RESEARCH OF OBJECTIVE MARKET PRICE FACTORS IN THE FORMATION OF PRICES ON THE OIL MARKET

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Abstract: *"Brent" oil prices (BOP) serves as a global standard for commodity market and it strongly influences the world economy. Forecasting BOP presents a significant and at the same time an arduous task. The main question related to "Brent" prices forecasting is the correct determination of the cause-effect relations. In order to conduct the causality analysis, we have employed adaptive-neuro fuzzy interface system based on the if-then rules and a great potential for the determination of cause-effect relations. The modeling has shown unobvious results. Despite the fundamental law, which claims that the balance of supply and demand forms the oil price, we have proved that the fundamental dependencies are not valid for "Brent" oil pricing. We have revealed that precious metals prices (Palladium, Gold, Silver and Platinum) and commodity currencies exchange rates (USD/NOK, USD/AUD, USD/CAD and USD/ZAR) serve as a signal or cause for the "Brent" price changes. Additionally, we have examined the efficiency of the forecasting model in terms of forecasting oil price trends, achieving maximum 62% of accuracy on the daily data.*

Keywords: *ANN, ANFIS, "Brent" Oil Prices, Causality Analysis, Fuzzy Logic, Forecasting.*

JEL Classification: *C12, C45,C53.*

Introduction

"Brent" is considered as a global oil price standard and it has a huge impact on the global economy. Forecasting BOP is an important and at the same time a challenging task. For forecasting, the modern economic practice employs mathematical modelling. Mathematical prediction approaches can be divided into two groups: structured and unstructured models. Under the structured models we mean an approach based on the fundamental economic researches and including economics relation directly, usually, in the form of differential or difference equations. We refer to the models, whose structure does not change significantly depending on the implementation, to unstructured, this type of models is rather universal. Both approaches have advantages and disadvantages.

Structured models allow the researcher to gain a deeper understanding of the processes flowing in the modelling and of interdependencies between variables. These models provide the highest results for the scenario analysis, or, when the modeled situation is restricted, for investigation of the defined fundamental basis. In other words, the models show an appropriate performance while facing determined or low abstract tasks. However, the main issues in forecasting with the approach is a high risk of misspecification, i.e. if one of the fundamental rules is not in force for the moment, the whole model has the wrong parameterization. Moreover, these type of models requires high professionalism in both system dynamics and economics. However, as is noted in (Crookes and De Wit, 2014), there are many methodological errors caused by the lack of professionalism. Methodological errors lead to significant models misspecification.

For building the structured models authors have included some theoretical fundament in the models, and as we have already noted the result of the researches highly depend on the chosen basis. Structured models have served as an accurate tool since the pioneering researches were conducted by J.D. Sterman (1985, 1988) and M. K. Hubbert (1959). Concerning modern researches, the results of the models do not provide such accuracy, but still, they present a very important direction for the economic thought. For instance, in (Rafieisakhaei et al, 2015, 2016) authors proposed a system dynamic approach for BOP forecasting, they had considered BOP formation as a result of supply and demand aggregation. The analysed period was 2015, the model caught the main trend of the year. Analysis of prices for "Brent" oil in relation to supply and demand had shown quite precise results until the 2000s (Lyneis, 2000). However, there have been some deflections from this fundament since the 2000s, which was considered in the paper (Fratzscher et al, 2014). The authors conducted an analysis of the cause-effect relations between asset and oil prices. The research indicated that oil prices had been highly affected by other financial assets since the 2000s, and had reacted to changes in the financial assets immediately.

