**SUMMER TRAINING REPORT**

**ON**

**"ARIMA Forecasting for Electric Vehicles Stocks Prices "**

Submitted to Shri Vishwakarma Skill University in partial

fulfilment of the requirement of the award of the

Degree of

Master of Business Administration

Submitted by:


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SKILL DEPARTMENT OF MANAGEMENT AND STUDIES,

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**Certificate of Internship**


14364000012672607

# Certificate of Completion

*presented to*

## Raj Kumar

has successfully completed one month Data Analytics certificate program cum internship on Thursday, Nov 02 2023 at Ybi Foundation

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**Introduction:-**

Electric vehicles (EVs) are vehicles that are powered by electricity stored in rechargeable batteries or obtained from an external source, such as through a power grid. Unlike traditional internal combustion engine vehicles that rely on gasoline or diesel, electric vehicles use electric motors for propulsion, providing a cleaner and more energy-efficient alternative.

Here's a brief overview of electric vehicles:

**1)Types of Electric Vehicles:**

a) **Battery Electric Vehicles (BEVs):** These vehicles run entirely on electric power stored in rechargeable batteries. They do not have an internal combustion engine and produce zero tailpipe emissions.

b) **Plug-in Hybrid Electric Vehicles (PHEVs):** PHEVs have both a conventional internal combustion engine and an electric motor. They can operate in electric-only mode for a certain distance before switching to the internal combustion engine or using both for longer ranges.

**2)Component**

a) **Electric Motor:**

The primary source of propulsion in EVs. Electric motors are known for their efficiency and instant torque delivery.

b) **Battery Pack:**

Stores the electric energy that powers the vehicle. The capacity of the battery determines the range an EV can travel on a single charge.

c) **Power Electronics:**

Convert the electric energy from the battery to the form needed to drive the electric motor.

d) **Charging System:**

Allows the battery to be recharged. Charging can be done at home, at charging stations, or through fast-charging ne

**3)Advantage**

a. **Environmental Benefits:** EVs produce lower or zero emissions, reducing air pollution and greenhouse gas emissions.
b. **Energy Efficiency:** Electric motors are more efficient than internal combustion engines, leading to better energy utilization.
c. **Reduced Dependence on Fossil Fuels:** As the electricity grid becomes cleaner and more renewable, the overall environmental impact of EVs continues to improve.

**4)Challenges:**

a) **Range Anxiety:** Concerns about the limited range of some EVs on a single charge, though advancements in battery technology are addressing this.
b) **Charging Infrastructure:** The availability and convenience of charging stations are crucial for the widespread adoption of EVs.
c) **Initial Cost:** While the cost of EVs is decreasing, initial purchase prices can still be higher than traditional vehicles, though this is often offset by lower operating costs over time.

**5)Market trends:**

The electric vehicle market has been experiencing rapid growth, driven by advancements in battery technology, supportive government policies, and increasing awareness of environmental issues.
Many major automakers are investing heavily in electric vehicle development, with a focus on expanding EV model offerings.

Forecasting stock prices is crucial for several reasons, Here are some key reasons why forecasting stock prices is important:

**Investment Decisions:** Investors rely on stock price forecasts to make informed investment decisions. Predictions about future stock movements help investors determine when to buy or sell stocks, manage their portfolios, and potentially maximize returns. **Risk Management:** Forecasting helps investors and financial institutions assess and manage risks. By understanding potential future stock price movements, investors can implement risk mitigation strategies and protect their investments.

**Portfolio Management:** Investors with diversified portfolios use stock price forecasts to optimize their asset allocation. Predicting which stocks are likely to perform well in the future allows for a more balanced and strategic portfolio.
**Valuation:** Stock price forecasting is closely tied to the valuation of companies. Analysts use various methods to estimate the intrinsic value of stocks, and these valuations contribute to determining whether a stock is overvalued or undervalued.

**Financial Planning:** Individuals and institutions use stock price forecasts for financial planning purposes. This includes retirement planning, education funding, and other long-term financial goals. **Market Efficiency:** Efficient financial markets rely on the availability of information. Stock price forecasts contribute to market efficiency by incorporating expectations and information into stock prices, allowing investors to make decisions based on the most up-to-date information. **Corporate Decision-Making:** Companies use stock price forecasts to make strategic decisions, such as issuing new shares, buying back existing shares, or making acquisitions. Understanding how the market values their stock influences corporate actions.

**Economic Indicators:** Stock prices are often considered leading indicators of econo mic health. Changes in stock prices can reflect changes in investor sentiment and expectations about the future economic environment. **Market Sentiment:** Stock price forecasts also provide insights into market sentiment. Positive or negative expectations about a stock can influence overall market sentiment, affecting trading volumes and market dynamics. **Regulatory Compliance:** In regulated financial environments, institutions may be required to provide stock price forecasts and financial projections as part of compliance with reporting standards and regulations.

IN this project we are going to forecasting the electrical vehicles stock price with the help of "E view software" . and using ARIMA Model for forecasting, there are some objectives and scopes
The scope of a project using the ARIMA (Auto Regressive Integrated Moving Average) model involves time series forecasting. ARIMA is a popular statistical method for analyzing and forecasting time-series data. Here's the scope for a project using the ARIMA model:

**Project Scope: Objective:** The objective is to forecast future values of a time series variable using the ARIMA model. Use in domains such as finance, economics, sales, or any field where historical data is available. **Data Collection:** Identify and collect historical time-series data relevant to the project's objective. Ensure the data is clean, complete, and covers a sufficient time span for meaningful analysis.

**Data Exploration and Preprocessing:** Conduct exploratory data analysis (EDA) to understand the characteristics of the time series. Handle missing values, outliers, and ensure that the data is in a suitable format for time series analysis. **Model Selection:** Choose appropriate ARIMA model parameters based on the characteristics of the time series data. This involves determining the order of the autoregressive (AR), integrated (I), and moving average (MA) components. **Model Training:** Split the historical data into training and testing sets. Train the ARIMA model on the training set, adjusting model parameters as needed.

**Model Evaluation:** Evaluate the performance of the ARIMA model using the testing set. Common metrics for evaluation include Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). **Forecasting:** Apply the trained ARIMA model to make future forecasts. The forecasting horizon will depend on the specific needs of the project, whether short-term or long-term predictions.
**Visualization:** Present the results visually through graphs and charts. This could include the original time series data, predicted values, and confidence intervals. **Sensitivity Analysis:** Conduct sensitivity analysis to understand how changes in model parameters impact

**Limitation of using ARIMA model** While the ARIMA (Auto Regressive Integrated Moving Average) model is a powerful tool for time series forecasting, it comes with certain limitations. One significant limitation is its assumption of linearity in the underlying data patterns. ARIMA models are effective when dealing with linear trends and stationary time series, but they may struggle to capture more complex, non-linear relationships or abrupt changes in the data. Additionally, ARIMA models are sensitive to outliers and can be influenced by extreme values, impacting the accuracy of predictions. Another constraint is that ARIMA models may not perform optimally when dealing with datasets that exhibit irregular or non-seasonal patterns. Moreover, the model's reliance on historical data for forecasting might make it less suitable for scenarios where sudden and unforeseen events significantly impact the time series. Despite these limitations, ARIMA models remain a valuable tool in time series analysis, especially when applied to datasets that align with its assumptions and in situations where the underlying patterns are relatively stable and linear over time. Consideration of these limitations is essential when choosing an appropriate forecasting method, and in cases where data exhibits non-linear patterns or frequent irregularities, alternative models or a combination of methods may be more suitable.

