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Forecasting WTI and Brent Crude Oil Prices: Evaluating The Performance of Hybrid EMD-ARMA-BiLSTM Models

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Abstract

Given the critical importance of crude oil prices in the global economy, this study focuses on forecasting WTI and Brent crude oil futures prices. To incorporate both price series as independent variables in our predictive model, we employed Vector Autoregression (VAR) to analyze their interdependence. Results from impulse response analysis, variance decomposition, and Granger causality tests revealed a significant spillover effect between the two crude oil futures prices over the past 12 lagged periods. Consequently, the lagged data from the past 12 periods of both price series were utilized as independent variables for the deep learning framework. We developed a hybrid model integrating Empirical Mode Decomposition (EMD), Autoregressive Moving Average (ARMA), and Bidirectional Long Short-Term Memory (BiLSTM) to predict WTI and Brent prices. Our findings demonstrate that predictive performance improves with increased model complexity. Specifically, the hybrid model (EMD+ARMA+BiLSTM) outperforms both the EMD+BiLSTM model and the standalone BiLSTM model. For WTI, the hybrid model achieved a Mean Squared Error (MSE) of 57.77, Mean Absolute Error (MAE) of 5.66, and Mean Absolute Percentage Error (MAPE) of 8.78%. For Brent, the corresponding metrics were 62.15, 5.87, and10.40%, respectively. These results validate the robustness and rationality of our hybrid model, offering a reliable methodology for crude oil price prediction and providing valuable insights for researchers and practitioners in the energy markets.

Keywords: Crude Oil Prices; EMD; BiLSTM; Hybrid Model.

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1. Introduction

WTI and Brent are key crude oil benchmarks used globally for pricing and analysis. WTI, produced mainly in the U.S., is traded on NYMEX and represents high-quality, light, low-sulfur oil. Its price volatility is a crucial indicator of the U.S. oil market. Brent, sourced from the North Sea, is traded on ICE and serves as the pricing basis for European and international markets(Iglesias & Rivera-Alonso, 2022). Both prices are influenced by a multitude of factors, including supply and demand dynamics, market sentiment, geopolitical tensions, economic policies, and natural disasters.

Fluctuations in these benchmarks have far-reaching implications for household spending, business costs, national revenues, and global trade, and can sometimes trigger economic crises. Given these complexities, accurate forecasting of WTI and Brent prices is essential for investors, policymakers, and market participants to make informed decisions, manage risks, and develop effective strategies (Peng et al., 2023)

In recent years, various methods have been proposed to enhance the accuracy of crude oil price forecasting. For instance, (L. Huang et al., 2024) employed a combination of variational and empirical mode decompositions (EMD) alongside the Transformer model to forecast crude oil futures prices. This approach capitalizes on the ability of EMD to decompose complex time series into simpler components, which are then processed by the Transformer model to capture long-term dependencies and improve prediction accuracy. Similarly,(Xu et al., 2024) developed a BiLSTM-Attention model to forecast the volatility of crude oil futures, highlighting the dynamic role of events such as the COVID-19 pandemic and the Russia-Ukraine conflict. The BiLSTM model captures bidirectional dependencies in the data, while the attention mechanism enhances the model's ability to focus on critical features. (Mohammadi & Su, 2010) further

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demonstrated the effectiveness of ARIMA-GARCH models in capturing the volatility and non-stationary characteristics of oil prices. Given the strengths of these methods, we propose an innovative approach that integrates EMD, BiLSTM, and time series models to achieve more accurate and robust predictions of crude oil prices.

To address the complexities of crude oil price forecasting, we propose a novel hybrid approach inspired by recent advancements in time series decomposition and forecasting models. Specifically, we first decompose the crude oil price series using EMD to transform the non-stationary and highly volatile time series into simpler intrinsic mode functions (IMFs). This decomposition technique has been shown to be effective in breaking down complex time series into more manageable components (Abdollahi & Ebrahimi, 2020). Next, we test each IMF for stationarity. For non-stationary IMFs, we employ the BiLSTM model to capture the complex dynamics and bidirectional dependencies inherent in the data. This approach has demonstrated superior performance in handling non-stationary time series, as shown in previous studies (J. Wu et al., 2023). To identify the appropriate input variables for the BiLSTM model, we aim to explore suitable candidates through the analysis of spillover effects. In addressing this challenge, we draw upon the methodology presented in (Ren et al., 2024), which proposes the use of Vector Autoregression (VAR) as a means to resolve such issues. For stationary IMFs, we use the ARMA model to further refine the predictions, leveraging its ability to model stationary sequences effectively.

