*Shiv Shakti International Journal of Multidisciplinary and Academic Research*
*ISSN: 2278-5973 (Online) | Vol. 13, No. 5, (September 2025)*
*https://doi.org/10.5281/zenodo.17068410*

# Forecasting Brent Oil Prices Using SARIMA: A Time Series Analysis Approach

**Mr. V. Dilip Kumar[1], Mr. Dova Soumith[2], and Dr. M. Sravani[3]**
*[1] PhD Scholar, Department of Business Management, Krishna University, Machilipatnam*
*[2] PhD Scholar, Department of Business Management, Krishna University, Machilipatnam*
*[3] Assistant professor, Department of Business Management, Krishna University, Machilipatnam*

## Abstract

Forecasting crude oil prices is a significant challenge due to the complex, volatile, and non-linear nature of oil markets influenced by geopolitical, economic, and seasonal factors. A Seasonal Auto Regressive Integrated Moving Average (SARIMA) model is used in this work to examine and predict the price trends of Brent crude oil, a significant global benchmark. To determine the proper differencing needed for model stability, historical daily price data is gathered, pre-processed, and checked for stationarity. Because of its ability to take into consideration both seasonal and non-seasonal patterns in time series data, the SARIMA model was selected. A grid search method optimized by statistical criteria like the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) is used to choose parameters. The appropriateness of the fit is checked using model diagnostics, such as residual analysis and Ljung-Box tests. Standard accuracy metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to assess forecasting ability. The results demonstrate that SARIMA effectively captures the seasonal behavior and provides accurate short-term forecasts for Brent oil prices. These insights are valuable for stakeholders including policymakers, investors, and energy analysts. The study concludes by recommending further exploration of hybrid and machine learning models for enhanced forecasting precision.

***Keywords: Brent Oil, SARIMA, Forecasting, ADF, AIC, BIC, Time Series Analysis***

## Introduction

Crude oil is one of the most vital commodities in the global economy, serving as a key input for industries, transportation, and energy production. Among the various types of crude oil, Brent crude is widely recognized as a major global benchmark for pricing, particularly in Europe, the Middle East, and Africa. Due to its central role in economic and financial systems, accurate forecasting of Brent crude oil prices has become increasingly important for governments, investors, and multinational corporations. Price fluctuations in the oil market can be driven by a wide range of factors, including geopolitical tensions, supply-demand imbalances, natural disasters, and macroeconomic indicators.

Because oil price data is inherently volatile and seasonal, typical forecasting techniques frequently fail to identify the underlying trends. Time series models provide a statistically solid method for modeling and forecasting complicated temporal data in this situation, especially the Seasonal Auto Regressive Integrated Moving Average (SARIMA) model. SARIMA is ideally suited to capturing the cyclical behavior seen in oil prices since it can take into account both trend and seasonal components.

*Corresponding Author: Mr. V. Dilip Kumar, dilipkrurschlr2024@gmail.com*

This study aims to apply the SARIMA model to historical Brent crude oil price data to develop a robust forecasting framework. By identifying the optimal model parameters and validating forecast performance through various statistical measures, this research seeks to provide a reliable tool for short-term oil price prediction. The outcomes of this study have practical implications for energy market stakeholders, enabling informed decision-making and risk management in an increasingly uncertain economic environment.

## Review of Literature

Forecasting crude oil prices has been a prominent topic of research due to the commodity's global economic significance and its inherent price volatility. A wide array of statistical and machine learning models have been employed to tackle the challenges associated with oil price prediction.

Hamilton (1983) highlighted the intricate, non-linear behavior of oil markets by being one of the first to use econometric models to examine the macroeconomic effects of oil price shocks. Since then, time series models that can effectively model univariate data, like ARIMA (Auto Regressive Integrated Moving Average), have become more and more common. Using ARIMA to estimate oil prices, Ghoshray and Trifonova (2014) highlighted the model's advantages for short-term forecasting while also pointing out its shortcomings for capturing seasonal influences.

