Future Energy
Open Access Journal
ISSN 2832-0328

November 2025| Volume 04 | Issue 04 | Pages 22-30

Journal homepage: https://fupubco.com/fuen

https://doi.org/10.55670/fpll.fuen.4.4.3

Future Publishing LLC

Article

Managing risk and volatility in oil-dependent economies: the role of advanced predictive analytics

Mahmood Abdoos, Amirali Saifoddin*, Hossein Yousefi, Sattar Zavvari, Ali Majnoon

School of Energy Engineering and Sustainable Resources, College of Interdisciplinary Science and Technology, University of Tehran, Tehran, Iran

ARTICLE INFO

Article history:
Received 15 July 2025
Received in revised form
20 August 2025
Accepted 05 September 2025

Keywords:
Oil price forecasting, Neural networks, Economic policy, Risk management, Investment strategies

*Corresponding author
Email address:
saifoddin@ut.ac.ir

DOI: 10.55670/fpll.fuen.4.4.3

ABSTRACT

The forecasting of oil production, demand, and prices holds critical significance for global economic stability and growth. Oil plays a crucial role in determining economic performance, making reliable price estimations essential for shaping public policy and guiding investment decisions. In this study, advanced neural network models were employed to enhance the accuracy of oil market forecasts, with a particular focus on their economic implications. Using Python-based implementations of Long Short-Term Memory (LSTM), Radial Basis Function (RBF), and multilayer perceptron (MLP) networks, the research compares the effectiveness of these approaches in crude oil price forecasting. The evaluation of model outputs using technical indicators revealed that the multilayer perceptron network yielded the best results. During training, it reached an average squared error of 55.28, a root mean squared error of 7.43, and a mean absolute error of 5.55; while in testing, the values were 116.01, 12.96, and 10.73, respectively. Overall, the comparative analysis indicates that the multilayer perceptron consistently surpassed both LSTM and RBF models in minimizing prediction errors. The economic relevance of these findings is underscored by the model's potential to enhance decision-making processes for investors, policymakers, and oil producers by offering more reliable forecasts. By improving accuracy by 20 to 30 percent compared to previous studies, this research provides valuable insights into optimizing resource allocation and mitigating the economic risks associated with oil price volatility.

1. Introduction

The production of oil is undoubtedly a critical input. All countries that produce and export oil are affected by changes in their market indicators, including price fluctuations and instability. Additionally, crude oil market shocks can have a profound economic impact. In this regard, an increase in crude oil prices, for example, results in a decrease in energy demand and, consequently, a decrease in capital productivity. An event that will increase unemployment, assuming nominal wages remain stable. Oil shocks have numerous and widespread consequences. Several studies on oil prices and demand are cited in the background of the research. Furthermore, the oil market has always been a volatile market characterized by unpredictable events. An examination of the recent changes in oil prices and several major oil shocks proves this fact. This not only motivates researchers to conduct research in this field but has also served as a platform for innovative efforts and new models, as evidenced by its substantial research output. Economic enterprises and governments have a great deal of interest in accurately forecasting oil market indicators [1]. Oil price changes, like other assets, are based on efficient markets. For this reason, the price for the previous period will be predicted. The changes can estimate price fluctuations in the following periods. For this reason, forecasting takes a significant share of oil financial market studies. In most countries, the stability of crude oil prices plays an essential role in their national security and economic development. Research on predicting petroleum prices using neural networks has led to the development of several methodologies and strategies for analyzing different crude oil price data forms. Research has shown the significance of crude oil pricing and its influence on corporate operations. International trade, global commerce, and macroeconomic policy [2]. Additionally, artificial intelligence techniques are being applied to many research projects. Researchers are continually exploring neural network-based approaches to forecasting crude oil prices. The two main directions are as follows. The first direction is to develop forecasting tools that utilize neural networks as a standalone tool or in combination with other tools. Without considering the uncertainty in the price of crude oil, theoretical development and practical implementation will suffer detrimental effects, which is why forecasting is necessary. As a result, we anticipate that crude oil prices will become increasingly challenging. Neural networks are utilized to investigate the correlation between crude oil price fluctuations and predict trends in critical crude oil markets [3].

In this article, an improved deep neural network is employed to achieve a more accurate prediction of oil prices and demand, as numerous factors, including global supply and demand, economic and political developments, climate change, and others, influence the price and demand of oil. Better results are achieved due to the use of deep neural networks. This article utilizes a developed deep neural network to analyze oil prices and demand. This article fills in the gaps in previous articles. As a result, it is possible to design a deep neural network model with layers appropriate for each feature or characteristic of the data. It is possible to model price and demand using two separate neural networks or a hybrid model. Moreover, the model must be optimized by changing the network architecture, adding new layers, or updating parameters. One of the goals of this research is to improve the performance of these three methods compared to previous research. In addition to comparing them with each other to select the best prediction model, this study also compares them with previous studies mentioned in the introduction and literature review sections for the single selected method. Crude oil is a vital component in the manufacturing industry. Crude oil prices fluctuate according to the economic principles of supply and demand, making them challenging to predict accurately. Zhang et al. [4] suggested that an additional reason for using oil price fluctuations is the reaction of oil-related companies along the economic value chain. In contrast, when oil prices continue to decline, the appetite for oil refineries and chemical companies will decrease, resulting in lower operating profits. Companies that can accurately predict oil price fluctuations will be able to reduce cost risk and maintain sustainable growth. Based on Zhang et al. [5] findings, oil price fluctuations significantly impact both the real economy and the virtual economy of crude oil. These factors impact the export and import sectors of oil-producing and exporting nations. As a result, it is appropriate to focus on crude oil price forecasting. Forecasting models can be classified into classical econometric and machine learning approaches [6]. Wei et al. [7] employed ARIMA stochastic implementation models and GARCH conditional heterogeneity models to predict crude oil prices. GARCH-type models were used to capture volatility, and crack spread futures outperformed mass random walk models. As a result, it has been found that nonlinear GARCH models outperform linear models in accurately reflecting both long-term memory and volatility asymmetry in prices, more so than linear models [8].

