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Forecasting the Weekly Spot Oil Price Using a Hybrid Model ARMA-GARCH-MLP and Prophet Forecasting Method

Abstract. *We analyse the WTI Spot oil price from January 3, 1986 to September 20, 2024, as well as the Europe Brent Spot oil price from May 15, 1987, to 20, 2024. We present the most recent data for the weekly WTI Spot OP for 2024, which is approximately 75–80 US $/b, and the weekly Europe Brent Spot OP, which is approximately 80–85 US $/b. The optimal hybrid model for the weekly WTI Spot OP is ARMA-GARCH-MLP (5, 6, 1) with ARMA (3, 0) and GARCH (1, 1). On the other hand, the optimal hybrid model for the weekly Europe Brent Spot OP is ARMA-GARCH-MLP (6, 3, 1) with ARMA (3, 1) and GARCH (1, 1). These hybrid models provide forecasted values ranging from 53.8105 US $/b to 72.2258 US $/b for WTI and from 69.575 US $/b to 76.1401 US $/b for Europe Brent, thus aligning the most recent data with IEA forecasting outcomes.*

Keywords: *WTI Spot oil price, Europe Brent Spot oil price, realised volatility, ARMA-GARCH-MLP, Prophet Forecasting Method.*

JEL Classification: C22, C45, Q31, Q35.

1. Introduction

Crude oil (CO) is the primary energy source in the world and in contemporary society with 54,564TWh global primary energy consumption and almost 30% of total energy consumption in 2023 (Our World in Data, 2024). CO is one of the most significant industrial raw materials and strategic reserves, and its development along with the world economy and the rapidly increasing energy demand has a significant impact on the global economy and market (Tan et al., 2024). Global CO production rose by 1% in 2023, with higher production in the US, Brazil, and Iran, which is more than OPEC+ production cuts. While, refined oil products production has slightly increased by 1.8% in 2023. Also, refined oil products consumption raised by 2.4% in 2023 (Enerdata, 2024).

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Zhang et al. (2024) recognise that unforeseen circumstances, such as Russia-Ukraine or geopolitical conflict, which are still evolving and taking on new and unclear features, will have an impact on the volatility and predictability of crude oil price (COP). Several economic factors, including inflation, interest rates, exchange rates, and overall economic development, can be significantly impacted by changes in the COP (Baumeister and Kilian, 2016). The oil price (OP) has changed significantly in recent years, rising and falling significantly at different times. The global economy has been significantly impacted by these changes on several fronts, including national economies, corporate profits, and household budgets (Jha et al., 2024). The equilibrium between supply and demand is an important factor in determining the COP. COP is directly impacting energy costs, consumption, and investment decisions. Ensuring the sustainability and profitability of energy companies' businesses through strategic planning and investment is crucial for decision-making processes such as oil production, refining, and energy investment (Liu et al., 2024).

Therefore, forecasting the COP may be helpful in preparing domestic energy resources and tax laws, which can assist in addressing the possible effects of OP fluctuations on inflation and economic stability (Yu et al., 2019). The following Fig. 1 shows both WTI spot OP between 1986 and September 23rd-27th, 2024 and Europe Brent spot OP between May 15th, 1987 and September 23rd-27th, 2024.

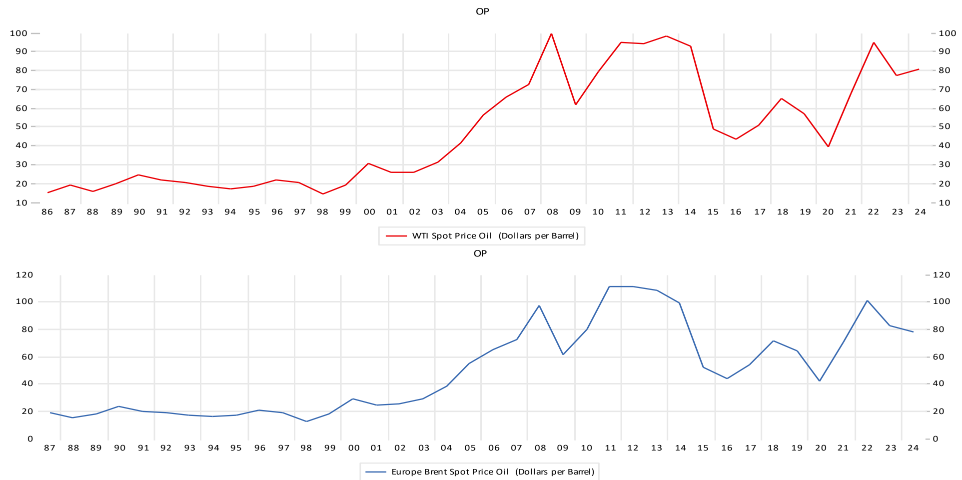

Figure 1. Annual WTI OP and Brent OP data

Source: Authors' own creation.

