ISSN 0323-9004

Economic Archive

Svishtov, Year LXXIX, Issue 1 - 2026

D. A. TSENOV ACADEMY OF ECONOMICS
SVISHTOV

Editorial address:
2, Emanuil Chakarov street, Svishtov 5250
Prof. Teodora Dimitrova, PhD – Editor-in-Chief
☎ (++359) 631 66 201
Elena Petkova – technical secretary
☎ (++359) 631 66 201, e-mail: nsarhiv@uni-svishtov.bg
Blagovesta Borisova – computer graphic design
☎ (++359) 882 552 516, e-mail: b.borisova@uni-svishtov.bg
Milena Aleksandrova – computer graphic design
☎ (++359) 888 303 402, e-mail: m.aleksandrova@uni-svishtov.bg

In 2026, the journal will be printed using a financial grant from the Scientific Research Fund – Agreement № KP-06-NP7-66 from Bulgarska Nauchna Periodika – 2026 competition.

ECONOMIC ARCHIVE

YEAR LXXIX, BOOK 1 – 2026

CONTENTS

EVALUATING MODELS FOR OIL PRICE FORECASTING

Plamen Georgiev Parushev
St. Cyril and St. Methodius University – Veliko Tarnovo
E-mail: *D1634@sd.uni-vt.bg, Plamen_Parushevv@abv.bg*

Abstract: The present study is aimed at forecasting oil prices through the application of several quantitative models—moving averages, trend projection, Monte Carlo simulations, and autoregressive models. The analysis covers the period from 12 May 2024 to 12 May 2025, using daily-frequency historical data on Brent crude oil prices. For the moving average model, the classical accuracy indicators—Mean Absolute Deviation (MAD), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE)—were calculated and compared. In the case of trend projection, the evaluation was carried out using standard error, relative standard error, and Absolute Percentage Error (APE). For the Monte Carlo simulations and autoregressive models, the emphasis was placed on the process parameters, forecasted values, and confidence intervals, without using the full set of classical error indicators. The obtained results show that moving averages with shorter periods provide lower error, whereas longer periods lead to smoothing but also to a loss of accuracy. Trend projection and Monte Carlo simulations complement the analysis with a broader scenario-based perspective, while autoregressive models demonstrate good predictive performance in short-term forecasting. This highlights the importance of a combined approach in modelling oil price dynamics and provides a basis for more reliable forecasts under conditions of market uncertainty.

Key words: oil price, Brent, moving averages, trend projection, Monte Carlo simulations, autoregressive models, forecasting.

This article shall be **cited** as follows: **Parushev, P.** (2026). Evaluating Models for Oil Price Forecasting. Narodnostopanski Arhiv. p. 13-29.

URL: nsarhiv.uni-svishtov.bg

DOI: https://doi.org/10.58861/tae.ea-nsa.2026.1.01.en

JEL: C22, C15, C53, Q41.

* * *

Introduction

Forecasting oil prices is among the most significant topics in economic and financial research because of the key role of this commodity in the global economy. Under conditions of increasing market instability, caused by the COVID-19 crisis and geopolitical disruptions such as the war between Russia and Ukraine, predicting price dynamics has become even more important for investors, governments, and the business community. Against this background, the present study is **of particular relevance**.

The subject of the study concerns the methods for forecasting oil prices through moving averages, trend projection, Monte Carlo simulations, and autoregressive models.

The aim is to examine and evaluate the predictive performance of selected statistical and simulation models for forecasting oil prices.

To achieve this aim, the following **research tasks** have been formulated**:**

- ✓ to review the literature on the topic of oil price forecasting;
- ✓ to apply moving averages for smoothing and forecasting;
- ✓ to examine trend projection as a forecasting tool;
- ✓ to use the Monte Carlo method for the simulation of future values;
- ✓ to apply autoregressive models for forecasting;
- ✓ to compare the results using accuracy indicators (MAD, MSE, RMSE, MAPE);
- ✓ to formulate conclusions regarding the applicability of the different methods under conditions of market instability.

