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Application of ARIMA and LSTM Models for Crude Oil Price Forecasting

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Abstract— *Crude oil prices are highly volatile and influenced by numerous factors, including global economic conditions, political events, and market supply-demand dynamics. Accurate oil price forecasting is therefore a critical focus for researchers. This study applies the deep learning LSTM model and the traditional econometric ARIMA model to forecast crude oil prices, comparing their predictive performance. The results indicate that the LSTM model outperforms the ARIMA (7,1,7) model, yielding lower forecasting errors based on MAE, MAPE, and RMSE metrics. These findings highlight the potential of LSTM models to enhance time-series forecasting accuracy for crude oil prices, supporting better economic risk management.*

Keywords— *Crude oil price, ARIMA model, deep learning LSTM model.*

I. INTRODUCTION

Crude oil is one of the most important energy sources in the world and has a direct impact on economic growth. The value of oil mainly depends on the demand for refined petroleum products, especially in the transportation sector, such as vehicles, jet fuel, and fuel oil. Sudden fluctuations in oil prices, also known as "oil price shocks", can have far-reaching and complex consequences for the economy. Forecasting crude oil prices is very meaningful, but due to the non-linear, complex, unstable, asymmetric and long-memory characteristics of fluctuations in the crude oil price chain, accurate forecasting of crude oil prices is always quite difficult. Although many methods and approaches have been developed to predict oil prices, finding suitable models and forecasting methods is still being studied by researchers.

In recent years, many methods and approaches have been developed to predict oil prices. A basic and popular tool for modeling and forecasting in time series is the ARIMA model. Ahmed and Shabri (2014) forecasted crude oil prices based on three Support Vector Machines (SVM) techniques compared with the performance of ARIMA and GARCH, the results showed that the SVM method outperformed the other two methods in terms of forecast accuracy. Nguyen Trung Hung et al. (2017) used models such as GARCH(1,1), EGARCH(1,1), GJR-GARCH(1,1) to forecast WTI crude oil prices, the results obtained were EGARCH(1,1) model with Student distribution with the smallest forecast error. Mujtaba Suleiman et al. (2025) showed that the ARIMA (3,1,1) model is suitable for forecasting monthly crude oil prices of Nigeria.

The advancement of computer technology has led to the adoption of machine learning, artificial intelligence, and deep learning methods in economic measurement and forecasting, demonstrating remarkable effectiveness. Varun (2018) utilized the LSTM model to predict oil prices, revealing that excessively increasing the number of lookback periods did not enhance accuracy. Additionally, the study indicated that merely adding more LSTM layers had limited impact on accuracy. Instead, it was essential to integrate more market factors and political conditions into the model to improve oil price forecasting. Pedro Lara-Benítez et al. (2021) highlighted the advantages of GRU and LSTM networks in forecasting crude oil prices, with findings showing that LSTM and CNN emerged as the most effective forecasting methods. Similarly, Michael Brown et al. (2024) and W. Jiang et al. (2024) conducted a comparative analysis of LSTM models against traditional time series forecasting methods. Both studies concluded that LSTM outperformed conventional statistical models in forecasting accuracy.

Therefore, deep learning models have gained traction in time-series forecasting. This study applies the ARIMA and LSTM models to forecast crude oil prices, comparing their performance.

II. RESEARCH METHODOLOGY

A. Data

The study utilizes WTI crude oil futures price data traded on the NYMEX commodity exchange, covering the period from January 31, 2014, to December 1, 2024. The data was analyzed using the Python programming language.

To estimate parameters for both the LSTM and ARIMA models and evaluate their forecasting performance, the sample dataset was divided into two subsets:

Training dataset: Comprising 2,198 observations (70% of total data), collected from January 31, 2014, to November 7, 2021.

Test dataset: Consisting of 943 observations (30% of total data), collected from November 8, 2021, to December 1, 2024.

