

Artificial Intelligence in International Finance**An Empirical Comparison of Traditional and Machine-Learning Models for Brent Crude Oil Price Forecasting**Author: Jeffry Al Achkar¹*Affiliation:*

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Abstract:

Oil prices are important to international finance because they affect the cost of imports, inflation, company earnings and, in many countries, the balance of payments. They are also difficult to predict because the market reacts to changes in supply, demand, financial conditions and unexpected events. This paper compares four forecasting approaches for monthly Brent crude oil prices: a random-walk benchmark, an ARIMA model, a Random Forest model and a multilayer perceptron (MLP) neural network. The data cover January 2010 to December 2025. The first 80 percent of the observations are used for model estimation and the remaining 20 percent are kept for out-of-sample testing. The results show clear differences between the models. The Random Forest gives the smallest MAE and RMSE in the test period, while the MLP records the highest directional accuracy. ARIMA also performs better than the random-walk benchmark on the main error measures. The results suggest that machine-learning methods can be useful for forecasting oil prices, but their performance depends on the measure used to judge the forecast. For international finance, this is important because a model that gives a small numerical price error is not necessarily the same model that gives the most accurate prediction of whether prices will rise or fall.

Brent Crude Oil, International Finance, Artificial Intelligence, Machine Learning, ARIMA, Random Forest, Neural Networks, Price Forecasting

Keywords:

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Introduction:

Crude oil has a direct connection with international economic activity. It is traded across borders, priced mainly in U.S. dollars and used as an input in transportation, manufacturing and many other industries. As a result, changes in oil prices can affect countries differently. An oil-importing country may face a higher import bill when prices increase, while an oil exporter may receive more foreign-currency revenue. Oil prices can also influence inflation and exchange-rate pressures. For these reasons, understanding and forecasting oil-price movements is relevant to financial institutions, companies and governments.

Brent is one of the main international reference prices for crude oil. The monthly series used in this paper is the FRED series MCOILBRENTU, which is supplied by the U.S. Energy Information Administration and reported in U.S. dollars per barrel. The series is available over a long historical period, which makes it suitable for a time-series forecasting exercise. The FRED database currently identifies the series as a monthly, not-seasonally-adjusted Brent price series.

1.2 Problem Statement

The main problem is that oil prices do not move in a simple and stable pattern. A model may perform well during a relatively calm period and then perform poorly when the market changes quickly. Traditional time-series models are useful because they focus directly on the relationship between current and past observations. Machine-learning models take a different approach and can capture nonlinear relationships in the lagged data. The question is therefore not simply whether artificial intelligence is more advanced, but whether it actually improves the forecast when both approaches are tested on the same data.

1.3 Research Questions

This paper focuses on the following questions:

- How well does a traditional ARIMA model forecast monthly Brent crude oil prices compared with a simple random-walk benchmark?
- Do the Random Forest and MLP neural-network models reduce out-of-sample forecasting errors?
- Does a model with a smaller price error also predict the direction of the next monthly movement more accurately?

1.4 Objectives

The objectives are to compare the four forecasting methods, measure their performance using the same test observations, and discuss what the results mean for international financial decision-making. The analysis is deliberately kept straightforward so that the results can be followed and reproduced.

Literature Review:

2.1 Traditional Forecasting Models

ARIMA models have been used for many years in economic and financial forecasting. Their main advantage is that the model is built around the time-series itself. Past observations, differencing and past forecast errors can be used to describe the behavior of a series. The Box-

Jenkins approach remains one of the standard references for this type of analysis (Box et al., 2015). For a project such as this one, ARIMA is also useful as a benchmark because its structure is easier to explain than many modern machine-learning models.

2.2 Machine Learning in Oil-Price Forecasting

Machine-learning methods have become increasingly common in energy-price forecasting. Random Forests, for example, use many decision trees rather than relying on one fitted equation. Breiman (2001) introduced the Random Forest method as an ensemble approach that can handle nonlinear relationships and interactions. This is potentially useful for oil prices because the effect of a recent price observation may not be the same in every market period.