The thesis of the study *is that the use of a combination of classical and simulation models (moving averages, trend projection, Monte Carlo simulations, and autoregressive models) makes it possible to obtain more accurate and reliable forecasts of oil prices under conditions of high uncertainty.*

1. Review of existing models of oil price forecasting

Forecasting oil prices is of key importance both for the global economy and for individual national economies. As a strategic commodity, oil has a direct impact on inflation, energy security, and industrial competitiveness. Price fluctuations are often driven by a combination of economic, political, and geopolitical factors, which makes the task of forecasting particularly complex. Recent years have clearly demonstrated the vulnerability of oil markets: the COVID-19 pandemic caused a historic decline in demand and even a temporary negative price shock, while the war between Russia and Ukraine led to sharp price spikes and significant disruptions in energy markets. In this context, reliable models for forecasting oil prices provide valuable information for governments, companies, and investors by supporting decision-making under conditions of extreme uncertainty and rapid change.

Classical statistical methods for forecasting oil prices occupy a central place in the economic and energy literature, as they offer tools that are relatively easy to apply and interpret. Among them, **ARIMA (AutoRegressive Integrated Moving Average)** models stand out, as they combine autoregressive relationships and moving averages in order to capture complex temporal dynamics in price series. Another widely used approach is **exponential smoothing**, which assigns greater weight to more recent observations and allows flexible forecasting in the presence of trend or seasonality. These are complemented by **Moving Averages (MA)**, which smooth short-term fluctuations and highlight long-term trends in price movements. Although these methods are often criticized for their limited ability to capture sudden shocks, their simplicity and stability make them an important starting point in the analysis and forecasting of oil markets (Hamilton, 2009).

ARIMA models are particularly popular. For example, in a 2016 study, Tularam and Saeed compare exponential smoothing (ES), the Holt-Winters (HW) method, and the ARIMA model in forecasting WTI crude oil prices, finding that ARIMA (2,1,2) produces the most accurate results. In a similar analysis of Urals oil, the use of ARIMA (0,1,1) proves to be a reliable approach for short-term forecasting, especially in the context of the war in Ukraine and COVID-19.

Exponential smoothing (Single and Double ES, Holt-Winters) is also frequently applied in energy markets. It assigns greater weight to the most recent observations and is well adapted to time series with trend or seasonality.

Moving Averages (MA) serve as a simple and efficient tool for smoothing price data, especially in the context of ARIMA models, where the MA component helps capture random fluctuations.

Simulation models and scenario-based approaches have become established as a valuable tool in the analysis and forecasting of oil prices, especially under conditions of high uncertainty and strong market volatility. The Monte Carlo method, for example, makes it possible to generate multiple possible paths of future prices through the use of random variables, thereby taking into account the probabilistic nature of the process and providing a range of possible values rather than a single point forecast. This is particularly important in the context of external shocks, such as the COVID-19 pandemic or the war in Ukraine, which make traditional models less reliable. On the other hand, trend projection is used to capture long-term tendencies in price dynamics, simplifying the analysis and allowing the identification of the dominant direction of market development. Although more elementary from the point of view of mathematical complexity, these approaches are often used as a starting point for more complex models and provide a valuable basis for comparison and verification of the results obtained by other methods.

Monte Carlo simulations are used effectively to model future price paths under uncertainty. Alquist constructs forecasts through Monte Carlo integration using **10,000 iterations**, which confirms the reliability of this approach in macroeconomic analysis (Alquist, 2011).

Geometric Brownian motion (GBM), combined with Monte Carlo simulation, is also a proven tool. Nwafor and Oyedele (Nwafor & Oyedele, 2017) apply this method to forecast crude oil prices, showing that GBM-based modelling provides more accurate results compared to naive strategies, and they perform simulations to assess risk at the budgetary level (for example, for Nigeria).

Trend models are based on the assumption that historical price movements contain a persistent tendency that can be projected into the future. They are frequently used in oil price forecasting when researchers aim to assess long-term levels and directions of change, without necessarily emphasizing short-term fluctuations. A major advantage of this approach is its simplicity and interpretability, which allows relatively easy comparison with other forecasting methods. However, in the event of abrupt market disruptions, such as geopolitical conflicts or demand crises, the results may be limited (Hamilton, 2009).