Figure 1 illustrates that during the early years of the 1986–1999 period, OP was at its lowest point as a result of the overproduction caused by OPEC and non-OPEC, the Gulf War, the strong US dollar, and slower economic growth in certain countries. Significant political and economic fallout resulted from this collapse, especially for nations that export oil. However, in order to stabilise OP, many countries have agreed to set production quotas since the 2000s. They have also prioritised efficiency gains and technological advancements in oil exploration and production, which has led to lower energy costs and, in some cases, stimulated economic growth. The highest level of OP was observed between 2000 and 2014, when it increased from an average of $30 per barrel to nearly $100 per barrel. This period known a peak in the price especially in 2008, then experienced a severe drop during the world financial crisis before rising once more until 2014. Rising worldwide demand, particularly in developing nations like China and India, the US dollar's weakness, natural disasters like Hurricane Katrina in 2005, OPEC's maintenance of production quotas, and conflicts and instability in oil-producing regions like the Iraq War and tensions with Iran all had an impact on global supply by increasing the value of OP. The oil market saw a dramatic change after 2014, going from over $100 per barrel in June 2014 to under $50 by early 2015. The US shale oil boom, OPEC's decision to maintain high production, and a slower growth in demand, particularly in China, were the factors contributing to this decline in the global oil market. To try to rebalance the market and support prices, OPEC and some non-OPEC nations, most notably Russia, agreed to production cuts in late 2016. Then, in 2017–2018, prices began to partially recover, reaching about $70-80 per barrel, but they remained well below the pre–2014 levels due to decreased investments, financial strain on numerous oil companies, economies dependent on oil, sanctions against Iran, and the Venezuelan crisis. In 2020, the global pandemic dropped demand and prices sharply, even briefly pushing US oil futures into negative territory, and as a result, the oil market experienced yet another major shock. Geopolitical tensions and the recovery in demand drove OP's sharp rise in early 2022 following the global pandemic. The energy crisis was caused by the Russian-Ukrainian conflict in February 2022, which severely disrupted markets and drove prices even higher. This was especially true for Europe, which was heavily dependent on Russian gas and oil. OP reached the 80$ per barrel level in 2023 as a result of market volatility. In an attempt to lower prices, a number of nations, including the US, released oil from their strategic petroleum reserves, which inadvertently helped to ease tensions. Most recent data, which spans January 2024 to September 16–20, 2024. The Europe Brent Spot OP ranged from 70.31 to 92.01 dollars per barrel, while the WTI Spot OP was between 66.73 and 86.5 dollars per barrel.

The new analysis regarding Weekly WTI and Europe Brent COP is the paper's contribution. We also present the ARMA-GARCH-MLP hybrid model as a new forecasting model. The data outcomes of this hybrid model will be applied to prophet method forecasting. We then present updated projections for the period beginning on September 27th, 2024, and ending on December 26th, 2025. Several previous studies did not analyse the world oil market, did not offer enough support, and did not offer data projections for the future. This paper is divided into five sections. The introduction is covered in the first section. A brief review of several studies on the forecasting method of COP and OP is presented in the second section. Section three describes the data and methodology, while Section four discusses the main empirical findings. The final section discusses the conclusion and implications for policy.

2. Literature review

Early research on stochastic price processes is limited to examining them at the overall level, which captures price drivers over a specific time scale, and primarily concentrates on their volatility. Xiang and Zhuang (2013) employ ARIMA to forecast COP, and Naderi et al. (2019) employ ARIMA method to forecast COP obtained from the Central Bank of the Islamic Republic of Iran. They established that The RMSE values of ARIMA-based monthly, daily, annual COP are 3.440, 0.071, 4.261, respectively. While Klein and Walther (2016) use GARCH-type models to predict COP based on historical price data. However, these models are unable to handle nonlinear, dynamic, and complex price data because they are dependent on specific assumptions, such as the stability and linear variation of data. In order to predict the daily spot price of Brent CO, which is gathered from Refinitiv Eikon**.** Hasselgren et al. (2024) use Generalised Autoregressive Conditional Heteroskedasticity with Mixed Data Sampling (GARCH-MIDAS) models. The study looks at how professional forecasters' disagreements about OP can be used to predict oil return volatility between 2002Q1 and 2023Q4. They find that a rise in forecaster disagreement corresponds to increased volatility in the oil market. Moreover, taking forecaster disagreement into account provides insightful information that significantly improves the volatility prediction of CO returns. However, Kristjanpoller and Minutolo (2016) state that ANN improves forecasting accuracy over the GARCH and ARFIMA model prediction.

On the other hand, computer scientists have advanced the field by applying a variety of sophisticated machine learning models and machine learning algorithms, such as support vector regression (SVR), to the forecasting of COP (Wang et al., 2020). Kristjanpoller and Minutolo (2016) find that the ANN-GARCH represent a powerful method for COP prediction using the dataset from July 2002 to May 2014. Weng et al. (2021) created an online extreme learning machine using a genetic algorithm regularisation and a forgetting factor to predict the volatility of CO futures. They find that the ability to learn online updates is necessary for more accurate volatility forecasting during the COVID-19 pandemic, especially when considering news related to the Pandemic. In particular, the time-dependent patterns in the historical data are captured by recurrent neural network (RNN) models, such as long short-term memory (LSTM) and gated recurrent unit (GRU) models, to fit the temporal data well. Jha et al. (2024) predict spot prices for CO using multivariate analysis. They employ ridge regression, LASSO regression, SVR, and multivariate regression models with and without several variables such as total CO supply, total CO demand, price of silver, rouble exchange rate, price of gold, natural gas prices, and dollar exchange rate. They discover that the SVR model with radial basis function (RBF) kernel does not only provide better forecasting accuracy and more stability with an R^2 of 0.9951, RMSE of 0.0766, MAPE of 4.25 and MSE of 0.005, but outperforms the other 3 models for predicting COP as well. Liu et al. (2024) combine ARIMA, back propagation neural network (BPNN), extreme learning machine (ELM), and long short-term memory neural network (LSTM) into one combined forecasting model named Jaynes weight hybrid (JWH). They use weekly and monthly WTI and Brent COP for prediction during the period of 1986 to 2022. They discover that compared to multiple comparison models, the novel combined method's prediction accuracy is noticeably higher.

