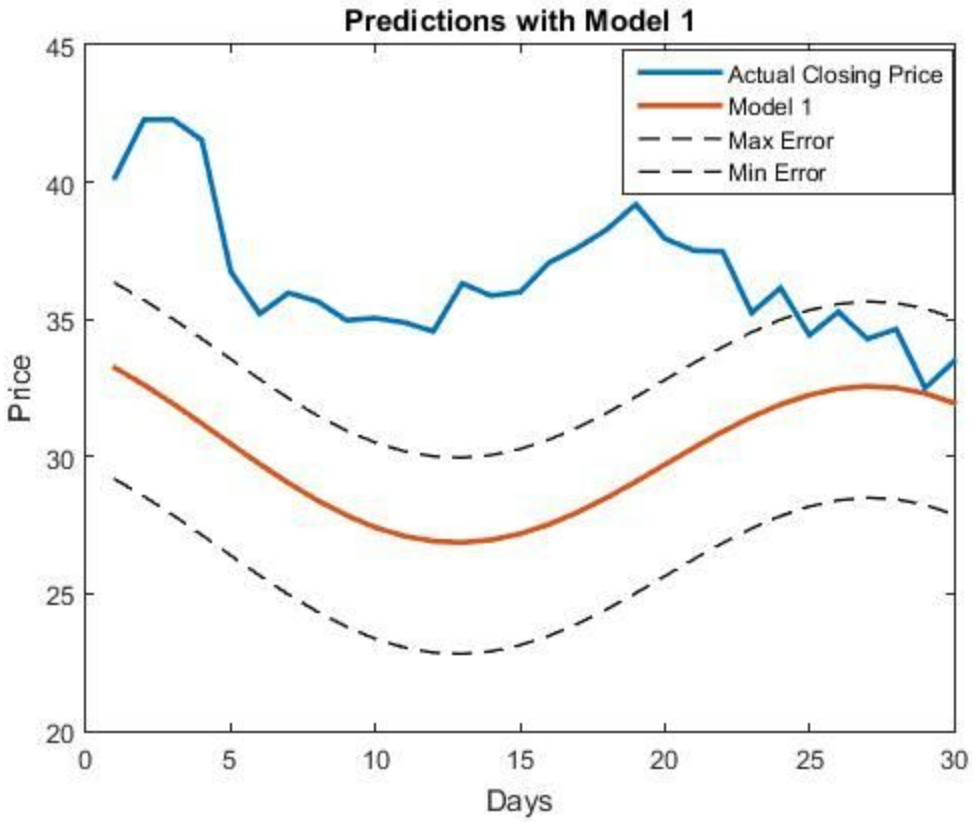

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
46
45
44
43
42
41
40
39
38
37
36
0
10
20
30
40
50
60
70


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
46
44
42
40
38
36
34
32
30
0
10
20
30
40
50
60
70


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
4
2
0
-2
-4
-6
-8
-10
0
10
20
30
40
50
60
70

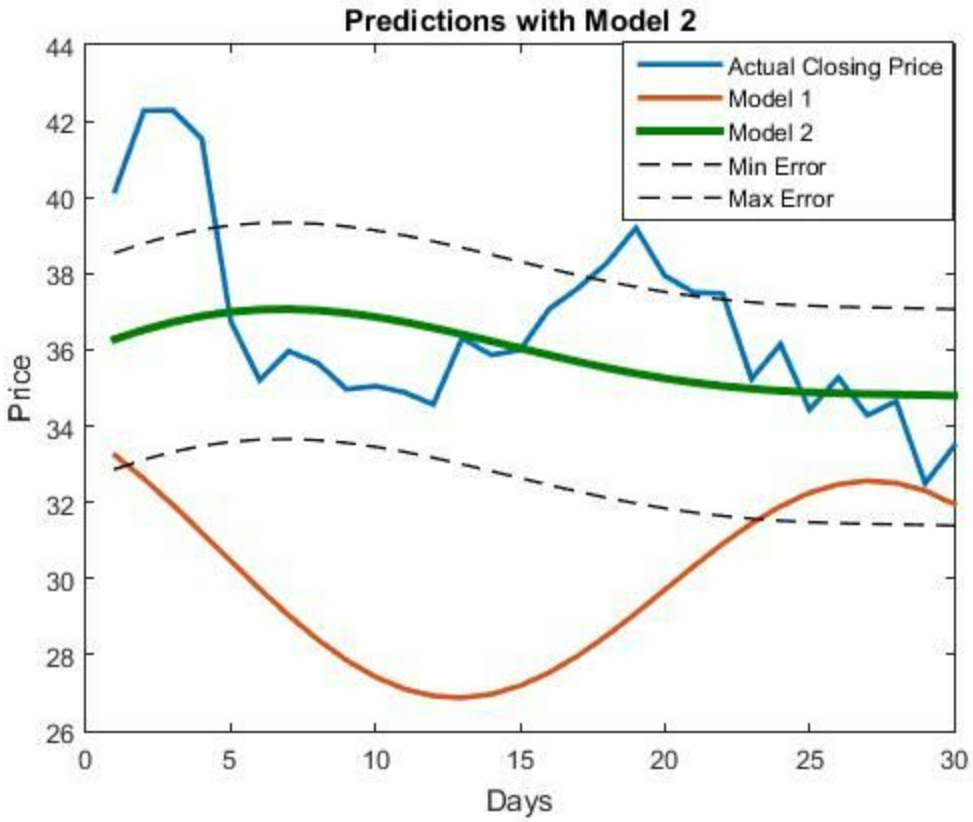

Error Function
Difference
Days
4
2
0
-2
-4
-6
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Price
Days
46
44
42
40
38
36
34
32
30
28
26
0
10
20
30
40
50
60
70



Max Error : 8.8%

Min Error : -11.8%



Max Error : 5.6%

Min Error : -8.3%

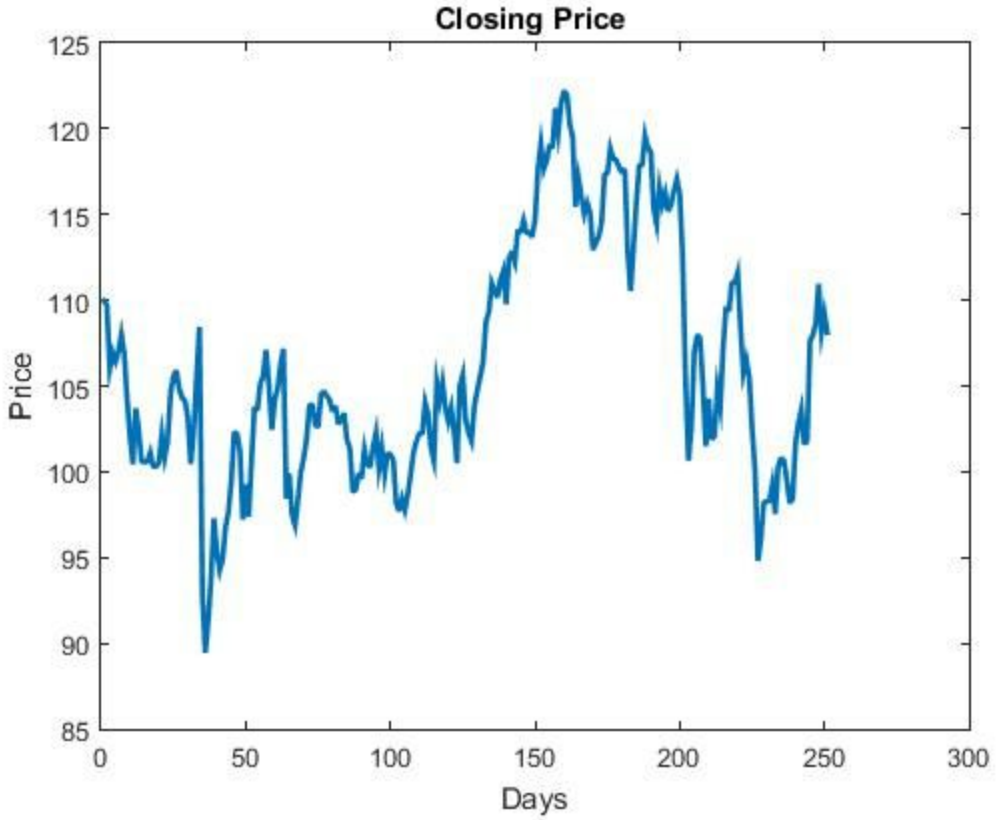
Gilead Sciences (NASDAQ: GILD)

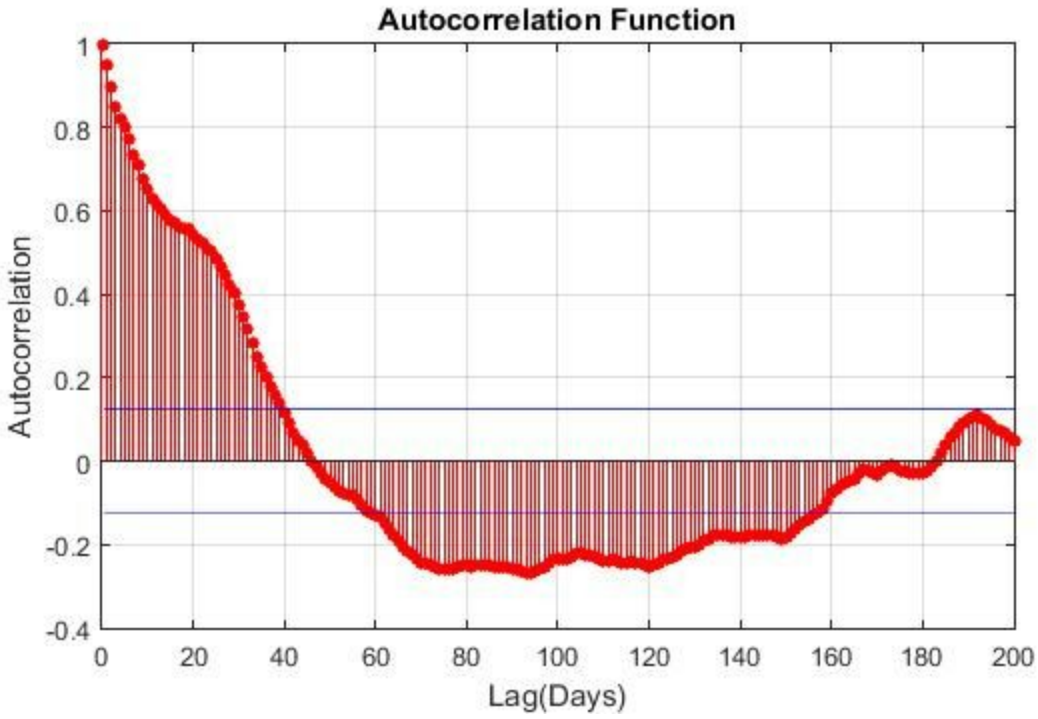
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

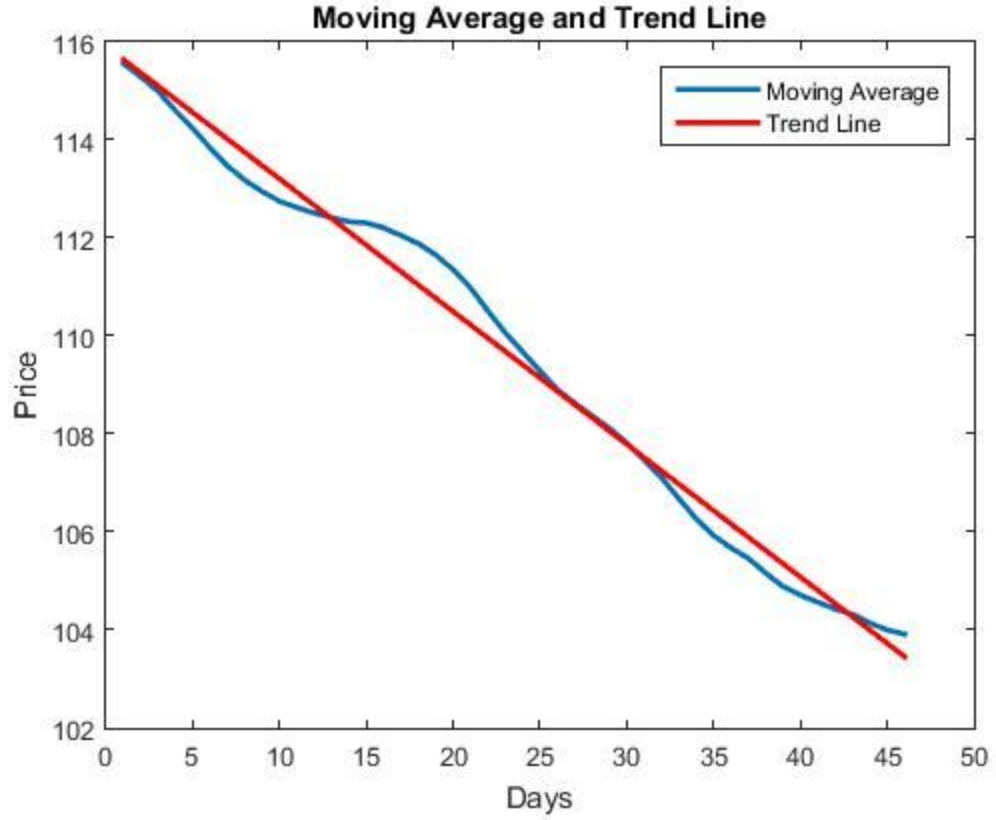
Moving Average Window: 50 Days.

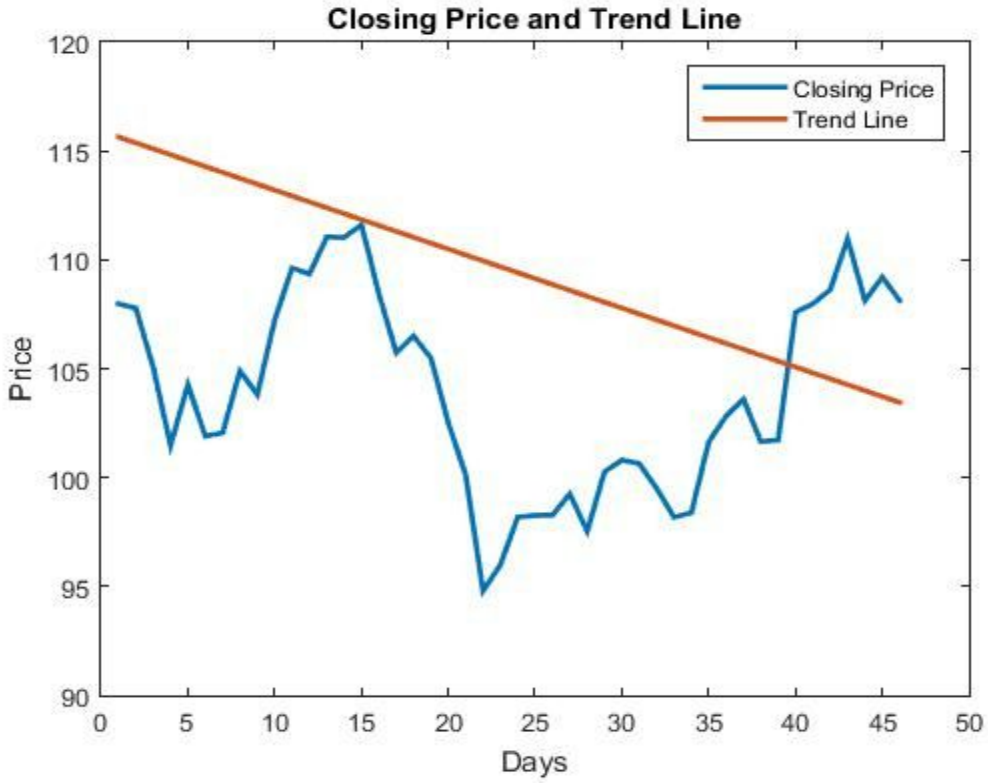
Autocorrelation Days : 46

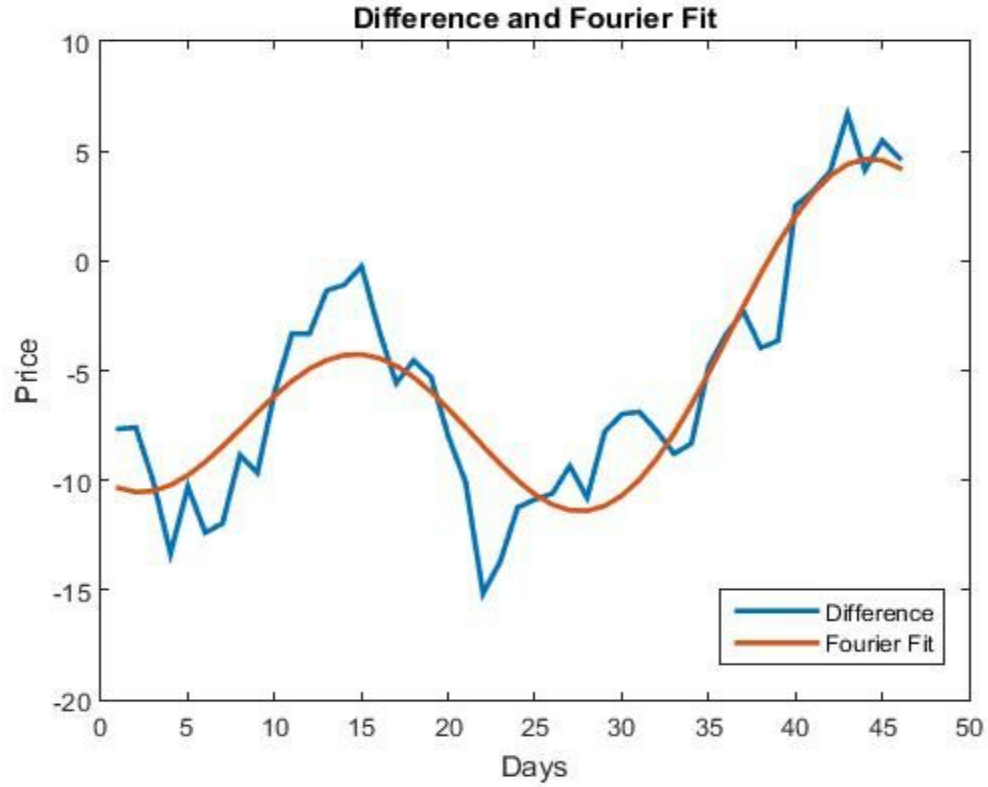
Correlation with the index : 0.7310

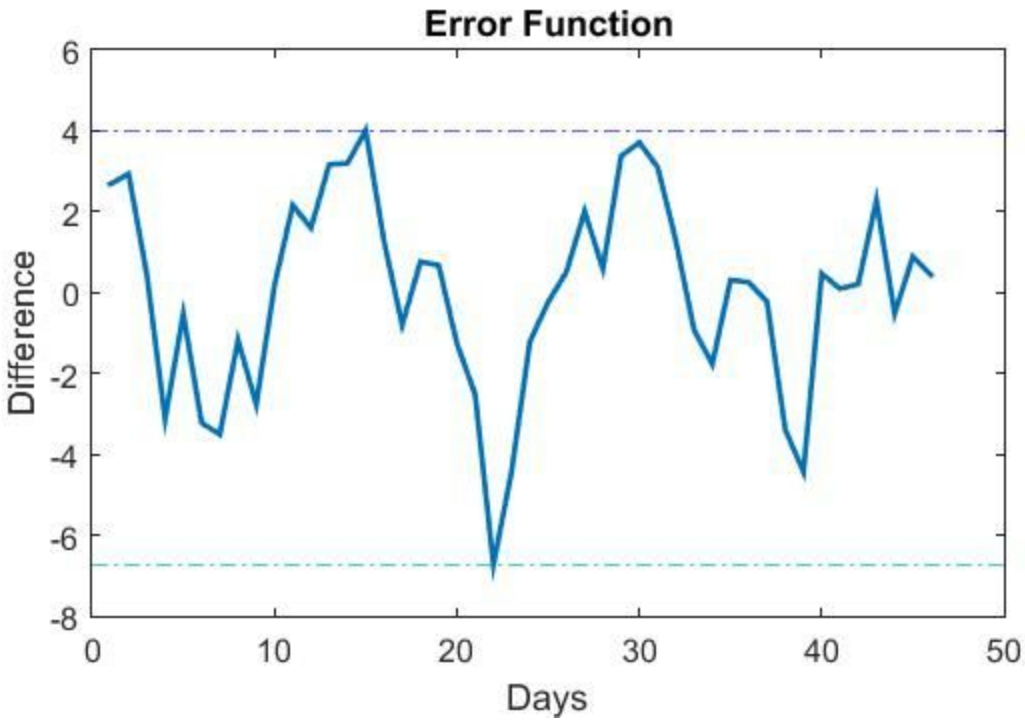


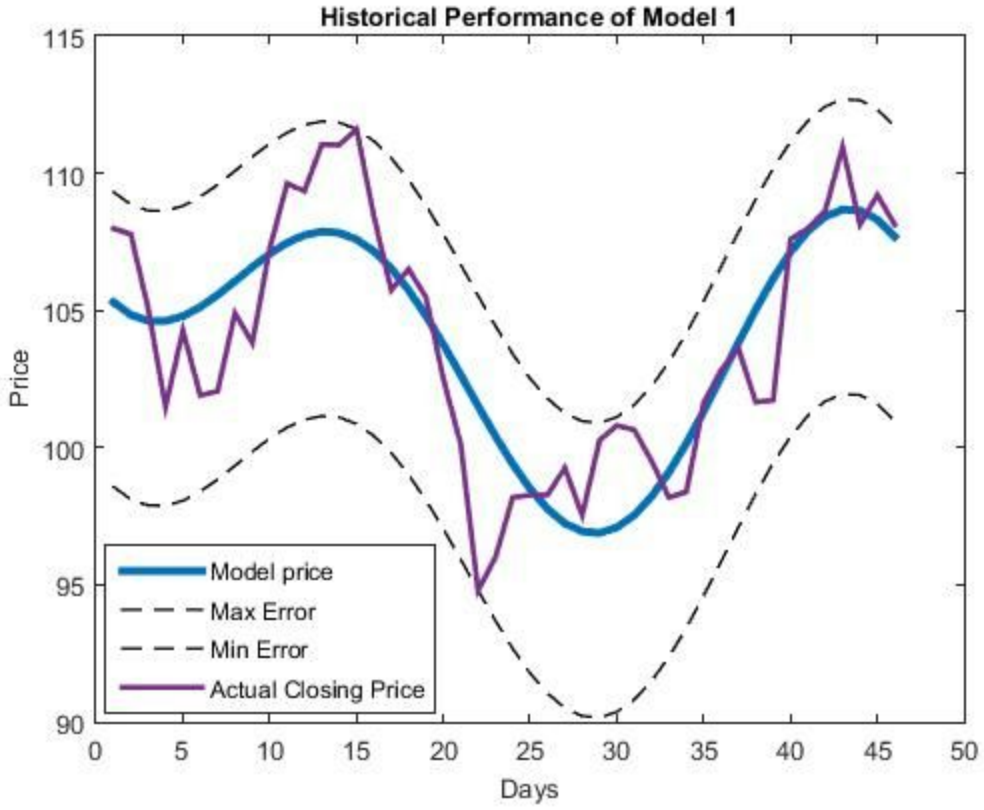

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

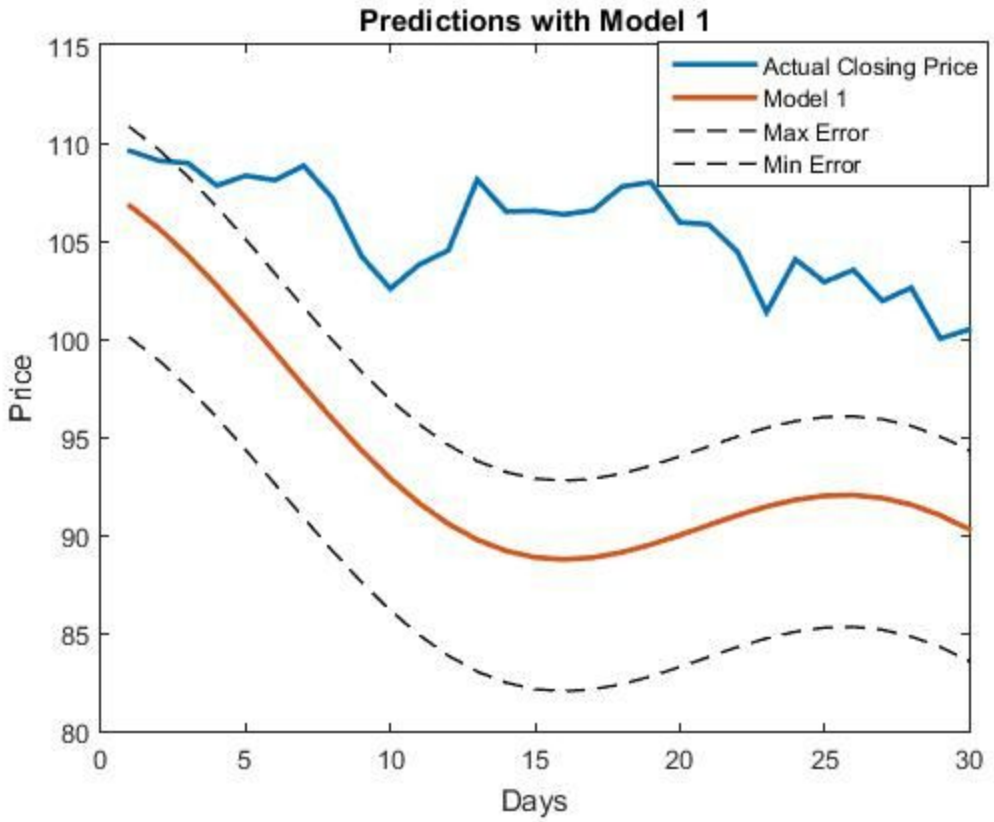

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
116
114
112
110
108
106
104
102
0
5
10
15
20
25
30
35
40
45
50


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
120
115
110
105
100
95
90
0
5
10
15
20
25
30
35
40
45
50


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
10
5
0
-5
-10
-15
-20
0
5
10
15
20
25
30
35
40
45
50

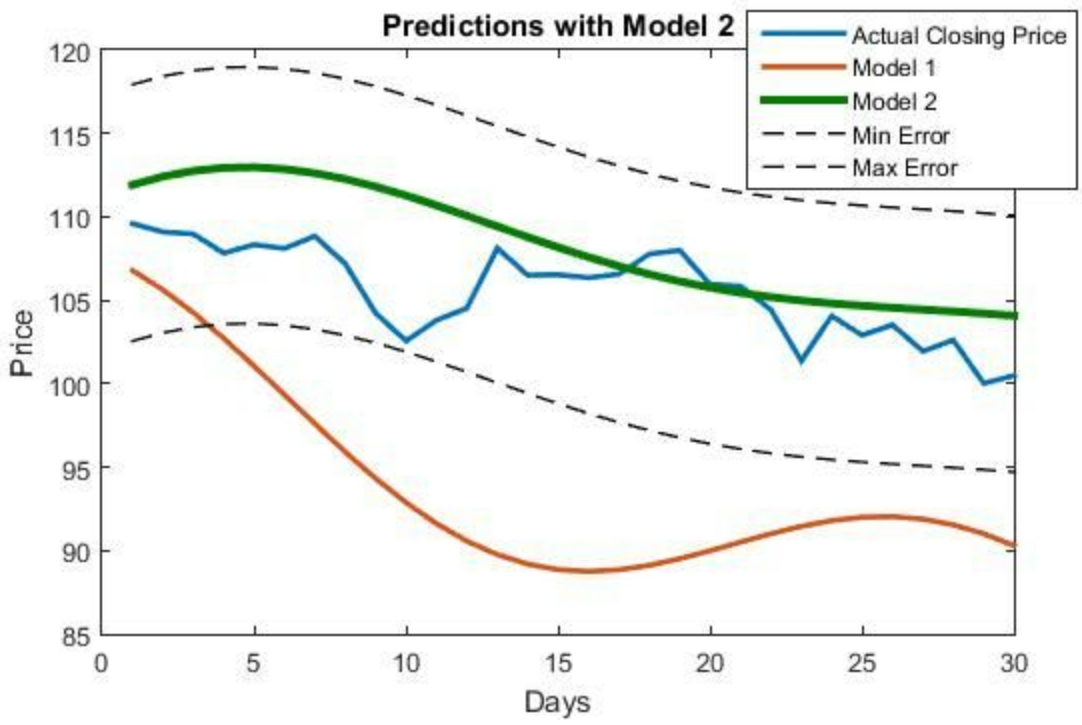

Error Function
Difference
Days
6
4
2
0
-2
-4
-6
-8
0
10
20
30
40
50


Historical Performance of Model 1
Price
Days
Model price
Max Error
Min Error
Actual Closing Price
115
110
105
100
95
90
0
5
10
15
20
25
30
35
40
45
50



Max Error : 3.7%

Min Error : -6.5%



Max Error : 4.5%

Min Error : -8.9%

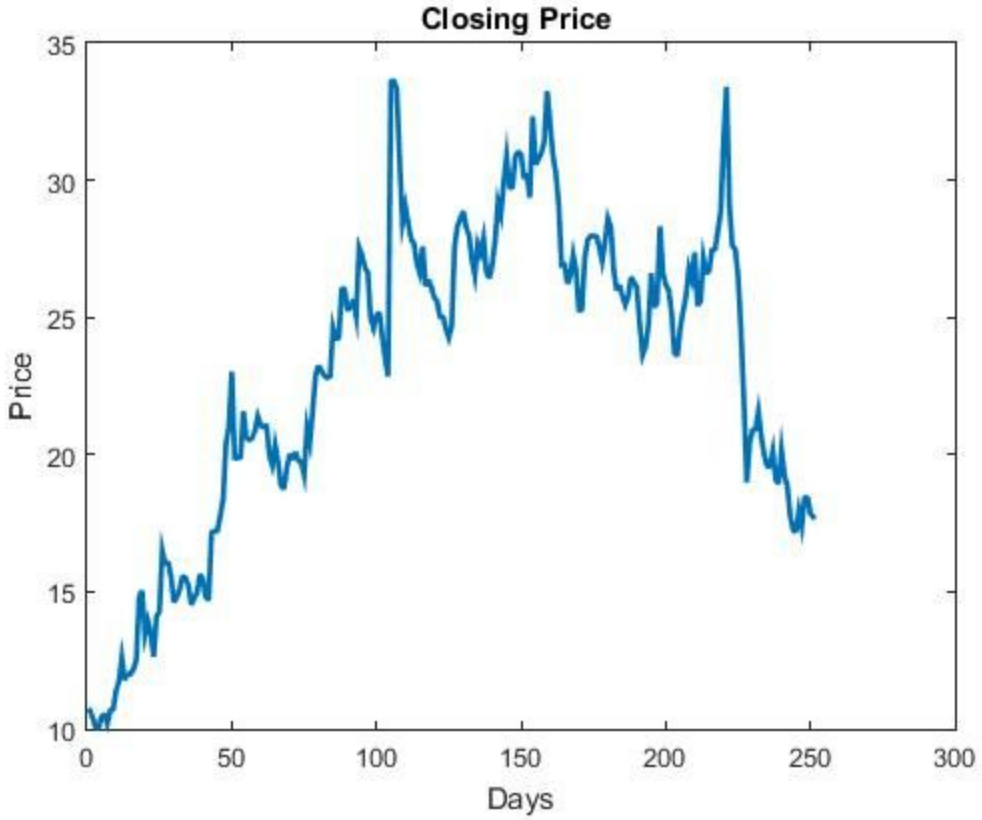
uniQure N.V. (NASDAQ: QURE)

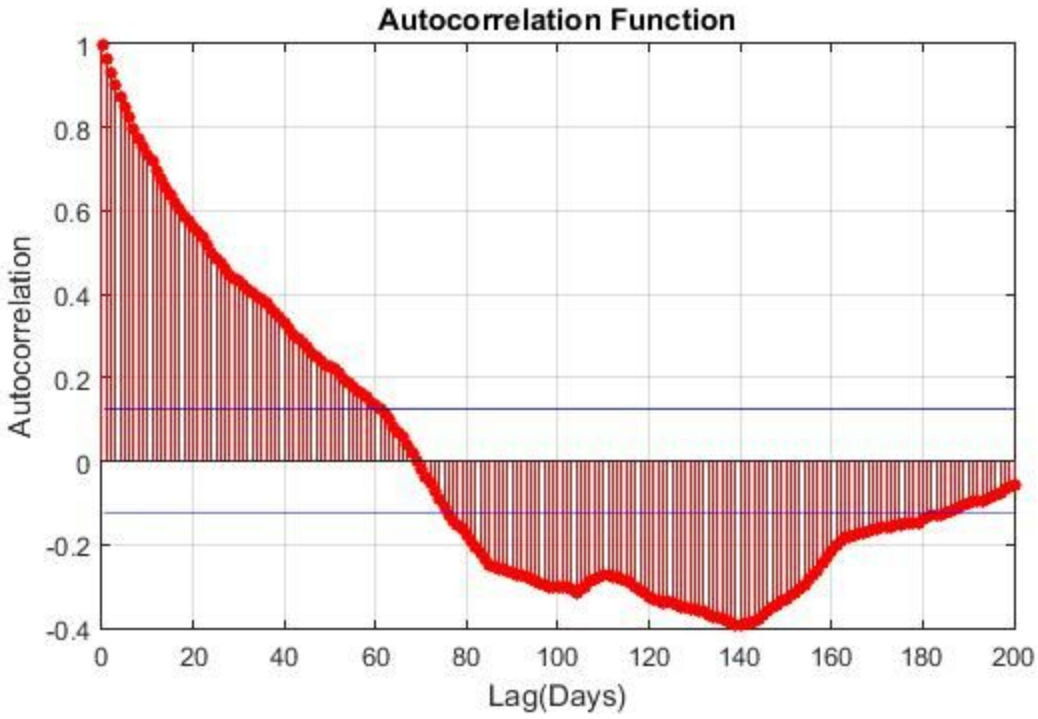
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

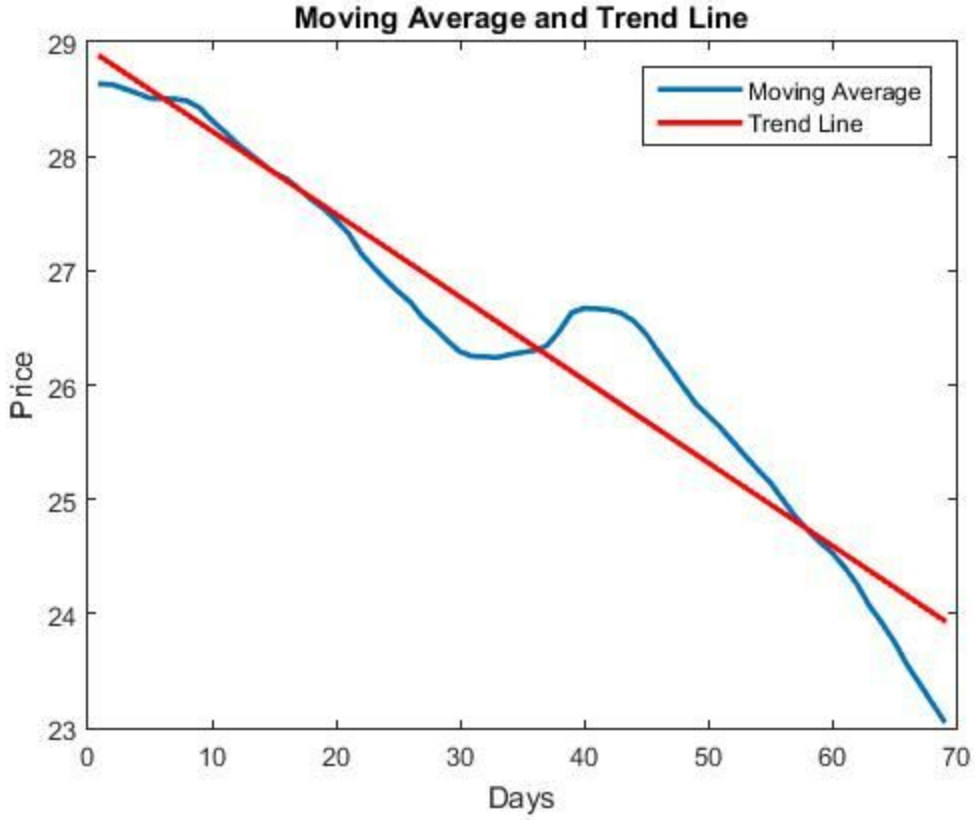
Moving Average Window: 50 Days.

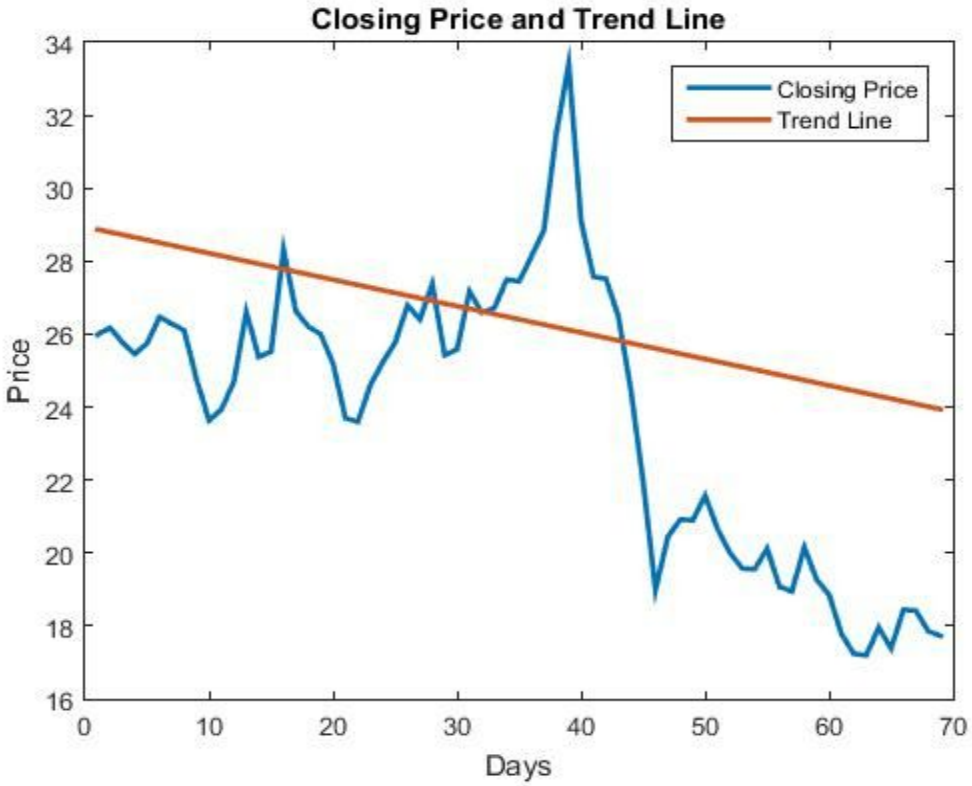
Autocorrelation Days : 79

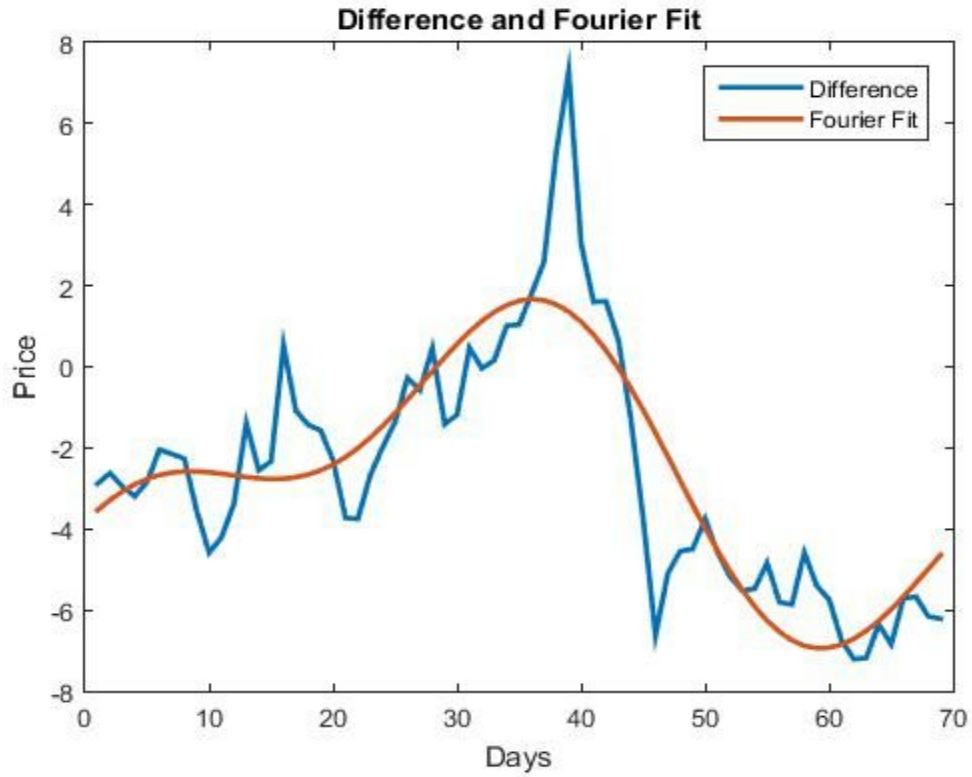
Correlation with the index : 0.8590

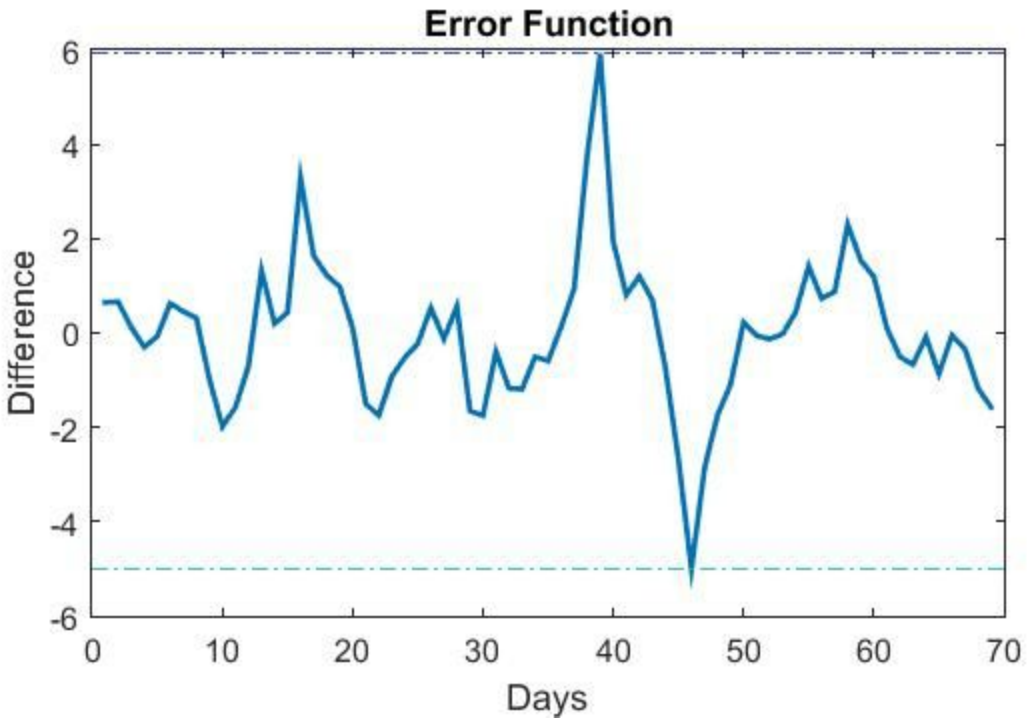


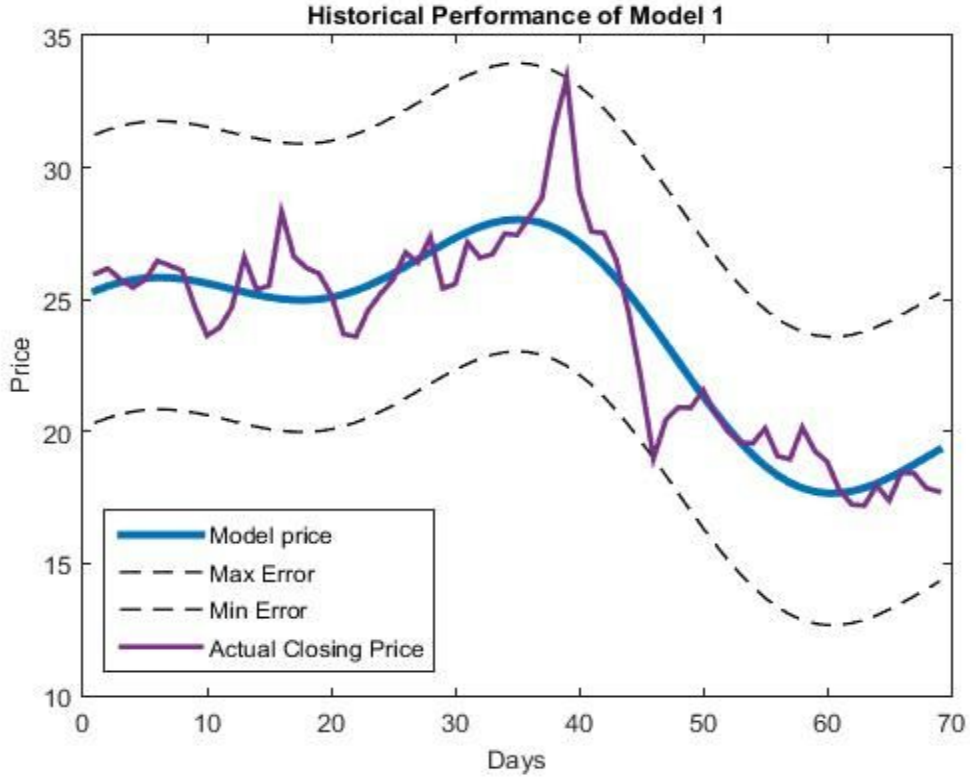

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

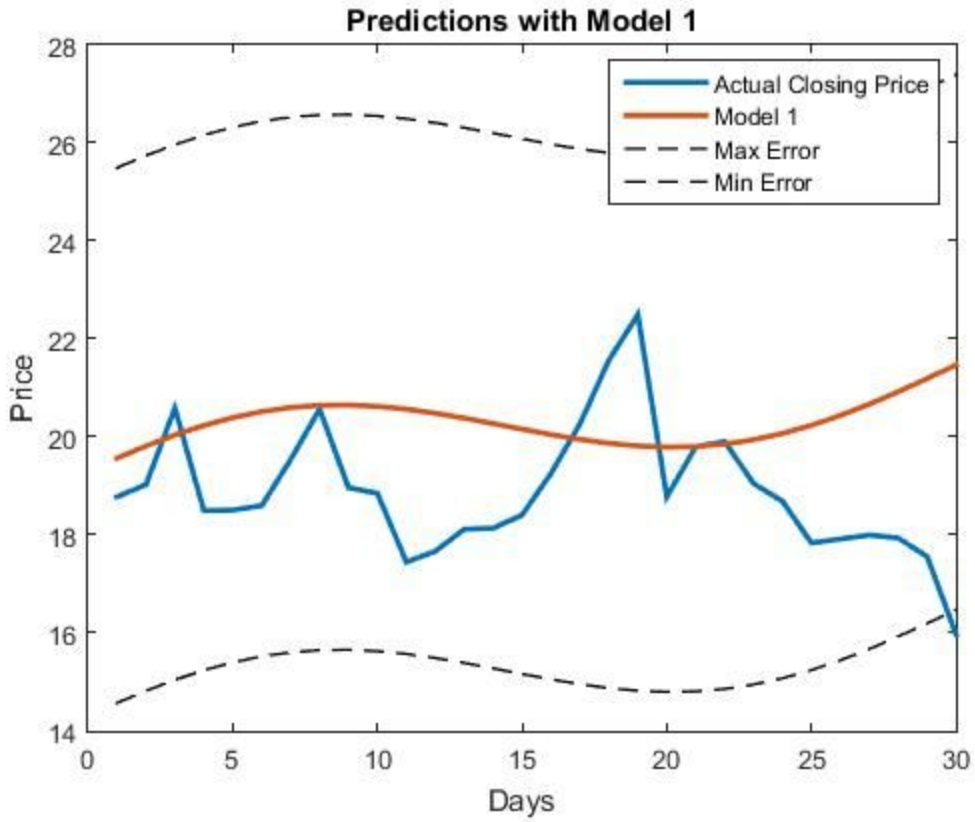

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
29
28
27
26
25
24
23
0
10
20
30
40
50
60
70


