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REVIEW ARTICLE

HYBRID PARTICLE SWARM OPTIMIZATION-GRAVITATIONAL SEARCH ALGORITHMS DEEP LEARNING NETWORKS TO SIMULTANEOUSLY PROJECT MULTIPLE CRUDE OIL PRICE

Samson Isaac[a*], Barna Thomas Lass[b], Hajara Idris[a], Umar Miqdad Bello[a], Yusuf Kakangi Ibrahim[c]

[a]Department of Computer Science, Kaduna State University, Kaduna, Nigeria
[b]Department of Computer Science, College of Education, Gidan-Waya Kaduna, Nigeria
[c]Department of Mathematical Sciences, Kaduna State University, Kaduna, Nigeria
**Corresponding Author Email: samson.isaac@kasu.edu.ng*

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ABSTRACT

The conventional linear econometric and statistical models are not effective for forecasting the nonlinear and complex nature of crude oil prices. Computational intelligence techniques and hybrid modelling principles have been proposed to address this issue. Multiple forecasts can be combined using linear or nonlinear methods to create an aggregate forecast. Currently, there is no study on the optimization of deep learning with a hybrid of gravitational search algorithm (GSA) and particle swarm optimization (PSO) for forecasting crude oil price benchmarks, including WTI, Brent, and Dubai. Additionally, most studies have focused only on using West Texas Intermediate (WTI) crude oil spot prices as their benchmark. A Bidirectional Long Short-Term Memory with hybrid gravitational search algorithm (GSA) and particle swarm optimization (PSO) to forecast Crude Oil prices is proposed. The proposed model outperformed FNNPSOGSA, FNNGA, LSTM and BiLSTM models with root mean square errors (RMSE) of 0.0029, 0.0011, and 0.0029, respectively. The proposed model is suited for Crude Oil forecasting.

KEYWORDS

intelligence techniques, conventional linear, forecast, optimization

1. INTRODUCTION

Crude oil is a vital resource in the global economy, impacting various sectors and individuals, and often referred to as the lifeblood of the world's economy (Su et al., 2020). The fluctuations of crude oil prices have a significant impact on the global economy, making it an indispensable task to forecast them accurately (Li et al., 2021). The forecasting of crude oil prices is a complex process due to various factors, including non-linear relationships, volatility, and uncertainty in the datasets, making it challenging (Li et al., 2021). Crude oil prices are influenced by various factors such as inventory levels, political considerations, foreign exchange rates, and GDP growth (Bashiri et al., 2021). Any fluctuation in crude oil prices can have an impact on the economic growth of countries that import or export oil, affecting regional security and stability. The redistribution of wealth for both oil-producing and importing nations is another potential impact of changes in crude oil prices. The instability of crude oil prices has been a cause for concern, especially for policymakers, investors, and energy companies, who need to make informed decisions to manage risks and optimize profits. The unpredictability of crude oil prices has led to the development of various techniques, including statistical models, machine learning, and deep learning, to forecast them accurately (Guliyev and Mustafayev, 2022).

In the late1970s, oil prices skyrocketed as a result of the expectation of future supply shortages and an increase in global demand following the Iraq-Iran war. It was from this time the international crude oil price has never been stable(Al-Shamri and Al-Salem, 2022). Over the years, researchers have conducted several studies aimed at understanding the underlying factors driving fluctuations in crude oil prices. Traditional methods such as economic and statistical models have been extensively used to forecast oil prices. However, due to the limitations of these methods in dealing with non-linear, non-stationary, chaotic, volatile, and complex characteristics of crude oil prices, computational intelligence techniques have been proposed as an alternative (Karasu and Altan, 2022). Nature-inspired metaheuristic algorithms have emerged as a popular and effective approach in various computational intelligence applications. One of the most commonly used techniques is the Artificial Neural Network (ANN), which has been employed for crude oil price prediction since the 1980s (Jovanovic et al., 2022).

In recent years, several studies have also explored the use of Deep Learning in conjunction with other nature-inspired algorithms to forecast crude oil prices (Manickavasagam et al., 2020). Deep Learning techniques have become increasingly popular due to their ability to learn from large datasets and handle non-linear relationships between variables (Korfmann et al., 2023). Despite the numerous studies proposing various prediction models, accurately predicting crude oil prices remains an open research problem.