**ARIMA Model significant importance** The ARIMA (Auto Regressive Integrated Moving Average) model holds significant importance in the realm of time series analysis and forecasting. Its relevance stems from its ability to capture and model temporal dependencies in data, making it a valuable tool in predicting future values based on historical observations. ARIMA is particularly well-suited for datasets exhibiting trends and seasonality, providing a systematic framework for understanding and forecasting patterns over time. The model's versatility lies in its adaptability to various types of time series data, enabling analysts and researchers to make informed predictions across diverse fields such as finance, economics, epidemiology, and more.

One key advantage of the ARIMA model is its simplicity and interpretability. The model's parameters (autoregressive, integrated, and moving average components) are intuitively linked to specific characteristics of the time series, facilitating a clear understanding of the underlying processes. This simplicity also enhances the model's accessibility, making it a valuable tool for both experts and those new to time series analysis.

ARIMA's importance further extends to its role as a benchmark model. While more sophisticated models exist, ARIMA serves as a foundational approach, often used as a baseline for comparison when evaluating the performance of more complex forecasting techniques. This benchmarking helps researchers assess whether the additional complexity of advanced models provides a meaningful improvement in predictive accuracy.

In conclusion, the ARIMA model matters due to its adaptability, simplicity, and effectiveness in capturing temporal patterns. Its widespread application in diverse fields and its role as a benchmark model highlight its enduring relevance in the field of time series forecasting. As researchers continue to explore innovative approaches, ARIMA remains a fundamental tool for understanding and predicting trends in sequential data.

**how we organise ARIMA model** Organizing the ARIMA (Auto Regressive Integrated Moving Average) model involves a systematic process to leverage its capabilities for time series forecasting. The first step is to gather and preprocess the relevant time series data. This may include addressing missing values, handling outliers, and ensuring the data is stationary, a crucial assumption for ARIMA models.

Following data preparation, the next step is exploratory data analysis (EDA), which involves examining the time series for trends, seasonality, and other patterns. EDA helps guide decisions on differencing, an integral part of the ARIMA model. Differencing transforms the time series data to achieve stationarity, reducing or eliminating trends and seasonality.

Once the data is stationary, model selection becomes paramount. Determining the appropriate orders for autoregressive (AR) and moving average (MA) components is crucial. This involves analyzing autocorrelation and partial autocorrelation plots to identify the lags that significantly impact the time series.

After determining the orders, the ARIMA model is trained using historical data. This involves estimating parameters and validating the model's performance. Hyperparameter tuning may be necessary to optimize the model's accuracy, involving adjustments to the order of differencing or the number of AR and MA terms.

Validation and testing follow, where the model's performance is assessed on a separate dataset not used during training. This step ensures the model's ability to generalize to new, unseen data. Once validated, the ARIMA model is ready for forecasting, providing predictions for future values based on the learned patterns in the historical data.

Performance evaluation metrics, such as Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE), are used to quantify the accuracy of the model's predictions. Documentation of the entire process, including data sources, preprocessing steps, and model selection rationale, is essential for transparency and reproducibility.

In summary, organizing an ARIMA model involves a structured approach from data preparation through model selection, training, validation, and ultimately forecasting. The iterative nature of the process, coupled with thorough documentation, ensures a robust and well-understood forecasting tool for time series analysis.

**Literature review**

**Why it has worth:** Investing in electric vehicle (EV) stocks is increasingly considered a worthy venture due to the transformative impact of the global shift towards sustainable and environmentally friendly transportation. The rise of electric vehicles represents a significant response to the challenges of climate change and the depletion of fossil fuel resources. As governments worldwide implement policies to encourage the adoption of EVs and consumers increasingly prioritize eco-friendly options, the electric vehicle market is poised for substantial growth. Companies involved in the production of electric vehicles, as well as those contributing to the development of EV-related technologies, stand to benefit from this trend. The growing demand for electric vehicles not only reflects a commitment to cleaner energy but also presents a lucrative opportunity for investors. However, as with any investment, it's crucial for investors to conduct thorough research, consider market dynamics, and stay informed about the evolving landscape of the electric vehicle industry. The potential for significant returns exists, but it is essential to approach electric vehicle stocks with a balanced understanding of the risks and opportunities associated with this dynamic and rapidly evolving sector.

**The problem addressed by employing an ARIMA** (Auto Regressive Integrated Moving Average) model lies in the realm of time series forecasting. Time series data often exhibits complex patterns, trends, and seasonality, making accurate predictions challenging. The ARIMA model aims to address this challenge by capturing and modeling the autocorrelation, differencing, and moving average components inherent in time series data. The problem statement centers on the need to predict future values in a time series based on historical observations, with the understanding that conventional statistical methods might fall short in capturing the intricacies of the data. The ARIMA model, through its combination of autoregressive and moving average components, as well as differencing operations, provides a framework for mitigating the impact of these complexities. However, the effectiveness of the ARIMA model depends on the appropriateness of its parameter selection and the assumption that the underlying data follows a stationary trend. Therefore, the problem extends to optimizing the model's parameters and ensuring its suitability for capturing the dynamics of the specific time series under consideration.

**When using an ARIMA** (Auto Regressive Integrated Moving Average) model for forecasting stock prices, several key terms are important to understand:

**ARIMA Model:**

ARIMA stands for Auto Regressive Integrated Moving Average. It is a time series forecasting model that combines autoregression (AR), differencing (I), and moving average (MA) components to capture and predict patterns in time series data.

**Autoregressive (AR) Component:**

The autoregressive component represents the relationship between the current observation and its past observations. The "p" in ARIMA(p, d, q) denotes the order of the autoregressive component.

**Integrated (I) Component:**

The integrated component refers to the differencing of the time series data to make it stationary. The "d" in ARIMA(p, d, q) represents the order of differencing.

**Moving Average (MA) Componen**t:

The moving average component represents the relationship between the current observation and a residual error from a moving average process. The "q" in ARIMA(p, d, q) denotes the order of the moving average component.

**Stationarity:**

Stationarity is a key assumption of ARIMA models. It implies that statistical properties of a time series, such as mean and variance, remain constant over time. Differencing is applied to achieve stationarity.

**Order of Differencing (d):**

Differencing involves taking the difference between consecutive observations. The order of differencing, denoted by "d," indicates how many times differencing is applied to make the data stationary.

**Seasonal ARIMA (SARIMA):**

SARIMA is an extension of the ARIMA model that incorporates seasonality. It includes additional seasonal components (P, D, Q) to address patterns that repeat at regular intervals.

**Residuals:**

Residuals are the differences between the observed values and the values predicted by the ARIMA model. Analyzing residuals is important to assess the model's performance and identify areas for improvement.

**Training and Testing Data:**

Training data is used to estimate the parameters of the ARIMA model, while testing data is used to evaluate its performance. The model's accuracy is assessed by comparing its predictions to the actual values in the testing dataset.

