



ARTIFICIAL INTELLIGENCE IS AN EFFECTIVE TOOL FOR PREDICTING THE SPOT PRICE OF CRUDE OIL

A. M. Abbasov¹, A. I. Borodin^{*2,3}, E. I. Dzyuba⁴, M. T. Narci⁵, O. M. Kulikova⁶

¹*Odla Yurdu University, Baku, Azerbaijan*

²*Plekhanov Russian University of Economics, Moscow, Russia*

³*Azerbaijan State University of Economics, Baku, Azerbaijan*

⁴*Republican Resource Center «Family» of the Ministry of Family, Labor and Social Protection of the Population of the Republic of Bashkortostan, Ufa, Russia*

⁵*Istanbul Aydin University, Istanbul, Turkey*

⁶*Vladivostok State University, Vladivostok, Russia*

ABSTRACT

Currently, oil and gas companies play a key role in ensuring the economic growth of various countries around the world. In this regard, highly accurate forecasting of energy prices is of paramount importance for the leadership of various countries of the world and commodity producers. One of the modern methods of such forecasting is artificial intelligence, more precisely artificial neural networks. To date, quite a lot of research has been accumulated on predicting the prices of Brent and WTI crude oil using artificial intelligence. At the same time, there are practically no similar works for Urals crude oil. The purpose of this study is to predict the spot price of Urals crude oil using artificial intelligence. Unlike most well-known works, both types (trend and regression) of neuromodels are used simultaneously. Moreover, for trending neuromodels, a series of computational experiments are conducted first in NeuroSolutions, and subsequently in Google Colab (in the Python programming language), respectively, with artificial neural networks of classical (MLP, GFF, JEN and MNN) and new topologies (LSTM, WLSTM, GRU and CNN with the attention mechanism). Based on the results of these experiments, three ensembles of neuromodels of different topology and configuration were developed. They allow us to generate a short-term forecast of both the daily and monthly spot prices of Urals crude oil with a high degree of accuracy.

Keywords: spot price; Urals brand oil; artificial intelligence; regression neuromodels; trending neuromodels; ensemble of neuromodels; convolutional neural networks; recurrent neural networks; GRU; mechanism of attention.

Date submitted: 24.12.2025

Date accepted: 04.05.2026

© 2026 «OilGasScientificResearchProject» Institute. All rights reserved.

1. Introduction

The global trend is towards a low-carbon or decarbonized economy. However, environmentally friendly energy resources still account for only a small proportion of the total amount of fuel consumed by various countries of the world. At the same time, oil, gas, and coal remain the classic fuels. Currently, oil and gas companies play a key role in ensuring the economic growth of various countries around the world. At the same time, due to a number of objective reasons (in particular, the decisions of OPEC countries, COVID-19, military conflicts), high volatility in energy prices and, above all, crude oil of all reference grades is observed on world markets [1-2].

The largest crude oil exporting countries are Saudi Arabia, Russia, Iraq, the United States, Canada, the United Arab Emirates, Kuwait, Norway, Nigeria and Brazil. For

natural reasons (each deposit stores a unique raw material), a wide range of crude oil grades circulate in the modern market. At the same time, the so-called marker or reference grades of crude oil are distinguished. The most famous of them are European Brent crude, American WTI (West Texas Intermediate), Middle Eastern Dubai Crude and Russian Urals. Economic growth is influenced by many factors. However, at the same time, all researchers emphasize the important role of energy resources in the business activity of entities of all industries and sectors of the national economy in almost every country. Considering the above, it can be concluded that economic growth in various countries of the world largely depends on crude oil prices.

There are many studies on the dynamics and forecasting of oil prices. However, it is dominated by works focusing on Brent and WTI crude oil. At the same time, there are practically no studies devoted to the dynamics and forecasting of prices for Dubai Crude and Urals oil. This study seeks to address

*E-mail: aib-2004@yandex.ru

<http://dx.doi.org/10.5510/OGP20260301237>

this gap in the scientific literature. The purpose of the study is to forecast the price of Urals crude oil. In the modern world, there are many economic and mathematical methods that make it possible to form such a forecast with a high degree of accuracy [3-7]. A fairly detailed overview of known methods is presented, for example, in [6]. However, particular attention is given to a relatively new group of artificial intelligence methods – artificial neural networks. The choice of method is not accidental. For example, neural networks allow, in particular, to work with noisy source information and include all significant factors in the models, even those that are closely interrelated. Currently, scientists from all over the world are paying special attention to artificial neural networks. The scientific literature addresses not only applied problems, but also works on the development of tools [8, 9]. For example, there are many search studies devoted to the modification of a relatively new topology of recurrent artificial neural networks LSTM [10-12]. However, these studies mostly focus on trend-type neuromodels, while insufficient attention is paid to regression-type neuromodels. Therefore, within the framework of this work, both types of artificial neural networks are used for the prospective assessment of Urals crude oil prices, i.e. both trend and regression neuromodels.

In the course of this empirical research, two working hypotheses are consistently tested: 1) the possibility of providing highly accurate short-term forecasting of Urals crude oil prices using trend and regression neuromodels of classical topologies; 2) improving the accuracy of short-term forecasting by using relatively new topologies of artificial neural networks.

2. Literature review

The objective of the study determined the logic and structure of the literature review: 1) works devoted to the study of factors that have a significant impact on the change of crude oil prices; 2) works focused on the development of tools for forecasting crude oil prices. Most researchers share the view that the key factors influencing crude oil prices are oil reserves, supply and demand, as well as the situation on financial markets. In the article [13], it was proposed to divide all the factors involved in the formation of Brent crude oil price into two groups: classical determinants, coronavirus with a mechanism of direct and indirect effects. One of the key determinants is the price of gold. For instance, studies [14, 15] revealed a correlation between the prices of crude oil and gold. In other works [16], gold is considered an important indicator of future inflation and inflation expectations, which ultimately affects crude oil prices. In addition to gold, oil prices are also influenced by the foreign exchange market [17, 18]. In particular, researchers have recorded a joint movement between oil prices and the euro [16] and the US dollar [19]. At the same time, the weakening of the national currency of an oil exporting country, as a rule, leads to lower export prices for its oil, which, in turn, creates price competition in the world market with an impact on domestic and world oil prices [20- 22].

