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Research Article

The Prediction of Brent Crude Oil Trend Using LSTM and Facebook Prophet

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Abstract

Crude oil and petroleum products are among the critical inputs of industrial production and have an essential role in logistics and transportation. Hence, sudden increases and decreases in oil prices cause particular problems in global economies and thus, they have a direct or indirect effect on economies. Furthermore, due to crises in developing economies, trade disputes between major economies, and the dynamic nature of the oil price effect on demand and supply for oil and petroleum products, and time to time volatility in the oil price are very severe. The uncertainty in oil prices can leave both consumers and producers with heavy potential losses. Due to this rapid variability, predicting oil prices has global importance. In this study, to increase the accuracy and stability, the Long-Short Term Memory (LSTM) and Facebook's Prophet (FBPr) were applied to foresee future tendencies in Brent oil prices considering their previous prices. Comparing the two models made using the 32-year data set between June 1988 and June 2020 weekly for oil prices, and the model with the best fit was determined. The dataset was split into two sets: training and test sets—the twenty-five years are used for the training set and the seven years are used to validate forecasting accuracy. The coefficient of determination (R^2) for the LSTM and FBPr models was found as 0.92, 0.89 in the training stage, and 0.89, 0.62 in the testing stage, respectively. According to the results obtained, the LSTM model has superior results to predict the trend of oil prices.

Keywords: Brent Oil, Forecasting, Deep Learning, LSTM, Facebook Prophet.

LSTM ve Facebook Prophet Kullanarak Brent Ham Petrol Trendinin Tahmini

Öz

Ham petrol ve petrol ürünleri, endüstriyel üretimin önemli girdileri arasında olduğu kadar lojistik ve taşımacılıkta da kritik bir rol oynamaktadır. Dolayısıyla, petrol fiyatlarındaki ani artışlar ve düşüşler küresel ekonomilerde ve dahası ekonomiler üzerinde doğrudan veya dolaylı bir etkisi vardır. Ayrıca, gelişmekte olan ekonomilerdeki krizler, büyük ekonomiler arasındaki ticaret anlaşmazlıkları ve petrol fiyatının dinamik doğası, petrol arz ve talebi üzerinde etkisi olmaktadır ve petrol fiyatında zaman zaman oynaklık çok sert olmaktadır. Petrol fiyatlarındaki bu belirsizlikler hem tüketicilere hem de üreticilere ağır potansiyel kayıplar yaratabilmektedir. Bu hızlı değişkenlik ve dalgalanma nedeniyle petrol fiyatlarının tahmin edilmesi küresel öneme sahiptir. Bu çalışmada, Brent Petrol fiyatlarının gelecekteki trendini tahmin edilebilmek için geçmiş değerleri girdi alan Uzun Kısa Süreli Bellek (LSTM) ve Facebook Prophet (FBPr) yöntemleri kullanılmıştır. İki modelin petrol fiyatları için Haziran 1988 ile Haziran 2020 arasında haftalık 32 yıllık veri seti kullanılarak karşılaştırılmış ve en uygun model belirlenmiştir. Veri seti eğitim ve test setleri olmak üzere iki gruba ayrılmıştır; eğitim seti için ilk yirmi beş yıl seçilirken ve son yedi yıl ise tahmin doğruluğunu onaylamak için kullanılmıştır. LSTM ve FBPr modelleri için katsayı tayini (R^2) eğitim aşamasında 0.92, 0.89 ve test aşamasında 0.89, 0.62 bulunmuştur. Elde edilen sonuçlar incelendiğinde, LSTM modelinin petrol fiyatlarındaki trendi tahmin etmek için daha iyi sonuç verdiği görülmüştür.

Anahtar Kelimeler: Brent Petrol, Tahmin Etme, Derin Öğrenme, LSTM, Facebook Prophet.

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1. Introduction

All countries, even producers, are petroleum and petroleum products consumers, so the price of petroleum depends on economic activities around the world. The cost of other goods and services depends on changes in oil prices directly or indirectly. Moreover, globalization has revealed the effect of the prices of goods and services on each other more clearly. Many countries' economy depends on oil production, oil, and petroleum products trade, so estimating oil prices is an important task. Besides, some sectors are directly dependent on oil prices, such as manufacturing, logistics, and transportation. Therefore, oil prices affect not only these sectors but also the political and economic processes that determine countries' economic growth and development.