Over the last decade, increasing attention in oil price forecasting has been devoted to *machine learning and artificial intelligence methods*. These approaches build upon classical statistical models by allowing the processing of large volumes of data, including non-financial indicators such as news publications, social media, and geopolitical factors. Neural networks, long short-term memory (LSTM) models, and deep learning have shown strong performance in capturing nonlinear relationships and complex market dynamics. In this way, they offer greater accuracy in short-term forecasts, although at the cost of higher computational complexity (Yu, Wang, & Lai, 2008).

In recent years, a growing tendency has emerged toward the use of *hybrid models that combine the advantages of classical statistical methods with the power of artificial intelligence*. These approaches are based on the idea that statistical models (for example, ARIMA or exponential smoothing) can capture linear relationships in the data, while machine learning algorithms and neural networks are better able to deal with nonlinear and dynamic processes. Thus, hybrid models provide more stable and reliable forecasts of oil prices, especially under conditions of high volatility and structural changes in the market (Zhang, Patuwo, & Hu, 1998).

In summary, research in the field of oil price forecasting points to three main directions. Classical statistical methods such as ARIMA, exponential smoothing, and moving averages continue to serve as a reliable starting point, especially for short-term forecasts. Simulation- and scenario-based models, including Monte Carlo methods and trend projection, offer flexibility in assessing uncertainty and long-term trends. At the same time, modern approaches based on machine learning and artificial intelligence demonstrate significant advantages in capturing complex, nonlinear relationships and market dynamics. This outlines a picture of increasing integration between classical and modern techniques, which promises more accurate and adaptive forecasts of future oil price movements.

2. Methodological framework

2.1. Moving averages

As a basic approach to forecasting oil prices, the Simple Moving Average (SMA) method was employed. It makes it possible to smooth price fluctuations and capture the underlying trends, as the average price value is calculated over a predetermined number of observations (window). The SMA is one of the most commonly used approaches for smoothing time series and identifying trends (Cryer & Chan, 2008).

The following variants were tested in this study:

- MA(10), MA(20), MA(30) – short-term moving averages, sensitive to rapid changes in the market;
- MA(40), MA(50), MA(60) – medium-term moving averages, combining stability and relative responsiveness;
- MA(70), MA(80), MA(90), MA(100) – long-term moving averages, which smooth price movements and are more suitable for capturing persistent trends.

This set of moving averages makes it possible to assess how the choice of a different window affects the forecasting accuracy and stability of the model. The comparison of the results was carried out using the statistical metrics **RMSE** and **MAPE**, thus providing an objective evaluation of the performance of each model.

Root Mean Squared Error (RMSE) measures the average magnitude of the errors between forecasted and actual values. It is calculated as the square root of the average of the squared differences:

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

where:

y_t are actual values;

$\hat{y}_t$ – forecasted values;

n – number of observations.

The lower the value of RMSE, the more accurate the forecast. RMSE is particularly useful because it assigns greater weight to larger errors, which makes it possible to distinguish the models that produce substantial deviations.

Mean Absolute Percentage Error (MAPE) measures the average error between the forecasted and the actual values in percentage terms. It is calculated using the following formula:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|,$$

where:

y_t are actual values;

$\hat{y}_t$ – forecasted values;

n – number of observations.

MAPE allows the results to be interpreted easily, as it shows the average error as a percentage of the actual value. For example, MAPE = 5% means that the model's forecasts deviate on average by 5% from the actual prices.

2.2. Trend projection

Another method used for forecasting oil prices is **trend projection**. It is based on the assumption that the historical movement of the time series can be described by a specific functional relationship reflecting the main tendency in the data. Trend projection is among the basic methods of time series analysis, allowing the identification and projection of long-term tendencies in the dynamics of the observed data (Gujarati & Porter, 2009).

In its most general form, the trend projection model is formulated as:

$$y_t = f(t) + \varepsilon_t,$$

where:

y_t is the value of the time series at time *t*;

$f(t)$ – the trend function (linear, exponential, polynomial);

ε_t – a random error term.

