FUEL PRICE PREDICTION USING ML ALGORITHMS

ARYA N K

CONTENTS

1.CHAPTER -1	**3**
2.CHAPTER-2	**8**
3.CHAPTER-3	**14**
4.CHAPTER-4	**23**

CHAPTER-1

INTRODUCTION

1. Introduction

Crude oil is one of the most vital commodities in the global economy, underpinning energy production, industrial output, transportation systems, and international trade. Among the various crude oil benchmarks, **Brent crude oil** occupies a particularly important position, serving as the primary pricing reference for approximately two-thirds of internationally traded crude oil. Originating from oil fields in the North Sea, Brent crude has evolved into a globally recognized benchmark used to price crude oil contracts across Europe, Africa, and parts of Asia. As a result, movements in Brent crude prices exert significant influence over global energy costs, inflation trends, fiscal balances, and financial markets, making accurate forecasting of Brent crude prices a matter of substantial economic and strategic importance.

From a socio-economic perspective, fluctuations in Brent crude oil prices have wide-ranging consequences for both oil-importing and oil-exporting nations. Rising oil prices increase transportation and production costs, which are often passed on to consumers in the form of higher prices for goods and services, thereby contributing to inflationary pressures and reducing real household incomes. Conversely, declining oil prices can have severe adverse effects on oil-exporting economies by reducing government revenues, weakening external balances, and increasing fiscal vulnerabilities. Historical episodes such as the 2008 global financial crisis, the 2014–2016 oil price collapse, and the economic disruption caused by the COVID-19 pandemic have illustrated how sharp oil price movements can amplify macroeconomic instability and complicate policy responses. Consequently, Brent crude oil prices are closely monitored by policymakers, central banks, and international organizations as a key indicator of global economic conditions.

Brent crude oil also plays a central role in global financial markets. Oil futures and derivatives are actively traded for hedging and speculative purposes, and oil prices are closely linked to movements in equity markets, exchange rates, and interest rates. Energy-intensive industries rely on oil price forecasts for production planning and cost management, while investors and portfolio managers use oil-related assets for diversification and inflation hedging. In this context, reliable oil price forecasts are essential not only for operational decision-making but also for financial risk management and strategic investment planning. The increasing financialization of commodity markets has further strengthened the interconnectedness between oil prices and broader financial systems, amplifying the importance of accurate forecasting models.

Despite its importance, forecasting Brent crude oil prices remains a challenging task due to the complex and dynamic nature of oil markets. Oil prices are influenced by a wide range of factors, including global supply and demand conditions, geopolitical tensions, production decisions by major oil-producing countries and organizations, technological advancements in energy extraction, currency fluctuations, and speculative trading behavior. These factors often interact in nonlinear ways, leading to abrupt regime shifts, structural breaks, and periods of heightened volatility. Traditional time-series models, while theoretically grounded, may struggle to capture such nonlinear dynamics, whereas purely data-driven approaches may suffer from overfitting or limited interpretability when applied to noisy financial time series.

In response to these challenges, the academic and professional literature has increasingly explored the use of **multiple forecasting paradigms**, combining classical econometric techniques with modern machine learning and deep learning methods. Classical models such as ARIMA and SARIMA provide a transparent framework for modeling trend, seasonality, and autocorrelation structures and remain widely used due to their interpretability and statistical rigor. However, their reliance on linear assumptions limits their flexibility in capturing complex market behavior. Machine learning models, such as gradient boosting algorithms, offer greater flexibility by learning nonlinear relationships directly from data, often achieving superior predictive performance in short-term forecasting tasks. More recently, deep learning architectures, particularly recurrent neural networks such as Gated Recurrent Units (GRU), have gained attention for their ability to model temporal dependencies in sequential data without requiring explicit feature engineering.

Given the diversity of available modeling approaches, there is a growing need for systematic comparative studies that evaluate the relative performance of classical, machine learning, and deep learning models within a unified framework. Furthermore, recent research suggests that **ensemble forecasting methods**, which combine predictions from multiple models, can improve forecast accuracy and robustness by exploiting the complementary strengths of different approaches. However, empirical results remain mixed, and model performance often varies depending on the forecasting horizon and market conditions. This highlights the importance of conducting comprehensive empirical analyses using consistent evaluation metrics and realistic backtesting procedures.