Unstructured models, oppositely, are more flexible in terms of the required information, i.e. a researcher must not characterise all variables' dependencies. On the one hand, it raises the issue that the model, which tries to find dependencies by itself, will catch insignificant or noisy information as a base for the analysis. However, on the other hand, it gives an ability to investigate hidden dependencies and nonobvious fundamental changes. At the moment, models based on a vector autoregression are most common (VAR). C. Sims proposed the first model of vector autoregression in 1980. Significant advantages of the proposed model in comparison with models based on differential equations were the ease of identification, implementation and solution of the problem of overfitting the model. Since then, the methodology of constructing autoregressive models has been greatly advanced. The models VEC, ARIMA and Autoregressive conditional heteroskedasticity (GARCH) were developed, removing restrictions on the use of only stationary time series. These models are the most common solutions for forecasting because with the simplicity of realisation they allow to receiv fairly accurate forecasts (Zhang and Frey, 2015, Kambouroudis D. S., 2016, Corrêa J.M., 2016). For instance, in (Baumeister and Kilian, 2015) authors, applying VAR model, gained 72% of the trend forecasting accuracy on the quarterly data and 65% on the monthly data. In (Baumeister and Kilian, 2014) VAR model showed trend forecasting accuracy at the level of 57% – 69% on the monthly data.

1 Statement of a problem

All the models mentioned above are linear, which is a significant drawback taking into account the non-linear nature of the relationships between economic time series. To solve this problem, models based on nonlinear autoregression (NAR), proposed in (Leontaritis, 1985), are used. To implement NAR models, dynamic artificial neural networks are used, which also have a nonlinear character and show better results when working with noisy time series (Jiang and Song, 2011). For example, in (Diaconescu, 2008), a model of a nonlinear autoregressive neural network with exogenous inputs (NARX) and ARIMA models was compared. Based on the simulation results, the root-mean-square error of the NARX model is an order of magnitude smaller than the error of the ARIMA model (NARX - 0.0004, ARIMA - 0.0061). In (Chaudhuri and Ghosh, 2016), the superiority of the NARX model over generalised models of autoregressive conditional heteroscedasticity (GARCH, EGARCH) is shown.

Finally, it should be noted that last time unstructured models provide better results in terms of the forecasting accuracy caused partly by rapidly changing economic fundament, which gives rise to misspecification of the structured models, partly to onrush of the development of this approach, especially in the field of artificial neural network (ANN) and boosting methods.

We have two hypotheses for the BOP formation to test. First, “Brent” oil prices depend on the supply and demand. Second, “Brent” is dependent on instruments traded on world foreign exchanges. These hypotheses are contrary, hence finally we have proved one and rejected another because fundamentally oil prices should depend on the supply and demand balance and have an impact on the commodity instruments.

Thus, the purpose of this research is to determine the variables that influence the formation of BOP, to develop a model for forecasting oil prices and to test the model on historical data (back-test).

2 Methods

For the formal determination of the causality between exogenous and endogenous variable, we considered the Granger causality test. Before testing the given time series, we had examined it on the randomly generated 200-time series with 100 observations (expected value equalled zero, and standard deviation equalled one). We separated 200-time series into two groups: “cause” and “effect”, thus we gain 100 cause-effect pairs to test. We chose the following test parameters: max number of lags is 7; Alpha coefficient is 0.05.

The test showed that 40 out of 100 pairs had a cause-effect relation, which is obviously an incorrect result. Thus, we decided to use some non-linear forecasting model as an indicator of cause-effect relations. If the model shows better performance in terms of forecasting for the pair and if it shows worse performance after changing cause and effect in the pair, then there is a cause-effect relation in the given pair. We set the threshold for the minimum change in model performance on the level of 10% in trend forecasting accuracy. In addition, we should gain improvement in forecasting performance from using the exogenous time series comparing to forecasting from endogenous time series only. All of mentioned correlates with the intuitions of the Granger causality theory (Granger, 1969).