As demonstrated in our previous study (Liang & Ismail, 2025), we found that integrating decomposition models with machine learning can significantly enhance the predictive capability for financial time series. By integrating EMD, BiLSTM, and ARMA models, our proposed hybrid approach aims to provide more accurate and robust predictions of crude oil prices. This method leverages the strengths of each component to address the challenges posed by non-stationarity and complex dynamics in oil price data, thereby offering a comprehensive solution for forecasting in this highly volatile market.

2. Literature Review

In recent years, forecasting crude oil prices has attracted considerable attention due to the strategic importance of energy markets and the substantial volatility observed in oil price series. A large body of literature has attempted to improve forecasting performance by combining traditional time-series techniques with modern machine learning and deep learning approaches. Compared with single-model frameworks, hybrid forecasting models are often considered more effective because they can simultaneously capture linear statistical patterns and nonlinear dynamics embedded in financial time series.

The need for more robust forecasting frameworks has become particularly evident in recent years. The global oil market experienced significant structural changes following the COVID-19 pandemic and the Russia–Ukraine conflict, both of which triggered sharp increases in price volatility and uncertainty. Such events introduced stronger nonlinear behavior and structural breaks in crude oil price series, making accurate forecasting increasingly challenging. Consequently, researchers have increasingly explored advanced modeling strategies capable of dealing with complex market dynamics and potential cross-market interactions.

One important line of research focuses on applying deep learning techniques to capture nonlinear dependencies in oil price movements. For instance, (Alruqimi & Di Persio, 2024) developed an ensemble deep learning framework enhanced with multi-aspect metaheuristic optimization for multi-step Brent oil price forecasting. Their results suggest that combining deep learning architectures with optimization strategies can substantially improve forecasting accuracy in complex market environments. In a different but related context, (Kearney & Shang, 2020) investigated the predictability of the WTI oil futures curve. Rather than relying solely on machine learning techniques, their study examined how information contained in the futures term structure can help predict future oil price dynamics. Although both studies aim to enhance predictive performance, they adopt different perspectives: the former emphasizes the optimization of deep learning models, while the latter highlights the informational role of market structure in forecasting crude oil prices.

Another stream of research has focused on hybrid forecasting models that integrate statistical approaches with machine learning techniques. For example, (Yifan et al., 2020) proposed a hybrid framework that combines multi-scale data analysis with traditional forecasting models. By decomposing the oil price series into multiple temporal scales, their approach allows the model to capture both short-term fluctuations and longer-term trends. Their empirical results show that such hybrid structures often outperform single-model approaches, particularly when dealing with highly volatile financial time series.

More recently, several studies have introduced signal decomposition techniques to further improve forecasting performance. In particular, decomposition methods such as empirical mode decomposition can separate complex time series into multiple intrinsic components with different frequency characteristics. For instance, (Y.-X. Wu et al., 2019) applied Ensemble Empirical Mode Decomposition (EEMD) to decompose crude oil price series before using LSTM networks to model each component individually. Their findings indicate that decomposition can significantly enhance forecasting accuracy by allowing neural networks to focus on simpler sub-series rather than the original complex signal. Similarly, (Hu, 2021) proposed a CEEMDAN-LSTM framework that incorporates additional market indicators to improve prediction performance under volatile market conditions. Both studies demonstrate that decomposition-based hybrid models can effectively handle the nonlinear and non-stationary characteristics commonly observed in oil price data.

Further evidence supporting the usefulness of decomposition techniques can be found in (Lin & Sun, 2020) who proposed a CEEMDAN-based multi-layer GRU forecasting model for crude oil prices. Their approach decomposes the original price series into several intrinsic mode functions and models each component using deep learning networks. The empirical results show that such decomposition-based frameworks can significantly outperform traditional time-series models by capturing multi-scale dynamics more effectively.

Despite these advances, several challenges remain in the current literature. First, many hybrid forecasting models incorporate multiple oil price series directly into machine learning or deep learning frameworks without formally examining the econometric relationships between major benchmarks such as WTI and Brent. Ignoring potential spillover effects between these markets may limit the structural interpretability of forecasting models. Second, most decomposition-based approaches apply a single forecasting architecture to all decomposed components, which may not fully exploit the heterogeneous statistical properties of stationary and non-stationary series.