Different forms of trend functions are possible:

Linear trend: $y_t = \alpha + bt$, which assumes a constant rate of change in price;

Exponential trend: $y_t = \alpha e^{bt}$, appropriate in the case of accelerated growth or decline;

Polynomial trend: $y_t = \alpha + bt + ct^2$, which makes it possible to capture more complex nonlinear dynamics.

The parameters of the models were estimated using the Ordinary Least Squares (OLS) method. The quality of the forecasts was assessed through the standard metrics RMSE and MAPE, as well as through visual analysis of the deviations between the actual and the forecasted values.

Trend projection is particularly suitable for the analysis of oil prices because, despite considerable short-term fluctuations, the market follows certain long-term tendencies. These are often the result of factors such as global supply and demand, technological developments in extraction, OPEC policy, as well as macroeconomic conditions. By using an appropriate trend function, it is possible to separate the main development path from random noise. This makes it possible to construct more stable forecasts of future price movements, especially in the medium and long term.

2.3. Monte Carlo simulation

An important approach to forecasting oil prices is **Monte Carlo simulation**. The method is based on the repeated generation of random scenarios through the use of probability distributions in order to assess the range of possible future values. Monte Carlo simulations are an established method for modelling stochastic processes and are widely used in finance and time series analysis (Kroese et al., 2014).

This approach is particularly suitable for forecasting oil prices, since the market is characterized by high volatility and the influence of numerous external factors that are difficult to describe through purely deterministic models. The basic idea of the method is to create a probability distribution of future price values through a large number of randomly generated scenarios. Thus, instead of obtaining a single forecast, Monte Carlo simulation makes it possible to determine a range of possible outcomes and their probabilities. This provides the researcher not only with an expected forecast, but also with information about the risk of extreme fluctuations.

The dynamics of the oil price S_t are described by the following stochastic differential equation:

$$dS_t = \mu S_t dt + \sigma S_t dW_t,$$

where:

S_t is the price of the asset at time *t*;

μ – the expected return;

σ – the volatility (standard deviation of returns);

W_t – standard Brownian motion (Wiener process).

The discretized form used for the simulations is:

$$S_{t+1} = S_t * \exp\left(\left(\mu - \frac{\sigma^2}{2}\right)\Delta t + \sigma\sqrt{\Delta t} * Z_t\right),$$

where:

$Z_t \sim N(0,1)$ is a standard normally distributed random variable.

For each day within the forecasting horizon, a new oil price value is simulated. After repeated iteration (for example, 10,000 simulations), a probability distribution of future prices is obtained.

This makes it possible:

- to calculate **the expected values** of the future price;
- to determine **confidence intervals** (for example, 95%);
- to assess the risk of large fluctuations.

2.4. Autoregressive models

Autoregressive models have become established as a fundamental method in time series analysis precisely because of their ability to describe the internal dependence of data and to provide a reliable basis for forecasting (Box, Jenkins, Reinsel, & Ljung, 2016).

Autoregressive models are among the most frequently used tools in time series analysis because of their flexibility and their ability to capture the internal dynamics of processes. They are particularly effective for data that exhibit dependence on their own past values, as is the case with crude oil prices. The use of models of different orders makes it possible to examine the influence of both short-term and more distant lags on current prices. In this way, a more comprehensive understanding of the structure of the time series is obtained, contributing to more accurate forecasts and reducing the risk of systematic errors.

In the study, **autoregressive (AR) models** with different lag lengths, ranging from AR(1) to AR(10), were evaluated. The basic idea behind these models is that the current value of the time series depends on its own past values. The general form of an AR(p) is:

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \varepsilon_t,$$

where:

y_t the value of the time series at time *t*;

α – the constant term;

β_t – the model parameters;

ε_t – the stochastic error term (white noise).

The parameters α and β were estimated using the Ordinary Least Squares (OLS) method. The gradual increase in the order of the model from 1 to 10 makes it possible to examine the influence of more distant lags on the dynamics of oil prices. The standard metrics RMSE and MAPE were used to evaluate the forecasting performance of the different AR models.