B. Research Models

The study employs ARIMA and LSTM models to forecast WTI crude oil time-series data. LSTM gained prominence in 1997 as a training model capable of recognizing patterns based on historical data, while ARIMA is renowned for forecasting target variables through linear combinations of their past values.

ARIMA Model

The ARIMA (AutoRegressive Integrated Moving Average) model is one of the most widely used models in time series analysis and forecasting. The general form of the ARIMA (p, d, q) model is:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \varepsilon_t$$

In which:

p: AutoRegressive order (AR).

d: Differencing order for stationarity (I).

q: Moving Average order (MA).

$\beta_1, \beta_2, \ldots, \beta_p$: Autoregressive coefficients, β_0: Constant term, ε_t: White noise.

Steps for forecasting using the ARIMA model:

Step 1: Assess the stationarity of the observed time series using visual plots and the Augmented Dickey-Fuller (ADF) test.

Step 2: Identify the ARIMA(p, d, q) model.

The determination of p and q relies on the Sample Autocorrelation Function (SACF) and Sample Partial Autocorrelation Function (SPACF) plots. The SACF is a function or plot showing the correlation of the sample at lags k = 1, 2, ... The SPACF is a list or plot of partial autocorrelation values at lags k = 1, 2, ... These plots help identify patterns:

p is selected if the SPACF shows significant values at lags 1, 2, ..., p and drops sharply afterward, while the SACF decays gradually.

q is chosen if the SACF has high values at lags 1, 2, ..., q and cuts off sharply after q, while the SPACF decays gradually.

Step 3: Estimate the parameters of the ARIMA(p, d, q) model.

The model parameters are estimated using the Ordinary Least Squares (OLS) method.

Step 4: Perform model diagnostics.

After selecting and estimating the ARIMA model, evaluate its adequacy by analyzing the residuals. Key checks include:

Testing for residual autocorrelation (e.g., using the Box-Pierce or Ljung-Box test).

Verifying stationarity of residuals (e.g., via the ADF test).

Checking if residuals follow a normal distribution.

The goal is to ensure the model's error term behaves like white noise.

Step 5: Use the finalized ARIMA model to generate forecasts and evaluate their accuracy using metrics such as MAE, MAPE, and RMSE.

LSTM Model

Long Short-Term Memory (LSTM) is a type of recurrent neural network introduced by Hochreiter and Schmidhuber in 1997. Designed to process and analyze time series data, LSTM excels at capturing long-term dependencies. While structurally similar to RNNs, LSTM incorporates specialized mechanisms called gates to regulate information flow during computations.

The key gates in an LSTM are:

Forget Gate: Determines which information from the previous state should be discarded or retained.

Input Gate: Decides what new information from the current input will be stored in the next state.

Output Gate: Controls which part of the current state will be output by the LSTM.

The Cell State acts as the memory core of the LSTM unit, maintaining information across time steps. Its content is selectively updated or erased via the gates, enabling precise control over long-term dependencies. This architecture combines a sigmoid layer and pointwise multiplication to filter and propagate relevant information.

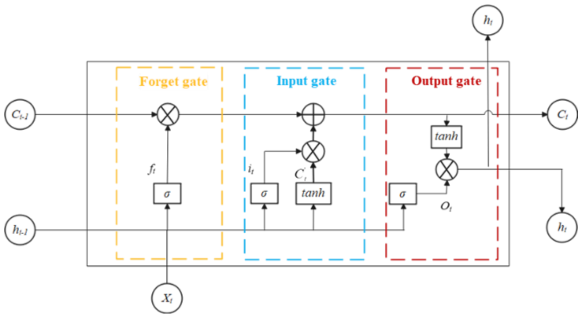

Fig. 1: LSTM Model Architecture

In which:

Output: C_t (cell state) and h_t (hidden state);

Input: C_{t-1}(previous cell state), h_{t-1}(previous hidden state).

x_t : input at time step t

C_{t-1}, h_{t-1} are the outputs from the preceding layer.