Motivated by these observations, the present study proposes a hybrid forecasting framework that integrates Vector Autoregression (VAR), Empirical Mode Decomposition (EMD), ARMA models, and Bidirectional Long Short-Term Memory (BiLSTM) networks. In particular, VAR is first employed to examine spillover effects between WTI and Brent crude oil prices, providing an econometric basis for incorporating cross-market information. The oil price series is then decomposed using EMD, after which stationary components are modelled using ARMA while nonlinear components are modelled using BiLSTM. By allocating different models to components with distinct statistical properties, the proposed framework aims to improve forecasting accuracy while maintaining a more interpretable modelling structure.

3. Methodology

3.1. Data Collection

We obtained ten years of historical weekly data (from December 14, 2014, to December 8, 2024) for WTI and Brent crude oil futures from https://www.investing.com/. We utilized their weekly closing prices as the raw data for our modeling purposes, the level series is shown in Figure 1.

We selected data from December 14, 2014, to October 7, 2018 (a total of 200 periods) as the training set, while the remaining data was used as the test set.

3.2. Correlation and Spillover Effect

In analyzing the correlation between the two time series, we employed Pearson correlation analysis to examine the correlation coefficient between WTI and Brent crude oil prices. Additionally, we utilized the Vector Autoregression (VAR) model to jointly model the two time series, allowing us to investigate the spillover effect between them.

The VAR model is a multivariate time series model that captures the dynamic interdependencies among multiple variables by expressing each variable as a linear function of its own past values and the past values of other variables in the system (Rajab et al., 2022). The spillover effect between time series can be analyzed using the VAR model through impulse response analysis, variance decomposition, and Granger causality tests (Brahmasrene et al., 2014)

3.3. EMD Decomposition

EMD (Empirical Mode Decomposition) is a signal processing technique that decomposes complex nonlinear signals into a series of Intrinsic Mode Functions (IMFs), offering a more detailed representation of the signal’s components and characteristics (N. E. Huang, 2001). Furthermore, (Zhou et al., 2021) provides a detailed algorithmic flowchart, offering deeper insights into the implementation of the EMD method.

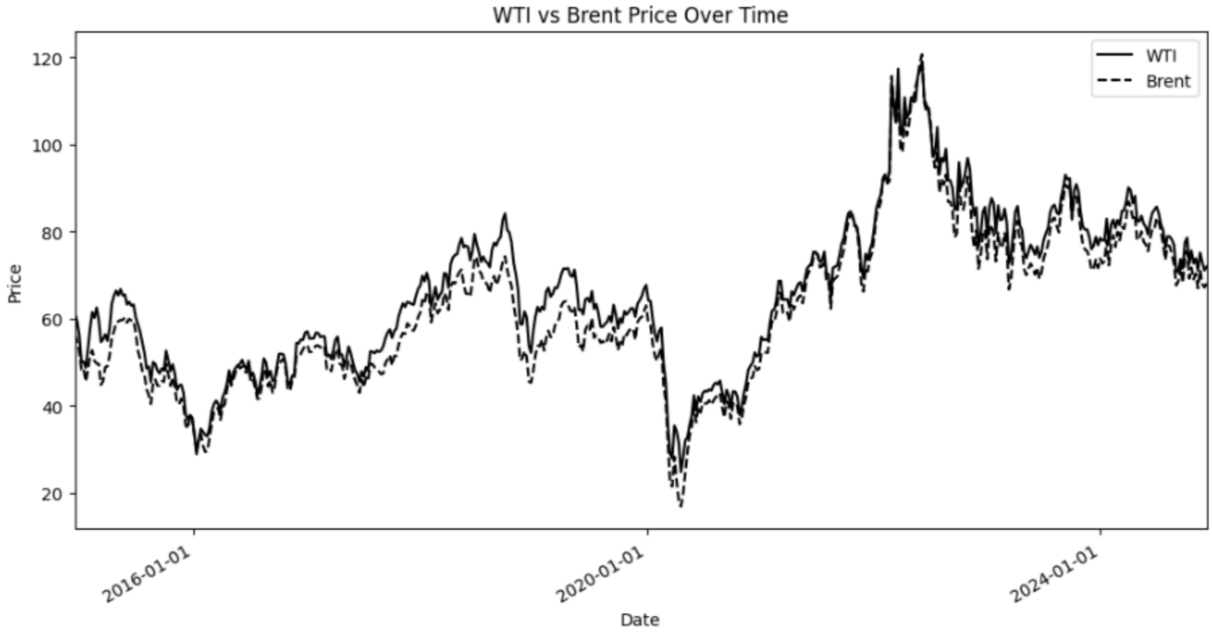

Figure 1 Level Series of WTI and Brent

3.4. BiLSTM

The Long Short-Term Memory (LSTM) regression algorithm is an advanced method widely used in time series analysis and forecasting. Originally introduced by researchers such as (Yao & Wang, 2021) and (Sunny et al., 2020), LSTM models belong to the class of recurrent neural networks (RNNs) and are specifically designed to capture long-term dependencies and complex temporal patterns in sequential data through their unique architectural structure.