3. Application of the models for forecasting oil prices

3.1. Forecasting oil prices through moving averages

In the analysis, moving averages with window lengths ranging from 10 to 100 days were applied. This method makes it possible to smooth short-term fluctuations and identify the main tendency in price dynamics. Short-term moving averages respond more quickly to emerging changes, whereas long-term moving averages smooth fluctuations and emphasize long-term movements.

Table 1

Trend Projection of Oil Prices (12.05.2024 – 12.05.2025)

MA_{10}	62.60
MA_{20}	64.28
MA_{30}	65.54
MA_{40}	67.18
MA_{50}	67.78
MA_{60}	68.87
MA_{70}	69.80
MA_{80}	70.77
MA_{90}	71.70
MA_{100}	71.94

The results show that for shorter periods (e.g. MA_{10}) the forecasted values are lower and closer to current market fluctuations. As the averaging period increases (MA_{50} – MA_{100}) the forecasts become smoother and higher, approaching the long-term upward tendency. This confirms the property of the moving average method to reduce the influence of short-term fluctuations and to emphasize the general direction of price dynamics.

It can be clearly seen from Table 2 that for shorter moving average periods (MA_{10} and MA_{20}) the MAD values are significantly lower (1.69 and 2.22, respectively), which indicates better forecast accuracy in relation to the actual data.

As the smoothing period increases, the MAD values gradually rise and reach about 4.00 for MA_{90} and MA_{100}. This is an expected result, since long-term moving averages smooth fluctuations, but at the same time reduce sensitivity to short-term changes and increase the forecast error.

Table 2

Mean Absolute Deviation (MAD) for Different Moving Average Periods (MA_{10} – MA_{100})

$MAD\ MA_{10}$		1.69
$MAD\ MA_{20}$		2.22
$MAD\ MA_{30}$		2.66
$MAD\ MA_{40}$		2.96
$MAD\ MA_{50}$		3.26
$MAD\ MA_{60}$		3.53
$MAD\ MA_{70}$		3.72
$MAD\ MA_{80}$		3.97
$MAD\ MA_{90}$		4.04
$MAD\ MA_{100}$		4.04

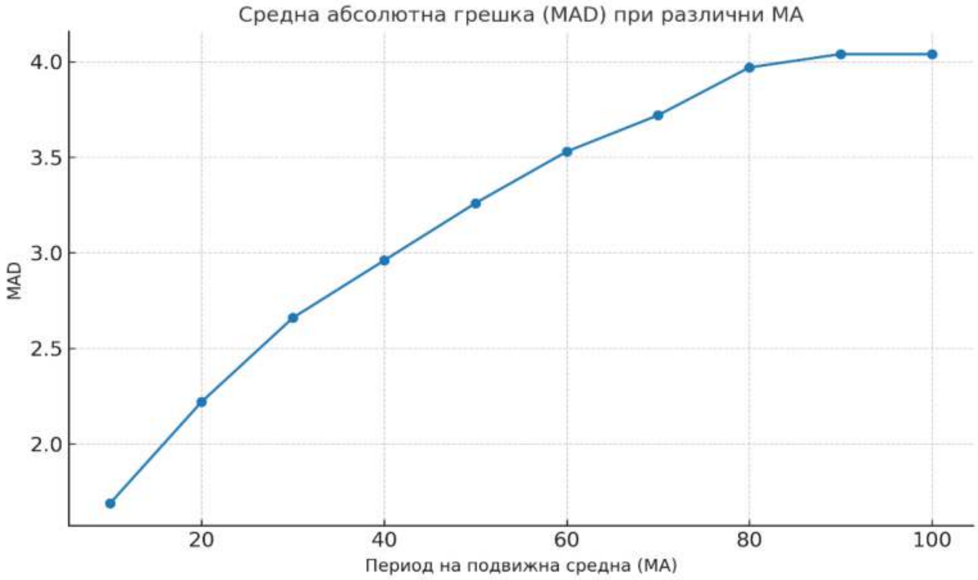

Figure 1. ***Mean Absolute Deviation (MAD) for Different Moving Average Periods (MA_{10} – MA_{100})***

The data show that for shorter moving average periods (MA_{10} – MA_{20}) the MSE values are relatively low (4.75 and 7.94, respectively), which reflects a better approximation to the actual prices (see Table 3).