Recent research has applied machine learning and neural networks specifically to crude oil prices. Hasan et al. (2025) compared a range of ensemble approaches using Brent and WTI data and found that combining different learning methods can improve forecasting performance. Another study examined nonlinear neural-network models for Brent and WTI prices and reported useful forecasting results from relatively simple neural-network specifications. More recent work has also examined hybrid models that combine machine learning with volatility models.

2.3 Machine Learning and AI in general finance

Even though AI and Machine learning has caused in many cases the need for organizational redesign (Subrahmanyam & Saber, 2027) yet Kamel et al. (2026) discuss that in many cases digitalization has caused a surge in innovation. Recent literature highlight how machine learning has massively scaled the performance of SMEs (Khalife et al., 2024) both in financial terms (Azoury et al., 2024) and (Rizk & Sassine, 2023) and other non-financial metrics (Kaspard et al., 2025 ; Kaspard et al., 2026). Furthermore, AI enables smarter decisions (Subrahmanyam & Beainy, 2027) however this is directly related to the degree of business experience of the employees of the organization (Chaanine et al., 2023).

2.4 What the Literature Does Not Answer

The recent literature contains many sophisticated models, including ensemble and hybrid deep-learning systems. These studies are useful, but their results do not automatically mean that a more complicated model will perform better on every dataset. Forecasting results depend on the period studied, the frequency of the observations, the variables included and the way the test sample is constructed. For this reason, the present paper uses a smaller set of models and compares them using exactly the same monthly Brent series and the same out-of-sample period.

2.5 Link to International Finance

The international-finance connection is straightforward. Oil is traded internationally and changes in its price can affect trade flows and the foreign-currency cost of energy. Oil-price changes can also affect inflation and the financial position of companies that import or export energy. Rao et al. (2025), for example, emphasize the connection between crude-oil volatility and macroeconomic variables such as inflation, exchange rates and trade balances.

Methodology:

3.1 Data

The analysis uses monthly Brent crude oil prices from January 2010 through December 2025, giving 192 observations. The variable is measured in U.S. dollars per barrel. The source series is MCOILBRETEU in FRED, which identifies the U.S. Energy Information Administration as the source.

3.2 Training and Testing

The observations were divided chronologically rather than randomly. The first 153 observations, from February 2010 to October 2022, were used for estimation. The remaining 39 observations, from November 2022 to January 2026, were kept as the test period. This is important in a forecasting exercise because randomly mixing past and future observations would make the evaluation less realistic.

3.3 Models

Four models were compared.

- Random walk. The forecast for every month in the test period is the last price observed in the training sample (89.76 dollars per barrel).
- ARIMA. Candidate specifications with p from 0 to 2, d from 0 to 1 and q from 0 to 2 were estimated. The model with the lowest Akaike Information Criterion was selected.
- Random Forest. The model uses the previous twelve monthly prices as predictors, with 500 trees, a maximum tree depth of 6 and a minimum leaf size of 2.
- MLP neural network. The model also uses twelve monthly lags. The inputs are standardized and the network contains two hidden layers with 32 and 16 neurons. Early stopping is used to limit unnecessary training.

3.4 Evaluation Measures

Four measures are reported. Mean Absolute Error (MAE) shows the average size of the forecast error without giving extra weight to large mistakes. Root Mean Squared Error (RMSE) gives more weight to large errors. Mean Absolute Percentage Error (MAPE) expresses the error as a percentage of the actual price. Finally, directional accuracy records how often the model correctly identifies whether the price increased or decreased compared with the previous month.

3.5 Research Procedure

The models were fitted using the training observations only. Forecasts were then produced for the test period. The actual test values were not used to change the model parameters. The same observations were used to calculate the four performance measures for every model. No attempt

was made to turn the forecasts into a trading strategy, so the results should be interpreted as a forecasting comparison rather than evidence of investment profitability.