We employ BOP as an endogenous time series and the following groups of exogenous time series:

1) Prices on precious metals: Palladium, Gold, Silver and Platinum;

2) Prices on the commodity currencies exchange rates: USD/NOK, USD/AUD, USD/CAD and USD/ZAR;

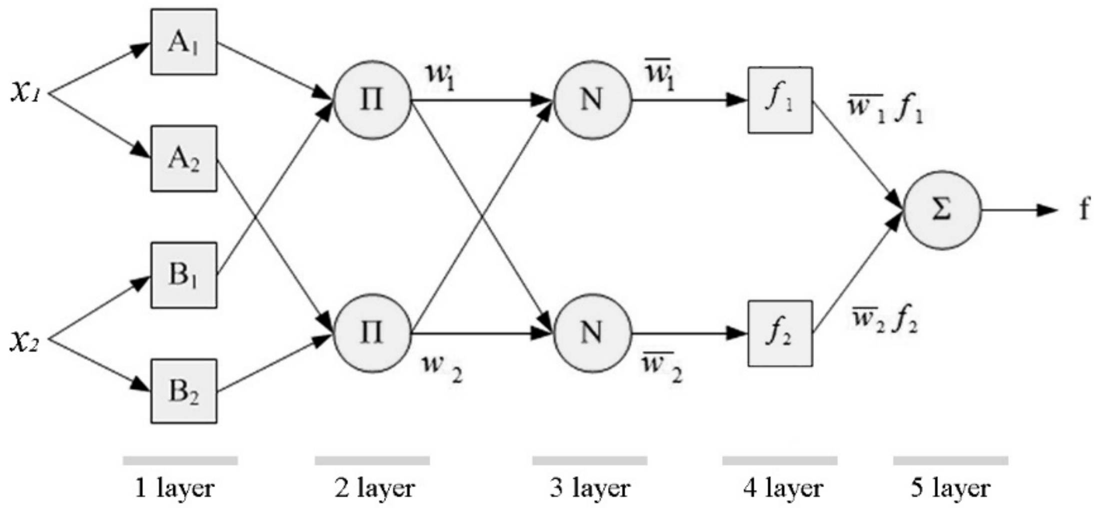
3) Supply and demand balance.

2.1 Forecasting model

We employ adaptive neuro-fuzzy interface system (ANFIS) as a tool for time series forecasting since it bases on the if-then logic rules and has a huge potential for solving tasks connected with the determination of the cause-effect relationships. ANFIS is an ANN based on Takagi-Sugeno fuzzy interface system (FIS). It combines advantages of both fuzzy logic and ANN. J.S.R. Jang introduces ANFIS in the paper (Jang, 1991), the author develops methods for transforming human knowledge or experience into the rule base and database of a fuzzy inference system. The model aims to solve the problem of the classical equation-based system dynamics modelling, which is connected with the uncertainties involved in the real systems (Jang, 1993). The most interesting moment is that ANFIS provides statistically estimated fuzzy if-then rules, which are observable and understandable for the human, unlike other ANN models.

The architecture of ANFIS with inputs $x_1$and x_2 is presented in fig. 1.

Fig. 1: ANFIS architecture



Source (J.S.R. Jang, 1991)

The example of Takagi-Sugeno if-then rules are presented as follows:

IF x_1 is A_1 AND x_2 is B_2 THEN $f_1 = p_1 x_1 + q_1 x_2 + r_1$

IF x_1 is A_2 AND x_2 is B_2 THEN $f_1 = p_2 x_1 + q_2 x_2 + r_2$

Where:

x_1, x_2 - inputs;

A_1, A_2, B_1, B_2 - the fuzzysets;

f_1, f_2 - the outputs within the fuzzy region by the fuzzy rules;

p_1, p_2, q_1, q_2, r_1, r_2 - the coefficients, which are determined by the training of ANFIS.

ANFIS architecture is defined as follows:

The first layer: every node in the layer contains membership function for the term of the corresponded linguistic variable. This layer presents fuzzification procedure for original inputs values.

For instance:

$$O_i^1 = \mu_{A_j}(x_i) \qquad i = 1 \ldots k \tag{1}$$

$$O_i^1 = \mu_{B_j}(x_i) \qquad i = k+1 \ldots n \tag{2}$$

The second layer: every node in the layer gets membership functions from the previous layer and produces multiplication.

