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PREDICTING OIL PRICES

Key words

Forecasting, forecast quality, the price of crude oil, Holt-Winters model, artificial neural networks.

Abstract

The purpose of this article is the use of artificial intelligence methods and exponential smoothing methods to determine the short-term forecast of BRENT oil prices. Another important objective of the research is to conduct a comparative analysis of the quality of the forecasts and make recommendations concerning the constructed forecasting models. Historical data used in this study came from the London Stock Exchange and covered the period from January 2012 to April 2013. The selection of forecasting models was based on the visual decomposition of the time series. The comparative analysis of the quality of the forecasts was carried out, inter alia, on the basis of such measures as mean error (ME), mean absolute error (MAE), root of mean squared error (RMS), mean relative error (MAPE), and the relative error (APE).

Introduction

The oil market is a global market. Crude oil referred to as "black gold" is crucial for the world economy as a raw material of the chemical industry, but primarily as one of the most important energy resources. Oil accounts for about 35–40% of the world's energy. It is the main raw material for the petrochemical industry, used for the production of, among others, gasoline, kerosene, oils, grease, paraffin, asphalt, petroleum residue, petroleum jelly, and many synthetic materials. Crude Oil is extracted in North and Central America, Asia, Mexico, Siberia, northern Africa, the United States and Canada. Exploitation of "black gold" takes place not only on land but also from the bottom of the seas, including the Gulf region, the Caspian Sea, the Gulf of Mexico and the North Sea. The biggest companies in the world are largely companies involved in oil trade. In many countries, the proceeds from the sale of crude oil constitute an important part of the economy.

The price of oil affects the price of other commodities; therefore, information on the oil prices is extremely important for both the buyers and businesses trading oil or other raw materials.

The purpose of this article is to determine the short-term forecasts of prices per barrel of BRENT crude oil calculated in USD, based on the data on quotations of oil prices on the LSE stock exchange (London Stock Exchange) for the period from 2 January 2012 to 5 April 2013. Another important goal is to use both the classical methods and artificial intelligence methods for forecasting electricity prices, as well as comparing the quality of the forecasts and recommending the method best suited to the actual data.

1. Literature Review

Accurate prediction of oil prices is difficult but very important for governments, companies, and investors [10]. The more accurate the forecasts of oil prices, the greater the impact they have on improving the accuracy of forecasts of a wide range of macroeconomic results [1, 6].

When reviewing the literature, it was noted that the problem of forecasting oil prices is not often discussed in literature [7]. For example, to predict oil prices, Yu, Wang, Lai [11] and Bao Y., Zhang X., Yu L., Lai K.K., Wang S [3] used the method of artificial neural networks. In turn, M. Arouri, A. Lahiani, A. Lévy A. and D. Nguyen used the GARCH [2] models, and G. Mishra, A. Singh used the ARIMA [8] models.

In this study, both the statistical methods and the methods of artificial intelligence were used to predict the price of oil. An important element of this study is a detailed comparative analysis of the errors in the obtained forecasts, which is unprecedented in literature.

2. Testing method

Forecasting methods used in this study were selected based on a detailed graphical analysis of the analysed variable of BRENT oil prices in the period from 2 January 2012 to 5 April 2013, on working days from Monday to Friday (Fig. 1).