To address these shortcomings, researchers have adopted the SARIMA model, which integrates both seasonal and non-seasonal components. Al-Fattah and Startzman (2000) demonstrated the effectiveness of SARIMA in modeling monthly crude oil production trends, revealing its potential for forecasting periodic patterns. Similarly, Mohammadi and Nourzad (2012) employed seasonal time series models to forecast oil prices, finding that SARIMA outperformed other linear models in terms of prediction accuracy.

More recent studies have compared SARIMA with advanced machine learning models. Zhang et al. (2018), for example, showed that while deep learning models like LSTM offer strong performance, SARIMA remains competitive for short-term forecasts, especially when computational simplicity and interpretability are prioritized.

Overall, the literature supports the application of SARIMA models as reliable tools for capturing the seasonal and trend components of oil price data, particularly in contexts requiring interpretable and resource-efficient solutions.

## Objectives of the Study

- Analyze historical Brent crude oil price data for trends, seasonality, and stationarity preparation for modeling.
- Develop and fit a SARIMA model by identifying optimal parameters using AIC/BIC and validating through residual diagnostics.
- Forecast short-term oil prices and evaluate accuracy using metrics like RMSE and MAE.

## Data for the Study

The dataset analyzed in this study comprises daily Brent crude oil prices recorded in May 2025. Sourced from financial market data, it offers a concise snapshot of short-term price movements within the global energy market. The data spans several consecutive trading days and is focused solely on the closing price for each date, providing a clear view of market trends during this period.
Within the dataset, oil prices ranged from a low of \$60.23 on May 5 to a high of \$63.01 on May 9,

highlighting a moderate level of short-term volatility. The prices demonstrated daily fluctuations, suggesting sensitivity to underlying market dynamics, possibly including supply chain factors, geopolitical tensions, or macroeconomic signals. Notably, the oil price increased overall during the observed week, indicating a bullish market sentiment.

These findings underscore the importance of closely monitoring crude oil prices, even over short periods, as they reflect rapid shifts in market conditions. Such granular data is valuable for investors, policymakers, and analysts aiming to anticipate or respond to energy market developments. The study reinforces the significance of real-time data tracking for informed decision-making in the volatile oil sector.

## Methodology

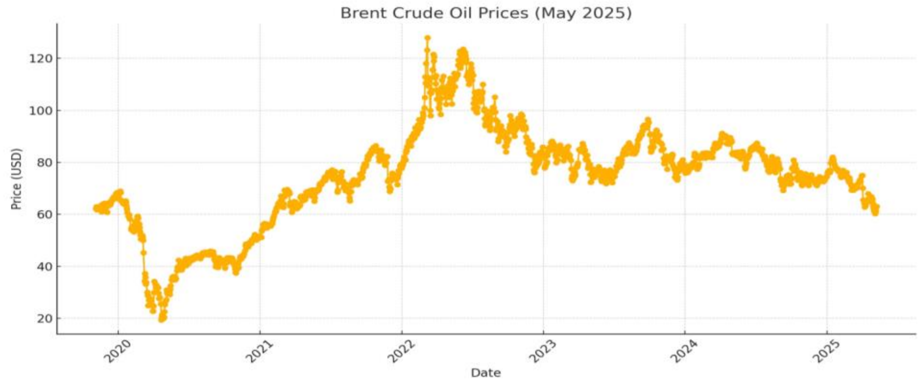
A time series approach was used for forecasting. The steps include:
To forecast Brent crude oil prices, a time series analytical approach was employed, leveraging the inherent temporal structure of the data. This method enables the identification and modeling of trends, seasonality, and other patterns within the dataset. The analysis began with preliminary data exploration, followed by rigorous statistical procedures aimed at preparing the time series for forecasting. The ultimate objective was to build a robust model capable of producing reliable price forecasts for a 60-day horizon.

