pISSN 2073-8005
eISSN 2311-9438

Financial Theory

Translated Article†

APPLICATION OF THE COMMITTEE MACHINE METHOD TO FORECAST THE MOVEMENT OF EXCHANGE RATES AND OIL PRICES

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Article history:
Received 30 October 2017
Received in revised form
13 November 2017
Accepted 27 November 2017
Translated 12 March 2018
Available online 27 March 2018

JEL classification: C38, C53, C65, G17

Keywords: committee machine method, data analysis, financial market, currency rate, oil

Abstract

Importance This article discusses the forecasting of financial asset prices considering the most liquid and known financial assets of currency and commodity markets, such as currency pairs of USD/RUB, EUR/RUB, CAD/USD and the Brent crude oil.

Objectives The paper aims to show that in financial markets, a great number of traders and analysts are shaping the demand for new interesting analytical tools, develop a methodology for establishing committee machine designs and principles of their use in financial markets, and show real practical results of the committee machine method use.

Methods To forecast the price of financial assets, we used a committee machine method based on majority voting. Data from the Moscow Exchange (MOEX) and FOREX market are used as a source of information on market prices.

Results The paper shows the conditions for the applicability of the decision rules received in real trade. For illustration purposes, the decisions given in the article are analyzed by income from January 7, 2010 to May 23, 2017.

Conclusions and Relevance The paper concludes that the committee machine method is applicable as a tool for forecasting real time financial asset prices.

The editor-in-charge of this article was Irina M. Vechkanova
Authorized translation by Andrey V. Bazhanov

Please cite this article as: Akberdina V.V., Chernavin N.P., Chernavin F.P. Application of the Committee Machine Method to Forecast the Movement of Exchange Rates and Oil Prices. *Digest Finance*, 2018, vol. 23, iss. 1, pp. 108–120.
https://doi.org/10.24891/df.23.1.108

Introduction

Financial markets can be called a unique place where data are not just ephemeral figures, but can be a source of unlimited profit. For this reason, millions of people are constantly watching them every day, seeking to understand the dependencies invisible to the unaided eye.

It is because of this desire, almost all known methods of data analysis are reflected in the financial market. If previously, the main attention was paid to simple empirical models built on the subjective perception of the market by an analyst or trader, now due to the development of computing technologies, complex mathematical models that can provide an objective view of the market are getting more and more practiced.

People implementing such models are called *quantum hedge fund managers*. Hedge funds applying the models are respectively called *quantum hedge funds*. At the beginning of 2010, quantum funds accounted for only about 13.75 percent of total trading session in the American market, and they were significantly inferior to the traditional asset managers and other hedge funds. However by the beginning of 2017, quantum funds performed about 27.5 percent of total trading session, becoming the absolute leader in terms of this indicator[1].

Thus, we can say that the study of mathematical modeling methods in financial markets is one of the most demanded areas of research in the field of data analysis.

The *committee machine method* refers to classification methods, yet despite its considerable analytical potential, it has not been widely applied in financial markets.

The concept of committee method was introduced in the articles on recognition of images by C.M. Ablow and D.J. Kaylor back in 1965 [1, 2]. Further contribution to the development of the method was made by S. Bláha [3], M.L. Osborne [4], R. Takiyama [5]. Russian scientists have significantly developed the method theoretically and practically. Especially, the works by Drs. Sci. in Physics and Mathematics V.D. Mazurov and M.Yu. Khachai, and other authors [6, 7, 8, 9, 10, 11, 12, 13, 14], N.N. Krasovskii Institute of Mathematics and Mechanics of the Ural Branch of the Russian Academy of Sciences (IMM UB RAS), can be noted.

As part of this work, we assume that the committee machine method can effectively predict the direction of financial asset price movements. So, this work aims to show the practical application of the committee machine method to forecast exchange rates and oil prices.

Technical Analysis

Technical analysis of financial markets is a set of methods to predict the future changes in the price of a financial asset based on the past movement of its price and volume of trading session. The objective of this analysis is to answer a simple question: whether the financial asset quotations are going to go up or down, or slightly fluctuate.

There are numerous methods of technical analysis, which can be divided into the following two main types in the general form[2]:

– a graphical analysis;

– a quantitative (mathematical) analysis.

The methods of graphical analysis are related to the construction and analysis of the financial asset price charts. Such an analysis seeks to find price models on different charts representing a certain construction, which is manifested on the price chart in such a way that its finished formation predetermines the future direction of the trend.