Predictors of fuel and oil consumption play a key role for the oil market. For example, the estimated indicators of prospective energy consumption are closely interrelated with the corresponding indicators of economic development [23-26]. Industrial production indices and freight transport indicators are often used as indicators forecasting economic activity [27-29]. The Organization of the Petroleum Exporting

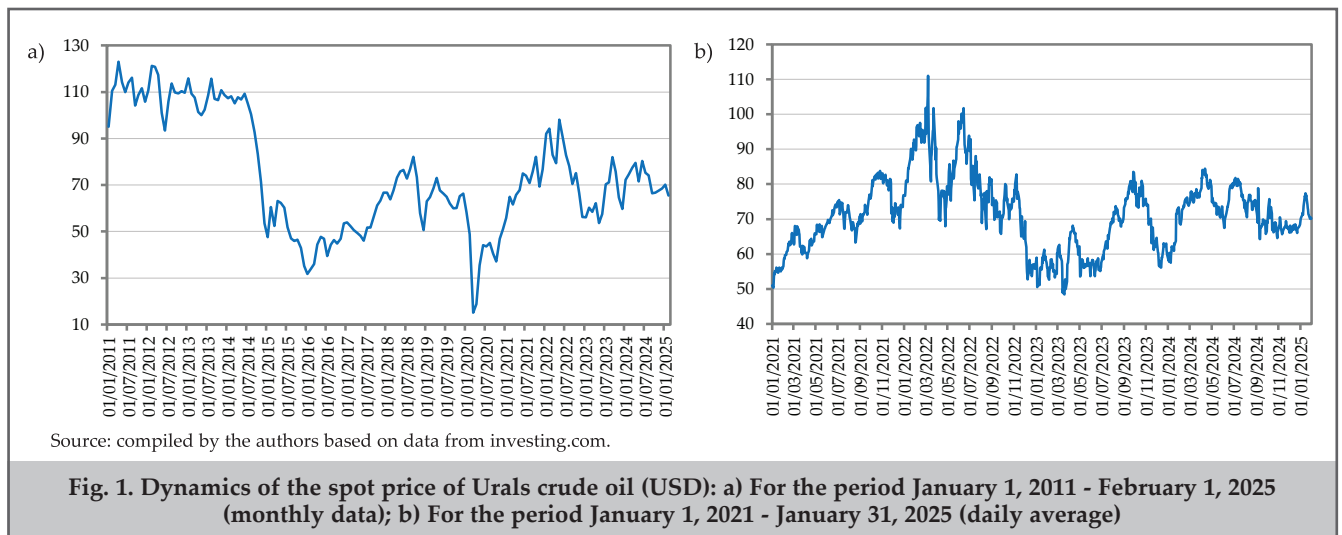
Countries (OPEC) has a significant impact on the oil market. Based on global oil demand conditions, it sets oil production for its member states, thus maintaining a certain kind of market equilibrium. The influence of OPEC summits [30] and decisions taken during these meetings [31] on domestic and global oil prices has been empirically proven. It worth mentioning that in the modern world, prices for various energy resources tend to move together. For example, the study [32] empirically proved a close correlation between oil, gas and coal prices. The influence of classical determinants on crude oil prices was distorted by the coronavirus pandemic [33-37]. Thus, the pandemic affected the GDP of all countries of the world, as the restrictions imposed and the incidence of diseases directly led to a drop in production in many industries, and consequently, to a reduction in overall economic output. The adverse impact of the pandemic on macroeconomics [38] contributed to a decrease in oil demand. The direct and indirect effects of the coronavirus pandemic on Brent crude oil prices are presented in more detail in [13].

Currently, along with traditional econometric models, modern machine learning techniques, including artificial neural networks, are also used to predict oil prices [39-49]. It should be noted that they are dominated by trend-based neuromodels, rather than regression-based ones. Moreover, works using a relatively new topology of recurrent artificial neural networks, the so-called LSTM (Long Short-Term Memory) and their various modifications, are particularly popular [50-55]. Researchers usually confirm the selection of a certain neuromodel by the results of a comparative analysis of approximation accuracy and subsequent oil prices forecasting. For example, in [56], based on data from February 1986 to May 2021, the LSTM (compared to ANN/Artificial Neural Network and ARIMA / Autoregressive Integrated Moving Average) provided higher accuracy in forecasting crude oil prices. In the context of present study, the work presented in [57-59] should be highlighted. The authors of the article conducted computational experiments with recurrent artificial neural networks of relatively new topologies. In addition to LSTM and GRU (Gated Recurrent Unit), the model range also included such modifications of LSTM as WLSTM (LSTM with a preliminary wavelet transform of the initial data) and WLSTM with the attention mechanism. In an empirical study on an array of data from several stock indices (S&P 500, DJIA /Dow Jones Industrial Average and HSI /Hang Seng Index), high forecasting accuracy for stock quotes of indices was proved using WLSTM with the attention mechanism. Due to the versatility of such tools, it can also be used to predict crude oil prices.

3. Data and methods

In this work, artificial intelligence –specifically artificial neural networks - is used to approximate the initial data, and subsequently to predict the spot price of Urals crude oil. The information base of the study consists of monthly and daily financial series (fig. 1).

The data required for neuromodeling is disclosed on the official website investing.com. In the case of monthly data, the task is to form an ensemble of adequate regression neuromodels. Therefore, based on our previous research and the work of foreign and Russian scientists, a system of indicators (factors) has been developed that can have a significant impact on the price of Urals crude oil.



Based on the calculation and analysis of Pearson pairwise correlation coefficients, the strength of the relationship between each factor and the effective indicator is estimated. Regression-type neuromodels include only factors that have a strong influence on the spot price of Urals crude oil. If required, lagged variables are also included in the neuromodel. The lagged endogenous variable for the current month is the Urals crude oil price for the previous month. The data array in the case of lagged exogenous variables is constructed in the same way as for the lagged endogenous variables. Their number depends on the number of factors included in the neuromodel. In the case of trend neuromodels, the data set is constructed from daily financial series using a sliding window method. The input indicators (factors) for trend-type neuromodels in this study consist of fifteen lagged variables with a one-day offset back. For example, the value of the last input variable lags the value of the performance indicator by one day. In turn, the fourteenth lagged variable is also one day behind the fifteenth, and etc. To improve the accuracy of trend neuromodels, the study takes into account data for the post-covid period, i.e. starting from 2021. At the same time, in any case (both with monthly and daily data), information corresponding to the periods when the relevant financial instruments were traded is applied.

For two types of neuromodels (regression and trend), neuromodeling is first performed in a special software product (NeuroSolutions for Excel 6.0). Then, using the example of trending neuromodels, computational experiments are conducted in Google Colab (in the Python programming language). In the first case, computational experiments are conducted using five classical topologies of artificial neural networks:

1. Multilayer Perceptron (MLP);
2. Generalized Feed Forward neural Network (GFF);
3. Recurrent neural networks of Jordan and Elman (Jordan / Elman Network, JEN);
4. Principal Component Analysis (PCA); 5) Modular Neural Network (MNN).