Crude oil is a critical energy source from past to present. In recent days, both the emergence of new sources such as oil shale and the use of alternative energy sources caused a decrease in the demand for total oil prices. Likewise, the deceleration in an economic boost in general after the last global economic crises has further declined. Therefore, any increase or decrease in oil prices has a fluctuating effect on the global markets. The closest visible example is the world struggling with an epidemic called Covid-19, which started in December 2019. When the oil prices are analyzed during this period, it is seen that the oil prices are sensibly affected by this unexpected situation.

According to its origin, crude oil is classified as West Intermediate (WTI), Oman, and Brent Crude Oil. Among these, Brent oil attracts intense attention and is the most used in pricing crude oil. As a description, Brent oil is a quality crude oil extracted from the North Sea, and it is an international standard for a barrel. Therefore, this paper deals with the Brent oil price as a priority.

There is extensive literature on estimating oil prices. Since historical data of oil price constitutes a time series, prediction studies have been made mostly by using classical regression methods and by including indicators affecting oil prices in the literature. Nowadays, new estimation methods are developed via machine learning and deep learning, which are predicting oil prices.

There are some accepted methods in the literature that design forecast models using the time series of petrol price data such as Box Jenkins method [1], Neural Networks [2], Gray Prediction Method [3], Artificial Intelligence-based Prediction Models [4], Machine Learning (ML) based methods [5], Econometric structural models [6] and simulation models [7]. Table 1 summarizes the papers observing oil price prediction in the literature related to the Long Short-Term Memory (LSTM) and Facebook Prophet (FBPr).

Salvi et al. [8] built a model to predict Brent oil prices' future trends from previous prices using the LSTM neural network. Brent oil price dataset is split into two groups: train and test dataset. LSTM is used to estimate Brent oil price in the test data set according to the model produced by the training data set. As a result of the study, it is observed that the estimated values are distributed at an acceptable level [8]. An et al. [9] proposed a regression-based machine learning approach to estimate the oil price. The developed model can determine prices by including some indexes.

After the accuracy of the model validates, oil prices in 2019-2022 were estimated. According to the estimation results, it has been seen that the oil price will show a slight upward trend and will generally be stable [9].

Khashman and Nwulu [10] have developed a smart system that predicts crude oil price via Support Vector Machines (SVM). The system uses some economic indicators as input and the price of crude oil as output. The developed model was procured from the 24-year WTI dataset, and the simulation results [10].

Wang et al. [4] proposed a new model based on Support Vector Regression (SVR), LSTM, and a data-driven model. Data on the daily natural gas price are used before June 2018 to train the data, and the forecasting capability of models is tested using data between June 2018 and May 2019. The proposed hybrid model showed better prediction ability than all models studied [4].

Gabralla et al. [11] developed a hybrid network model for crude oil price estimation using LSTM. An analysis tool, called the visibility diagram, is used to map the dataset on the network. K-core centrality performs to eliminate the nonlinear properties of crude oil prices and reconstruct the dataset. LSTM was used to model restored data and compared with other studies in the literature to confirm the results. As a result of the study, it is seen that the proposed model has higher accuracy [11].

Ishaq [12] used four algorithms to estimate the stock price of oil. The best result of the algorithm was found to be Naïve Bayes and Neural Network. ML and a computational intelligence approach and ANN-Q are applied to estimate the monthly WTI crude oil price [12].

Guo [1] used time series and neural network models to estimate oil prices by analyzing oil prices' nonlinear properties. The results showed that neural networks have better accuracy with a more straightforward structure [1].

Gupta and Nigam [15] improved a model to predict crude oil prices based on the artificial neural network (ANN). The developed model finds the optimum delay and the number of delays that ensure the control of crude oil prices [15].

This study aims to predict Brent oil prices by using LTSM and FBPr methods. The Brent oil price was estimated, and the results of the two ways were compared with the identified performance criteria. The technique fits the best values that were selected, and the prediction was made. According to the obtained results, the trend of Brent oil prices can be seen, and precautions can be taken both for physical (increasing or decreasing the supply of manufactured products and evaluating pricing) and financial (hedging oil prices through estimation method) for the sectors directly affected by oil.

The difference of this study from the previous studies about Brent petrol prediction in literature is that both developed models can make predictions for 349 weeks without knowing the actual price in the previous period. Therefore, the developed model can be used for long-term forecasts.