III. Research Result

A. *Crude Oil Price Trends*

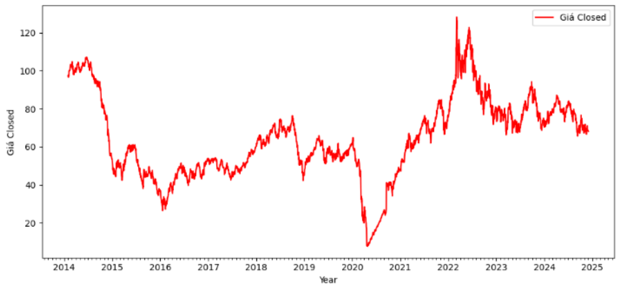

Fig. 2. Daily closing prices of WTI crude oil (2014–2024)

In the early 2000s, the advent of industrialization in emerging markets spurred an increase in demand, pushing the average price to $30.38 per barrel in 2000 and continuing to rise to $99.67 per barrel in 2008. However, the global financial crisis in 2008 caused a sharp decline, bringing the price down to $44.60 per barrel by the end of the year.

Subsequent recovery and geopolitical tensions in relevant regions pushed crude oil prices higher, with the average price reaching $94.88 per barrel in 2011. This volatility continued with the emergence of shale oil production in the United States, dragging the average price down to $48.66 per barrel in 2015. This trend persisted, driven by OPEC’s production adjustments and global demand fluctuations, resulting in an average price of $94.53 per barrel in 2022 before stabilizing at an average of $77.59 per barrel in 2023.

Moreover, the COVID-19 pandemic in 2020 marked one of the most significant shocks to the crude oil market in history. The plummeting demand, coupled with an oversupply, led to a dramatic fall in oil prices. Although the situation has somewhat improved as economies gradually recover, oil-producing

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countries' policies and ongoing geopolitical developments continue to influence the crude oil market.

The Russia-Ukraine conflict, which began in late February 2022, has significantly impacted the global energy market over the past decades. As one of the world's largest oil producers, Russia has faced economic sanctions that have substantially disrupted the global oil supply, leading to scarcity. During the event window from October 1, 2021, to August 25, 2022, it was observed that the war and its subsequent events caused the West Texas Intermediate (WTI) crude oil price to increase by $37.14, a rise of 52.33%, while the Brent crude oil price increased by $41.49, or 56.33%. During the event window, the Russia-Ukraine conflict accounted for 70.72% and 73.62% of the volatility in WTI and Brent crude oil prices, respectively. Moreover, the war has amplified oil price volatility and fundamentally altered the crude oil price trend.

Since the beginning of 2024, WTI oil prices have remained above $70 per barrel. This upward momentum has been driven by geopolitical events, OPEC+ actions, and economic conditions. OPEC+ continues to reduce oil production, leading to a decrease in the available global oil supply. Geopolitical tensions in the Middle East are also escalating, undermining the stability of oil supplies and raising investor concerns. Conflicts in the Middle East further contribute to maintaining prices above the $70 mark.

B. ARIMA Model

Firstly, the study conducts a stationarity test on the crude oil price series, utilizing the auto_ARIMA function from the pmdarima library to automatically identify the optimal parameters for the ARIMA model. The auto_ARIMA function searches for the optimal values of p, d, and q based on the training data. This function systematically tests various combinations of parameters and evaluates them using information criteria such as AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion). These criteria play a crucial role in balancing model fit and complexity, thereby helping to avoid overfitting and selecting the best-performing combination.