Bidirectional Long Short-Term Memory (BiLSTM) networks comprise both forward and backward LSTM layers, allowing data to be processed in both directions. The backward processing enhances the model's ability to capture hidden patterns and dependencies in the data that are typically overlooked by standard LSTM models (Singla et al., 2022) (Yildirim, 2018)

Furthermore,(C. Li et al., 2021) provides both a flowchart illustrating the model implementation and detailed insights into its execution.

3.5. Hybrid Model

We first construct a VAR model using the weekly closing prices of WTI and Brent crude oil to examine whether a spillover effect exists between the two time series. If a spillover effect is detected, we use the historical closing prices of both time series from m weeks prior as independent variables for the BiLSTM model. Unlike many hybrid forecasting studies that directly incorporate multiple time series into deep learning architectures without formal testing, our approach first justifies cross-market input variables through VAR-based spillover analysis. This econometric validation enhances the structural rationality of the modeling framework.

Next, we separately forecast the two oil price time series. First, we apply EMD to the past m weeks of the target time series, extracting k IMFs. Each IMF is then tested for stationarity using the Augmented Dickey-Fuller (ADF) test. If an IMF is found to be stationary, we employ an Autoregressive Moving Average (ARMA) model to predict its value for the following week (We selected the ARMA model because the corresponding IMF was found to be stationary. Therefore, we considered ARMA instead of ARIMA). Subsequently, the optimal parameters for the ARMA model were determined based on the Akaike Information Criterion (AIC). If the IMF is non-stationary, we use its most recent n values as dependent variables in the BiLSTM model, while the independent variables remain the same as previously defined. The BiLSTM model is then trained and used to predict the next week's IMF value.

Finally, the predicted values of all IMFs are aggregated to obtain the forecasted closing price of the target oil price time series for the next week. This process is iterated using a rolling window approach to generate sequential forecasts for future weeks.

The process of the hybrid model is following Figure 2.