Table 1. Studies Based on Forecasting via LSTM and FBPr

Reference	Year	Prediction Application	Methods
Salvi et al. [8]	2019	Brent oil price	LSTM
An et al. [9]	2019	Oil price	Regression-based ML
Khashman and Nwulu [10]	2011	Oil price	Support Vector Machines
Wang et al. [4]	2020	Natural gas price	A hybrid data-driven model
Gabralla et al. [11]	2013	Oil Price	ML
Ishaq [12]	2020	Oil price	Orange
Abdullah and Zeng [13]	2010	Crude Oil Price	ANN-Quantitative
Olofin et al. [14]	2019	Oil Price	ML
Guo [1]	2019	Oil Price	Deep Learning and ARIMA
Bristone et al. [5]	2019	Oil Price	LSTM
Gupta and Nigam [15]	2020	Crude Oil Price	ANN
Abdollahi and Ebrahimi [16]	2020	Crude Oil Price	ARFIMA, ANFIS, GA
Chiroma et al. [2]	2015	Crude Oil Price	Evolutionary N.N. Model
Latifoglu and Nuralan [17]	2020	Stream Flow	LSTM
Oğuz and Pekin [18]	2019	Fog Visibility	ANN
Gultepe [19]	2019	Air Pollution	ML
Alpay [20]	2019	USD / TRY Price	LSTM
Kızıloz [21]	2020	Citation Count	LSTM
Aguilera et al. [22]	2019	Groundwater-level	Prophet
Weytjens et al. [23]	2019	Cash flow	LSTM, ARIMA, Prophet
Duarte and Faerman [24]	2019	Healthcare	ARIMA, Prophet
Žunić et al. [25]	2020	Sales	Prophet
Samal et al. [26]	2019	Air pollution	SARIMA, Prophet
Borowik et al. [27]	2018	Crime	ARIMA, Prophet
Phutela et al. [28]	2020	The spread of Covid-19	Prophet Logistic Growth Model

2. Material and Method

2.1. Data Collection Process

The weekly Brent crude oil price data was provided by the NASDAQ Commodities [29] from 26 June 1988 to 14 June 2020, which covers 1669 weeks. The current 32- year data is separated into two pieces, with 80% (training with 1319 data points) training set and 20% (test with 350 data points) test set, approximately. Figure 1 illustrates the values of training and test data graphically.

Figure 1. Brent Crude Oil Price from 26 June 1988 to 14 June 2020 (Source: Nasdaq [29])

It is essential to normalize the data within the range of 0–1 to make more meaningful model comparisons in machine learning applications [30]. It is not only affecting prediction accuracy but also helping to overcome the model learning problem. Hence, gradient descent can converge more quickly. The min-max normalization formula can be seen in Eq. (1).

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where $x = (x_1, x_2, \ldots, x_n)$ x_i' is the ith normalized value, x_i is the ith observed value, x_{min} is the minimum value of x and x_{max} is the maximum value of x. The normalized values obtained as a result of the study were scaled back to real values. The statistical significance of the training and test sets can be seen in *Table 2*.

Table 2. The statistical description of Training, Test and Data Sets

	N	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Training set	1319	43,34	33,80	9,82	144,49	1,10	-0,15
Test Set	350	64,83	21,35	21,44	114,81	0,84	0,06
Data Set	1669	47,85	32,79	9,82	144,49	0,82	-0,51

2.2. Long-Short Term Memory

Recurrent neural networks (RNN) differ from traditional feed-forward neural networks based on their structure. These networks are sequence-based models that can establish temporal correlations between prior knowledge and current conditions. In other words, RNN's decision at the time t may be affected by the decision at the t-1 time step. This feature of RNN is ideal for oil price prediction problems because the real world dynamics can be one of the most critical factors for oil prices at the last time intervals.

Also, RNN generally has the drawback of gradient disappearance in real-life problems, meaning the former time node's detection is decreasing. Scientists have proposed LSTM to solve this problem that RNN is facing. As artificial intelligence models' interest has increased, it has become famous [4], which is an evolutionary model of RNN. Therefore, the LSTM model was employed in this study. The developed LSTM model has memory cells with a forget gate but without peephole connections. The fully bonded layer is created as output, and an element-wise sigmoid activation function is used. Also, the loss function is thought of as log loss.