Table 3

Mean Squared Error (MSE) for Different Moving Average Periods (MA_{10} – MA_{100})

MSE MA_{10}	4.75
$MSE\ MA_{20}$	7.94
$MSE\ MA_{30}$	10.86
$MSE\ MA_{40}$	13.53
$MSE\ MA_{50}$	16.73
$MSE\ MA_{60}$	20.26
$MSE\ MA_{70}$	22.78
$MSE\ MA_{80}$	25.51
$MSE\ MA_{90}$	25.42
$MSE\ MA_{100}$	24.83

As the smoothing period increases, the MSE values rise substantially, reaching a peak at MA_{80} (25.51). After MA_{80} a slight decline in MSE is observed (MA_{90} and MA_{100}), which indicates a certain stabilization; nevertheless, long-term moving averages remain less accurate than short-term ones.

For the shortest moving averages (MA_{10} and MA_{20}) RMSE values are 2.18 and 2.82, respectively, which indicates higher forecast accuracy.

Table 4

Root Mean Squared Error (RMSE) for Different Moving Average Periods (MA_{10} – MA_{100})

RMSE MA_{10}	2.18
$RMSE\ MA_{20}$	2.82
$RMSE\ MA_{30}$	3.30
$RMSE\ MA_{40}$	3.68
$RMSE\ MA_{50}$	4.09
$RMSE\ MA_{60}$	4.50
$RMSE\ MA_{70}$	4.77
$RMSE\ MA_{80}$	5.05
$RMSE\ MA_{90}$	5.04
$RMSE\ MA_{100}$	4.98

As the smoothing period increases, the error gradually rises and reaches a maximum at MA_{80} (5.05). For MA_{90} and MA_{100} a slight decrease in RMSE can be observed; however, the values remain higher compared to the short-term averages. This confirms that shorter moving averages are more suitable for short-term forecasting, whereas longer ones smooth the data excessively and lead to larger deviations.

In the study, both **Mean Squared Error** (MSE) and **Root Mean Squared Error** (RMSE) were used. MSE measures the mean of the squared errors and is particularly sensitive to larger deviations. RMSE, in turn, represents the square root of MSE and has the advantage that the error is expressed in the same units as the forecasted variable (in this case, the oil price). The use of both indicators makes it possible to provide a more comprehensive and reliable evaluation of the accuracy of the forecasting models.

The MAPE values show that the most accurate forecasts are obtained with shorter moving averages. For MA_{10} the error is only 2.29%, while for MA_{20} it reaches 2.99%. As the smoothing period increases, MAPE gradually rises and reaches 5.77% for MA_{100} (see Table 5).

Table 5

Mean Absolute Percentage Error (MAPE) for Different Moving Average Periods (MA_{10} – MA_{100})

MAPE MA_{10}	2.29%
$MAPE\ MA_{20}$	2.99%
$MAPE\ MA_{30}$	3.63%
$MAPE\ MA_{40}$	4.08%
$MAPE\ MA_{50}$	4.55%
$MAPE\ MA_{60}$	4.96%
$MAPE\ MA_{70}$	5.27%
$MAPE\ MA_{80}$	5.65%
$MAPE\ MA_{90}$	5.76%
$MAPE\ MA_{100}$	5.77%

These results confirm the observations from the previous indicators (MAD, MSE, and RMSE), according to which shorter moving averages provide better forecasting accuracy, whereas long-term moving averages smooth fluctuations excessively and lead to higher errors.

3.2. Forecasting oil prices through trend projection

The table presents the parameters of the estimated linear trend projection (see Table 6). The value of the constant (α = 83.83) and the slope coefficient (β = -0.06) indicate that the tendency is slightly downward, since β is negative, although close to zero. The forecasted value (TP = 67.55) reflects the estimated trend.

Table 6.