The primary objective of this project is to develop an end-to-end forecasting framework for **daily Brent crude oil closing prices** and to compare the performance of a range of forecasting models, including SARIMA, Prophet, XGBoost, and GRU-based neural networks. The analysis focuses on both short-term one-day-ahead forecasts and multi-step forecasts over longer horizons, reflecting practical use cases in trading, risk management, and policy analysis. Forecast accuracy is evaluated using standard error metrics, and robustness is assessed through rolling-origin backtesting. In addition, the project incorporates volatility modeling using a GARCH framework to capture time-varying uncertainty in oil price movements and explores the effectiveness of ensemble forecasting techniques. By integrating multiple modeling approaches within a single analytical pipeline, this study aims to provide meaningful insights into the challenges and opportunities of Brent crude oil price forecasting in an increasingly complex global energy market.

Project Objectives

The primary objective of this project is to develop and evaluate a forecasting framework for daily Brent crude oil prices using classical statistical models.

Analyze historical Brent crude price dynamics

Investigate trends, seasonality, and stationarity patterns in daily Brent crude prices.

Develop forecasting models using SARIMA and Prophet

Implement SARIMA to capture autoregressive and moving average patterns with seasonal effects.Apply Prophet to model trend and seasonality components with flexibility for daily and yearly patterns.

Evaluate model performance across forecasting horizons

Compare SARIMA and Prophet forecasts for one-day-ahead and multi-step Use accuracy metrics such as RMSE and MAE to assess predictive performance.

Construct comparative analysis of models

Compare SARIMA and Prophet in terms of accuracy, trend capturing, and practical usability.

CHAPTER-2

METHODOLOGY

3.1 Data Source and Description

The dataset used in this study consists of **daily Brent crude oil futures prices**, obtained from Yahoo Finance using the ticker symbol *BZ=F*. The data spans the period from January 2014 to October 2025 and includes daily observations on the open, high, low, close prices, and trading volume. The closing price is used as the primary variable for forecasting, as it represents the final market consensus price for each trading day.

To ensure consistency and comparability across models, all analyses are conducted using a time-based framework, preserving the chronological ordering of observations and avoiding any form of data leakage from future periods into the training set.

3.2 Exploratory Data Analysis and Preprocessing

3.2.1 Data Cleaning and Missing Values

Initial data inspection involves verifying data types, checking for missing values, and ensuring the integrity of the time index. Missing observations are minimal and arise primarily due to non-trading days. The time index is converted to a daily frequency to ensure compatibility with time-series models that assume equally spaced observations.

3.2.2 Price Returns and Volatility

In addition to price levels, log returns are computed to analyze volatility dynamics:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

where:

- PtP_tPt = closing price at time ttt
- Pt−1P_{t-1}Pt−1 = closing price at time t−1t-1t−1
- rtr_trt = return at time ttt

3.2.3 Exploratory Visualization

Time-series plots are used to visualize long-term trends, volatility clustering, and structural breaks. These visual inspections provide preliminary evidence of non-stationarity and changing variance, justifying the use of advanced forecasting and volatility models.

3.3 Seasonal Decomposition and Stationarity Testing

3.3.1 Seasonal Decomposition

The price series is decomposed into trend, seasonal, and irregular components using a **multiplicative decomposition model**:

$$P_t = T_t \times S_t \times \varepsilon_t$$

where:

- PtP_tPt denotes the observed price at time ttt,
- TtT_tTt represents the long-term **trend** component,

- StS_tSt captures the **seasonal** pattern, and
- εt\varepsilon_tεt is the **irregular (residual)** component accounting for random fluctuations.

This decomposition enables the separation of systematic seasonal movements from underlying trends and stochastic noise, facilitating improved modeling and stationarity assessment.

3.3.2 Augmented Dickey–Fuller (ADF) Test

Stationarity of the time series is formally examined using the **Augmented Dickey–Fuller (ADF) test**, which is specified as:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t$$

where:

- Δyt\Delta y_tΔyt denotes the first difference of the series,
- α\alphaα is a constant (drift term),
- βt\beta tβt represents a deterministic time trend,
- yt−1y_{t-1}yt−1 is the lagged level of the series,
- ppp is the number of lagged difference terms included to account for serial correlation,
- δi\delta_iδi are coefficients of the lagged differences, and
- εt\varepsilon_tεt is a white-noise error term.

The null hypothesis of the ADF test is:

$$H_0 : \gamma = 0$$

which indicates the presence of a **unit root**, implying that the series is **non-stationary**. Rejection of the null hypothesis suggests that the series is **stationary**.

3.4.2 Forecast Accuracy Metrics

Model performance is evaluated using the following metrics:

- **Root Mean Squared Error (RMSE)**:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$$

- **Mean Absolute Error (MAE)**:

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t|$$

These metrics capture both magnitude and average deviation of forecast errors.