3. Model specification

3.1 Data description

We used the weekly Europe Brent Spot OP between May 15th, 1987, and September 20th, 2024, and the weekly WTI Spot OP is used between January 3rd, 1986, and September 20th, 2024 as the two primary variables for forecasting. Both variables are measured in US dollars per barrel (US $/b). The raw data's descriptive statistics, along with their realised volatility (with log difference) are displayed in the following table.

Table 1. The raw data and realised volatility descriptive statistic

	Weekly WTI spot OP		**Weekly Europe Brent spot OP**	
	Raw data	**Realised volatility**	**Raw data**	**Realised volatility**
Mean	47.48245	0.0005	50.1867	0.0007
Maximum	142.5200	1.5543	141.0700	0.3238
Minimum	3.320000	-1.8017	9.440000	-0.4078
Jarque-Bera	185.2301	9634083	183.8655	6503.550
Probability	0.0000	0.0000	0.000000	0.0000
	2021	2020	1950	1949

Source: Authors' processing.

Table 1 demonstrates that the raw data for weekly WTI Spot OP maximum value is 142.52 US $/b, and the weekly Europe Brent Spot OP maximum value is 141.07 US $/b. Both values were reached on February 7th, 2008, indicating that the primary cause of this historical increase was the global financial crisis. However, weekly WTI Spot OP minimum value is 3.32 US $/b on April 22nd, 2020 due to the global Pandemic, while the weekly Europe Brent Spot OP maximum value is 9.44 US $/b on December 12th, 1998 due to The Asian financial crisis and this period fell on a Saturday, and that Brent crude prices during the ensuing weeks were probably between $10 and $12 per barrel. The Jarque and Bera (1987) test show that both data are following a non-normal distribution.

3.2 Methodology

In order to obtain stationary data, reduce heteroscedasticity, and gain some advantages, we transform the data into realised volatility with log difference. Then, we start with studying the ARMA model of both variables. In the 1920s and 1930s, Yule and Walker introduced the first autoregressive (AR) models, which take a given discrete time series with zero mean. The AR of order p is denoted by the notation AR(p). The model AR(p) is expressed as:

$$X_t = \sum_{i=1}^{p} \beta_i X_{t-i} + \varepsilon_t$$

Where $\beta_1, \dots, \beta_p$ are parameters, ε_t is an error term, typically independent and identically distributed (i.i.d.) normal random variables.

Herman (1938) created ARMA by fusing the AR and MA models in his 1938 dissertation, "A Study in the Analysis of Stationary Time Series”. The ARMA model has a notation ARMA (p, q), which both “p” and “q” are defined previously. We can Write ARMA (p, q) as follow:

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \beta_i X_{t-i} + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i}$$

We can use the autocorrelation functions and the partial autocorrelation functions to determine the proper values for p and q in the ARMA (p, q). However, in this paper, we focus on Akaike info criterion (Akaike, 1974), Schwarz criterion (Schwarz, 1978), and Hannan-Quinn criterion (Hannan and Quinn, 1979) to select the order of p and q.

Once the ideal ARMA model has been selected, we employ Engle's (1982) test of ARCH to provide a framework for volatility forecasting and to systematically capture volatility clustering. The specification of error term in the ARCH model can be written as follows:

$$\varepsilon_t = \sigma_t * \delta_t$$

where δ_t is a stochastic and random variable with a strong white noise process and σ_t is a standard deviation. We can define the variance of error as follows:

$$\sigma_t^2 = \gamma_0 + \gamma_1 * \varepsilon^2{}_{t-1} + \gamma_2 * \varepsilon^2{}_{t-2} + \cdots + \gamma_q * \varepsilon^2{}_{t-q}$$

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{q} \gamma_i * \varepsilon^2{}_{t-i}$$

where $\gamma_0 > 0$ and $\gamma_i \geq 0$, $i > 0$

Therefore, when the probability of F-statistic and LM test are greater than 5%, we accept the null hypothesis and it means that there is no ARCH component $\gamma_i = 0$ for all $i = 1, \dots, q$. While, whether the probability of F-statistic and LM test are inferior to 5%, we cannot reject the alternative hypothesis and it means that there is and evidence of ARCH component (at least one γ_i must be significant).

However, whether an ARMA model assumed for the error variance, the model is a generalised autoregressive conditional heteroskedasticity (GARCH) model developed by Bollerslev (1986). The GARCH (p, q) model with p is the order of GARCH terms σ^2, while q is the order of ARCH terms ε^2. The GARCH (p, q) is written as follow:

$$\sigma_t^2 = c + \gamma_1 * \varepsilon^2{}_{t-1} + \gamma_2 * \varepsilon^2{}_{t-2} + \cdots + \gamma_q * \varepsilon^2{}_{t-q} + \alpha_1 * \sigma_{t-1}^2 + \alpha_2 * \sigma_{t-2}^2 + \cdots + \alpha_p * \sigma_{t-p}^2$$

$$\sigma_t^2 = c + \sum_{i=1}^{q} \gamma_i * {\varepsilon^2}_{t-i} + \sum_{i=1}^{p} \alpha_i * {\sigma^2}_{t-i}$$

We create new variables from ARMA, ARCH, and GARCH after verifying the existence of the ARCH or GARCH model, and then we apply them to the multilayer perceptron (MLP), a contemporary artificial neural network (ANN). The first mathematical model of a neural network was developed by **McCulloch and Pitts (1943)**, laying the foundation for ANN. Then, **Rosenblatt (1958)** suggested MLP, which had three layers: an input layer, a hidden layer with randomised weights that did not learn and an output layer with connectable connections, as shown in Fig 2:

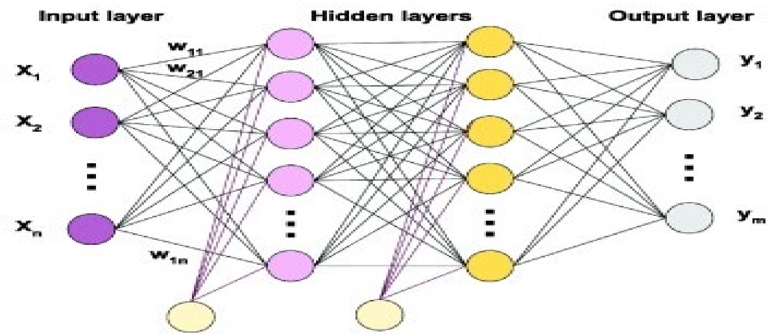

Figure 2. The three layers of MLP

Source: https://www.sciencedirect.com/topics/computer-science/multilayer-perceptron.

Besides, due to Rumelhart et al. (1986a) and Rumelhart et al. (1986b) rediscovery and popularisation of the backpropagation algorithm, which allowed MLPs to learn internal representations, neural network research experienced a renaissance.

The forward propagation phase of the MLP mechanism begins with each neurone $(X_1, \ldots, X_n)$ receiving inputs from the input layer or earlier hidden layers (we shall use the outcomes variables from ARMA, ARCH and GARCH models). The input is then multiplied by a weight for each connection, and the total of all the weighted inputs to a neurone is added along with a bias before being passed through an activation function to generate the neuron's output. The activation mechanisms Use ReLU, Sigmoid, and Tanh to introduce non-linearity into the network.

ReLU function is defined as follow: $ReLU(x) = max(x, 0)$

Sigmoid function is defined as follow: $sigmoid(x) = \frac{1}{1+exp(-x)}$

Tanh function is defined as follow: $tanh(x) = \frac{1-exp(-2x)}{1+exp(-2x)}$

Following the definition of the activation functions, the network learns through backpropagation. Using deeper networks (more layers) to learn more complex functions with fewer total neurones than wider networks, MLPs can approximate any continuous function. We can get the new realised volatility of the Europe Brent Spot OP and Weekly WTI after choosing the input layer and activation function, and we can compare it to the initial realised volatility using the mean squared errors (MSE) and root mean square deviation (RMSD).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y_i})^2 \text{ and } RMSD = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \widehat{Y_i})^2}{n}}$$

The final stage of the methodology is to make forecasts with Prophet for a data period that ends on December 26, 2025, using the newly realised volatility of the Weekly Europe Brent and WTI Spot OP.

Facebook (now Meta) created the Prophet forecasting method, which considers trend, seasonality, holiday effects, and error terms when predicting time series. When Prophet was first made available in 2017, it was able to manage weekly observations with missing values and holiday effects. It is resilient to trends and outliers. Prophet makes use of a time series model that can be broken down into three main parts: trend, seasonality, and holidays. Prophet fits the model using Stan in a Bayesian approach, enabling rapid model fitting and the retrieval of forecast uncertainty intervals. It is resilient to missing data and input outliers thanks to this approach. After it has been fitted, Prophet can produce future dates and forecast each one. Additionally, it gives its predictions' uncertainty intervals.

4. Results and discussion

4.1 ARMA estimation

The order in which p and q were included for the estimation of the ARMA of the Weekly Europe Brent and WTI Spot OP is shown in the following table.

Table 2. ARMA estimation

	Weekly WTI spot oil price	**Weekly Europe Brent spot oil price**
Variable	Coefficient (Prob)	Coefficient (Prob)
C	0.0007 (0.6183)	0.0007 (0.5734)
AR(1)	0.8097*** (0.000)	-0.3149** (0.015)
AR(2)	-0.3192*** (0.004)	0.0832** (0.0247)
AR(3)	0.0818*** (0.007)	0.1060*** (0.000)
MA(1)	-0.9511*** (0.000)	0.5313*** (0.000)
MA(2)	0.3423*** (0.007)	…
Akaike info criterion	-2.515	-3.3966
Schwarz criterion	-2.499	-3.3823
Hannan-Quinn criterion	-2.509	-3.3913
ARCH Test with lag 1		
F-statistic	475.6697*** (0.000)	223.9596*** (0.000)
LM test	385.1716*** (0.000)	201.0196*** (0.000)
ARCH Test with lag 2		
F-statistic	265.982*** (0.000)	163.6783*** (0.000)
LM test	421.353*** (0.000)	280.5473*** (0.000)
ARCH Test with lag 3		
F-statistic	187.4155*** (0.000)	128.9749*** (0.000)
LM test	440.224*** (0.000)	323.2241*** (0.000)

	Weekly WTI spot oil price	**Weekly Europe Brent spot oil price**
ARCH Test with lag 4		
F-statistic	insignificant	117.2347*** (0.000)
LM test	insignificant	378.513*** (0.000)

Source: Authors' processing.

Note: "***", '**', '*' refers to the confidence interval at 99%,95%, and 90% level.

Table 2 shows that the optimal model for the weekly WTI Spot OP is ARMA (3, 2), while the weekly Europe Brent Spot OP is ARMA (3, 1). The selection of such models was done after several estimations, and we selected both models according to the low value of Akaike, Schwarz and Hannan-Quinn criterion. The weekly WTI Spot OP has p=3 and q=2, therefore, AR (1) and AR (3) have a positive and significant impact at the level of 1%, while AR (2) has a negative and significant contribution at the level of 1%. Besides, MA (1) has a negative and significant influence at the level of 1%, while MA (2) has a positive and significant effect at the level of 1%. However, the weekly Europe Brent Spot OP has p=3 and q=1, therefore, AR (1) has a negative and significant contribution at the level of 5%, while AR (2) and AR (3) have a positive and significant impact at the level of 5% and 1%, respectively. Also, MA (1) has a positive and significant effect at the level of 1%.