**Forecast Horizon:**

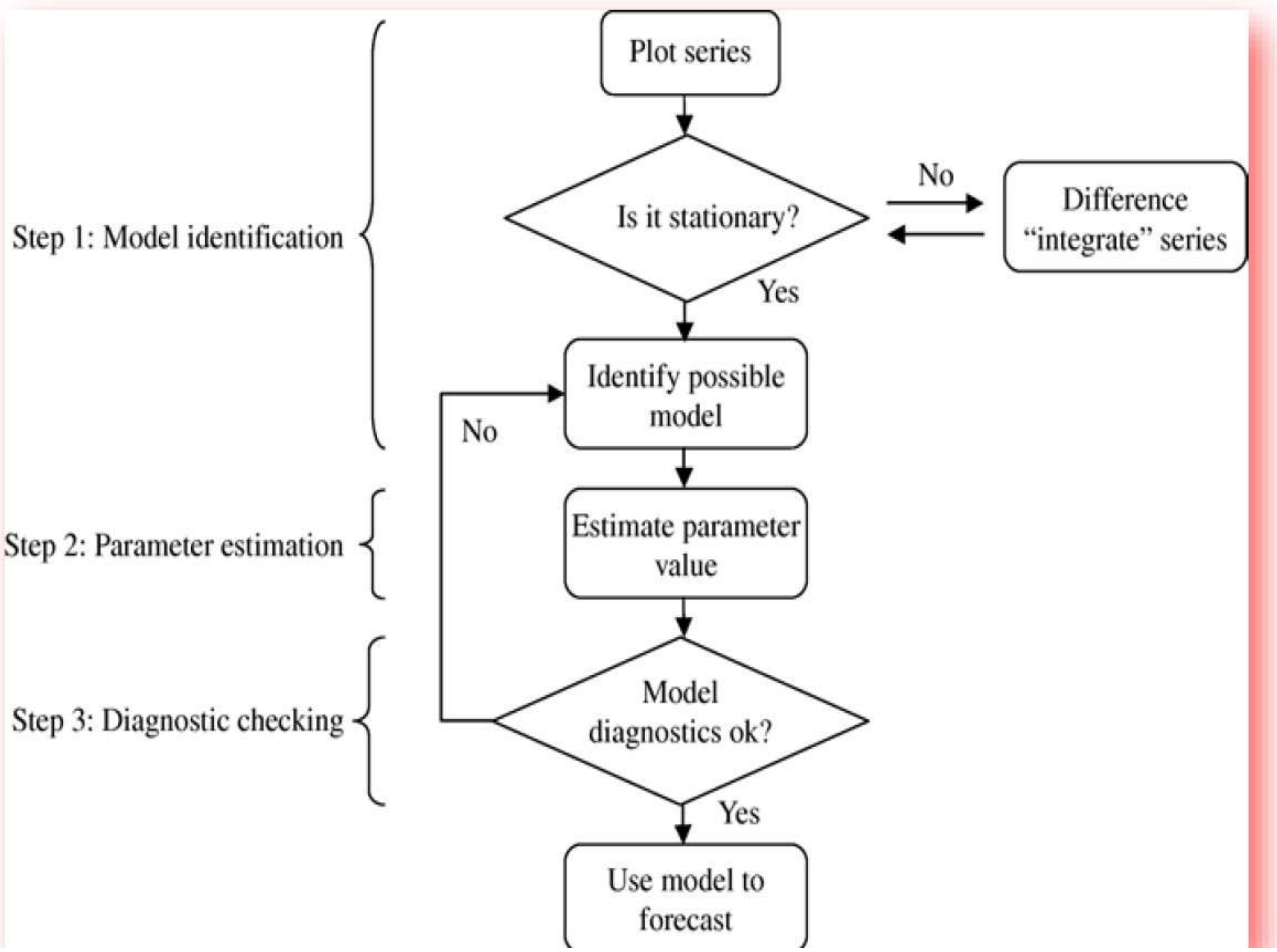
The forecast horizon represents the number of future time periods for which the ARIMA model predicts values. It is important to consider the appropriate forecast horizon based on the objectives of the analysis.

Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE):

These are commonly used metrics to measure the accuracy of the ARIMA model by comparing predicted values to actual values in the testing dataset.

Overview There has been a rapid increase in the demand for electric vehicles across the globe and so are their stock prices. The companies, like Mahindra and Hyundai have seen a rise and fall in their stock prices over a period of time. Various models have been used by researchers/analysts in this field for the stock price prediction using econometrics models, deep learning techniques using LSTM, RNN, etc. The purpose of this paper is to predict the stock prices of these two electric vehicles (along with their stock closing prices). The econometric model, ARIMA (p, d, q) in particular, has been fitted to predict the stock prices of electric vehicles. The ARIMA (p, d, q) model helps in forecasting by converting the non-stationary data into stationary one using the differencing technique.. In this project, we will predict the stock prices of electric vehicles by extrapolating the data to a future time period and then compare the forecasting accuracy. In terms of the managerial implications, the prediction is expected to help the case companies for better optional planning and execution.

# Box-Jenkins Approach can be summarized as …



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**Title:-** Forecasting Charging Demand of Electric Vehicles Using Time-Series Models

**Summery:-** This study compared the methods used to forecast increases in power consumption caused by the rising popularity of electric vehicles (EVs). An excellent model for each region was proposed using multiple scaled geographical datasets over two years. EV charging volumes are influenced by various factors, including the condition of a vehicle, the battery's state-of-charge (SOC), and the distance to the destination. However, power suppliers cannot easily access this information due to privacy issues. Despite a lack of individual information, this study compared various modeling techniques, including trigonometric exponential smoothing state space (i.e., Trigonometric, Box– Cox, Auto-Regressive-Moving-Average (ARMA), Trend, and Seasonality (TBATS)), autoregressive integrated moving average (ARIMA), artificial neural networks (ANN), and long short-term memory (LSTM) modeling, based on past values and exogenous variables. The effect of exogenous variables was evaluated in macro- and micro-scale geographical areas, and the importance of historic data was verified. The basic statistics regarding the number of charging stations and the volume of charging in each region are expected to aid the formulation of a method that can be used by power supplier

**Conclusion:-** This study examined a model that shows the best results when using only past data and public data due to privacy issues. The results were presented in the geographical scales of a nation, city, and station using actual measured data for applicability to other areas. Therefore, analyzing multivariate models of ARIMA, ANN, and LSTM showed higher accuracy than univariate models. However, in single station data, exogenous variables did not significantly influence accuracy because individual behavior is an important factor in determining consumption. Therefore, in order to increase the predictive power in microunits, privacy issues must be resolved

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**Title:-** Time-series Forecasting of Stock Prices using ARIMA: A Case Study of TESLA and NIO

**Summery:-** There has been a rapid increase in the demand for electric vehicles across the globe and so are their stock prices. The companies, like TESLA and NIO, have seen a rise and fall in their stock prices over a period of time. Various models have been used by researchers/analysts in this field for the stock price prediction using econometrics models, deep learning techniques using LSTM, RNN, etc. The purpose of this paper is to predict the stock prices of these two electric vehicles (along with their stock closing prices). The econometric model, ARIMA (p, d, q) in particular, has been fitted to predict the stock prices of electric vehicles. The ARIMA (p, d, q) model helps in forecasting by converting the non-stationary data into stationary one using the differencing technique. Further, with the help of the ML algorithms, the model appropriately uses the data (training data) and then validates (testing data) in a fixed proportion. In this paper, we will predict the stock prices of electric vehicles by extrapolating the data to a future time period and then compare the forecasting accuracy. In terms of the managerial implications, the prediction is expected to help the case companies for better optional planning and execution