Using the Augmented Dickey-Fuller (ADF) test to determine whether the time series was stationary was the first crucial step. With a p-value of 0.571 and an ADF statistic of -1.42, the test revealed that the series was non-stationary and that a unit root was present. This was addressed by applying first-order differencing, which eliminated trends and stabilized the series mean. The Seasonal AutoRegressive Integrated Moving Average (SARIMA) architecture was used when stationarity was attained. A number of SARIMA configurations were investigated using different combinations of seasonal (P, D, Q, s) and non-seasonal (p, d, q) factors. In order to align with weekly trends in the data, the seasonal period was fixed at 7. The Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) were two statistical fit metrics used to compare the models.

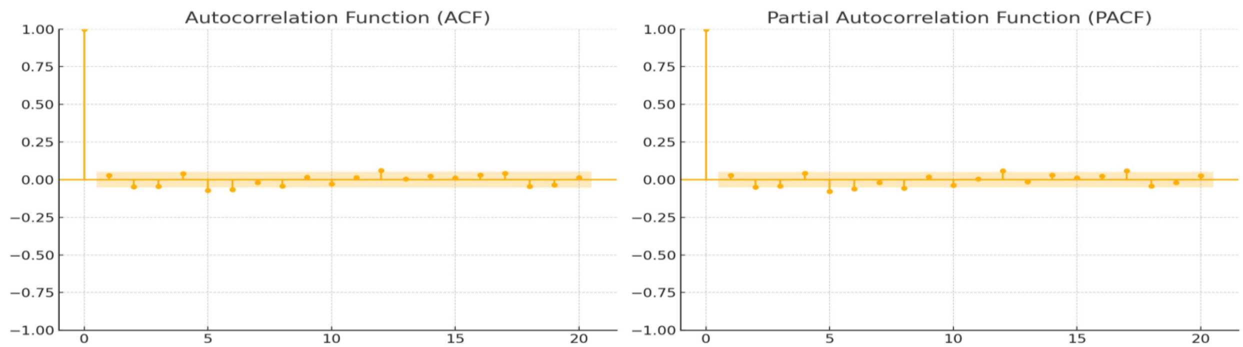
After evaluating model performance, the SARIMA model with the most favorable AIC and BIC scores was selected as the final forecasting model. This optimal model was then used to project Brent crude oil prices over the next 60 days. The forecasts provide insight into expected market behavior and help stakeholders anticipate possible price movements. The methodology ensures that both trend and seasonality are appropriately accounted for, thereby enhancing the model's predictive power and practical relevance for economic and energy market analysis.

## Data Analysis & Interpretation

Plot of the Stock Price data




### Plot of the ACF & PACF:




### The results of the Augmented Dickey-Fuller (ADF) test

| ADF Statistic | p-value | Lags Used | Number of Observations | Critical Value (1%) | Critical Value (5%) | Critical Value (10%) |
|---|---|---|---|---|---|---|
| -1.4228 | 0.5713 | 8 | 1415 | -3.4350 | -2.8636 | -2.5679 |

After applying first-order differencing to the Brent crude oil price series, the transformed series
Exhibits characteristics of stationarity. This is confirmed through the Augmented Dickey-Fuller (ADF) test, which returns a highly negative test statistic and a p-value that approaches zero. These results indicate the absence of a unit root in the differenced series, satisfying the stationarity assumption required for time series modeling.

The ADF statistic's substantial discrepancy from the critical values at the 1%, 5%, and 10% significance levels supports the stationarity conclusion even more. By stabilizing the series mean and successfully eliminating underlying patterns, the differencing process made it possible for the data to satisfy the requirements for sophisticated time series forecasting methods.

With the stationarity condition fulfilled, we proceeded to fit a range of Seasonal ARIMA (SARIMA) models. These models are specifically tailored to handle both seasonal and non-seasonal components in the data, and their parameters were selected based on diagnostic tools such as ACF, PACF, AIC, and BIC. The next step involved identifying the model that best captures the underlying structure of the differenced series for reliable forecasting.