2. LITERATURE REVIEW

The forecasting of crude oil prices has been a popular research topic in the field of finance and economics for many years. Conventional methods such as statistical and economic models have been widely used for predicting crude oil prices (Li et al., 2021). However, these models have limitations in dealing with the complex, nonlinear, and volatile nature of crude oil price data. To overcome these limitations, computational intelligence techniques have been proposed and applied to the field of crude oil price forecasting. One of the most commonly used computational intelligence techniques for crude oil price forecasting is the artificial neural network

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(ANN) model. The ANN and Deep Learning models are common techniques used for crude oil price forecasting (Wang et al., 2018). ANN and Deep Learning models have been shown to outperform traditional statistical models in terms of accuracy and forecasting performance (Li et al., 2021).

Ding (2018) proposed a novel prediction process called EEMD-ANN-ADD which combines EEMD and ANN for accurate prediction. The model involves selecting a suitable model using AIC, decomposing data via EEMD, making individual predictions with ANN, and ensemble prediction through the addition ensemble method. The experimental results showed that EEMD-based outperforms EMD-based, and the "decompose-ensemble" model outperforms hybrid models in terms of accurate prediction. Li, Shang and Wang proposed a deep learning approach for text-based crude oil price forecasting (Li et al., 2019). They employed a convolutional neural network (CNN) and a long short-term memory (LSTM) neural network to process the text data and predict future price movements. The results indicate that the proposed deep learning model outperforms traditional time series forecasting methods in predicting crude oil price movements. The proposed method achieved a high accuracy rate in predicting crude oil price trends. Abdollahi and Ebrahimi propose a new hybrid model for forecasting Brent crude oil price, combining an autoregressive integrated moving average (ARIMA) model with a wavelet neural network (WNN) to improve accuracy (Abdollahi and Ebrahimi, 2020).

The study found that the proposed method outperformed other state-of-the-art models, demonstrating the effectiveness of combining linear and nonlinear models for crude oil price forecasting. A group researchers proposes a new approach for crude oil price prediction called CPPCNDL, which combines complex network analysis and deep learning algorithms to model the interdependence among various factors affecting crude oil prices and predict future prices (Bristone et al., 2020). The study evaluates the proposed method on several crude oil price datasets and compares its performance with other state-of-the-art methods, and shows that CPPCNDL outperforms other methods in terms of forecasting accuracy. A group researchers proposes a variable selection-LSTM integrated model for analysing and forecasting crude oil pricesb (Lu et al., 2021). The authors used a feature selection algorithm to identify the most relevant factors affecting crude oil prices and integrated them into a long short-term memory (LSTM) neural network model to forecast future crude oil prices.

The study evaluated the proposed method on several crude oil price datasets and found that it outperformed other state-of-the-art methods such as autoregressive integrated moving average (ARIMA) and support vector regression (SVR) in terms of forecasting accuracy. Guo proposes a hybrid approach for crude oil price forecasting that combines deep learning and autoregressive integrated moving average (ARIMA) models (Guo, 2019). The study evaluates the proposed approach on several crude oil price datasets and compares its performance with other state-of-the-art methods, including univariate ARIMA and long short-term memory (LSTM) neural networks. The results show that the hybrid model outperforms the other methods in terms of forecasting accuracy and stability, demonstrating the effectiveness of integrating deep learning and ARIMA for crude oil price forecasting. A group researcher proposed a new method for crude oil price forecasting based on variational mode decomposition (VMD) and random sparse Bayesian learning (RSBL) (Li et al., 2021). VMD was used to decompose the crude oil price time series into several sub-signals with different frequency bands, and RSBL was used to model each sub-signal and predict future crude oil prices.

The proposed method outperformed other state-of-the-art methods, including ARIMA, SVR, and LSTM neural networks, in terms of forecasting accuracy and stability, demonstrating the effectiveness of combining VMD and RSBL for crude oil price forecasting. The study by proposed a combined architecture for crude oil price forecasting that integrates multivariate LSTM with Mahalanobis and Z-Score transformations (Urolagin et al., 2021). The authors used Mahalanobis transformation to identify and remove outliers in the data and Z-Score transformation to normalize the data, followed by feeding it into the multivariate LSTM model for forecasting future oil prices. The proposed model outperformed other state-of-the-art models, including univariate and multivariate LSTM models, in terms of forecasting accuracy and stability. Some researchers proposes a hybrid approach for crude oil price forecasting by integrating multiple data sources, including economic indicators, news articles, and social media sentiment (Yang et al., 2021). They use a feature selection algorithm to identify the most relevant features and combine machine learning techniques like LSTM neural network and SVR into a hybrid model.