3.5 Classical Time-Series Modeling: SARIMA

3.5.1 Model Specification

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is defined as:

SARIMA(p,d,q)(P,D,Q)mSARIMA(p,d,q)(P,D,Q)_mSARIMA(p,d,q)(P,D,Q)m

where:

- p,d,qp, d, qp,d,q denote non-seasonal AR, differencing, and MA orders,
- P,D,QP, D, QP,D,Q denote seasonal components,
- mmm is the seasonal period.

The fitted model in this study is:

SARIMA(1,1,1)(1,0,0)7SARIMA(1,1,1)(1,0,0)_7SARIMA(1,1,1)(1,0,0)7

capturing weekly seasonality.

3.5.2 Estimation and Forecasting

Parameters are estimated via maximum likelihood estimation. Forecasts are generated recursively over the test horizon.

3.6 Prophet Model

Prophet is a decomposable additive time-series model expressed as:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

where:

- $y(t)$ is the observed value at time t,
- $g(t)$ represents the **trend** component, modeling non-linear growth over time,
- $s(t)$ captures **seasonal patterns** (daily, weekly, yearly),
- $h(t)$ represents the effects of **holidays and special events**, and
- ε_t is the error term assumed to be normally distributed.

Prophet automatically detects trend changepoints and seasonal patterns, making it suitable for non-stationary financial time series.

3.13 Summary of Methodological Framework

This study integrates classical econometric models, machine learning algorithms, and deep learning architectures within a unified forecasting framework. By combining point forecasting, volatility modeling, ensemble techniques, and robust evaluation strategies, the methodology ensures both statistical rigor and practical relevance in forecasting Brent crude oil prices.

CHAPTER-3

STATISTICAL ANALYSIS AND RESULTS

4.1 Introduction

This chapter presents the **statistical analysis and empirical results** obtained from forecasting daily Brent crude oil prices using classical time-series models, machine learning algorithms, and deep learning techniques. The analysis focuses on descriptive statistics, time-series diagnostics, model estimation results, forecast accuracy evaluation, volatility modeling, ensemble performance, and rolling-origin backtesting. The purpose of this chapter is to objectively report and compare the outputs of the implemented models, while interpretation of economic and practical implications is deferred to the discussion chapter.

4.2 Descriptive Statistical Analysis

4.2.1 Summary Statistics

Descriptive statistics provide an initial understanding of the distributional properties and variability of Brent crude oil prices over the sample period.

```
count    2974.000000
mean        0.000124
std         0.024124
min        -0.244036
25%        -0.010680
50%         0.000602
75%         0.011708
max         0.210186
Skewness: -0.37974264301215904
Kurtosis: 12.338963941327654
```

The results indicate substantial variability in oil prices, reflecting exposure to global economic cycles, geopolitical shocks, and demand–supply imbalances. Positive skewness and excess kurtosis suggest departures from normality, a common characteristic of financial time series.