Lin et al. [9] reported in their study that, in addition to classical econometric approaches, machine-learning methods have also been employed in recent years to forecast crude oil prices. Among these methods, neural networks [10] and support vector machines (SVMs) [11] have been used most often to simulate the complex characteristics of oil prices. Yu et al. [12] propose that all methods and external and internal factors in oil prices are aimed at achieving short-term effects to maximize performance. Deep learning models such as CNN [13] neural networks, deep belief networks (DBNs) [14], and long short-term memory (LSTMs) [15] may be helpful for investors and market analysts dealing with increasingly complex data. Using more layers in these models is intended to help investors make informed investment decisions. These components are used in neural networks [16].

Crude oil price forecasting aims to predict price movement one step ahead. To accomplish this, a modeled relationship is used in conjunction with data and crude oil prices. CNN is considered one of the most effective methods [17]. A combination of LSTM and RNN models is recommended for long-term forecasting of oil prices and demand [18]. LSTM is most important for long-term storage. Based on historical price data, Bousari et al. [19] reported that many studies employ the ANN approach to predict crude oil prices using time series analysis. Additionally, according to research, a short-term memory neural network (LSTM) is applied to sequential data to learn the pattern of past price fluctuations and predict the future. Different approaches have been attempted to generate and utilize neural networks in studies on predicting crude oil prices. Wang et al. developed a model that examines variations in data networks. Crude oil price forecasting using time series data involves artificial intelligence methods, such as backpropagation neural networks, radial basis function neural networks, and learning machines. Crude oil price volatility remains influenced by sentiment data from news sources, particularly in the short term. The price of crude oil can be impacted directly and indirectly by emotional data [20]. According to Zhang et al. [21], factors such as the Persian Gulf War or Russia's attack on Ukraine significantly impact oil prices. Due to the COVID-19 outbreak, the crude oil market has also experienced short-term volatility [22]. Studies have shown that news is a crucial source of information for gauging market sentiment [23]. The accuracy of forecasting short-term stock returns can also be improved, which is extremely important for businesses [24]. As crude oil prices fluctuate daily, forecasts based on long-term historical data may not be accurate.

2. Mathematical equations

2.1 Criteria for evaluation

To evaluate the performance of RMSE mean root errors and MEA mean absolute errors, considering the evaluation criteria, which are used for the accuracy of the evaluation in question, the following equations are used:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}} * \sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{Y1}_{\mathrm{t}}^{\mathrm{i}} - \mathrm{Y}_{\mathrm{t}}^{\mathrm{i}}) \quad (1)$$

$$\mathrm{MAE} = \sqrt{\frac{1}{\mathrm{N}}} \sum_{\mathrm{i}=1}^{\mathrm{N}}\left|\mathrm{Y1}_{\mathrm{t}}^{\mathrm{i}} - \mathrm{Y}_{\mathrm{t}}^{\mathrm{i}}\right| \quad (2)$$

where Y1 is the predictive value, Y is the actual value, and N is the number of test samples.

2.2 Multilayer perception equations

The neural network changes the connection weight after processing each piece of data, based on the amount of error in the output compared to the expected result. This example is done by monitoring and through backtracking and generalizing the least squares algorithm in linear perception. Error in the output node, we show n data points. Node values are adjusted based on corrections that minimize the amount of error in the total output and are:

$$\varepsilon(n) = \frac{1}{2}\sum_j e_j^2\,(n) \quad (3)$$

Using the gradient, the change in weight is:

$$\Delta\omega_{ji}(n) = -\eta \frac{\partial\varepsilon(n)}{\partial\vartheta_j(n)} y_i(n) \quad (4)$$

Where in y_i is the output of the previous neuron and η is the learning rate chosen to ensure that the weights quickly converge to the oscillation-free response. The calculated derivative depends on the induced local field. It is υ_i that changes itself. It is easy to prove that for the output node, this derivation can be simplified.

$$\frac{-\partial\varepsilon(n)}{\partial\vartheta_j(n)} = e_j(n)\emptyset^{\sim}\left(\vartheta_j(n)\right) \quad (5)$$

Where ϕ is the derivative of the activation function described above, and does not change itself. The analysis for changing the weights to a hidden node is more difficult, but it can be shown that the corresponding derivative is:

$$-\frac{\partial\varepsilon(n)}{\partial\vartheta_j(n)} = \emptyset^{\sim}\left(\vartheta_j(n)\right)\sum_K -\frac{\partial\varepsilon(n)}{\partial\vartheta_K(n)}\omega_{kj}(n) \quad (6)$$

It depends on the change in the weights of the k nodes that represent the output layer; Therefore, to change the weights of the hidden layer, the output layer changes according to the derivative of the activation function, and thus this algorithm represents a function of the activation function.