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
34
32
30
28
26
24
22
20
18
16
0
10
20
30
40
50
60
70


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
8
6
4
2
0
-2
-4
-6
-8
0
10
20
30
40
50
60
70

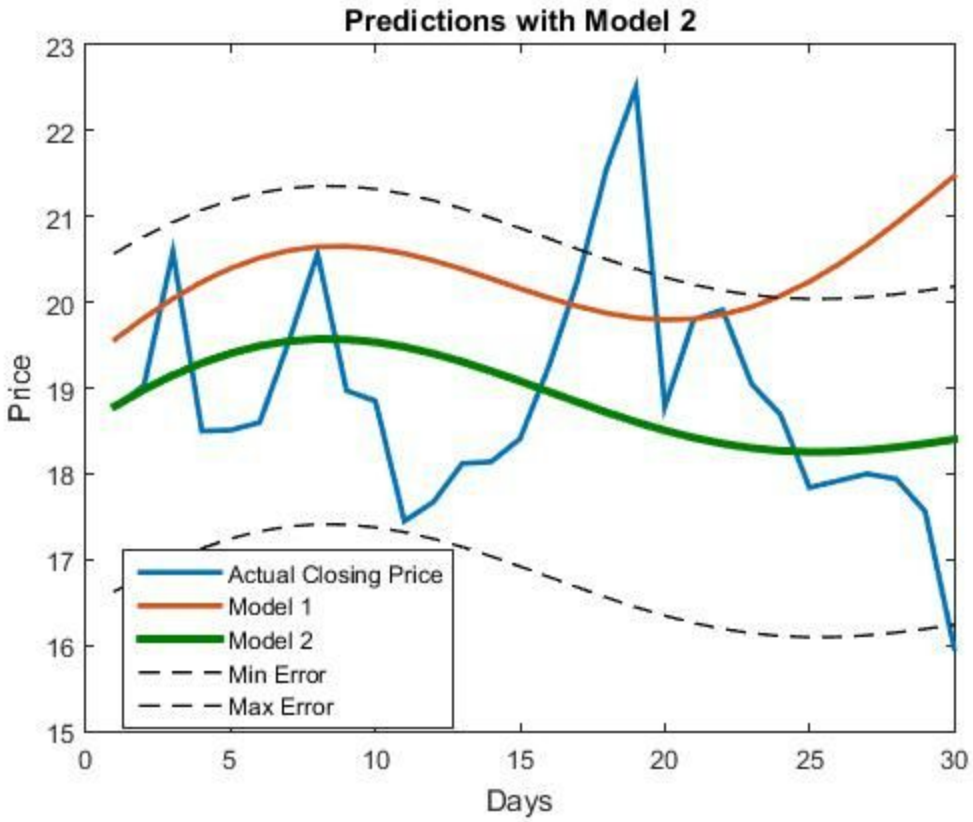

Error Function
Difference
Days
6
4
2
0
-2
-4
-6
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Price
Days
Model price
Max Error
Min Error
Actual Closing Price
35
30
25
20
15
10
0
10
20
30
40
50
60
70



Max Error :30%

Min Error : -30%



Max Error : 10.5%

Min Error : -10.5%

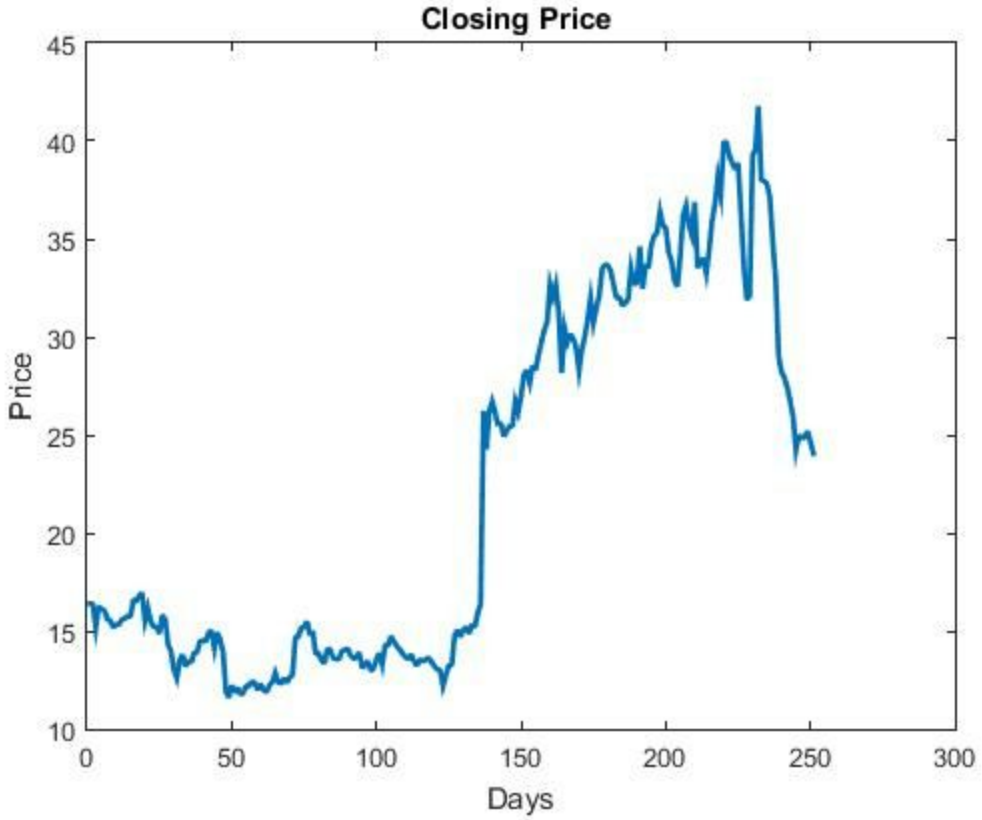
Sarepta Therapeutics (NASDAQ: SRPT)

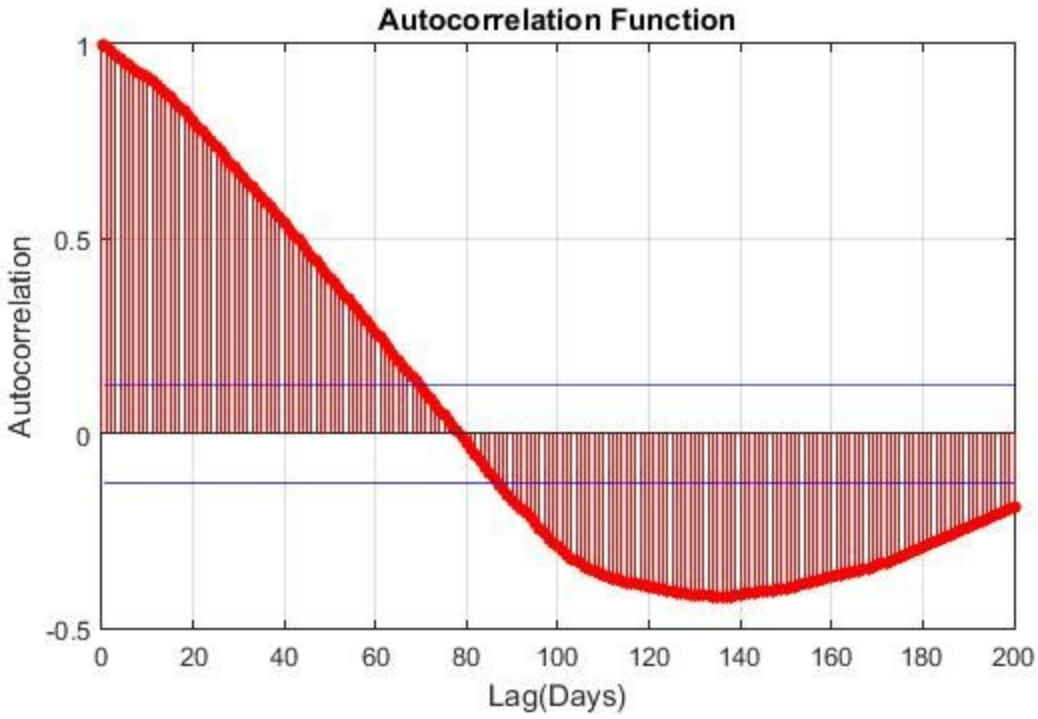
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

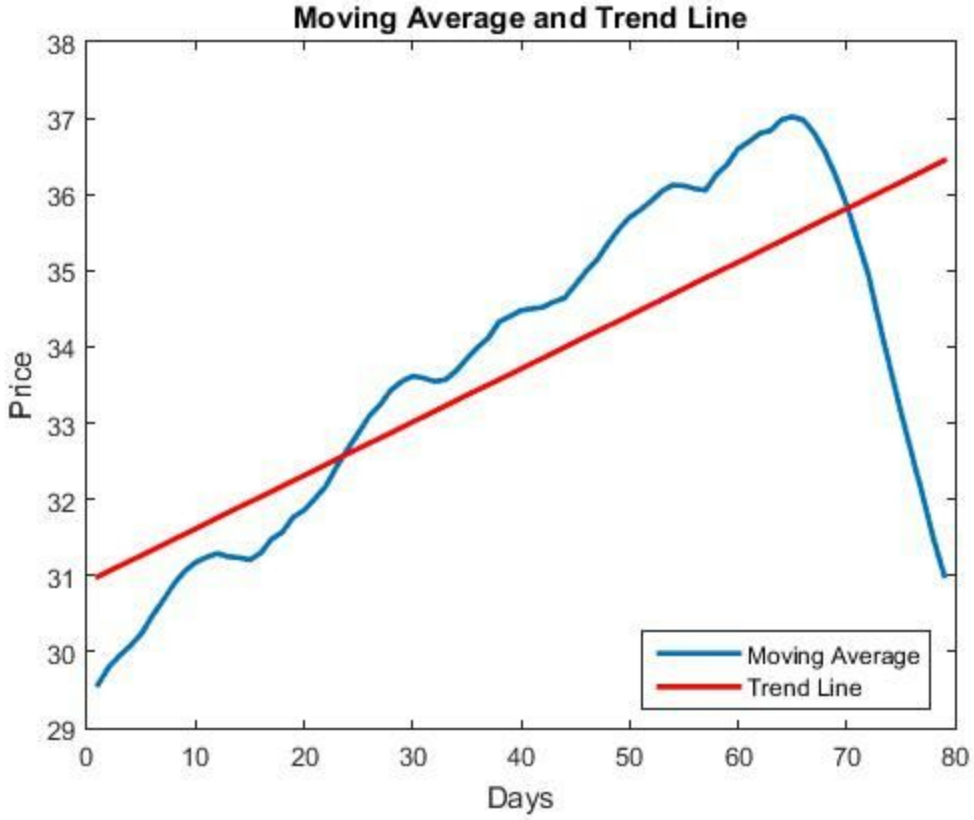
Moving Average Window: 50 Days.

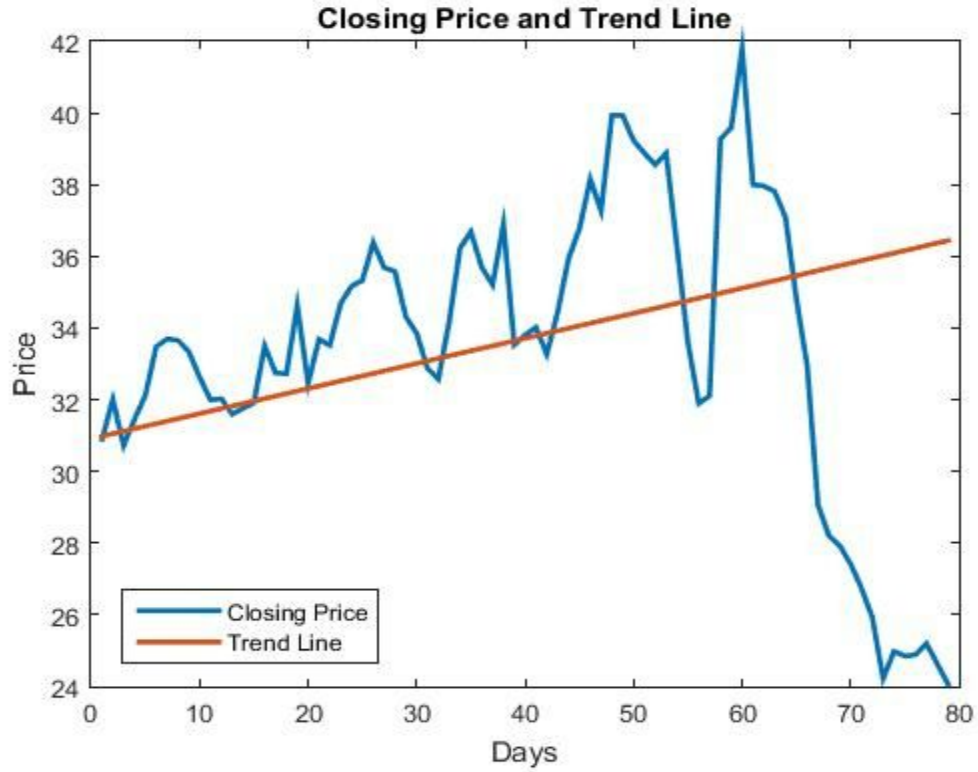
Autocorrelation Days : 79

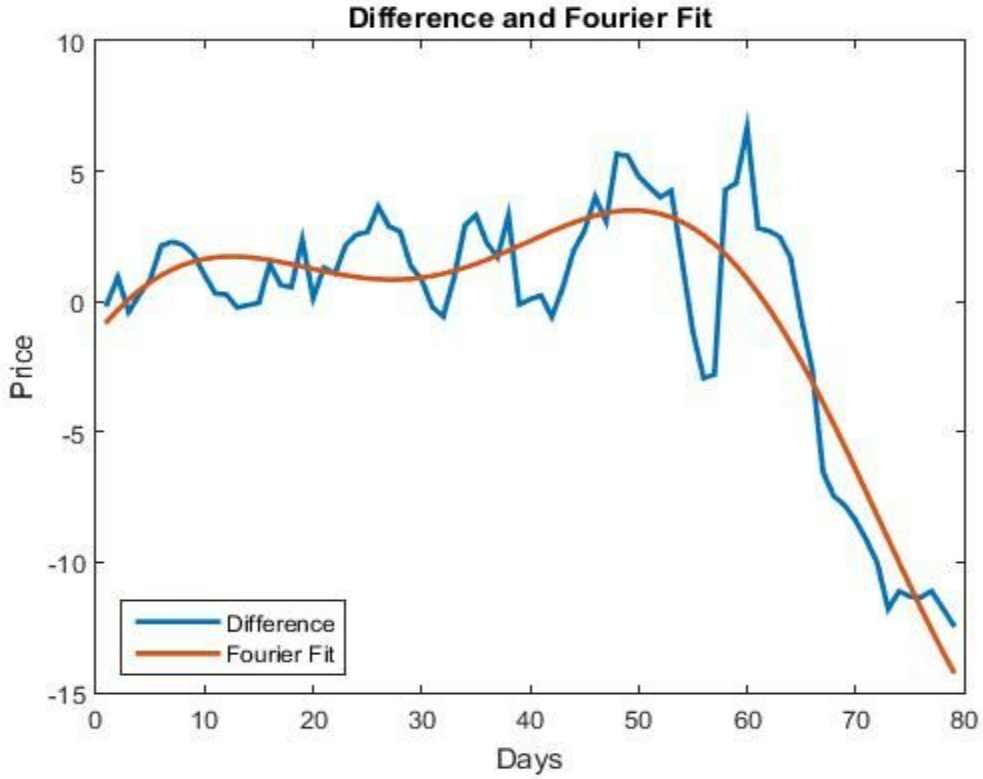
Correlation with the index : 0.3935

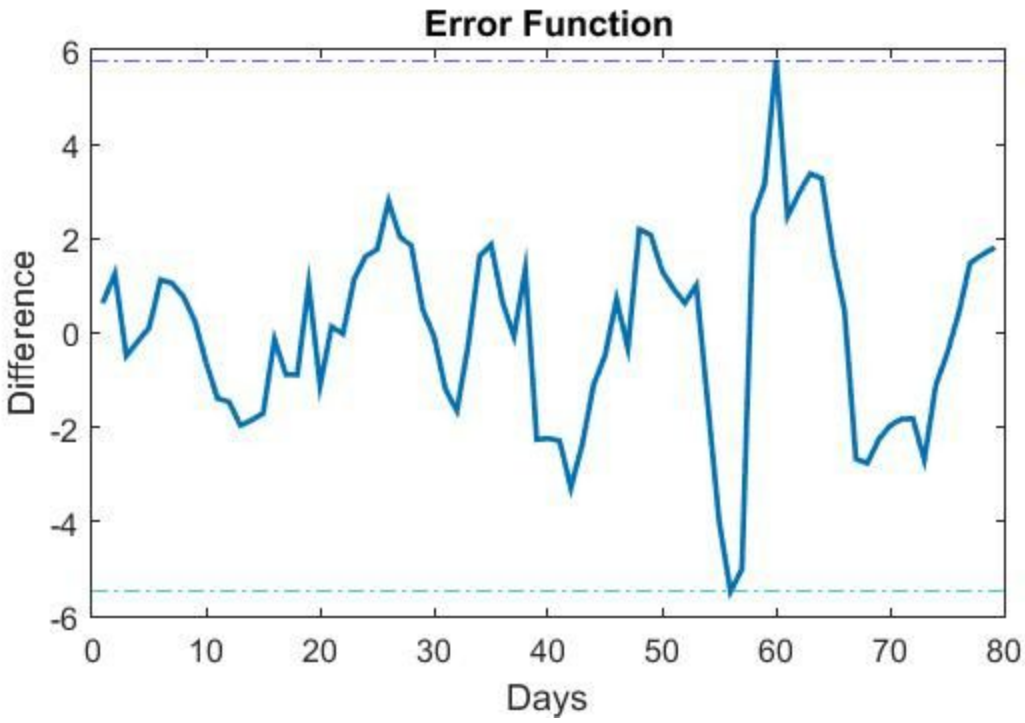


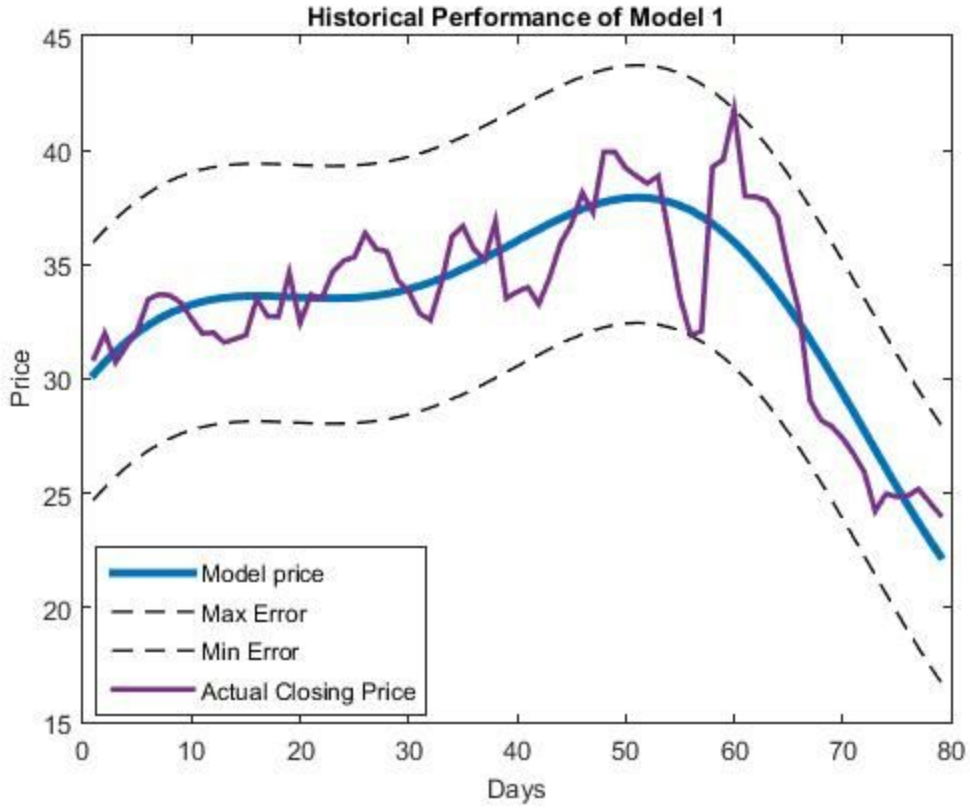

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.5
0
-0.5
0
20
40
60
80
100
120
140
160
180
200

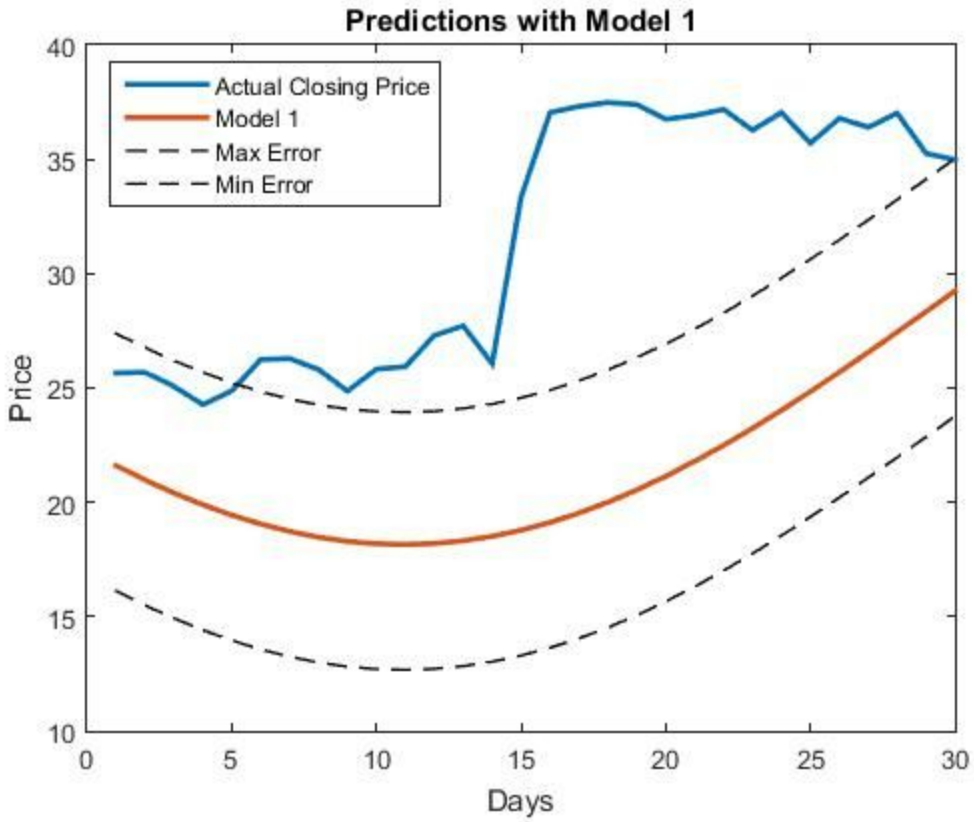

Moving Average and Trend Line
Price
Days
Moving Average
Trend Line
38
37
36
35
34
33
32
31
30
29
0
10
20
30
40
50
60
70
80


Closing Price and Trend Line
Price
Days
Closing Price
Trend Line
42
40
38
36
34
32
30
28
26
24
0
10
20
30
40
50
60
70
80


Difference and Fourier Fit
Price
Days
Difference
Fourier Fit
10
5
0
-5
-10
-15
0
10
20
30
40
50
60
70
80

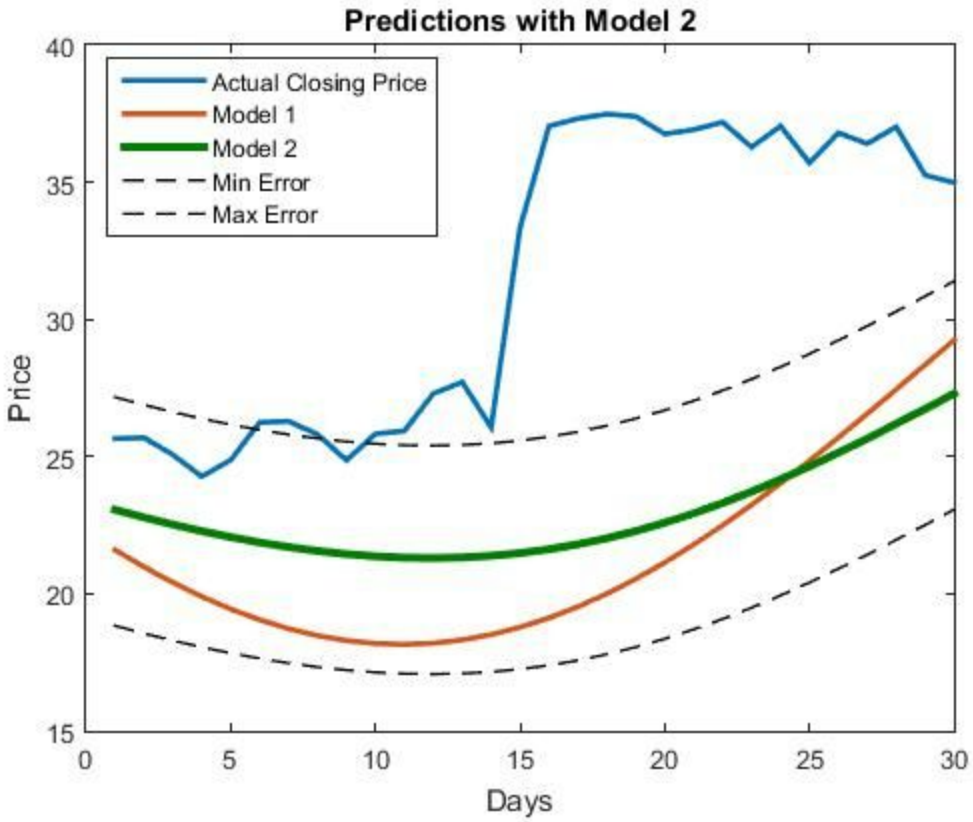

Error Function
Difference
Days
6
4
2
0
-2
-4
-6
0
10
20
30
40
50
60
70
80


Historical Performance of Model 1
Price
Days
Model price
Max Error
Min Error
Actual Closing Price
45
40
35
30
25
20
15
0
10
20
30
40
50
60
70
80



Max Error : 22.7%

Min Error : -22.7%



Max Error : 22.7%

Min Error : -22.7%

- **Technology Sector:**

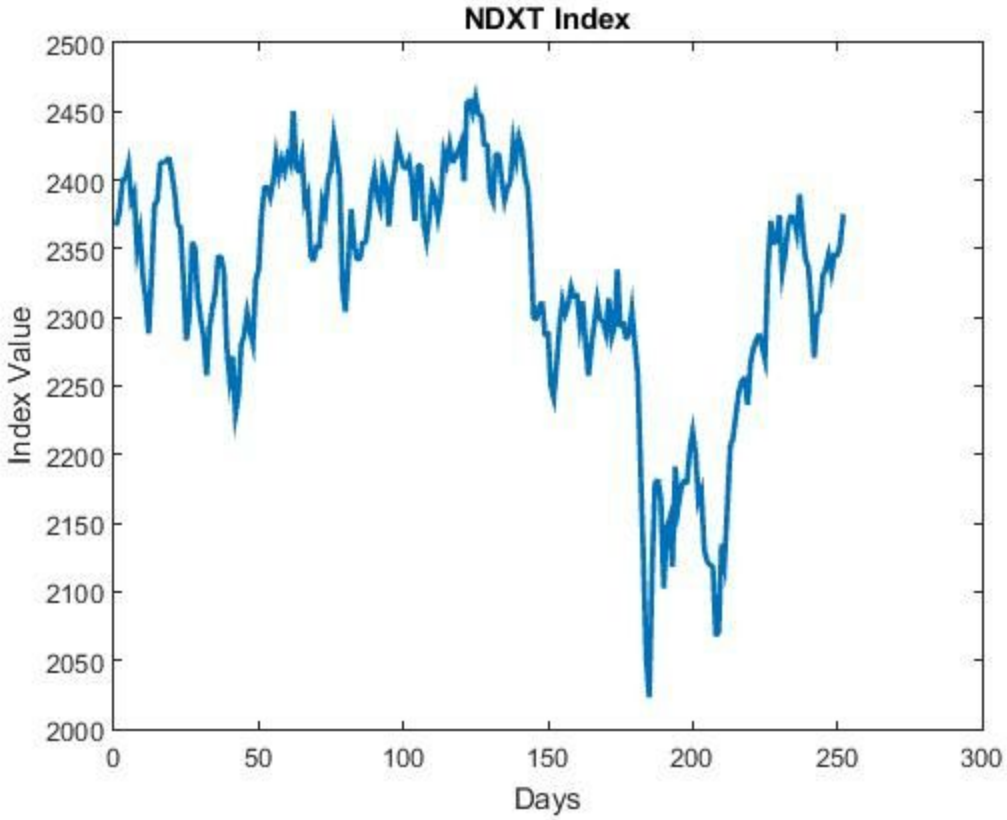
Index: The NASDAQ-100 Technology Sector Index was used in the creation of model 2, due to the highest overall correlations with the stocks chosen. The Nasdaq-100 Technology Sector is a subset of the NASDAQ 100, focused on the biggest tech companies.

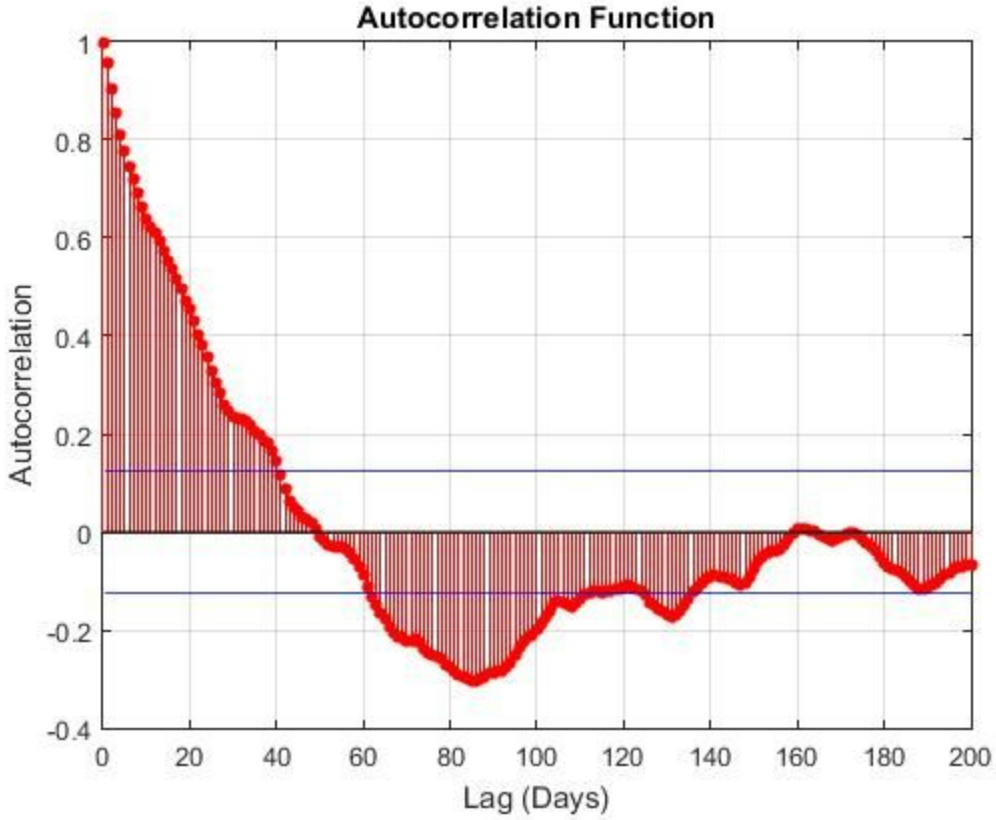
Nasdaq-100 Technology Sector Index (NDXT)

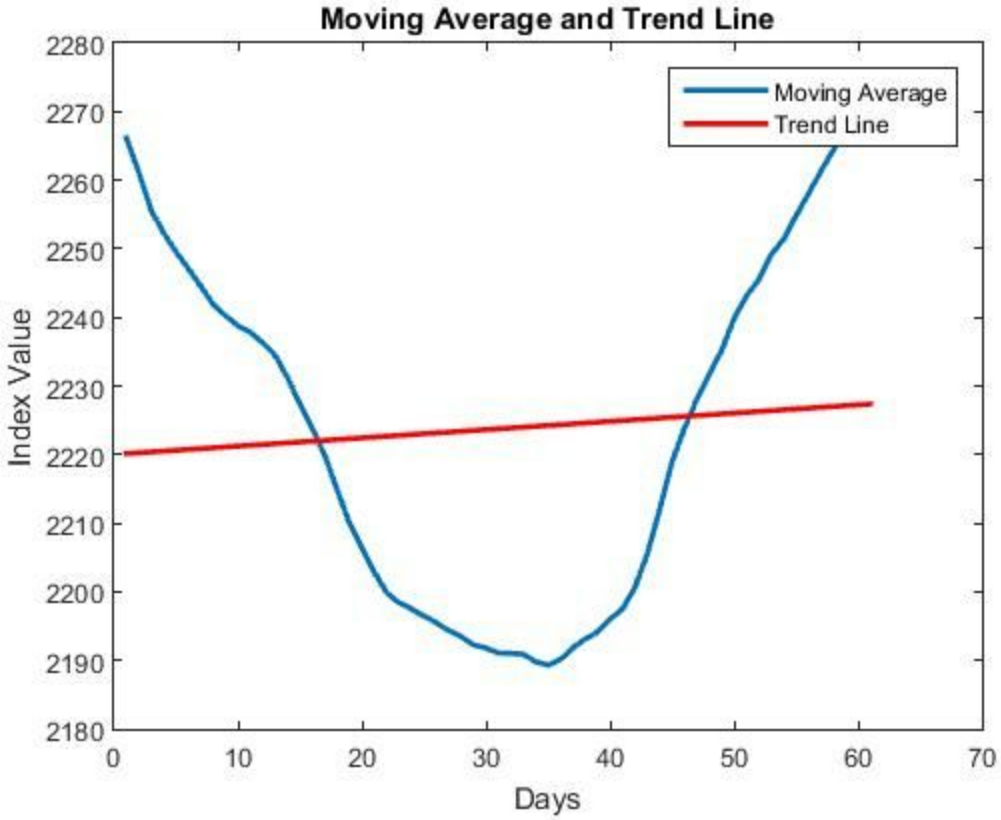
Prediction Range: 12/1/15 - 1/13/16 (30 Business Days)

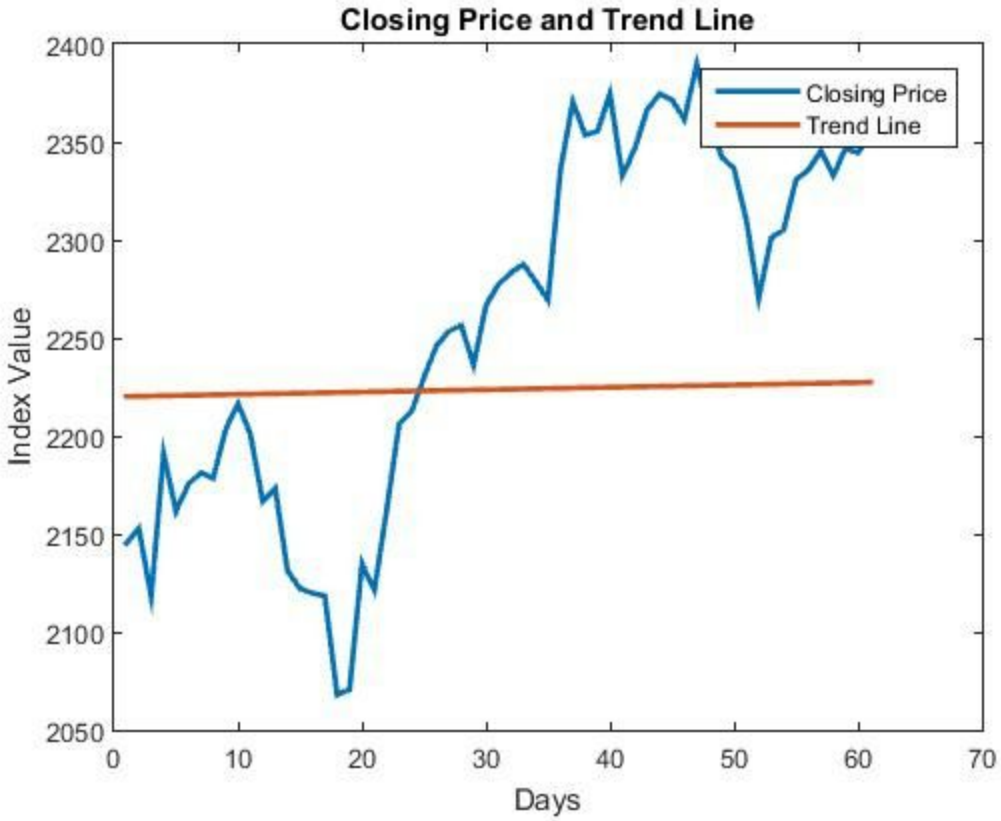
Autocorrelation Days: 50 Days

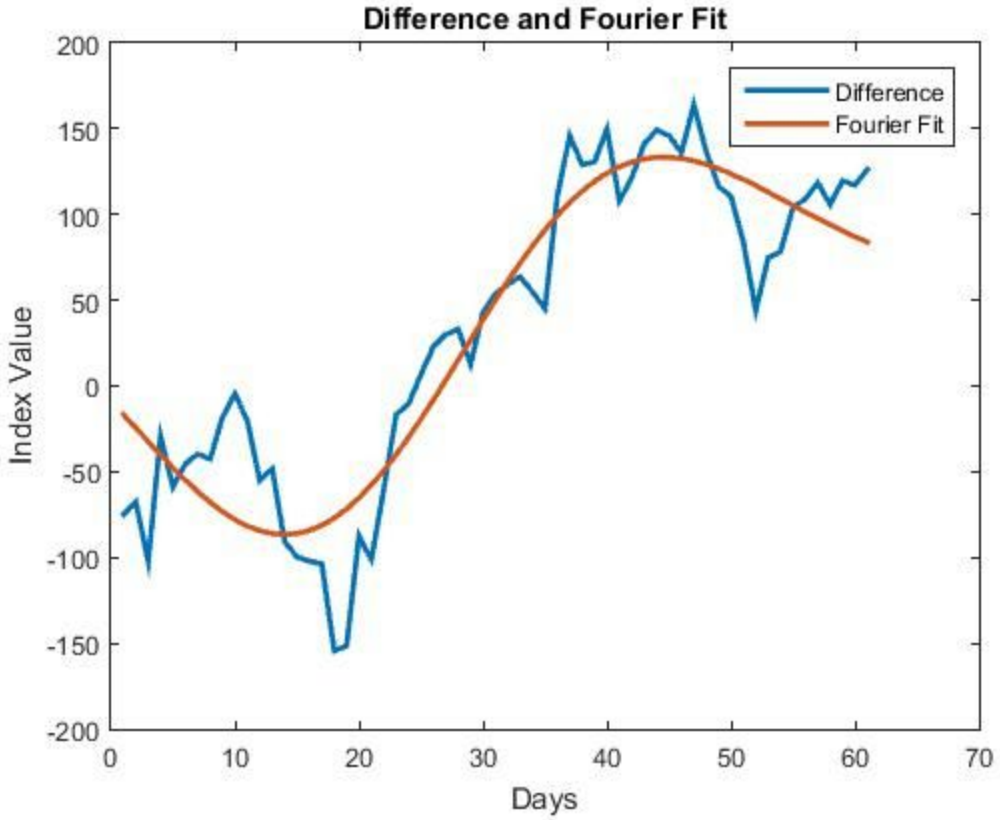
Days of Lag for Moving Average: 50 Days

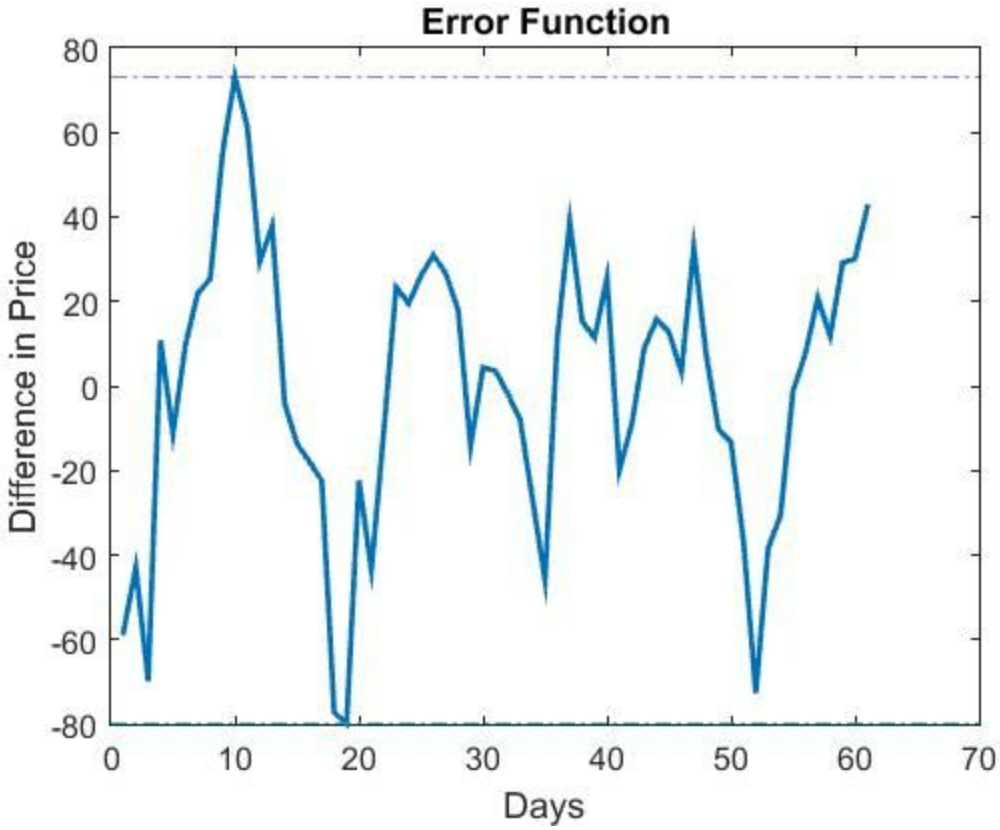

NDXT Index
Index Value
Days
2500
2450
2400
2350
2300
2250
2200
2150
2100
2050
2000
0
50
100
150
200
250
300