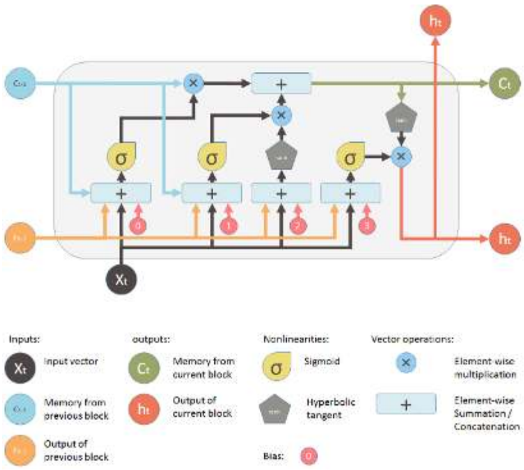

Figure 2. LSTM Cell (Source: Medium [31])

As shown in *Figure 2*, the network takes three inputs, such as x_t, h_{t-1}, and C_{t-1}, which are the input of the current period, output from the previous period, and "memory" of the previous unit. Thus, LSTM is a network that is deciding by considering these three inputs and generates a new output and alters its memory. As can be seen in *Figure 3*.

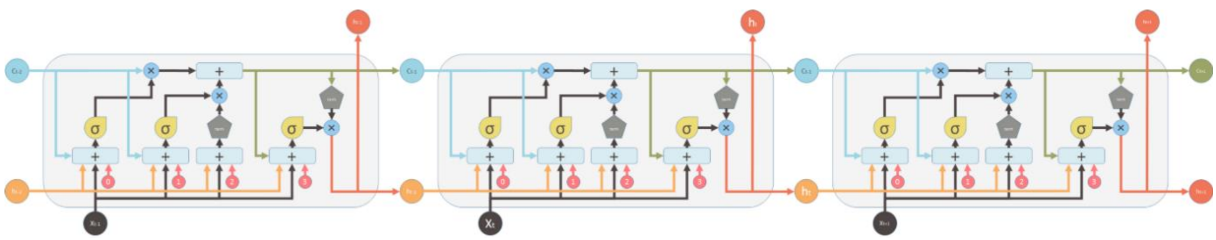

Figure 3. LSTM Networks (Source: Medium [31])

In the theoretical background, the input and outputs are calculated via Eq. (2). The equations give an update for memory cells hl(t) where hl-1(t) represents the previous layer in the same sequence step, and hl(t-1) serves the identical layer in the last step:

$$g_l^{(t)} = \emptyset\,(W_l^{gx}\, h_{l-1}^{(t)} + W_l^{gh}\, h_l^{(t-1)} + b_l^g)$$
$$i_l^{(t)} = \sigma(W_l^{ix}\, h_{l-1}^{(t)} + W_l^{ih}\, h_l^{(t-1)} + b_l^i)$$
$$f_l^{(t)} = \sigma(W_l^{fx}\, h_{l-1}^{(t)} + W_l^{fh}\, h_l^{(t-1)} + b_l^f) \qquad (2)$$
$$o_l^{(t)} = \sigma(W_l^{ox}\, h_{l-1}^{(t)} + W_l^{oh}\, h_l^{(t-1)} + b_l^o)$$
$$s_l^{(t)} = g_l^t \odot i_l^{(i)} s_l^{(t-1)} \odot f_l^{(t)}$$
$$h_l^{(t)} = \emptyset\, s_l^{(t)} \odot o_l^t$$

Where σ is an element-wise implementation of the sigmoid function, φ shows an element-wise implementation of the tanh function, and ⊙ is the element-wise product. The input, output, and forget gates are emitted by i, o, and f, respectively, and g is the input node with a tanh activation.

2.3. Facebook's Prophet

The Prophet is an algorithm used to estimate time series data developed by Facebook, which is perfectly capable of predicting long-term unstable trends or unseasonable data or processing missing data. Since Prophet is developed with R software and Python with open source code, users can use this estimation model in time series problems by making changes in parameters.

This model has often been used in the literature to predict sales amount and customer returns [32]. In this study, the Prophet model was used to estimate the Brent crude oil price that is essential for the global economy.

The Prophet model includes three major components, which are seasonality, holidays, and trend to predict y (t) via a time series. The mathematical formulation of the model is seen from Eq. (3).

$$y(t) = g(t) + s(t) + h(t) + \mathcal{E}_t \tag{3}$$

Where $\mathcal{E}_t$ is the error term that is expected to be normally distributed, g(t) represents a trend, s(t) shows seasonality term and h(t) symbolizes holidays [24].