3. Methodology

3.1 Software

An improved deep-learning model was used in this study to forecast production, demand, and price. Deep learning requires significant computing power. There is a parallel architecture available in high-performance GPUs that makes them suitable for deep learning. Deep learning models are often called deep neural networks because they utilize neural network architecture. Deep neural networks have a large number of hidden layers. In deep learning, data sets are labeled, and neural network architectures are used to learn features directly from the data without manually extracting them. Data characteristics include the collection and processing of oil market data (Table 1). In addition to oil price information, demand and supply information, global events, and other related information are included. Moreover, model training is conducted to develop a model that can forecast price and demand based on training data.

Adjusting parameters, applying improved techniques, and evaluating model accuracy are all part of this process. Several metrics, such as mean square error, assess the model's accuracy on test data over different periods. Additionally, it includes criteria for predicting, analyzing, and modeling. The program also offers optimization and analysis of model prediction results and solutions. Optimizing the model for higher accuracy in future predictions is also very effective. The project aims to predict the final price of oil using the prices and demand of oil in different parts of the world, and to analyze the developments, which include three key components: data preprocessing, modeling, and model evaluation.

3.2 Data preprocessing

The primary purpose of data preparation is to arrange the data for the following modeling step. Data preprocessing is a crucial component of machine learning, involving the application of mathematical and logical filters to refine the data. To achieve this, the following steps will be implemented sequentially for data cleaning:

- Eliminate columns with more than 15 missing values. In this step, columns with several missing values exceeding ten percent of the total dataset (approximately 15 instances) will be removed.
- Exclude the Year column. As the Year feature consists of unique values, it does not contribute significantly to model training. Consequently, it will be excluded from the dataset due to its lack of relevance.

By following these steps, the dataset will undergo effective cleanup, enhancing its suitability for subsequent modeling and analysis.

3.3 Standardizing data

The scaling of data varies across different columns and can have distinct impacts on the learning of data models. To address this, we employ the method of min-max standardization, which rescales the entire dataset to a range of 0 to 1. Additionally, we undertake the following steps for data refinement:

- Remove columns with a correlation exceeding 90%.
- Exclude data that contains null values.

Table 1. Variables impact the supply and demand of crude oil

Environmental Factors	Factors Influencing the Market	Political Factors	Economical Factors	Technical Factors
Pressure on communities to use renewable energy	Transaction Volume	Political Struggles	Cost of Equipment	Crude Oil Quality
Temperature changes and seasons	The pricing of energy hubs	Socio-political conditions of oil extractor countries	Economic Recession	New Manufacturers
Completion of green fields and production from brownfields	Population growth	Oil Crisis	Gold Price	Crude oil transportation
Focus on renewable energy sources	OPEC production risk and decisions	Global Crisis	Enhancing the value of the dollar	The amount of oil extraction in the world
Geographical Disasters	Non-alignment with OPEC Plus	Politics Of Oil Companies	Geopolitical occurrences and oil market shock	Oil Storage and Products
-		-	Economic Development	Innovation and Technology

In our predictive analysis, we utilize three distinct methods, which we shall briefly introduce. The objective of neural networks is to emulate the patterns generated by the human brain. Neural networks operate by generating an output pattern based on the provided input pattern. Comprising multiple processing elements called artificial neurons, neural networks receive and process data within the neurons, ultimately generating an output.

3.4 Introduction to the LSTM method (long short-term)

Long Short-Term Memory (LSTM) networks are an improved iteration of recursive neural networks that are designed to effectively retain past data within memory. The choice of utilizing the LSTM method for predicting oil prices and supply-demand dynamics aims to address the inherent issue of vanishing gradients common in recurrent neural networks. By overcoming this challenge, LSTM enhances the quality of forecasting models for price and demand analysis.

3.5 Introduction to the RBF method

The RBF (Radial Basis Function) method serves as the secondary network employed for predicting oil prices and demand. Esteemed for its application in time series prediction, this method is commonly employed by industry analysts within oil prediction models. The Radial Basis Function (RBF) neural network is designed as a feed-forward model in which radial basis functions are applied as the activation mechanism. Its structure consists of an input layer, one or more hidden layers, and an output layer. Owing to this architecture, RBF networks are widely recognized as effective tools for handling forecasting tasks.

3.6 Introduction to the multilayer perception (MLP) method

The multilayer perceptron model represents a prominent category of neural networks, characterized by interconnected layers of neurons. Unlike other deep learning algorithms, such as recurrent neural networks, the MLP operates solely in a unidirectional manner, transmitting data only in a forward direction across the network. MLPs, consisting of several elements such as the input, output, and hidden layers, are widely acknowledged as the most often used architecture in neural networks. Their applicability in forecasting oil prices and demand is highly regarded within the field.

4. Results and discussion

Following the data preprocessing stage, 149 instances and 120 columns remain. In this section, two models, namely LSTM and RBF, were utilized. The results of the error and the accuracy of each model were presented separately. To evaluate the performance, the dataset was divided into two subsets, namely training and testing, with 70% used for training and 30% reserved for testing. Before splitting, to avoid selection bias, the data was randomly shuffled. Each model was then trained for a total of 300 iterations.