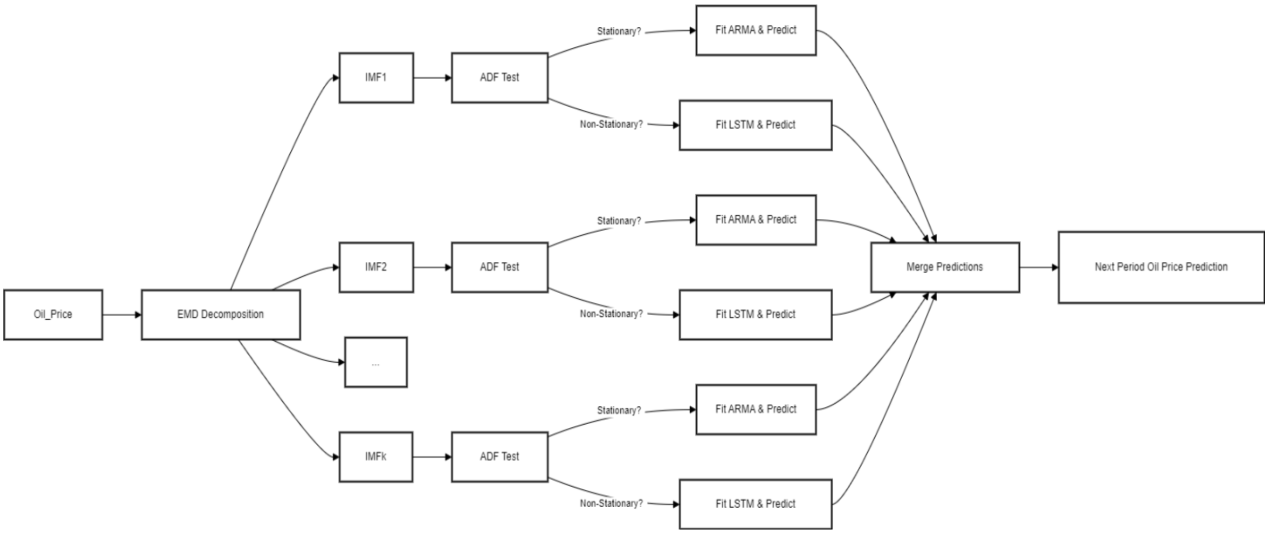

Figure 2: Flowchart of Hybrid Model

4. Empirical Result and Analysis

4.1. Data Description and Dependence

We conduct descriptive statistics on the crude oil closing prices over a ten-year period, with the results presented in Table 1. Additionally, we employ the z-score method to detect outliers in the two time series. The results indicate that no outliers are present in the WTI series, while Brent exhibits outliers on May 29, 2022, and June 5, 2022. This can be attributed to the Russia-Ukraine war, during which crude oil prices peaked. As we consider these price fluctuations reasonable, no further outlier treatment is applied. Although these extreme observations were retained to preserve market realism, additional inspection indicates that forecasting errors are moderately higher during this geopolitical shock period. This highlights the sensitivity of predictive models to abrupt regime shifts in crude oil markets. Moreover, the Pearson correlation coefficient between the two time series is 0.9370, indicating a strong positive correlation.

Table 1. Descriptive Statistics for WTI and Brent

Crude Oil	WTI	Brent
Mean	66.13	62.02
Median	65.23	59.62
Max	119.02	120.67
Min	24.81	16.94
Std. Dev.	17.87	18.06
Skewness	0.30	0.48
Kurtosis	-0.16	0.26
Jarque-Bera	8.45	21.86
Jarque-Bera p-value	0.0146	0.00002
ADF Statistic	-2.07	-1.98
ADF p-value	0.2573	0.2971

Table 2. Equation for WTI

Variable	Coefficient	Std. Error	t-stat	Prob
const	0.0004	0.0022	0.1916	0.8482
lag1.WTI	-0.3738	0.1288	-2.9013	0.0037
lag1.Brent	0.4077	0.1147	3.5538	0.0004
lag2.WTI	-0.1255	0.1298	-0.9671	0.3335
lag2.Brent	0.0265	0.1159	0.2288	0.8191
lag3.WTI	0.0042	0.1287	0.0323	0.9743

Variable	Coefficient	Std. Error	t-stat	Prob
lag3.Brent	0.0048	0.1157	0.0416	0.9667
lag4.WTI	0.1451	0.1279	1.1342	0.2568
lag4.Brent	-0.1147	0.1156	-0.9923	0.3212
lag5.WTI	-0.0276	0.1273	-0.2166	0.8286
lag5.Brent	0.0521	0.1152	0.4519	0.6514
lag6.WTI	0.0274	0.1305	0.2101	0.8336
lag6.Brent	0.0384	0.1175	0.3268	0.7439
lag7.WTI	0.2062	0.1303	1.5828	0.1135
lag7.Brent	-0.1582	0.1173	-1.3489	0.1774
lag8.WTI	-0.1343	0.1268	-1.0586	0.2898
lag8.Brent	0.1753	0.1139	1.5393	0.1238
lag9.WTI	0.2324	0.1267	1.8334	0.0668
lag9.Brent	-0.2785	0.1140	-2.4423	0.0147
lag10.WTI	-0.1159	0.1262	-0.9186	0.3584
lag10.Brent	0.0895	0.1134	0.7894	0.4301
lag11.WTI	0.1806	0.1245	1.4514	0.1468
lag11.Brent	-0.1843	0.1118	-1.6493	0.0992
lag12.WTI	-0.2082	0.1250	-1.6652	0.0960
lag12.Brent	0.1172	0.1123	1.0436	0.2967

To investigate the potential spillover effects between two crude oil prices, we employed a VAR model to analyze the two time series. Given that both time series were non-stationary, we applied a logarithmic transformation and performed first-order differencing to achieve stationarity. Subsequently, the optimal lag order for the VAR model was determined based on the AIC. The results indicated that the optimal lag order for both time series was 12. The estimated parameters of the model are presented in Tables 2 and 3.

Table 3. Equation for Brent

Variable	Coefficient	Std. Error	t-stat	Prob
const	0.0007	0.0024	0.3073	0.7586
lag1.WTI	-0.3869	0.1443	-2.6802	0.0074
lag1.Brent	0.4412	0.1285	3.4336	0.0006
lag2.WTI	0.0208	0.1454	0.1428	0.8865
lag2.Brent	-0.1453	0.1298	-1.1197	0.2629
lag3.WTI	-0.0570	0.1442	-0.3949	0.6929
lag3.Brent	0.1263	0.1296	0.9744	0.3299
lag4.WTI	0.2530	0.1433	1.7663	0.0773
lag4.Brent	-0.1677	0.1295	-1.2946	0.1955
lag5.WTI	0.3069	0.1426	2.1523	0.0314
lag5.Brent	-0.2283	0.1291	-1.7686	0.0769
lag6.WTI	0.2140	0.1462	1.4636	0.1433
lag6.Brent	-0.1061	0.1316	-0.8063	0.4201
lag7.WTI	0.4301	0.1459	2.9466	0.0032
lag7.Brent	-0.3672	0.1314	-2.7947	0.0053
lag8.WTI	-0.1287	0.1421	-0.9057	0.3651
lag8.Brent	0.1445	0.1276	1.1326	0.2574
lag9.WTI	0.1375	0.1420	0.9683	0.3330
lag9.Brent	-0.2304	0.1278	-1.8028	0.0715
lag10.WTI	-0.0189	0.1414	-0.1337	0.8936
lag10.Brent	-0.0107	0.1271	-0.0846	0.9326
lag11.WTI	0.2584	0.1394	1.8531	0.0639
lag11.Brent	-0.2431	0.1252	-1.9419	0.0523
lag12.WTI	-0.1091	0.1401	-0.7789	0.4361
lag12.Brent	0.0066	0.1258	0.0528	0.9579