The steps followed to make predictions using the LSTM and FBPr model, and they are also given in the flow chart in Figure 4

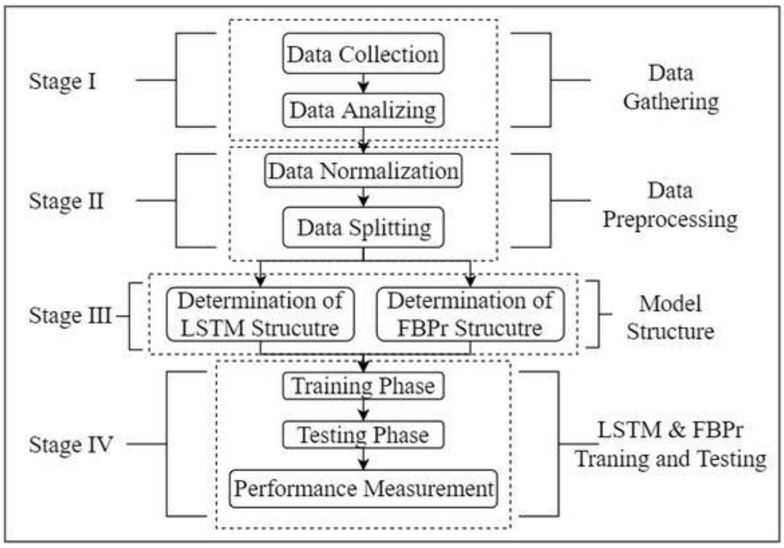

Figure 4. The Flowchart of LSTM and FBPr Forecasting Methodology (Source: Authors)

2.4. Performance Evaluation

The accuracy of the model can be specified using the Performance Measurements criteria. In order to evaluate the accuracy of the two methods, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), the coefficient of determination (R^2) values were used. Equations of these evaluation criteria are shown in Eq. (4) to Eq. (7), respectively [33].

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|OP_i^{observed} - OP_i^{predicted}\right| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(OP_i^{observed} - OP_i^{predicted})^2} \tag{5}$$

$$MAPE = 100\frac{\sum_{t=1}^{n}\frac{\left|OP_i^{observed} - OP_i^{predicted}\right|}{OP_i^{observed}}}{n} \tag{6}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(OP_i^{observed} - \overline{OP_i^{observed}})\,(OP_i^{predicted} - \overline{OP_i^{predicted}})}{\sqrt{\sum_{i=1}^{n}(OP_i^{observed} - \overline{OP_i^{observed}})^2\,(OP_i^{predicted} - \overline{OP_i^{predicted}})^2}}\right)^2 \tag{7}$$

Where n is the number of observed values, $OP_i^{observed}$ is the observed value at time i and $OP_i^{predicted}$ is the predicting value at time i.

3. Results and Discussion

3.1. Results of LSTM

The network structure has a significant impact on the computational complexity of the model and the accuracy of the predictions. Also, the performance prediction of the LSTM model is highly related to the number of hidden neurons. While the insufficient number of neurons can cause incompatibility, the excessive number of neurons can lead to overfitting. Therefore, various heuristic approaches can be used to determine the number of neurons for the hidden layer [34]. In this study, a visible input layer, ten hidden LSTM blocks, which have 50 units and one output layer shape to the LSTM network. Besides, the sigmoid activation function is chosen as default, and from 50 to 250 epochs with batch size between 1 to 100 be analyzed. Ultimately, 100 epochs with 52 batch size turned out the lowest MSE among them. Hyperparameter optimization has determined the best learning rate as 0.01 for the LSTM structure that was created with Python.

RMSE, MAE, MAPE, and R2 values were recorded for training and test data sets. These values are in the training stage; RMSE, MAE, R^2, and MAPE were found as 2.36, 4.28, 0.92, 8.2 respectively, and in the test stage, RMSE, MAE, R^2 and MAPE were found as 9.45, 6.40, 0.89, 11.50, respectively for LSTM. These performance measurement evaluation values can be seen in Table 3.