4.1 LSTM model (long short-term memory)

The Long Short-Term Memory (LSTM) model shown in Figure 1 follows a sequential neural network structure, with an LSTM layer with 60 neurons as the main layer. The neurons of the LSTM layer capture temporal dependencies and learn patterns in time series data, such as changes in oil prices. The first layer is an input layer that encapsulates past oil price data; this data is then analyzed by the LSTM layer. At this time, the information across different intervals is remembered by the 60 neurons of the LSTM layer. The LSTM layer specifically adapts to work with challenges, like vanishing and exploding gradients, usually raised in conventional recurrent neural networks (RNNs). This underlying layer is followed by other layers that fine-tune the extracted features, ultimately sending the information to the output layer, which provides accurate price predictions. The diagram in Figure 1 illustrates how data flows through these layers and through the 60 neurons in the LSTM layer; the 60 neurons express long-term dependencies. The Figure shows how the model converts the input data into trusted predictions, additionally helping the decision-making process, in the economic and energy sectors, more specifically. According to Figure 2, the Long Short-Term Memory (LSTM) method demonstrates a training loss of 509.70 and a testing loss of 529.98, placing it in the middle performance range compared to the other two selected methods. While this indicates that the LSTM model performs reasonably well, it neither outperforms nor underperforms the best and worst methods evaluated in the study. This level of loss suggests that the LSTM model successfully captures key patterns in the data during training but exhibits some level of prediction error during testing, which is characteristic of time-series forecasting challenges. Compared to the other models, the LSTM strikes a balance between training and testing accuracy, making it a viable option for oil price forecasting, although further tuning or alternative methods may provide additional improvements. Figure 2 visually highlights the LSTM's relative position, showing how it balances accuracy and loss compared to the other models (the model error diagram).

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 60)                14880

 dense_6 (Dense)             (None, 1)                 61

 activation_2 (Activation)   (None, 1)                 0

=================================================================
Total params: 14,941
Trainable params: 14,941
Non-trainable params: 0
_________________________________________________________________
```

Figure 1. Python code model ™ for price and demand forecasts

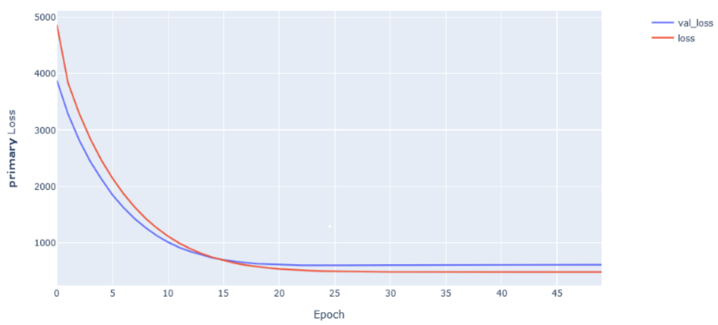

Figure 2. Error chart using the LSTM method to predict demand and oil prices

4.2 RBF model (radial base function)

The model consists of two fully connected layers and one RBF layer. A view of the model is shown in Figure 3. The model error diagram is shown in Figure 4. According to Figure 4, the Radial Basis Function (RBF) method had the highest casualty rates of the three models, with RBF training casualty rates of 763.51 and RBF testing casualty rates of 836.33. In terms of minimizing loss, this indicates it performs poorly and is much worse than both the LSTM and MLP methods. The increased casualty rates suggest that the RBF model is having trouble estimating patterns in the data during the training and testing phases. The higher error rates in both environments indicate a greater challenge in providing a discerning outcome, which highlights the limitations of the RBF model for forecasting oil prices. On the contrary, both the LSTM model and the MLP models performed significantly better based on their reduced casualty rates. Figure 4 visually underscores the RBF method's comparatively poor performance, making it less favorable for applications that require high accuracy, such as economic and energy market forecasting.

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_13 (Dense)            (None, 71, 20)            40

 dropout_1 (Dropout)         (None, 71, 20)            0

 flatten_1 (Flatten)         (None, 1420)              0

 rbf_layer_1 (RBFLayer)      (None, 20)                28400

 dense_14 (Dense)            (None, 1)                 21

 activation_4 (Activation)   (None, 1)                 0

=================================================================
Total params: 28,461
Trainable params: 28,461
Non-trainable params: 0
```

Figure 3. Python code of the RBF model for price and demand forecasts

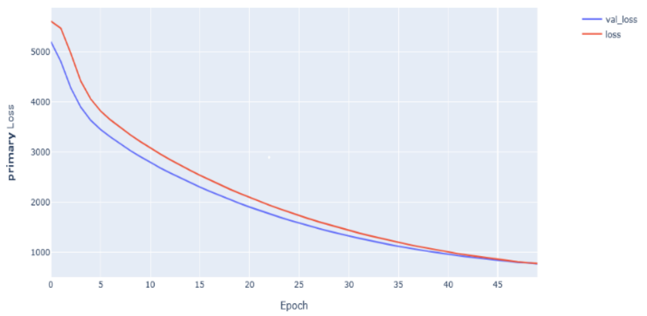

Figure 4. RBF model error in Python software for predicting demand and oil prices