4.2.2 Time-Series Visualization

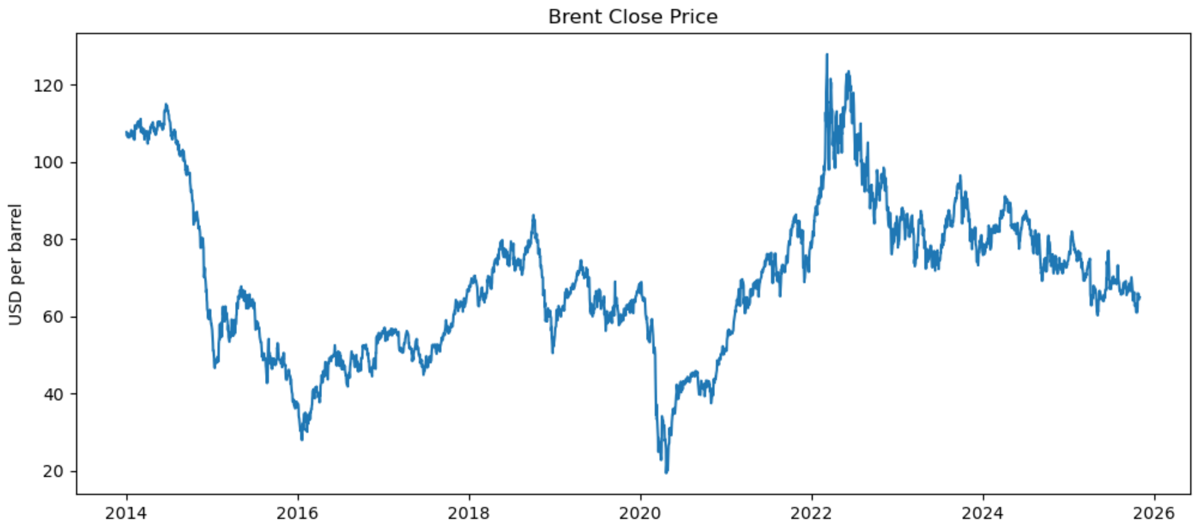
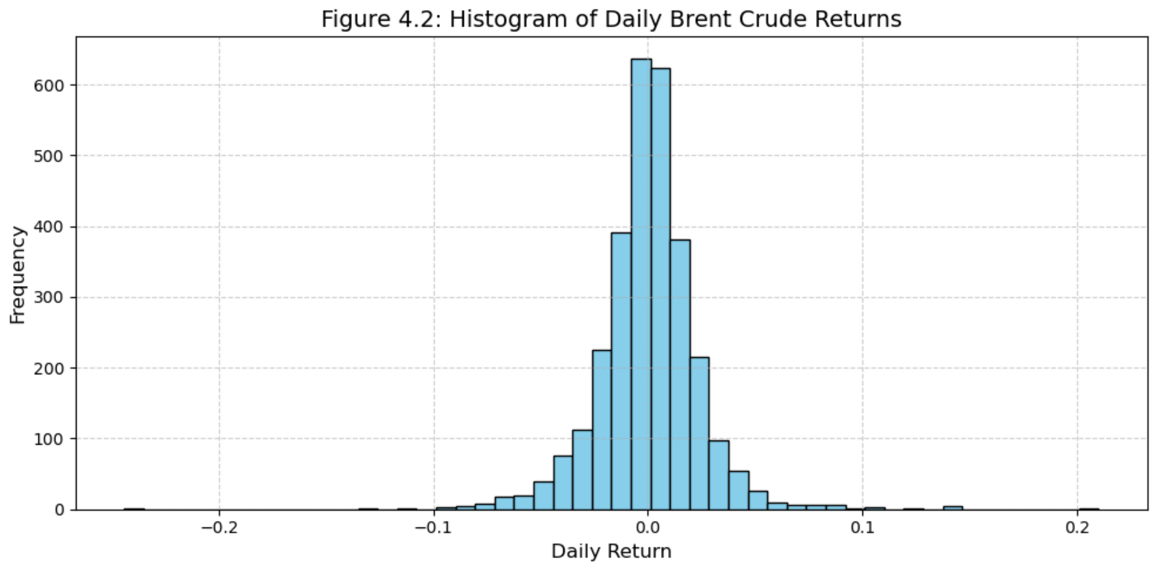