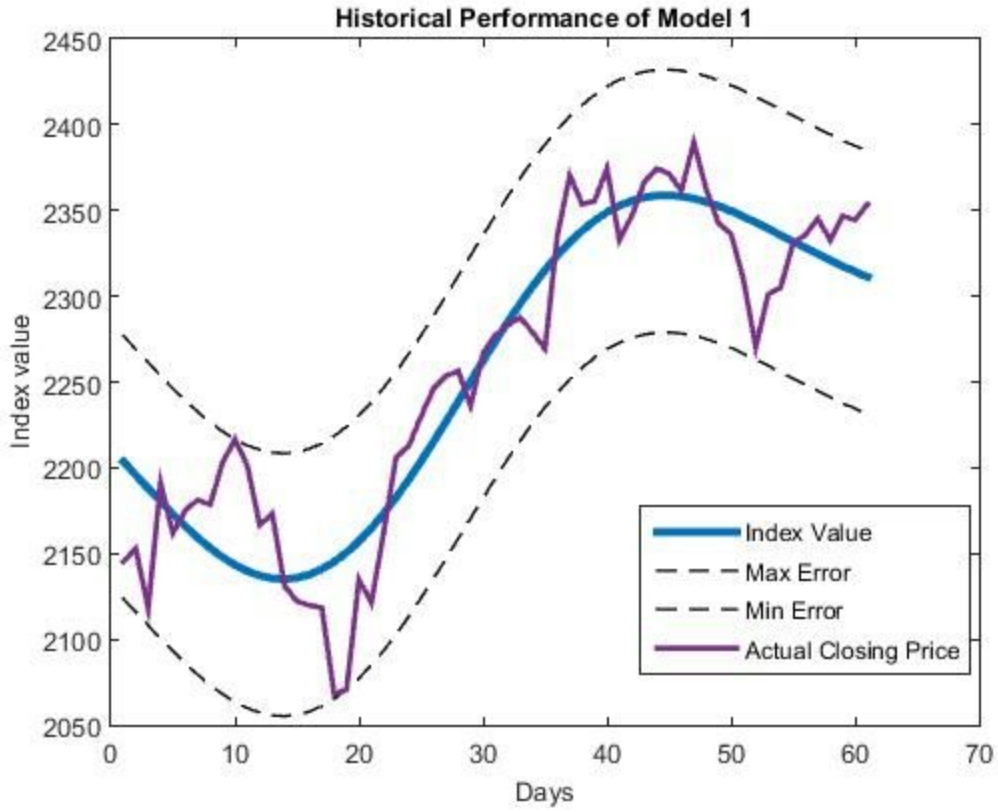

Autocorrelation Function
Autocorrelation
Lag (Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

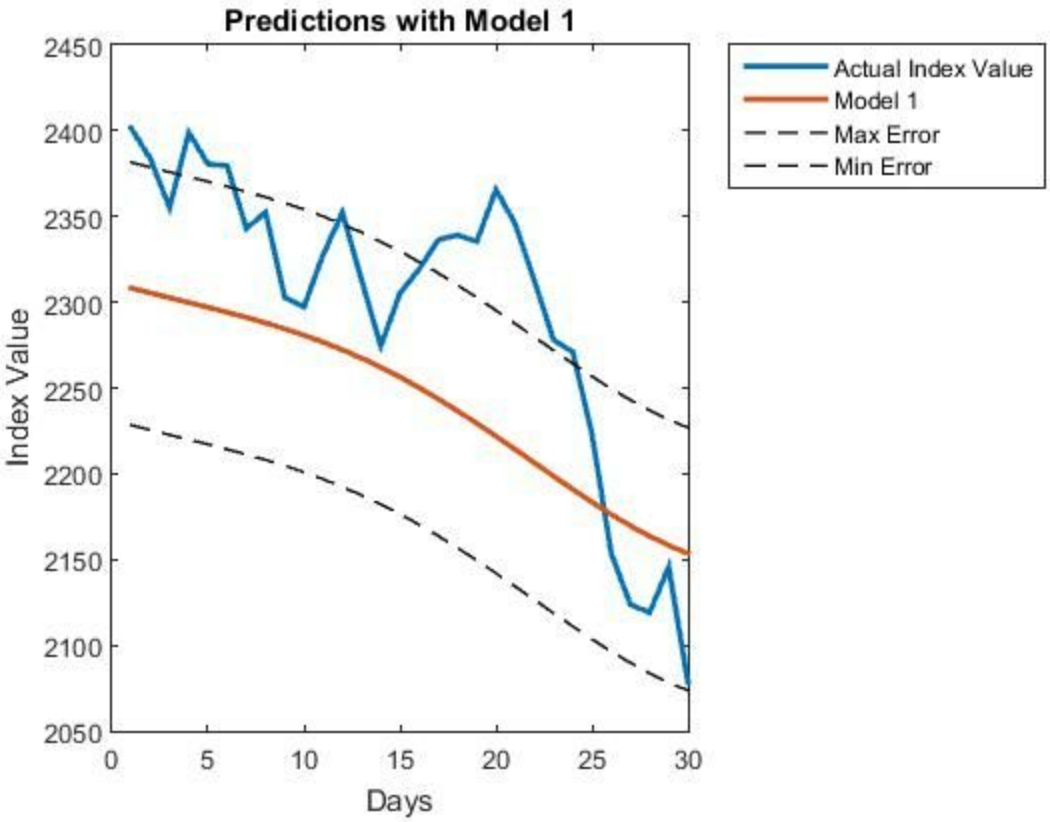

Moving Average and Trend Line
Moving Average
Trend Line
Index Value
Days
2280
2270
2260
2250
2240
2230
2220
2210
2200
2190
2180
0
10
20
30
40
50
60
70


Closing Price and Trend Line
Closing Price
Trend Line
Index Value
Days
2400
2350
2300
2250
2200
2150
2100
2050
0
10
20
30
40
50
60
70


Difference and Fourier Fit
Difference
Fourier Fit
Index Value
Days
200
150
100
50
0
-50
-100
-150
-200
0
10
20
30
40
50
60
70


Error Function
Difference in Price
Days
80
60
40
20
0
-20
-40
-60
-80
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Index value
Days
Index Value
Max Error
Min Error
Actual Closing Price
2450
2400
2350
2300
2250
2200
2150
2100
2050
0
10
20
30
40
50
60
70



Max Error: +3.5%

Min Error: -2.7%

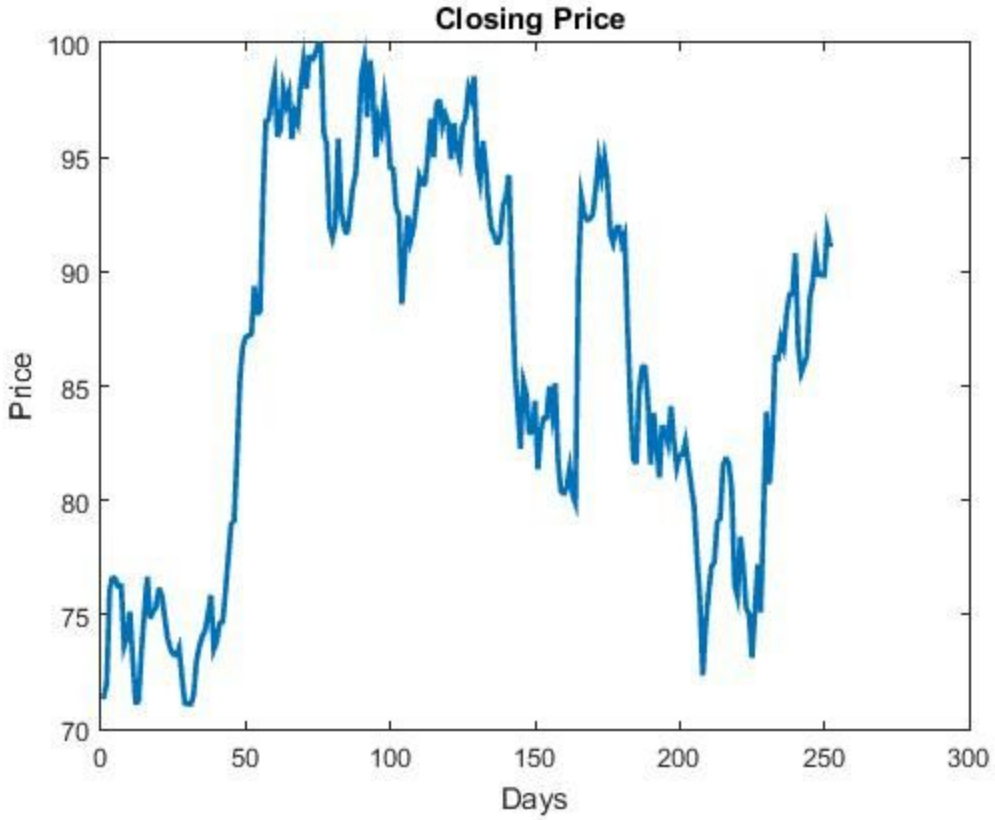
IPG Photonics (IPGP)

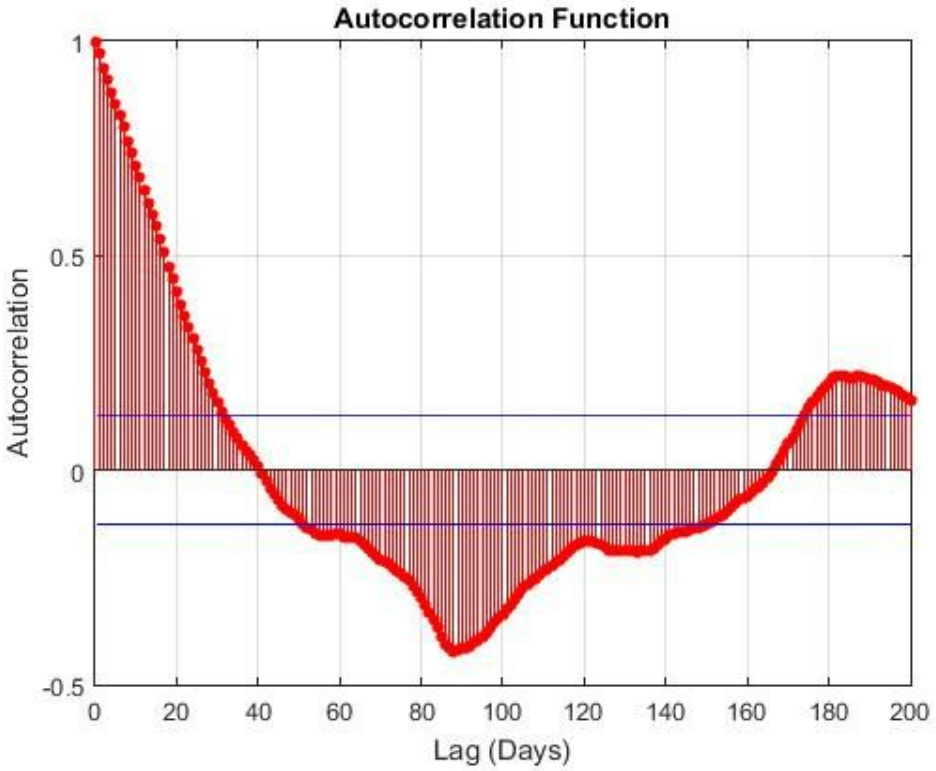
Prediction Range: 12/1/15 - 1/13/16 (30 Business Days)

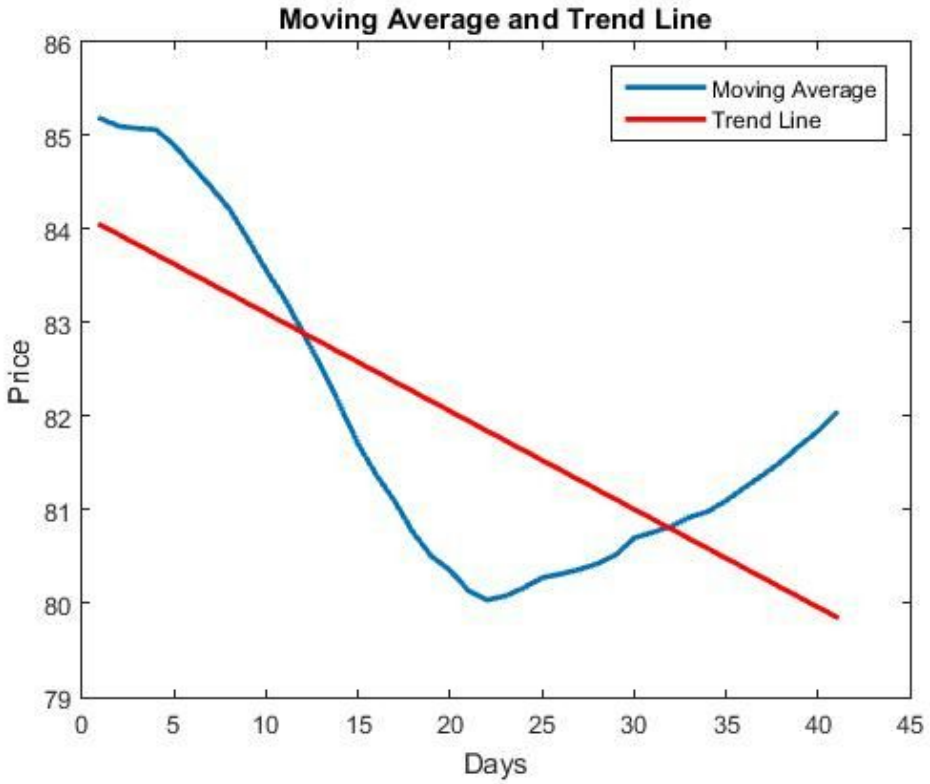
Autocorrelation Days: 41 Days

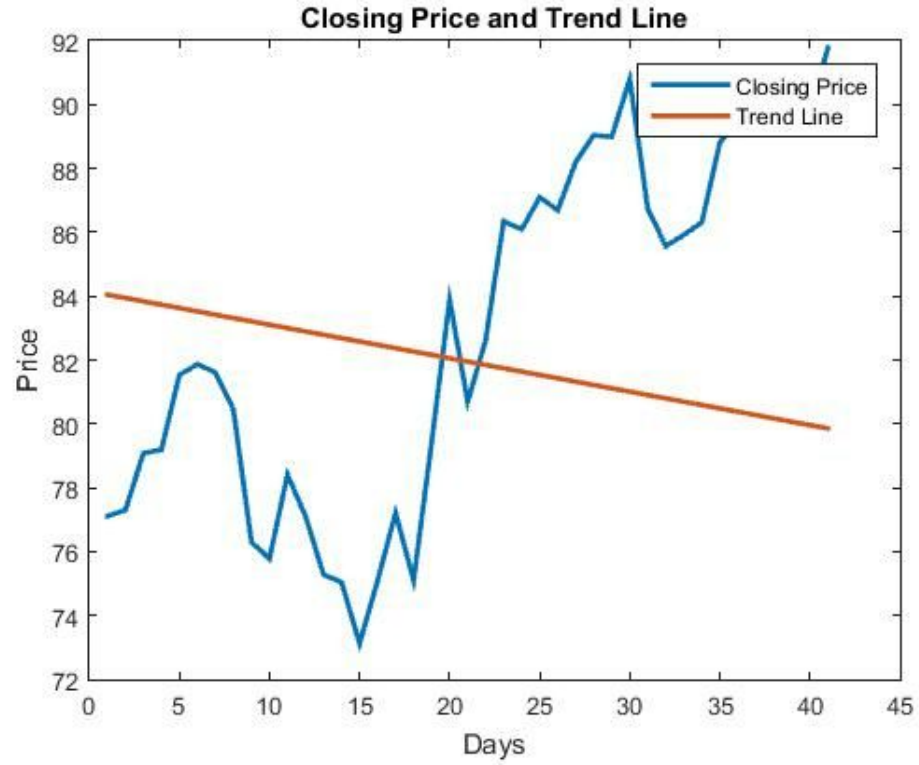
Moving Average Window: 50 Days

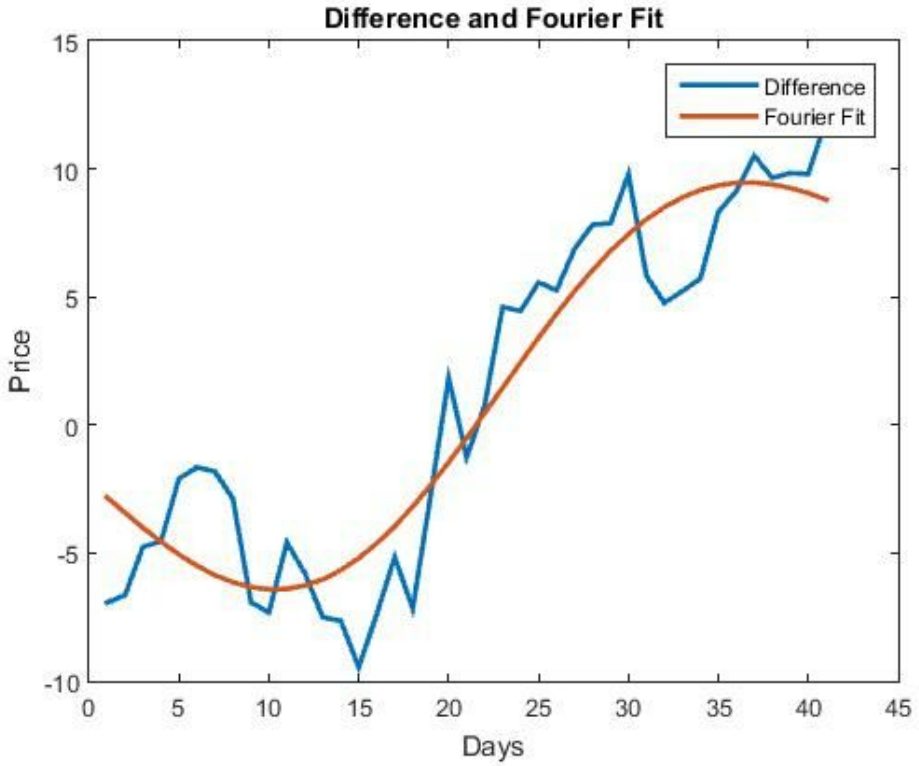
Correlation to NDXT: 0.7373

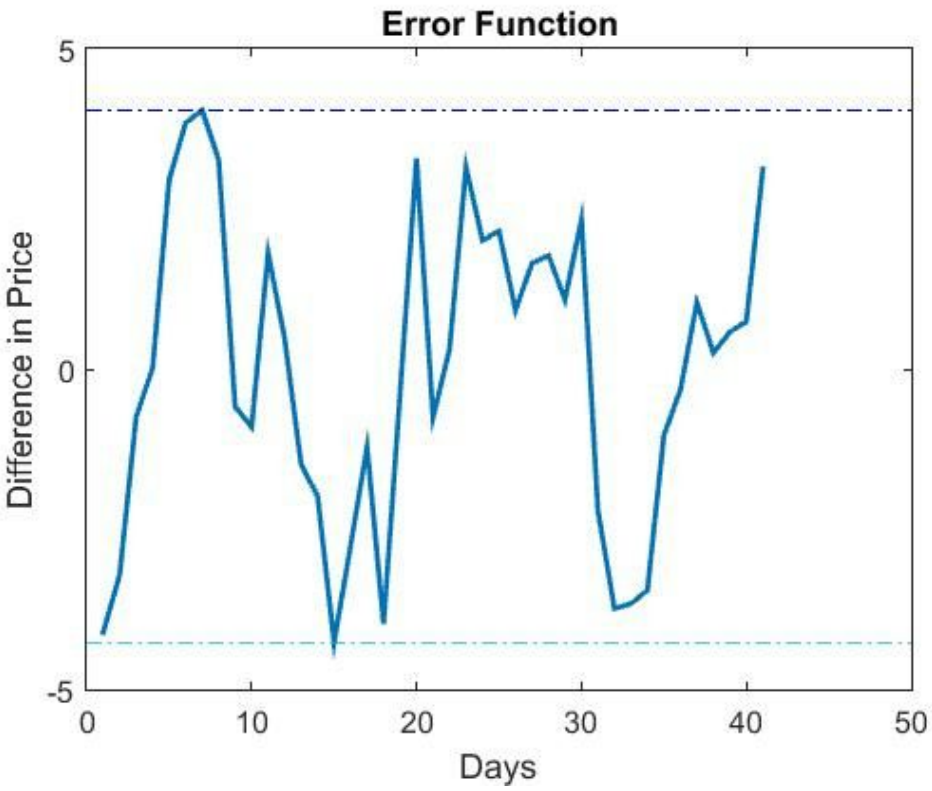


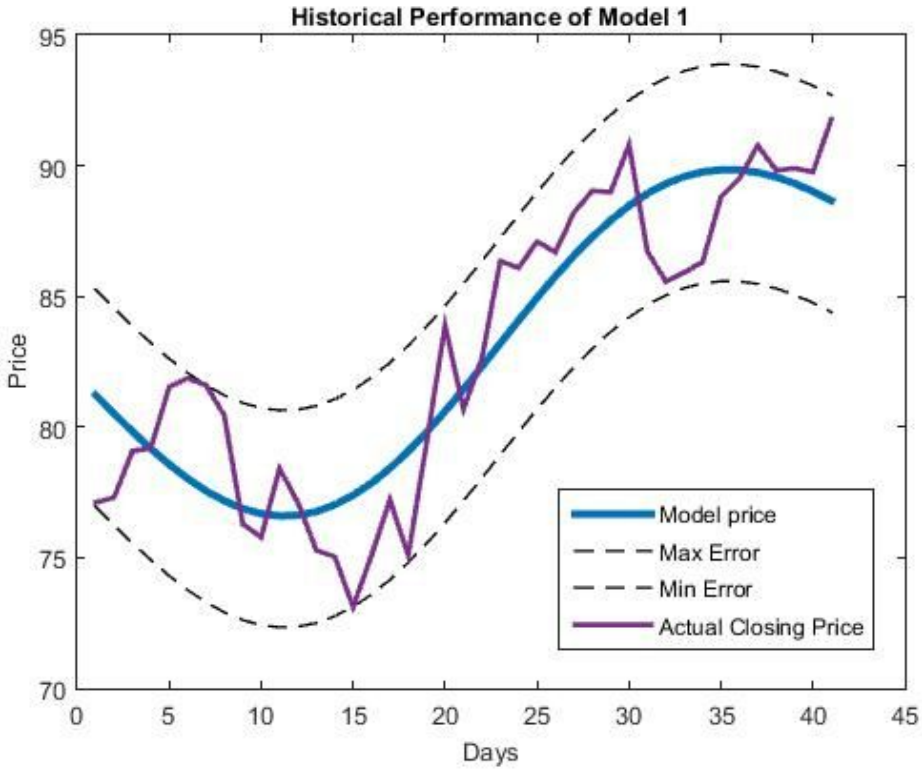

Autocorrelation Function
Autocorrelation
Lag (Days)
1
0.5
0
-0.5
0
20
40
60
80
100
120
140
160
180
200

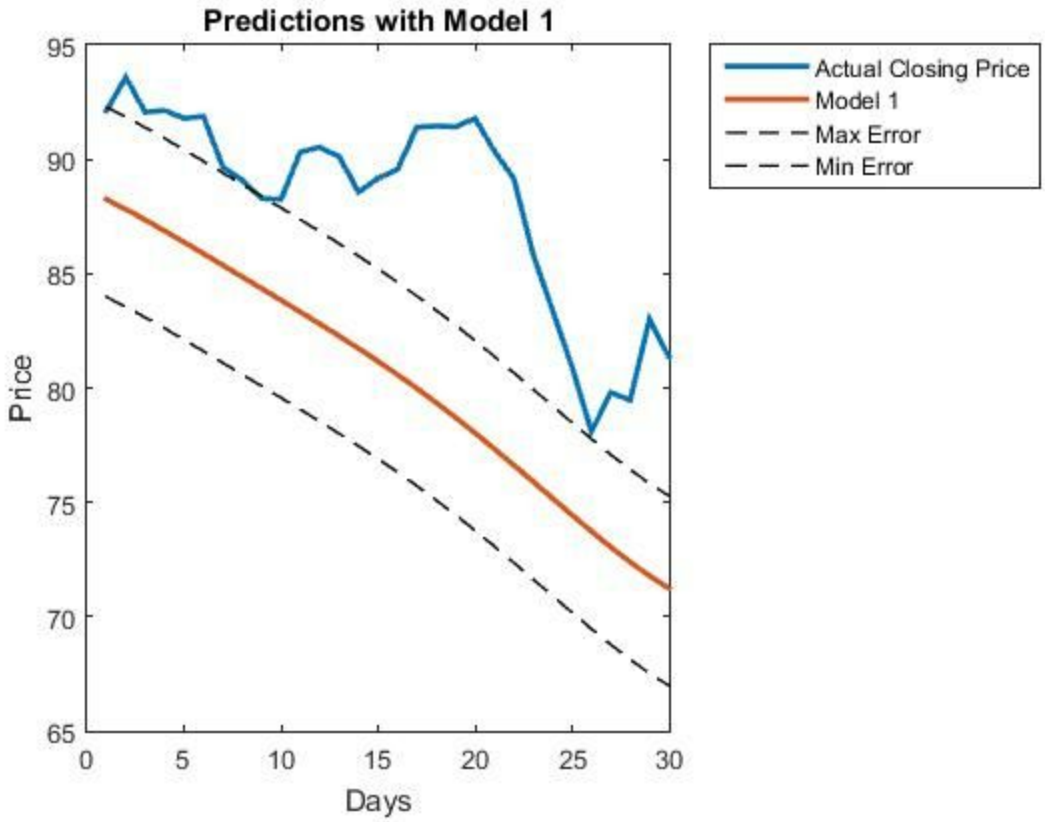

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
86
85
84
83
82
81
80
79
0
5
10
15
20
25
30
35
40
45


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
92
90
88
86
84
82
80
78
76
74
72
0
5
10
15
20
25
30
35
40
45


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
15
10
5
0
-5
-10
0
5
10
15
20
25
30
35
40
45

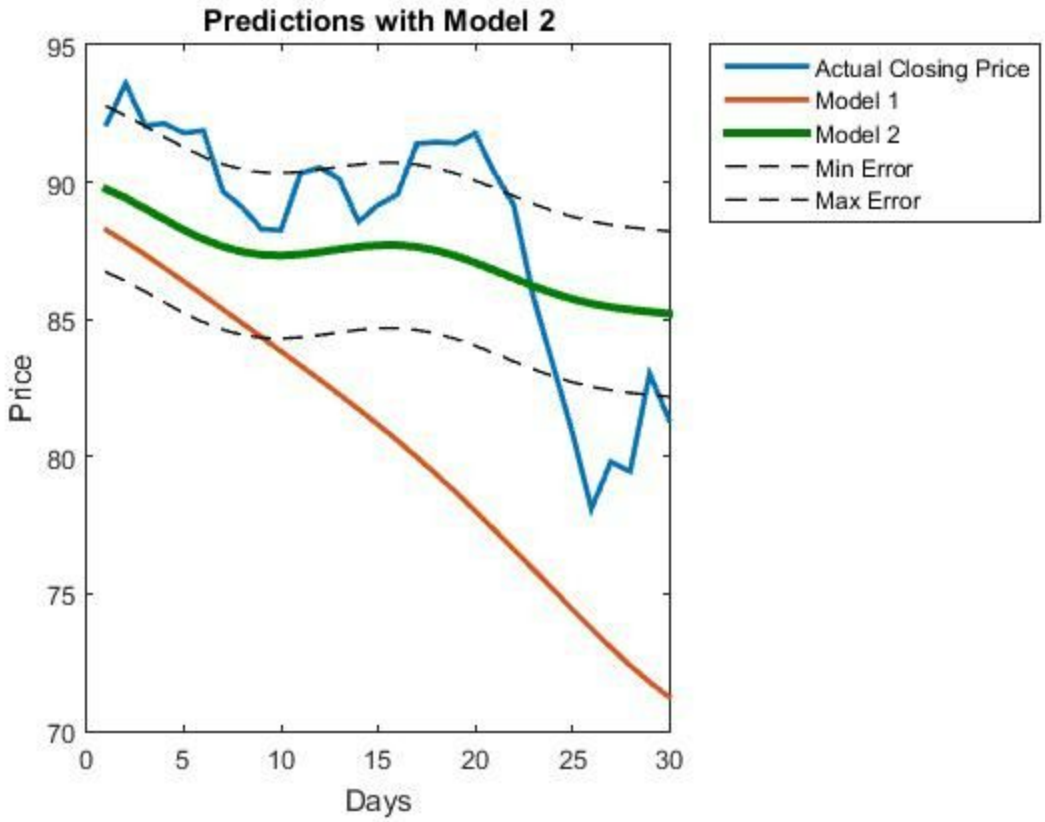

Error Function
Difference in Price
Days
5
0
-5
0
10
20
30
40
50


Historical Performance of Model 1
Price
Days
Model price
Max Error
Min Error
Actual Closing Price
95
90
85
80
75
70
0
5
10
15
20
25
30
35
40
45



Max Error: +4.5%

Min Error: -4.5%



Max Error: +4.4%

Min Error: -4.4%

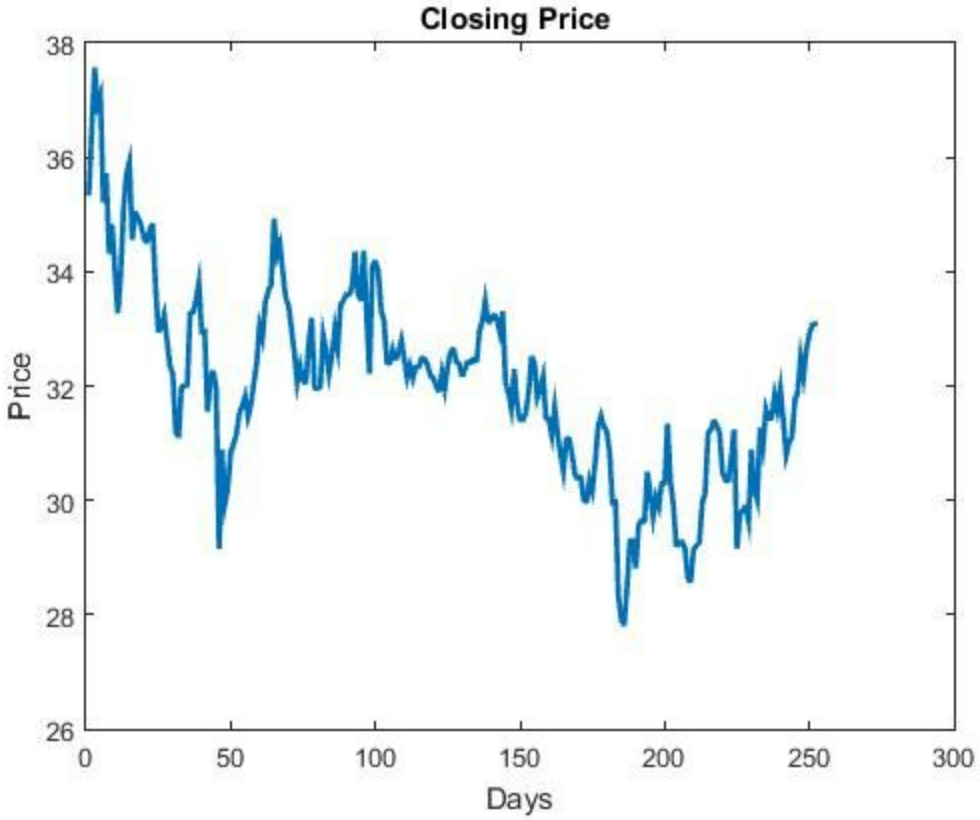
iRobot Corporation(IRBT)

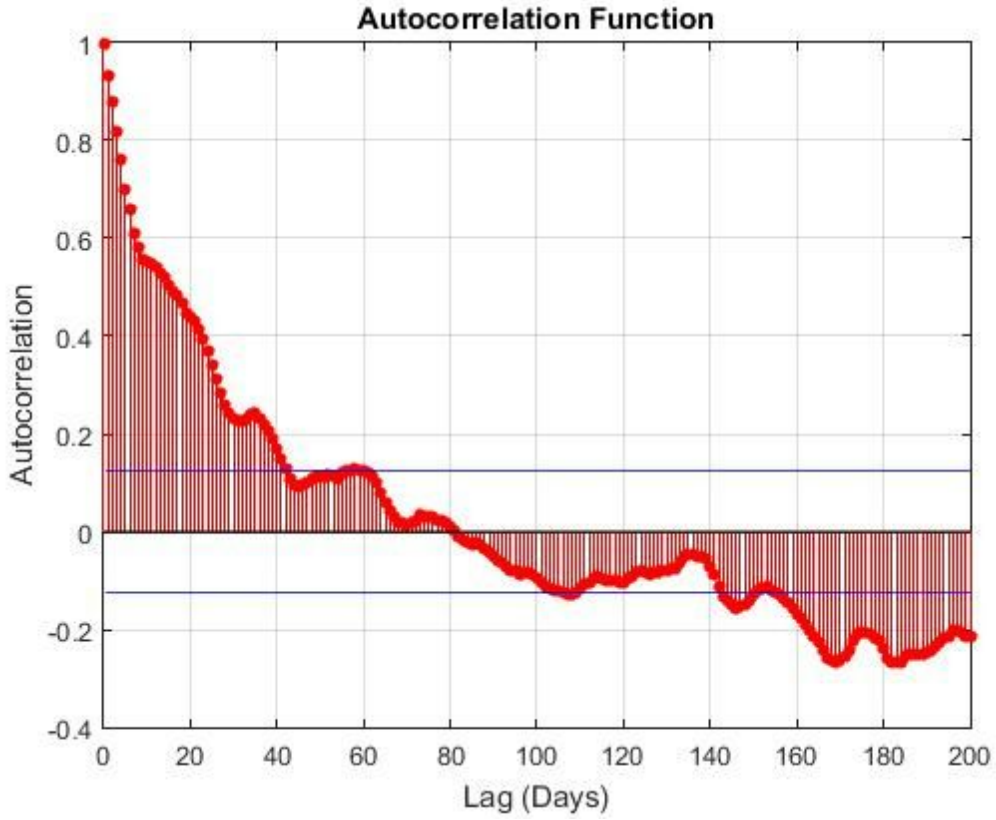
Prediction Range: 12/1/15 - 1/13/16 (30 Business Days)

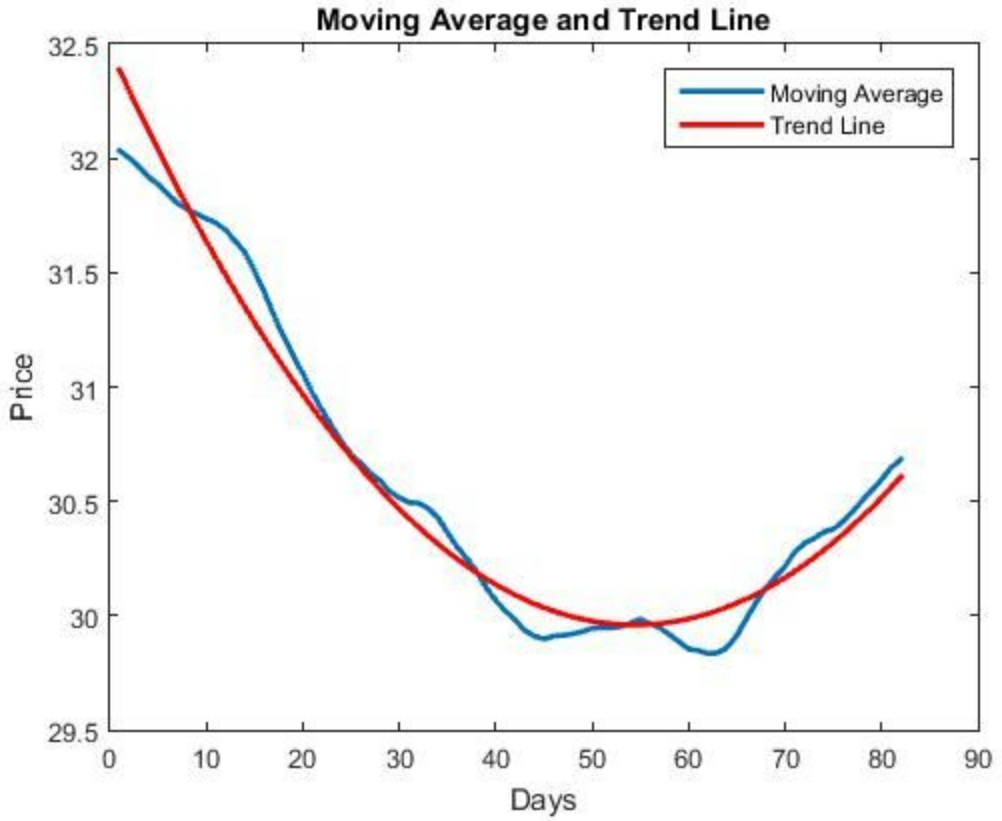
Autocorrelation Days: 82 Days

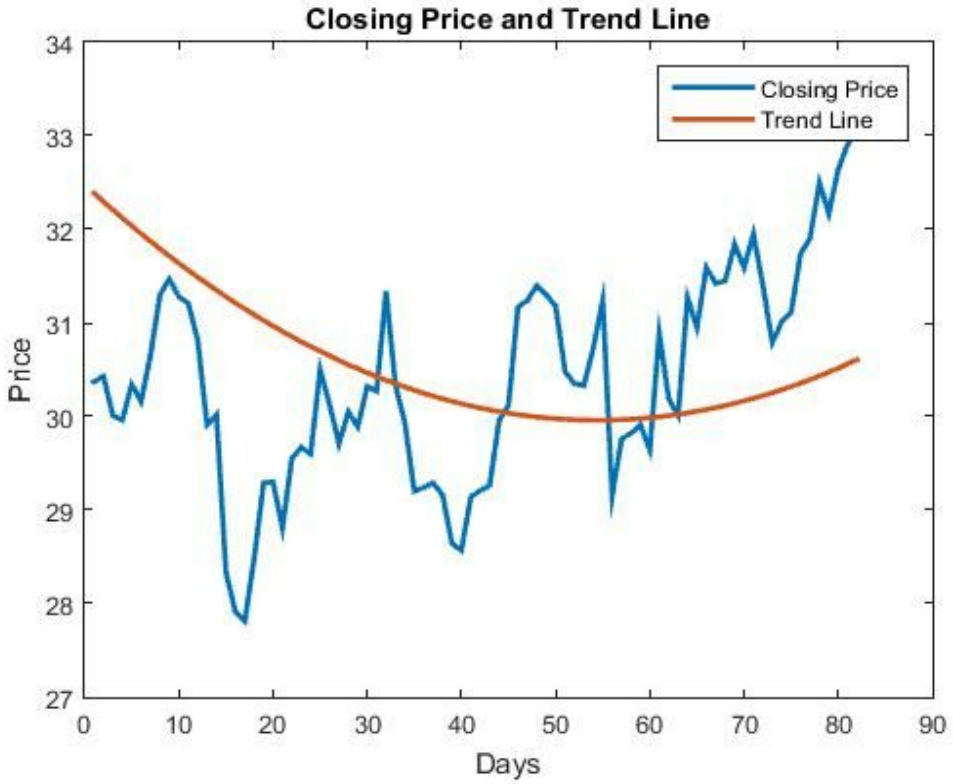
Moving Average Window: 50 Days

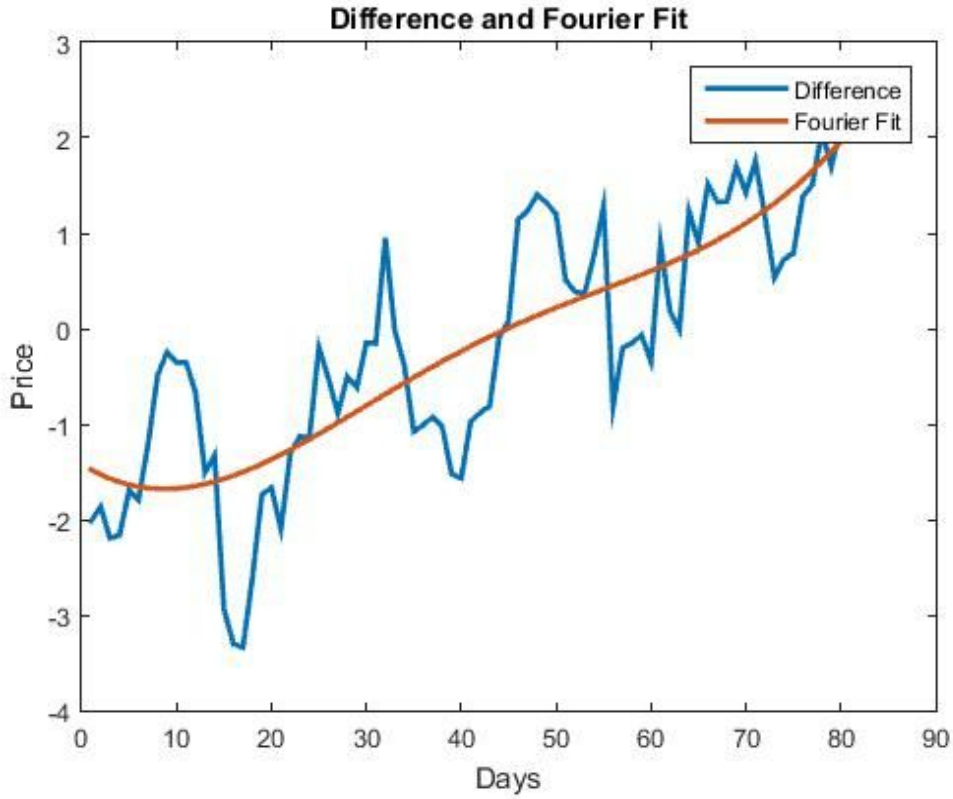
Correlation to NDXT: 0.7737

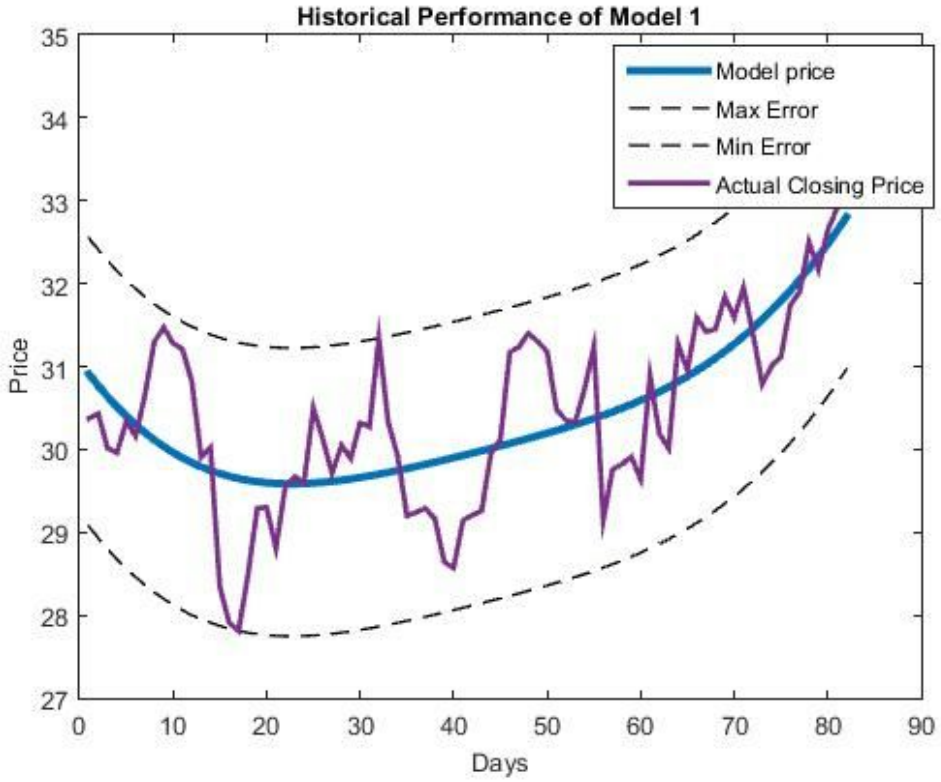


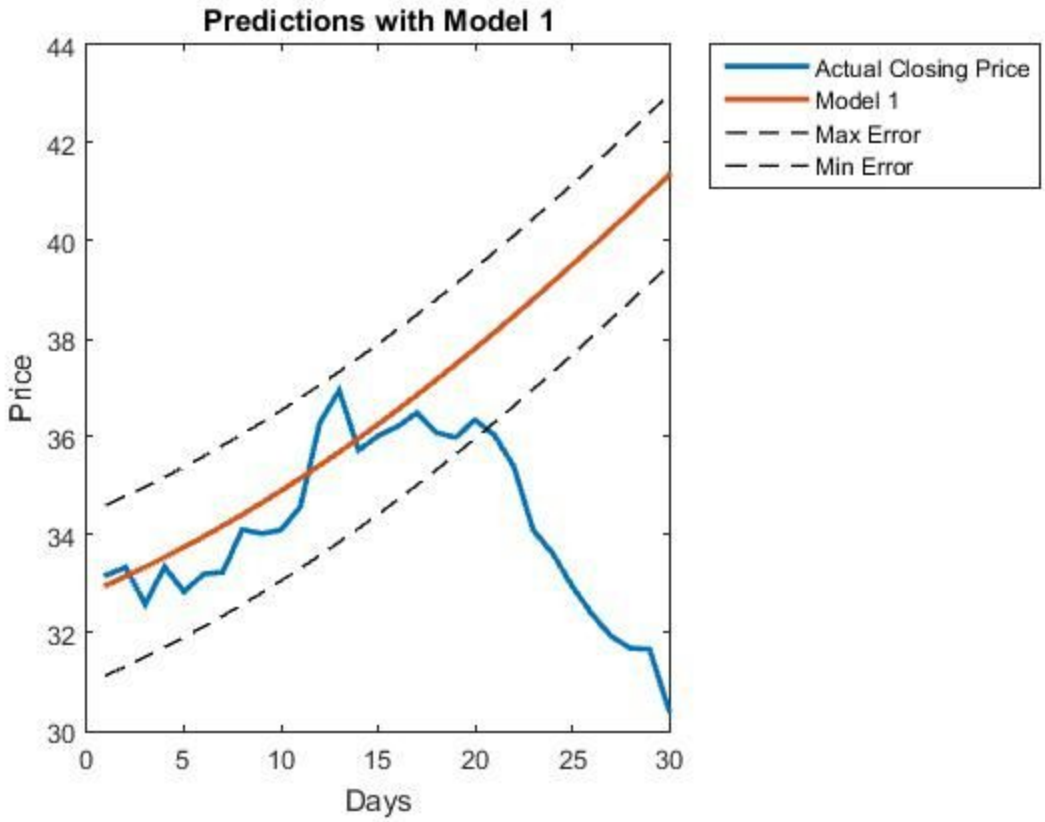

Autocorrelation Function
Autocorrelation
Lag (Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200


Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
32.5
32
31.5
31
30.5
30
29.5
0
10
20
30
40
50
60
70
80
90


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
34
33
32
31
30
29
28
27
0
10
20
30
40
50
60
70
80
90

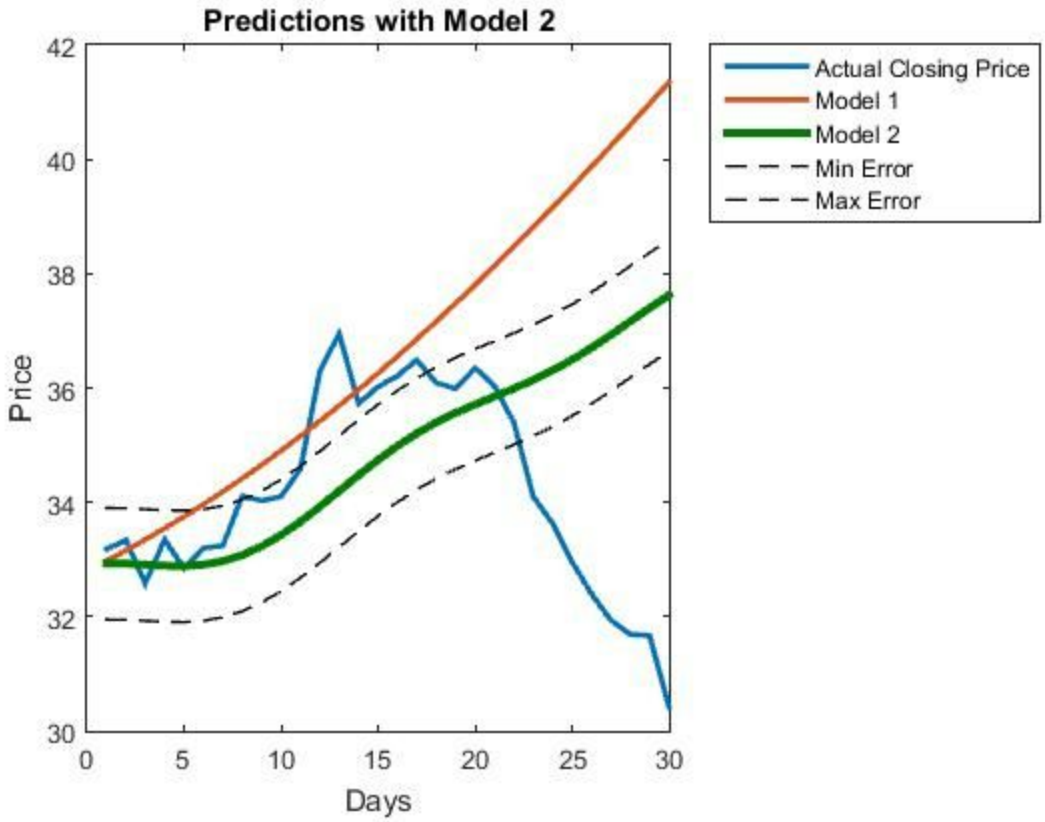

Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80
90


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Price
Days
35
34
33
32
31
30
29
28
27
0
10
20
30
40
50
60
70
80
90



Max Error: +4.8%

Min Error: -5.8%



Max Error: +4.8%

Min Error: -5.8%

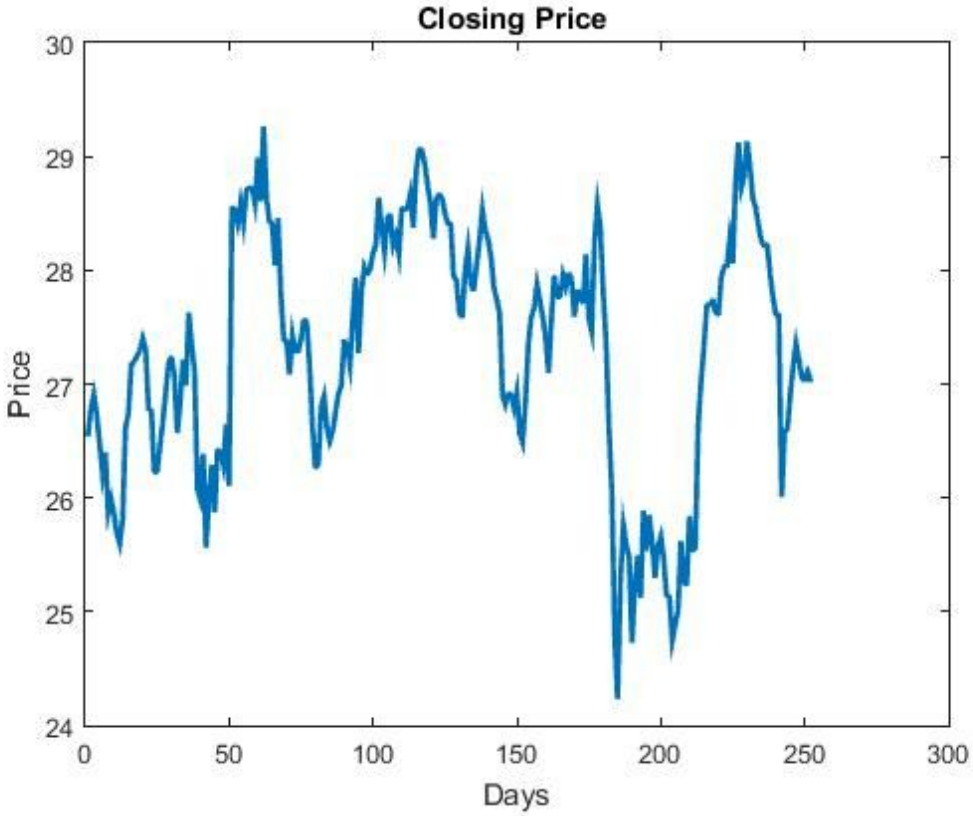
Cisco Systems(CSCO)

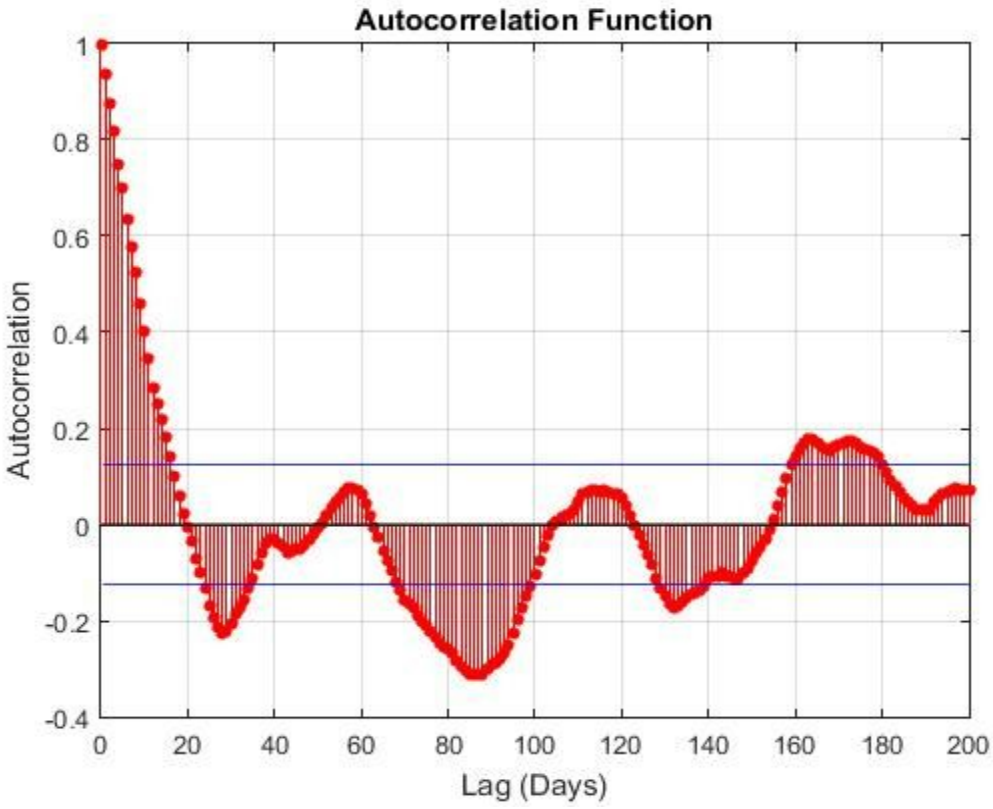
Prediction Range: 12/1/15 - 1/13/16 (30 Business Days)

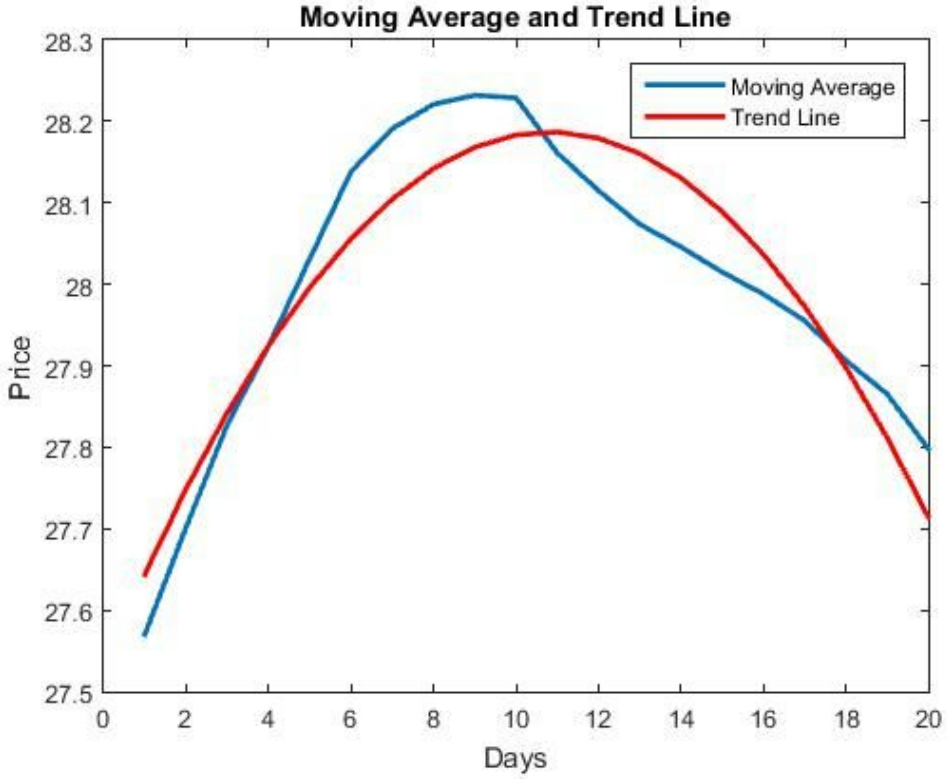
Autocorrelation Days: 20 Days

Moving Average Window: 25 Days

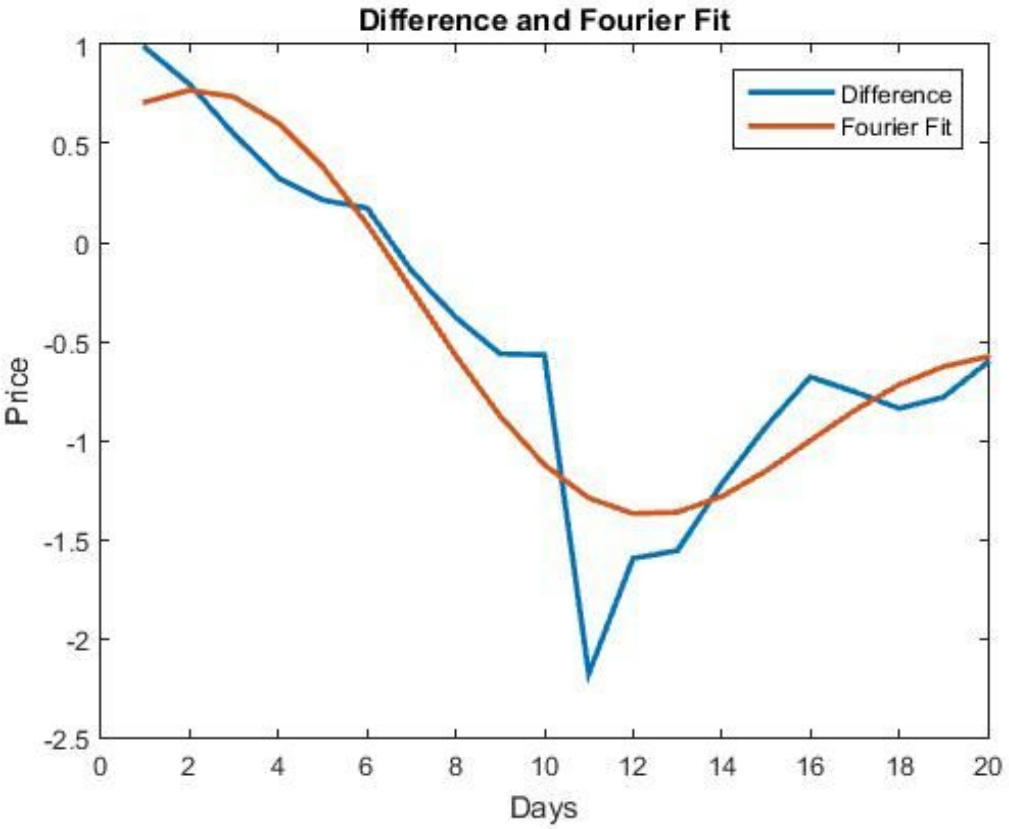
Correlation to NDXT: 0.784

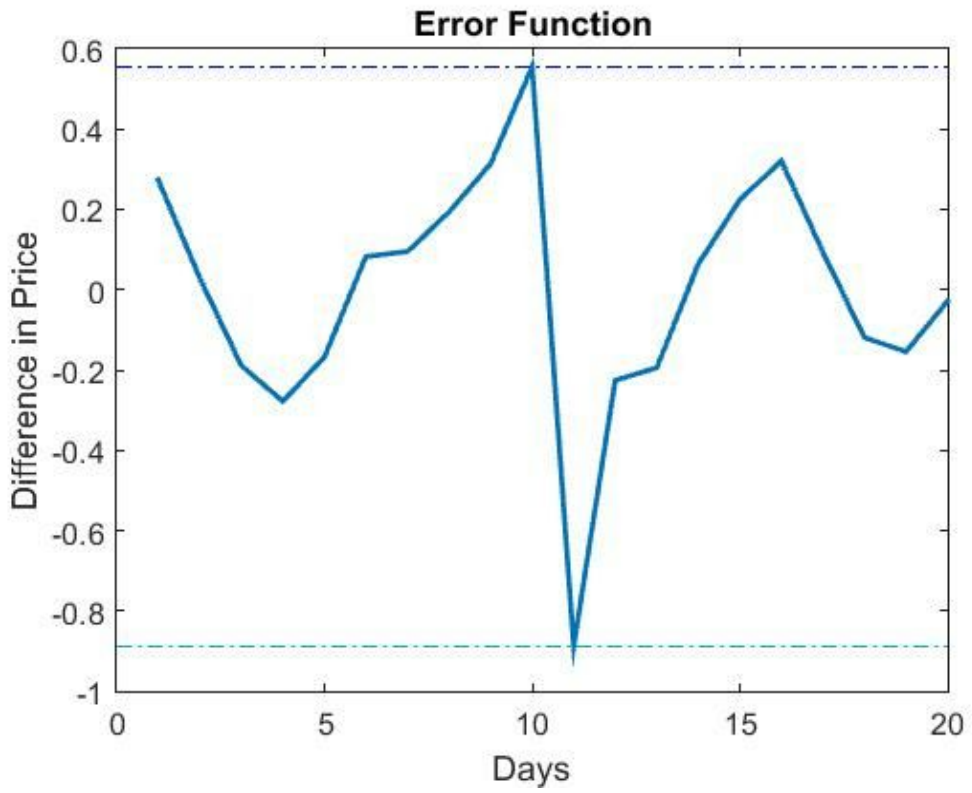


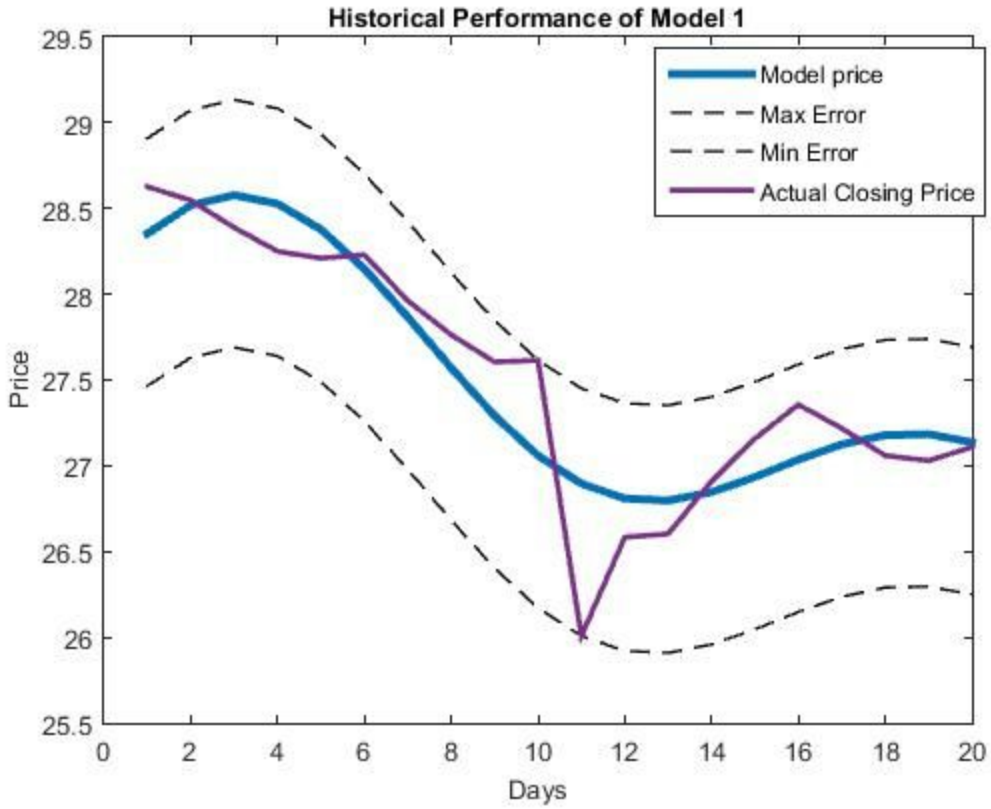

Autocorrelation Function
Autocorrelation
Lag (Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

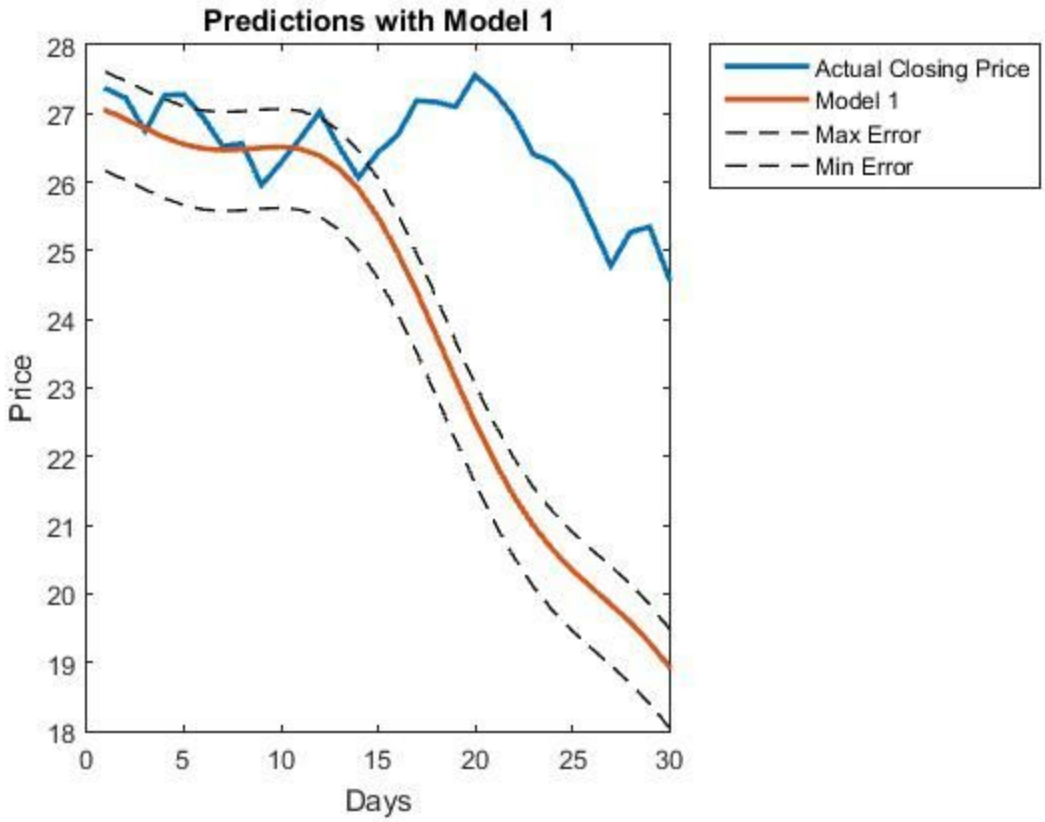

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
28.3
28.2
28.1
28
27.9
27.8
27.7
27.6
27.5
0
2
4
6
8
10
12
14
16
18
20


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
29
28.5
28
27.5
27
26.5
26
0
2
4
6
8
10
12
14
16
18
20


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
0
2
4
6
8
10
12
14
16
18
20

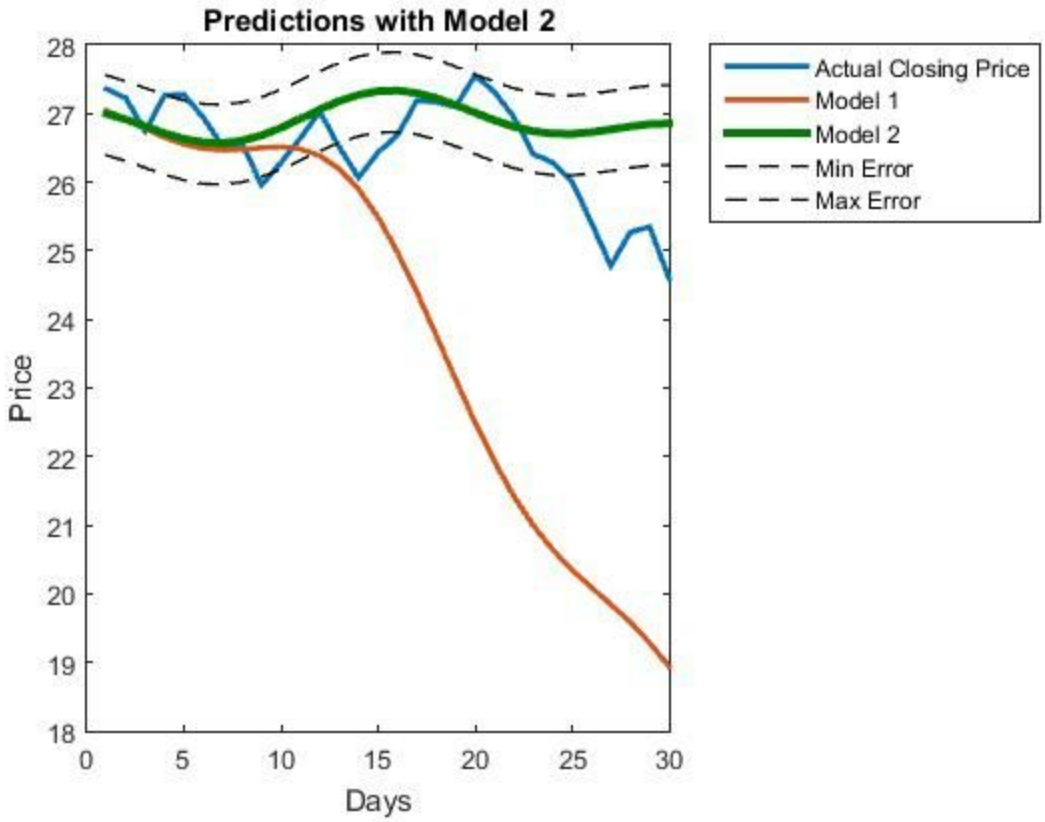

Error Function
Difference in Price
Days
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
0
5
10
15
20


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Price
Days
29.5
29
28.5
28
27.5
27
26.5
26
25.5
0
2
4
6
8
10
12
14
16
18
20



Max Error: +2.2%

Min Error: -3.3%



Max Error: +2.2%

Min Error: -3.3%

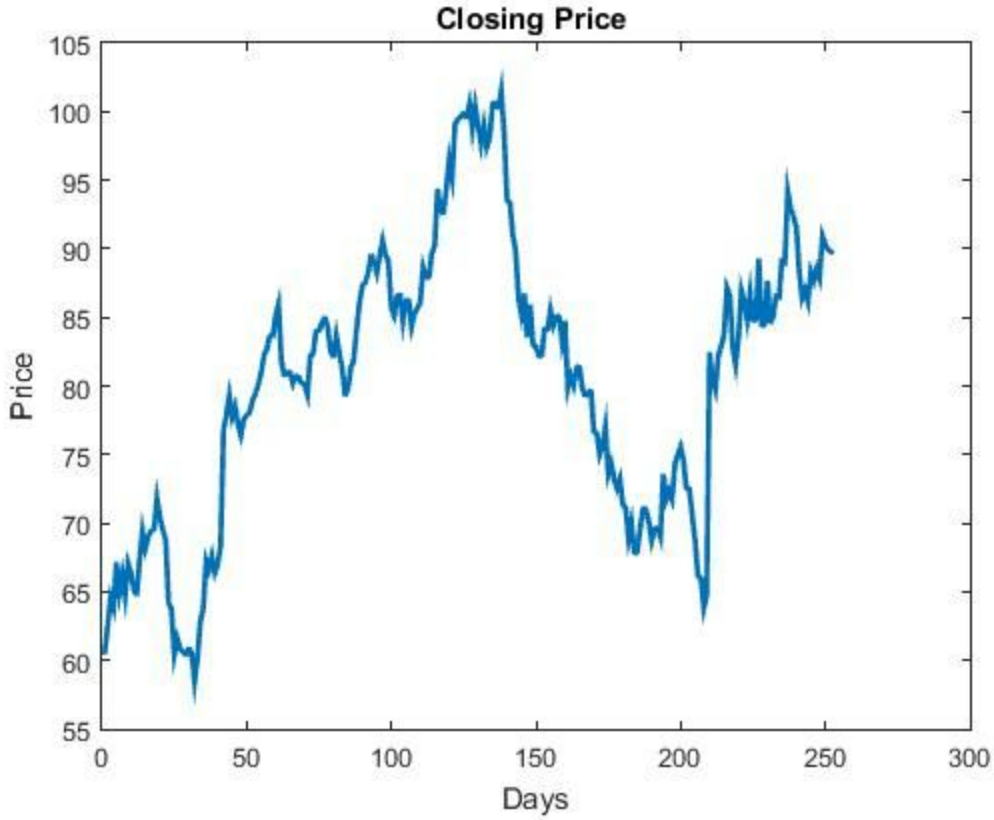
Synaptics (SYNA)

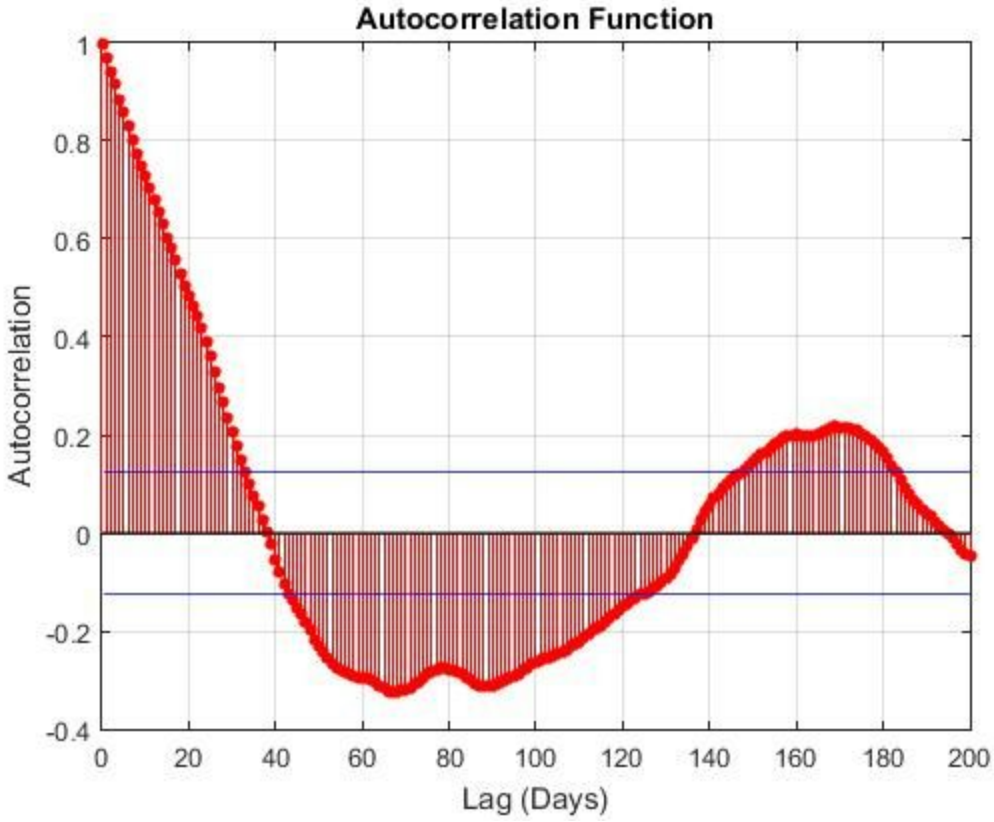
Prediction Range: 12/1/15 - 1/13/16 (30 Business Days)

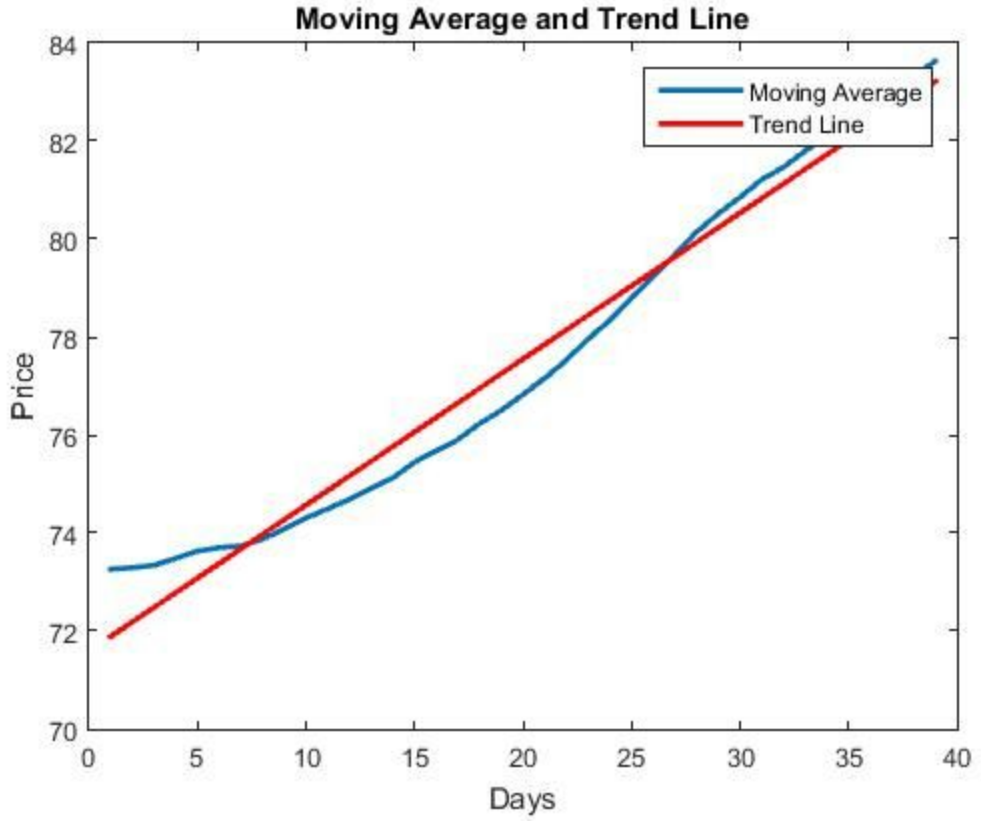
Autocorrelation Days: 39 Days

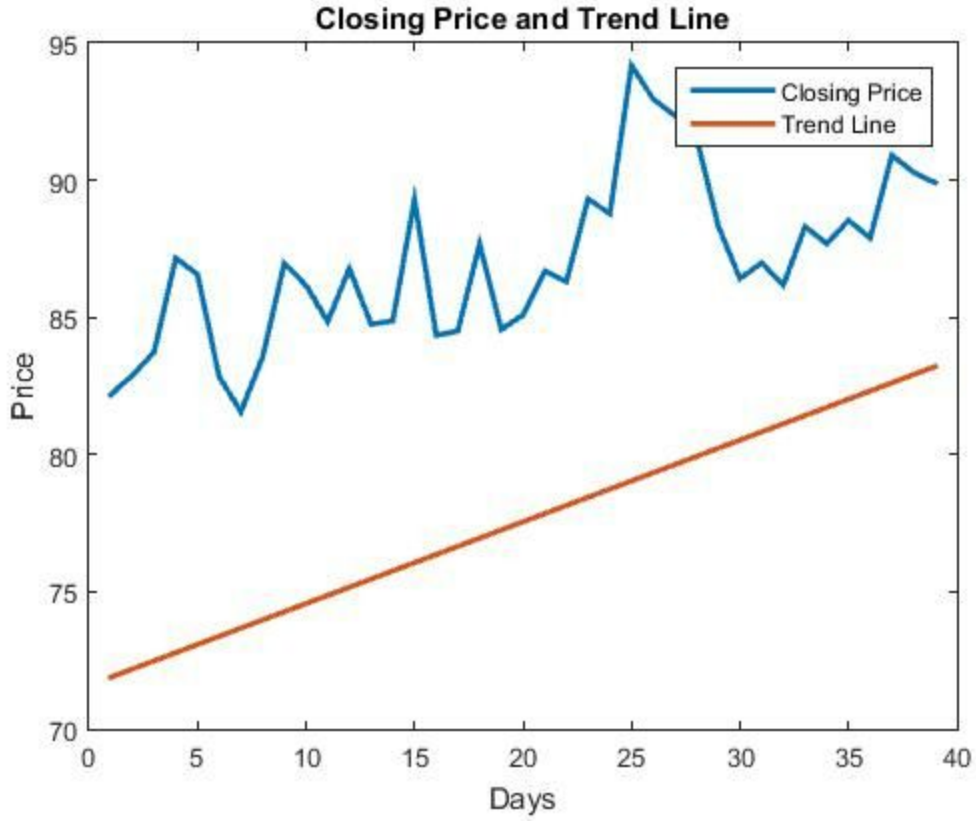
Moving Average Window: 50 Days

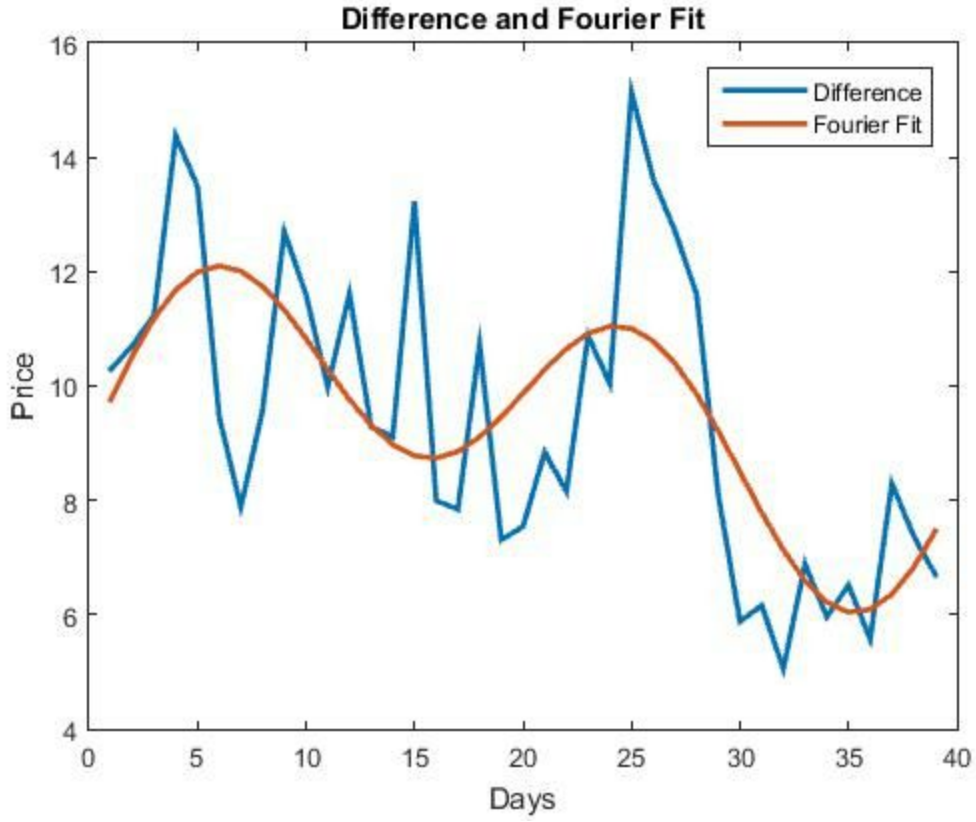
Correlation to NDXT: 0.8408

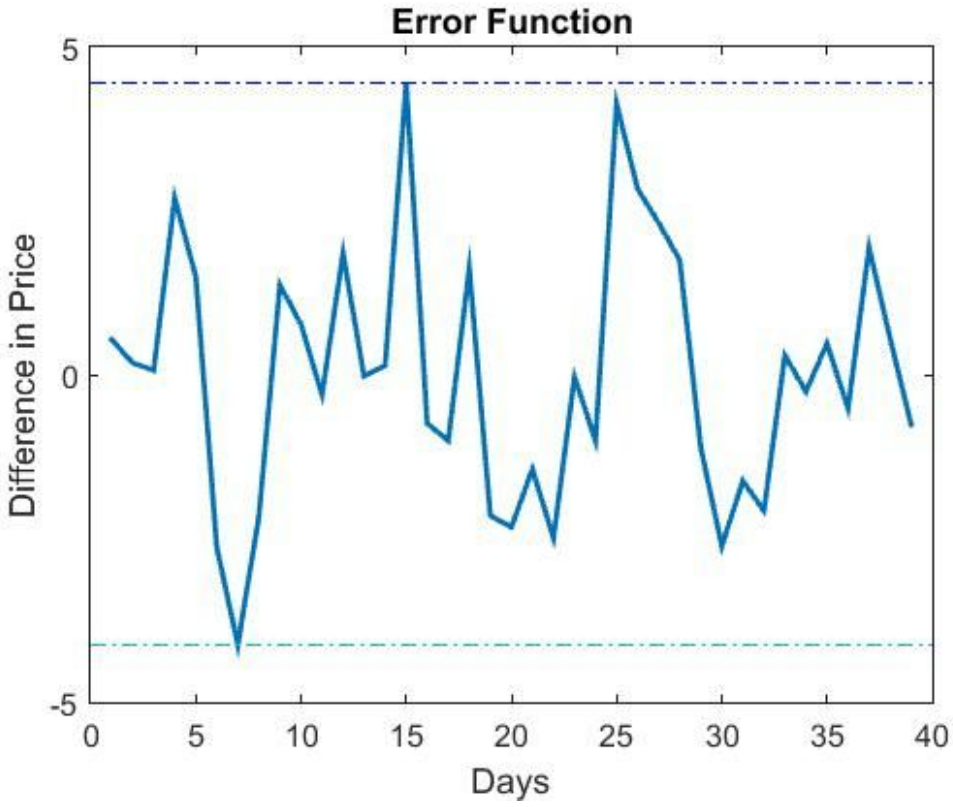


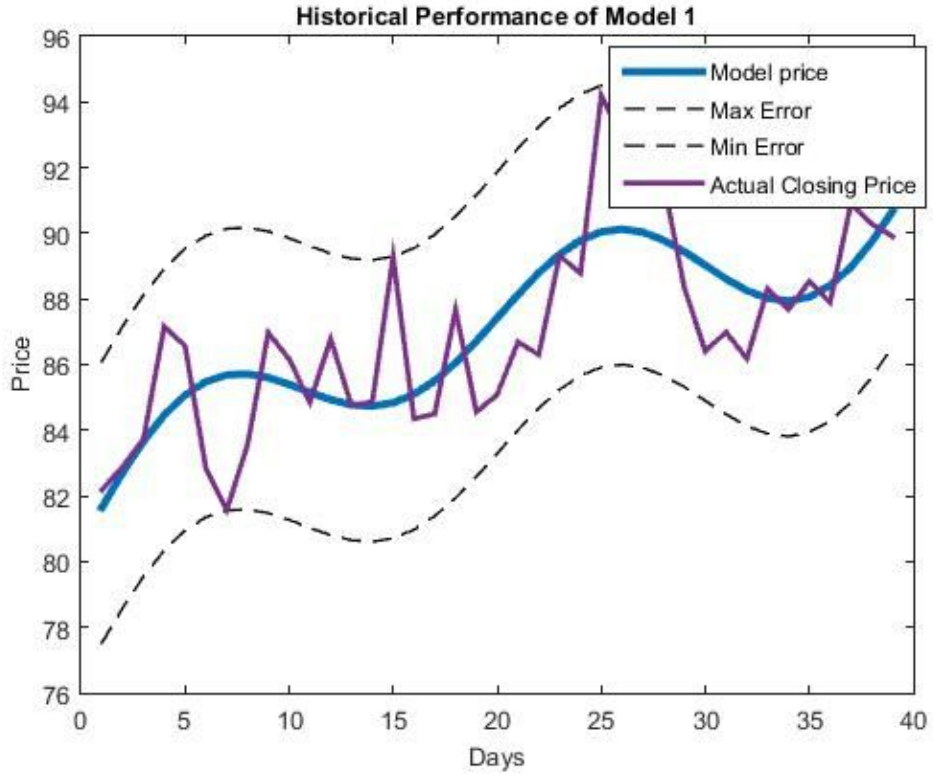

Autocorrelation Function
Autocorrelation
Lag (Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

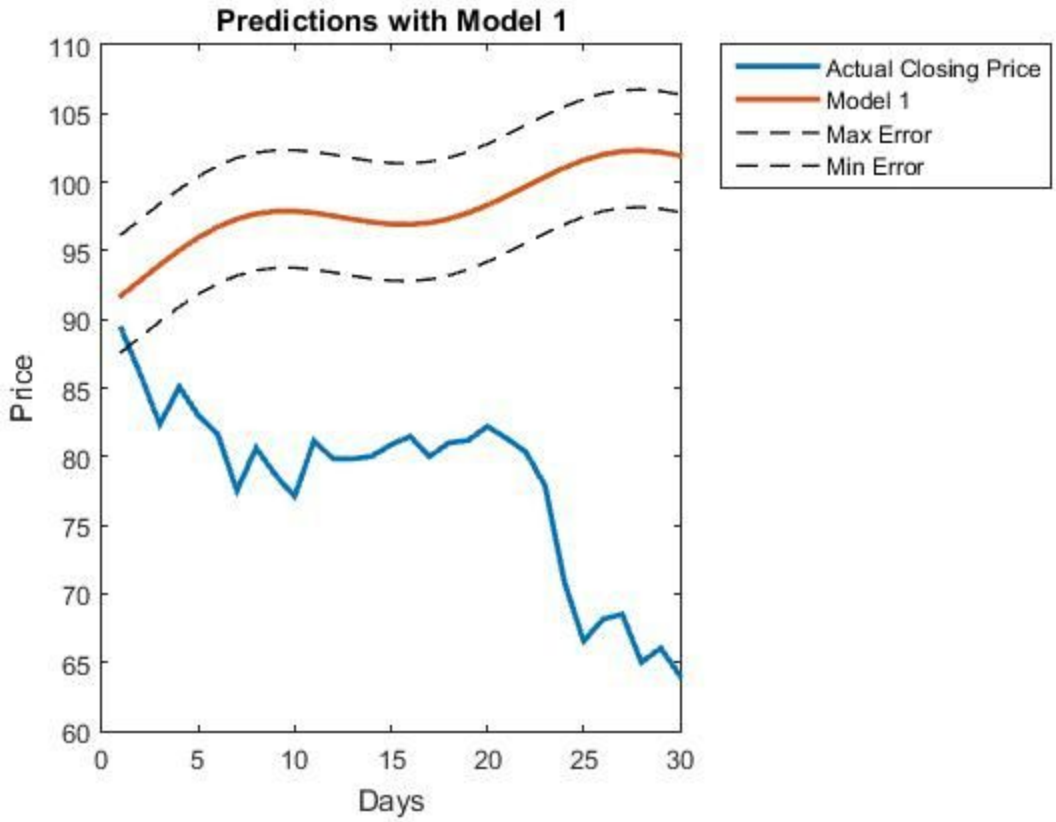

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
84
82
80
78
76
74
72
70
0
5
10
15
20
25
30
35
40