Table 3. LSTM Model Performance Evaluation Values

	MAE	RMSE	MAPE	R^2
Training set	4.28	2.36	8.20	0.92
Test set	6.41	9.45	11.50	0.89

The comparison of the observed and the predicted values can be seen in Figure 5 by using LSTM during the testing period. The diagram, as shown in Figure 5 visualizes the actual and predicted prices of Brent oil. The LSTM model grasps the trend of the actual prices. It is important to note that there is a sharp decrease between the end of 2013 to early 2015, and the suggested model showed impressive results. Since the model structure was built to predict trends instead of sudden changes, it behaves accordingly.

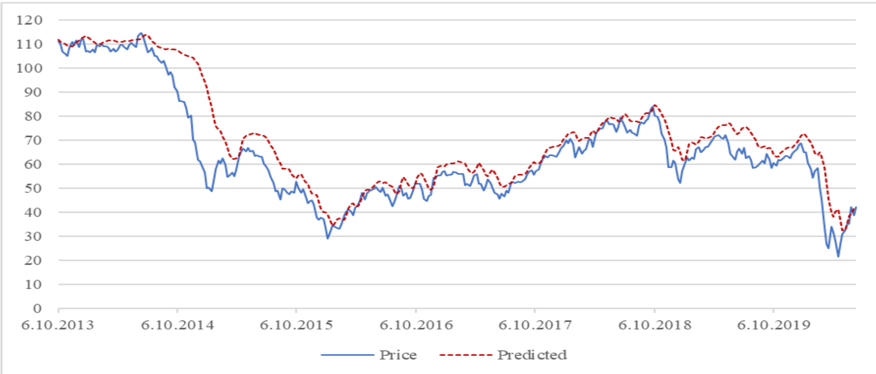

Figure 5. Actual and Predicted Brent Oil Price with LSTM

When the actual and the estimated Brent oil prices are examined graphically for the LSTM model in Figure 5, it looks like the estimates are lagging with one period. For this reason, a method, which includes the last period prices more weighted in the forecast model, can be tested. The Linear Weighted Moving Average (LWMA) method, which puts the last periods more weight and is frequently used in the literature, is also tested to predict the next period by weighing 52 weeks since the data are used weekly in LTSM and FbPr models. While the LWMA requires the actual value of the previous period for one step ahead prediction, the developed LSTM and FbPr methods can make multiple-step ahead predictions without needing the actual Brent Oil price of the previous period, so that it would not be an objective approach to compare the LWMA with LSTM and FbPr. In this study, the 25-year data were used as a training set between June 1988 and September 2013 weekly, and the following 7-year Brent oil prices were estimated. LSTM and FbPr can predict the 349 weeks without needing the actual price of the previous period. The LWMA is able to estimate for the short-term. The performance evaluation results obtained by weighing the Brent oil prices of the last 52 weeks with LWMA are given in Table 4.

Table 4. LWMA Model Performance Evaluation Values

	MAE	RMSE	MAPE	R^2
Training set	5.13	9.06	0.12	0.93
Test set	7.81	11.10	0.15	0.77

The graph in Figure 6 shows the actual and predicted values via LWMA during the testing period. It has been observed that the LSTM model gives better prediction results in the testing period than the LWMA model for long term predictions.

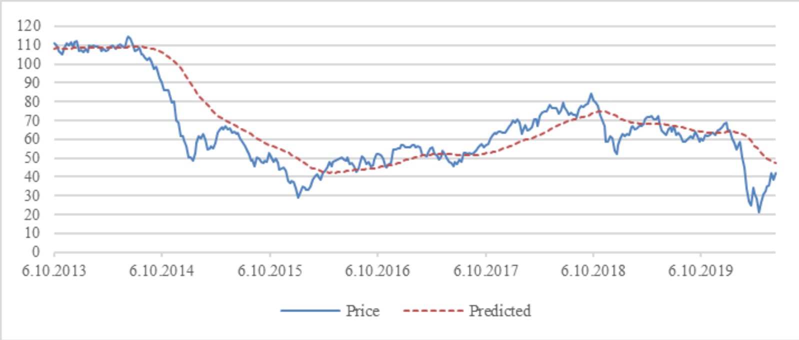

Figure 6. Actual and Predicted Brent Oil Price with LWMA

3.2. Results of FBPr

The 32-year data set (weekly) was used to create the FBPr model to predict the Brent oil price. Computational models were made using Python. The Prophet library was used for the development and implementation of the model. Also, the structural relationship between input and output has been established during the training phase.

The test dataset was used to verify the developed model. RMSE, MAD, MAPE, and R2 values are presented in Table 5 to show the training and test performance of the FBPr model.