**Conclusion:-** This paper attempts to predict the future stock prices of TESLA and NIO using ARIMA. Using ARIMA modeling has been simple and the results have been promising. Further, more advancement can be done using SARIMAX, and various other ML (machine learning) algorithms like logistic regression, KNN, and Decision tree (CART), etc. The stock prices of companies depend upon current events, tweets, political news, and other factors. Hence, we can overcome these limitations by using Sentiment Analysis. Thus, we can develop a model which can be more accurate than the proposed model. Throughout the whole analysis and after forecasting the Closing prices for both TESLA and NIO, we observe that TESLA stock prices have been increasing at a fast rate than the NIO stock prices, whereas NIO has seen a plunge in its stock, which rings an alarm for NIO to do the several modifications required to be done. If TESLA keeps going with this increase in its stock prices, certainly it will give it more edge over its EV rivals like NIO and other companies globally.

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**Title:-** ARIMA MODEL FOR FORECASTING OIL PALM PRICE

**Summary:-** This research is a study model of forecasting oil palm price of Thailand in three types as farm price, wholesale price and pure oil price for the period of five years, 2000 – 2004. The objective of the research is to find an appropriate ARIMA Model for forecasting in three types of oil palm price by considering the minimum of mean absolute percentage error (MAPE). The results of forecasting were as follows: ARIMA Model for forecasting farm price of oil palm is ARIMA (2,1,0), ARIMA Model for forecasting wholesale price of oil palm is ARIMA (1,0,1) or ARMA(1,1), and ARIMA Model for forecasting pure oil price of oil palm is ARIMA (3,0,0) or AR(3)

**Conclusion:-** In this paper, we developed model for three types of oil palm price, were found to be ARIMA (2,1,0) for the farm price model, ARIMA(1,0,1) for whole sale price, and ARIMA(3,0,0) for pure oil price. Which we can see that the MAPE for each model very small.

**Objective:-**

Can we forecast Electric Vehicles stock prices by using ARIMA Model.

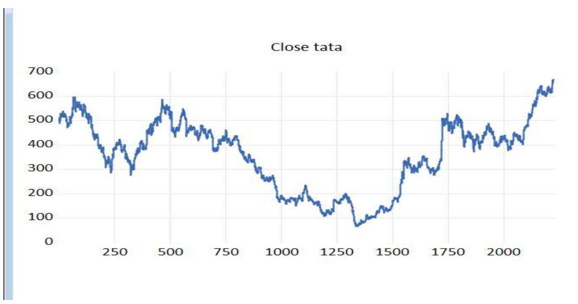
**Methodology**

Here past 10 years data of companies Tata, Mahindra, Hero, Hyundai and Bajaaj were collected.

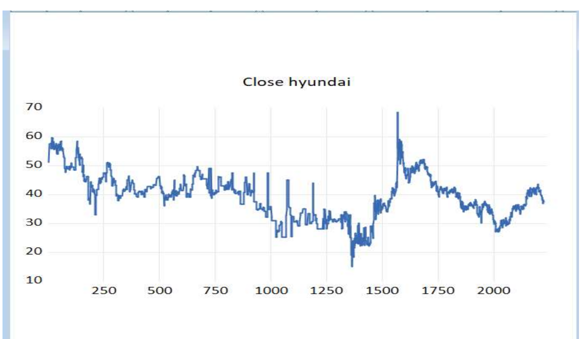
This time series historical data were collected from Yahoo finance between 20/10/2014 and 19/10/2023 time period. The ARIMA model has been fitted for forecasting.

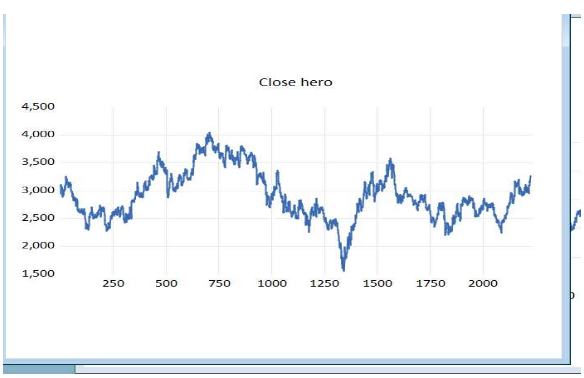
**Step 1**

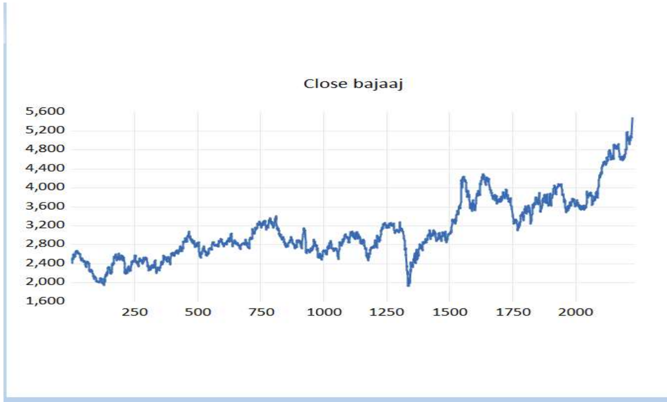
To observe variance and trend in the data, time series data has been plotted below










First, five companies' stock's closing price graphs have been plotted to check the stationarity of the data i.e whether the data fluctuates with respect to time or not. The graphs given above show fluctuation with respect to time i.e the mean and standard deviations keep on fluctuating with respect to time, hence we assume that the data is non-stationary.

**Correlogram of mahindra at diff 1**

A correlogram is a graphical representation of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of a time series. These functions help in understanding the correlation between observations at different time lags.

The order of the ARIMA model can often be determined by

examining the significant peaks in the ACF and PACF plots.

Common patterns include exponential decay in ACF for AR terms

and a sharp cutoff in PACF for MA terms.

The presence of seasonality may also be evident in the ACF and PACF plots at regular intervals.

The model is (5, 1, 20).