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
95
90
85
80
75
70
0
5
10
15
20
25
30
35
40


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
16
14
12
10
8
6
4
0
5
10
15
20
25
30
35
40

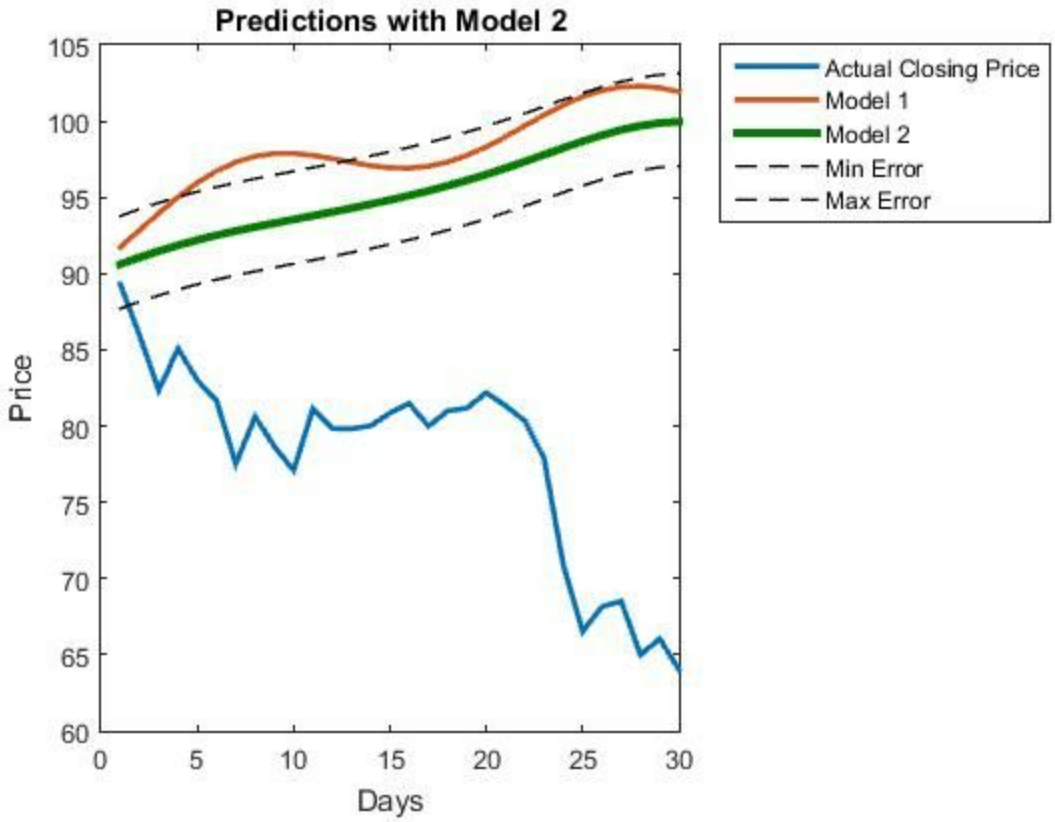

Error Function
Difference in Price
Days
5
0
-5
0
5
10
15
20
25
30
35
40


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Price
Days
96
94
92
90
88
86
84
82
80
78
76
0
5
10
15
20
25
30
35
40



Max Error: +4.3%

Min Error: -4.0%



Max Error: +4.3%

Min Error: -4.0%

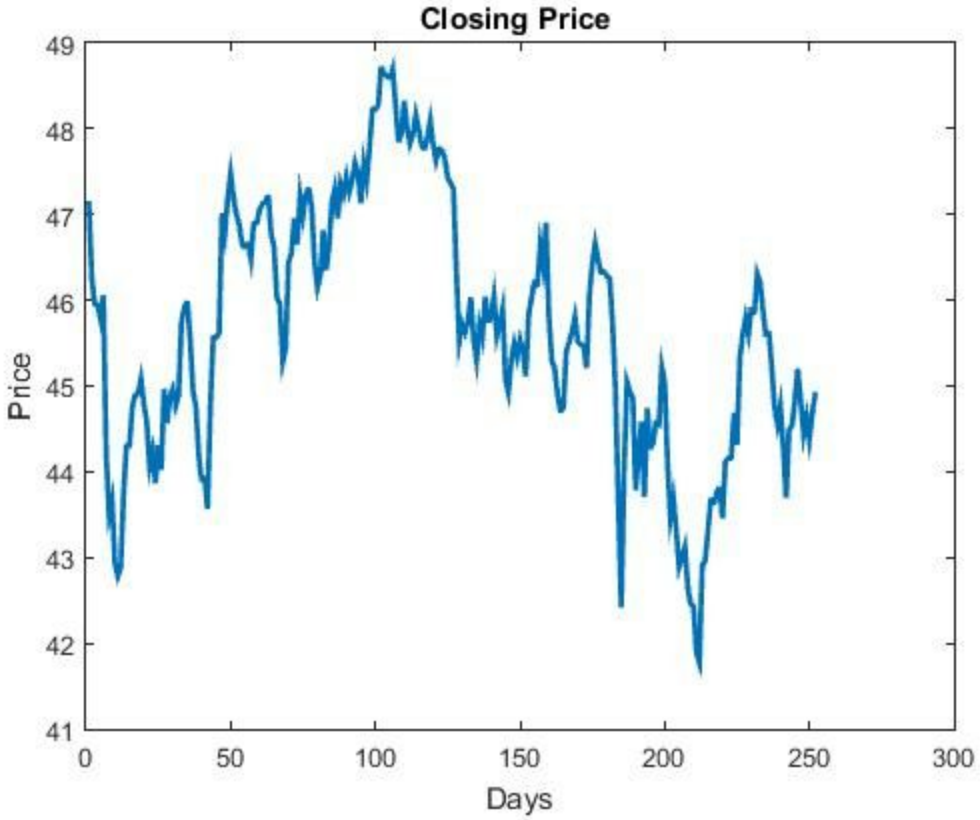
Verizon Communications (VZ)

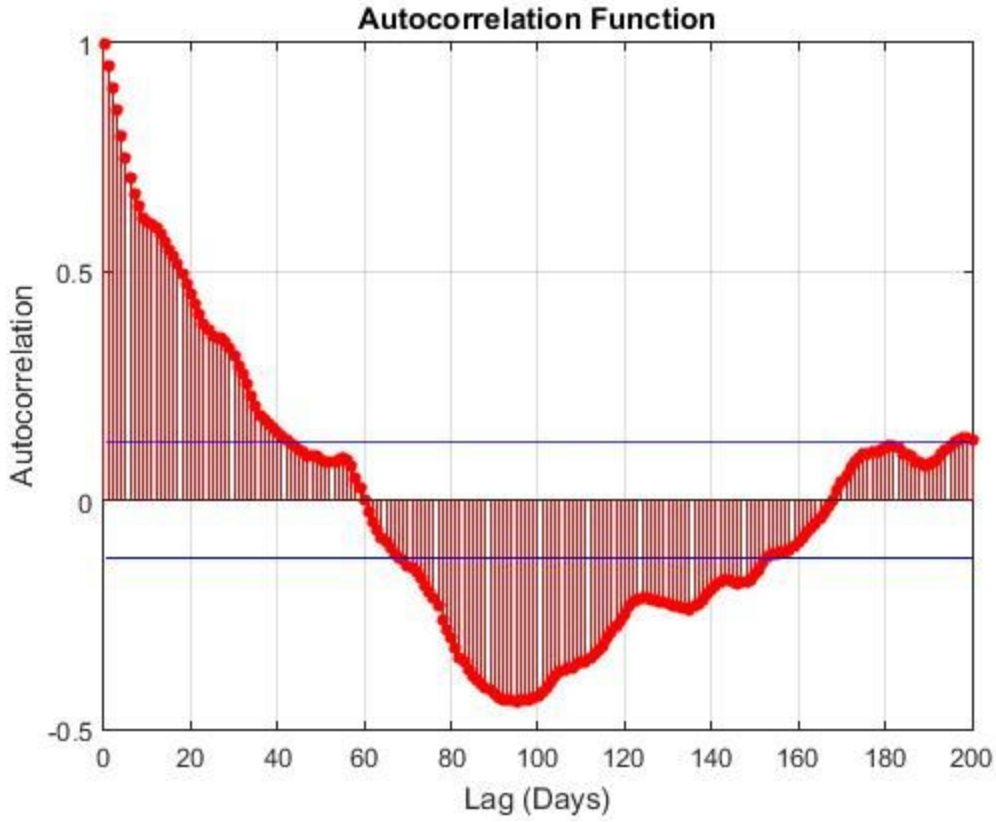
Prediction Range: 12/1/15 - 1/13/16 (30 Business Days)

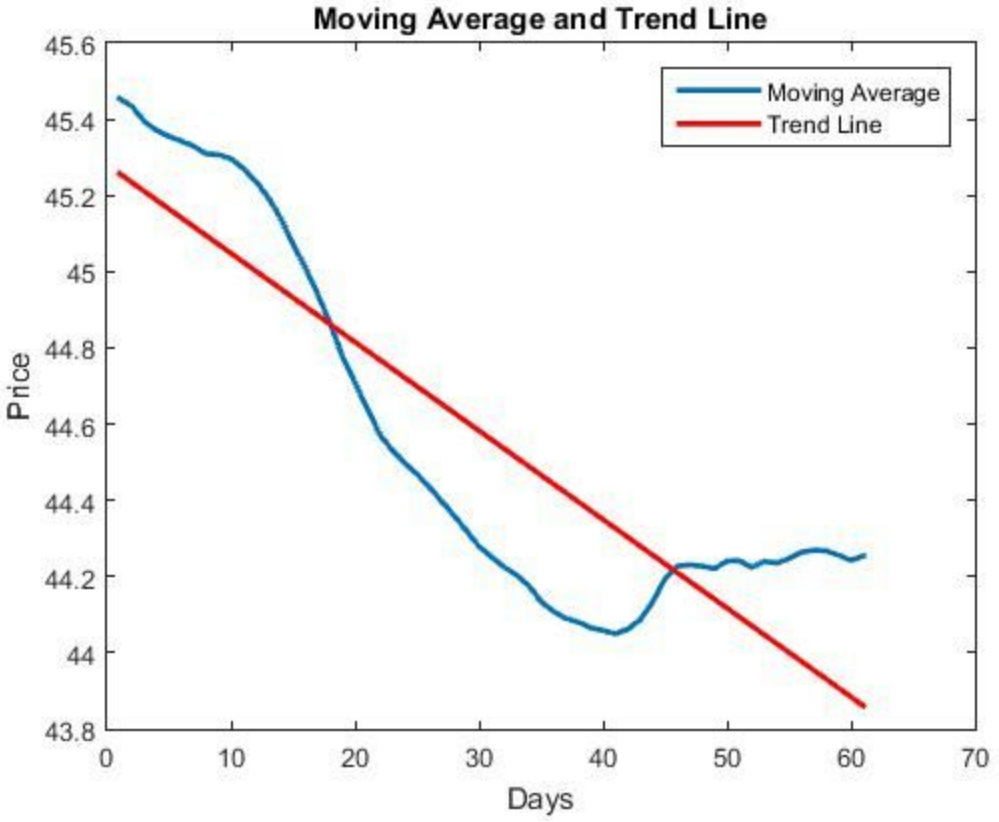
Autocorrelation Days: 61 Days

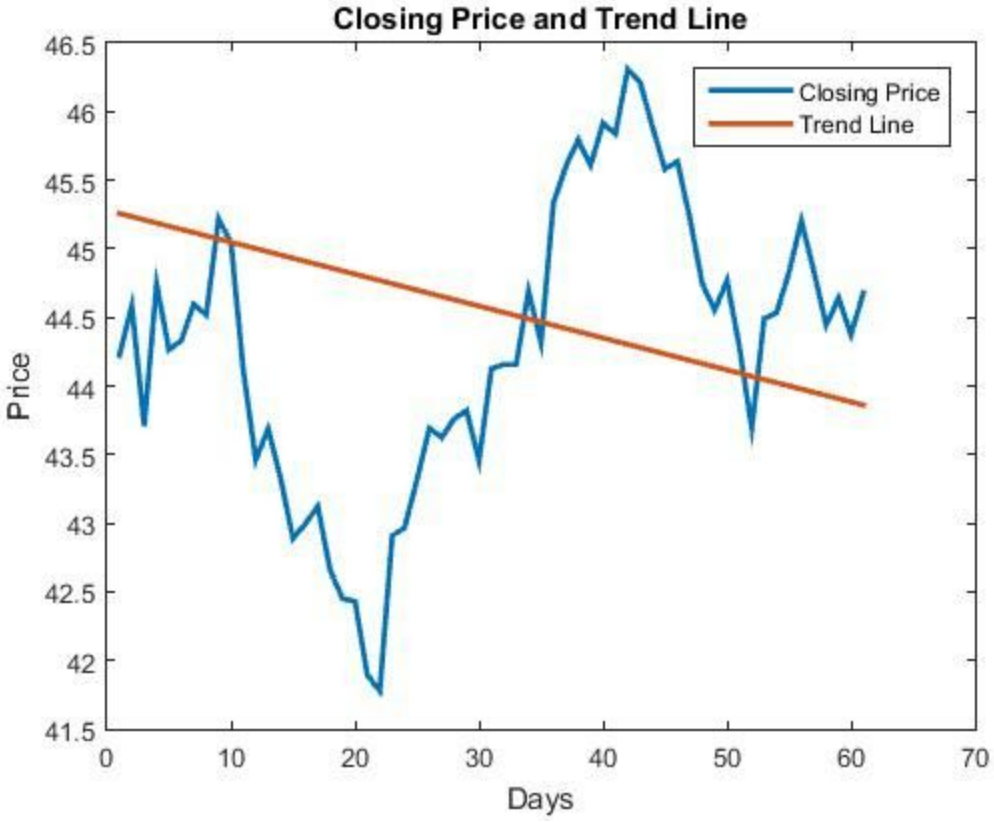
Moving Average Window: 50 Days

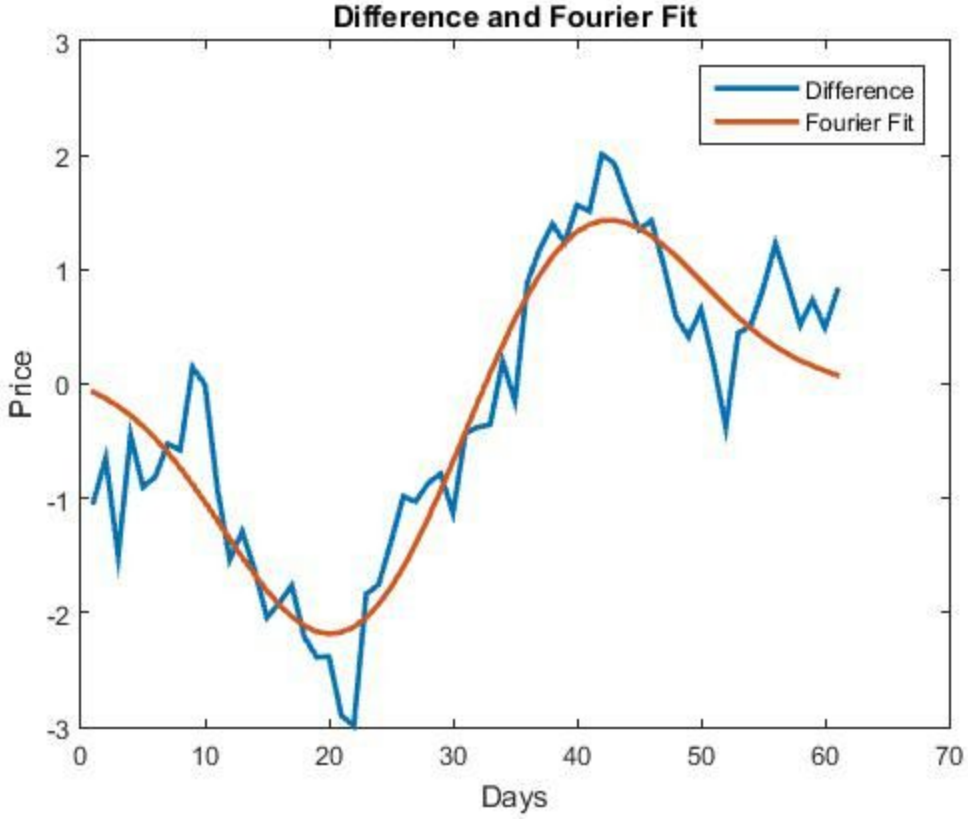
Correlation to NDXT: 0.8351

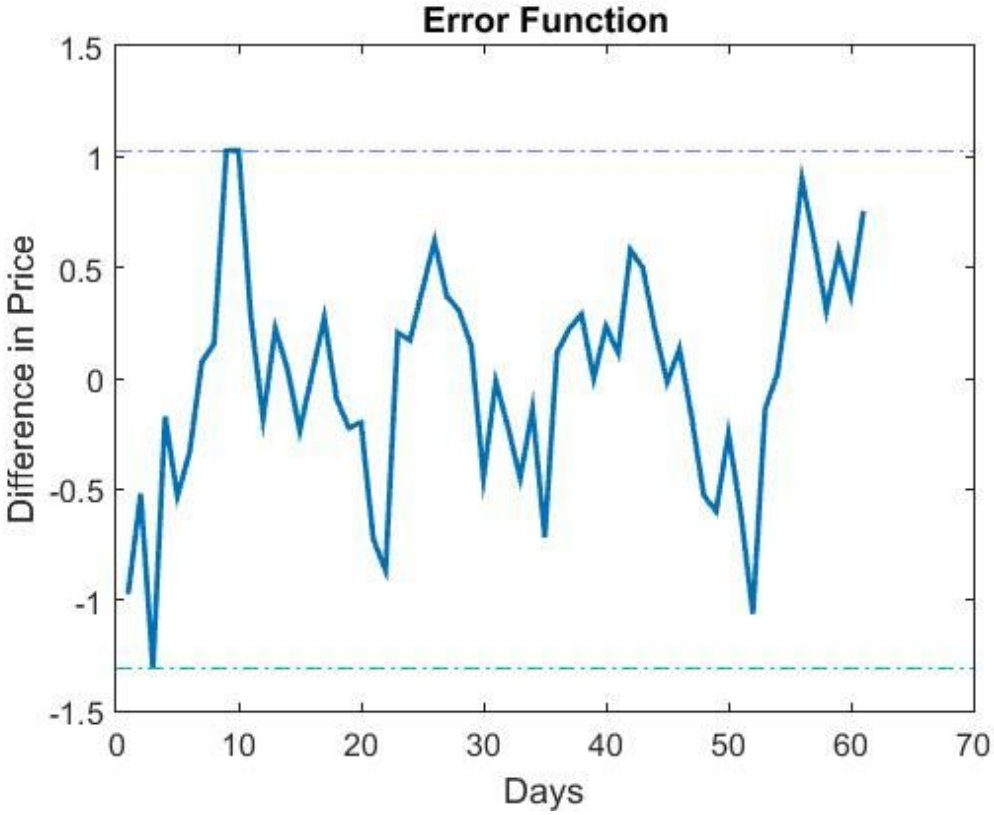


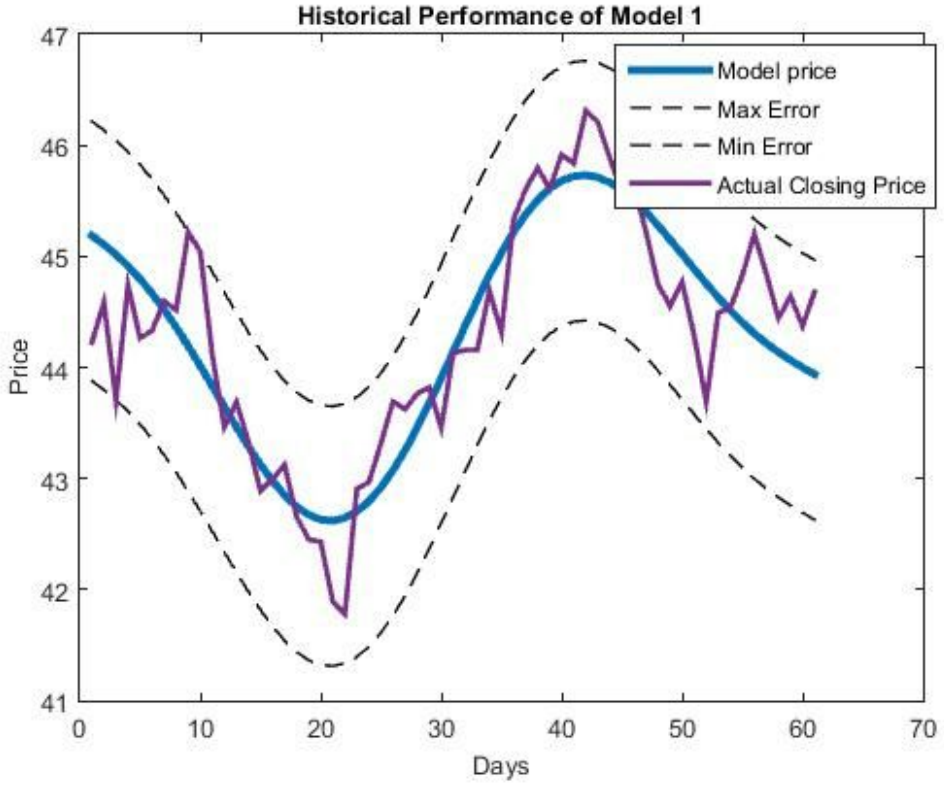

Autocorrelation Function
Autocorrelation
Lag (Days)
1
0.5
0
-0.5
0
20
40
60
80
100
120
140
160
180
200


Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
45.6
45.4
45.2
45
44.8
44.6
44.4
44.2
44
43.8
0
10
20
30
40
50
60
70

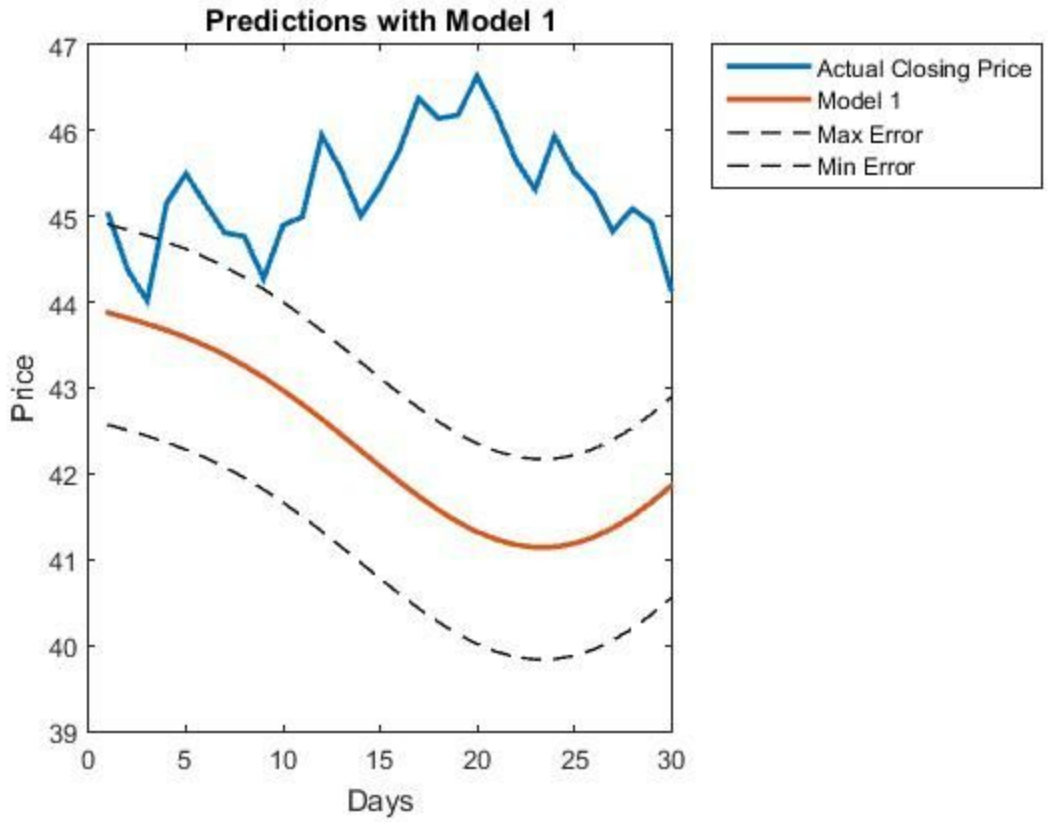

Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
46.5
46
45.5
45
44.5
44
43.5
43
42.5
42
41.5
0
10
20
30
40
50
60
70


Difference and Fourier Fit
Difference
Fourier Fit
Price
Days
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70


Error Function
Difference in Price
Days
1.5
1
0.5
0
-0.5
-1
-1.5
0
10
20
30
40
50
60
70

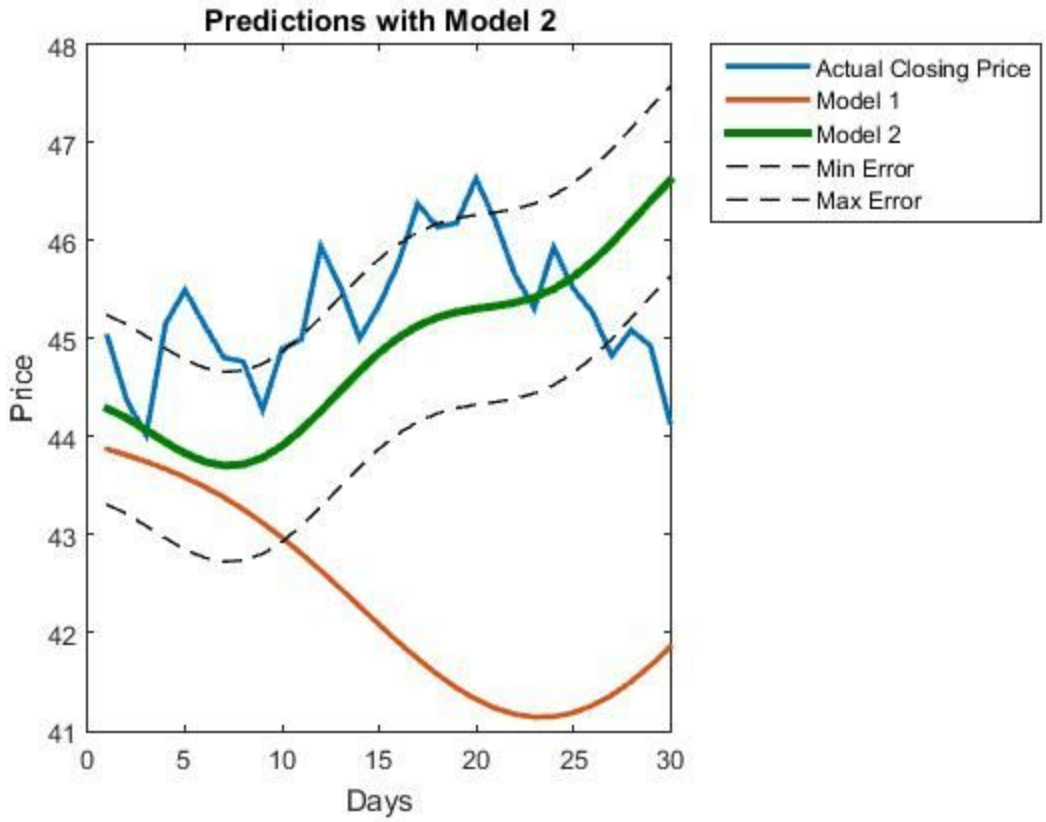

Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Price
Days
47
46
45
44
43
42
41
0
10
20
30
40
50
60
70

-



Max Error: +2.3%

Min Error: -3.2%



Max Error: +2.3%

Min Error: -3.2%

- Information Technology and Electric Cars Sector

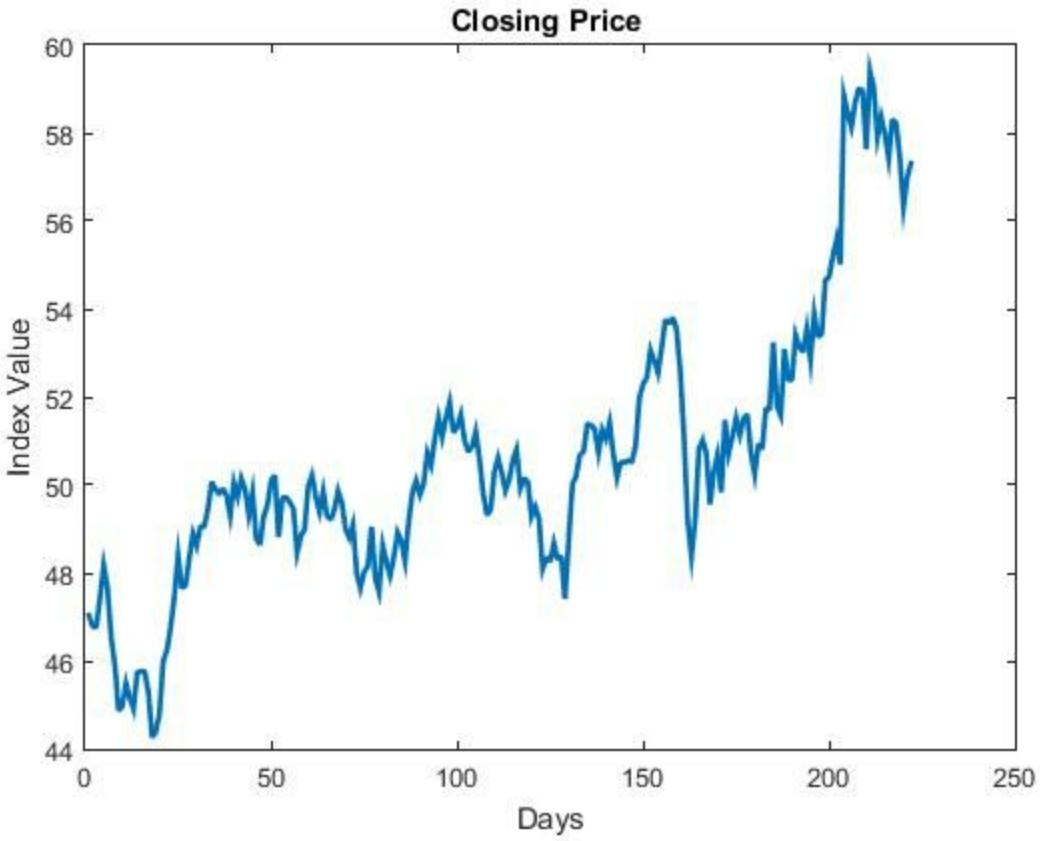
Index: Nasdaq is the index for the technology sector, so it is chosen when building the model 2. However, some of the stocks do not have a strong correlation with the index, so their performances in Model 1 are better than in Model 2 in my situation.

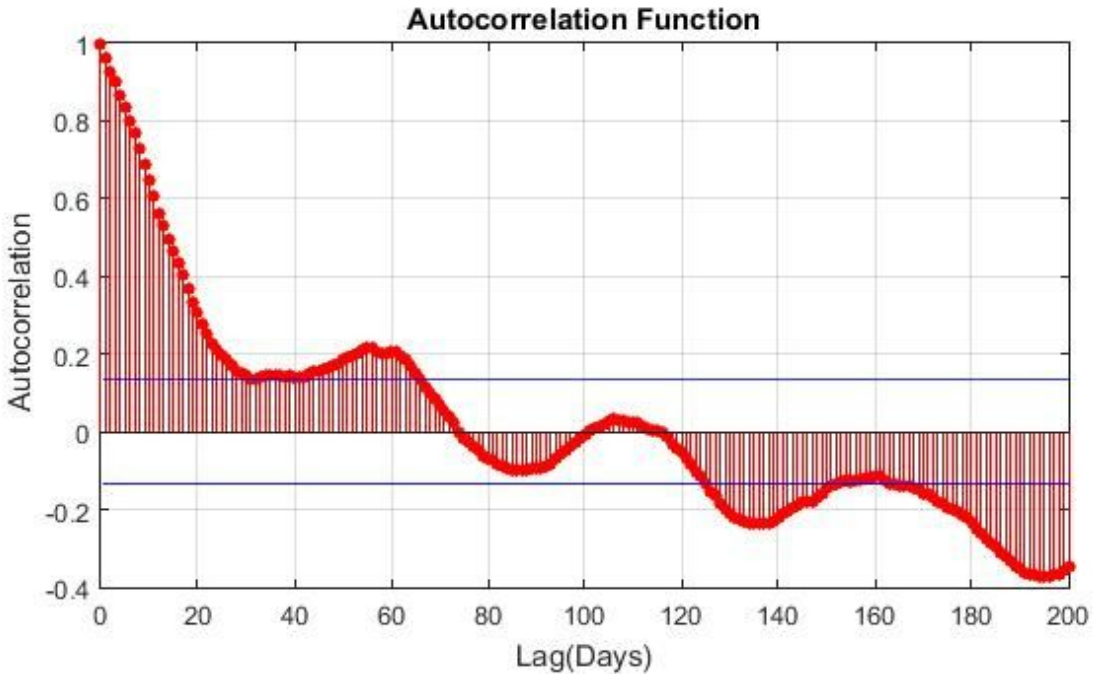
Nasdaq Composite (IXIC)

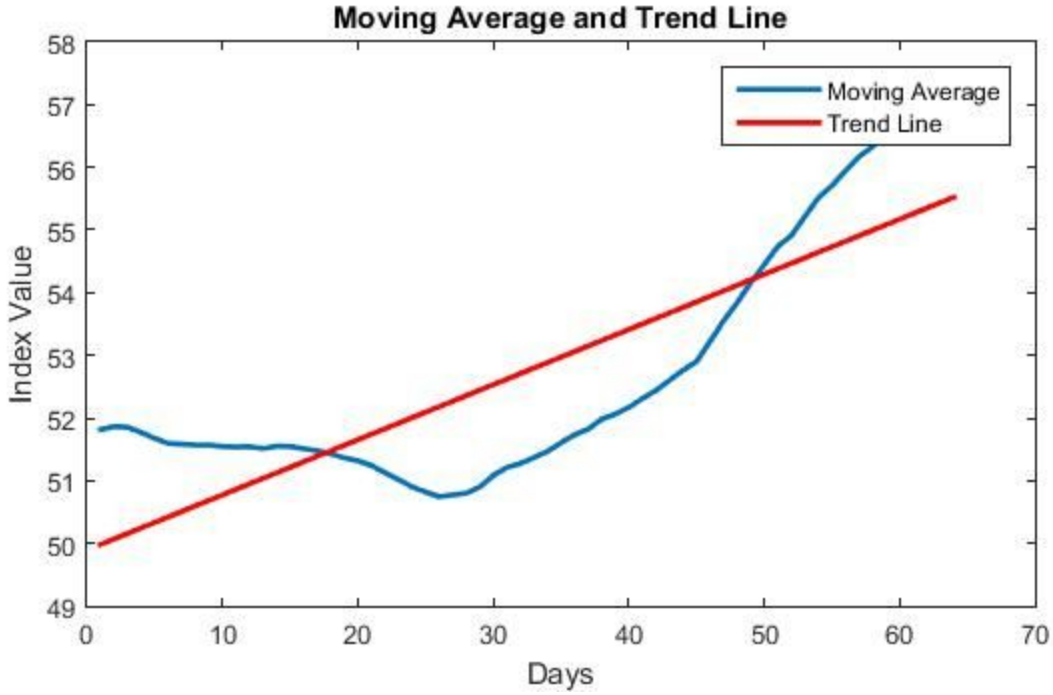
Prediction Range: 12/1/15 - 12/31/15

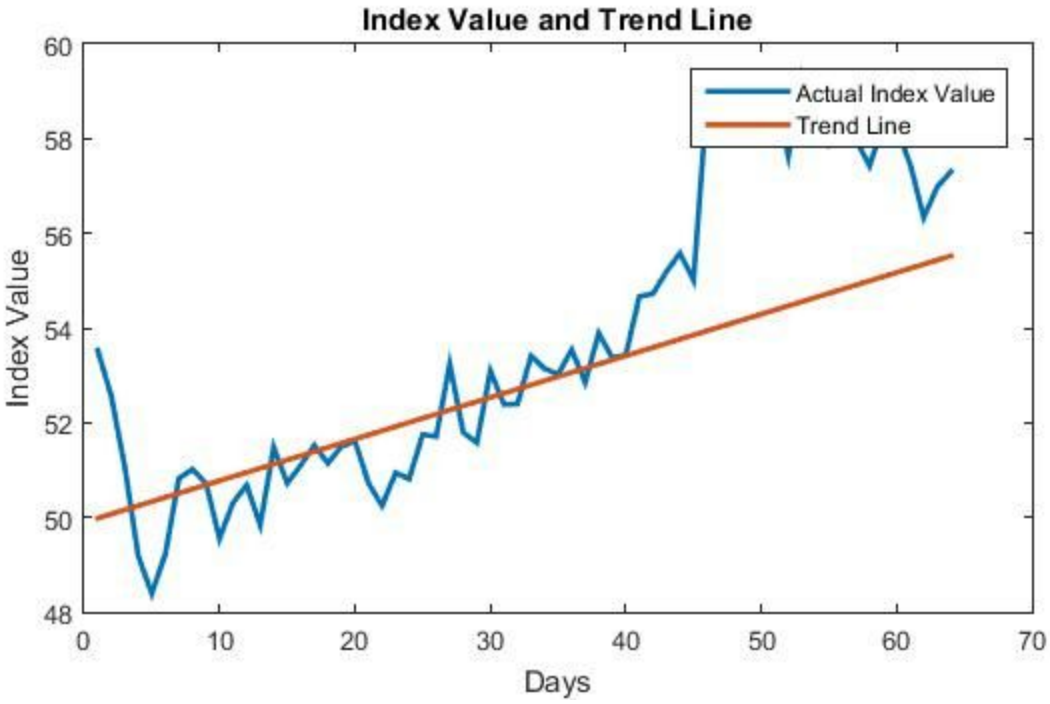
Autocorrelation Days: 50 Days

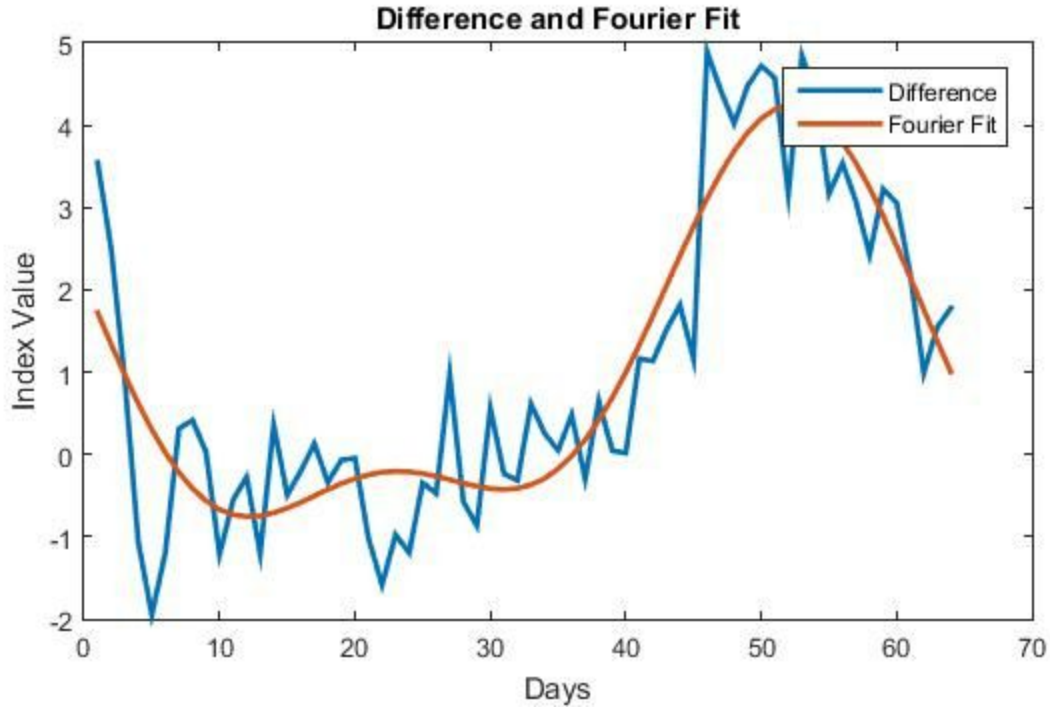
Days of Lag for Moving Average: 50 Days

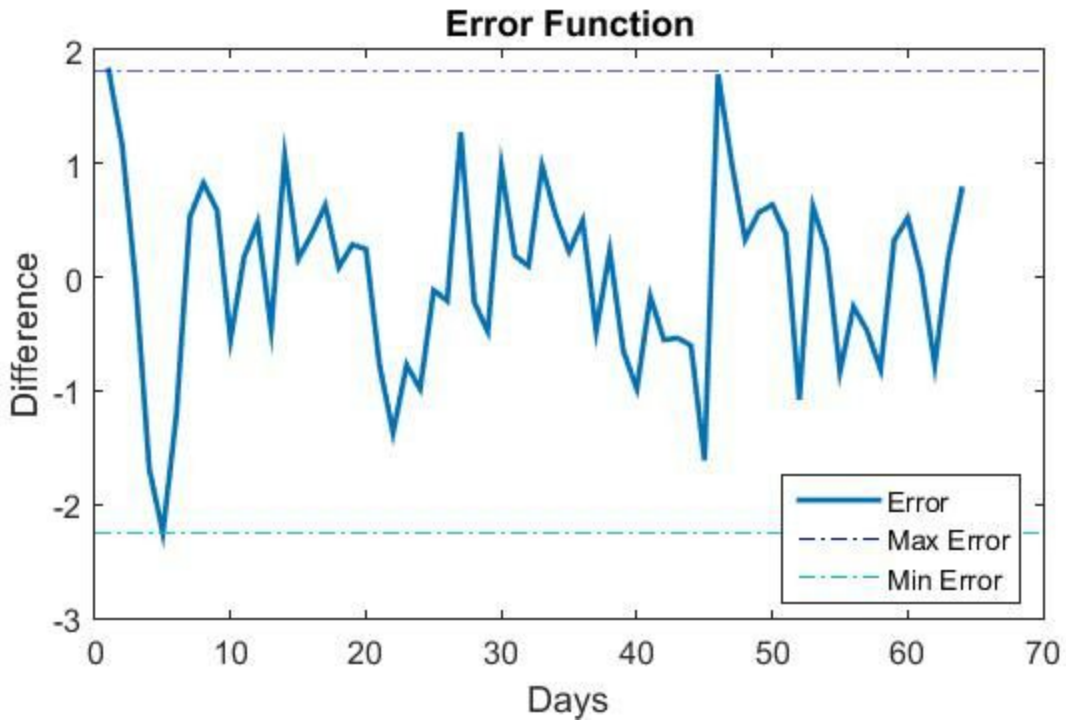


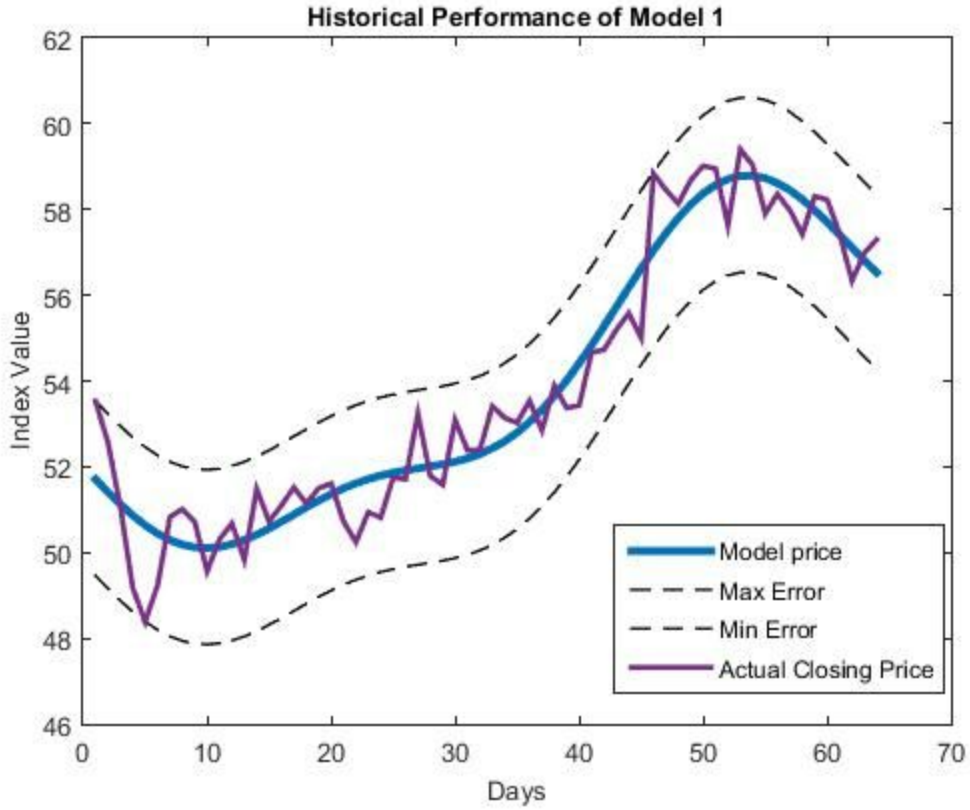

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
20
40
60
80
100
120
140
160
180
200