Figure 4.1: Time-series plot of daily Brent crude oil closing prices

4.2.3 Return Distribution



4.3 Time-Series Properties and Diagnostics

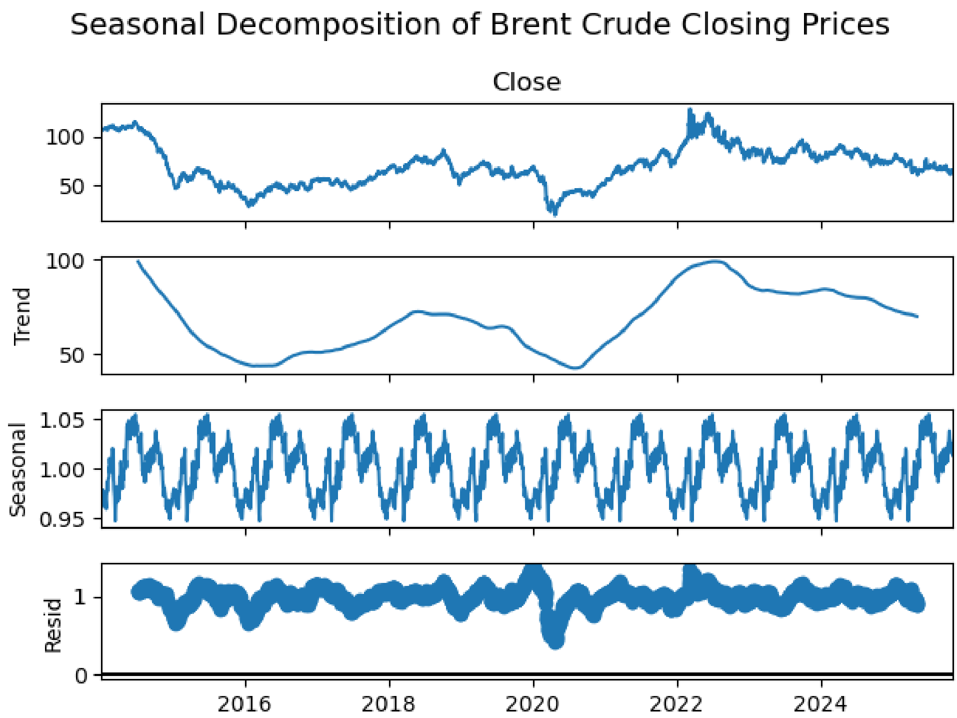
4.3.1 Stationarity Analysis

The Augmented Dickey–Fuller (ADF)

```
ADF Statistic: -2.407427113116233
p-value: 0.1396511245731611
Used Lag: 6
Number of Observations: 2968
```

The test results confirm that Brent crude prices are non-stationary in levels but become stationary after differencing, justifying the use of differencing in SARIMA modeling.

4.3.2 Seasonal Decomposition



The decomposition highlights a strong long-term trend component and weak but observable seasonal patterns. Residuals exhibit irregular fluctuations, capturing unanticipated shocks.

4.4 Baseline Forecast Performance