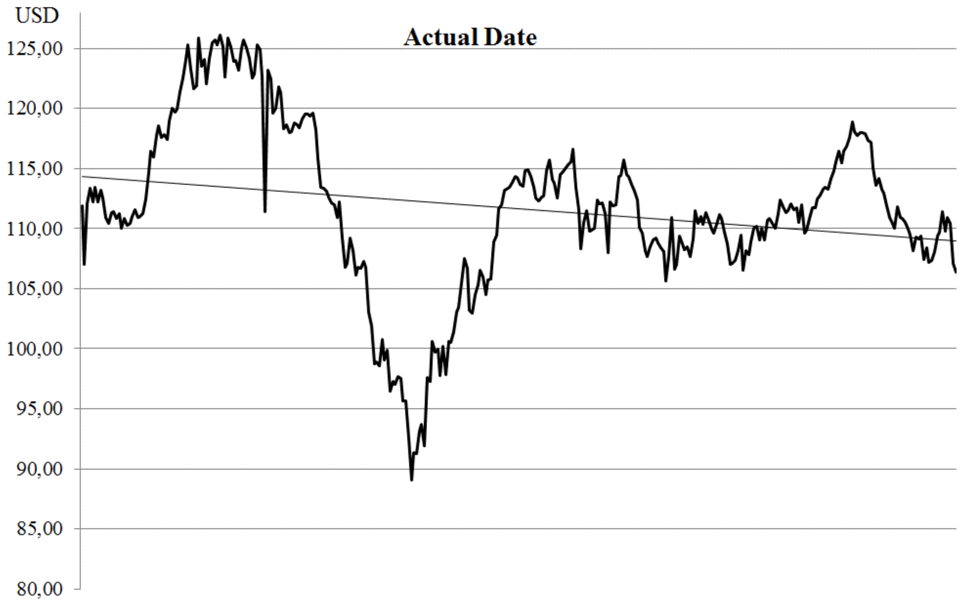

Fig. 1. BRENT oil price in the period 2.01.2012–5.04.2013

Based on visual assessment (Figure 1), we can conclude that there is a systematic component in the form of a linear decreasing trend and small random fluctuations. As a result of a detailed analysis of the graphs, the seasonal variations of the weekly seasonal cycle s = 5 have also been noted.

Due to the nature of the identified components, the Holt-Winters model and artificial neural networks were used for forecasting. Artificial neural networks are a perfect match for the data used in this study. The advantage of ANN is the fast execution time compared to the Holt-Winters model and a smaller risk of error when determining the prognosis.

3. Test results

Initially, we used the method of exponential smoothing – Holt-Winters model. It can be used to construct short-term forecasts for several future steps (m). There are two forms of the Holt-Winters model: multiplicative and additive.

Due to the nature of the data for forecasting the price of oil, the multiplicative version of the Holt-Winters model was used, which described by the following formula [9]:

$$y^*_{t+m} = (L_t + b_t m) S_{t-s+m} \tag{1}$$

Where:

y^*_{t+m} – forecast of variable Y, defined for a moment or period $t+m$,

L_t – smoothed assessment of the level of the series for a date or period t,

b_t – smoothed assessment of trend growth of the series for a date or period t,

S_{t-s+m} – smoothed assessment of the seasonality index value for a date or period t-s+m,

s – length of the seasonal cycle (the number of phases in the seasonal cycle).

The values of individual components are determined using the formulas based on the model of simple exponential smoothing [9]:

$$L_t = \alpha \frac{y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{2}$$

$$b_t = \beta (L_t - L_{t-1}) + (1-\beta) b_{t-1} \tag{3}$$

$$S_t = \gamma \frac{y_t}{L_t} + (1-\gamma) S_{t-s} \tag{4}$$

Where: α , β , γ – model parameters with values in the range of (0,1).

The forecast of the price of BRENT oil as of 6 April 2013, determined using the multiplicative Holt-Winters model, was USD 106.59 per barrel. The actual values covered in the survey from 2 January 2012 to 5 April 2013 and the predicted values from 2 January 2012 to 6 April 2013 are shown in Figure 2.

Another method used was the artificial neural networks, which are methods of data analysis with considerable application possibilities. The artificial neuron can be considered as a simple system, which processes the signal values introduced at its input into a single output value, transmitted on its only outlet. The neural network is composed of input neurons (they are used to introduce the values of variables observed on the outside) and output neurons (defining the result of the calculations – in the analysed problem it is a projected value of electricity prices). There may also be neurons that perform internal functions in the network, which mediate the analysis of information and participate in signal processing decisions. These are called hidden neurons, because they cannot be directly observed. The input, hidden, and output neurons must be interconnected, forming a solid structure. To determine the forecast of the price of BRENT oil, a MLP network was used (*Multi-Layer Perceptron*).