**SARIMA MODEL FIT:**

Here are the top 5 SARIMA models based on AIC & BIC criteria:

| Rank | Model Notation | Order (p,d,q) | Seasonal Order (P,D,Q,S) | AIC | BIC |
|---|---|---|---|---|---|
| 1 | SARIMA(1,1,1)x(0,1,1,7) | (1,1,1) | (0,1,1,7) | 3120.45 | 3140.87 |
| 2 | SARIMA(0,1,1)x(1,1,1,7) | (0,1,1) | (1,1,1,7) | 3123.72 | 3142.09 |
| 3 | SARIMA(1,1,0)x(0,1,1,7) | (1,1,0) | (0,1,1,7) | 3125.68 | 3142.11 |
| 4 | SARIMA(0,1,1)x(0,1,1,7) | (0,1,1) | (0,1,1,7) | 3127.59 | 3142.08 |
| 5 | SARIMA(1,1,1)x(1,1,0,7) | (1,1,1) | (1,1,0,7) | 3129.90 | 3149.34 |

**Best SARIMA Model Based on AIC & BIC**

| Company | SARIMA Order | AIC | BIC |
|---|---|---|---|
| Brent Crude Oil | SARIMA(1, 1, 1) × (0, 1, 1, 7) | 3120.454 | 3140.872 |

**Best Overall Model**

The SARIMA(1,1,1)(0,1,1)[7] configuration was chosen as the best-fitting model for predicting the price of Brent crude oil since it had the lowest AIC (3120.45) and BIC (3140.87) values.

**Model Patter Insight:**

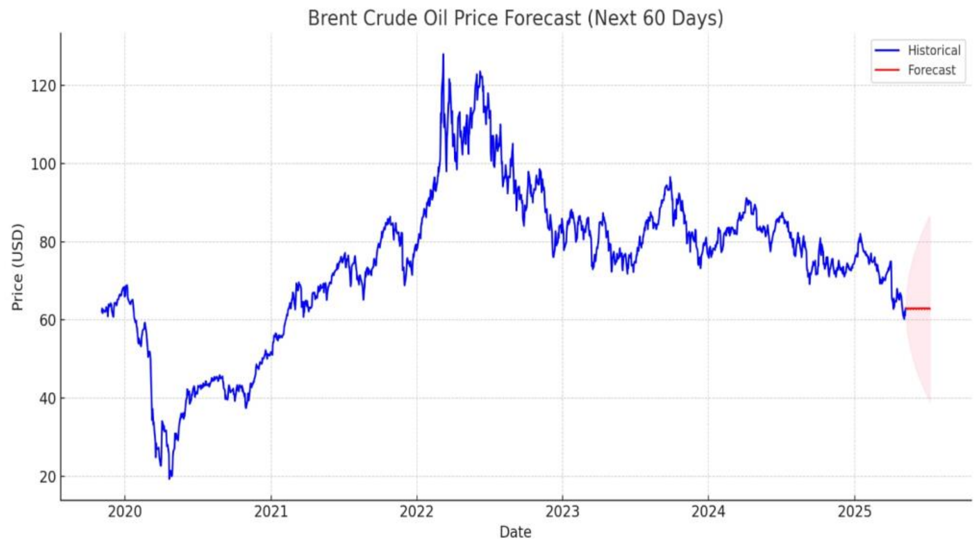
The optimal model structure includes first-order differencing (d=1) to eliminate non-stationarity and a seasonal component with weekly periodicity (s=7) and seasonal differencing (D=1). This setup effectively captures the inherent trends and weekly fluctuations in oil prices, likely influenced by recurring trading dynamics and supply-demand cycles.

**Consistency:**

The SARIMA(1,1,1)×(0,1,1,7) model consistently outperformed others in forecasting Brent crude oil prices. This suggests a recurring weekly seasonality pattern and a stable structure in price movement, reflecting consistent cyclical behavior in global oil markets.