The study shows that the proposed method outperforms other methods in terms of forecasting accuracy and stability, demonstrating the effectiveness of using multiple data sources and machine learning techniques for crude oil price forecasting proposed a novel approach for predicting crude oil price trends using multi-modal data features and machine learning classification algorithms (He et al., 2022). They extracted features from four different sources and evaluated several algorithms, finding that the Machine algorithm performed the best. Some researchers developed an approach to predict China's crude oil futures market by combining sentiment analysis and machine learning (Jiang et al., 2022). They extracted investor sentiment from social media and news articles and integrated it with machine learning models like SVR, RF, and GBDT to predict future prices. The results showed that the sentiment-based machine learning models outperformed traditional time-series models like ARIMA and GARCH, indicating the effectiveness of using investor sentiment and machine learning for crude oil futures price prediction. Wang and Fang proposed a method for crude oil price forecasting called WT-FNN, which uses a wavelet transform-based fuzzy neural network (Wang and Fang, 2022).

The method decomposes the time series data into different frequency components and trains a fuzzy neural network on each component to capture nonlinear relationships and time-varying patterns. The study compared the proposed method with other state-of-the-art methods and showed that the WT-FNN model outperforms them in terms of forecasting accuracy and stability. A group researcher proposes a new method for forecasting crude oil futures prices using chaos theory and a multi-objective slime mold algorithm (MOSMA) (Sun et al., 2022). The method outperformed other popular forecasting methods in terms of forecast accuracy. They suggest that this approach could have practical applications for investors and traders in the oil market. In addition, various studies have employed deep learning in conjunction with other nature-inspired algorithms, such as particle swarm optimization (PSO) and gravitational search algorithm (GSA), to improve the accuracy of crude oil price forecasting (Wang et al., 2022; Isaac et al., 2023).The combination of deep learning and nature-inspired algorithms has been shown to achieve superior forecasting results in the crude oil price prediction field.

In summary, computational intelligence techniques, particularly the use of deep learning and nature-inspired algorithms, have shown great potential for improving the accuracy of crude oil price forecasting. Furthermore, the use of hybrid models has emerged as a promising direction for simultaneously predicting multiple crude oil prices.

3. METHODOLOGY

This research proposes a methodology that implements combines the Particle Swarm Optimization and Gravitational Search Algorithm, referred to as PSOGSA, to train a Bi-Directional Long Short-Term Memory Network (BiLSTM) for simultaneously forecasting three crude oil price benchmarks: Brent, Dubai, and WTI. The PSOGSA algorithm integrates the social thinking (gbest) ability of PSO and the local search capability of GSA to optimize the performance of the BiLSTM network. To enable combination of these algorithms, the following is proposed:

$$V_i(t+1) = w \times V_i(t) + C_1' \times rand \times ac_i(t) + C_2' \times rand \times (gbest - X_i(t))$$

Where $V_i(t)$ is the velocity of agent i at iteration t, C_j' is a weighing factor, w is a weighing function, rand is a random number between 0 and 1, $ac_i(t)$ is the acceleration of agent i at iteration t, and *gbest* is the best solution so far.

In each of the iteration, update on position of particles are given as follows:

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

PSOGSA begins with the random initialization of all agents, where each agent is considered as an individual solution. Subsequently, the gravitational force, gravitational constant, and resultant forces among the agents are computed, following the prescribed equations:

$$F_{ij}^{d}(t) = G(t)\frac{M_{pi}(t)M_{aj}(t)}{R_{ij}(t)+\varepsilon}(x_j^d(t) - x_i^d(t))$$

$$G(t) = G_0 e^{-\alpha\frac{t}{T}} .$$

$$F_i^d(t) = \sum_{\substack{j=1 \\ j\neq i}}^{N} rand F_{ij}^d(t) ,$$

Thereafter, the accelerations of particles are defined as

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)},$$

The velocities of all agents can then be estimated using the equations bellow, once the accelerations and updates to the current best solutions have been calculated in each cycle.