Results:

4.1 Descriptive Statistics

The average Brent price over the sample was 77.56 dollars per barrel. The lowest observation in the dataset was 18.38, while the highest was 125.45. The series contains several periods of large price movements. The most obvious example is the sharp fall in 2020, followed by a strong recovery. These changes are useful for the present analysis because they provide a test of how the models behave when the series is not stable.

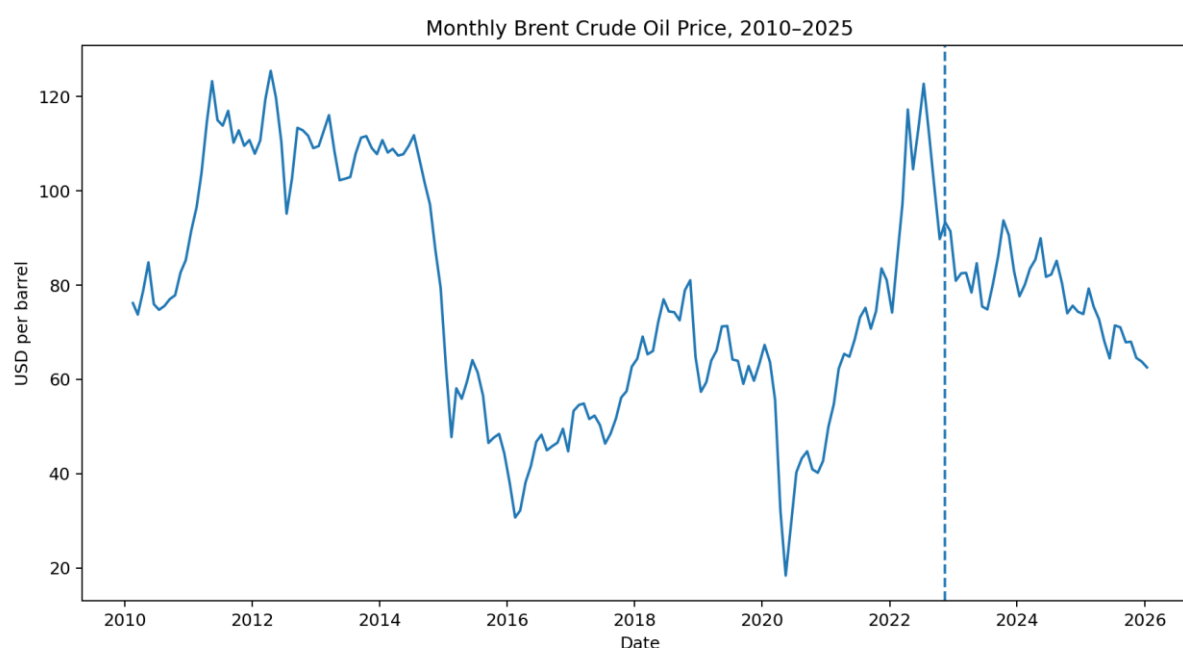


Figure 1. Monthly Brent crude oil price, 2010–2025.

4.2 Forecasting Results

Model	MAE	RMSE	MAPE (%)	Directional Accuracy (%)
Random Walk	12.057	14.159	16.614	53.85
ARIMA(0, 1, 1)	10.048	12.061	13.877	53.85
Random Forest	6.670	8.090	8.277	46.15
MLP Neural Network	7.546	8.576	9.772	56.41

The results show a clear difference between the traditional and machine-learning models. The random walk has an MAE of 12.057 and an RMSE of 14.159. The ARIMA model lowers these figures to 10.048 and 12.061. The Random Forest records an MAE of 6.670 and an RMSE of

8.090, the lowest error values in the comparison. The MLP has an MAE of 7.546 and an RMSE of 8.576.

The directional results tell a slightly different story. The Random Forest has a directional accuracy of 46.15%, while the MLP reaches 56.41%. The random walk and ARIMA models both record 53.85%. This means that the model with the smallest numerical price error is not automatically the model that gets the direction right most often.