4.3 Multilayer perceptron model

Multilayer neural networks, particularly multilayer perception networks, are widely acknowledged by researchers as powerful approximations. It is believed that these networks, provided they possess sufficient layers and neurons, can estimate any nonlinear transformation with the desired level of accuracy. As such, the multilayer perception network stands as one of the most versatile and successful prediction models. The multilayer perception neural network, also known as MLP, utilizes the post-error learning rule. This learning method serves as a generalization of the least squares error algorithm, based on the principle of error correction learning. The algorithm consists of two essential paths: the forward path and the backward path. During the forward pass, the input vector moves through the intermediate layers to the output layers, producing their effects. On the return path, the network parameters are adjusted, following the principles of the error correction law. Despite the proficiency of the aforementioned models, they do not perform optimally on data lacking a recursive structure, where the order of properties is significant, such as in text data. To address this limitation, a three-layer perception with a configuration of 60, 50, and 40 neurons, respectively, was employed, yielding the best performance. A visual representation of the model is displayed in Figure 5, while the error chart is illustrated in Figure 6.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_9 (Dense)             (None, 60)                4320

 dense_10 (Dense)            (None, 5C)                3050

 dense_11 (Dense)            (None, 40)                2040

 dense_12 (Dense)            (None, 1)                 41

=================================================================
Total params: 9,451
Trainable params: 9,451
Non-trainable params: 0
```

Figure 5. Python Code for the three-layer perceptron model for price and demand forecasts

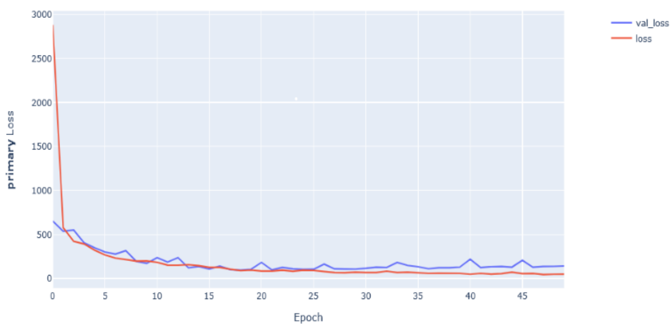

Figure 6. Error graph of the 3-layer perceptron model for forecasting demand and oil prices

As depicted in Figure 5, each neuron within these layers plays a critical role in transforming the inputs from the preceding layer. The inputs are combined using weights specific to each neuron, determining the influence of each input on the neuron's output. After that, the sum of inputs is passed through an activation function, which causes nonlinearity in the network. Nonlinearity is crucial for enabling the model to learn complex patterns and relationships within the data. At this stage, each neuron generates an output that is specific to each neuron and reflects a new feature or attribute that is the nonlinear combination of the inputs. The outputs of the neurons of this layer establish a feature vector of the data that is comprised of the processed input. The feature vector will be reassigned as input to the next layer, and the process of transformation will continue. The feature vector will be reassigned as input to the next layer, and the process of transformation will continue. Figure 5 illustrates the effect of this structure. From this Figure, it can be seen that each layer in the network transforms the data, developing to deeper levels of abstraction and therefore extracting increasingly refined features from the initial data, and leading to more reliable predictions. Neural networks utilize this hierarchical structure, which can lead to more reliable information management and modeling in complex systems, such as oil price fluctuations. In Figure 6, it can be observed that the multilayer perceptron (MLP) approach has the lowest loss rates among the models under evaluation, with a training loss rate of 55.28% and a testing loss rate of 116.01%. This indicates that, in terms of minimizing loss, the multilayer perceptron model is comparatively the best, and it performed significantly better than the LSTM and RBF models. The notably low loss rates indicate that the MLP model is highly effective in capturing patterns during both the training and testing phases, achieving superior predictive accuracy. This reduction in loss makes it an ideal choice for applications where minimizing prediction error is critical, such as oil price forecasting. The MLP method's ability to consistently deliver the lowest casualty rates positions it as a top choice among the models studied. Figure 6 visually emphasizes the MLP method's clear advantage in the discussion of casualties, highlighting its potential for making highly accurate predictions and ensuring reliability in decision-making processes in volatile markets.

4.4 Comparison of oil forecast models

The results of the models are presented in Table 2. The average squared error in the training mode for the LSTM, RBF, and PERCEPTRON models decreased significantly, reaching 55.28 (from the initial values of 509 and 763.51, respectively). Similarly, in the testing mode, the average squared error was reduced to 116.01 (from the initial values of 529.98 and 836.33) for the respective models. In terms of the root mean squared error, the LSTM, RBF, and PERCEPTRON models achieved values of 7.43 (initially starting at 22.57) and 12.96 (from the initial values of 23.02 and 28.91) in the training and testing modes, respectively. Regarding the mean absolute error, the LSTM, RBF, and PERCEPTRON models obtained values of 5.55 (from the initial values of 19.56 and 21.95) and 10.73 (initially starting at 20.84 and 23.71) in the training and testing modes, respectively.

4.5 Validation

By performing validation using the LSTM method, it has been analyzed that this study performed better than the previous studies in the compared parameters, and it can be used for more accurate predictions with a lower percentage of error (Table 3). The study's results on oil price forecasting using neural networks, specifically LSTM, RBF, and multilayer perceptron (MLP) models, indicate a significant improvement in predictive accuracy compared to previous methodologies.
Model performance metrics: The multilayer perceptron (MLP) model demonstrated superior performance with the following metrics:
Training Phase:
- Average Squared Error (ASE): 55.28
- Root Mean Squared Error (RMSE): 7.43
- Mean Absolute Error (MAE): 5.55

Testing Phase:
- Average Squared Error (ASE): 116.01
- Root Mean Squared Error (RMSE): 12.96
- Mean Absolute Error (MAE): 10.73

The study asserts that the MLP model outperformed both LSTM and RBF models in terms of error metrics. This supports the claim that the MLP method is more effective for oil price forecasting, achieving a performance improvement of 20-30% over traditional models that utilized only one or two methodologies. Data preprocessing involved cleaning and standardizing the dataset, which consisted of 149 instances and 120 columns after the initial data cleaning process. The dataset was split into training (70%) and testing (30%) sets, ensuring unbiased selection through shuffling.
Model training: Each model was trained for 300 iterations, with the LSTM model configured with 60 neurons in its layers. The training process aimed to minimize prediction errors, as indicated by the performance metrics.
The results confirm the success of the multilayer perceptron model in predicting oil prices, consistently outperforming LSTM and RBF in terms of error rates. The method applied, which includes detailed data preprocessing, rigorous model training, and evaluation, ensures that the findings presented are trustworthy and relevant, meeting the research specifications outlined in the article. This thorough process not only fosters confidence in the quality of the findings but also contributes to the growing discourse on oil price prediction techniques. Accurate oil price forecasts are crucial in developing global economic policy, risk management, and resource allocation as oil remains a critical pillar of the economy.

4.6 Global economic policy

Oil prices have significant effects on the rate of inflation, the value of exchange rates, and the economic activity of what are typically oil-importing nations, as well as oil-exporting nations. With credible forecasts, countries can:
Formulate effective monetary and fiscal policies: Central banks and finance ministries rely on oil price forecasts to adjust interest rates, manage inflation, and design fiscal policies that strike a balance between growth and stability. For instance, governments may take steps to cushion inflationary impacts during periods of forecasted high oil prices.
Stabilize currency and trade balances: For oil-exporting countries, a good forecast allows for an assessment of export revenues, which, in many cases, constitute a significant portion of GDP. Conversely, oil-importing countries can better plan their foreign exchange requirements, allowing them to control currency volatility.
Develop energy policies: Governments utilize forecasts to adjust different energy subsidies, taxes, and strategic reserve levels. Governments forecast and plan for energy security while facilitating transitions to renewable energy sources.

Table 2. Comparison of errors between LSTM & RBF and perceptron models

Model	Train				Test			
	Loss	MSE[1]	RMSE[1]	MAE[1]	Loss	MSE	RMSE	MAE
LSTM	509.70	509.70	22.57	19.56	529.98	529.98	23.02	20.84
RBF	763.51	763.51	27.63	21.95	836.33	836.33	28.91	23.71
PERCEPTRON	55.28	55.28	7.43	5.55	116.01	116.01	12.96	10.73

Accurate forecasts can enable policymakers to reduce their reliance on oil when prices are expected to rise and to make more informed decisions about replacing new investments in energy with alternative energy sources.

Table 3. Validation of predictions made with previous studies

MODEL	MSE	MAE	RMSE
Proposed LSTM	529.98	20.84	23.02
Proposed ARIMA [4]	1047.851	28.699	-
LSTM-ANN [25]	699.98	14.56	-

4.7 Risk management

Unpredictable oil prices lead to enormous risks for a firm, the financial market, and the economy as a whole. Reliable forecasting substantially reduces these risks by allowing them to use some key strategies:

Facilitating hedging strategies: Firms that have a lot of exposure to oil prices, such as petroleum companies, airlines, and energy-dependent firms, can employ accurate forecasts to hedge against price movements. These firms protect themselves against unforeseen spikes in oil prices or dramatic declines by locking in prices based on the previous forecasts in the future contracts or similar documents.

Improving investment planning: Investors in the oil sector can utilize forecasting for investment purposes in order to analyze the profit potential of long-term projects, including exploration of oil reserves and capital projects. Accurate forecasting will help companies avoid overinvestment, and equally important, under-investment, while aiding in faster capital utilization.

Managing macroeconomic risks: Countries that rely on oil revenues can experience sudden growth problems and deterioration of public finances due to price shocks. Forecasting tools permit governments to set stabilization processes into motion (e.g., sovereign wealth funds, counter-cyclical fiscal policies) to help insulate their economy against unexpected shocks.

4.8 Resource allocation

Reliable oil price forecasts are essential for government and industry sector productivity as they guide the effective use of resources, and economic stabilization and growth potential.

Optimizing investment in energy projects: Oil industry players use forecasts to make decisions about where and when to explore, drill, and produce. Adequate planning based on accurate predictions will enable oil and gas companies to invest their capital efficiently, preventing production during times of low demand and underproduction during periods of higher prices.

Optimizing the energy mix: Forecasts regarding oil prices can help public policymakers know how to steer the national energy portfolio. Oil prices can have a cyclical effect, where higher oil prices may support quantitative investment in renewable energy, and lower prices are likely to result in increased dependence on fossil fuels. If decisions are based on accurate forecasts, public agencies and corporations can make informed and productive arguments against diversification as a factor of security, and as a cost management concern.