In the second case, an artificial recurrent neural network of a relatively new topology is used – WLSTM with an attention mechanism. WLSTM is a modification of LSTM (Long Short-Term Memory Network), which involves a preliminary wavelet transform of the source data. During computational experiments, the number of hidden layers

(one or two) and the number of neurons within them are varied (from two to nine with a single step). In neuromodeling, a special software product searches for the optimal number of neurons for the first or second hidden layer. In the case of neuromodels consisting of two hidden layers, the results of the search for the optimal number of neurons for neuromodels with one hidden layer are taken into account. The type of activation function for the hidden layers and the output layer, respectively, the hyperbolic tangent and linear remains unchanged throughout all computational experiments. Prior to conducting computational experiments, the set of observations is divided into training and test subsets. In the case of regression -based neural models, the training and test subsets consist of 154 and 15 observations, respectively. For trending neuromodels, the number of observations of the training and test subsets is 935 and 101, respectively. Moreover, the test subset includes observations with dates closest to the time of the study.

Increased attention is paid to the accuracy of the approximation of the initial data when conducting computational experiments. Only adequate neuromodels are included in the ensemble. The adequacy assessment is based on the calculation (based on observations from the test subset) and analysis of the values (comparing the actual and experimental values of the output variable) of five indicators:

1. Correlation coefficient (r);
2. Average approximation error (E);
3. Maximum approximation error ($\max e$);
4. and 5. number and percentage of correctly recognized observations (N_{test} and P_{test}) with an individual approximation error (e) not exceeding 5 or 8 %.

The last two indicators jointly constitute the so-called frequency quality criterion. The limit values for each of the above five indicators are specified during computational experiments. At the same time, neural models with the largest approximation error exceeding 8% are not automatically included in the ensemble.

4. The results of the study and discussion

I. Regression-type neural models

Based on the works of foreign and Russian scientists presented in the literature review, an initial version of a factor system was constructed, consisting of 9 indicators that may influence the spot price of Urals crude oil (Y):

1. Futures price of Brent crude oil (X_1);
2. Spot price of gold (X_2);
3. Exchange rate of the US dollar against the Russian ruble (X_3);
4. Euro-US dollar exchange rate (X_4);
5. Dow Jones Industrial Average (X_5);
6. Bulk Cargo Shipping Cost Index / Baltic Dry Index (X_6);
7. Moscow Stock Exchange Oil and Gas index (X_7);
8. Market price of ordinary shares of PJSC NK Rosneft (X_8);
9. Futures price of natural gas (X_9).

The decision on the expediency of including certain factors in the neuromodel is made based on the calculation and analysis of the values of Pearson pairwise correlation coefficients (table 1).

As can be seen from the data presented in table 1, only two factors (the first and the fourth) exhibit a strong direct impact on the performance indicator in the present study. Only these pairwise Pearson correlation coefficients exceed 0.7. Therefore, only the two above factors are included in regression-based neural models. The specification of neuro-models is finally clarified based on the results of a series of computational experiments. In our case, in order to ensure the adequacy of the approximation of the initial data, each regression model includes not only an effective indicator and two factors, but also three lagged variables. The latter indicators are derived indicators, i.e. in our case it is an endogenous variable and two exogenous variables for the current month indicated with values for the previous month. As a result of

a series of computational experiments, an ensemble of adequate artificial neural networks of various configurations was constructed (table 2). This ensemble enables to predict the spot price of Urals crude oil depending on the futures price of Brent crude oil and the euro-US dollar exchange rate.

As can be seen from the data presented in table 2, the ensemble consists of six regression neural models: two artificial neural networks of three different topologies with both one and two hidden layers. The results of the adequacy assessment of the ensemble of regression neural models are presented in table 3.

As can be seen from the data presented in table 3, the constructed ensemble of regression neural models provides a high degree of approximation accuracy for the initial data and, consequently, enables forecasting of the spot price of Urals crude oil. In addition, it can be concluded that the results obtained are stable. Thus, for all adequacy indicators without exception, any regression neural model provides almost identical approximation accuracy and prediction. In particular, all neural models correctly identified observations with an individual approximation error within 8%. At the same time, across the neural models, both the average and maximum approximation errors varied slightly, respectively, ranging from 2.9 to 3.5 % and from 7 to 7.5 %. Visualization of the main results of regression-based neural modelling (using the example of MLP, GFF₁ and MNN₁), namely a graphical representation of the actual and experimental values of the effective indicator for the test subset of observations is shown in figure 2.

Table 1 Matrix of Pearson pairwise correlation coefficients										
Indicator	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
Y	1									
X_1	0.965	1								
X_2	0.065	0.160	1							
X_3	-0.668	-0.577	0.531	1						
X_4	0.740	0.625	-0.248	-0.805	1					
X_5	-0.357	-0.245	0.718	0.867	-0.665	1				
X_6	0.152	0.174	0.347	0.223	-0.022	0.463	1			
X_7	-0.461	-0.411	0.514	0.852	-0.662	0.888	0.467	1		
X_8	-0.336	-0.286	0.572	0.807	-0.559	0.878	0.522	0.957	1	
X_9	0.411	0.502	0.023	-0.249	0.119	0.024	0.336	-0.149	-0.098	1

Source: Compiled by the authors

Table 2 Ensemble of artificial neural networks (regression)		
The neuro-model	The optimal number of neurons:	
	in the first hidden layer	in the second hidden layer
MLP ₁	4	-
MLP ₂	4	9
GFF ₁	9	-
GFF ₂	9	7
MNN ₁	8	-
MNN ₂	8	9

Source: Compiled by the authors

Table 3 Adequacy assessment of the ensemble of artificial neural networks (regression)							
The neural models	r	E, %	max e, %	N _{test}		P _{test} , %	
				e<5%	e<8%	e<5%	e<8%
MLP ₁	0.913	2.9	7.0	12	15	80	100
MLP ₂	0.907	3.0	7.4	12	15	80	100
GFF ₁	0.908	3.4	7.0	12	15	80	100
GFF ₂	0.910	3.2	7.5	11	15	73.3	100
MNN ₁	0.912	3.1	7.3	12	15	80	100
MNN ₂	0.894	3.5	7.4	11	15	73.3	100
The ensemble of neural models:	0.907	3.2	7.3	12	15	77.8	100