Date: 11/19/23 Time: 22:23
Sample (adjusted): 10/21/2014 10/19/2023
Included observations: 2220 after adjustments

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.002 | 0.002 | 0.0120 | 0.913 |
| | | 2 | 0.002 | 0.002 | 0.0201 | 0.990 |
| | | 3 | -0.032 | -0.032 | 2.3198 | 0.509 |
| | | 4 | 0.040 | 0.040 | 5.9018 | 0.207 |
| | | 5 | 0.056 | 0.056 | 12.834 | 0.025 |
| | | 6 | -0.017 | -0.018 | 13.464 | 0.036 |
| | | 7 | -0.022 | -0.019 | 14.502 | 0.043 |
| | | 8 | -0.005 | -0.003 | 14.565 | 0.068 |
| | | 9 | -0.006 | -0.012 | 14.658 | 0.101 |
| | | 10 | -0.009 | -0.012 | 14.825 | 0.139 |
| | | 11 | -0.006 | -0.003 | 14.904 | 0.187 |
| | | 12 | -0.016 | -0.014 | 15.451 | 0.218 |
| | | 13 | -0.065 | -0.065 | 24.875 | 0.024 |
| | | 14 | 0.008 | 0.010 | 25.027 | 0.034 |
| | | 15 | -0.019 | -0.018 | 25.803 | 0.040 |
| | | 16 | 0.027 | 0.024 | 27.480 | 0.036 |
| | | 17 | 0.017 | 0.024 | 28.103 | 0.044 |
| | | 18 | 0.017 | 0.022 | 28.776 | 0.051 |
| | | 19 | -0.025 | -0.027 | 30.169 | 0.050 |
| | | 20 | 0.044 | 0.043 | 34.484 | 0.023 |
| | | 21 | 0.004 | -0.000 | 34.517 | 0.032 |
| | | 22 | 0.002 | -0.005 | 34.528 | 0.043 |
| | | 23 | 0.005 | 0.008 | 34.578 | 0.057 |
| | | 24 | 0.023 | 0.024 | 35.815 | 0.057 |
| | | 25 | 0.047 | 0.040 | 40.806 | 0.024 |
| | | 26 | 0.025 | 0.023 | 42.252 | 0.023 |
| | | 27 | 0.017 | 0.021 | 42.876 | 0.027 |
| | | 28 | 0.007 | 0.005 | 42.975 | 0.035 |
| | | 29 | -0.010 | -0.010 | 43.179 | 0.044 |
| | | 30 | 0.011 | 0.010 | 43.450 | 0.053 |
| | | 31 | -0.038 | -0.037 | 46.629 | 0.035 |
| | | 32 | 0.036 | 0.034 | 49.530 | 0.025 |
| | | 33 | -0.045 | -0.037 | 54.080 | 0.012 |
| | | 34 | 0.018 | 0.016 | 54.818 | 0.013 |
| | | 35 | -0.038 | -0.031 | 58.024 | 0.009 |
| | | 36 | -0.053 | -0.054 | 64.453 | 0.002 |

**ADf test of mahindar at diff 1**

Null Hypothesis: D(CLOSE_MAHINDRA) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=26)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -46.99567 | 0.0001 |
| Test critical values: | 1% level | -3.433102 | |
| | 5% level | -2.862642 | |
| | 10% level | -2.567402 | |

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE_MAHINDRA,2)
Method: Least Squares
Date: 11/19/23 Time: 22:31
Sample (adjusted): 10/22/2014 10/19/2023
Included observations: 2218 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| D(CLOSE_MAHINDRA(-1)) | -0.997677 | 0.021229 | -46.99567 | 0.0000 |
| C | 0.440617 | 0.298062 | 1.478274 | 0.1395 |

| | | | |
|---|---|---|---|
| R-squared | 0.499163 | Mean dependent var | 0.022193 |
| Adjusted R-squared | 0.498937 | S.D. dependent var | 19.82199 |
| S.E. of regression | 14.03116 | Akaike info criterion | 8.121339 |
| Sum squared resid | 436271.3 | Schwarz criterion | 8.126483 |
| Log likelihood | -9004.565 | Hannan-Quinn criter. | 8.123218 |
| F-statistic | 2208.593 | Durbin-Watson stat | 1.999523 |
| Prob(F-statistic) | 0.000000 | | |

Here, we first check whether the time series data shows stationarity or not, to check this, two tests have been used ADF test: It is used to check whether the time series data has unit root i.e. whether the series is grossly under or over-differenced, hence checking the stationarity. Setting up the Null Hypothesis HO: Series has a unit root and alternative hypothesis H1: Series has no unit root.

Here p value less than 0.05

Then null hypothesis is rejected

So data is stationarity at diff 1 level

**Estimated equation of mahindra**

Dependent Variable: D(CLOSE_MAHINDRA)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/19/23 Time: 22:28
Sample: 10/21/2014 10/19/2023
Included observations: 2220
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.421652 | 0.328763 | 1.282539 | 0.1998 |
| AR(5) | 0.054679 | 0.018094 | 3.021864 | 0.0025 |
| MA(20) | 0.042777 | 0.021487 | 1.990787 | 0.0466 |
| SIGMASQ | 195.9162 | 3.508875 | 55.83448 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.004953 | Mean dependent var | 0.423592 |
| Adjusted R-squared | 0.003606 | S.D. dependent var | 14.03496 |
| S.E. of regression | 14.00964 | Akaike info criterion | 8.119195 |
| Sum squared resid | 434934.0 | Schwarz criterion | 8.129475 |
| Log likelihood | -9008.307 | Hannan-Quinn criter. | 8.122950 |
| F-statistic | 3.676606 | Durbin-Watson stat | 1.994029 |
| Prob(F-statistic) | 0.011699 | | |

| | | | | |
|---|---|---|---|---|
| Inverted AR Roots | .56 | .17+.53i | .17-.53i | -.45-.33i |
| | -.45+.33i | | | |
| Inverted MA Roots | .84-.13i | .84+.13i | .76+.39i | .76-.39i |
| | .60-.60i | .60+.60i | .39-.76i | .39+.76i |
| | .13-.84i | .13+.84i | -.13-.84i | -.13+.84i |
| | -.39-.76i | -.39+.76i | -.60-.60i | -.60-.60i |
| | -.76-.39i | -.76+.39i | -.84+.13i | -.84-.13i |

When we run the (5,1,20) model (p,d,q) we get ar and ma is significance because “p” value is less than 0.05 and coefficient of SIGMASQ is less than outher models also AIC and SIC is less than others and R-square is higher then we say our model is significance.

For checking our model is good fit or not for prediction

We check residuals diagnostic. For this we generate correlogram of residuals which is given below in next step.

Residuals diagnostic of mahindra company

Date: 11/19/23 Time: 22:30
Sample (adjusted): 10/21/2014 10/19/2023
Q-statistic probabilities adjusted for 2 ARMA terms