Results of Trend Projection and Accuracy Evaluation

α	83.83
β	-0.06
TP	67.55
AD TP	2.59
SE TP	6.69
RSE TP	2.59
APE TP	3.98%

With regard to the errors, the mean absolute deviation (AD = 2.59) and the absolute percentage error (APE = 3,98%) indicate relatively good forecast accuracy. The standard error (SE = 6,69) and the root mean squared error (RSE = 2,59) also suggest that the model captures the main dynamics, although with certain deviations.

Overall, the trend projection indicates the adequacy of the model used, while the negative slope coefficient β points to a slightly declining long-term tendency.

3.3. Forecasting oil prices through Monte Carlo Simulation

The specified parameters indicate that, for the one-day horizon, a slight negative change in the dynamics of the variable is expected, but under relatively moderate volatility (σ = 1.79%).

Table 7

Parameters for Monte Carlo simulation

S	64.96
μ	-0.10%
σ	1.79%
σ^2	0.03%
Δt	1
Start Date	12.05.2025
End Date	13.05.2025

S = 64,96 – initial value of the forecasted variable;

μ = -0,10% – average expected return/change for the period (the negative value indicates a slight downward trend);

σ = 1,79% – standard deviation reflecting the volatility of the variable;

σ^2 = 0,03% – variance, a measure of the dispersion of values around the mean;

Δt = 1 – time interval of the simulation (one step);

Start Date = 12.05.2025, End Date = 13.05.2025 – range of the forecast period.

This provides a basis for carrying out a Monte Carlo simulation, in which the probable distribution of future forecast values can be assessed through a large number of random scenarios.

The results of the simulation show (see Table 8) that the forecasted oil price is **USD 64.90**, with an extremely narrow 95% confidence interval (**64.88 – 64.92**).

Table 8

Results of the Monte Carlo Simulation for Oil Prices (10,000 Iterations)

S	64.90
Simulated σ	1.16
Number of simulations	10,000.00
Standard error	0.012
Upper bound (95%)	64.92
Lower bound (95%)	64.88

This means that, under the specified parameters and the high number of simulations, the model predicts minimal uncertainty in the short term. The resulting standard error (0.012) further confirms the reliability of the simulation.

An interesting point is the comparison between the input parameters and the simulation results. The input volatility is σ = 1.79%, while the simulated volatility is – σ = 1.16%. The initially specified σ reflects the historical variability of the oil price over the selected period. The lower simulated σ means that, in most simulations, the fluctuations around the mean value are weaker. This may be due to the short simulation horizon (1 day), the stability of the most recently observed data, and the “averaging” of the results across 10,000 iterations.

The mean forecasted price is (S = 64.90 USD). It is very close to the currently observed price, which suggests that, for a short-term horizon (1 day), the model does not predict significant deviations.

The confidence interval is 95%, with a range of USD 64.88–64.92. This is an extremely narrow interval, which indicates high model stability. Over a longer time horizon, however, this interval would widen considerably.

The standard error is 0.012. This is a very low value, ensuring the reliability of the simulation. It shows that even if the analysis is repeated many times, the result will be almost identical.

The Monte Carlo simulation confirms the stability of oil prices in the short term. The lower simulated volatility compared with the historical one may be explained by the short horizon and the large number of repetitions, which smooth random deviations.

3.4. Forecasting oil prices through Autoregressive Models

To evaluate the predictive performance of the autoregressive models, AR(1) to AR(10) were applied sequentially. These models make it possible to analyze the relationship between the current values of the time series and its lagged values. Table 9 presents the estimated parameters of the constant term (α), the autoregressive coefficient (β), as well as the forecasted price values.

Table 9

Results of Autoregressive Models (AR(1) – AR(10))

	AR-1	AR-2	AR-3	AR-4	AR-5	AR-6	AR-7	AR-8	AR-9	AR-10
α	1.66	3.22	4.82	6.26	7.63	8.59	9.40	9.96	10.28	10.31
β	0.98	0.96	0.93	0.91	0.89	0.88	0.87	0.86	0.86	0.85
Forecast	65.13	65.29	65.46	65.59	65.73	65.79	65.84	65.85	65.84	65.84

The coefficient β (the autoregressive parameter) gradually declines from 0.98 in AR(1) to 0.85 in AR(10). This shows that, as the lag increases, the dependence of the current value on previous values decreases. **The coefficient α (the constant term)** increases substantially as the order of the model rises, from 1.66 in AR(1) to 10.31 in AR(10). This compensates for the decreasing weight of β.