$V_i(t+1) = w \times V_i(t) + C_1' \times rand \times ac_i(t) + C_2' \times rand \times (gbest - X_i(t))$

Finally the positions agents are defined as

$X_i(t+1) = X_i(t) + V_i(t+1)$

Only after meeting up with an end criterion can the process of updating velocities and positions be stopped.

LSTM is a type of Recurrent Neural Network (RNN) that addresses the vanishing gradient problem in traditional RNNs when dealing with sequential data. LSTM has three gates and a memory cell that control the flow of information. The gates, implemented as sigmoid activation functions, decide how much information to keep or discard. The forget gate determines how much of the previous cell state to forget, the input gate decides how much of the new input should be added to the cell state, and the output gate decides how much of the current cell state should be output. The memory cell retains the internal state of the LSTM unit and can store information over long time sequences.

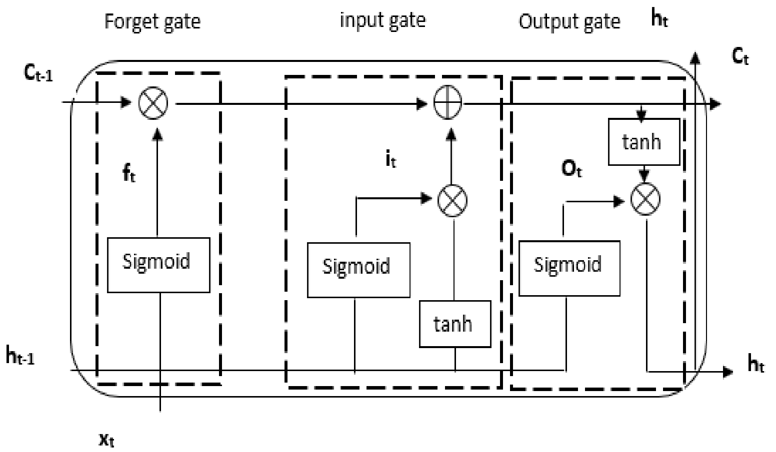


Figure 1: Structure of LSTM

A Bidirectional Long Short-Term Memory (BiLSTM) unit is an extension of the traditional LSTM unit that takes into account the context information from both directions of a sequence. It uses two sets of hidden states, one for the forward pass and the other for the backward pass, to capture the dependencies in both directions.

Input gate:	$i_t = \sigma(W_i[x_t, h_{t-1}] + b_i)$
forget gate:	$f_t = \sigma(W_f[x_t, h_{t-1}] + b_f)$
Output gate:	$o_t = \sigma(W_o[x_t, h_{t-1}] + b_o)$
Candidate memory cell:	$C_t = tanh(W_C[x_t, h_{t-1}] + b_C)$
Current Memory cell:	$C_t = f_t * C_{t-1} + i_t * \mathring{C}_t$
Hidden State:	$h_t = o_t * tanh(C_t)$

The BiLSTM model consists of two LSTM networks that accepts inputs from both the forward and backward directions. The forward LSTM analyses information from left to right, while the backward LSTM analyses data from right to left.

Hidden state of the Forward LSTM

$$\vec{h}_t = LSTM(x_t, \vec{h}_{t+1})$$

Hidden state of the Backward LSTM

$$\overleftarrow{h}_t = LSTM(x_t, \overleftarrow{h}_{t+1})$$

Output of BiLSTM is the concatenation of Forward and Backward sates

$h_t = [\vec{h}_t, \overleftarrow{h}_t]$

The following remarks should be noted in understanding how efficient PSOGSA is. The quality of solutions (fitness) in PSOGSA is considered in the updating procedure. Also, the agents that are near good solutions try to attract other agents which are exploring the search space. Furthermore, when all agents are near a good solution, they move very slowly. In this instance, the gBest help the agents to exploit the global best. PSOG uses a memory (i.e gBest) to save the best solution found so far, so that it can be accessible at any time. Noteworthy is that each agent can observe the best solution so far and move towards it. The abilities of global search and local search can be balanced with adjusting C_1' and C_2' (Mirjalili and Hashim, 2010).