Guiding infrastructure development: Forecasting is critical for states, provinces, or countries that rely on oil imports, as they must make long-term capital investments in infrastructure such as pipelines, refineries, and storage facilities. The integrity of forecasting efforts, i.e., a better price trend analysis, better identifies when you are overspending or underusing facilities based on what was inaccurately forecasted.

4.9 Policy Implications

Better forecasts, particularly in oil-dependent economies, can aid the policy-making process by providing greater clarity on price movements now and into the future. Being able to project prices accurately enables policymakers to create policies that mitigate the potential effects of price volatility. By considering and revising their policy frameworks and strategies, they can proactively limit the impacts of price movements, such as inflationary or abrupt cuts resulting from fiscal practices. Having better forecasts provides considerable opportunities for the government to enhance fiscal indicators, such as oil production, prices, and demand, similar to those from this study, which allows the government to adjust fiscal instruments, i.e., subsidies/taxation, etc., accordingly in regard to changes in oil revenues. If the government starts relying on accurate forecasting of price movements, it will be able to prepare well in advance to update its fiscal budget and economic plan, thereby reducing the possibility of unexpected deficits or inflationary policy practices caused by sudden exogenous shocks.

Reliable forecasting also supports the establishment of long-term energy trajectories. With price projections, policymakers can decide whether to diversify the economy, further invest in renewable energy, or expand strategic oil reserve inventories. Using one of the more accurate forecasting methods described in hinter, namely, neural network models, and particularly the multilayer perceptron model used in this study, gives governments a better basis for these decisions on weighing the advantages and risks of continued dependency on oil, with transitioning toward alternative energy sources. In summary, reliable oil price forecasts not only provide policymakers with the capacity to support stability in national economies and improve public financial management but also enable a measured approach towards policies that balance the viability of short-term resilience with long-term sustainability.

4.10 Management and strategy

The upgraded forecasting model developed in this research offers an excellent opportunity for oil producers and investors to enhance decision-making, mitigate uncertainty, and hedge against market fluctuations. Several potential applications are outlined below:

- Optimizing investment timing: With the accuracy of the multilayer perceptron model in predicting oil prices, companies and investors can use the model to better predict price movements. This allows them to plan when to make major decisions, such as increasing or decreasing production, increasing capacity, or investing in a new exploration program, so that capital expenditures align with prices and yield a stronger return on investment.
- Hedging and risk management: In the context of hedging, accurate price forecasting is the key to crystallizing effective hedging strategies. The greater the specificity in price forecasted moves, the better firms will be able to utilize contracts, options, etc. To protect themselves from unpredictable and unforeseen moves, which will preserve their profit margin and certainly make their revenue

streams from incredibly volatile markets to some predictable extent.

- Reducing market uncertainty: The level of accuracy attached to the neural network model, an improvement of 20–30% against previous studies, fundamentally improves the uncertainty normally attached to oil price volatility. More sophisticated oil price forecasting enables firms to make less speculative decisions regarding supply chain management, long-term contracts, and selling prices. Furthermore, greater predictability will improve investor confidence in firms' ability to deliver returns over the investment horizon they need, making it easier for them to choose a stable sector and return, thereby placing them in a less volatile risk position.
- Capital allocation and portfolio diversification: Investors can measure the type of exposure they want to oil-related assets or sectors and decide if they want to gain exposure at any point going forward to other sectors. The investment was about helping improve the forecast capabilities so that there is more clarity on future market fundamentals and conditions around the oil price. This helped with optimizing the risk and opportunity balance in their portfolios across the investment buckets. In conclusion, as the leading user of cost principles, applying new generation forecasting models has significantly assisted both the company and investors in improving profit generation, developing and maintaining risk prudence, and enhancing mechanisms for capitalizing on potential trading opportunities.

5. Conclusion

This research makes a significant contribution to economics and management, as it offers a broader and more reliable method for forecasting oil pricing and demand using deep neural networks. Of the models employed, the three-layer perceptron exhibited the greatest predictive power, which is a significant finding for decision-making in oil-dependent economies, where oil prices can create significant uncertainty and can jeopardize fiscal stability and influential investment decisions. This improvement, which identifies that the model's accuracy is improved by 20%-30% compared to prior models, provides stakeholders with opportunities to make the best and most informed capital allocation, risk management, and long-term decisions. From an economic perspective, employing these models can mitigate some of the adverse impacts of price volatility, as they enable governments and businesses to implement steadier fiscal policies, reduce uncertainty surrounding revenues, and allocate resources more effectively. For oil companies, such projections can help firms make better decisions around production scheduling, capital