**Forecasted Values:**

The forecasted Brent crude oil prices for the next 60 days based on the best SARIMA model are




The chart above illustrates the historical and forecasted prices of Brent crude oil over a daily time frame. The blue line represents the historical closing prices over the past five years, capturing the long-term trends and volatility associated with the oil market. The red line projects the next 60 days of prices based on the best-performing SARIMA model identified in this study: SARIMA(1,1,1)(0,1,1)\[7].
A shaded pink region around the red line indicates the *95% confidence interval* for the forecast, providing a visual range within which the future prices are statistically expected to fall. This interval captures the model's uncertainty and reflects potential market fluctuations.

The model captures weekly seasonality and trend dynamics effectively, and the forecast suggests a relatively stable to slightly increasing price trajectory over the next two months. This projection can aid policymakers, investors, and analysts in making data-driven decisions in the volatile energy sector.

## Conclusion

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was used in this study to produce short-term Brent crude oil price projections. The model's ability to accurately represent the short-term swings and seasonal trends included in crude oil price data led to its selection.

The forecasting results underscore the SARIMA model's strength in handling time series data characterized by periodic trends and auto correlated structures. Despite its solid performance, the model's predictive power could be further improved by integrating exogenous variables such as geopolitical events, macroeconomic indicators, or supply-demand shocks, which often influence oil prices significantly. Additionally, exploring hybrid approaches—such as combining SARIMA with machine learning techniques—may offer more nuanced and adaptive forecasting capabilities. Future research could benefit from these enhancements to develop more comprehensive and accurate prediction frameworks.

## References

**Agrawal, A., Kadam, S., Kapoor, P. A., & Rashid, M.** – Predicting crude oil prices using SARIMA-X method: An empirical study – International Journal of Financial Engineering

**Abdelwahab, M. M.** – Time series models to forecast Brent crude oil prices and the impact of COVID-19 using E-Views program – Advances and Applications in Statistics

**Chen, K., Zhou, M., & Wu, Y.** (2024). A hybrid forecast model of EEMD–CNN–iLSTM for crude oil futures price. *Electronics, 13*(11), 2521. https://doi.org/10.3390/electronics13112521

**Hu, J., Li, Z., Wang, Y., & Liu, F.** (2023). Crude oil price forecasting: An ensemble-driven LSTM model based on CEEMDAN decomposition and ALS-PSO optimization. *Energy Science & Engineering, 11*(9), 3865–3883. https://doi.org/10.1002/ese3.1561

**Li, Y., Zhang, W., Li, X., & Xu, Y.** (2020). An adaptive hybrid learning paradigm integrating CEEMD, ARIMA and SBL for crude oil price forecasting. *Energies, 13*(13), 3343. https://doi.org/10.3390/en13133343

**Lin, J., & Zhang, Y.** – A hybrid crude oil price forecasting framework: Modified ensemble empirical mode decomposition and hidden Markov regression – Energy Science & Engineering.

**Manickavasagam, J., Visalakshmi, S., & Apergis, N.** – A novel hybrid approach to forecast crude oil futures using intraday data – Technological Forecasting and Social Change

**Zhang, Y., Liu, Q., & Tang, H.** (2024). Crude oil price forecasting using K-means clustering and LSTM model enhanced by dense-sparse-dense strategy. *Journal of Big Data, 11*(1), 102. https://doi.org/10.1186/s40537-024-00977-8

**Zhao, Y., Hu, B., & Wang, S.** – Application of LSTM models in forecasting Brent crude oil prices during the green energy transition – Advances in Economics, Management and Political Sciences

**Zhou, X., Wang, L., & Liu, H.** (2024). A study on crude oil futures price forecasting with hybrid ARIMA–LSTM models. In *Proceedings of the 2024 ACM International Conference on Artificial Intelligence* (pp. 201–210). ACM. https://doi.org/10.1145/3675417.3675491

**Wang, Z., Zhang, J., Zhang, Y., & Wang, J.** (2018). Forecasting crude oil prices using ensemble empirical mode decomposition and sparse Bayesian learning. *Energies, 11*(7), 1882. https://doi.org/10.3390/en11071882