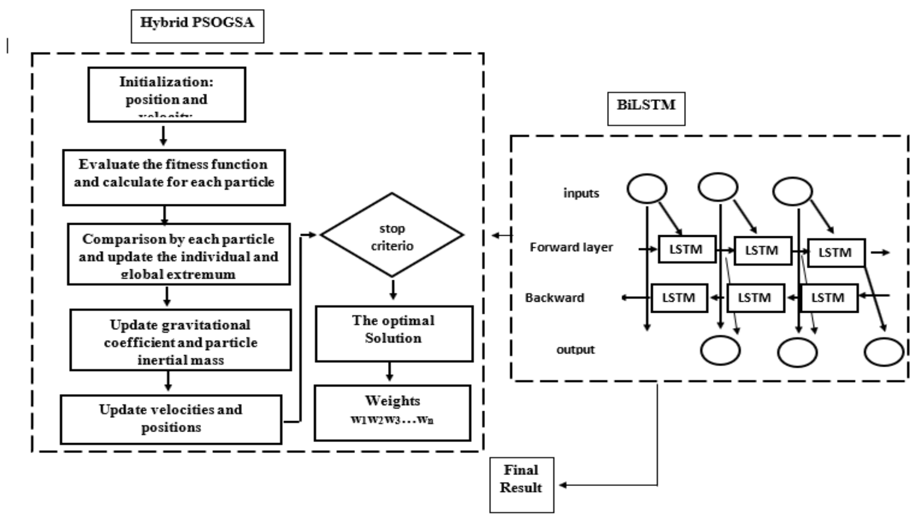


Figure 1: Model for Hybrid PSOGSA-BiLSTM

4. PERFORMANCE EVALUATION AND RESULTS

The following models were developed Feedforward Neural network optimized with Particle Swamp Optimization -Gravitational Search algorithm (FNNPSOGSA), Feedforward Neural network optimized with Particle Swamp Optimization (FNNGA), LSTM, BiLSTM, and BiLSTM-PSOGSA. The training performances are shown in Table 1, 2 and 3 respectively.

Table 1: Training Performance results of four Models of Brent Benchmark.

Model	FNNPSOGSA	FNNGA		LSTM	BiLSTM	BiLSTM-PSOGSA
MaxEpochs	1000	100		100	100	100
Architecture	7-15-1	7-15-1				
Hidden Units	1	200		200	200	200
Training Algorithm	Levenberg- Marquardt	SGDM		SGDM	PSOGSA -SGDM	PSOGSA -SGDM
RMSE	0.0443	0.8190		0.0074	0.0049	0.0029

Table 1 shows the performance of four models with the corresponding architectures, number of hidden units, training algorithms, training MSE, and RMSE values. The FNNPSOGSA, FNNGA, LSTM, BiLSTM and PSO-GSA-BiLSTM models were trained to obtain RMSE of 0.0443, 0.8190, 0.0074, 0.0049 and 0.0029 respectively.

From Table 1 above the first model trained with PSO-GSA-BiLSTM has the lowest RMSE of 0.0029 indicating a good training performance compared with the other models.

Table 2: Performance results of four Models of WTI Benchmark.

Model	FNNPSOGSA	FNNGA	LSTM	BiLSTM	PSO-GSA-BiLSTM
MaxEpochs	Na	100	100	100	100
Architecture	7-15-1	7-15-1	7-15-1		
Hidden Units	1	200	200	200	200
Training Algorithm	Levenberg- Marquardt	SGDM	SGDM	PSOGSA -SGDM	PSOGSA -SGDM
RMSE	0.0422	0.794	0.0042	0.0023	0.0011

Table 2 above shows the training performance of four models developed and trained with the crude oil data set as inputs and the WTI data set.The FNNPSOGSA, FNNGAm LSTM, BiLSTM and PSO-GSA-BiLSTM models were trained to obtain RMSE of 0.0422, 0.794, 0.0042, 0.0023 and 0.0011 respectively.The PSO-GSA-BiLSTM has the lowest RMSE of 0.0011 indicating a good training performance compared with the other models.