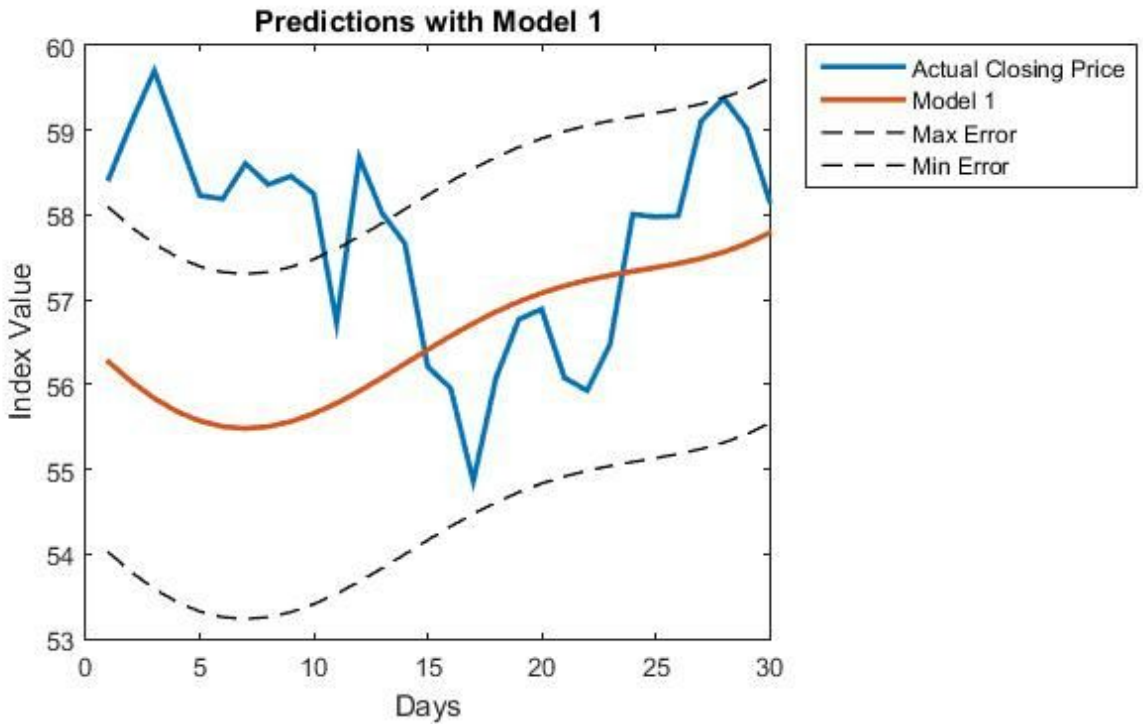

Moving Average and Trend Line
Moving Average
Trend Line
Index Value
Days
58
57
56
55
54
53
52
51
50
49
0
10
20
30
40
50
60
70


Index Value and Trend Line
Actual Index Value
Trend Line
Index Value
Days
60
58
56
54
52
50
48
0
10
20
30
40
50
60
70


Difference and Fourier Fit
Difference
Fourier Fit
Index Value
Days
5
4
3
2
1
0
-1
-2
0
10
20
30
40
50
60
70


Error Function
Difference
Days
Error
Max Error
Min Error


Historical Performance of Model 1
Index Value
Days
Model price
Max Error
Min Error
Actual Closing Price



Max Error: +3.7%

Min Error: -3.7%

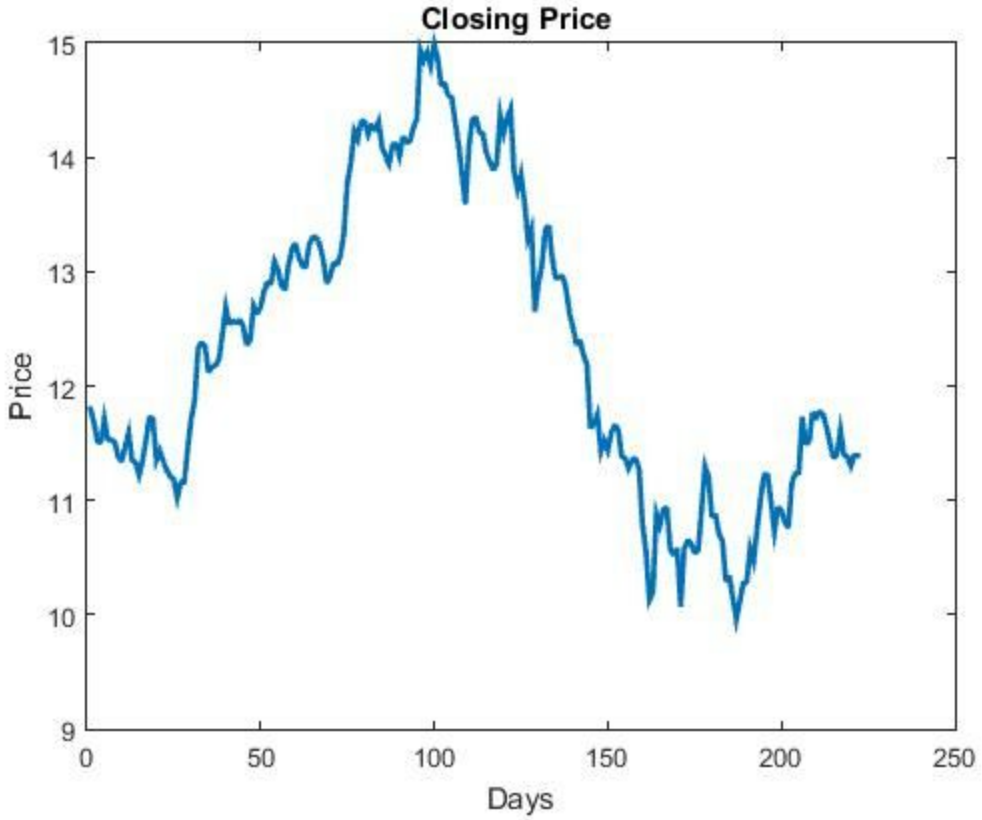
Panasonic (PCRFY)

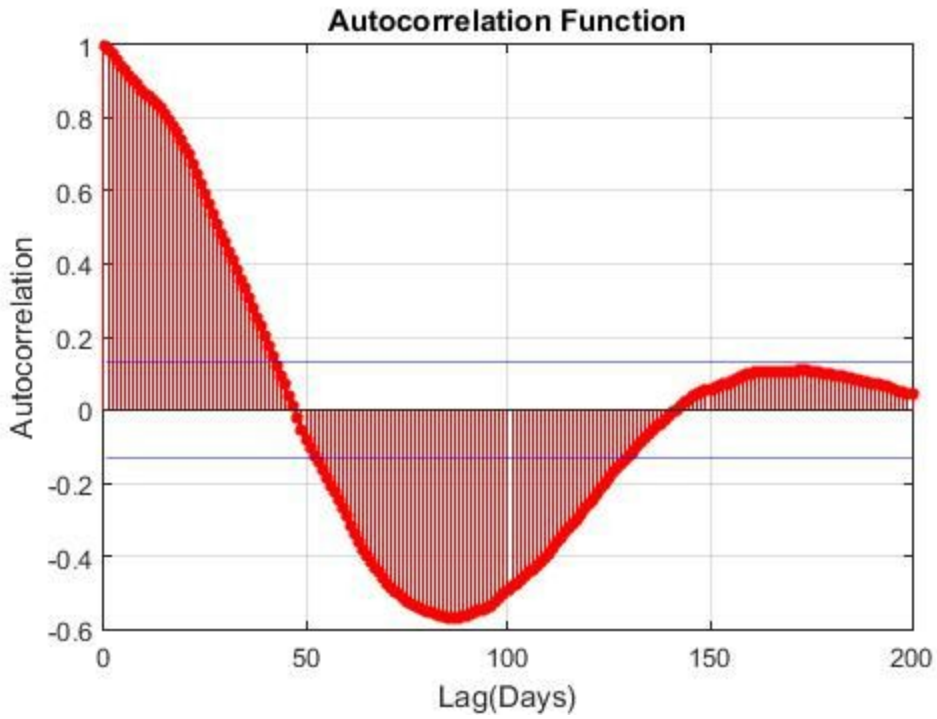
Range of Prediction : Nov.1.2015 --- Dec.14.2015 (30 work days)

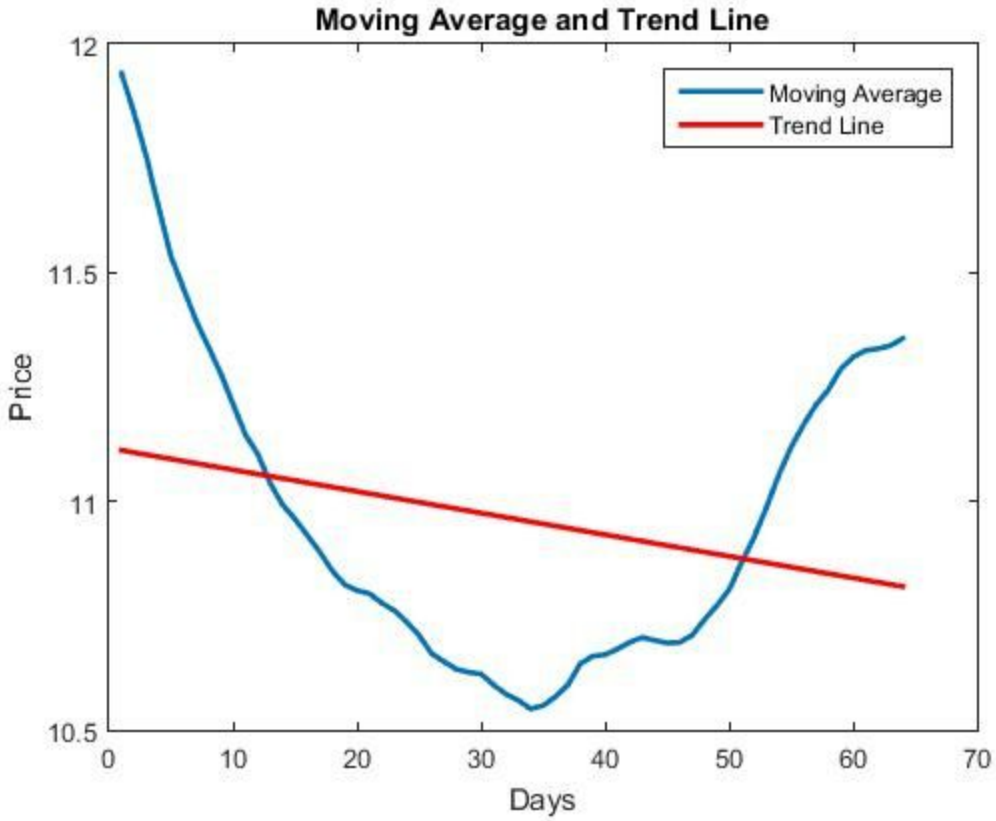
Moving Average Window: 50 Days.

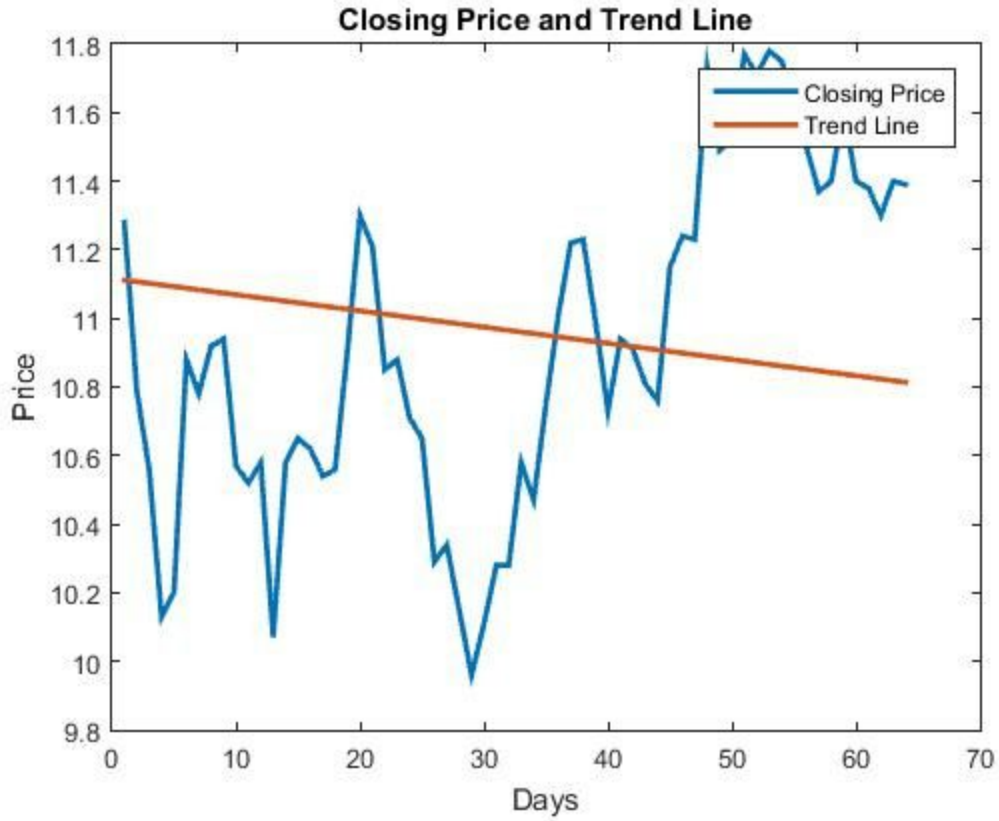
Autocorrelation Days : 79

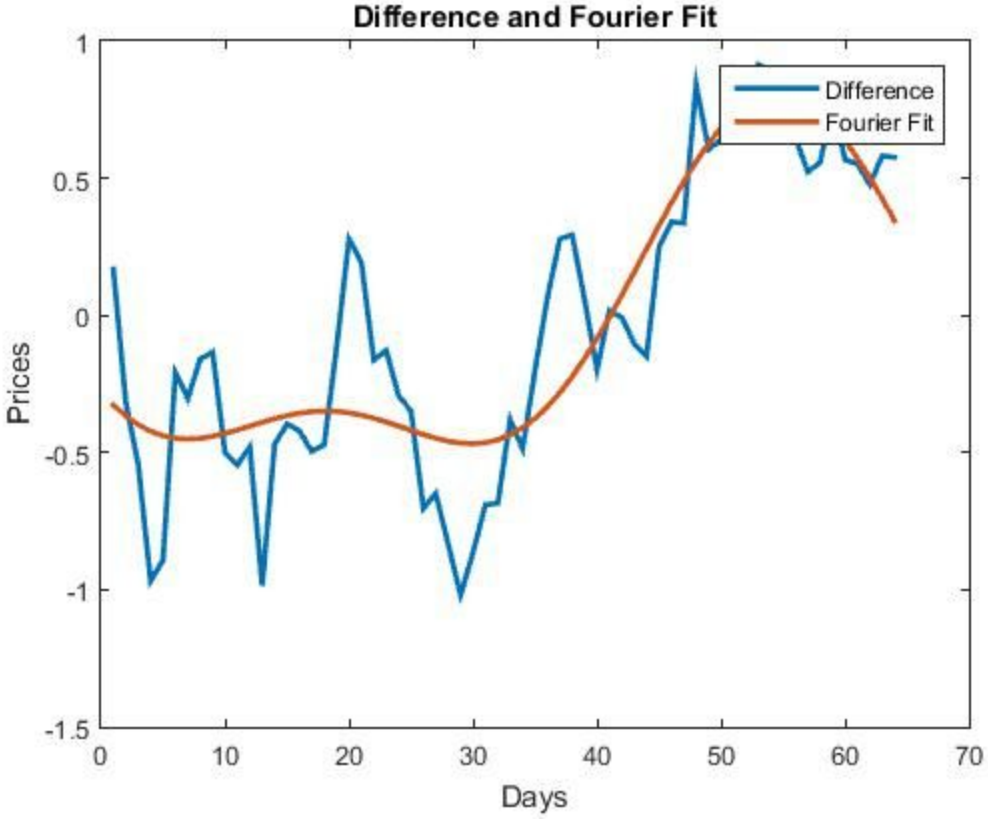
Correlation with the index : 0.8590

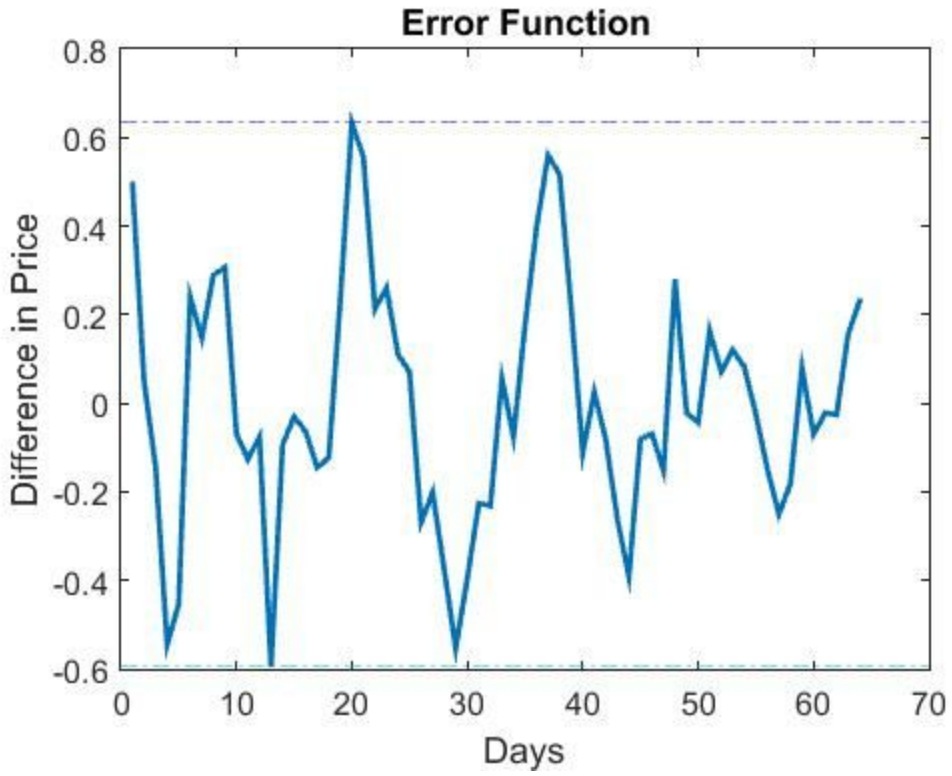


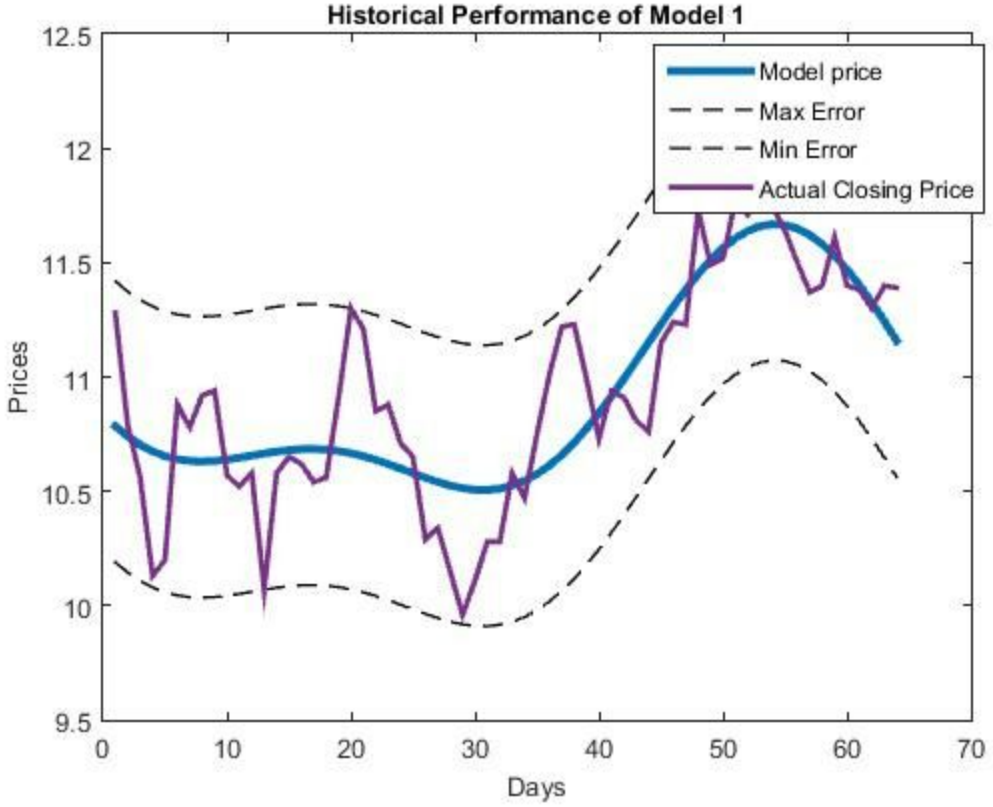

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
0
50
100
150
200

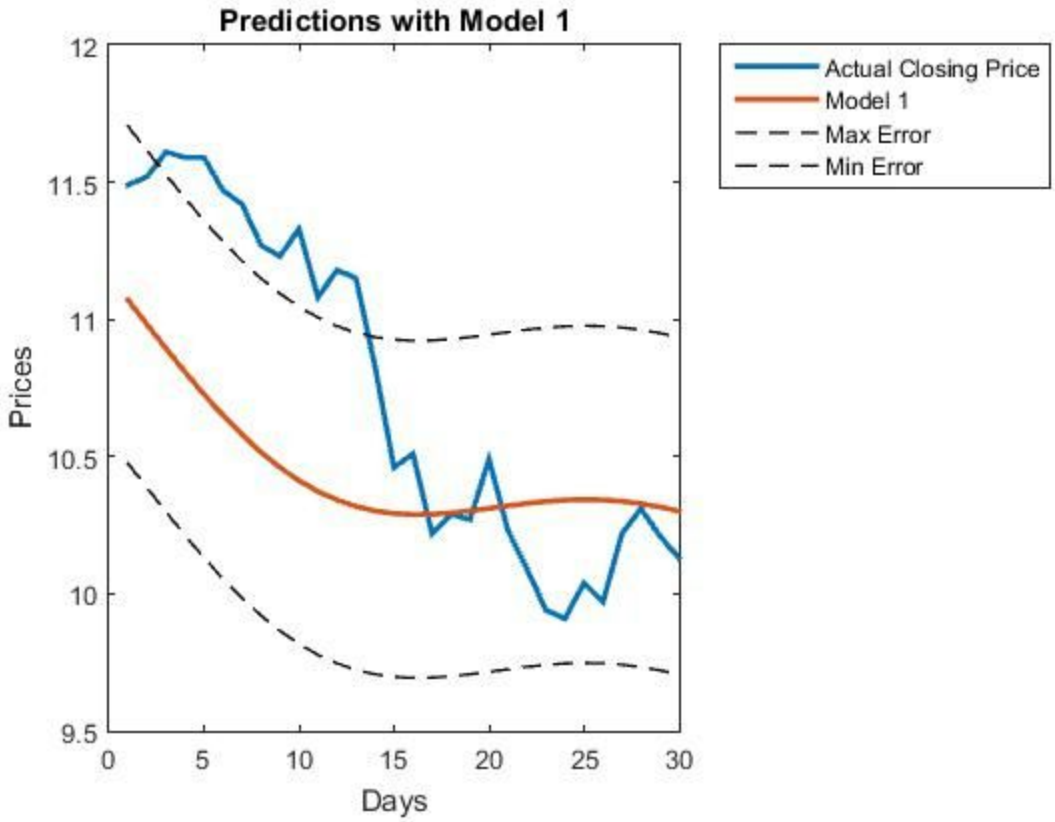

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
12
11.5
11
10.5
0
10
20
30
40
50
60
70


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
11.8
11.6
11.4
11.2
11
10.8
10.6
10.4
10.2
10
9.8
0
10
20
30
40
50
60
70


Difference and Fourier Fit
Difference
Fourier Fit
Prices
Days
1
0.5
0
-0.5
-1
-1.5
0
10
20
30
40
50
60
70

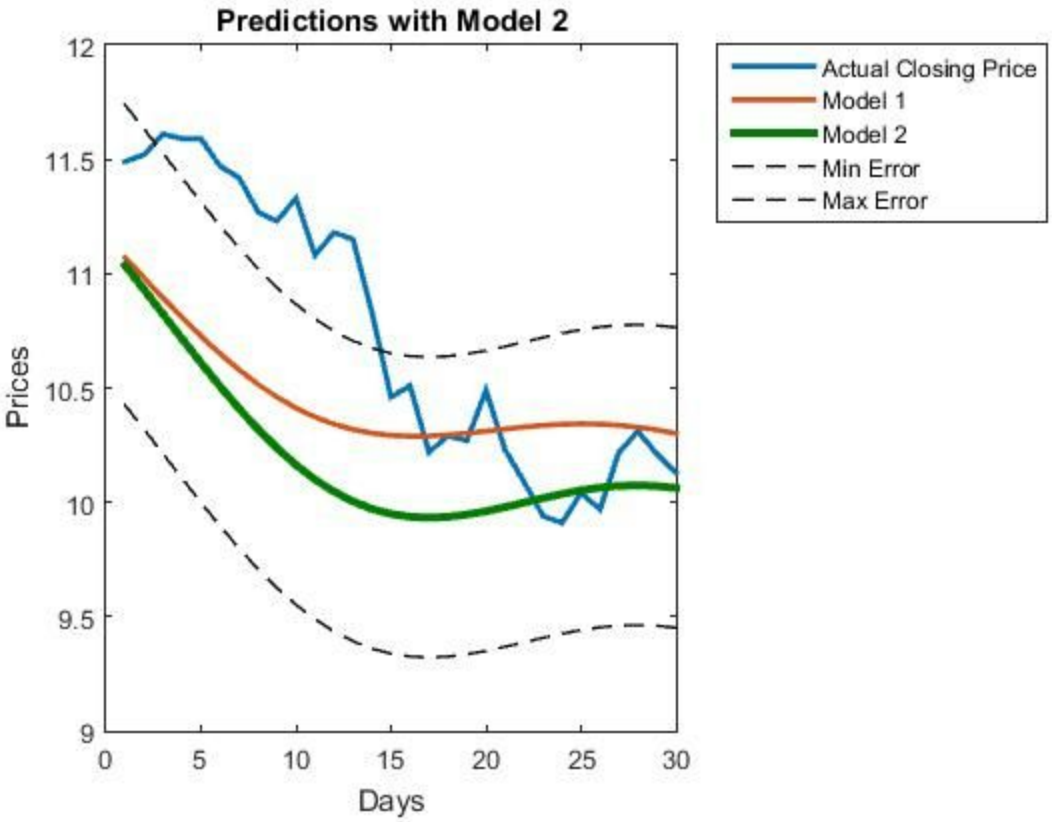

Error Function
Difference in Price
Days
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Prices
Days
12.5
12
11.5
11
10.5
10
9.5
0
10
20
30
40
50
60
70



Max error: +7.2%

Min error: -7.2%



Max error: +7.2%

Min error: -7.2%

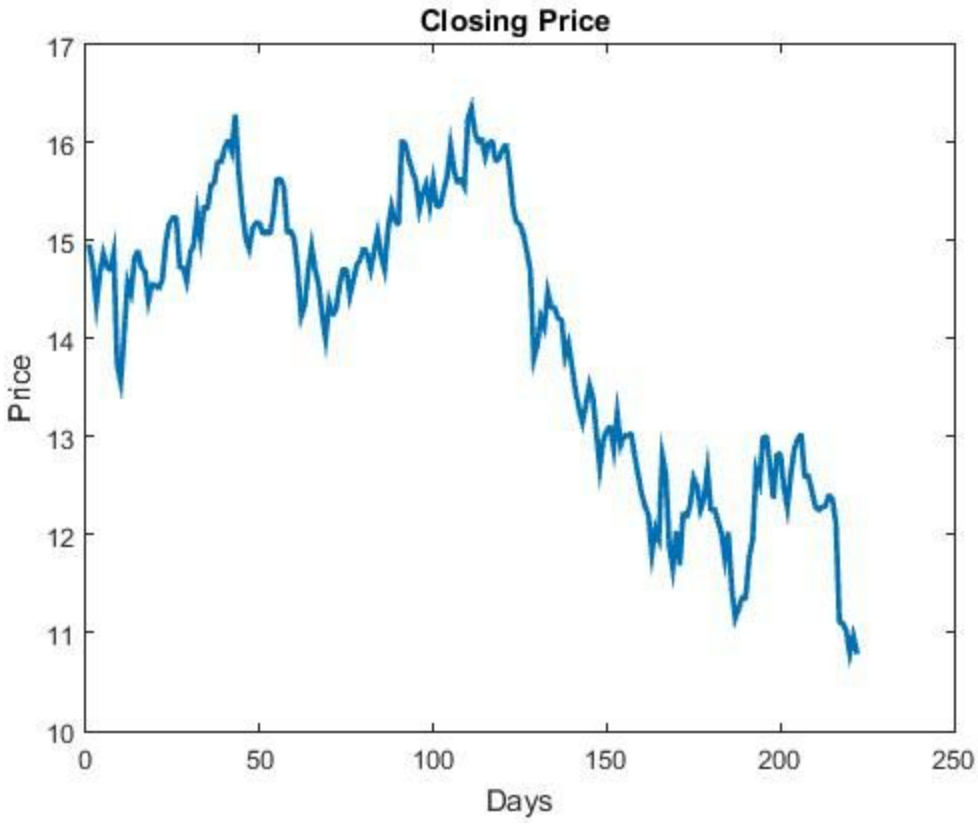
Sumitomo mining (SMMYY)

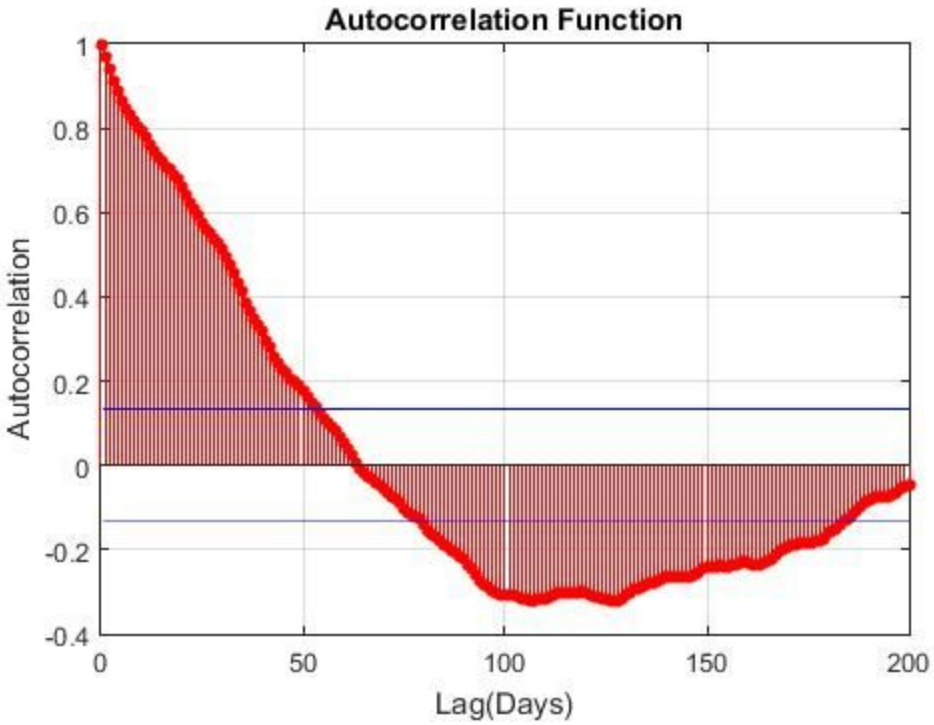
Autocorrelation: 64

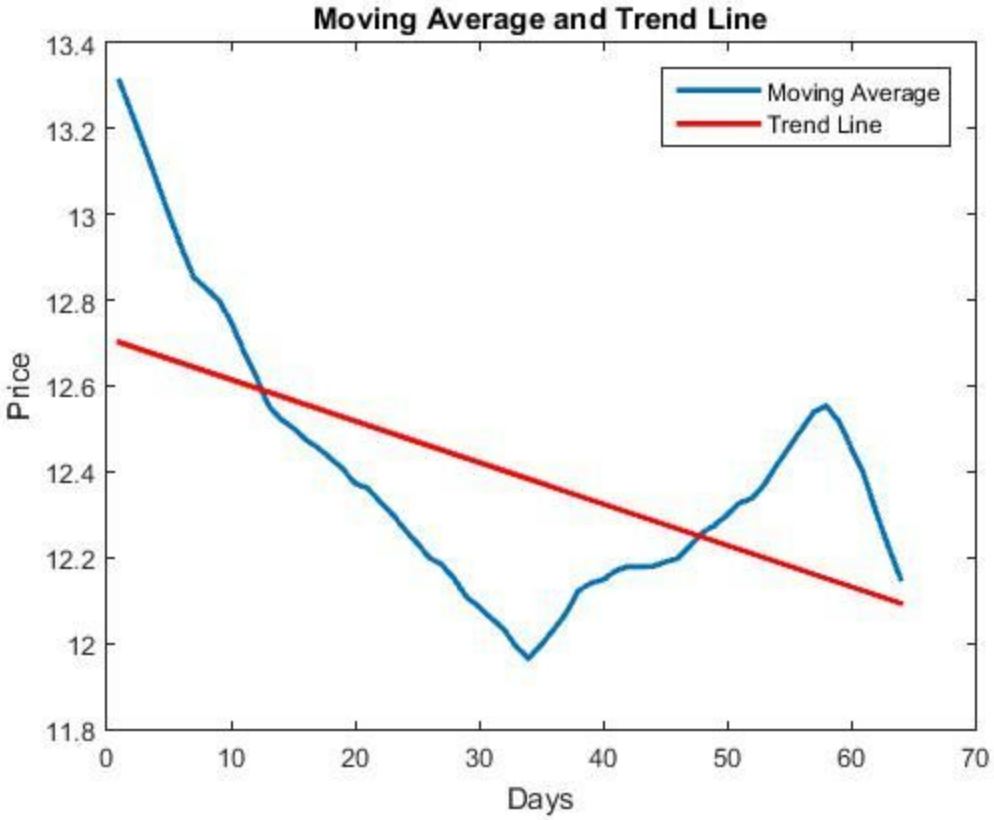
Prediction period: 12/01/2015-12/31/2015

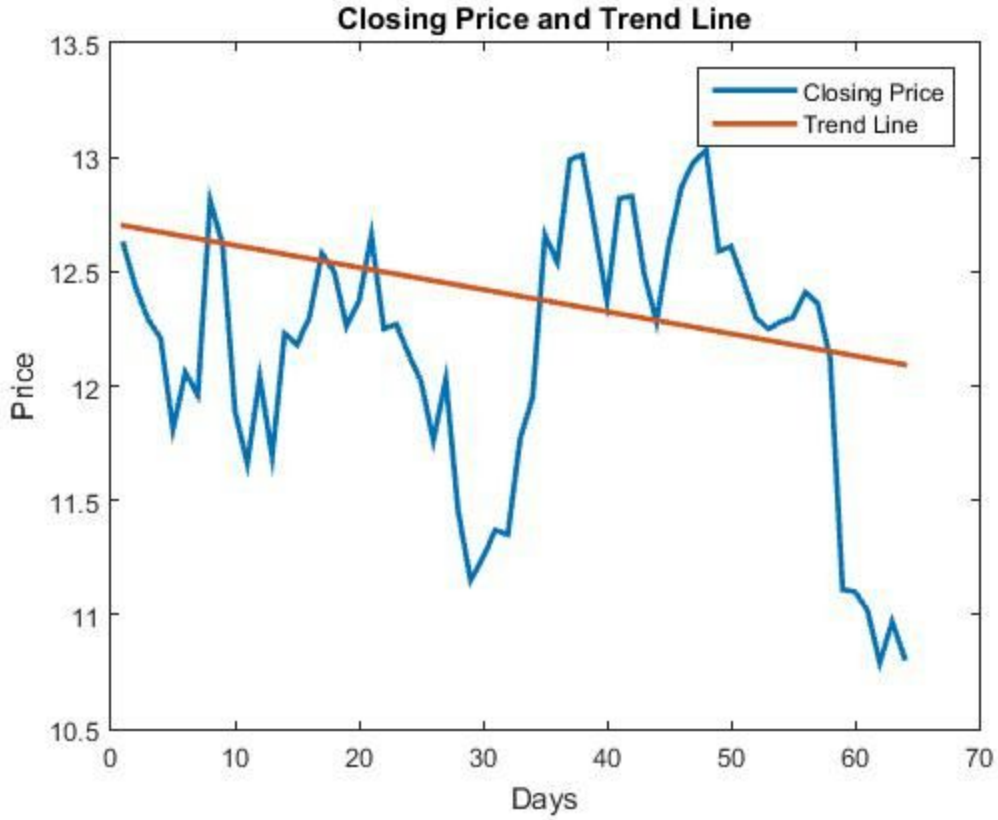
Window: 25

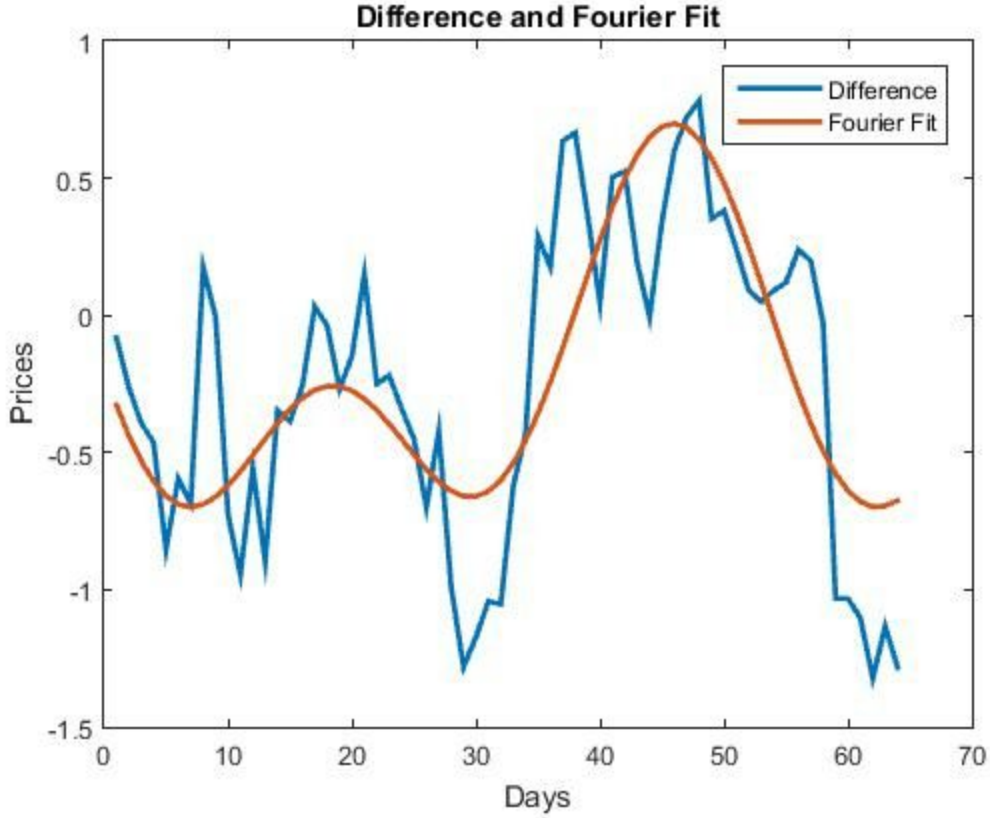
Correlation: -0.4572

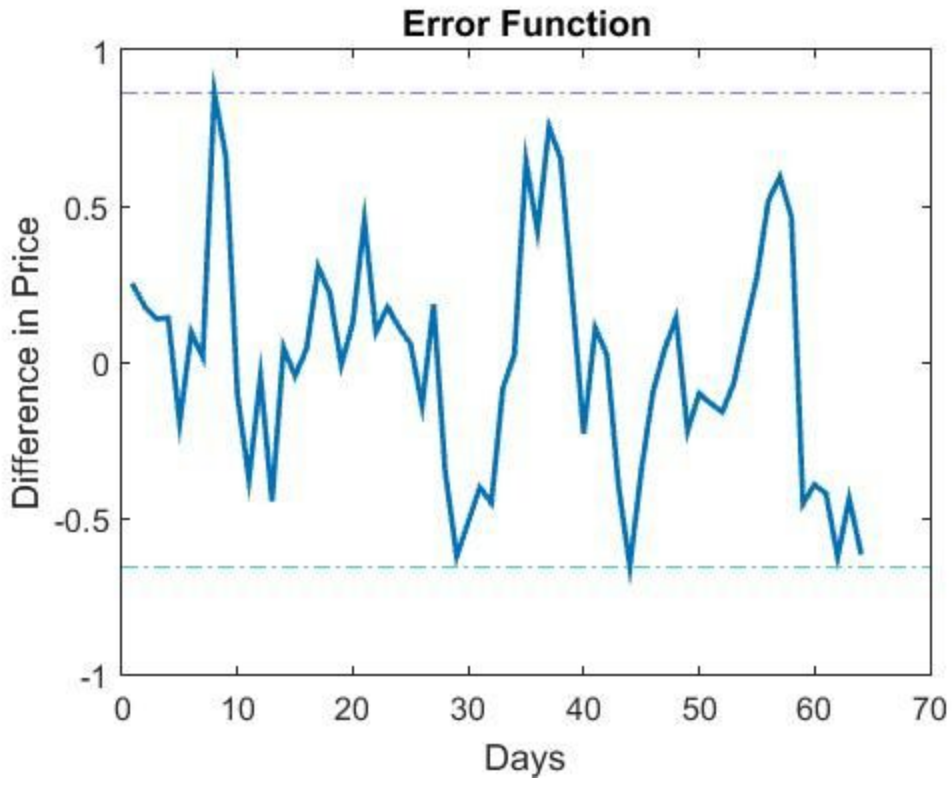


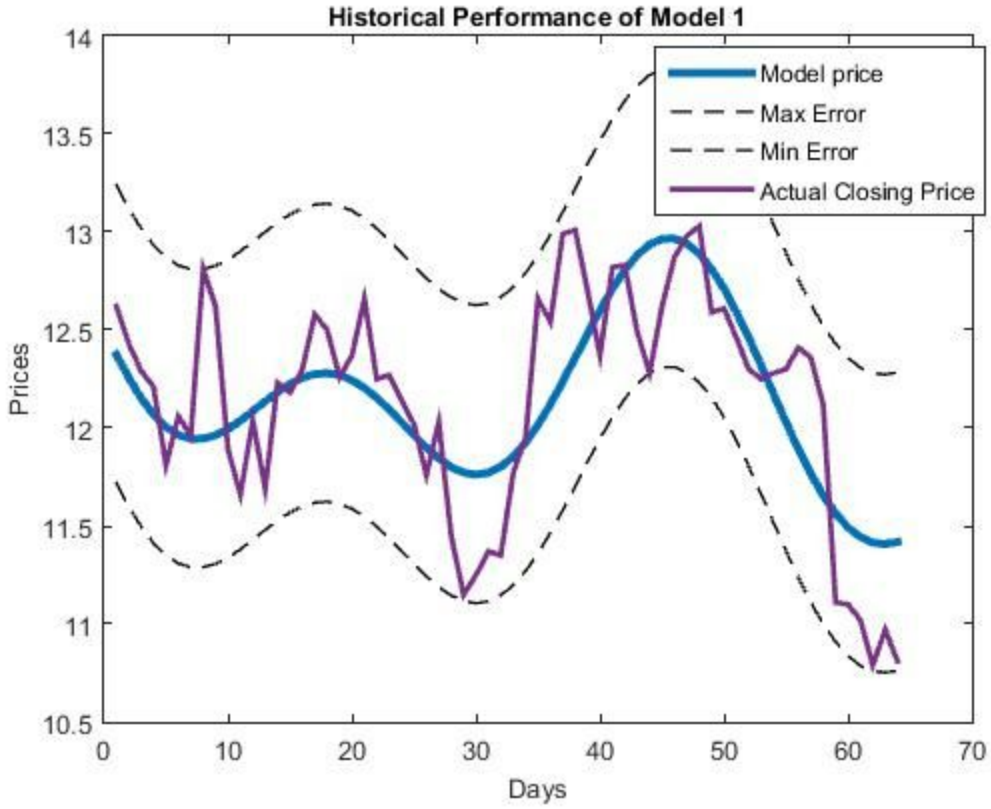

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
50
100
150
200

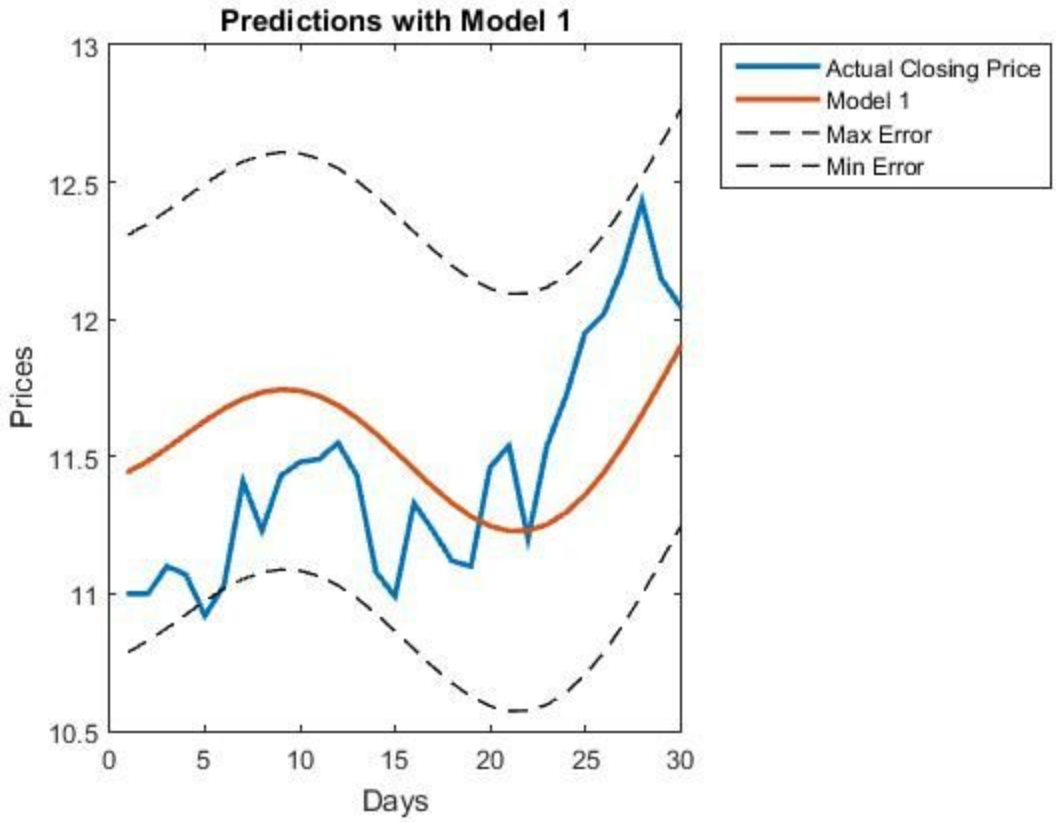

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
13.4
13.2
13
12.8
12.6
12.4
12.2
12
11.8
0
10
20
30
40
50
60
70