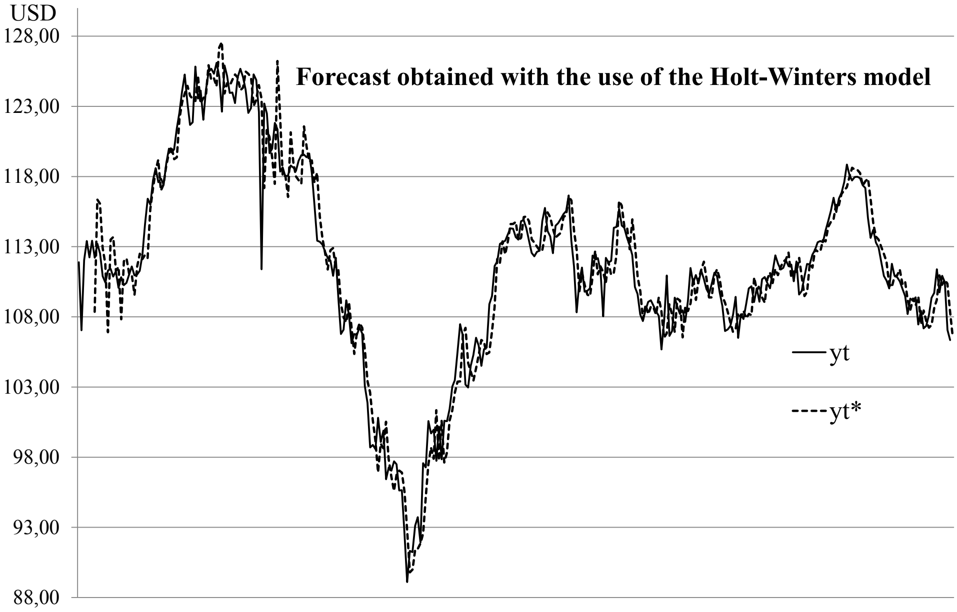

Fig. 2. Actual data (y_t) and the value of predictions (y^*_t)

Table 1. Errors in neural networks

Network	1	2	3
MAPE	1.05%	1.17%	**1.02%**
RMSE	1.65	1.76	**1.68**

Initially, several neural networks have been constructed with different numbers of neurons in the hidden layer. Then, three neural networks characterized by the best quality of learning and testing were selected for further analysis. For these networks, the mean squared forecast error (RMSE) and the mean relative error (MAPE) have been determined, Table 1. It was noted that each of the networks has a small number of MAPE and RMSE errors; therefore, further research could utilize each of these networks. Ultimately, however, network No. 3 was selected (MLP 5-2-1), characterized by the smallest values of MAPE and RMS errors.

4. Discussion of the Results

According to the method of exponential smoothing with the use of the Holt-Winters model, the forecast of the price of a barrel of BRENT crude oil for 6 April 2013 was USD 106.59. After determining the forecasts using the selected methods, an assessment of their accuracy was performed. This assessment took into account the following statistics [4], [5]: ME – Mean Error; MAE – Mean Absolute Error; maxAE – Absolute Error; RMSE – Root Mean Square Error; MAPE – Mean Absolute Percentage Error; MdAPE – Median Absolute Percentage Error; maxAPE – Absolute Percentage Error. The designated errors are summarized in Table 2.

Table 2. Determined values of errors

Error	Error value	
	Holta-Winters Model	SSN MLP 5-2-1
ME	-0.09	-0.004
MAE	1.37	1.13
max AE	12.18	11.68
MAPE	1.24%	1.02%
RMSE	1.86	1.68
MdAPE	0.93%	0.72%
max APE	10.93%	9.48%

When analysing the Table 2, it can be seen that the value of the forecasted variable deviates from the real value by an average of USD 1.86, which represents 1.24% of the actual value. Low values of MaxAE and MaxAPE mean that there are no errors significantly exceeding the average. The maximum difference between the actual value and the forecast occurred on April 6, 2012. It amounted to USD 12.18, which accounted for 10.93% of the actual value. The small ME value proves that there is no systematic underestimation or overestimation of the forecast.