Source: Compiled by the authors

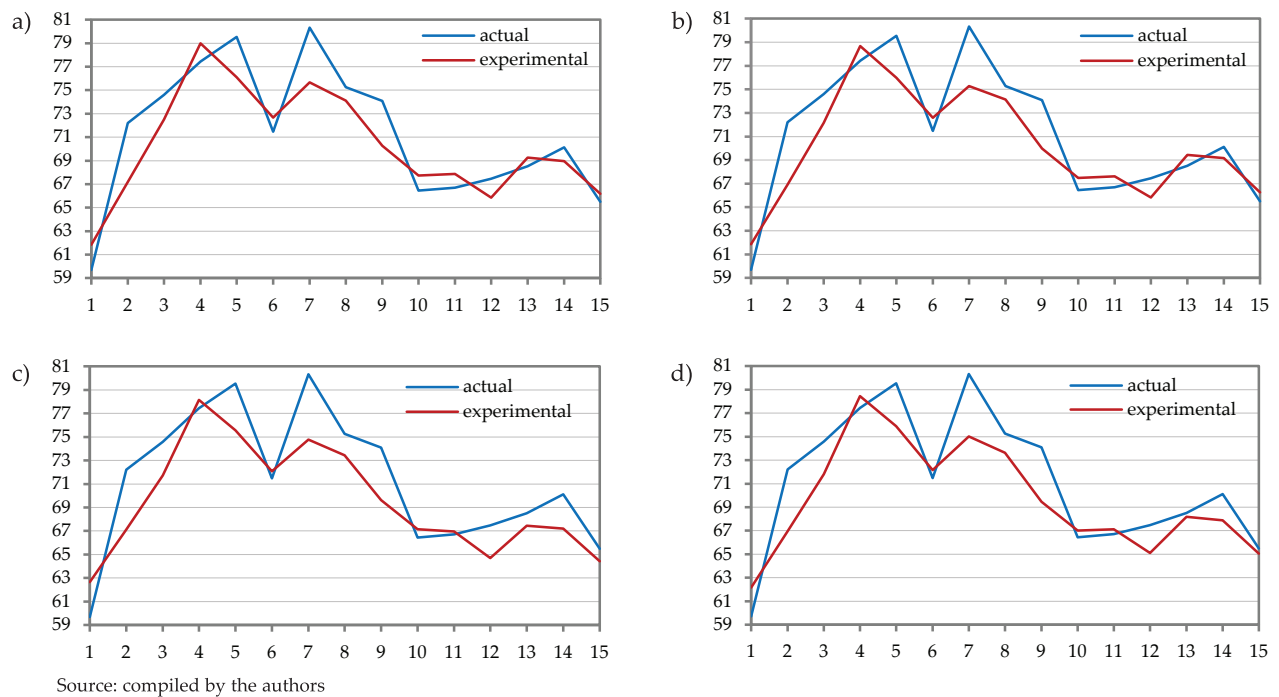


Fig. 2. Spot price of Urals crude oil (regression-based neural models, USD):
a) MLP_1 ; b) MLP_2 ; c) GFF_1 ; d) MNN_1

As part of the study, the analysis is limited to the development of a short-term forecast with a two-month lead period. Due to the presence of lagged variables in regression-based neural models, the forecasting procedure is implemented step-by-step. So, for the second month of forecasting, the initial information consists of the previously obtained forecasting results, i.e. for the first month of forecasting. On the one hand, this improves forecasting accuracy, on the other hand, it increases the complexity of the computational experiments. The resulting short-term forecast of the spot price of Urals crude oil is presented in table 4.

As can be seen from the data presented in table 4, against the background of a monthly increase in the futures price of Brent crude oil, a monthly increase in the spot price of Urals crude oil is expected for the period from February 1 to April 1, 2025. At the same time, the projected increase in the spot price of Urals crude oil should be 0.8 and 0.1 %, respectively, for February and March 2025. It should be noted that on the official website investing.com Urals crude oil spot price data are published with a delay. At the time of writing this article, only monthly data for February 1, 2025 were available. Therefore, it is not possible to assess the accuracy of the obtained short-term (monthly) forecast in the present study.

II. Trend- based neural models

Trending neuromodels can be considered an alternative to regression-based neural models. To ensure high accuracy

of the trend-based neural models, computational experiments in this work were carried out using daily data on spot prices of Urals crude oil.

1. Neuromodeling in a special software product (NeuroSolutions for Excel)

The configuration of the constructed ensemble of trend-based neural models of various topologies and the results of its adequacy assessment are presented, in tables 5 and 6 respectively.

As can be seen from the data presented in table 5, seven artificial neural networks of four topologies were included in the formed ensemble of trend based neural models on the results of computational experiments. At the same time, neuromodels with both one and two hidden layers were included in the ensemble according to three different topologies (with the exception of JEN). In the case of JEN, it was advisable to include only a neural model with one hidden layer in the ensemble. Thus, computational experiments demonstrated that the addition of another hidden layer led to a significant decrease in the approximation accuracy of the initial data using an artificial neural network of the JEN topology. A comparison of the results presented in tables 2 and 5 allows two conclusions to be drawn: 1) the presence of an artificial neural network of the JEN topology in the ensemble for trending neuromodels; 2) a differentiated optimal number of neurons in hidden layers, depending on the type of neuromodels (regression or trend) of identical topology.

Results of short-term forecasting of the spot price of Urals crude oil (monthly data)

Table 4

Date	Brent oil futures price, USD	Euro to US dollar exchange rate	Spot price of Urals crude oil, USD
01.03.2025	74.71	1.0818	66.01
01.04.2025	74.91	1.0801	66.08

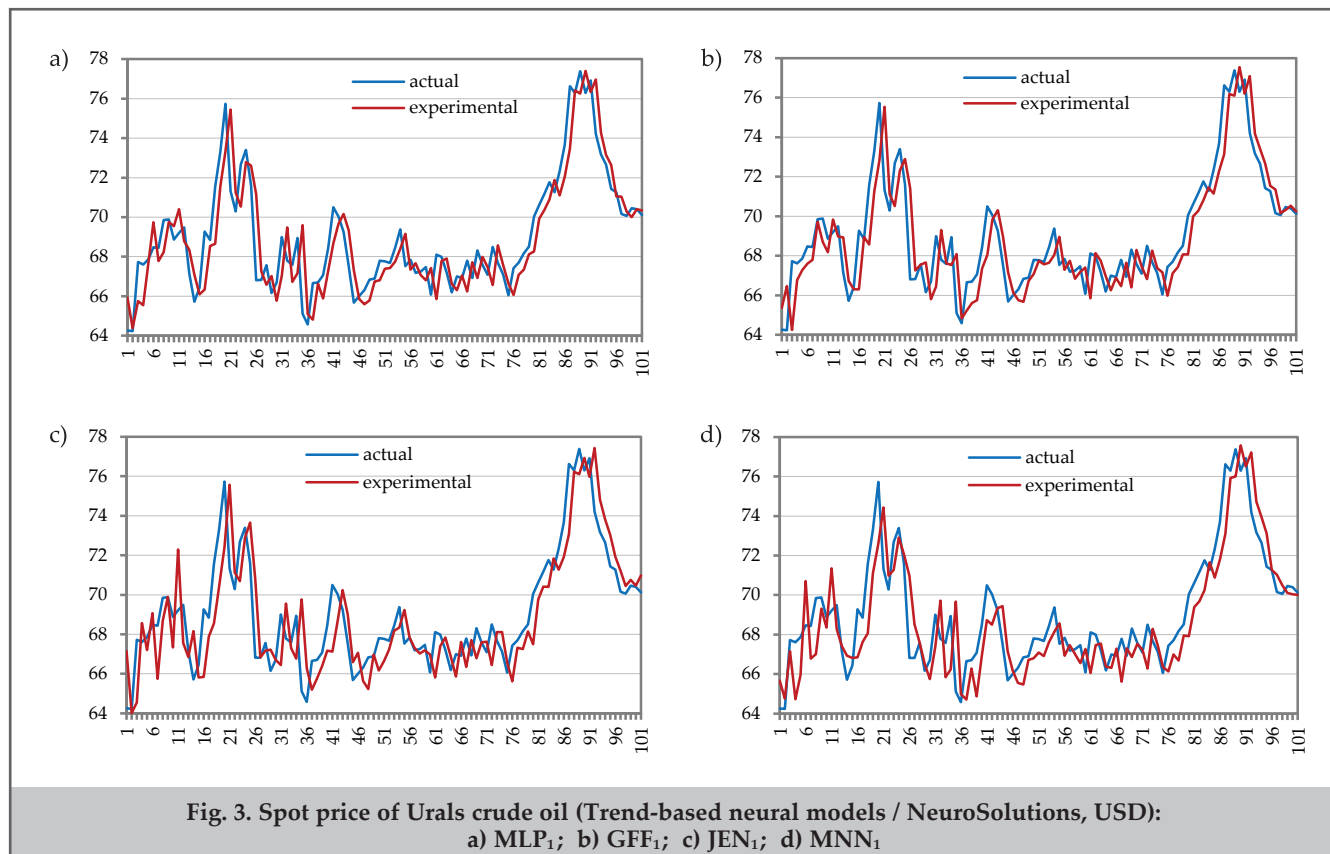
The neuro-model	The optimal number of neurons:	
	in the first hidden layer	in the second hidden layer
MLP ₁	5	-
MLP ₂	5	9
GFF ₁	8	-
GFF ₂	8	8
JEN ₁	8	-
MNN ₁	9	-
MNN ₂	9	4