For instance:

$$O_i^2 = w_i = \mu_{A_j}(x_i) \cdot \mu_{B_j}(x_i) \tag{3}$$

3rd layer: every node in the layer normalises weights, obtained from the previous layer.

For instance:

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum_i w_i} \tag{4}$$

4th layer: every node in the layer calculates the following function:

$$O_i^4 = \overline{w}_i f_i \tag{5}$$

5th layer: the layer contains the single node, which summarises all of the data, obtained from the previous layer.

$$O_i^5 = \mathrm{f} = \sum_i \overline{w}_i f_i \tag{6}$$

Fuzzy Logic Toolbox for MATLAB is the software used to design this model. Its functions provide many common methods, including fuzzy clustering and adaptive neuro fuzzy learning. We have developed ANFIS using the algorithm provided by Fuzzy C-means clustering (FCM). To clarify the developed ANFIS architecture, we provide some information about both ANFIS architecture parameters and the input parameters for the FCM function.

nCluster = 4 – the number of fuzzy clusters, Gaussian curve as membership function;

Exponent = 2 – this option controls the amount of fuzzy overlap between clusters, with larger values indicating a greater degree of overlap (the value greater than 1.0);

MaxIt = 100 – the maximum number of iterations;

MinImprovment = 1e-5 – the minimum improvement in objective function between two consecutive iterations.

The grid search was made with several nested loops which iterated through parameters (in range 2…10 with a step value 1 for the number of clusters; 1…5, step 0.2 – for the overlap option; 10, 100 and 1000 for the number of iterations).

For the training of ANFIS, we use a hybrid method, based on the error back propagation algorithm and the least squares method. The error back propagation algorithm configures the parameters of antecedent rules, i.e. membership functions. The method of least squares estimates the coefficients of the rule conclusions since they are related to the output of ANFIS linearly.

2.2 Back-test of the model

Concerning testing of the model forecasting ability, the first role plays correctly determined a trend, obviously, if we do not catch the trend, then it is unimportant what absolute error is, since the forecasted trend is the most significant value for practical decision making. Thus, in the scopes of the current research, we have a goal to forecast trend, but not absolute values.

The testing of the model against historical data (back-test) is done on the basis of the following algorithm:

1) The model is trained against a window of n points;

2) The forecast is built on the bases of q points;

3) Error of trend determining for each of the q points of the received forecast are calculated;

4) The window for model training is shifted 1 point forward;

5) Procedures 2-4 are repeated until the model reaches the last points of time series;

6) The mean absolute error and the error of trend definition are calculated.

The error of trend determination is calculated the following way:

The trend for each point *q* of the forecast and the respective actual trend are calculated by the following formula:

$$trend_q = sign(a_q - a_0) \tag{7}$$

where

$trend_q$ – trend;

a_q – the value of *q* point of forecast;

a_0 – the value of the last n points included into the training window (or the last actual value).

If the values of the forecasted and the actual trend do not coincide, then the variable $trend\_error_q^y$ is assigned the value 1; if they coincide, it is assigned the value 0.

The error of trend determining is calculated as the number of incorrectly defined trends of the point *q* to all the forecasts of the point *q*.

$$trend\_error_q = \frac{\sum trend\_error_q^y}{n} \tag{8}$$

where

$trend\_error_q$ – the error of trend definition for the point q;

$trend\_error_q^y$ – y incorrect forecast of the trend for the q point;

n – a number of forecasts.

The accuracy of the trend definition is expressed in the following way:

$$trend\_price_q = 1 - trend\_error_q \quad (9)$$

3 Problem solving

For the testing of the model, we have employed 230 daily observations on trading days from 27/05/2016 to 27/04/2016. The source of the statistics is Thomson Reuters.