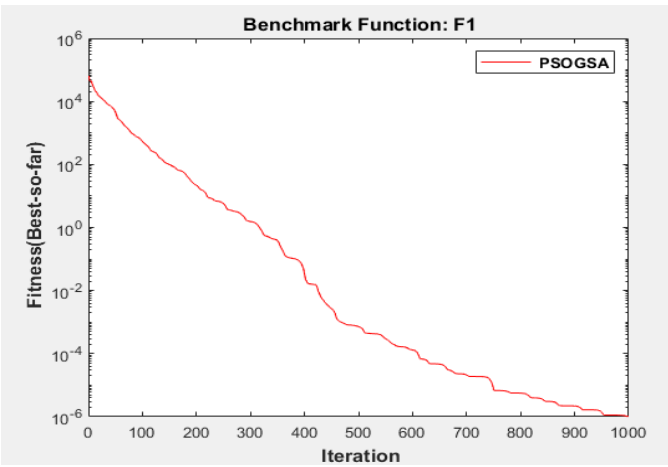
Table 3: Training Performance results of four Models of Dubai Benchmark.

Model	FNNPSOGSA	FNNGA	LSTM	BiLSTM	PSO-GSA-BiLSTM
MaxEpochs	Na	100	100	100	100
Architecture	7-15-1	7-15-1	7-15-1		
Hidden Units	1	200	200	200	200
Training Algorithm	Levenberg- Marquardt	SGDM	SGDM	PSOGSA -SGDM	PSOGSA -SGDM
RMSE	0.3210	0.7741	0.0045	0.003	0.0029

Table 2 above shows the training performance of four models developed and trained with the crude oil data set as inputs and the WTI data set.The FNNPSOGSA, FNNGAm LSTM, BiLSTM and PSO-GSA-BiLSTM models were trained to obtain RMSE of 0.3210, 0.7741, 0.0042, 0.003 and 0.0029respectively.The PSO-GSA-BiLSTM has the lowest RMSE of 0.0011 indicating a good training performance compared with the other models.

The PSO-GSA-BiLSTM model has a low training MSE of 0.0029, 0.0011, and 0. respectively for the Brent,WTI and Dubai Benchmarks.

5. DISCUSSION



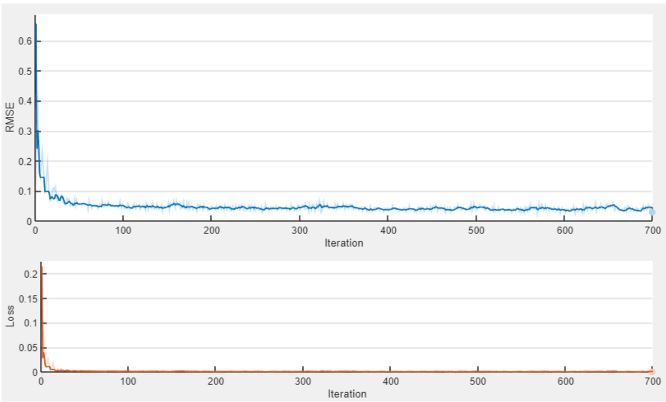


Figure 4: FNNPSOGSA Training plot for Brent Benchmark.

The number of function evaluations was at 500 and the best function value found was: 7.1312E-32 for the Brent Benchmark model in Figure 4 below. Figure 5 shows the training performance of the WTI benchmark with 500 iterations and 3.76E-28 best function value. The best function value of 1.44E-20 was obtained after 500 iterations (training epoch) for the Dubai benchmark model as shown in figure 6 below.

5.1 The Forecasted Output

The projected and actual crude oil prices benchmarks for Brent, WTI and Dubai benchmarks are shown in Figure 7, Figure 8 and Figure 9 respectively.

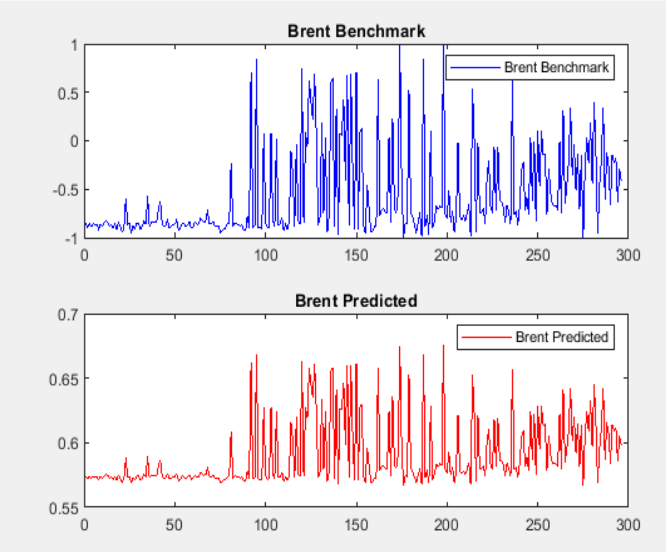


Figure 7: The Original and projected Brent Benchmark.