The neuromodel	r	E, %	max e, %	N _{test}		P _{test} , %	
				e<5%	e<8%	e<5%	e<8%
MLP ₁	0.878	1.6	6.9	98	101	97	100
MLP ₂	0.876	1.6	6.8	98	101	97	100
GFF ₁	0.871	1.6	6.9	98	101	97	100
GFF ₂	0.872	1.6	6.1	98	101	97	100
JEN ₁	0.835	1.9	7.2	98	101	97	100
MNN ₁	0.859	1.8	7.0	99	101	98	100
MNN ₂	0.866	1.7	7.4	98	101	97	100
The ensemble of neuromodels:	0.865	1.7	6.9	98	101	97.2	100

As can be seen from the data presented in table 6, the ensemble of trend-based neural models, as well as regression-based models provides high accuracy in approximating the initial data and subsequent forecasting of the spot price of Urals crude oil. In addition, the results obtained on the basis of trend neuromodels are stable. Thus, for almost all adequacy indicators (with the exception of the correlation coefficient), approximately the same values are observed for any delusional neural model included in the ensemble. Visualization of the main results of trend-based neural modelling (using the example of MLP₁, GFF₁, JEN₁ and MNN₁), namely a graphical representation of the actual and experimental values of the effective indicator for the test subset of observations is shown in figure 3.

Based on the results of a comparative analysis of the data presented in tables 3 and 6, as well as figures 2 and 3, it can be concluded that the ensemble of trend-based neural mod-

els (compared with the ensemble of regression-based neural models) provides higher approximation accuracy of the initial data. This is indicated by the analysis of the values of the average approximation error (E) and the so-called frequency quality criterion (N_{test} and P_{test}) at e<5%. In the case of trend-based neural models, even at e<5%, each artificial neural network allows almost completely correct recognition of observations. As previously noted, for regression-based neural models, only a more «mild» condition (at e<8%) ensures complete correct recognition of observations. It should also be noted that the ensemble of trend-based neuromodels provides a significantly lower (almost twice less) value of the average approximation error. A short-term forecast (for February, in daily terms) of the spot price of Urals crude oil is generated using the ensemble of trend-based neuromodels. The forecasting results are presented in table 7 and in figure 4.



As can be seen from the data presented in table 7 and figure 4, the ensemble of trend-based neuromodels ensures high forecasting accuracy for the price of Urals crude oil. For example, according to several observations (6, 10, 12, 17, 20 and 24 February), the deviation between the forecasted and actual price values did not exceed 0.3%, i.e. it was an arithmetic error. For the entire forecast period, the largest deviation between the forecasted and actual price values did not exceed 3.5% (observed on February 11 and 25, respectively, there was an underestimation and overestimation of the actual price).

2. Neural modelling in Google Colab (in Python programming language)

Based on the results of a series of computational experiments conducted in Google Colab (in the Python programming language), an optimal ensemble of 4 neural models of two topologies CNN (Convolutional Neural Network, convolutional neural network) and GRU (Gated Recurrent Unit, controlled recurrent unit) was constructed. It should be noted that based on empirical results CNN and GRU should be included in the optimal ensemble, rather than LSTM and WLSTM, as originally planned, due to a more accurate approximation of the initial information. The main parameters of the neural models included in the optimal ensemble are presented in table 8.

As can be seen from the data presented in table 8, each neural model included in the optimal ensemble has a unique architecture and parameters. The main differences are related to the following characteristics or distinguishing features:

- the type (or topology) of neuromodels (CNN/GRU);
- the size of the time window («window size») and, as a result, the variation in the number of «input» parameters of neuromodels;
- hyperparameters of regularization (L2 Lambda and dropout);
- the number of layers and neurons within them.

Key features of neural models:

1. Model 1 (CNN):

1.1. The largest time window («window size» / 10), which allows the analysis of long-term dependencies.

1.2. An attention mechanism with 5 heads is used.

1.3. A low L2 Lambda regularization value (0.001645), which may indicate a lower risk of overfitting.

2. Model 2 (CNN):

2.1. A two-layer architecture with a high L2 Lambda regularization value (0.009396), which compensates for the complexity of the model.

Date	Spot price of Urals crude oil, USD		Deviation of the forecast price value from the actual value, %
	actual	forecast	
03.02.2025	68.51	70.07	2.3
04.02.2025	70.05	68.95	-1.6
05.02.2025	68.53	69.91	2.0
06.02.2025	68.32	68.28	-0.1
07.02.2025	68.15	68.44	0.4
10.02.2025	68.3	68.07	-0.3
11.02.2025	70.62	68.13	-3.5
12.02.2025	70.01	70.03	0.0
13.02.2025	68.77	69.72	1.4
14.02.2025	67.71	68.65	1.4
17.02.2025	67.79	67.91	0.2
18.02.2025	68.71	67.73	-1.4
19.02.2025	69.59	68.03	-2.2
20.02.2025	69.69	69.51	-0.3
21.02.2025	68.06	69.31	1.8
24.02.2025	67.76	67.82	0.1
25.02.2025	65.49	67.80	3.5