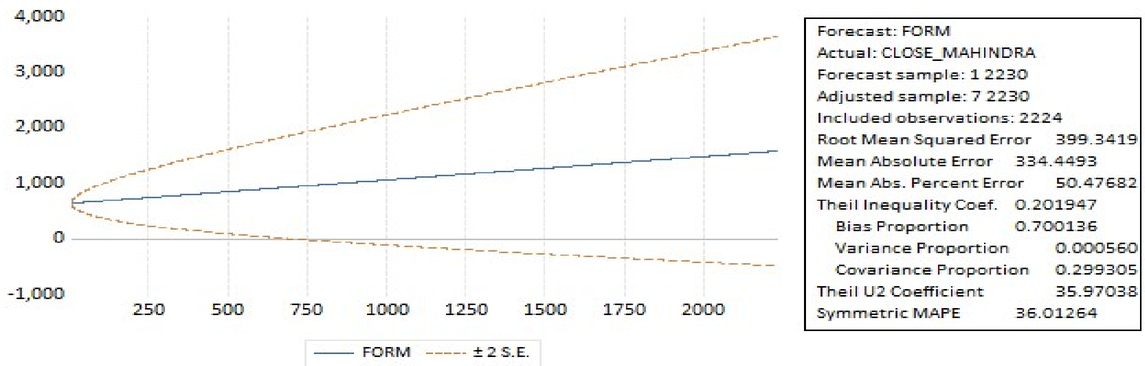
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.002 | 0.002 | 0.0109 | |
| | | 2 | 0.004 | 0.004 | 0.0468 | |
| | | 3 | -0.033 | -0.033 | 2.4920 | 0.114 |
| | | 4 | 0.038 | 0.038 | 5.7592 | 0.056 |
| | | 5 | 0.001 | 0.001 | 5.7604 | 0.124 |
| | | 6 | -0.018 | -0.020 | 6.5209 | 0.163 |
| | | 7 | -0.019 | -0.016 | 7.3222 | 0.198 |
| | | 8 | 0.000 | -0.001 | 7.3223 | 0.292 |
| | | 9 | -0.008 | -0.009 | 7.4721 | 0.381 |
| | | 10 | -0.011 | -0.011 | 7.7415 | 0.459 |
| | | 11 | -0.005 | -0.003 | 7.7931 | 0.555 |
| | | 12 | -0.017 | -0.018 | 8.4472 | 0.585 |
| | | 13 | -0.063 | -0.064 | 17.386 | 0.097 |
| | | 14 | 0.010 | 0.011 | 17.610 | 0.128 |
| | | 15 | -0.019 | -0.020 | 18.418 | 0.142 |
| | | 16 | 0.028 | 0.025 | 20.201 | 0.124 |
| | | 17 | 0.021 | 0.026 | 21.198 | 0.131 |
| | | 18 | 0.019 | 0.016 | 22.039 | 0.142 |
| | | 19 | -0.027 | -0.027 | 23.632 | 0.130 |
| | | 20 | 0.000 | -0.002 | 23.632 | 0.167 |
| | | 21 | 0.001 | -0.000 | 23.634 | 0.211 |
| | | 22 | 0.001 | -0.003 | 23.637 | 0.259 |
| | | 23 | 0.002 | 0.005 | 23.648 | 0.310 |
| | | 24 | 0.024 | 0.025 | 24.926 | 0.301 |
| | | 25 | 0.045 | 0.043 | 29.544 | 0.163 |
| | | 26 | 0.029 | 0.025 | 31.388 | 0.143 |
| | | 27 | 0.015 | 0.018 | 31.878 | 0.162 |
| | | 28 | 0.010 | 0.010 | 32.117 | 0.189 |
| | | 29 | -0.013 | -0.011 | 32.509 | 0.214 |
| | | 30 | 0.010 | 0.013 | 32.739 | 0.245 |
| | | 31 | -0.036 | -0.032 | 35.639 | 0.184 |
| | | 32 | 0.040 | 0.038 | 39.196 | 0.121 |
| | | 33 | -0.045 | -0.042 | 43.864 | 0.063 |
| | | 34 | 0.019 | 0.016 | 44.668 | 0.068 |
| | | 35 | -0.039 | -0.032 | 48.034 | 0.044 |
| | | 36 | -0.051 | -0.054 | 53.857 | 0.017 |

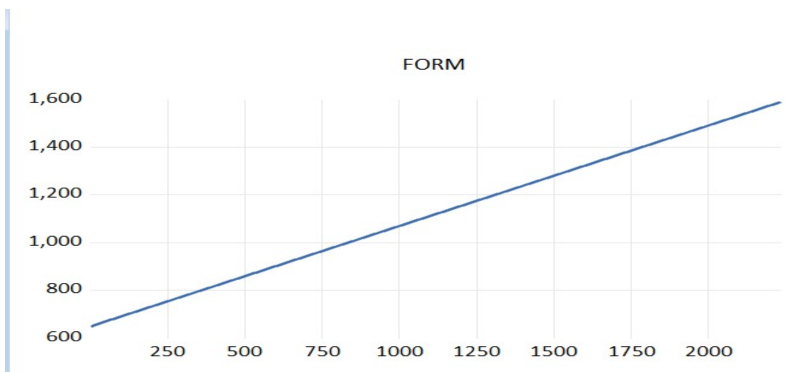
Q Plot (Quantile-Quantile Plot)

show the p value is greater than 0.05

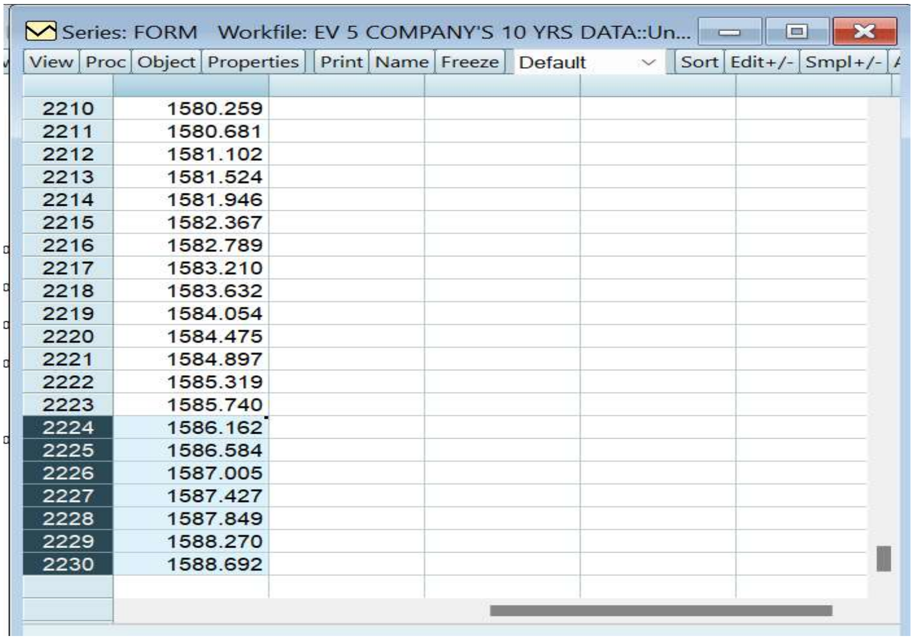
this show we can forecasted with the help of our model (5,1,20).Our model is good fit.

Forecasting of mahindra




The model has been designed to predict the closing stock prices for the next 7 days. The ARIMA model forecasts closing stock prices. This trend on upward direction show the close prices of mahindra company is increase it was also showed on the excel table



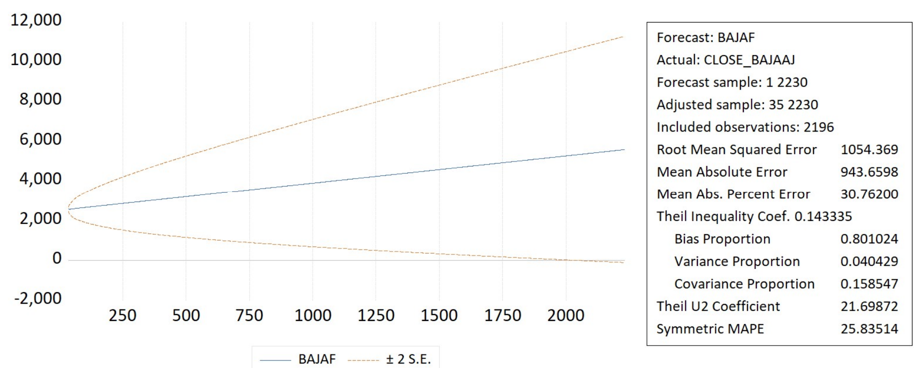
Series: FORM Workfile: EV 5 COMPANY'S 10 YRS DATA::Un...