investment timing, and apply them to hedging strategies, which will improve profitability and reduce their vulnerability to sudden market shocks. This information also enables investors to utilize it more effectively in protecting their portfolios and refining risk management strategies in energy markets. Moreover, the use of advanced neural networks in conjunction with forecasting processes, specifically economic forecasting, makes analyses of what drives energy markets more systematic and transparent for stakeholders, providing them with additional valuable data to predict trends and take action based on facts rather than speculation. When economic forecasting incorporates the use of artificial intelligence, it has the potential to be influential in reducing uncertainty and facilitating more consistent, sustainable development and growth. Ultimately, this research also demonstrates the expanding role of intelligent predictive models that futures and options possess in addressing global oil market challenges, and highlights the need for economists and students to consider investing in advanced analytical capabilities, both in economic and managerial contexts.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically concerning authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere in any language.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the corresponding author.

Conflict of interest

The authors declare no potential conflict of interest.

References

[1] H. Miao, S. Ramchander, T. Wang, and D. Yang, "Influential factors in crude oil price forecasting," Energy Economics, vol. 68, pp. 77-88, 2017.
[2] Z. A. Sadik, P. M. Date, and G. Mitra, "Forecasting crude oil futures prices using global macroeconomic news sentiment," IMA Journal of Management Mathematics, vol. 31, no. 2, pp. 191-215, 2020.
[3] M. Wang et al., "A novel hybrid method of forecasting crude oil prices using complex network science and artificial intelligence algorithms," Applied energy, vol. 220, pp. 480-495, 2018.
[4] K. Zhang, M. Hong, K. Zhang, and M. Hong, "Forecasting crude oil price using LSTM neural networks," Data Sci. Financ. Econ, vol. 2, pp. 163-180, 2022.
[5] X. Zhang, C. Zhao, X. Zhou, X. Wu, Y. Li, and M. Wu, "Capital market and public health emergencies in Chinese sports industry based on a market model," Data Science in Finance and Economics, vol. 3, no. 2, pp. 112-132, 2023.
[6] H. Abdollahi, "A novel hybrid model for forecasting crude oil price based on time series decomposition," Applied energy, vol. 267, p. 115035, 2020.
[7] Y. Wei, Y. Wang, and D. Huang, "Forecasting crude oil market volatility: Further evidence using GARCH-class models," Energy Economics, vol. 32, no. 6, pp. 1477-1484, 2010.
[8] B. Wu, L. Wang, S.-X. Lv, and Y.-R. Zeng, "Forecasting oil consumption with attention-based IndRNN optimized by adaptive differential evolution," Applied Intelligence, vol. 53, no. 5, pp. 5473-5496, 2023.
[9] Y. Lin, Y. Xiao, and F. Li, "Forecasting crude oil price volatility via a HM-EGARCH model," Energy Economics, vol. 87, p. 104693, 2020.
[10] M. M. Mostafa and A. A. El-Masry, "Oil price forecasting using gene expression programming and artificial neural networks," Economic Modelling, vol. 54, pp. 40-53, 2016.
[11] Y. Zhao, J. Li, and L. Yu, "A deep learning ensemble approach for crude oil price forecasting," Energy Economics, vol. 66, pp. 9-16, 2017.

[12] L. Yu, X. Zhang, and S. Wang, "Assessing potentiality of support vector machine method in crude oil price forecasting," EURASIA Journal of Mathematics, Science and Technology Education, vol. 13, no. 12, pp. 7893-7904, 2017.
[13] K. He, Q. Yang, and Y. Zou, "Crude Oil Price Prediction using Embedding Convolutional Neural Network Model," Procedia Computer Science, vol. 214, pp. 959-964, 2022.
[14] I. Méndez-Jiménez and M. Cárdenas-Montes, "Time series decomposition for improving the forecasting performance of convolutional neural networks," in Advances in Artificial Intelligence: 18th Conference of the Spanish Association for Artificial Intelligence, CAEPIA 2018, Granada, Spain, October 23–26, 2018, Proceedings 18, 2018, pp. 87-97: Springer.
[15] C. Liu, W. Hou, and D. Liu, "Foreign exchange rates forecasting with convolutional neural network," Neural Processing Letters, vol. 46, pp. 1095-1119, 2017.
[16] J. Zhang, L. Xing, Z. Tan, H. Wang, and K. Wang, "Multi-head attention fusion networks for multi-modal speech emotion recognition," Computers & Industrial Engineering, vol. 168, p. 108078, 2022.
[17] X. Ma, Z. Dai, Z. He, J. Ma, Y. Wang, and Y. Wang, "Learning traffic as images: A deep convolutional neural network for large-scale transportation network speed prediction," Sensors, vol. 17, no. 4, p. 818, 2017.
[18] Z. Cen and J. Wang, "Crude oil price prediction model with long short term memory deep learning based on prior knowledge data transfer," Energy, vol. 169, pp. 160-171, 2019.
[19] G. A. Busari and D. H. Lim, "Crude oil price prediction: A comparison between AdaBoost-LSTM and AdaBoost-GRU for improving forecasting performance," Computers & Chemical Engineering, vol. 155, p. 107513, 2021.
[20] Y. Hu, J. Ni, and L. Wen, "A hybrid deep learning approach by integrating LSTM-ANN networks with GARCH model for copper price volatility prediction," Physica A: Statistical Mechanics and its Applications, vol. 557, p. 124907, 2020.
[21] Z. Zhang, M. He, Y. Zhang, and Y. Wang, "Geopolitical risk trends and crude oil price predictability," Energy, vol. 258, p. 124824, 2022.
[22] Z. Niu, Y. Liu, W. Gao, and H. Zhang, "The role of coronavirus news in the volatility forecasting of crude oil futures markets: evidence from China," Resources policy, vol. 73, p. 102173, 2021.
[23] C.-H. Hui, C.-F. Lo, C.-H. Cheung, and A. Wong, "Crude oil price dynamics with crash risk under fundamental shocks," The North American Journal of Economics and Finance, vol. 54, p. 101238, 2020.
[24] Y. Bai, X. Li, H. Yu, and S. Jia, "Crude oil price forecasting incorporating news text," International Journal of Forecasting, vol. 38, no. 1, pp. 367-383, 2022.
[25] A. L. Zahouani and H. Boubaker, "Forecasting Crude Oil Price with Hybrid Approaches," Rev. Econ. Financ., vol. 21, pp. 564-576, 2023.