Table 5. FBPr Model Performance Evaluation values

	MAE	RMSE	MAPE	R^2
Training set	7.21	11.22	66.11	0.89
Test set	17.53	19.56	31.65	0.62

The scatter graph in Figure 7 shows the actual and predicted values by using FBPr during the testing period. In the long run, the FBPr model works well when comparing R^2. However, the last decade for Brent oil has been highly volatile, and there is no specific pattern such as seasonality over these years.

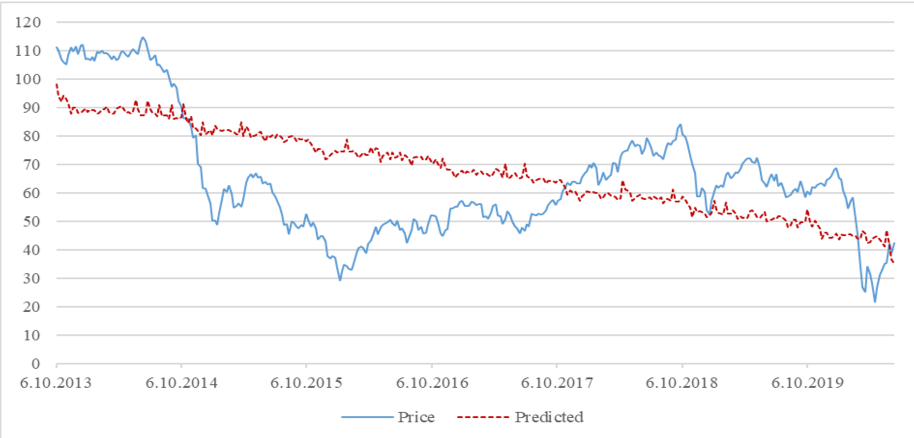

Figure 7. Actual and Predicted Brent Oil Price with FBPr

3.3. Statistical evaluation

The comparison of the Prophet and LSTM model used in this study was made by considering the RMSE, MAE, MAPE, and R^2 values. Evaluation of all methods was done by scaling back normalized values in both observed and predicted datasets. The comparative results are shown in Table 6.

Table 6. Comparison of Performance Measurement

		LSTM	FBPr
Training set	**MAE**	4.28	7.21
	RMSE	2.36	11.22
	MAPE	8.20	66.11
	R^2	0.92	0.89
Test set	**MAE**	6.41	17.53
	RMSE	9.45	19.56
	MAPE	11.50	31.65
	R^2	0.89	0.62

Table 6 represents the perfect fit gained by the LSTM model, which was exemplified to be able to predict the Brent oil price with high accuracy. Besides, the coefficient of determination (R2) value of LSTM was more significant than the Prophet for estimation, which is found as 0.89 and 0.62, respectively, for the testing stage.

4. Conclusions and Recommendations

After the oil crisis in the 1970s, the rise of a new system in all over the world for crude oil was developed, and it paved the way for free fluctuation. When the historical values of oil prices fluctuated, economists concern about oil price shocks since these shocks influence economic decisions in numerous ways. The fluctuation of oil prices and its shock affect expectations about the future oil prices trail, and such expectations mostly negatively impact future projects, investments, and even consumer behaviors. Moreover, higher oil prices are problematic even for existing projects to be abandoned, and lower oil prices create a problem for the producers, and it also affects those countries' economies.

Because of these reasons, predicting a trend of oil price is crucial. Although a couple of benchmarks for oil pricing, Brent oil is one of the most important ones, and it shows a global benchmark for crude oil. However, Brent oil price is highly complex and fluctuates, and determining the trend of the Brent oil price is a challenging problem. In order to cope with this problem, predictions can be made using classical methods, but these estimation methods can only give beneficial results for short periods. In this study, the LWMA method, which is tested, is an example of the classical method.

On the other hand, to observe the long-term price trend, the artificial neural networks, which are suitable and useful for long-term trends, are developed. LSTM and FBPr models are chosen to predict Brent oil prices considering their previous prices. The weekly 25-year data were used as a training set, then the next 7-year Brent oil prices were predicted. Performance evaluation criteria are calculated and compared using the prediction values and actual values. According to the results, the LSTM model has preferable to grasp the trend of oil prices on a weekly basis with high R^2 (0,8927). The proposed method can be applied in the future with different critical economic indicators to compare its validity

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