Following the selection of the best models, the ARCH test was run, and the results showed that both models had an ARCH effect. The weekly WTI Spot OP has an ARCH effect with 3 lags, while the weekly Europe Brent Spot OP has an ARCH effect with 4 lags. This is because the inclusion of residual with 4 lags for WTI and 5 lags for Europe Brent was not significant.

4.1. ARCH and GARCH estimation

The following table shows the estimation of ARCH and GARCH model for both models:

Table 3. ARCH and GARCH estimation

	Weekly WTI spot price oil		**Weekly Europe Brent spot price oil**	
Variable	ARCH (3)	GARCH (2,1)	ARCH (4)	GARCH (1,1)
	Coefficient (Prob)	Coefficient (Prob)	Coefficient (Prob)	Coefficient (Prob)
C	0.0015 (0.6260)	0.0017*** (0.000)	0.0013 (0.3662)	0.0018 (0.1210)
AR(1)	0.112 (0.953)	0.484*** (0.006)	-0.3012 (0.2484)	-0.3656 (0.2002)
AR(2)	0.0465 (0.817)	0.4237*** (0.007)	0.0887 (0.1613)	0.099 (0.1354)
AR(3)	0.0143 (0.9526)	-0.1336*** (0.000)	0.0498 (0.1042)	0.0267 (0.3775)
MA(1)	0.107 (0.9549)	-0.3017** (0.037)	0.5256** (0.0480)	0.590** (0.0407)
MA(2)	0.041 (0.9385)	-0.521*** (0.000)	…	…

	Weekly WTI spot price oil		**Weekly Europe Brent spot price oil**	
Variance equation				
C	0.0036*** (0.000)	0.0002*** (0.000)	0.0015*** (0.000)	0.0004*** (0.000)
(Residualt-1) ²	0.1333*** (0.000)	0.1302*** (0.000)	0.1200*** (0.000)	0.1491*** (0.000)
(Residualt-2) ²	0.0444* (0.095)	0.041*** (0.000)	0.0400*** (0.008)	…
(Residualt-3) ²	0.0444 (0.2015)	…	0.0400** (0.0241)	…
(Residualt-4) ²	…	…	0.0400** (0.0285)	…
GARCHt-1	…	0.532*** (0.000)	…	0.600*** (0.000)
Akaike info criterion	-3.0966	-3.3003	-3.5466	-3.600
Schwarz criterion	-3.0688	-3.2725	-3.5180	-3.5780
Hannan-Quinn criter.	-3.0864	-3.2901	-3.5360	-3.5924
ARCH Test				
F-statistic	7.607*** (0.006)	1.8583 (0.173)	1.1275 (0.2884)	0.041 (0.8396)
LM test	7.586*** (0.006)	1.8584 (0.173)	1.1280 (0.2882)	0.041 (0.8395)

Source: Authors' processing.

Note: "***", '**', '*' refers to the confidence interval at 99%,95%, and 90% level

Table 3 demonstrates that GARCH (2, 1) is the best model for the weekly WTI Spot OP, whereas GARCH (1, 1) is the best model for the weekly Europe Brent Spot OP. After making multiple estimations, we chose both of these models based on the ARCH test and the low value of the Akaike, Schwarz, and Hannan-Quinn criteria.

Following estimation, we are able to produce 8 new variables for the weekly WTI Spot OP, which serves as the MLP input layer, and 6 new variables for the weekly Europe Brent Spot OP, which serves as the MLP input layer.

4.2. ARMA-GARCH-MLP estimation

The weekly WTI and Europe Brent Spot OP MLP data information is displayed in the following table:

Table 4. MLP data information

	Weekly WTI Spot OP	**weekly Europe Brent Spot OP**
Training data (%)	1415 (70.2%)	1357 (69.7%)
Testing data (%)	602 (29.8%)	589 (30.3%)
Valid (%)	2017 (100%)	1946 (100%)
Input layer	5	6
Hidden layer	1	1
number of units in hidden layer	6 with the exclusion of bias	3 with the exclusion of bias
Output layer	1	1
MSE in training	95.951	2.227
RMSD in training	9.795	1.492

	Weekly WTI Spot OP	weekly Europe Brent Spot OP
MSE in testing	190.776	0.576
RMSD in testing	13.812	0.759

Source: Authors' processing.

The MLP model for the weekly WTI Spot OP uses ARMA (3, 0) and GARCH (1, 1). However, we eliminate MA (1 and 2) and the second lags from GARCH to create the ideal hybrid model, ARMA-GARCH-MLP (5, 6, 1), which yields the best results and minimum of errors. While, the MLP model for the weekly Europe Brent Spot OP uses all new variables to generate the hybrid model ARMA-GARCH-MLP (6, 3, 1), which it gives the best results and minimum of errors.

4.3. Forecasted data with Prophet and discussion

The results of evaluating the Prophet method's quality are displayed in the following table:

Table 5. Measuring the quality of Prophet method

	Weekly WTI Spot OP	Weekly Europe Brent Spot OP
MSE	0.00486	0.00203
RMSD	0.0697	0.045

Source: Authors' processing.