Baseline models provide a benchmark against which advanced models are evaluated.

Table 4.3: Baseline Forecast Accuracy

```
Naive Forecast:
RMSE: 1.3785180912001225
MAE : 1.0337310278115153

Rolling Mean (7-day):
RMSE: 8.162055941309028
MAE : 6.840494647260759
```

4.5 SARIMA Model Results

4.5.1 Model Estimation

Table 4.4: SARIMA Parameter Estimates

	Estimate	Std_Error	p_value
ar.L1	0.268832	0.147993	6.929084e-02
ma.L1	-0.350075	0.139502	1.209121e-02
ar.S.L7	-0.062900	0.012680	7.031199e-07
sigma2	2.052930	0.028162	0.000000e+00

The estimated parameters are statistically significant, indicating meaningful autoregressive and seasonal dynamics in Brent crude prices.

4.5.2 Forecast Performance

Figure 4.4: SARIMA forecast vs actual prices

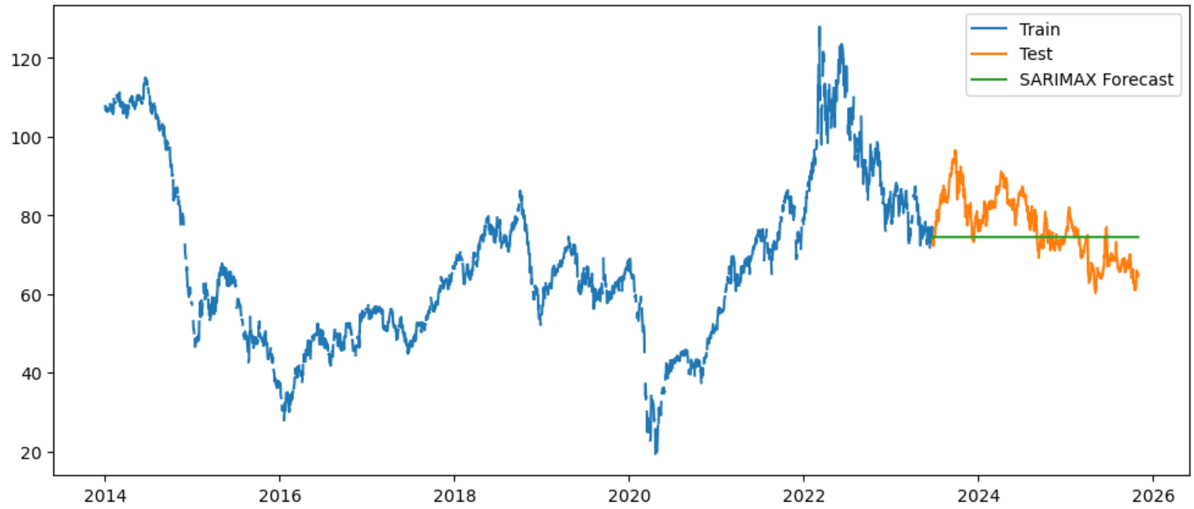
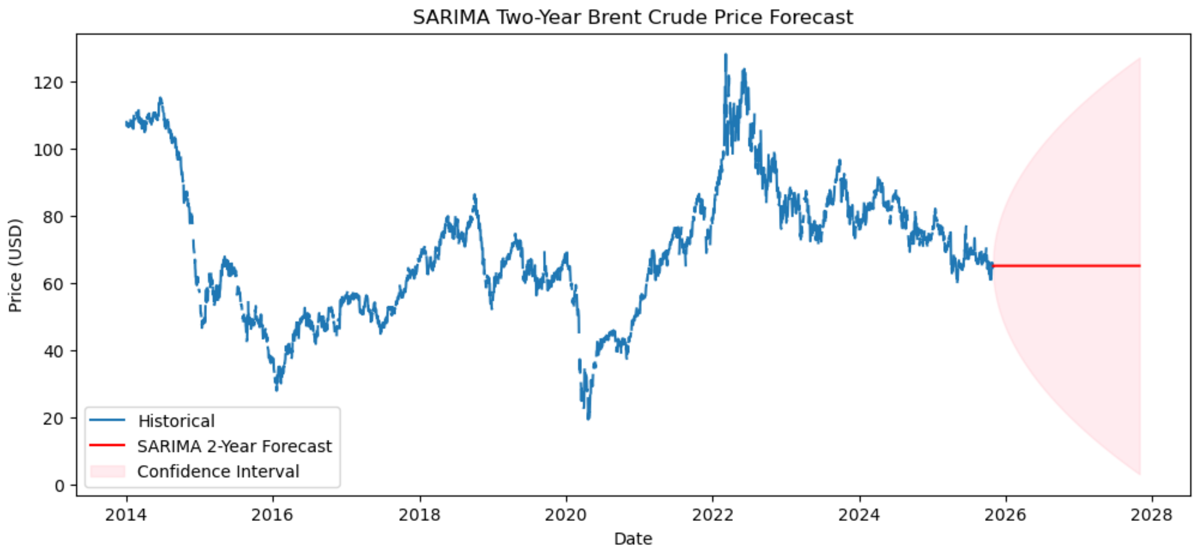