The model is specified with the following parameters:

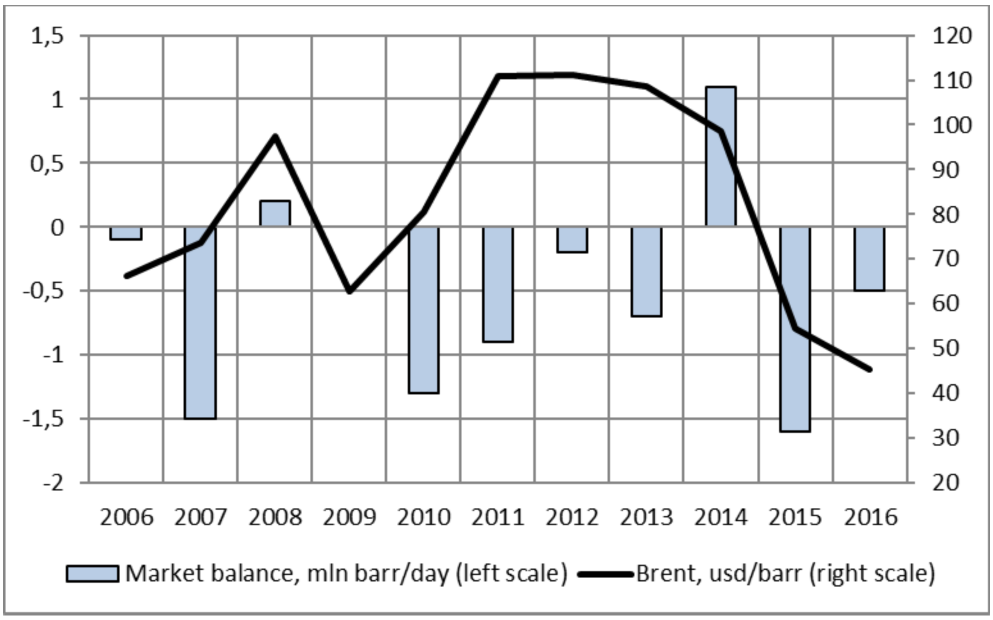
forecasting points number: 5;
maximum number of lags: 4;
clusters number: 4;
train window: 30.

The training set is determined to include 30 observations, thus the first 30 observations are used for the initial training of ANFIS and we have 200 observations remaining for the back-test.

Before forecasting, we are going to investigate cause-effect relationships between supply, demand on oil and BOP, in order to examine the hypothesis that "Brent" oil prices have no direct dependencies on supply and demand, but highly depend on the precious metals and commodity currencies exchange rates.

Supply and demand balance dynamic in comparison with BOP dynamic charts are presented in the fig. 2. Fig. 2 does not show significant cause-effect relations between supply and demand balance in the oil market and the BOP, ANFIS proves it (the difference in the trend forecasting accuracy between cause-effect and effect-cause pairs for the given time series are less than 5%, while the average accuracy does not exceed 53%).

Fig. 2: The supply and demand balance and the average annual prices of "Brent" oil