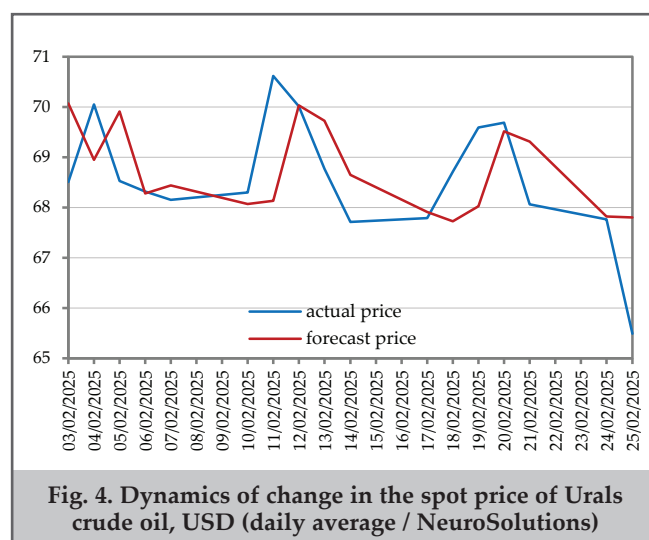


Fig. 4. Dynamics of change in the spot price of Urals crude oil, USD (daily average / NeuroSolutions)

Parameter	Model 1 (CNN)	Model 2 (CNN)	Model 3 (GRU)	Model 4 (CNN)
Window Size	10	9	4	3
Units	117	171	172	229
Dropout Rate	0,25	0,16	0,34	0,26
Dense Units	42	75	34	16
Batch Size	16	16	16	16
L2 Lambda	0.001645	0.009396	0.000082	0.008686
Number of Layers	1	2	1	3
Attention Heads	5	3	7	3

2.2. A high window size (9) combined with a low dropout value (0.16).

3. Model 3 (GRU):

3.1. The only artificial neural network of the GRU topology in the ensemble.

3.2. A short window (4), focusing on short-term patterns.

3.3. A high dropout value (0.34) to reduce overfitting.

4. Model 4 (CNN):

4.1. The shortest window (3) and three-layer architecture.

4.2. The highest number of Units (229) in convolutional layers.

The strategy for constructing the optimal ensemble is as follows:

1. Heterogeneity of architectures:

First, the combination of CNN and GRU enables to cover both spatial (through CNN / «convolutions») and temporal (through GRU) dependencies.

Second, variation in the «window size» provides an analysis of patterns on different time scales.

2. Regularization:

Dropout and L2 Lambda regularization are configured individually for each model, which reduces the risk of joint retraining.

3. Aggregation of predictions:

The outputs of neural models are averaged or combined through weighted voting, which improves generalizing ability.

The adequacy of the formed ensemble of neural models is evidenced by the values of 3 metrics (indicators):

1. MAE (Mean Absolute Error, average absolute error) – 1.5306;
2. MSE (Mean Squared Error) – 4,2191;
3. RMSE (Root Mean Squared Error, the derived indicator is the square root of MSE) – 2.0540.

The low values of MAE, MSE, and RMSE indicate high forecasting accuracy. At the same time, the presence of various topologies within the ensemble of neural models reduces error variance, which is typical for bagging methods.

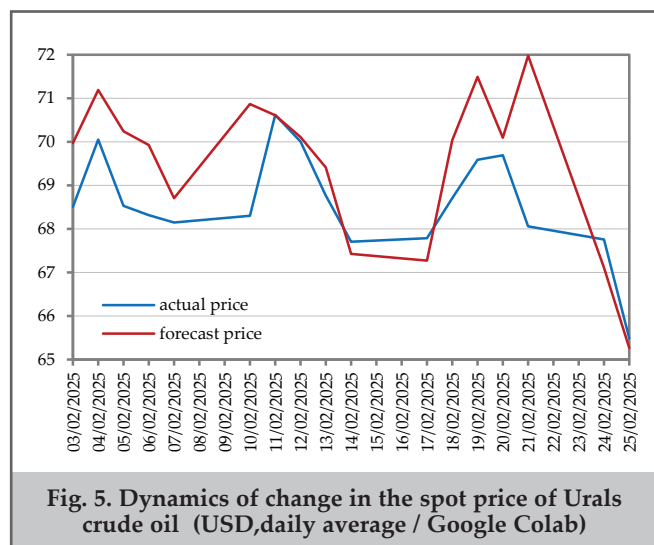
However, the adequacy of the optimal ensemble can be further improved in the following areas:

1. Using different aggregation methods (for example, stacking).
2. Adding transformers to analyze global dependencies.
3. Optimization of model weights within the ensemble.

The results of short-term forecasting obtained using an optimal ensemble of 4 neural models (Google Colab) are presented in table 9 and visualized in figure 5.

In this case, a comparative analysis is carried out with the previously obtained results (table 7 and fig. 4) to determine the preference of the methodology used. As can be seen from the data presented in table 9 and figure 5, which also shows that, as in the previous case (computational experiments were conducted in NeuroSolutions), the ensemble of trend-based neuromodels enables to generate a short-term forecast of the price of Urals crude oil with a high degree of accuracy. For example, for several (i.e. 9) observations, or 52.9% of their total number, the discrepancy between the forecasted and actual prices did not exceed 1%. A comparison of the newly obtained results with the data presented in table 7 and figure 4 do not allow to draw an unambiguous conclusion regarding the preference of a particular methodology. On the one hand, the optimal ensemble of 4 neural models (Google Colab) allows to get a larger number of observations that deviate from the actual values of the effective indicator within 1%. However, on the other hand, the ensemble of neural models (NeuroSolutions) demonstrates the best results based on the number of observations that ensure almost complete coincidence between the experimental and actual values of the Urals crude oil price.

Date	Spot price of Urals crude oil, USD		Deviation of the forecast price value from the actual value, %
	actual	forecast	
03.02.2025	68.51	69.97	2.1
04.02.2025	70.05	71.19	1.6
05.02.2025	68.53	70.25	2.5
06.02.2025	68.32	69.93	2.4
07.02.2025	68.15	68.71	0.8
10.02.2025	68.3	70.87	3.8
11.02.2025	70.62	70.61	0.0
12.02.2025	70.01	70.11	0.1
13.02.2025	68.77	69.41	0.9
14.02.2025	67.71	67.43	-0.4
17.02.2025	67.79	67.27	-0.8
18.02.2025	68.71	70.04	1.9
19.02.2025	69.59	71.49	2.7
20.02.2025	69.69	70.10	0.6
21.02.2025	68.06	71.98	5.8
24.02.2025	67.76	67.11	-1.0
25.02.2025	65.49	65.27	-0.3