View | Proc | Object | Properties | Print | Name | Freeze | Default | Sort | Edit+/- | Smpl+/-

| | |
|---|---|
| 2210 | 1580.259 |
| 2211 | 1580.681 |
| 2212 | 1581.102 |
| 2213 | 1581.524 |
| 2214 | 1581.946 |
| 2215 | 1582.367 |
| 2216 | 1582.789 |
| 2217 | 1583.210 |
| 2218 | 1583.632 |
| 2219 | 1584.054 |
| 2220 | 1584.475 |
| 2221 | 1584.897 |
| 2222 | 1585.319 |
| 2223 | 1585.740 |
| 2224 | 1586.162 |
| 2225 | 1586.584 |
| 2226 | 1587.005 |
| 2227 | 1587.427 |
| 2228 | 1587.849 |
| 2229 | 1588.270 |
| 2230 | 1588.692 |

Like Mahindra compony methodology we follow the same methodology for the rest of four company

**Then forecasted values and  graphs for bajaaj company stock close price**

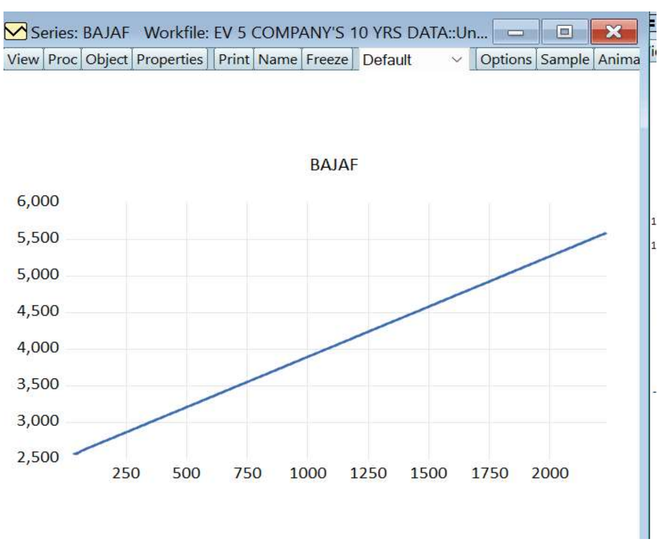


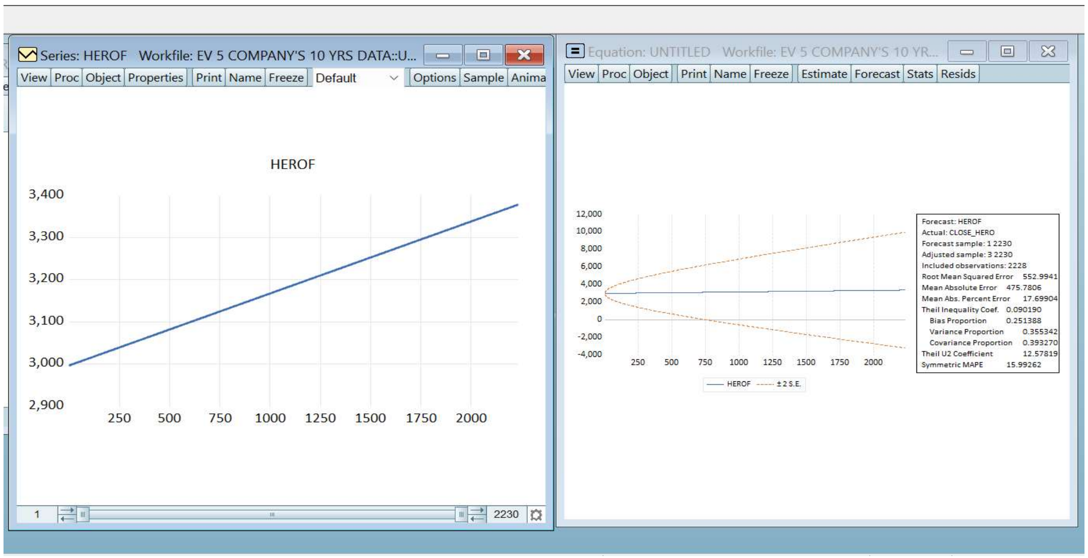
Series: BAJAF Workfile: EV 5 COMPANY'S 10 YRS DATA::Un...

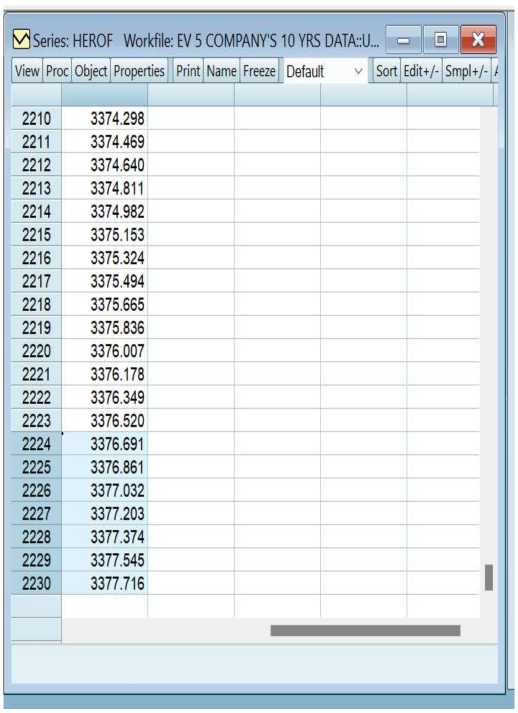
| | |
|---|---|
| 2210 | 5555.077 |
| 2211 | 5556.451 |
| 2212 | 5557.826 |
| 2213 | 5559.200 |
| 2214 | 5560.575 |
| 2215 | 5561.949 |
| 2216 | 5563.323 |
| 2217 | 5564.698 |
| 2218 | 5566.072 |
| 2219 | 5567.446 |
| 2220 | 5568.821 |
| 2221 | 5570.195 |
| 2222 | 5571.570 |
| 2223 | 5572.944 |
| 2224 | 5574.318 |
| 2225 | 5575.693 |
| 2226 | 5577.067 |
| 2227 | 5578.442 |
| 2228 | 5579.81[illegible] |
| 2229 | 5581.190 |
| 2230 | 5582.565 |