The peculiarity of the graphical method is its simplicity. Finding price models on the chart does not require special knowledge and performance of thorough calculations. However, the main drawback of such

[†]For the source article, please refer to: Акбердина В.В., Чернавин Н.П., Чернавин Ф.П. Применение метода комитетов к прогнозированию движения валютных курсов и цен на нефть. Финансы и кредит. 2017. Т. 23. № 46. С. 2746–2761. URL: https://doi.org/10.24891/fc.23.46.2746

[1] Zuckerman G., Hope B. The Quants Run Wall Street Now. URL: https://www.wsj.com/articles/the-quants-run-wall-street-now-1495389108

[2] Gavrilov A.E., Loginova V.A., Bayanova Yu.A., Smelova T.A. *Rynok tsennykh bumag (tekhnicheskii analiz)* [Securities Market (Technical Analysis)]. Volgograd, VolgSTU Publ., 2006, 170 p.

methods is that the selection of any model is a subjective process, the result of which depends more on the analyst than the market condition. Any trader has his own thoughts concerning the movement of market quotes, and often unconsciously, he diligently searches and selects those models only that are in line with his ideas.

Because of the subjectivity of graphical analysis tools, their application requires a confirmation through other methods that provide a greater objectivity. These methods include the methods of quantitative analysis based on the comparison of quantitative values calculated by certain mathematical formulas on the basis of stock-exchange information about the asset (price, volume, number of deals, etc.).

Such a comparison allows to determine the market's condition objectively and, on the basis of that, make the final decision on securities purchase or sale operations. Despite the objectivity of such methods, they do have some shortcomings though. The main drawback of quantitative analysis methods is the lagging nature of the signals obtained by it. At the same time, many methods require complicated calculations and appropriate understanding.

Committee Machine Method

Mathematical analysis of financial markets has an impressive arsenal of data analysis methods. This article examines the operation and use of the committee machine method, which helps get some generalized decision in contradictory situations, when there is no unambiguous decision [6].

From a mathematical point of view, the committee machine method is a linear discriminant combination, dividing a set of points in the space of factors into two classes. Due to simultaneous use of several linear discriminant classifiers, the committee machine method takes into account nonlinear relations of variables that increases the quality of classification [15].

The method name is related to the fact that the method's operation logic resembles the logic of work of an ordinary committee as a collegial governing body, where the combined response and decision are made on the basis of its multiple members and experts' responses and decisions.

In the committee machine method, such experts (neural networks, predictors) are several dividing linear discriminant hyperplanes called committee constituent experts. Each of them votes for the decision individually, dividing the set into two classes. The majority, unanimity and precedence logic can be used to make a single combined decision based on all individual decisions of the committee predictors.

Let us make a reservation that we are going to consider the committee machine method based on *majority* voting in this work. The simplest geometric example of the committee of majority (hereinafter for brevity sake, majority committee) of three experts for two classifiers is shown in *Fig. 1*.

Fig. 1 shows the division of a set of points into two classes with the help of a three-expert committee machine. The arrows show the direction of voting of each committee expert, and the oval curves circle classification errors. The mathematical representation of the majority committee of *t*-experts is as follows:

$$\sum_{i\in I} p_{ij}\cdot x_i^t + b^t - L\cdot z_j^t \le \varepsilon_j \in J_1, t\in T;$$

$$\sum_{i\in I} p_{ij}\cdot x_i^t + b^t + L\cdot z_j^t \ge -\varepsilon_j \in J_2, t\in T;$$

$$\sum_{t\in T} z_j^t \le m + L\cdot y_j\, j\in J_1, t\in T;$$

$$\sum_{t\in T} z_j^t \le m + L\cdot y_j\, j\in J_2, t\in T.$$

With the following minimum objective function:

$$\min \sum_{j\in J} y_j,$$

where J_1 и J_2 are the sets to be divided;

$J = J_1 \cup J_2$ is the set of observations;

I is the set of observation parameters;

T is the set of committee experts (hyperplanes);

i, *j*, *t* are the indices of the corresponding sets;

p_{ij} is the *i*-th parameter of the *j*-th observation (a constant);

x_i^t are the coefficients of hyperplanes (decision variables);

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https://doi.org/10.24891/df.23.1.108

b^t are the absolute terms of hyperplanes (sought quantities);

L is the gillion used for the conditions fulfillment rigor;

ε means very small numbers used for the rigid restrictions;

z_j^t is the Boolean variable to commit a violation of the sets partition conditions;

y_j is the computation error;

m is a minority, that is, less than half of the experts (a set constant).

Trading Strategy

To determine the parameters of the mathematical model, we first need to make a trading strategy of a trader.

To develop a strategy, we posit the following as a hypothesis: *In a trading day, it is possible to single out certain periods of time, the change in prices during which has the greatest impact on the market*.

Within the framework of this hypothesis, we selected some time periods for the analysis (all the periods are specified according to Moscow Time) based on the following logic.