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
13.5
13
12.5
12
11.5
11
10.5
0
10
20
30
40
50
60
70


Difference and Fourier Fit
Difference
Fourier Fit
Prices
Days
1
0.5
0
-0.5
-1
-1.5
0
10
20
30
40
50
60
70

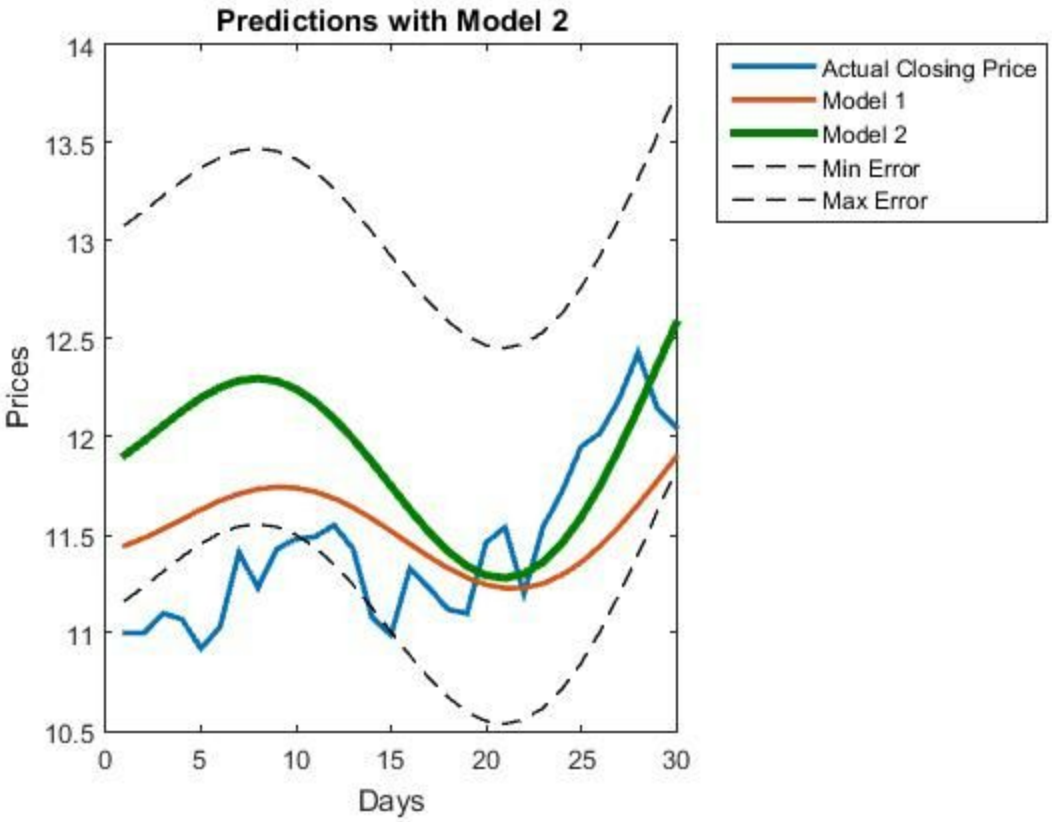

Error Function
Difference in Price
Days
1
0.5
0
-0.5
-1
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Prices
Days
14
13.5
13
12.5
12
11.5
11
10.5
0
10
20
30
40
50
60
70



Max error: +6.3

Min error: -6.3



Max error: +6.3

Min error: -6.3

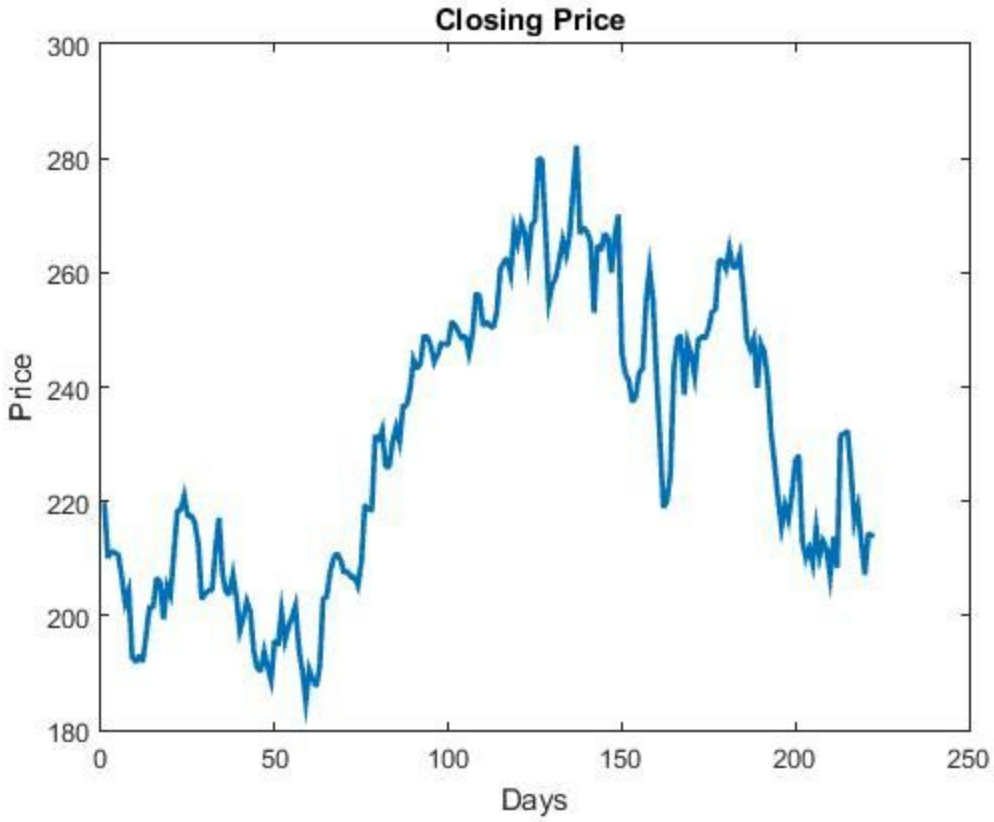
Tesla (TSLA)

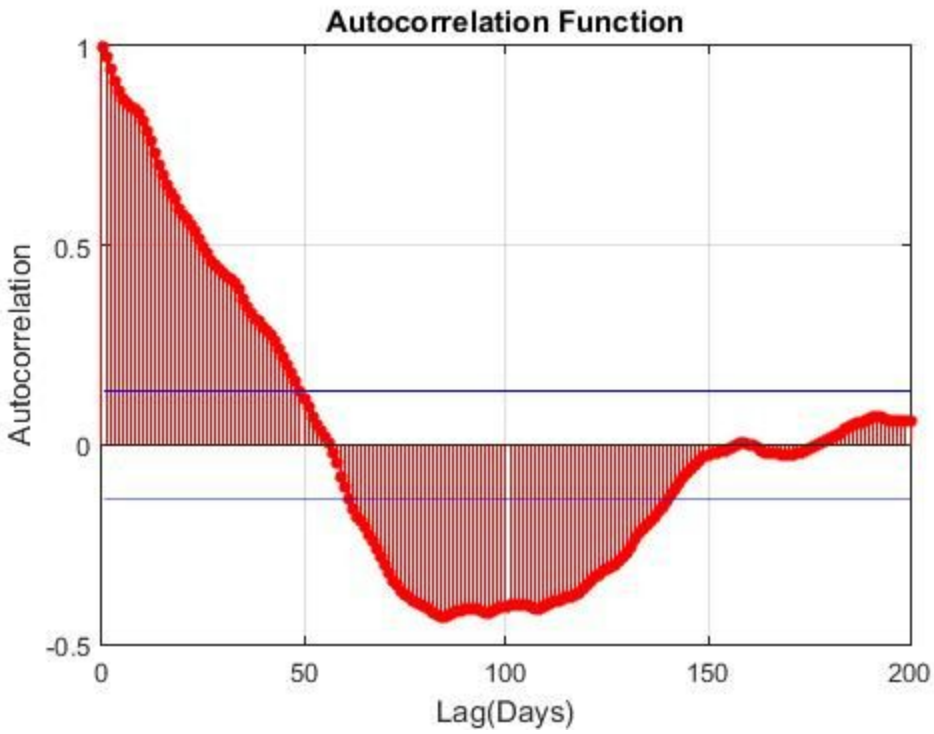
Autocorrelation: 57

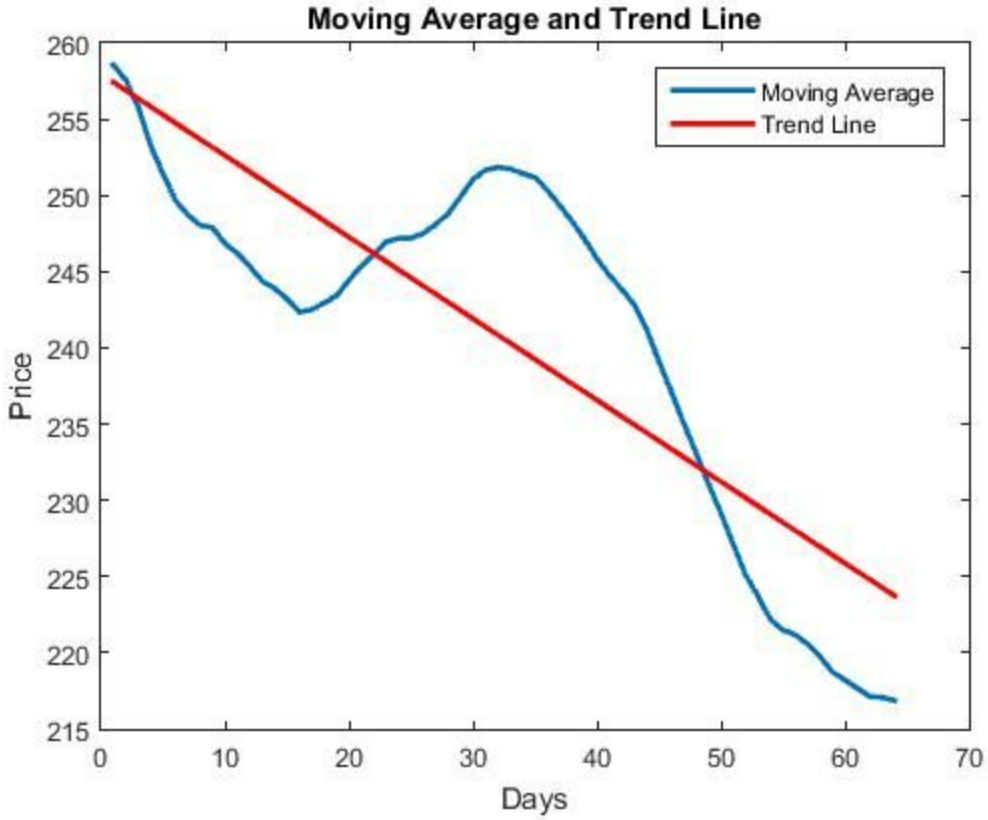
Prediction period: 12/01/2015-12/01/2015

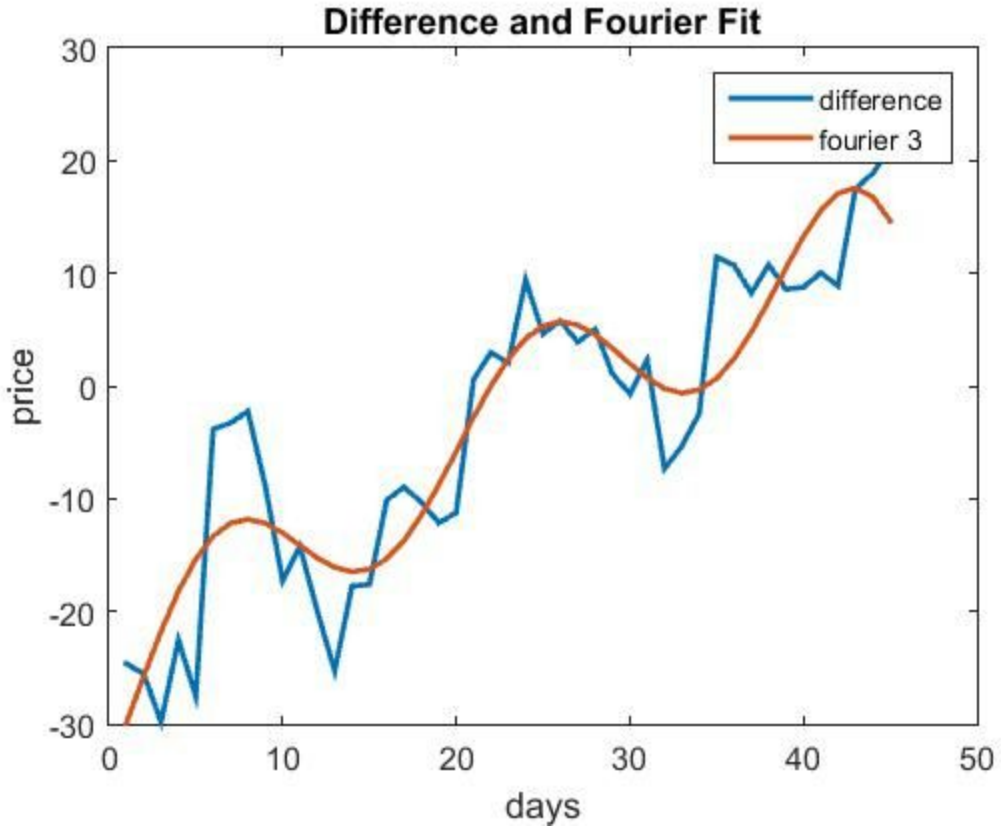
Window: 25

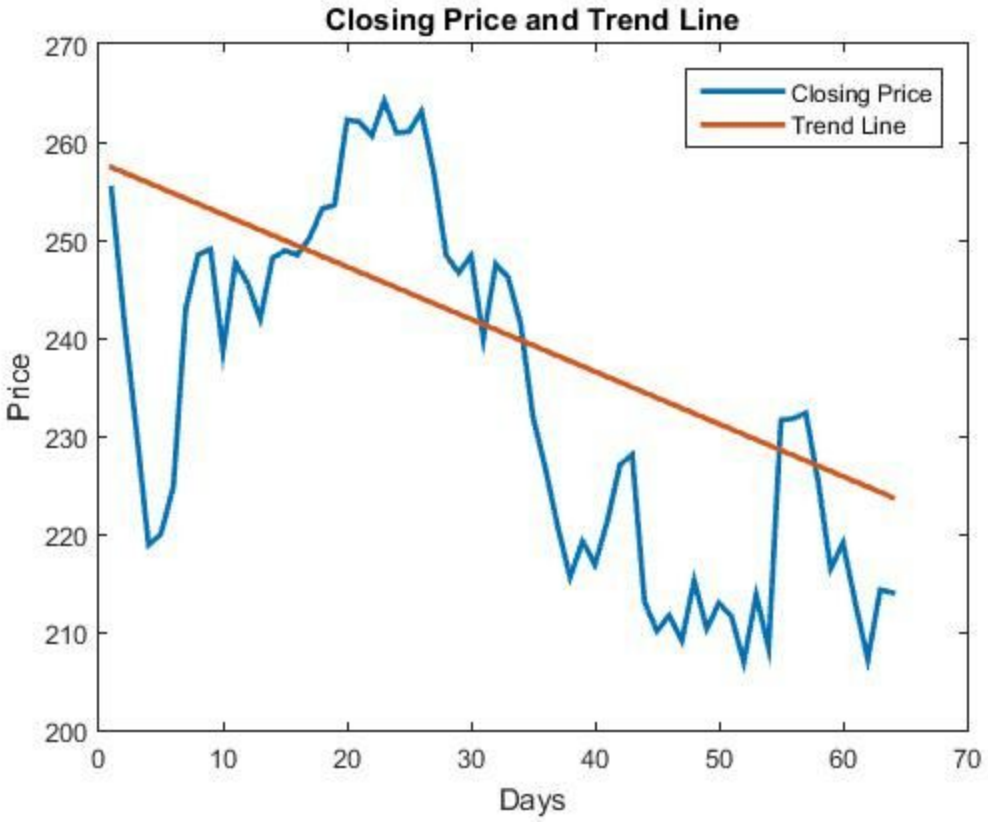
Correlation: 0.1532

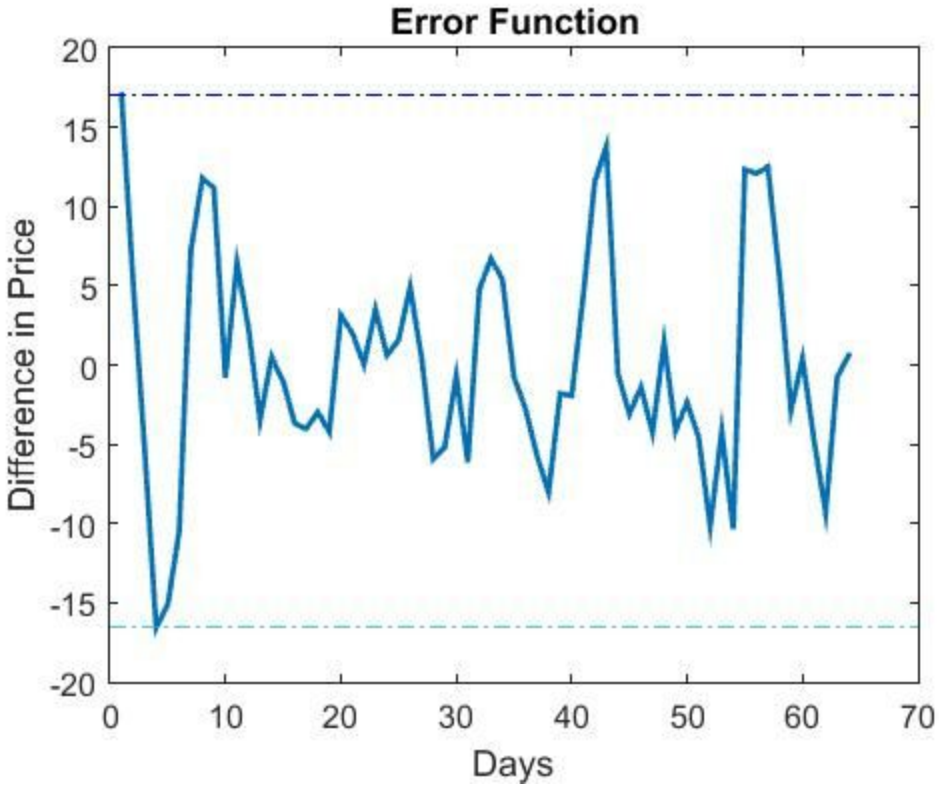


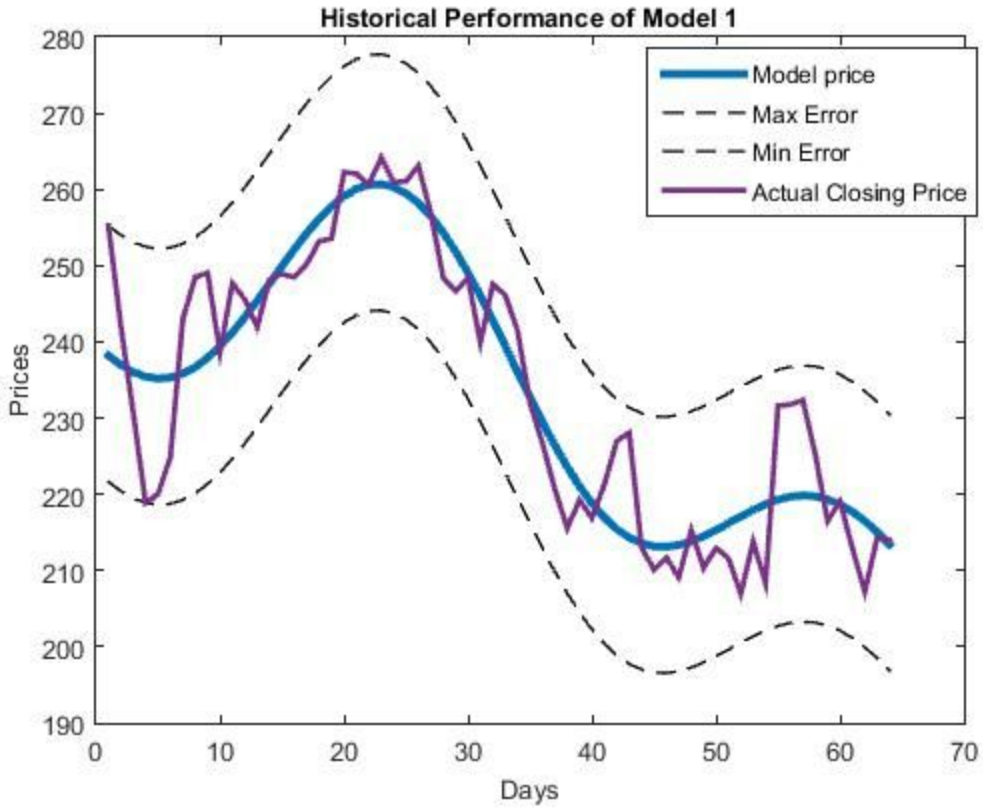

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.5
0
-0.5
0
50
100
150
200

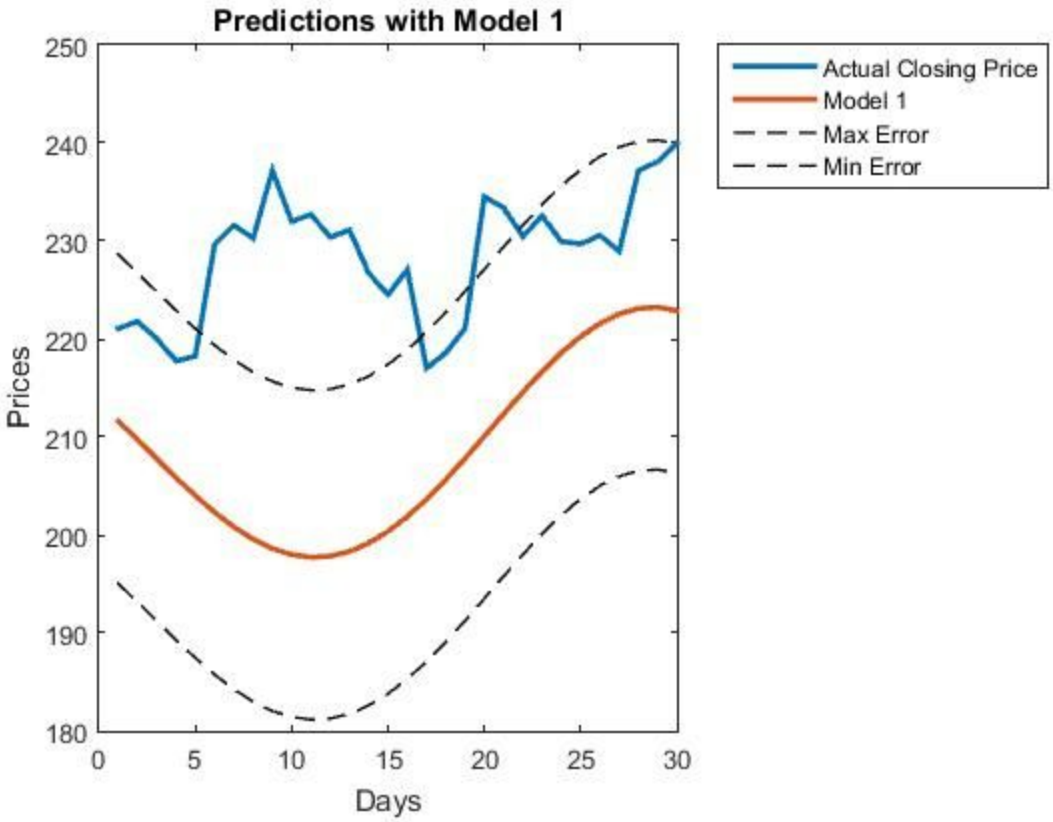

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
260
255
250
245
240
235
230
225
220
215
0
10
20
30
40
50
60
70


Difference and Fourier Fit
difference
fourier 3
price
days
30
20
10
0
-10
-20
-30
0
10
20
30
40
50


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
270
260
250
240
230
220
210
200
0
10
20
30
40
50
60
70

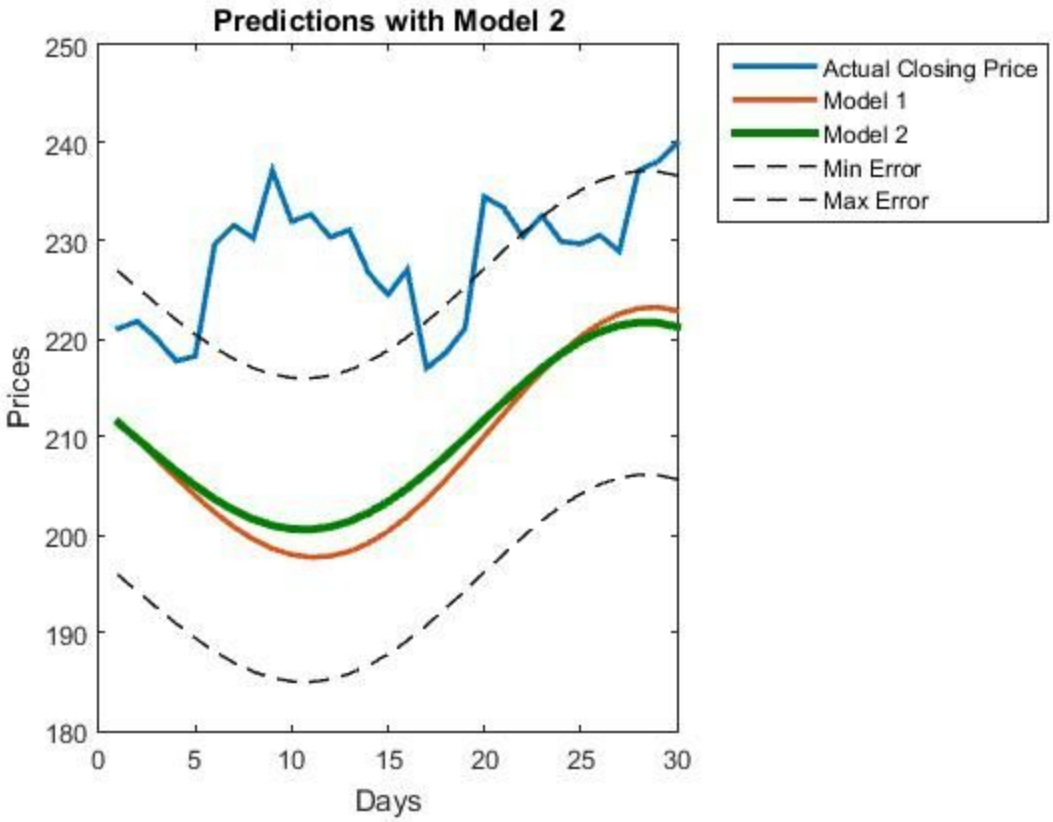

Error Function
Difference in Price
Days
20
15
10
5
0
-5
-10
-15
-20
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Prices
Days
280
270
260
250
240
230
220
210
200
190
0
10
20
30
40
50
60
70



Max error: +11.2%

Min error: -11.2%



Max error: +11.2%

Min error: -11.2%

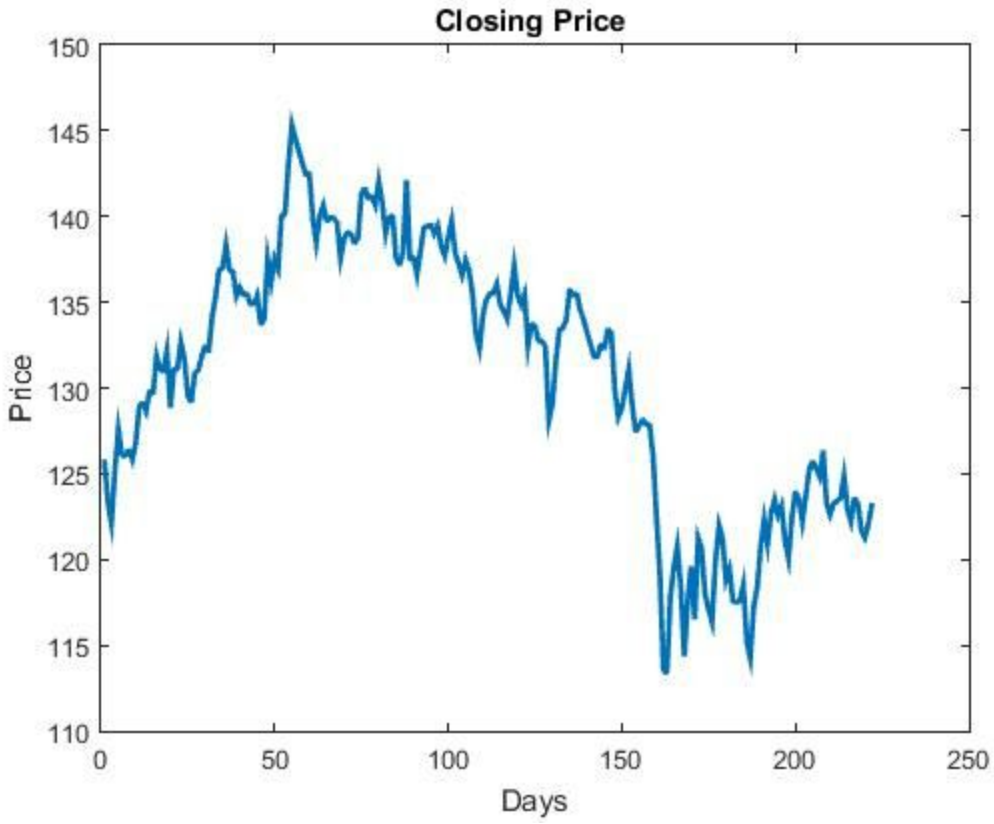
Toyota (TM)

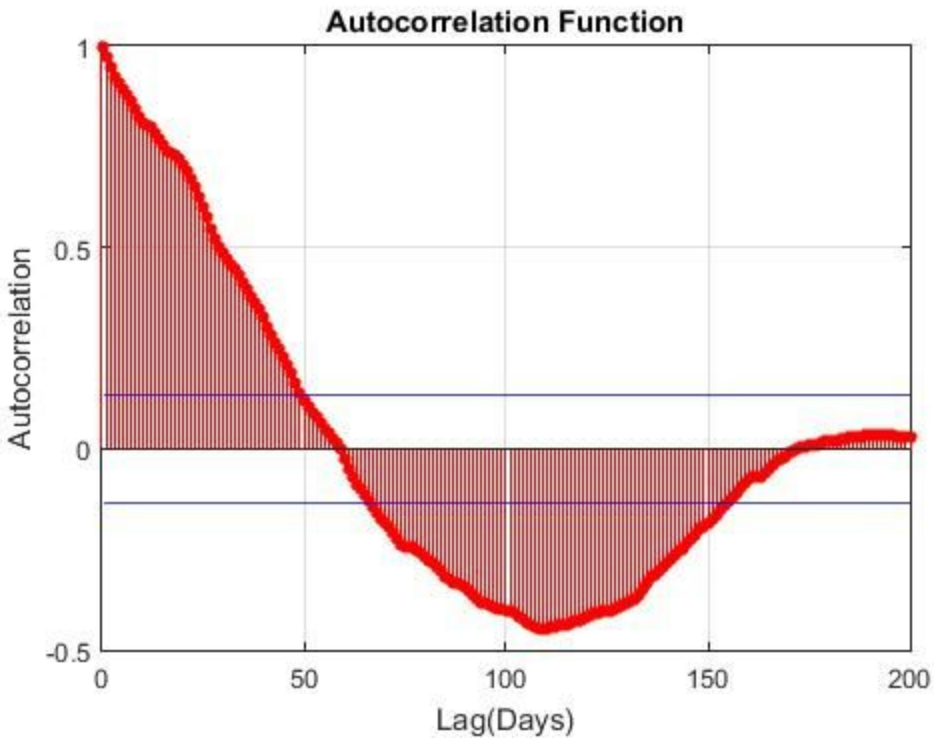
Autocorrelation 59

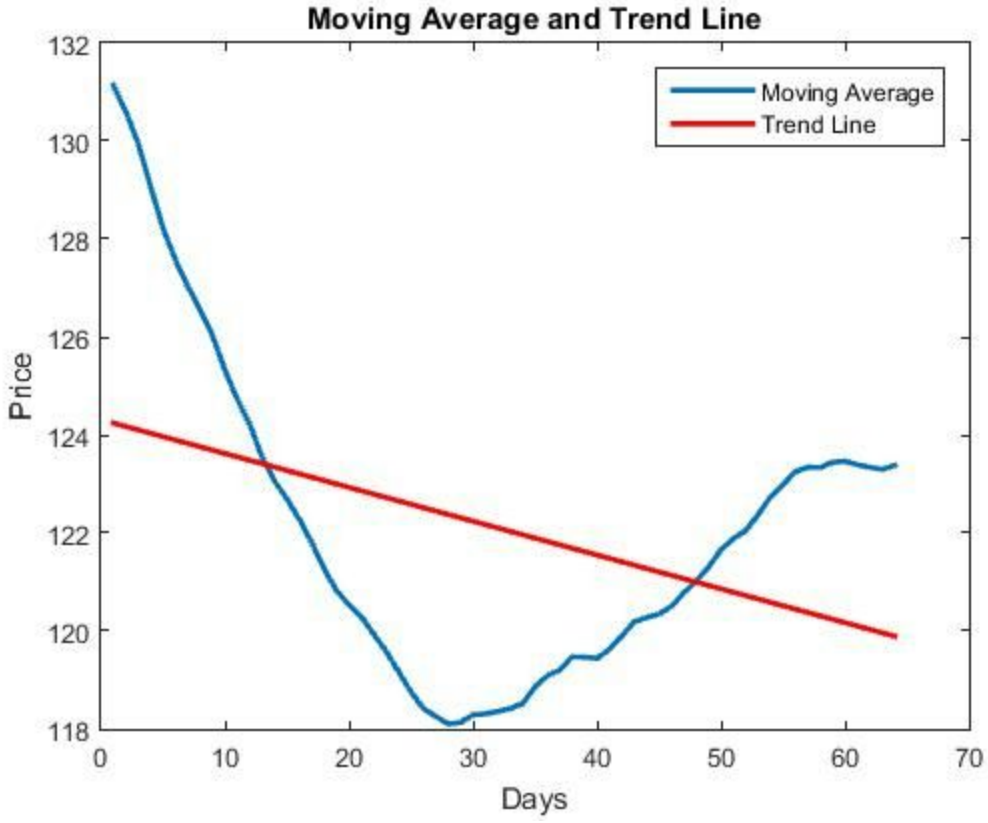
Prediction period: 12/01/2015-12/31/2015

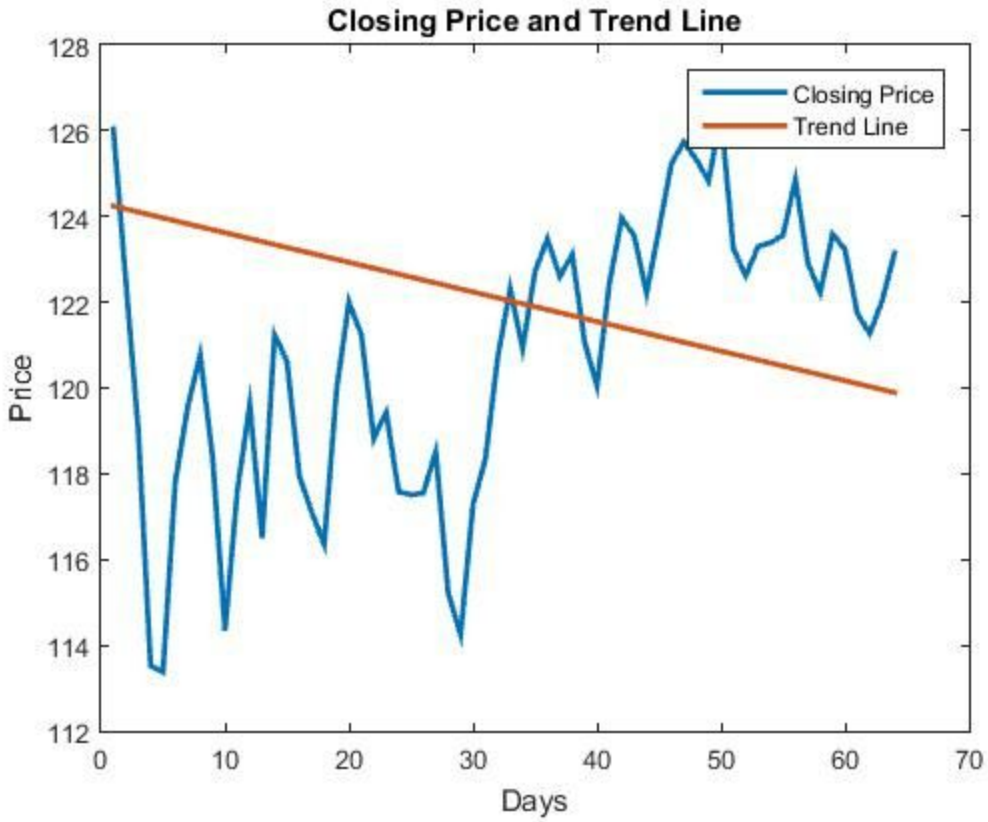
Window: 15

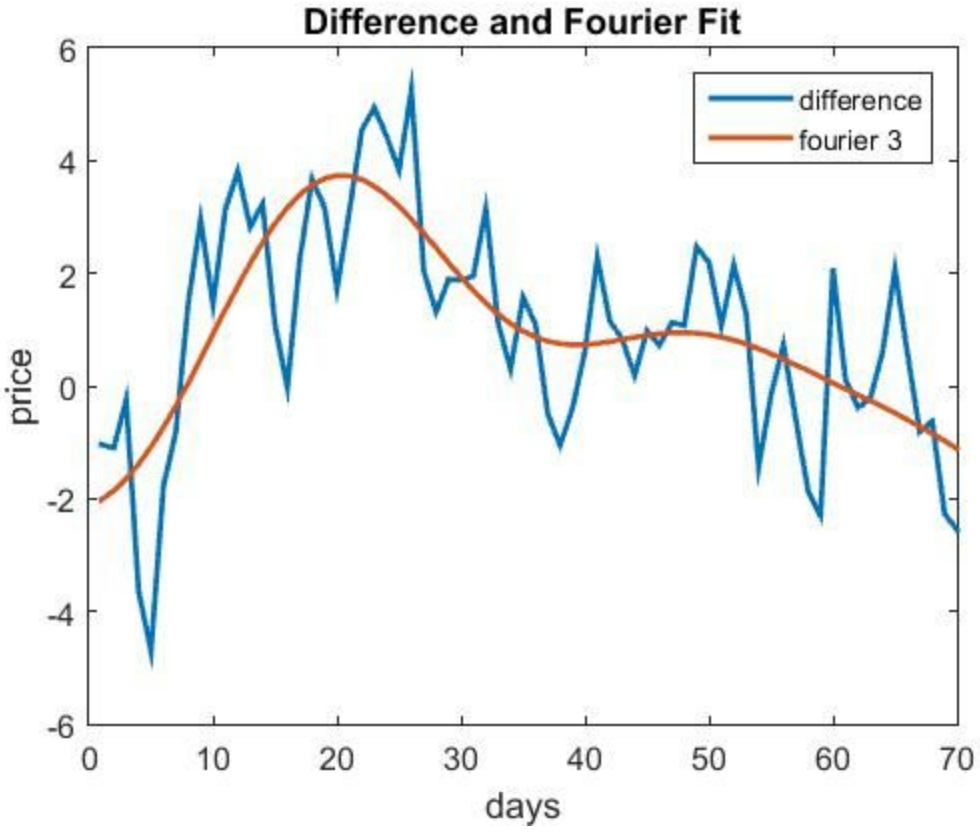
Correlation: -0.3827

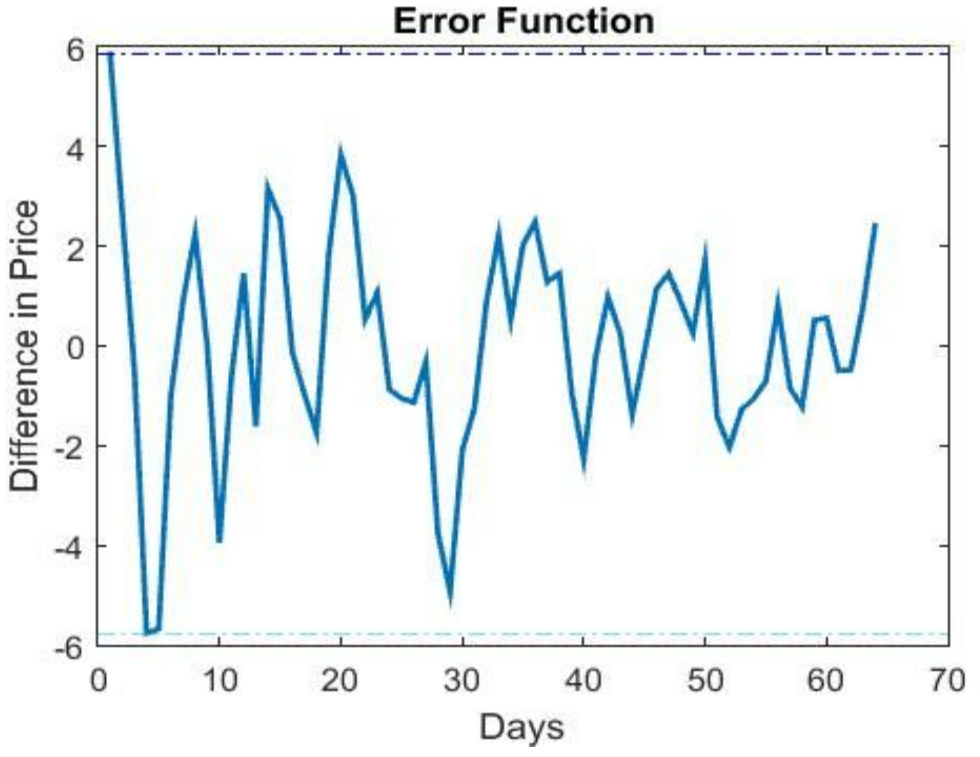


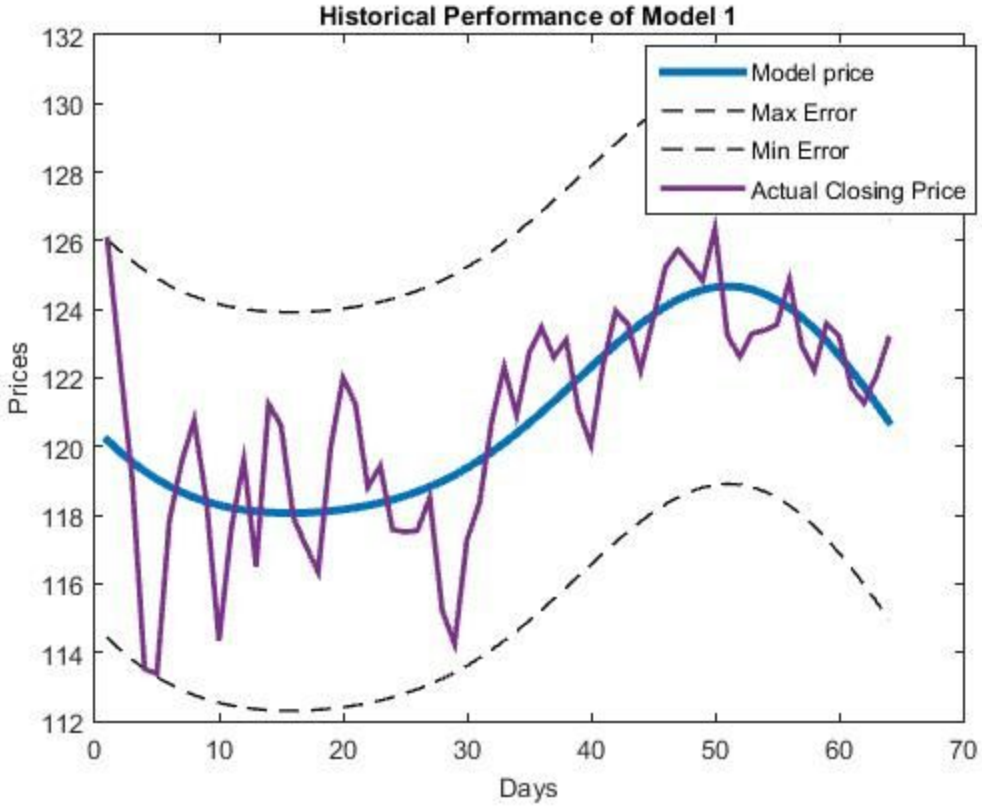

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.5
0
-0.5
0
50
100
150
200

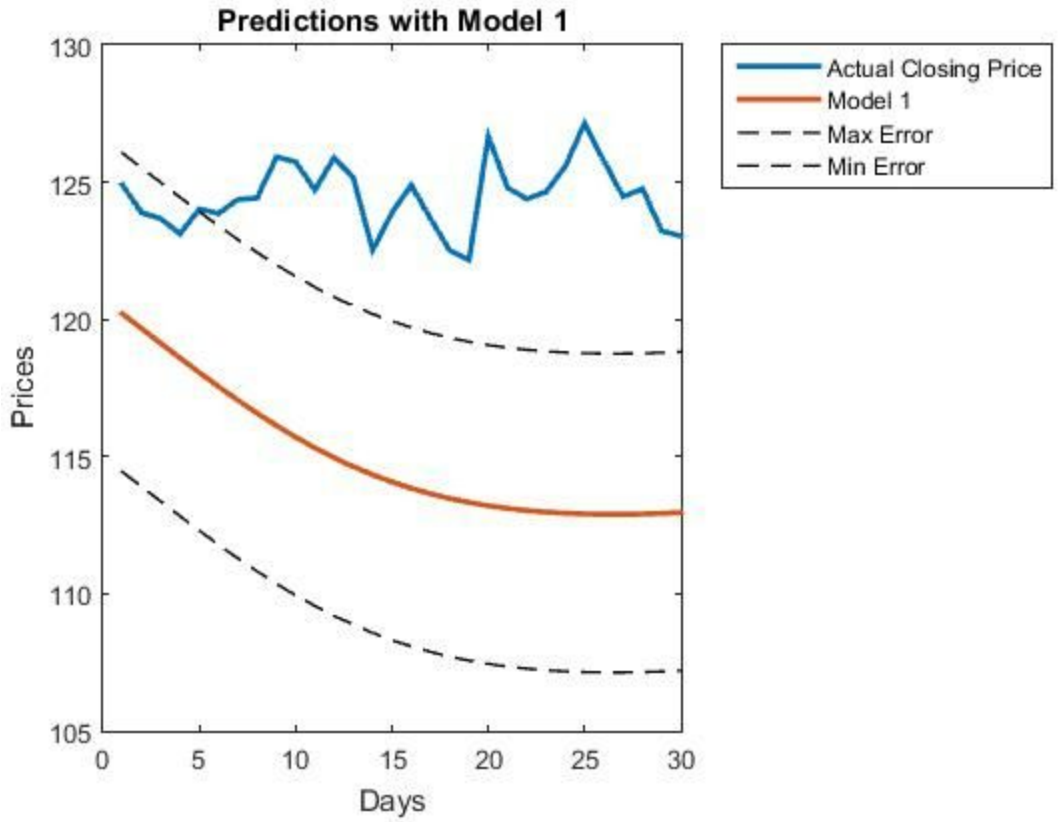

Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
132
130
128
126
124
122
120
118
0
10
20
30
40
50
60
70