Conclusion

Based on the literature review, the authors developed an initial system of factors influencing crude oil prices. This system of factors was refined based on the calculation and analysis of Pearson pairwise correlation coefficients. Based on the monthly data for the period from January 1, 2011 to February 1, 2025, it was defined that the spot price of Urals crude oil was strongly influenced by only 2 factors, the futures price of Brent crude oil (Factor 1) and the EUR/USD exchange rate (Factor 4). The results obtained («screening out» of insignificant factors) were taken into account later during the formation of an ensemble of regression-type neuromodels. Specifically, based on a series of computational experiments conducted using a special software product (NeuroSolutions), 6 neuromodels of 3 different topologies (MLP, GFF and MNN) were included in the ensemble. An analysis of the values of the main adequacy indicators allowed to conclude that the monthly spot price of Urals crude oil can be accurately forecast. Currently, trend-type neuromodels represent an alternative to regression-type neuromodels. Therefore, in the framework of the study, increased attention was paid specifically to trend-type neuromodels. Initially, computational experiments were conducted in NeuroSolutions using artificial neural networks of classical topologies (MLP, GFF, JEN, and MNN). Subsequently, similar experiments were carried out in Google Colab (Python programming language) for relatively recent (modern) topologies of artificial neural networks (LSTM, WLSTM, GRU and CNN with an attention mechanism). It was experimentally established that both ensembles of neuromodels allow for short-term forecasting of the daily spot price of Urals crude oil with a high degree of accuracy. According to the results of the empirical study, the first hypothesis was confirmed. Both trend-based and regression-type neuromodels provided high accuracy in approximating the initial data and subsequent short-term forecasting. The second hypothesis was only partially confirmed. Trend-based neuromodels of relatively new topologies demonstrated better predictive capabilities only in terms of individual adequacy indicators compared to neuromodels of classical topologies. The results obtained may be applied in practice, for example, in the planning and forecasting the values of the main indicators of the production and financial activities of oil companies worldwide. In this case, artificial intelligence can contribute to making such plans and forecasts more realistic.

References

1. Khan, M. N. (2024). Market volatility and crisis dynamics: a comprehensive analysis of U.S., China, India, and Pakistan stock markets with oil and gold interconnections during COVID-19 and Russia-Ukraine war periods. *Future Business Journal*, 10, 22.
2. Abbasov, A., Mamedov, Z., Tvaronavičienė, M., et al. (2022). Estimation and Prediction dynamics of the spread of the coronavirus infection using minimax approximation criterion and polynomial splines. *Applied and Computational Mathematics*, 21(1), 101-117.
3. Brignone, R., Gonzato, L. (2026). Econometric analysis of crude oil price dynamics using time series of option prices. *Annals of Operations Research*. Published: 21 January.
4. Pillai, G. S., Mary, M. I. (2026). Forecasting of gold prices using hybrid markov weighted fuzzy intuitionistic crayfish time series. *Computational Economics*. Published: 13 February.
5. Taiwo, B. O., Hosseini, S., Kahraman, E., et al. (2026). Multi-objective optimization inspired by behaviour of jellyfish searching process for silver prices forecasting. *Progress in Artificial Intelligence*, 15, 93-116.
6. Zhang, Y., He, M., Wang, Y. (2025). Forecasting crude oil prices. In: Wang, Y., Zhang, Y. (Eds.) *Energy forecasting. Climate change and energy transition*. Singapore: Springer.
7. Borodin, A., Akhunov, R., Kulikova, O., et al. (2025). Forecasting the capitalization oil and gas companies using artificial intelligence. *SOCAR Proceedings*, 4, 178-187.
8. Foroutan, P., Lahmiri, S. (2024). Deep learning systems for forecasting the prices of crude oil and precious metals. *Financial Innovation*, 10, 111.
9. Kumar, K. (2025). Forecasting crude oil prices using reservoir computing models. *Computational Economics*, 66, 2543-2563.
10. Qurbanov, S. H., Dzyuba, E. I., Borodin, A. I., Mamedov, Z. F. (2024). Assessment of the return on equity of PJSC «Rosneft» using artificial intelligence. *SOCAR Proceedings*, 4, 130-138.
11. Yaswanth, G., Lohith, H., Jerusha, M., et al. (2025). A study on forecasting of crude oil prices employing optimized deep learning models and LUBE method. *Asia-Pacific Financial Markets*, Published: 29 July.
12. Kljajic, M., Mizdrakovic, V., Jovanovic, L., et al. (2025). Gasoline and crude oil price prediction using multi-headed variational neighbour search-tuned recurrent neural networks. *Computational Economics*, 67, 3087-3122.
13. Nepp, A. N., Zykov, A. S., Egorova, Yu. V. (2023). Oil in the age of coronavirus: Hysteria or appropriate market fall? *Economics and Mathematical Methods*, 59(1), 48-64.
14. Astafyeva, E., Turuntseva, M. (2024). Forecast evaluation improving using the simplest methods of individual forecasts' combination. *Applied Econometrics*, 74(2), 78-103.
15. Samanta, S. K., Zadeh, A. H. (2012). Co-movements of oil, gold, the US dollar, and stocks. *Modern Economy*, 3(1), 111-117.