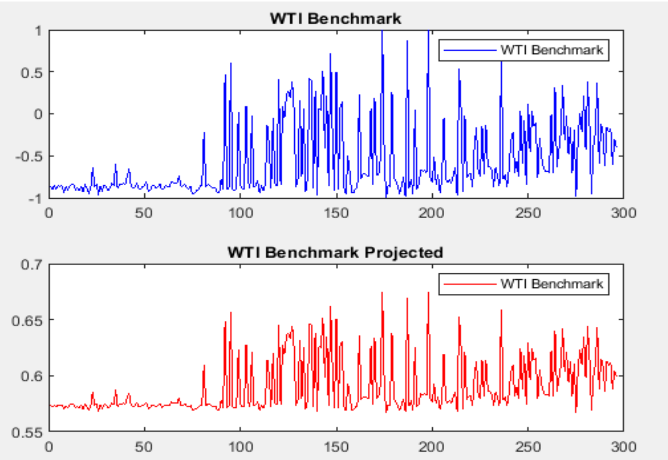


Figure 8: The Original and projected WTI Benchmark.

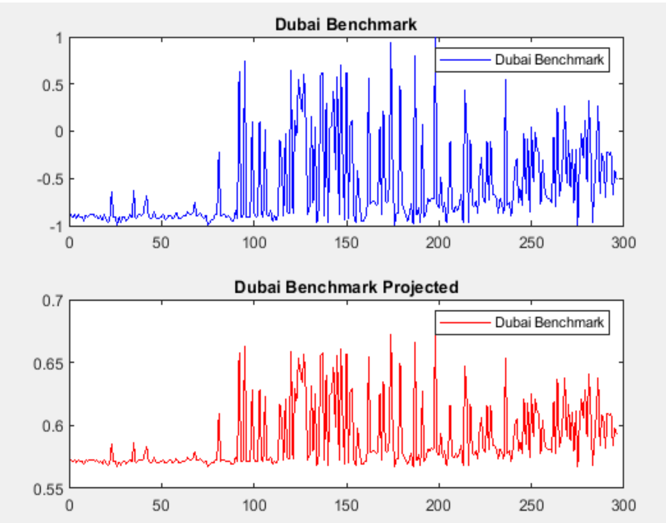


Figure 9: The Original and projected Dubai Benchmark.

Based on the analysis of figures 7, 8, and 9, the study found that the projected benchmarks using the BiLSTM-PSOGSA network were identical to the original benchmarks for Brent, WTI, and Dubai crude oil prices. Any deviations between the original and projected benchmarks were attributed to exogenous independent variables that affect crude oil prices, such as political climate and OPEC oil quotas. The study also found that the BiLSTM-PSOGSA network is a suitable tool for forecasting crude oil benchmarks when trained with adequate data sets. The root mean square errors (RMSE) of the Brent, WTI, and Dubai models were reported as 0.0029, 0.0011, and 0.0029, respectively. Overall, the study suggests that using the hybrid PSOGSA to optimize BiLSTM can improve decision-making in the oil industry. The results obtained were within acceptable limits, indicating the potential usefulness of this approach for forecasting crude oil benchmarks.

6. Conclusion

The importance of crude oil price benchmark projection for managers in oil companies and government regulatory bodies cannot be overemphasized, as it enables them to make informed decisions to maximize profits. However, the complexity of crude oil price patterns and the influence of various extraneous factors, such as politics and economics, make crude oil benchmark projection a challenging task. The BiLSTM-PSOGSA algorithm was proposed in this study as a suitable tool for projecting crude oil benchmarks using crude oil benchmark datasets. The model was trained using an epoch of 100 to avoid overfitting, and the hybrid PSOGSA algorithm was used to achieve low generalization error with accurate estimates.The results obtained from the study justify the use of PSOGSA hybrid global search algorithms in projecting crude oil prices. Overall, the study highlights the importance of using state-of-the-art tools, such as BiLSTM-PSOGSA, to enhance decision-making in the oil industry and improve the accuracy of crude oil price benchmark projections.

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