Note: "***", '**', '*' refers to the confidence interval at 99%,95%, and 90% level

Table 5 shows that the average squared difference or the average distance between the estimated values from prophet and the actual value of realised volatility are very close, meaning that the errors are minimum or almost inexistent. We leverage the strengths of both machine learning and econometrics techniques, which makes this possible. This outcome demonstrates that prophet outcomes, with a forecasting period ending on December 26th, 2025, can provide the best forecast data for both weekly WTI Spot OP and weekly Europe Brent Spot OP.

Table 6. Estimation of future data for weekly WTI and Europe Brent Spot OP

	Weekly WTI Spot OP			Weekly Europe Brent Spot OP		
	Forecasted data	**Lower value**	**Upper value**	**Forecasted data**	**Lower value**	**Upper value**
9/27/2024	72.1335	67.3123	77.0371	75.4267	71.0209	79.6524
10/4/2024	72.2258	67.4324	77.3114	75.6421	71.7717	80.1989
10/11/2024	72.1425	67.5841	77.4282	75.7449	71.5323	80.2304
10/18/2024	71.6035	66.6072	76.6169	75.4087	71.4963	80.2801
10/25/2024	70.6458	66.017	75.6582	74.5733	70.6735	79.356
11/1/2024	69.6123	65.1107	74.6842	73.5605	69.3872	77.9012
11/8/2024	68.7793	63.8582	73.6031	72.7758	68.888	76.7667
11/15/2024	68.0616	63.5774	72.9914	72.3221	68.0916	76.5186
11/22/2024	67.1447	62.5799	72.0171	71.943	67.7012	75.9344
11/29/2024	65.9058	61.53	70.5985	71.3433	67.6306	75.8446
12/6/2024	64.6349	60.637	69.0906	70.5378	66.7856	75.6701
12/13/2024	63.7917	59.6468	68.3233	69.8472	66.062	73.6723
12/20/2024	63.588	59.1894	67.9912	69.575	65.615	73.1855

	Weekly WTI Spot OP			Weekly Europe Brent Spot OP		
	Forecasted data	Lower value	Upper value	Forecasted data	Lower value	Upper value
12/27/2024	63.8272	59.4869	68.2663	69.7357	66.036	73.3879
1/3/2025	64.1036	60.0036	68.7949	70.0803	66.1602	74.27
1/10/2025	64.1247	59.8481	68.7994	70.3342	66.2971	74.5717
1/17/2025	63.8506	59.672	68.0315	70.3928	66.5018	74.8454
1/24/2025	63.3979	59.3106	67.7196	70.3252	66.2533	74.6964
1/31/2025	62.9161	58.6456	67.0012	70.27	66.6333	74.4663
2/7/2025	62.5654	58.1858	67.2467	70.3594	66.326	74.4627
2/14/2025	62.4929	58.3465	66.7553	70.6763	66.7482	74.7807
2/21/2025	62.7106	58.2694	67.2122	71.1818	67.2621	75.229
2/28/2025	62.994	58.7167	67.2753	71.6622	67.6707	75.891
3/7/2025	63.0114	58.6256	67.4665	71.8305	67.7772	76.4855
3/14/2025	62.6548	58.5945	67.1709	71.5853	67.5144	76.5623
3/21/2025	62.2083	58.2493	66.676	71.1689	67.2377	75.5289
3/28/2025	62.0902	58.2344	66.2511	70.9941	66.9291	74.9787
4/4/2025	62.4112	58.2908	66.8013	71.2724	67.1544	75.111
4/11/2025	62.8292	58.6867	67.0454	71.8285	67.7754	75.6897
4/18/2025	62.8925	58.6531	67.2394	72.3035	68.2905	76.777
4/25/2025	62.5393	58.1818	67.0993	72.5535	68.3443	76.8935
5/2/2025	62.1713	57.7886	66.5184	72.7912	68.3097	77.0047
5/9/2025	62.1948	58.3656	66.642	73.2903	68.9521	77.3126
5/16/2025	62.5703	58.5797	66.9117	73.9964	69.9008	78.0287
5/23/2025	62.8607	58.7634	67.0112	74.5066	70.4438	79.2391
5/30/2025	62.7219	58.6389	66.8969	74.4756	70.1706	79.3237
6/6/2025	62.287	58.1187	66.5803	74.0104	69.9934	79.0051
6/13/2025	61.992	57.8201	66.5289	73.5848	69.6464	77.711
6/20/2025	62.0803	57.9129	66.606	73.5793	69.751	77.7566
6/27/2025	62.3669	57.9916	66.4131	73.9668	70.1631	77.8795
7/4/2025	62.4814	58.2044	66.6466	74.4262	70.5849	79.0554
7/11/2025	62.2833	58.0392	67.0488	74.704	70.6464	79.1804
7/18/2025	61.9711	58.214	66.4626	74.8172	70.6738	79.4993
7/25/2025	61.8037	57.6781	66.1889	74.9215	70.9163	79.5126
8/1/2025	61.8173	57.4721	66.4163	75.078	70.639	79.5102
8/8/2025	61.8512	57.791	66.022	75.2191	70.9346	79.7107
8/15/2025	61.7835	57.4027	66.5565	75.2983	70.985	79.9326
8/22/2025	61.653	57.761	66.1944	75.3748	71.0724	79.8139
8/29/2025	61.5478	57.4238	65.842	75.514	71.3474	80.0706
9/5/2025	61.4636	57.5056	65.807	75.669	71.7905	80.5152
9/12/2025	61.3415	57.3079	65.9233	75.738	71.5578	80.5024
9/19/2025	61.2066	57.1843	65.7753	75.7321	71.5291	80.1259
9/26/2025	61.1666	57.1987	65.3397	75.7947	71.5487	80.2776
10/3/2025	61.2315	57.071	65.5064	75.9948	71.9572	80.3697
10/10/2025	61.1984	57.2132	65.7552	76.1401	71.9321	80.6343
10/17/2025	60.8075	56.8011	65.0108	75.8929	71.6466	80.516
10/24/2025	60.0317	56.2347	64.3538	75.1239	71.0437	80.1738
10/31/2025	59.1333	55.0757	63.2079	74.1002	70.2855	78.6746
11/7/2025	58.3827	54.5909	62.6373	73.2468	69.4395	77.5653
11/14/2025	57.7654	53.8485	61.9483	72.7384	68.9209	76.607
11/21/2025	57.0258	53.1799	61.339	72.3663	68.4019	76.6362
11/28/2025	56.007	52.4485	60.1335	71.8097	68.0758	76.2306