Source: Authors calculations

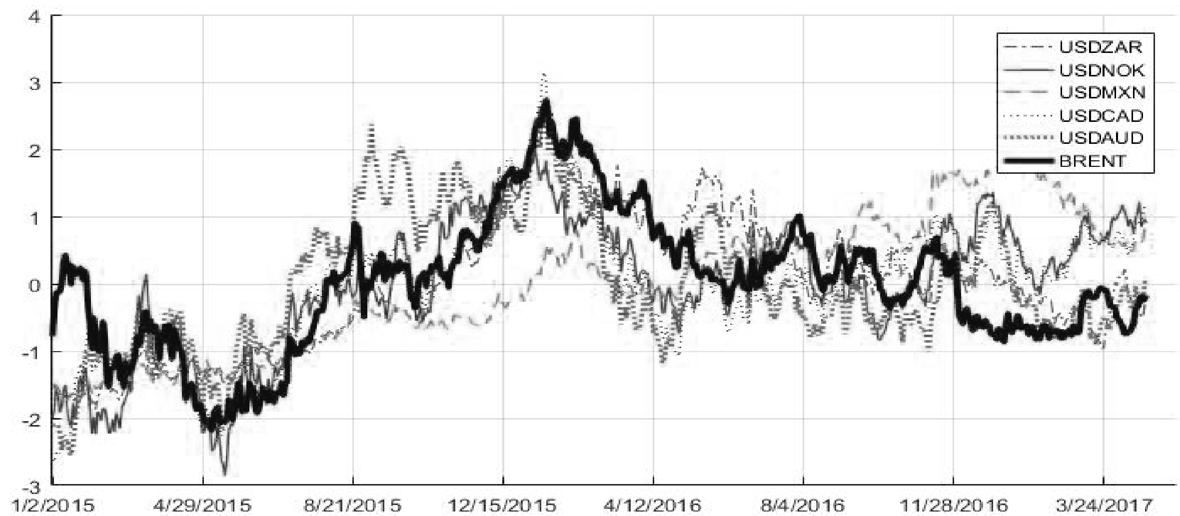
From the fig. 3, we see that precious metals have a high impact on the “Brent” prices. ANFIS proves this conclusion, showing the difference between cause-effect and effect-cause pairs in the range from 11% to 18%.

Fig. 3: Precious metals and “Brent” oil prices (normalized data)

Source: Authors calculations

Fig. 4 illustrates that the currencies influence the “Brent” prices. It seems that the relation between currencies and “Brent” prices is stronger than influence of the precious metals; ANFIS shows the difference between cause-effect and effect-cause pairs in the range from 15% to 26%, also it shows that we gain mean performance improvement with exogenous time series about 4-5% (see the table). It is determined that the Norwegian Krone have the most significant impact on the “Brent” prices, using only these two-time series (Norwegian Krone – exogenously and “Brent” prices – endogenously), we get from 57% to 63% trend forecasting accuracy.

Fig. 4: Commodity currencies exchange rates and “Brent” oil price (normalized data)



Source: Authors calculations

In order to gain more precise estimation of the model forecasting performance, we simulate it 5 times for each point. Results of the back-test of the model are presented in the table below. The results show that we obtain stable forecasts on the 1, 2 and 3 points.