Forecasted values of bajaaj company

**Forecasted value and graph of Hero**

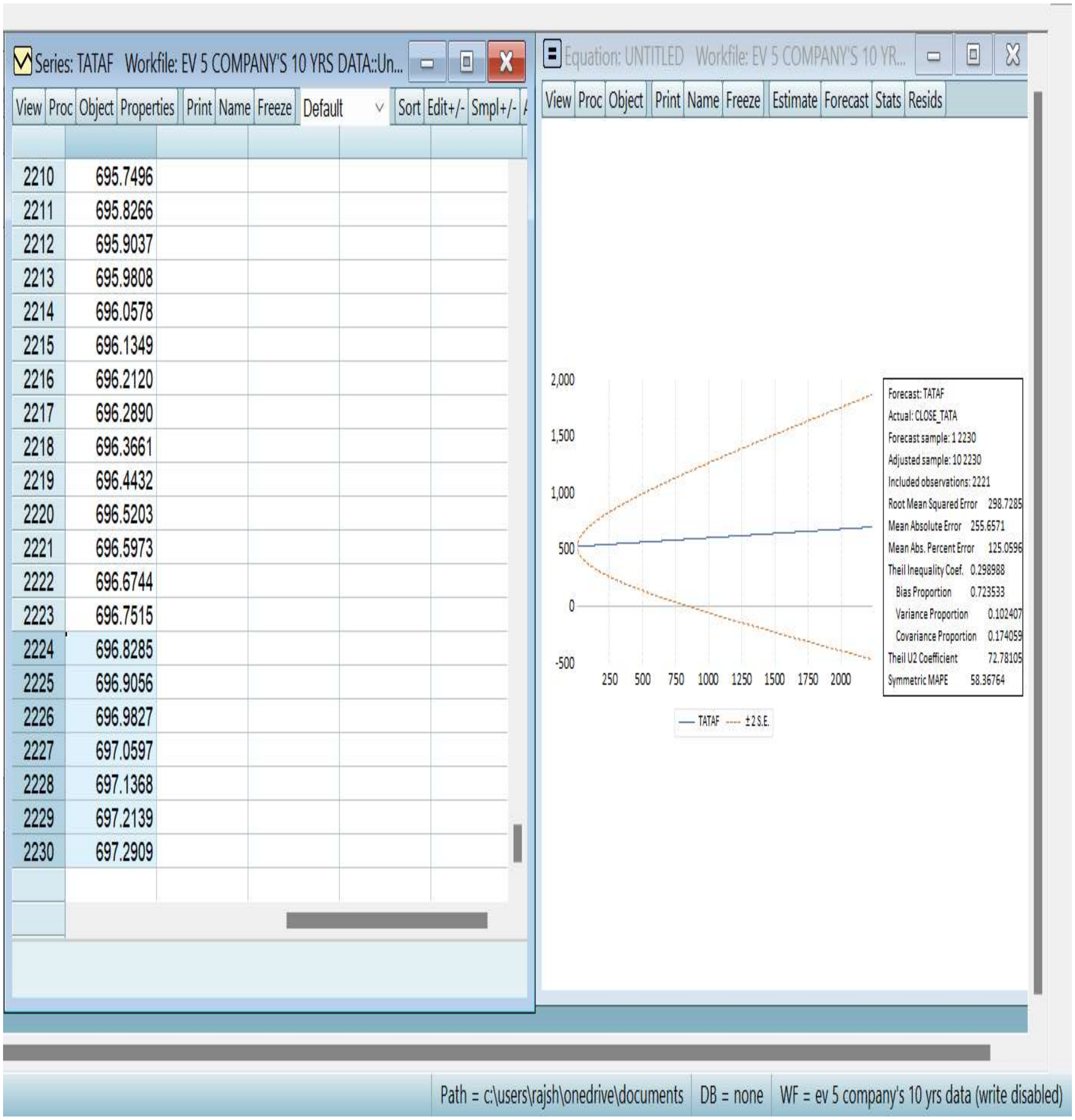


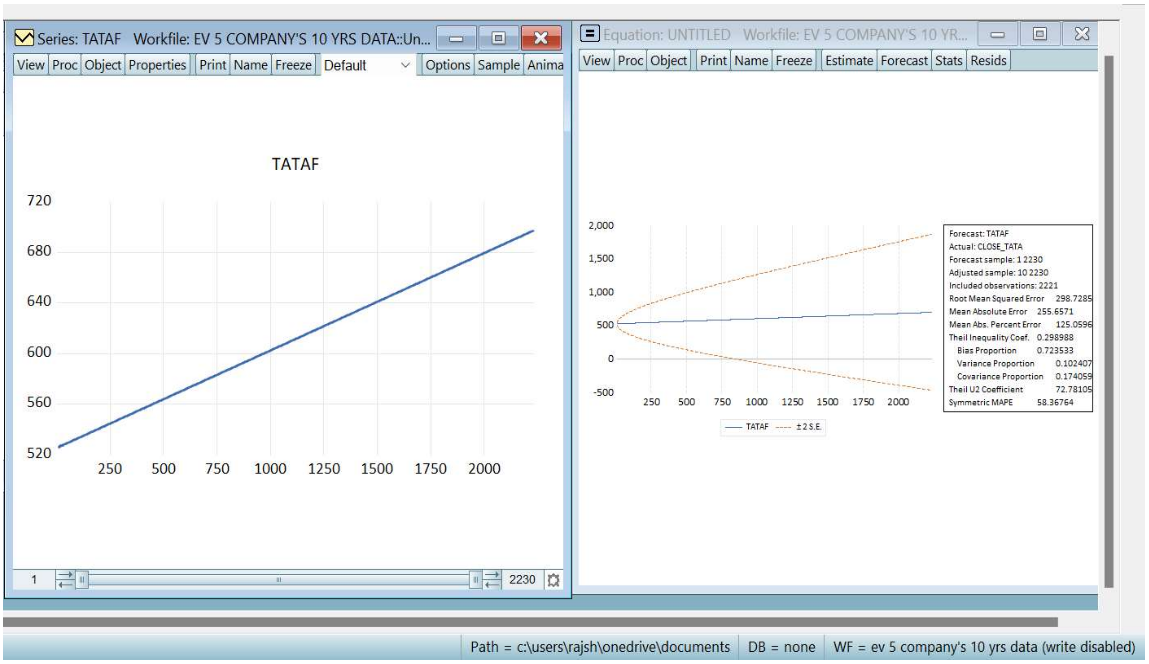



| | |
|---|---|
| 2210 | 3374.298 |
| 2211 | 3374.469 |
| 2212 | 3374.640 |
| 2213 | 3374.811 |
| 2214 | 3374.982 |
| 2215 | 3375.153 |
| 2216 | 3375.324 |
| 2217 | 3375.494 |
| 2218 | 3375.665 |
| 2219 | 3375.836 |
| 2220 | 3376.007 |
| 2221 | 3376.178 |
| 2222 | 3376.349 |
| 2223 | 3376.520 |
| 2224 | 3376.691 |
| 2225 | 3376.861 |
| 2226 | 3377.032 |
| 2227 | 3377.203 |
| 2228 | 3377.374 |
| 2229 | 3377.545 |
| 2230 | 3377.716 |

Forecasted value and graph of Tata






**Conclusion and direction for future research :-**

This paper attempts to predict the future stock prices of Mahindra, Hero, Hyundai, Bajaaj, and Tata electric vehicles using ARIMA. In summary, the conclusion of an ARIMA model involves a comprehensive evaluation of its fit, diagnostic checks, parameter significance, and forecasting performance.

With the help of ARIMA model we forecasted the close stock price of electric vehicles and found that the close stock price is increasing but in the case of Hyundai everything is ok but residuals not significant so for this company we can’t forecast the future value.

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