	Weekly WTI Spot OP			Weekly Europe Brent Spot OP		
	Forecasted data	**Lower value**	**Upper value**	**Forecasted data**	**Lower value**	**Upper value**
12/5/2025	54.8968	51.3563	58.8878	71.0152	67.1497	75.4893
12/12/2025	54.0859	50.5573	58.0321	70.2689	66.4714	74.0144
12/19/2025	53.8105	50.0656	57.7986	69.9054	66.1109	74.0349
12/26/2025	53.9606	50.3928	57.9135	69.9985	66.0017	73.7248

Source: Authors' processing.

Note: "***", '**', '*' refers to the confidence interval at 99%,95%, and 90% level

Table 6 shows a range of projected values for the weekly Europe Brent Spot OP and WTI, with the highest value estimated at 72.2258 US $/b and the lowest value estimated at 53.8105 US $/b for WTI. But for Europe Brent, the highest value was estimated at 76.1401 US $/b, and the lowest value was estimated at 69.575 US $/b. Therefore, barring any significant disruptions in supply or geopolitical events, OP is expected to stay volatile but generally stable. Precise range would depend on current prices (September 2024), with Europe Brent at 74.5 US $/b and WTI stable at about 70 US $/b. But even with moderate global economic growth and rising demand, OP will undoubtedly rise once more and surpass 80 US $/b if OPEC+ member countries do not boost their production or if US shale oil output does not increase. Long-term underinvestment in exploration and production may result in the depletion of readily accessible oil reserves or possible supply constraints, which would raise the OP by more than 100 US $/b. On the other hand, there is a chance that over time, the use of renewable energy, more stringent environmental regulations, carbon pricing, and technological advancements in oil extraction and alternative energy could cause the OP to drop to the level of 55 US $/b.

Figure 3. Projected values for the weekly WTI Spot OP
Source: Authors' processing.

According to our forecast, the decline in COP in 2025 is mostly due to a slowdown in the growth of global oil demand. The Middle East's escalating conflict has caused COP to rise recently, despite our reduced forecast. This raises the possibility of disruptions in the oil supply and additional COP increases. There could be multiple reasons for WTI's potential decline from 72 US $/b to 53 US $/b within a year. Reduced prices and oversupply may result from increased supply, particularly from large producers like the United States and the OPEC nations. Besides, Middle East geopolitical factors, shifts in international relations, and policy decisions, may play a major role in reducing OP. Moreover, speculative trading and the release of strategic reserves, which increase supply and drive down prices, could be responsible for the OP decline. Despite growing costs, more supply is expected in 2030, mostly from production from OPEC countries, where costs are low and resource potential is high, according to recent research from oilprice.com (2024)[1]. Around 55 US $/b will be the new equilibrium price of oil in 2030, assuming 105 million barrels per day of demand.

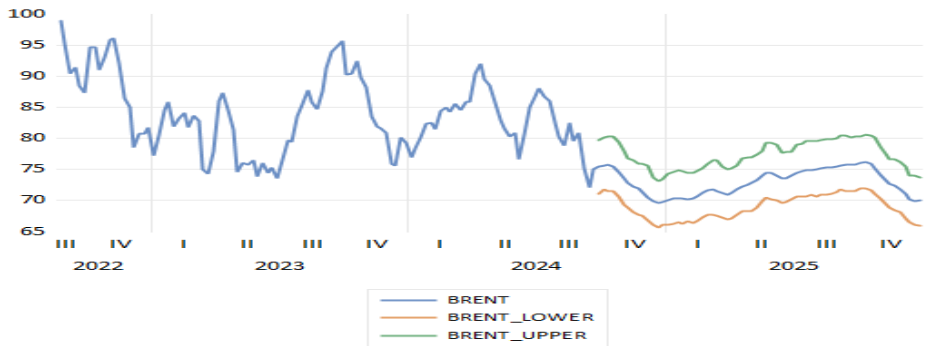

Figure 4. Projected values for the weekly Europe Brent Spot OP

Source: Authors' processing.

The Brent OP is moving in the same direction as the International Energy Agency's (IEA, 2024) forecast[2]. The sharp selling in the oil markets has been sparked by the recent sharp decline in the growth of the world's oil demand. China's oil consumption fell in July for the fourth consecutive month as the country's economy as a whole slowed down, and attention was drawn to speeding the switch from oil to alternative fuels. The decrease in OP could be attributed to a slowdown in the world's oil demand, and a rise in supply, with higher oil flows from Guyana, Brazil, and other countries offsetting disruptions brought on by a political conflict in Libya and maintenance in Kazakhstan and Norway. Boosting the quantity of refineries worldwide and declining the global observed oil stocks are additional factors contributing to the drop in OP. In addition, oil deliveries continue to decline in several advanced economies due to structural challenges, weak economic growth, and Israel's threats against Iran's oil facilities, which have sparked concerns about significant supply disruptions and the potential loss of up to 4% of the world's oil supply.