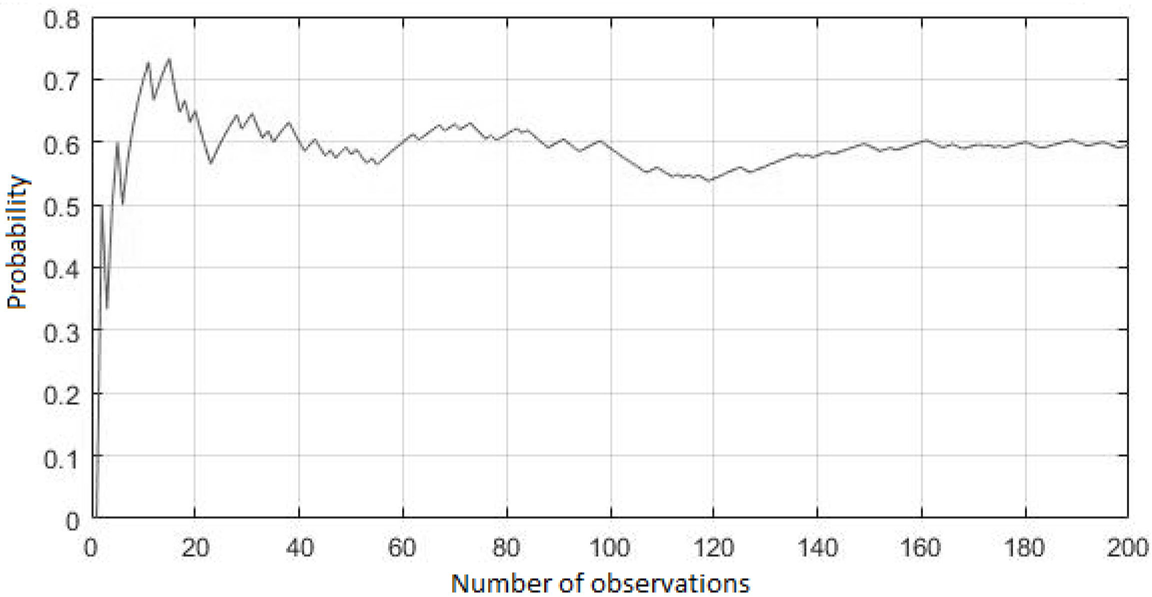
Tab. 1: Results of the back-test

Forecasting point	1	2	3	4	5
Min trend forecasting accuracy	0.57	0.55	0.51	0.48	0.48
Mean trend forecasting accuracy	0.60	0.59	0.55	0.48	0.51
Max trend forecasting accuracy	0.62	0.61	0.58	0.51	0.54
Mean trend forecasting based on the BOP only	0.56	0.53	0.48	0.39	0.41

Source: Authors calculations

Fig. 5 represents average dynamics of the trend forecasting accuracy of the model for BOP on the first predicted point.

Fig. 5: Average dynamic of the trend forecasting accuracy of the "Brent" oil prices



Source: Authors calculations

It should be noted that the accuracy of the trend forecasting does not have significant deviations from the final value, so we can consider model results as a reliable.

4 Discussion

Economists have been arguing about the mechanisms of pricing in the oil market for a long time. Some argue that supply and demand in the real market determine its dynamics. Other researchers assume that speculative sentiments prevailing in global financial markets play the leading role in pricing in the oil market. The fall of oil prices in 2014 showed the importance of speculative factors, their subsequent recovery in 2016-2017 were triggered by the OPEC + agreement that by imposing the oil supply limitation in the market stabilized the price dynamics.

The oil market reacts briefly to all events taking place on the global market. If we consider the long-term horizon, then the classical supply and demand in the oil market do not play a role in determining the price dynamics. It is enough to have look at oil price fluctuations during the last decade (fig. 2) to compare the strong price fluctuation of the BOP with the more stable balance of supply and demand in the world market.

The reasons for such a significant fluctuation in oil prices lie in the financial mechanisms for pricing instruments traded on world commodity exchanges, which are based on the marginal position of bidders. The marginality of the market forming the effect of leverage allows to open market positions that are many times greater than the real security, which can shift the price from the equilibrium level much more than it would be possible without this option.

However, without the marginality of the market and derivatives, there would not be an effective opportunity to hedge market risks to both real producers and oil consumers. Therefore, such fluctuations will continue and they have to be taken for granted. The question remains, which factors determine the movement of oil prices, if the fundamental reasons are in doubt? The research of the interconnectedness and synchronization of the dynamics (or cause-effect relations) of a number of sectors of the commodity and currency markets allows to answer this question.

We have concluded that fundamental factors have little effect on the dynamics of market prices (fig. 2). In any case, the relationship between the balance of supply and demand and oil prices in the long-term interval is not visible. Rather, the dynamics of the oil prices follows market prices, and not vice versa as showed by the modeling (fig. 3 and fig. 4).

Conclusion

In the framework of the current research, we conducted a study of the dependences of the prices of precious metals and commodity currencies exchange rates on “Brent” oil prices. To evaluate these dependencies and predict the BOP time series, the ANFIS model is applied.

The model was also evaluated on daytime data from 27/05/2016 to 27/04/2017 for forecasts of 5 points. The modelling confirmed that there are no obvious dependencies between the balance of supply and demand and BOP and revealed the existence of a causal relationship between prices for precious metals and BOP, as well as between commodity currencies and BOP. It should be noted that the model showed the strongest impact of Norwegian Krona on “Brent” oil prices.

The average accuracy of forecasting the trend for the price of oil: for the first point - 60.0%, for the second - 59.0%, for the third - 55%. Thus, the model showed accurate results when predicting the given time series and can be used to solve other prediction problems.

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