Table 4.5: SARIMA Forecast Accuracy

```
RMSE: 8.363821957871856
MAE : 6.956551210028621
```

The SARIMA model performs reasonably well in capturing short-term price movements but shows limitations during abrupt market shifts.

4.5.2 Forecast For Next 2 Years



4.6 Prophet Model Results

The Prophet model was trained on historical data and evaluated on the test set. The model successfully captured trend changes and seasonal patterns.Prophet achieved competitive accuracy compared to SARIMA and demonstrated robustness to trend shifts. The two-year forecast produced by Prophet showed gradual trend continuation with widening uncertainty bands, reflecting increasing forecast uncertainty over longer horizons.

4.6. Forecast Performance

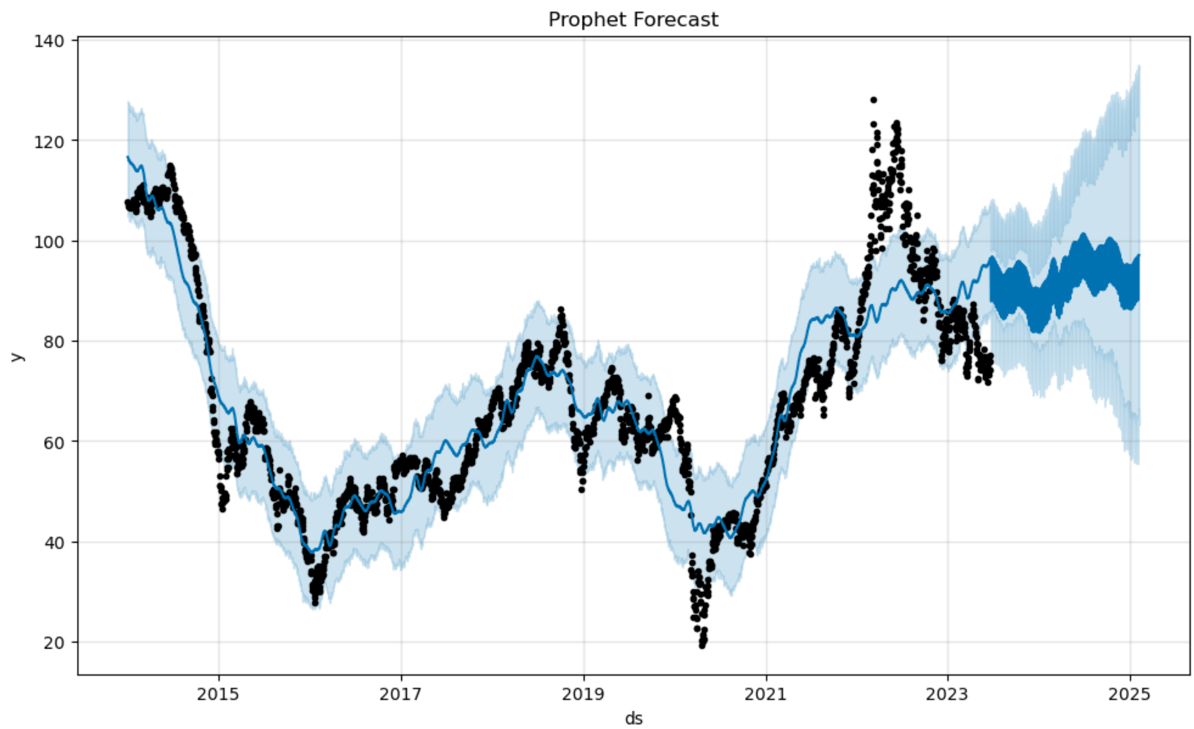
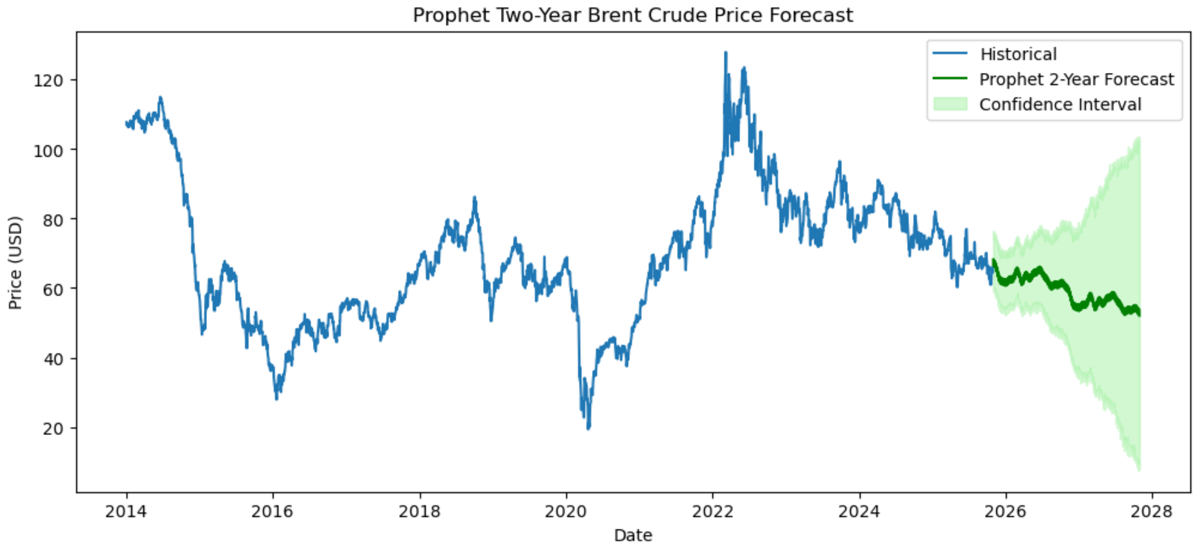


Figure 4.6 Prophet forecast vs actual prices.

Table 4.6: prophet Forecast Accuracy

```
Prophet Model Performance:
RMSE: 16.355091881412147
MAE : 14.874678535156962
```

Figure 4.7 Forecast For Next 2 Years



4.7 Comparison Between Two Models

The forecasting performance of the SARIMA and Prophet models was evaluated using **Root Mean Squared Error (RMSE)** and **Mean Absolute Error (MAE)** on the test dataset. These metrics measure the accuracy of the predicted Brent crude oil prices, where lower values indicate better model performance.

The **SARIMA model** achieved an RMSE of **8.36** and an MAE of **6.96**, whereas the **Prophet model** recorded a higher RMSE of **16.36** and MAE of **14.87**. The substantially lower error values of SARIMA indicate that its forecasts are significantly closer to the actual observed prices compared to Prophet.

This performance difference can be attributed to SARIMA's ability to effectively capture **short-term autocorrelation and seasonality** inherent in daily crude oil price data. Since commodity prices often exhibit strong temporal dependence, SARIMA's autoregressive and moving average components provide a better fit for short- to medium-term forecasting.