Next, we extracted the results of the Impulse Response Function, Variance Decomposition, and Granger Causality Analysis. Figure 3 presents the results of the Impulse Response Function, indicating that both WTI and Brent exhibit spillover effects with the prices of WTI and Brent at lag 1.

However, the spillover effects become insignificant when the lag exceeds 1. Table 5 displays the results of the Variance Decomposition, revealing that the primary component contributing to both WTI and Brent is WTI itself. As the lag increases, the importance of Brent becomes more pronounced. Additionally, the results of the Granger Causality Analysis show that Granger causality exists between WTI and Brent across all lags from 1 to 12. See Table 4 for details.

Table 4. Granger Causality Test Results between WTI and Brent Prices (Vertical Format)

Lag Order	WTI → Brent (p-value)	Brent → WTI (p-value)
1	0.0002	0.0009
2	0.0004	0.0029
3	0.0010	0.0019
4	0.0033	0.0057
5	0.0049	0.0048
6	0.0092	0.0049
7	0.0103	0.0004
8	0.0102	0.0005
9	0.0027	0.0014
10	0.0059	0.0046
11	0.0057	0.0022
12	0.0076	0.0005

Specifically, WTI Granger-causes Brent, and Brent Granger-causes WTI, for lags 1 through 12.

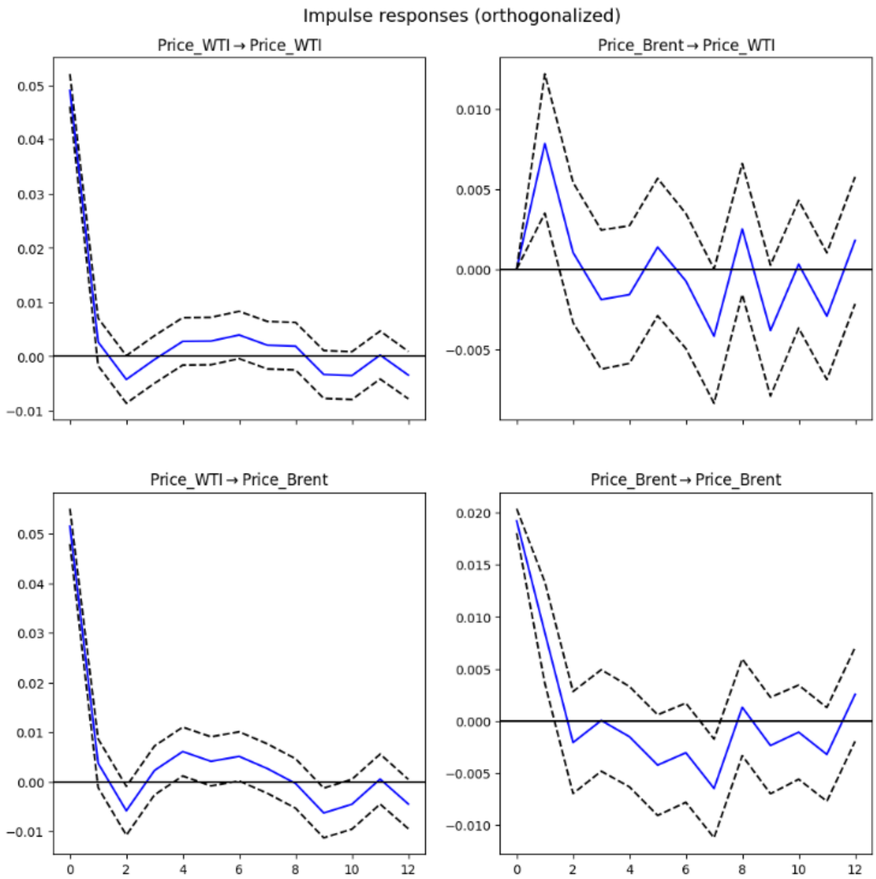

Figure 3. Impulse Response Function

Table 5. Variance Decomposition Results

Variance Decomposition of WTI

Lag	WTI	Brent
3	0.9750	0.0250
6	0.9720	0.0280
9	0.9631	0.0369
12	0.9548	0.0452

Variance Decomposition of Brent

Lag	WTI	Brent
3	0.8585	0.1415
6	0.8557	0.1443
9	0.8434	0.1566
12	0.8419	0.1581

4.2. Result of the Hybrid Model From