16. Malliaris, A. G., Malliaris, M. (2013). Are oil, gold and the euro inter-related? Time series and neural network analysis. *Review of Quantitative Finance and Accounting*, 40(1), 1–14.
17. Lomonosov, A., Polbin, D., Fokin, N. (2021). The impact of global economic activity, oil supply and speculative oil shocks on the Russian economy. *The HSE Economic Journal*, 25(2), 227–262.
18. Zehir, C., Özyeşil, M., Borodin, A., et al. (2026). Derivative impacts on capital markets: a quantitative exploration of capital market stability and management strategies. *International Journal of System Assurance Engineering and Management*, Published: 29 January.
19. Aloui, R., Aïssa, M. S. B. (2016). Relationship between oil, stock prices and exchange rates: A vine copula based GARCH method. *The North American Journal of Economics and Finance*, 37, 458–471.
20. Shin, K., Choi, B Y., Shamsutdinova, I. (2025). Unraveling the impact of russian sanctions and oil prices on exchange rate: A comparative approach. *Comparative Economic Studies*, 67, 723–749.
21. Borodin, A., Panaedova, G., Frumina, S., et al. (2021). Modeling the business environment of an energy holding in the formation of a financial strategy. *Energies*, 14, 8107.
22. Valiyev, V. M., Aliyeva, R. G. (2026). Optimal resource allocation in energy production: a dynamic programming model for oil, gas, and renewable energy sources. *SOCAR Proceedings*, 1, 143-149.
23. Wang, Q., Sun, X. (2017). Crude oil price: demand, supply, economic activity, economic policy uncertainty and wars – from the perspective of structural equation modelling (SEM). *Energy*, 133, 483–490.
24. Dong, M., Chang, C. P., Gong, Q., Chu, Y. (2019). Revisiting global economic activity and crude oil prices: a wavelet analysis. *Economic Modelling*, 78, 134–149.
25. Yadigarov, T. A., Ramazanov, M. K., Alirzayev, E. V. (2025). Assessment of the formation of investments in the oil and gas sector under conditions of uncertainty. *SOCAR Proceedings*, 4, 196–204.
26. Köse, N., Ünal, E., Süt, A. T. (2025). The effects of oil price shocks: a dynamic SVAR analysis of the terms of trade, industrial production, and inflation. *Open Economies Review*, 37, 483-519.
27. Punjabi, H., Kumar Chandar, S., Malik, M. (2026). A machine learning approach to crude oil price prediction using support vector machine (SVM). In: Lanka, S., Cabezuelo, A.S., Tugui, A. (Eds.) Trends in sustainable computing and machine intelligence. ICTSM 2025. Lecture Notes in Networks and Systems, 1755. Springer, Cham.
28. Deabl, Rihab A., Al-Jawad, Mohammed S. (2026). Application of machine learning technique in water, chemical, and thermal flooding: review paper. *SOCAR Proceedings*, 2, 60-78.
29. Giannarakis, G., Lemonakis, C., Sormas, A., Georganakis, C. (2017). The effect of Baltic Dry Index, gold, oil and USA trade balance on Dow–Jones sustainability index world. *International Journal of Economics and Financial Issues*, 7(5), 155.
30. Dbouk, W., Jamali, I. (2018). Predicting daily oil prices: Linear and non-linear models. *Research in International Business and Finance*, 46, 149–165.
31. Razek, N. H., Michieka, N. M. (2019). OPEC and non-OPEC production, global demand, and the financialization of oil. *Research in International Business and Finance*, 50, 201–225.
32. Griffin, J. M., Teece, D. J. (2016). OPEC behaviour and world oil prices. London: Routledge.
33. Zonova, O. V., Kumaneeva, M. K., Sheveleva, O. B. (2023). The factors of modern pricing in the energy market. *Russian Coal Journal*, 5, 90–95.
34. Binder, C. (2020). Coronavirus fears and macroeconomic expectations. *Review of Economics and Statistics*, 102(4), 721–730.
35. Gil-Alana, L. A., Monge, M. (2020). Crude oil prices and COVID-19: persistence of the shock. *Energy Research Letters*, 1(1), 13200.
36. Maliszewska, M., Mattoo, A., Van Der Mensbrugghe, D. (2020). The potential impact of COVID-19 on GDP and trade: a preliminary assessment. *World Bank Policy Research Working Paper* 9211.
37. McKibbin, W., Fernando, R. (2021). The global macroeconomic impacts of COVID-19: Seven scenarios. *Asian Economic Papers*, 20(2), 1–30.
38. Wu, Y., Abdul Rahman, R., Yu, Q. (2025). Can the price fluctuations of Shanghai crude oil futures affect Asian financial markets? Evidence from the time and frequency dynamics analysis of spillover connectedness. *Portuguese Economic Journal*, 24, 241–269.
39. Ovcharov, A. O., Terekhov, A. M. (2024). Financial contagion of the Russian economy: intersectoral aspect. *Finance: Theory and Practice*, 28(3), 183–193.
40. Alokley, S., Araichi, S., Alomair, G. (2024). Exploring the relationship and predictive accuracy for the Tadawul All Share index, oil prices, and bitcoin using copulas and machine learning. *Energies*, 17(13), 3241.
41. Chen, H., Liu, Y., Li, X., Gu, X. (2024). An ensembled model for the prediction of oil price. *Finance Research Letters*, 67(10), 105789.
42. Guo, L., Huang, X., Li, Y., Li, H. (2023). Forecasting crude oil futures price using machine learning methods: Evidence from China. *Energy Economics*, 127, 107089.
43. Hao J., Feng Q., Yuan J., et al. (2022). A dynamic ensemble learning with multi-objective optimization for oil prices prediction. *Resources Policy*, 79, 102956.
44. Hao, J., Yuan, J., Wu, D., Xu, W., Li, J. (2023). A dynamic ensemble approach for multi-step price prediction: Empirical evidence from crude oil and shipping market. *Expert Systems with Applications*, 234, 121117.
45. Jo, J., Kim, U., Lee, E., Lee, J., Kim, S. (2023). A supply chain-oriented model to predict crude oil import prices in South Korea based on the hybrid approach. *Sustainability*, 24(15), 16725.

46. Liang, Q., Lin, Q., Guo, M., Lu, Q. (2025). Forecasting crude oil prices: a gated recurrent unit-based nonlinear Granger causality model. *International Review of Financial Analysis*, 102(4), 104124.
47. Sun, B., Bai, J., Chu, X., et al. (2022). Interval prediction approach to crude oil price based on three-way clustering and decomposition ensemble learning. *Applied Soft Computing*, 123(2), 108933.
48. Xu, K., Wang, W. (2023). Limited information limits accuracy: Whether ensemble empirical mode decomposition improves crude oil spot price prediction? *International Review of Financial Analysis*, 87, 102625.
49. Yuan, J., Li, J., Hao, J. (2023). A dynamic clustering ensemble learning approach for crude oil price forecasting. *Engineering Applications of Artificial Intelligence*, 123, 106408.
50. Zhang, X., Cheng, S., Zhang, Y., Wang, J., Wang, S. (2024). An attention-PCA based forecast combination approach to crude oil price. *Expert Systems with Applications*, 240, 122463.
51. Lu, Q., Sun, S., Duan, H., Wang, S. (2021). Analysis and forecasting of crude oil price based on the variable selection-LSTM integrated model. *Energy Informatics*, 4, 47.
52. Qiu, J., Wang, B., Zhou, C. (2020). Forecasting stock prices with long-short term memory neural network based on attention mechanism. *PLoS ONE*, 15(1), e0227222.
53. Simsek, A. I., Bulut, E., Gur, Y. E., Tarla, E. G. (2024). A novel approach to predict WTI crude spot oil price: LSTM-based feature extraction with Xgboost Regressor. *Energy*, 309(6), 133102.
54. Soladoye, A. A., Falade, M. B., Odeyemi, C. S., Barkindo, A. (2024). Hybridized LSTM-GRU model for forecasting the prices of crude oil. *FUOYE Journal of Engineering and Technology*, 9(2), 246–257.
55. Wang, S. (2024). A study of crude oil price forecasting based on long short-term memory model. *Advances in Economics Management and Political Sciences*, 99(1), 93–97.
56. Zhang, K., Hong, M. (2022). Forecasting crude oil price using LSTM neural networks. *Data Science in Finance and Economics*, 3(2), 163–180.
57. Zhao, J., Liu, G. (2025). Forms of artificial neural networks for international crude oil price forecasting research based on ADF and GCT post-tests. *Highlights in Science Engineering and Technology*, 136, 130–138.
58. Aghalarov, M. Sh., Muradkhanli, L. G. (2026). Deep learning-based oil spill detection using satellite imagery: a domain adaptation approach for offshore monitoring. *SOCAR Proceedings*, 1, 158-166.
59. Mirzeydarova, A. I., Mammadova, E. G. (2025). Mechanism of strategic management of innovative activity in industry. *SOCAR Proceedings*, 2, 153-158.