The results indicate that the ARIMA(7,1,7) model is the most suitable. Subsequently, the model estimation is performed using the maximum likelihood estimation (MLE) method. The estimation results for the ARIMA(7,1,7) model are presented in the table below:

TABLE I: Estimation Results of the ARIMA (7,1,7) Model

	Coefficient	Std. Error
C	-0.007198***	0.02520
AR(1)	-0.03705***	0.00217
AR(2)	-0.99694***	0.00213
MA(1)	0.043274***	0.00472
MA(2)	1.00000***	0.20499
***: *At the 1% significance level*		

All coefficients in the ARIMA(7,1,7) model are statistically significant at the 1% significance level. After estimating the model, the study conducted goodness-of-fit tests by examining the residual series for autocorrelation, stationarity, and the assumption of normal distribution. The test results indicate that the ARIMA(7,1,7) model is appropriate for forecasting the oil price series. Subsequently, the study will forecast oil prices on the test set and evaluate the forecasting accuracy. The dynamic forecasting results are visually presented in the following chart:

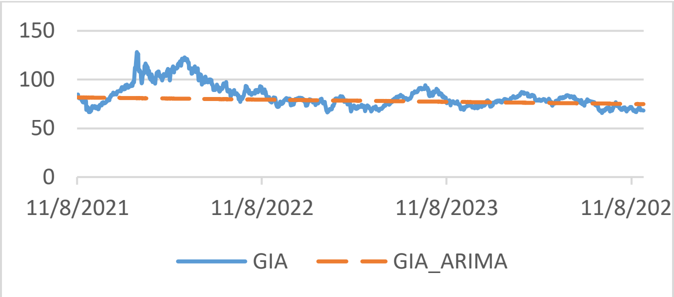

Fig. 3: Comparison between Actual Prices and Forecasted Prices using the ARIMA (7,1,7) Model

The chart shows that the forecasted line doesn't closely follow the actual price trend, instead reflecting the average tendency without capturing complex fluctuations. This characteristic is inherent to the ARIMA model, which typically predicts the average trend rather than short-term variations. During periods when crude oil prices exhibit relatively stable patterns, ARIMA forecasts tend to perform better compared to periods of significant price volatility.

C. LSTM Model

The LSTM model is constructed using Keras, a popular deep learning library. The study initializes a Sequential model and adds an LSTM layer with 50 units (neurons). This LSTM layer takes as input time series sequences with dimensions defined by the number of time steps and the number of features in the data. Following the LSTM layer, a Dense layer with a single output unit is added to predict the continuous value of the time series. The model is compiled using the Adam optimizer and the Mean_squared_error loss function. The Adam optimizer is selected due to its proven effectiveness across various tasks, while the Mean_squared_error loss function is suitable for regression problems.

Next, the model is trained using the training data and evaluated on the testing data. The training process is conducted over multiple iterations (epochs = 100). Each epoch represents a complete pass through the entire training dataset to update the model's weights. The study employs a fixed batch size (batch size = 32). During training, the testing data is also utilized to evaluate the model's performance after each epoch. This approach enables monitoring of the learning process and assessing whether the model is prone to overfitting.

Subsequently, the trained LSTM model is utilized to forecast oil prices on the testing dataset, and evaluate the effectiveness of the forecast. The forecast results on the testing dataset are illustrated in the following chart.

The comparative chart indicates that the predictive model accurately captures the trend and closing price of crude oil within the training set for the majority of periods. However, during certain phases of high price volatility—such as early March and October 2022—the model's predictions failed to fully capture the fluctuations. This suggests that the model has successfully learned the essential features of the data and can effectively forecast the upward or downward trend of crude oil prices.