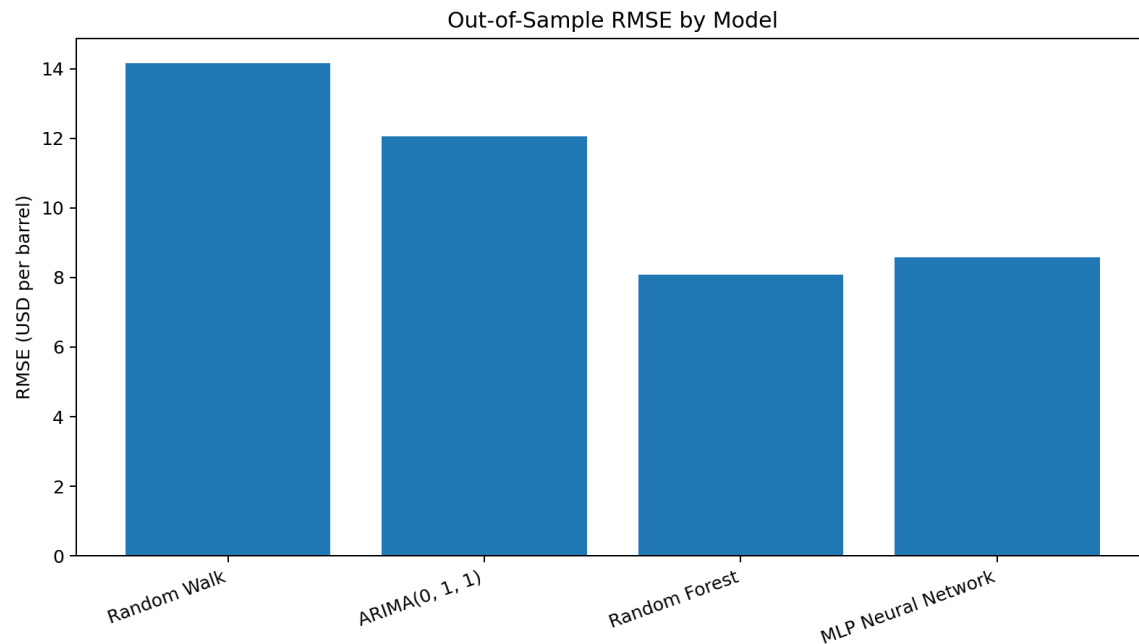


Figure 2. Out-of-sample RMSE for the four models.