Section 4.1 indicates that a spillover effect exists between WTI and Brent. Therefore, when predicting prices using the BiLSTM model, we will incorporate the weekly closing price data of both WTI and Brent as independent variables in the model. Following the steps outlined in Section 3.5, we separately predict the prices of WTI and Brent. Here, we set n = 12 (the optimal lag order determined by the VAR model) and m = 100 (the length of the training set).

In the parameter configuration of the BiLSTM model, we set hidden size to 64, number of layers is set to 3, the learning rate is set to 0.005, and the number of epochs is set to 10. For the loss function, we selected the Mean Squared Error (MSE). These parameter values and loss function were determined based on references from (Arslan, 2024) and (Shrivastava et al., 2023). The results of prediction are shown in Figure 4 and Table 6.

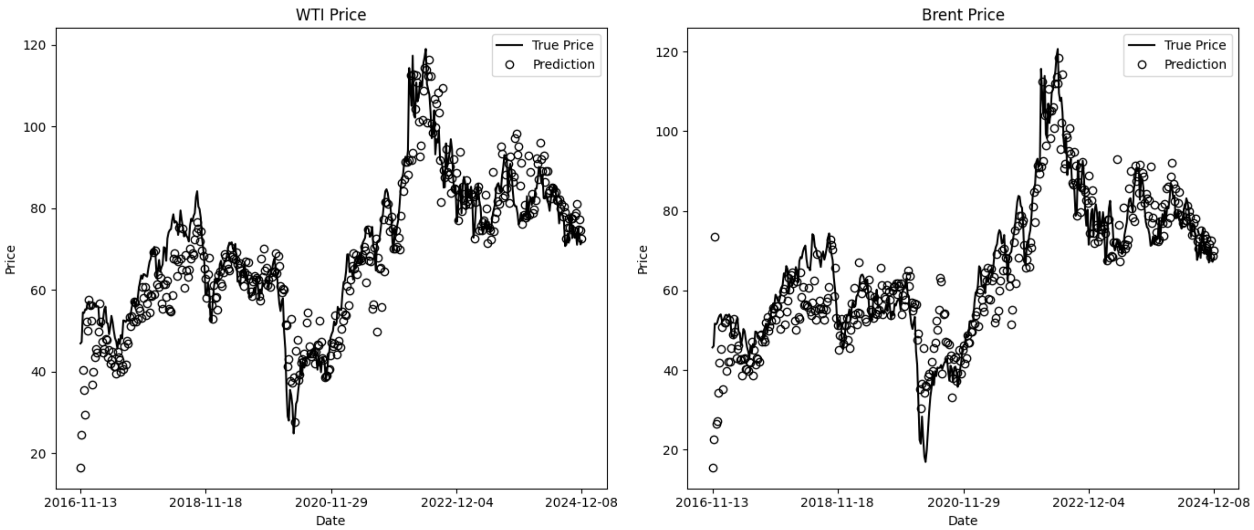

Figure 4. Prediction of WTI and Brent

Table 6. Evaluation Metrics for WTI and Brent Prediction

Dataset	MSE	MAE	MAPE (%)
WTI	57.77	5.66	8.78
Brent	62.15	5.87	10.40

From the results in Table 6, we observe that the prediction errors of the model for WTI are consistently lower than those for Brent. This suggests that our hybrid model demonstrates superior predictive capability and effectiveness in forecasting WTI compared to Brent.

Based on the forecasting results illustrated in Figure 4, we further conducted an additional error analysis by calculating yearly evaluation metrics for each test period. This analysis allows us to examine whether forecasting performance varies across different market conditions.

While the hybrid model achieves relatively low statistical errors, it is important to note that in leveraged oil futures trading environments, even a MAPE of 8–10% may imply substantial financial risk. Therefore, the model should be interpreted as a medium-term forecasting tool rather than a short-term speculative trading strategy.