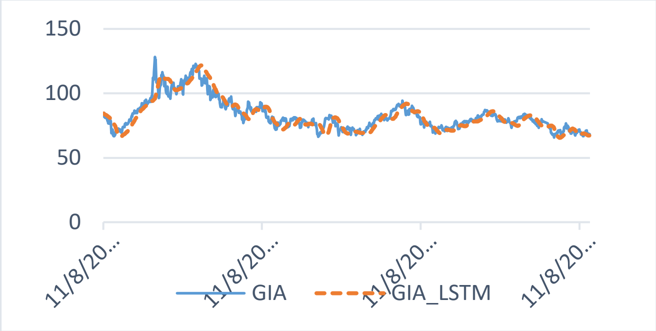

Fig.4: Forecasting Results Using the LSTM Model

D. Comparison of Forecasting Performance between the ARIMA Model and the LSTM Model

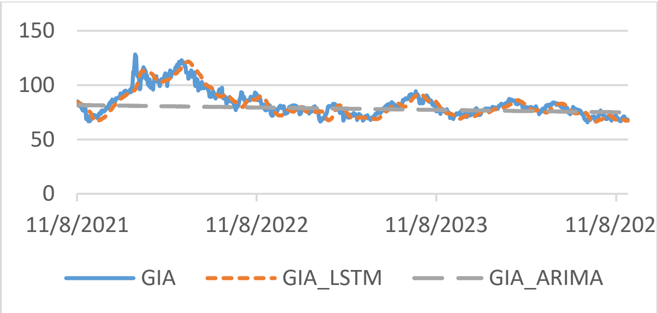

Fig. 5: Comparison of Forecasts between the ARIMA Model and the LSTM Model

The predicted price curve on the test set of the LSTM model closely aligns with the actual price curve, while the forecasted curve of the ARIMA(7,1,7) model only reflects the average trend. This indicates that the LSTM model has effectively learned from the training dataset. It can be observed that the LSTM model demonstrates superior forecasting performance compared to the ARIMA(7,1,7) model. To further substantiate this observation, the study evaluated several forecasting performance metrics based on prediction errors at each time point. The results are presented in the following table:

TABLE II: Evaluation Metrics of Forecasting Performance for the Two Models

Model	MAE	MAPE	RMSE
ARIMA (7,1,7)	8.4267	9.2806	12.177
LSTM	*3.86*	*4.5896*	*5.11*

The error evaluation metrics on the test set indicate that the performance of the LSTM model is significantly better compared to the ARIMA(7,1,7) model. Therefore, it can be concluded that the LSTM model outperforms the ARIMA(7,1,7) model in forecasting daily WTI crude oil prices.

Given that the LSTM model provides more accurate forecasts for WTI crude oil prices, this study utilizes the LSTM model to predict the oil prices for the next 10 days, with the results as follows:

The forecasted results for the next 10 days, starting from the end of the sample data series, exhibit relatively small errors, particularly during the first 7 days.

TABLE III: 10-Day Forecast Using the LSTM Model

Date	Actual Prices	Forecast	Error
02/12/24	67.84	67.53	0.31
03/12/24	69.54	67.59	1.95
04/12/24	68.19	67.64	0.55
05/12/24	67.96	67.67	0.29
06/12/24	66.98	67.71	-0.73
09/12/24	68.09	67.74	0.35
10/12/24	68.27	67.75	0.52
11/12/24	69.87	67.73	2.14
12/12/24	69.66	67.70	1.96
13/12/24	70.82	67.62	3.20

IV. Conclusion

Crude oil is a crucial energy source that directly impacts economic growth through sectors such as transportation and manufacturing. Oil price shocks strongly influence macroeconomic variables such as output, inflation, and unemployment. An increase in oil prices raises production costs, reduces corporate profits, while a decrease in prices may stimulate investment and growth. As a highly volatile commodity, oil prices are affected by numerous factors, including the global economy, political conditions, and supply-demand dynamics. Therefore, accurately forecasting oil prices remains a key concern for policymakers. This study applies the ARIMA(7,1,7) model and the deep learning LSTM model to forecast crude oil prices. The results indicate that the LSTM model outperforms the ARIMA model in terms of forecasting accuracy. The LSTM model captures the volatility of oil price movements effectively and exhibits significantly smaller forecasting errors compared to the ARIMA(7,1,7) model. Using the LSTM model, the study provides a 10-day forecast for West Texas Intermediate (WTI) crude oil prices.

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