4.3 Forecast Paths

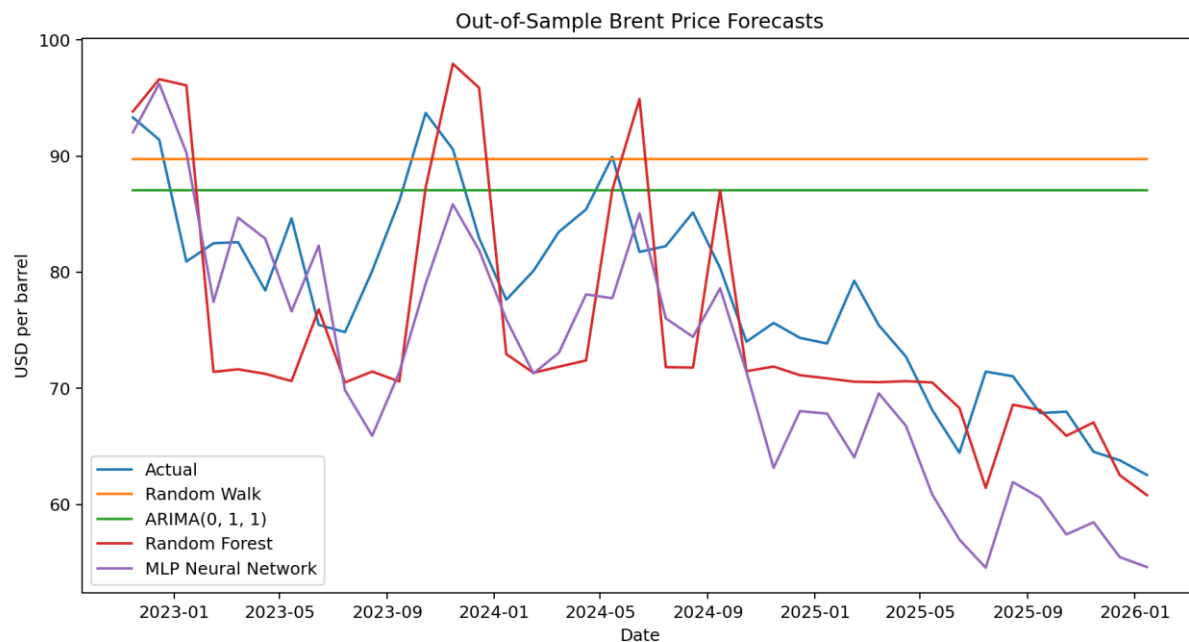


Figure 3. Actual and forecast Brent prices during the test period.

The forecast graph helps explain the numerical results. The random-walk line is flat because it simply carries the last training observation forward. The ARIMA forecast is smoother and changes gradually. The two machine-learning models move more closely with the recent pattern in the lagged observations. Even so, the test-period results show that following the shape of the series does not guarantee the correct direction every month.

4.4 Discussion

The findings support a cautious interpretation of machine learning in financial forecasting. The Random Forest performs well on the two main measures of price-level error, which suggests that the nonlinear relationships represented by the trees contain useful information in this sample. The MLP does not achieve the lowest MAE or RMSE, but it has the highest directional accuracy. Therefore, the answer to the research questions depends partly on what the forecast is being used for.

The results also show why a simple benchmark should not be ignored. The random walk is difficult to beat consistently in many financial markets because prices can contain a large unpredictable component. In this sample, ARIMA improves on that benchmark in terms of price-level error, while the machine-learning models produce further reductions in those errors. At the same time, the directional results are much less decisive.

Discussion and Conclusion:

5.1 Main Findings

This paper compared four approaches to forecasting monthly Brent crude oil prices. The analysis used a chronological training and testing design so that the final part of the sample could be evaluated without being used during model estimation. The results show that ARIMA performs better than the random-walk benchmark on the main error measures. The Random Forest gives the lowest MAE and RMSE, while the MLP gives the highest directional accuracy.

The findings do not mean that machine learning will always produce better forecasts than traditional time-series models. They show that, for this particular sample and these model specifications, nonlinear models can reduce the numerical size of forecast errors. The difference between the error results and the directional results is also important. A financial decision-maker should choose the evaluation measure according to the purpose of the forecast.

5.2 Implications for International Finance

For companies with international operations, better forecasts of energy prices can be useful when preparing budgets and estimating future costs. For financial institutions, oil prices are one of the variables that can affect inflation expectations, exchange-rate conditions and the financial performance of energy-related borrowers. The present results therefore support the use of forecasting models as an input into financial analysis, but not as a substitute for broader economic information.

5.3 Limitations

- The models use only historical Brent prices. Variables such as exchange rates, interest rates, inventories, production and geopolitical events are not included.
- The observations are monthly, so short-lived changes in the oil market are not captured.
- The machine-learning hyperparameters were kept relatively simple rather than being optimized through a large search.
- The study compares forecast accuracy and does not test whether a trading strategy based on the forecasts would generate economic profits.
- The conclusions apply to the sample and specifications used in this paper and should not be treated as a general rule for all oil-price forecasting problems.

5.4 Suggestions for Further Research

A larger study could add macroeconomic and financial variables and compare the models using rolling estimation windows. It would also be useful to test LSTM networks and hybrid ARIMA-machine-learning models, as well as formal tests of whether forecast differences are statistically significant. Using daily rather than monthly data could provide a different picture, particularly around major market events.

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