We further observe that forecast deviations increase during extreme volatility periods, particularly around geopolitical shocks. This suggests that structural breaks may temporarily weaken the effectiveness of decomposition-based frameworks.

4.3. Result Comparison

To evaluate the predictive performance of the models, we additionally employed the following methods for time series forecasting:

- BiLSTM: The BiLSTM model was fitted to a time series of 100 periods and then used for one-step-ahead rolling window forecasting.
- EMD with BiLSTM (EMD+BiLSTM): The time series of 100 periods was decomposed using EMD, and a BiLSTM model was fitted to each IMF, we employed the same independent variables as those used in the original BiLSTM model. One-step-ahead rolling window forecasting was performed for each IMF, and the final prediction was derived by summing the predicted values of all IMFs.
- Hybrid Model (EMD+ARMA+BiLSTM): Following the methodology outlined in 4.2, we similarly conducted predictions using the window rolling approach.

The comparison results are presented in Table 7.

Table 7. Comparison of Forecasting Performance

Method	Dataset	MSE	MAE	MAPE (%)
BiLSTM	WTI	245.34	12.19	18.75
BiLSTM	Brent	242.54	11.79	19.70
EMD+BiLSTM	WTI	81.54	7.09	11.38
EMD+BiLSTM	Brent	65.32	6.36	10.85
Hybrid Model	WTI	57.77	5.66	8.78
Hybrid Model	Brent	62.15	5.87	10.40

From the results, we observe that the prediction errors of our constructed hybrid model are consistently the smallest, indicating that the hybrid model achieves superior predictive performance. The improvement from EMD+BiLSTM to EMD+ARMA+BiLSTM suggests that separating stationary linear components from nonlinear components enhances forecasting efficiency. By modeling short-memory linear structures using ARMA, the BiLSTM network can focus more effectively on capturing complex nonlinear dependencies, thereby reducing unnecessary modeling burden and overfitting risk. Furthermore, it is evident that the prediction errors decrease as the complexity of the model increases, which reflects the rationality of our model construction. Our findings are consistent with the results reported in (Y.-X. Wu et al., 2019), where a hybrid model combining EEMD decomposition and LSTM was used to predict daily crude oil prices, demonstrating that the hybrid model outperforms individual models in terms of predictive capability. Additionally, our results align with those of (Peng et al., 2023)), which, although employing different decomposition and deep learning models, also focused on weekly crude oil price data and similarly found that the hybrid model exhibited greater predictive power compared to standalone deep learning models. Moreover, (Ke et al., 2023), while studying different assets such as gold, copper, soybean, and white sugar futures, utilized a hybrid model combining EEMD and various LSTM models to predict prices. Their results, consistent with our findings on crude oil, also showed that predictive capability improved with increased model complexity.

5. Conclusion

In this study, we draw on relevant research findings that demonstrate the enhancement of deep learning predictive performance through EMD. Given the critical role of crude oil prices in the global economy, we selected WTI and Brent crude oil futures prices as our research targets. To incorporate both crude oil futures prices as independent variables in our predictive model, we employed VARCRUDE OIL PRICES WITH EMD-ARMA-BILSTM MODELS 13to fit the two price series. The results from impulse response analysis, variance decomposition, and Granger causality tests revealed the presence of a spillover effect between the two crude oil futures prices over the past 12 lagged periods. Consequently, we decided to use the lagged data from the past 12 periods of both crude oil futures prices as independent variables for the deep learning model. We constructed a hybrid model integrating EMD, ARMA, and BiLSTM to predict WTI and Brent prices separately. Our findings indicate that the predictive performance improves as the complexity of the model increases. Specifically, the EMD+ARMA+BiLSTM hybrid model outperforms the EMD+BiLSTM model, which in turn surpasses the standalone BiLSTM model. These results validate the rationality of our hybrid model construction and provide researchers and traders in the crude oil market with a robust methodology and tool for price prediction. Despite the promising performance of the proposed hybrid model, several limitations should be acknowledged. First, EMD is known to suffer from the mode-mixing problem, which may affect the stability of decomposition results. Second, the model does not explicitly incorporate regime-switching mechanisms, which may limit adaptability under abrupt structural breaks. Finally, forecast performance may deteriorate during extreme geopolitical shocks, reflecting the inherent uncertainty of crude oil markets. For future research, we aim to optimize our model by comparing more decomposition methods similar to EMD and experimenting with additional deep learning algorithms to further enhance the predictive accuracy of crude oil prices. Additionally, we plan to extend the application of our optimized model to other time series data, aiming to develop an advanced predictive tool for a broader range of financial assets.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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