In the case of artificial neural networks, the forecast of the price of a barrel of BRENT crude oil amounted to USD 106.83. The value of the forecasted variable deviates from the real value by an average of 1.68 USD and represents a 1.02% of the actual value. Low values of MaxAE and MaxAPE prove that there are no errors significantly exceeding the average. The maximum difference between the actual value and the forecast occurred on April 9, 2012. It amounted to 11.68 USD, which accounted for 9.48% of the actual value. The small value of the ME proves that there is no systematic underestimation or overestimation of the prognosis.

In the assessment of prediction errors determined by both methods, it can be concluded that both the multiplicative Holt-Winters model and the artificial neural networks reproduce the actual values very well. This means that the selected method is suitable for the prediction of such data.

5. Conclusions and Implications

The aim of this study was to determine the price of BRENT oil calculated in U.S. dollars (USD / bbl) for 6 April 2013. Another essential objective was to assess the quality of the forecasts and to recommend a method – characterized by the best accuracy – for forecasting oil prices. To determine the forecast, the exponential smoothing method was used with the use of the model of Holt-Winters model and the artificial neural networks.

The value of the forecasted BRENT oil price determined with the use of the first method for the selected day amounts to USD 106.59 per barrel. The value of the average relative forecast error amounted 1.24% of the actual value. This means that the model was well matched to the data.

In the case of artificial neural networks, the forecast of the price of a barrel of BRENT crude oil amounted to 106.83. The value of the forecasted variable deviates from the real value by an average of USD 1.68 and represents 1.02% of the actual value. Therefore, the application of ANN allowed obtaining even better results than the Holt-Winters model.

The method of exponential smoothing with the use of the Holt-Winters model is simple, but time-consuming. However, it is a method that requires large expenditures arising from the need to purchase specialized software. Moreover, it allows for the designation of forecasts with more than a one-step time horizon.

In turn, the main advantage of the artificial neural networks is the lack of need for a preliminary analysis of the data, because has been performed using the Holt-Winters model. Besides, re-applying the once-trained network is quick and easy. Unfortunately, this method without special software is impossible.

In making a comparative evaluation of both methods, based on the generated errors, the artificial neural networks method produces higher quality results. It should be noted, however, that differences in the size of errors of both methods are insignificant; therefore, it can be concluded that both forecasts are of comparable satisfactory quality, and these methods are recommended for this type of data.

The authors recommend the use of artificial neural networks because of the shorter time and smaller effort required to designate forecasts compared with the Holt-Winters method.

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Prognozowanie cen ropy naftowej

Słowa kluczowe

Prognozowanie, jakość prognozy, cena ropy naftowej, model Holta-Wintersa, sztuczne sieci neuronowe.

Streszczenie

Celem niniejszego artykułu jest zastosowanie metod sztucznej inteligencji oraz metod wygładzania wykładniczego do wyznaczenia krótkookresowej prognozy ceny ropy naftowej BRENT. Kolejnym istotnym celem badań jest przeprowadzenie analizy porównawczej jakości otrzymanych prognoz i dokonanie rekomendacji zbudowanych modeli prognostycznych. Dane historyczne wykorzystane w niniejszym badaniu pochodziły z giełdy London Stock Exchange i obejmowały okres od stycznia 2012 r. do kwietnia 2013 r. Wyboru modeli prognostycznych dokonano na podstawie wizualnej dekompozycji szeregu czasowego. Analiza porównawcza jakości otrzymanych prognoz została przeprowadzona między innymi na podstawie takich miar jak średni błąd (ME), średni bezwzględny błąd (MAE), pierwiastek ze średniego kwadratowego błędu (RMS), średni względny błąd (MAPE) oraz względny błąd (APE).