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
128
126
124
122
120
118
116
114
112
0
10
20
30
40
50
60
70


Difference and Fourier Fit
difference
fourier 3
price
days
6
4
2
0
-2
-4
-6
0
10
20
30
40
50
60
70

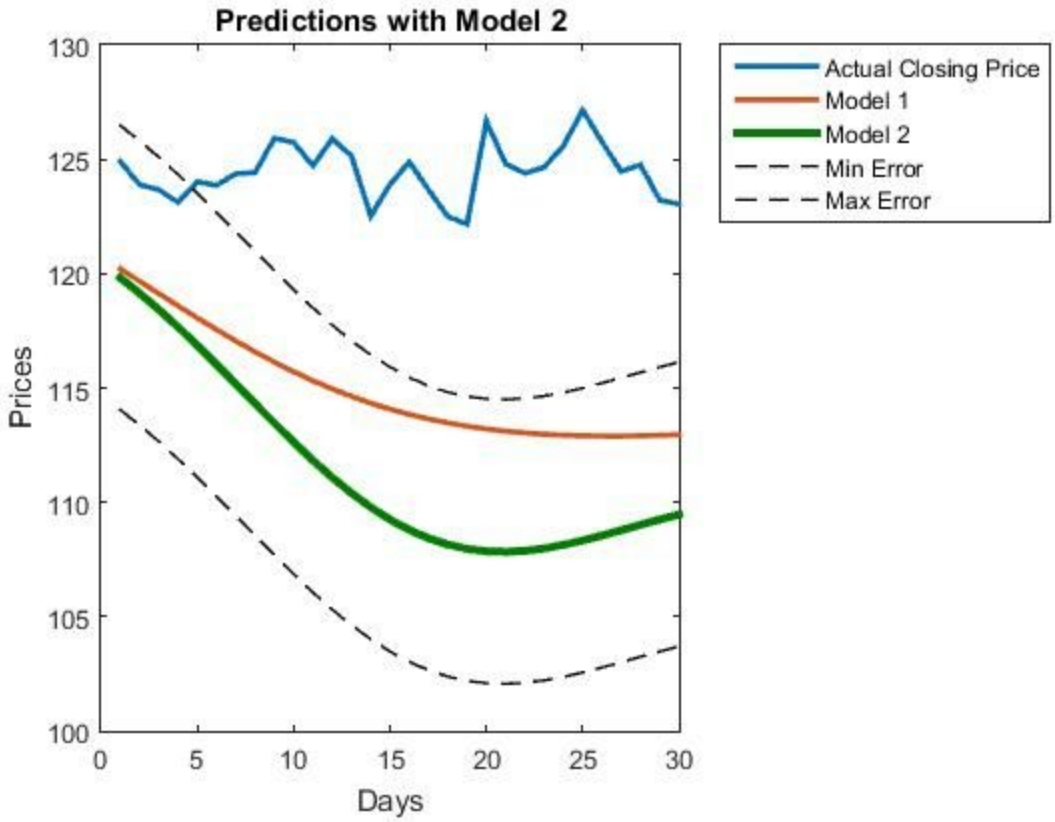

Error Function
Difference in Price
Days
6
4
2
0
-2
-4
-6
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Prices
Days
132
130
128
126
124
122
120
118
116
114
112
0
10
20
30
40
50
60
70



Max Error: +3.6%

Min Error: -3.6%



Max Error: +3.6%

Min Error: -3.6%

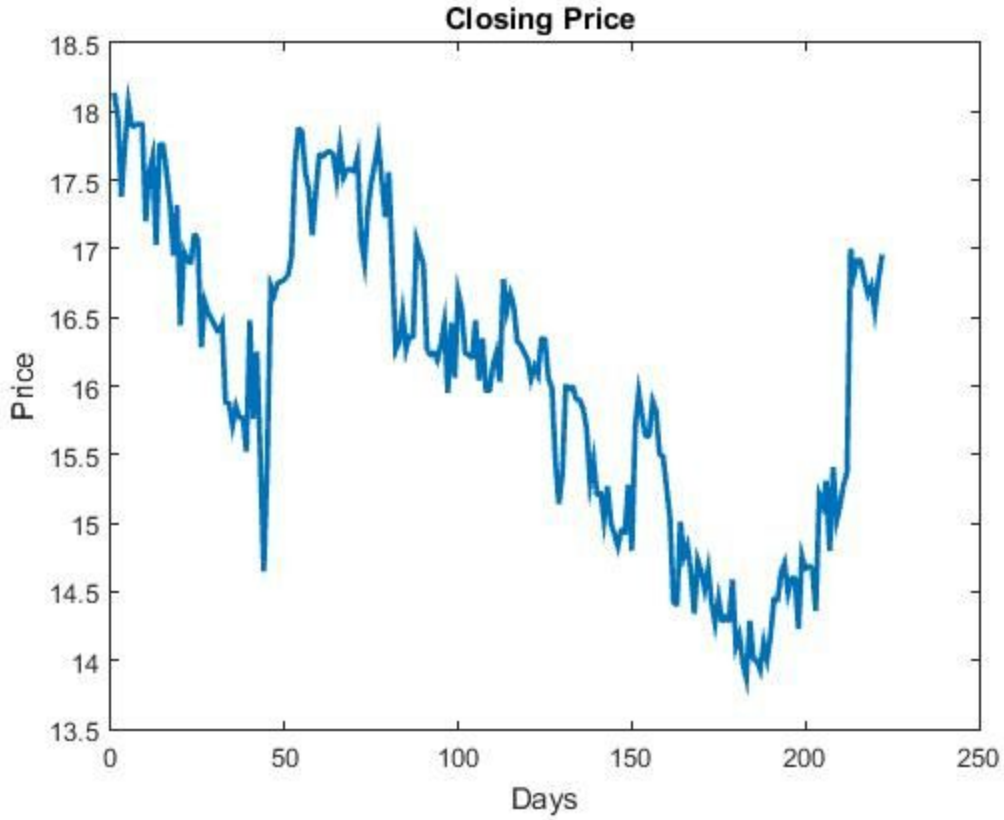
XO Group (XOXO)

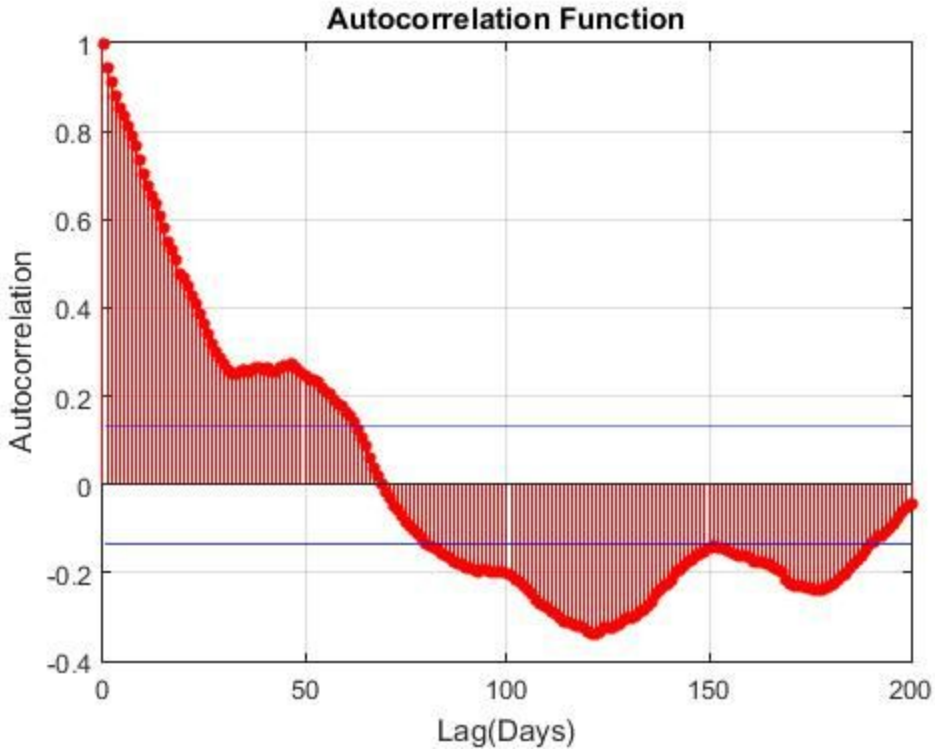
Autocorrelation 70

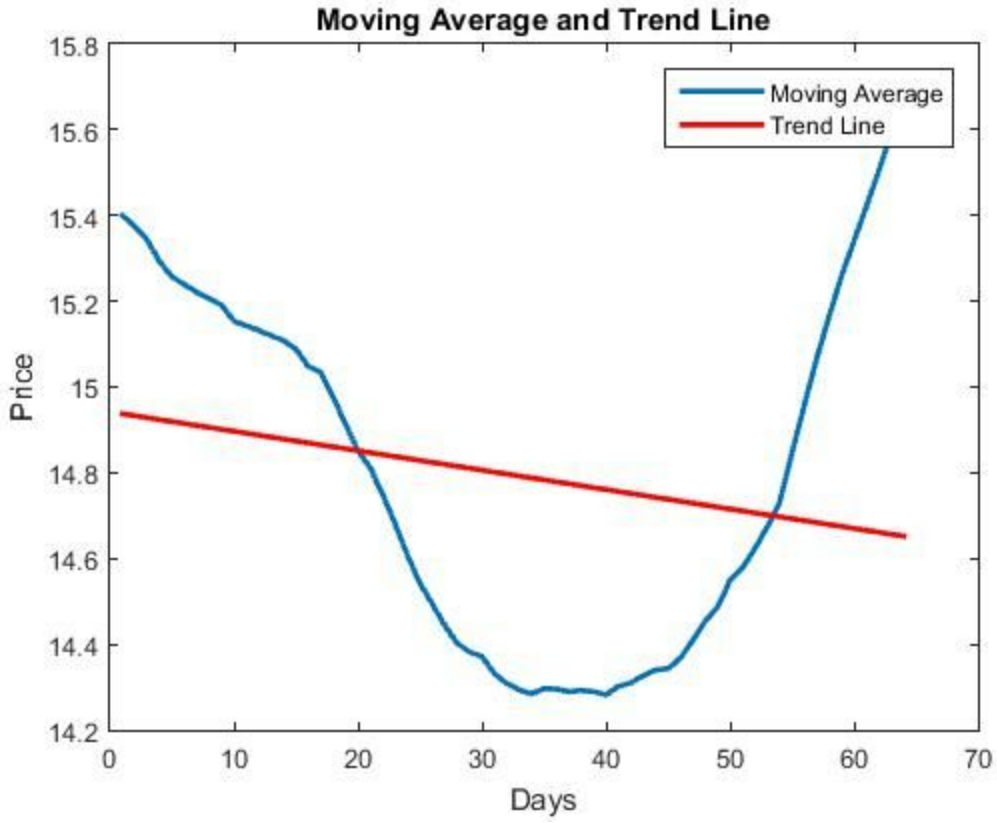
Prediction period: 12/01/2015-12/01/2015

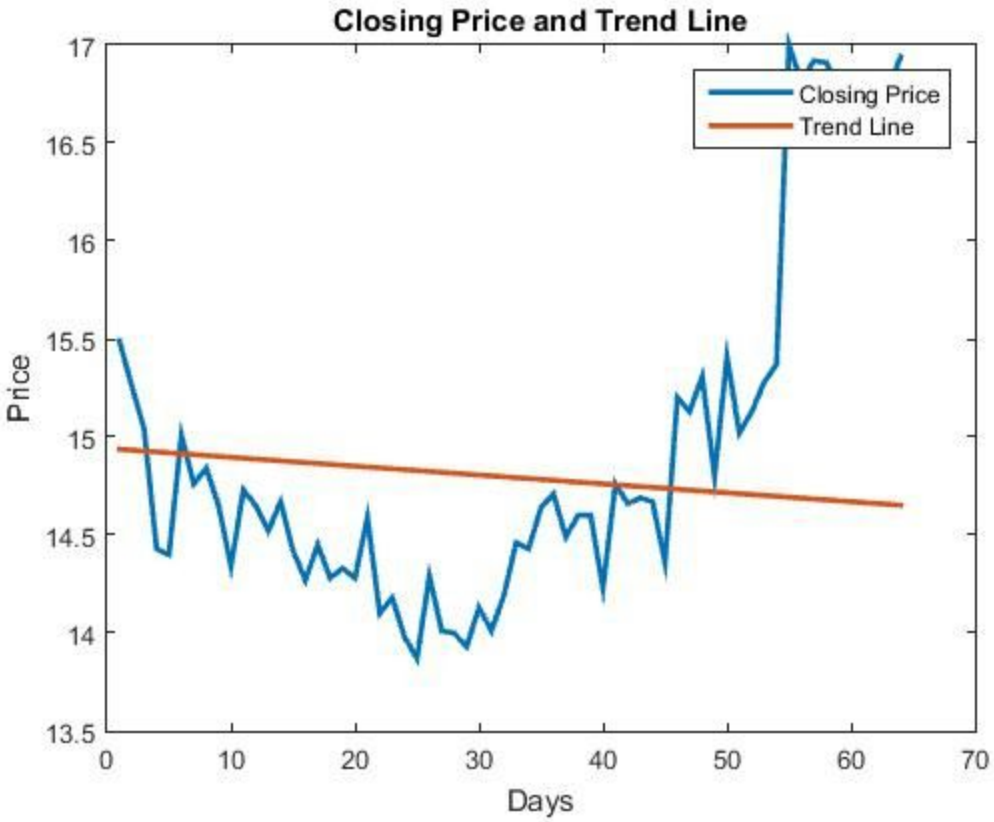
Window: 25

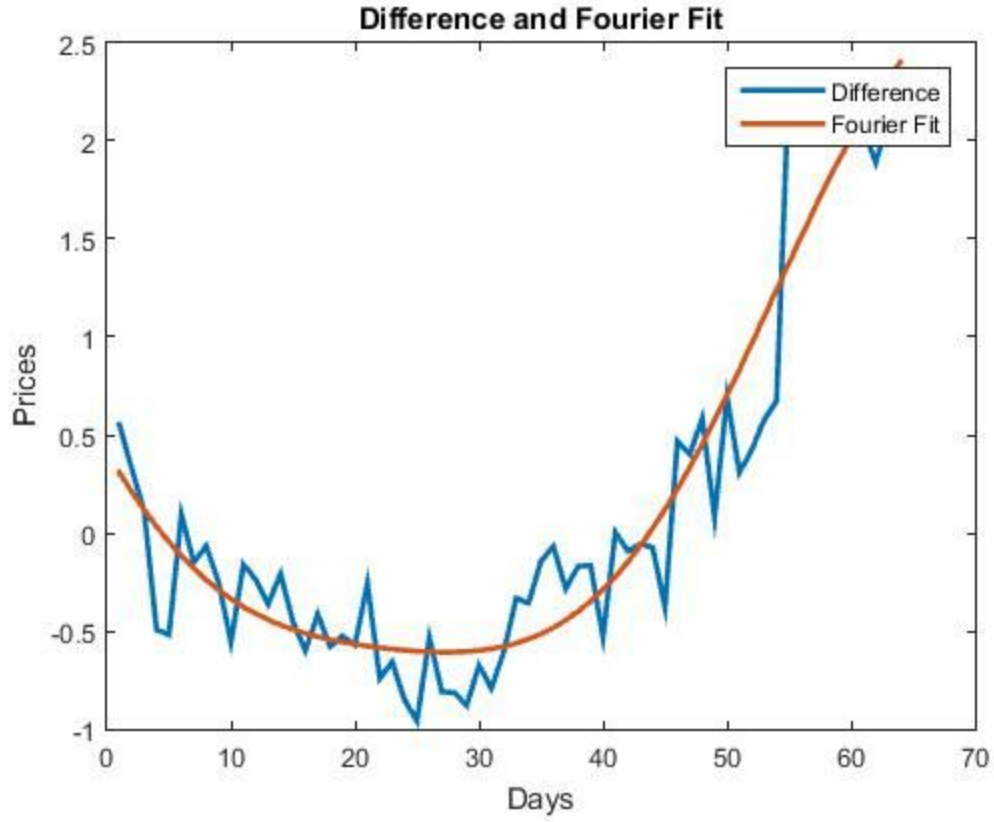
Correlation: -0.4426

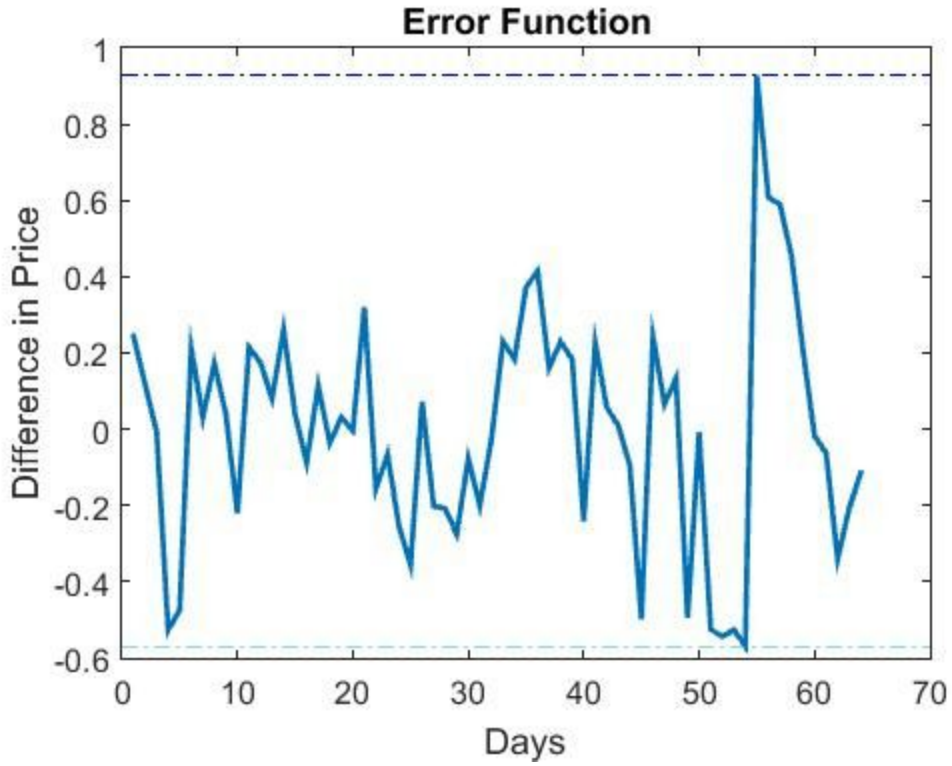


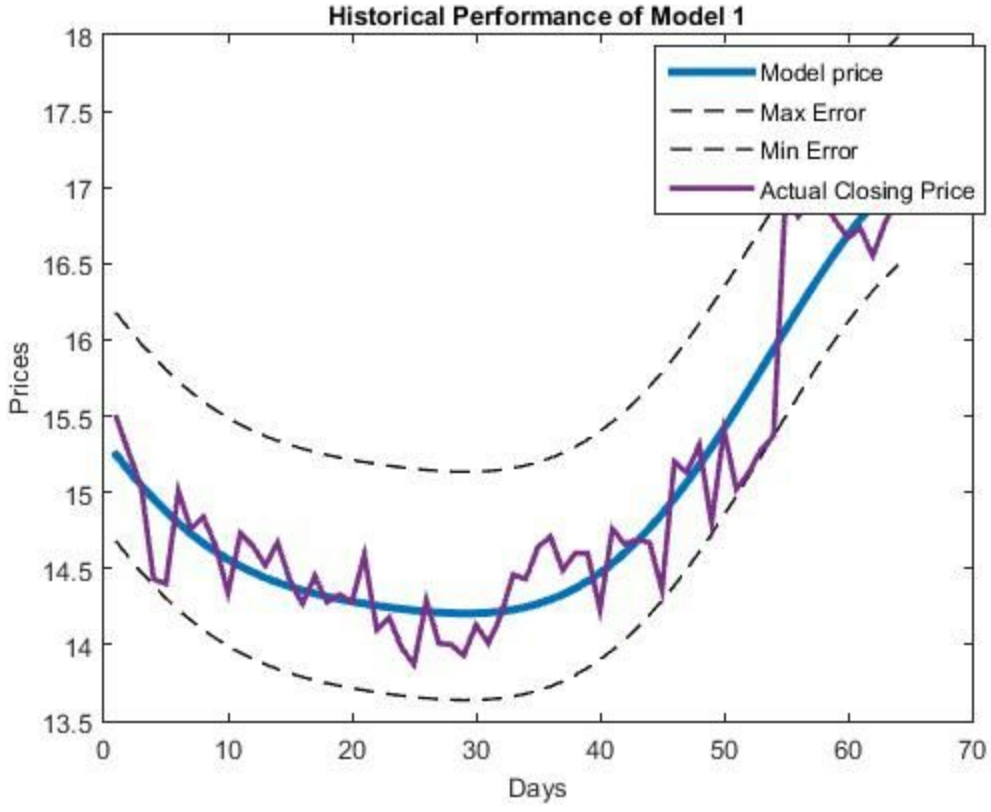

Autocorrelation Function
Autocorrelation
Lag(Days)
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
50
100
150
200


Moving Average and Trend Line
Moving Average
Trend Line
Price
Days
15.8
15.6
15.4
15.2
15
14.8
14.6
14.4
14.2
0
10
20
30
40
50
60
70


Closing Price and Trend Line
Closing Price
Trend Line
Price
Days
17
16.5
16
15.5
15
14.5
14
13.5
0
10
20
30
40
50
60
70


Difference and Fourier Fit
Difference
Fourier Fit
Prices
Days
2.5
2
1.5
1
0.5
0
-0.5
-1
0
10
20
30
40
50
60
70


Error Function
Difference in Price
Days
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
0
10
20
30
40
50
60
70


Historical Performance of Model 1
Model price
Max Error
Min Error
Actual Closing Price
Prices
Days
18
17.5
17
16.5
16
15.5
15
14.5
14
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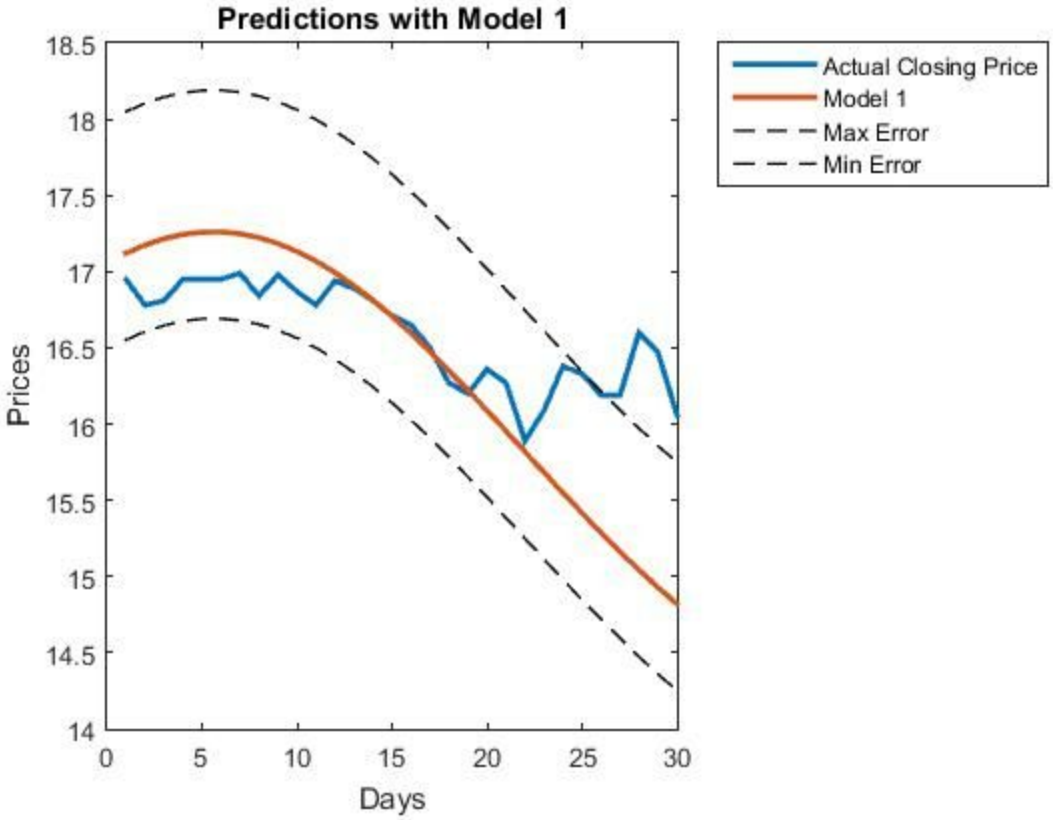
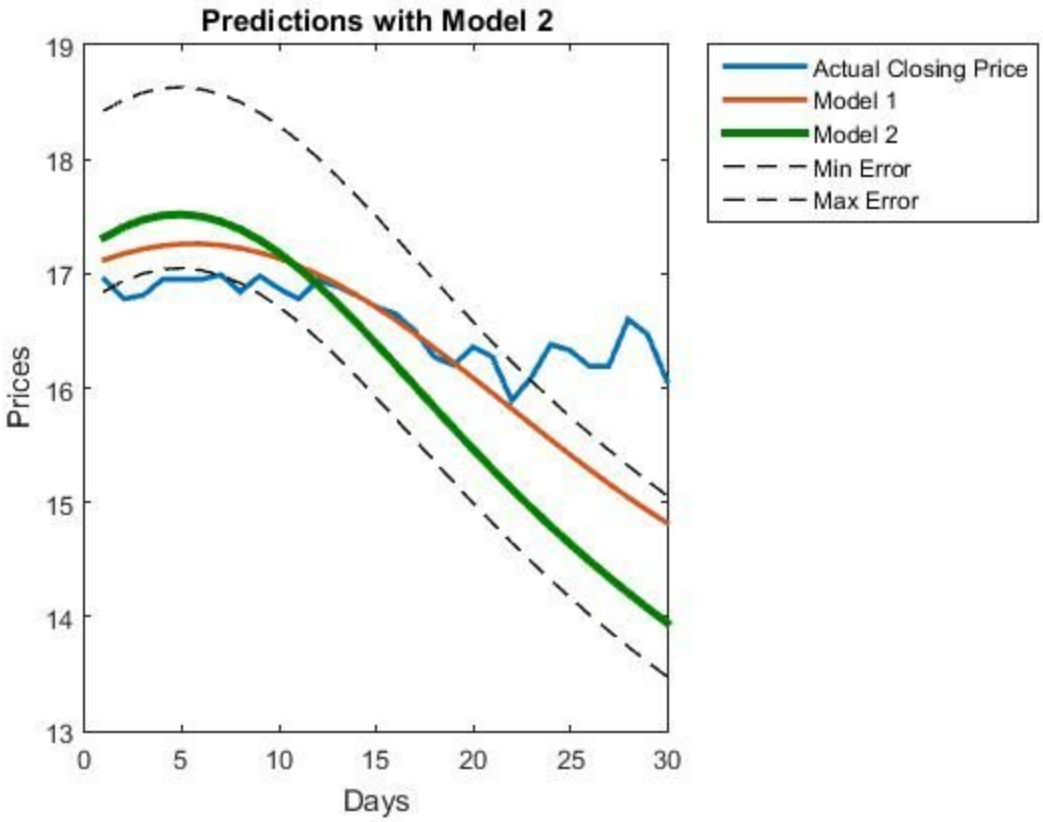


Max Error: +8.3%

Min Error: -8.3%



Max Error: +8.3%

Min Error: -8.3%

Results and Analysis

- Petroleum Sector

Table of days within error margins

Stock	Model 1 (Days)	Model 2 (Days)
Chevron Corporation (CVX)	0	30
Phillips 66 (PSX)	20	18
Alon USA Partners LP(AlDW)	22	18
Tesoro Corporation(TSO)	23	12
Valero Energy Corporation(VLO)	23	12

In these 5 stocks we chose, 4 of them(ALDW, PSX, TSO, VLO) have a negative correlation with the index, and Model 1 works better than Model 2 on those stocks. On the contrary, Model 1 completely fails on CVX, which has a strong and positive correlation with this index. From these results, we could find that in the petroleum sector, the correlation between the stock and the index determines which model works better for that stock. This observation is helpful for building models of stocks in the petroleum sector.

Chevron Corporation (CVX):

Our Model 1 failed completely on predicting this stock. On the contrary, Model 2 worked perfectly well(100% confidence interval) since CVX has a very strong correlation with the index (about 0.8). The future closing price falls in the error margin for entire predicting period. However, the error bounds in Model 2 are large (10% and -8.5%). Overall, this stock is relatively easy to predict if we have an accurate prediction for the index.

Phillips 66 (PSX) :

The correlation between PSX and the index is negative and small (about -0.3), therefore, the results from Model 1 and Model 2 are close to each other. Both models were more accurate for the first 20 days of prediction and went too high compared to the actual closing price. Model 1 performed better and had a 66.7% confidence interval. We could conclude that this stock cannot be predicted for a long period of time.

Alon USA Partners LP(AlDW):

ALDW has a lot of fluctuation, according to the plot of the closing price. And it also has a negative correlation with the index (about -0.5). Model 1 and Model 2 are close to each other, except that Model 2 went higher in the end of the predicting period. Similar to the results for PSX, both models are accurate for the first 20 days of predicting period, and Model 1 works a little better than Model 2. The confidence interval of the prediction using Model 1 is about 73%. However, the error bounds are very large (8% and -12%). We could then conclude that this stock could only be predicted for less than 20 days.

Tesoro Corporation(TSO):

TSO has a large and negative correlation with the index (about -0.7), so Model 2 is not working so well on TSO. Instead, Model 1 works better and have about 77% confidence interval. Model 1 could capture the trend of the future closing price for the entire prediction period, and only few days went above the error margin. The error bounds of Model 1 are also small compared to others (7% and -7%). Overall, Model 1 made an accurate prediction for this stock and the prediction could probably remain accurate for a longer period.

Valero Energy Corporation(VLO):

Similar to TSO, VLO also has a large and negative correlation with the index (about -0.6). Model 1 also works better than Model 2 for this stock and the confidence interval is about 77%. In both Model 1 and Model 2, unlike other stocks, the prediction was more accurate for the last 10 days than at the beginning of the period. Thus, this stock is stable enough to predict for a longer period of time.

- Pharmaceutical Sector

Table of days within Error

Stock	Model 1 (Days)	Model 2 (Days)
Clovis Oncology (CLVS)	4	10
ACADIA Pharmaceuticals (ACAD)	6	20
Gilead Sciences(GILD)	2	30
uniQure N.V.(QURE)	29	27
Sarepta Therapeutics(SRPT)	5	6

Overall, Model 1 is not working so well, only one stock(QURE) has an accurate prediction; in Model 2, three stocks(ACAD, GILD, QURE) have relatively accurate results, because all the stocks chosen in the pharmaceutical sector have strong correlations with the NBI index. However, two stocks (CLVS, SRPT) do not have a good results in both models. This is because unexpected sudden changes of the stock price appeared in their prediction periods and our models are not able to predict those sudden changes.

Clovis Oncology (CLVS):

After announcing that the response rate on its lead cancer drug, Rociletinib, is less than previously reported, shares in Clovis Oncology (NASDAQ:CLVS) dropped 68.5% in November.

There might be a delay to the expected timeline for the FDA's decision on rociletinib, due to the FDA's rejection, or due to the FDA requiring additional studies proving rociletinib efficacy before approving it.

(Images From *Yahoo Finance*)

ACADIA Pharmaceuticals (ACAD):

The correlation between ACAD and the index is high (about 0.9), therefore, the results from Model 1 is bad, but Model 2 gives out a good prediction that is accurate for 20 days with a 66.7% confidence interval. We would conclude that the accuracy of the prediction of this stock depends mainly on the correlation with the index.

Gilead Sciences(GILD):

Using Model 2, the prediction is perfect since the confidence interval is 100%. The index improves the prediction a lot since the correlation between the stock and the index is high. The error margin is also relatively low (4.5% and -8.9%).

uniQure N.V.(QURE):

uniQure Announced a conference call and webcast to discuss third quarter financial results and released earnings on 11/23/2015, which caused the jump in stock price. This is a situation that we cannot know in advance. Besides this jump, the predictions given by Model 1 and Model 2 are very accurate, with confidence interval around 93%. The error margin of Model 1 is too large (30% and -30%).

Model 2 has a much smaller and reasonable error margin (10% and -10%).

Sarepta Therapeutics(SRPT):

BioMarin is the main competitor of Sarepta. The FDA panel gave largely negative opinions of BioMarin's drisapersen. Opinion was already mixed on whether the drug will be approved by its Dec. 27 FDA deadline, and in research notes Wednesday (Date), opinion shifted negatively. This is why the stock price of SRPT jumps at the 15th prediction days, which causes the prediction from both Models to be inaccurate. Also, the error margin is as large as 22% and -22%.

- Technology Sector

Table of days within Error

Stock	Model 1 (Days)	Model 2 (Days)
IPG Photonics (IPGP)	9	24
iRobot Corporation (IRBT)	20	23
Cisco Systems (CSCO)	16	24
Synaptics Inc (SYNA)	2	2
Verizon Communications (VZ)	3	27

Following the patterns before, Model 2 works well with these tech stocks, due to high correlations with NDXT. With the exception of Synaptics (SYNA), every stock was predicted at least reasonably. SYNA was one of the worst performances by any of our predictions, but this can happen with the unpredictability of the stock market, and the inherent limitations of our models.

IPG Photonics (IPGP):

Model 1 isn't very accurate with a roughly 30% confidence interval, but Model 2 captures the trend within 24 days (80% confidence interval), and only after becomes inaccurate. It is clear that for this stock at least, Model 2, which includes the NDXT index, makes the prediction more accurate. This is backed up by the fact that IPGP has a high correlation (0.7373) with the NDXT Index. Model 1 predicts a drop in price much greater than what actually ended up happening, while Model 2 predicts a more steady price change. This could reflect that Model 2 is better in situations with generally stable prices.

iRobot Corporation (IRBT):

The price for IRBT was keeping steady at first, so the initial few weeks for both models fit well. While both models predict a sharp increase afterwards, the price drops instead. Model 2 tends to follow the actual price closer after the prediction is wrong, which corresponds with a high correlation of 0.7737, which seems to validate the index's usefulness in modeling. The sharp decrease is hard to predict, and may be caused by any number of reasons, that we may not have the information to account for. Model 2 seems to maintain a closer prediction in the case that the price drops. This may indicate that in the case of a high correlation, Model 2 is more accurate even with unexpected changes.

Cisco Systems (CSCO):

Model 2 is much closer to the actual price than Model 1 was, especially after 2 weeks or so. This corresponds to a correlation of 0.7845, which follows the pattern of higher correlations working better with Model 2. Model 2 brings the confidence interval up from 53% up to 80%. Model 2 seems to predict consistent prices well, whereas Model 1 often seems to predict a significant change. It is difficult to know whether a significant change will happen or not, but Model 2 seems to be more reliable, especially if prices are expected to stay at a similar level.

Synaptics (SYNA):

Neither model is particularly good for this stock. This can happen due to the unpredictability of stock prices, and due to unforeseen circumstances that our models can't account for. For example, for Synaptics, this drop in stock performances coincides with the growth of their biggest competitor, Fingerprint Cards. Our model doesn't account for competitor performance, so this price drop is not projected.

Verizon Communications (VZ):

Verizon was chosen for analysis since it is one of the most stable tech stocks. Tech stocks tend to be more volatile than stocks from other sectors, which can be seen in the fluctuation in tech stock prices and predictions. In comparison, Verizon's consistency is clear from the performance of the stock in the 30 days, the price stays at roughly the same level throughout the prediction period. With a

high correlation of 0.8351, and Verizon's status as a major technology company, this suggests that Model 2 will work better. As predicted, Model 2 again depicts this consistency better than Model 1, and thus Model 2 for Verizon is relatively accurate for longer than for the other stocks.

- Information Technology and Electric Cars Sectors

Table of days within Error

Stock	Model 1 (Days)	Model 2 (Days)
Panasonic (PCRFY)	17	16
Sumitomo Mining (SMMYY)	29	18
Tesla (TSLA)	15	20
Toyota (TM)	29	27
XO Group (XOXO)	5	6

When building Model 2 we used different indices, NASDAQ for Tesla, XO Group and Panasonic, Dow Jones for Toyota and Sumitomo Mining, because these five companies are from different sectors, Tesla, XO Group and Panasonic belong to the technology sector and Sumitomo Mining and Toyota belong to the industry sector. In general, all of the stocks work well in both models. These companies are all cooperators in business so it is reasonable that they have the similar performances. However, most of the stocks have better performance in Model 1 than in Model 2, because the correlations between the stocks and index are weak or negative. (correlations: : -0.241, -0.4572, 0.1532, -0.3827, -0.4426)

Panasonic(PCRFY):

The correlation for Panasonic is -0.241. Panasonic is the main battery manufacturer for electric cars. At the same time, it is also a manufacturer for electronic devices. At the end of 2015, its competitors like Samsung came up with some new models. This dropped the stock price for Panasonic. The performances in Model 1 and Model 2 are quite similar, but Model 1 works a little better.

Sumitomo Mining (SMMYY):

The correlation for Sumitomo Mining is -0.4572. There are 29 days inside the prediction for Model 1, but taking a closer look at the prices on the final days in the prediction period, the predictions in model 2 are much closer to the actual prices, which could imply that the prediction would be work well in the next few days.

Tesla (TSLA):

The correlation for Tesla is 0.1532. The stock price has a significant increase at the end of the year because Tesla released a new model of car. In Nov.28, Tesla showed off the Model X.[11] Although this makes the price outside the prediction, it is not bad news. Tesla is the only stock has the positive correlation with the index, so it works better in Model 2 than in Model 1.

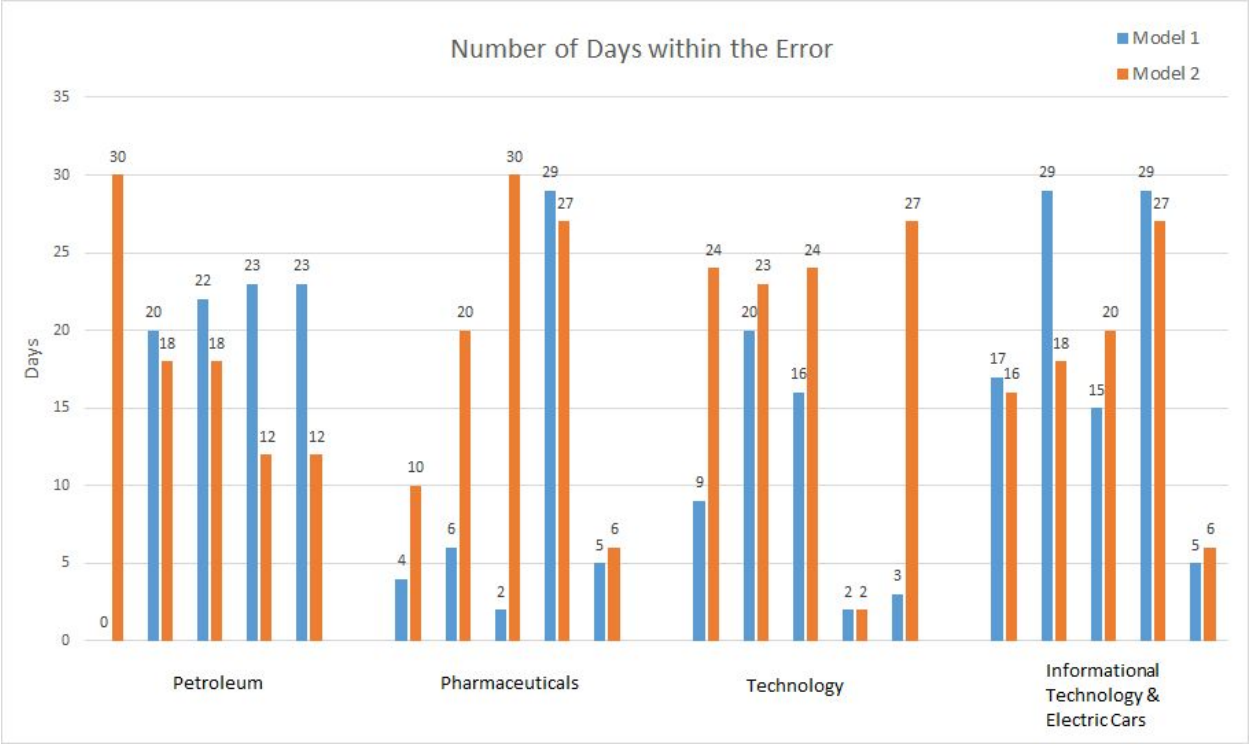
Toyota (TM):

The correlation for Toyota is -0.3827. There is fluctuation in the stock prices because there are a lot of influences for Toyota. (Returning problems, new models for Tesla, etc.) The trend for the prediction goes up but the stock at the end of prediction period is going down, however, the error margin is large so the price is still inside the prediction.

XO Group(XOXO):

The correlation for XO Group is -0.4426. The reason that XO Group was chosen for analysis was for its good sector performance. The fluctuation for the stock price is small, so it follows the trend in Model 1. After considering the index, the slope of the prediction becomes large, then the data at the end of the prediction period is outside the error.

Overall, our results can be demonstrated in the following chart.



The mean of Model 1 is 13.95 days with a standard derivation of 10.11 days.

The mean of Model 2 is 18.5 days with a standard derivation of 8.32 days.

Conclusion & Suggestions For the Future

The goal of our project is to provide a way to make short-term predictions in the stock market. Under the guidance of Professor Humi Mayer, we presented two different models and applied them to 20 individual stocks in four different sectors. With Model 1, 10 out of 20 stocks have more than 20 days within the prediction range. With Model 2, 12 out of 20 stocks have more than 20 days within the prediction range. From these results we can conclude that in general, Model 2 works better than Model 1 for the stocks we selected. However, most of stocks that works better in Model 2 have large and positive correlations with the index; and stocks that works better in Model 1 usually have negative correlations with the index. Therefore, we discover that the correlation between the stock and the index determines which model is better in predicting this stock. In order to get a more accurate prediction in a 30-day period, we recommend investors to choose stock which has a strong correlation with a related index and apply Model 2 to make the prediction, since our results show that Model 2 has better performance.

Our models could be improved by reducing the error margins of the prediction. Even though most of our stocks have more than 20 days within the error margins, some of them have very large error bounds(the largest error bounds were ±23%). We didn't investigate this issue due to time constraints, but we feel like this should be improved in a future project. A better prediction involves small error margins, otherwise the prediction would not be very helpful for investors.

Another shortcoming of our project is that we are not able to predict a sudden change of the stock market. In our application, we noticed that one of our stocks (CLVS) plunged more than 50 percent in one day. However, neither of our models was able to detect that plunge in advance. This phenomenon should also be investigated in a future project.

It is extremely difficult to make a perfect model that will accurately predict the prices of such a wide variety of stocks. The models we presented are just as a reference or tool to help investors make their decisions. It is strongly recommended that when using our models or any other tools, investors should combine them with

other available resources. THEIR USE IS COMPLETELY AT THE RISK OF THEIR USERS.

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