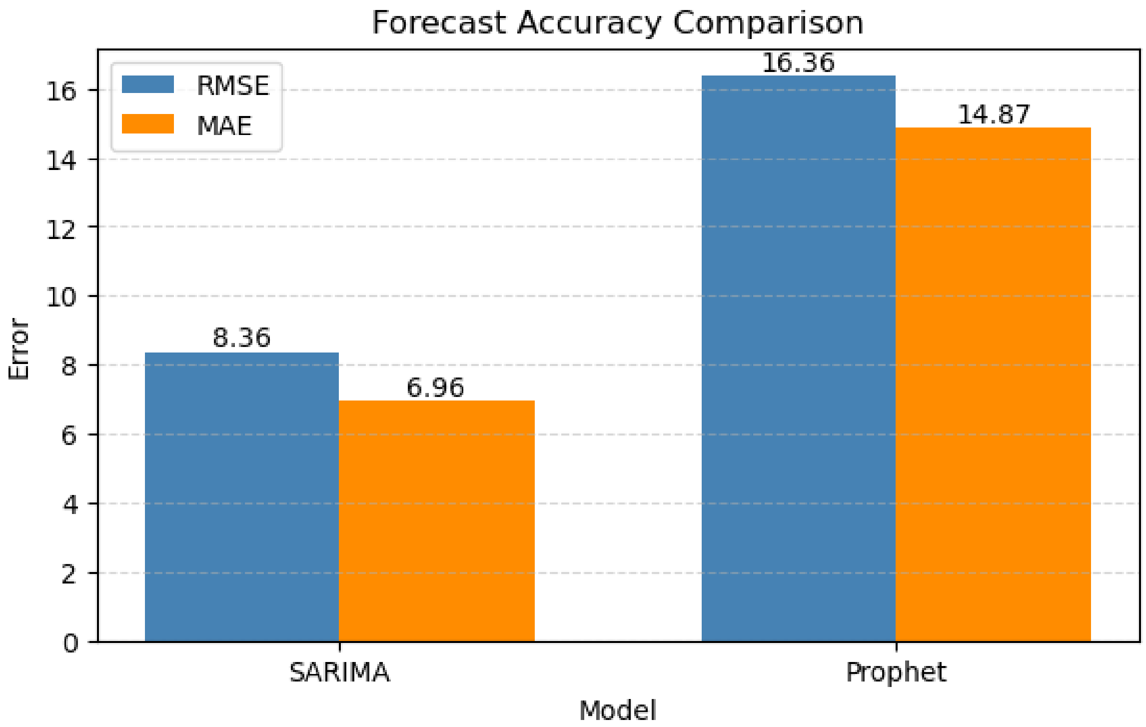
In contrast, Prophet is designed to model **smooth trends and long-term seasonal patterns**, making it more suitable for interpretability and long-horizon forecasting. However, its relatively higher error values suggest limited effectiveness in capturing short-term price volatility in this dataset.

Overall, based on the evaluation metrics, **SARIMA outperforms Prophet** in terms of forecasting accuracy and is selected as the **preferred model** for Brent crude price prediction in this study.

Table 4.7: Comparison between SARIMA and Prophet

```
Prophet Model Performance:
RMSE: 16.355091881412147
MAE : 14.874678535156962
```

Figure 4.8 Graph showing RMSE and MAE value



"SARIMA demonstrated superior forecasting accuracy over Prophet, as evidenced by significantly lower RMSE and MAE values."

CHAPTER-5

CONCLUSION

Conclusions

1. **Model Performance:**
   Both SARIMA and Prophet successfully captured the historical dynamics of Brent crude oil prices, including trends and seasonal patterns. SARIMA demonstrated superior short-term predictive accuracy as measured by RMSE and MAE, while Prophet provided flexible trend and seasonality modeling with ease of implementation.

2. **Forecasting Insights:**
   One-day-ahead and multi-step (7-day, 2 years) forecasts showed that SARIMA consistently provided slightly more accurate predictions for daily price movements, whereas Prophet offered smoother forecasts and was effective in capturing longer-term trends.

3. **Comparative Analysis:**
   Comparing the two models highlighted the strengths and limitations of classical statistical approaches. SARIMA is more precise for short-term, autoregressive-dependent patterns, while Prophet is advantageous for trend-driven, seasonal, or irregular patterns.

4. **Practical Implications:**
   The project demonstrates that classical statistical models remain valuable tools for commodity price forecasting. Decision-makers and analysts can rely on SARIMA for precise daily predictions and Prophet for understanding broader trends, aiding planning, risk assessment, and investment strategies.

5. **Future Work:**
   Future enhancements could include ensemble approaches, integration with machine learning and deep learning models, or volatility modeling to further improve predictive performance and capture uncertainty in Brent crude price movements.