All forecasts fall within a relatively narrow range (USD 65.13–65.85). As the lag increases, the forecasted value rises slightly and then stabilizes around USD 65.8–65.9. The AR(1)–AR(3) models are simpler and show stronger autocorrelation, whereas the higher-order models, AR(7)–AR(10), smooth the influence and produce similar results. In practical terms, this means that the more complex AR models do not provide a substantial improvement over the lower-lag specifications. The autoregressive models forecast a relatively stable oil price of around **USD 65.8**, while the more complex models (AR(7)–AR(10)) do not lead to a significant change compared with AR(3) or AR(4).

Conclusion

Forecasting oil prices is a particularly challenging process, given the dynamics of global energy markets and the influence of multiple factors—economic, political, and technological. In the present study, several approaches were applied and compared: moving averages, trend projection, Monte Carlo simulations, and autoregressive models.

The results showed that each method has its own advantages and limitations. Moving averages provide good smoothing and short-term forecasting, but over longer periods they lead to greater error. Trend projection proved useful for capturing long-term tendencies, although it does not account for sudden market disruptions. Monte Carlo simulations demonstrated their strength in modelling uncertainty and constructing probabilistic scenarios. Autoregressive models showed good predictive power, especially over short-term horizons, as they reflect the autocorrelation structure of time series.

The comparative analysis based on indicators such as MAD, MSE, RMSE, and MAPE showed that a combination of methods could lead to more reliable forecasts than the use of a single model alone. This confirms the thesis that integrating classical statistical approaches with simulation models provides more robust results under conditions of high market instability

In conclusion, the study emphasizes that oil price forecasting should be based on flexible and adaptive methodologies that combine different tools in order to account for the complex nature of the market. Prospects for future research lie in the application of modern machine learning and artificial intelligence models, which could build upon classical statistical methods and contribute to more precise forecasts.

References

Alquist, R. (2011). How important is the global financial cycle? Evidence from capital flows. International Finance Discussion Papers, 1022. Board of Governors of the Federal Reserve System. https://www.federalreserve.gov/pubs/ifdp/2011/1022/ifdp1022.pdf

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., &Ljung, G. M. (2016). *Time series analysis: Forecasting and control* (5th ed.). Wiley.

Cryer, J. D., &Chan, K. S. (2008). *Time series analysis: With applications in R* (2nd ed.). Springer. https://doi.org/10.1007/978-0-387-75959-3

Gujarati, D. N., &Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill.

Hamilton, J. D. (2009). *Causes and Consequences of the Oil Shock of 2007–08*. Brookings Papers on Economic Activity, 40(1), 215–261. https://doi.org/10.1353/eca.0.0047

Kroese, D. P., Brereton, T., Taimre, T., &Botev, Z. I. (2014). *Why the Monte Carlo method is so important today. Wiley Interdisciplinary Reviews: Computational Statistics, 6*(6), 386–392. https://doi.org/10.1002/wics.1314

Nwafor, C., &Oyedele, I. (2017). Simulation of crude oil prices using Geometric Brownian Motion (GBM). European Journal of Business and Management, 9(18), 56–66. https://researchonline.gcu.ac.uk/files/24776117/Simulation_of_Crude_Oil_Prices_EJBM_Vol.9_No.pdf

Yu, L., Wang, S., &Lai, K. K. (2008). Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm. *Energy Economics, 30*(5), 2623–2635. https://doi.org/10.1016/j.eneco.2008.05.003

Zhang, G. P., Patuwo, B. E., &Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting, 14*(1), 35–62. https://doi.org/10.1016/S0169-2070(97)00044-7

Plamen Parushev is a PhD student in the Department of Economic Theory and International Economic Relations at St. Cyril and St. Methodius University of Veliko Tarnovo, Veliko Tarnovo, Bulgaria. His **research interests** include international markets, pricing, trade, market surveillance, quality control of liquid fuels, legal issues related to trade and market relations between economic operators and consumers, and other.