[1] https://oilprice.com/Energy/Crude-Oil/Oil-Production-Costs-Surge-But-Shale-Projects-Remain-Profitable.html

[2] https://www.eia.gov/outlooks/steo/report/global_oil.php

5. Conclusions and policy implication

In this paper, we use various tools to analyse and forecast the weekly Europe Brent Spot OP and the weekly WTI Spot OP. The predicted time frame was from September 27, 2024, to December 26, 2025. We present the most recent data for the weekly WTI Spot OP for 2024, which is approximately 75–80 US $/b, and the weekly Europe Brent Spot OP, which is approximately 80–85 US $/b. The optimal hybrid model for the weekly WTI Spot OP is ARMA-GARCH-MLP (5, 6, 1) with ARMA (3, 0) and GARCH (1, 1). On the other hand, the optimal hybrid model for the weekly Europe Brent Spot OP is ARMA-GARCH-MLP (6, 3, 1) with ARMA (3, 1) and GARCH (1, 1). These hybrid models provide forecasted values ranging from 53.8105 US $/b to 72.2258 US $/b for WTI and from 69.575 US $/b to 76.1401 US $/b for Europe Brent, thus aligning the most recent data with IEA forecasting outcomes. If the global oil market is stable and consistent, these outcomes could be noteworthy.

However, some analysts predict that the OP would skyrocket in response to an Israeli attack on Iran's oil infrastructure. There are even predictions that the price of a barrel could rise to $200. Since the Strait of Hormuz is where 20% of the world's oil flows, any disruption here could have catastrophic effects on global markets. Although geopolitical risks are driving up prices, one negative factor is still the weak demand from major economies, especially China. According to the latest oil consumption statistics, China's manufacturing activity has decreased, which is indicative of the weak demand for CO. Despite government stimulus measures, there is no indication of a robust rebound in oil consumption as China continues its transition towards electrification and decarbonisation.

Moreover, the US dollar has strengthened due to the Federal Reserve's interest rate policies, causing the OP to decline even more. Demand decreases when crude becomes costlier for holders of other currencies due to the stronger dollar. The risk of Middle Eastern supply disruptions is real, but weak demand and ample global supply, including growing US shale production, have prevented prices from rising too much. Also, global supply is crucially maintained by US shale production in addition to OPEC+ spare capacity. By the end of the year, US output is predicted to reach a record 13.49 million barrel per day, accounting for 13% of global crude production. This provides a sizable buffer against any supply shocks from the Middle East. This buffer has limits, though, as these might not be sufficient as the conflict intensifies, unless other Gulf states are also at risk and it goes beyond Iran.

We should expect more volatility in the future, with the possibility of large price fluctuations triggered by news about geopolitics. The safety net of excess capacity in the market will be monitored carefully because any indications of pressure on US or OPEC+ production could cause OP to change. OP is predicted to stay in the 70-90 US $/b range for the time being, but there is still room for major disruptions ahead.

Renewable energy, on the other hand, is a different source that has the potential to affect OP over time. There will be a faster shift to clean energy technologies by

2030. Increased demand for renewable energy products, ongoing vehicle efficiency improvements, and the switch from oil to renewable energy in the power sector will all help to drastically reduce the amount of oil used in transportation and the production of electricity. China and India will lead growth as the oil demand continues to shift towards emerging markets. However, the two Asian economic giants' demands will evolve in quite different ways. The petrochemical industry is expected to be the main driver of growth in China, as the demand for transportation fuels is reduced by the rapid adoption of clean energy technologies and significant infrastructure investments in high-speed rail. Transport fuel prices in India are expected to rise sharply, defying the global trend. Other emerging and developing Asian economies will also see significant gains.

Furthermore, Asia's growing structural shortfall in the supply of crude and products, coupled with its growing crude surplus, will continue to dictate global oil trade. Over the outlook period, increased volumes from the Atlantic Basin to the east of Suez will be driven by growing non-OPEC+ crude supply, sanctions against Russian crude exports, and voluntary cuts by OPEC+. Growing supplies from Brazil, Guyana, and Canada help to partially offset the loss of medium sour crudes from the Middle East due to OPEC+ cuts. The expanded Trans-Mountain pipeline to the Pacific Coast has opened up Asian markets to Canadian crude. The movement of light sweet US crude oil to refiners in Asia, Europe, and Africa is expected to increase.

Future studies could incorporate additional crude oil market-related sources, such as extreme weather, Internet news, and political policies, into their decomposition schema for forecasting. We think that by including these variables and appropriately deriving hidden patterns from them, greater predictive accuracy can be produced. Tracking crude oil prices also depends on the transmission of price fluctuations across stock markets, commodity futures, and international oil markets, in addition to temporal characteristics. As a result, some graph-based deep learning models show promise in enhancing the accuracy of crude oil price forecasts. In the near future, more pertinent research should be carried out.

Nomenclature:

Crude oil: CO	International Energy Agency: EIA
Oil price: OP	Autoregressive moving average: ARMA
Crude oil price: COP	Autoregressive conditional heteroskedasticity: ARCH
US Dollars barrel: US $/b	West Texas Intermediate: WTI
Multilayer Perceptron: MLP	Mean squared errors: MSE
Artificial neural network: ANN	Root mean square deviation: RMSD
General autoregressive conditional heteroskedasticity: GARCH	

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