1. The first fifteen minutes after opening the market should not be taken into account. At the opening, the behavior of market participants is unpredictable, since this is the time for *Main Street traders*, not *Wall Street traders*. Hence, such price movements will be a sort of information noise for the mathematical model.
2. The next point for the analysis is 11:45am. By this time, it is possible to judge the first reaction of the market already. Moreover, the European markets have already opened by this time (in the winter time, they open at 11:00am), and the Bank of Russia exchange rate (11:30am) has been set already, which matters for a number of commercial operations.
3. The opening of the American market is another important point in trade for all markets.
4. As the end point of the last period, we specify 20:40, as by 20:00 Moscow Time (MSK), the business activities decline in the American market[3] and taking into account a biological clock of the trader.

In accordance with the strategy, we specify the parameters of the future model in the form of a relative price change, *Table 1*.

Naturally, time intervals and logic of behavior may be different, but to form a decision rule, they should be clearly articulated, because the collection and processing of information for previous periods are done according to a certain trader's behavior model.

In addition, it is necessary to determine the depth of historical analysis, that is, for how many previous periods we are going to take into account the information in the mathematical model.

Moreover, the information can be presented in absolute and relative forms. However, as the methods of presenting the information do not affect the form of mathematical models, we will use the model shown earlier.

The Results

For the comparative analysis, we have collected the exchange rate data on USD/RUB, CAD/USD and EUR/RUB, and Brent crude oil price for the period from January 8, 2015 to May 23, 2017 on the website of the Finam Holdings company[4].

The sampling of these financial assets is not random, as the USD/RUB and EUR/RUB currency pairs are the most liquid instruments of the currency section of the Moscow Exchange. The CAD/USD currency pair was also chosen for comparison, since RUB and CAD are referred to currencies dependent on the movement of oil prices. *Table 2* presents the correlation of currency pairs data and Brent oil price.

Based on the correlation coefficients from *Table 2*, we can say that there is a strong inverse correlation between EUR/RUB, USD/RUB and Brent oil price (from ± 81% to ± 100%). There is a moderate direct correlation between CAD/USD and Brent oil price (from ± 61% to ± 80%). In connection with such a strong relationship, we

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[3] *Strategii Foreks. Teoriya torgovli po chasam* [Forex Strategy. Time-schedule Trading Theory]. URL: http://stocktime.ru/strategy.html (In Russ.)

[4] FINAM. URL: https://www.finam.ru/analysis/quotes/ (In Russ.)

will also analyze Brent oil quotations using the committee machine method.

On the basis of the information for the previous periods, we have formed a learning set. For simplicity, it is broken down into two classes: rising and falling quotes. To make a committee expert decision, we choose a learning set from January 8, 2015 to February 28, 2017, which contains 510 observations. Accordingly, the validation set includes the rates from March 1, 2017 to May 23, 2017, which contains 55 observations. *Table 3* presents the number of observations in the learning and validation sets dividing the quantity into classes J_1 and J_2.

In accordance with the trader's strategy described earlier, the analysis task is to make a committee decision for predicting the direction of price movement for the selected instruments from 10:15am to 20:45.

Table 4 shows the results of classification of the majority committee of three experts as a percentage of correct predictions for each particular class and for the whole set.

Table 4 indicates that the majority committee shows the result above 54.73 percent in the learning set for all the instruments. The final result in the validation set for all the instruments, except USD/RUB, differs from the result in the learning set by no more than two percent. In case of USD/RUB, the result in the validation set has decreased significantly, i.e. to 45.45 percent.

However, it should be noted that all the results show a prevalence of predictive ability of the decision rule to successful prediction (above 50 percent) for only one class of sets with the highest number of observations in a period.

For example, in case of Brent oil, the correct predictions for J_2 are 20.22 percent in the learning set, and in the validation set, they are 3.85 percent only. As market trends are subject to change, it is necessary to consider the conditions of applicability of the model as a trading strategy.

Let us call the model applicable as a trading strategy, if by its characteristics, it is not inferior to random actions without strategy, that is if it meets the following conditions:

- the final classification on the learning and validation sets has more than 50 percent of success;
- the classification for each class on the learning and validation sets has more than 50 percent of success.

In accordance with the indicated conditions of applicability of the model, all the results from *Table 1* do not fit on real trading.

Let us try to improve the quality of the model by increasing the number of committee experts to five. *Table 5* presents the results of classification of the majority committee of five experts.

The results from *Table 5* show that on the learning sample the majority committee shows the result of more than 58.94 percent for all instruments, which is more than four percent more than the minimum result in *Table 4*.

The validation set of USD/RUB and CAD/USD shows a decrease to less than 50 percent.

It can be noted that the results by class have become more adjusted. The minimum result in the learning set is 43.41 percent, which is more than 20 percent higher than the minimum result in the learning set in *Table 4*.

Although the results for the model of five committee experts are lower in the validation set than for the three committee experts model, in the case of five committee experts, Brent oil quotation shows a significant increase in quality.

The final result for both the learning and validation sets is higher than 63 percent. Moreover, in each particular class, the correct predictions make not less than 50 percent, so this decision rule can be called satisfactory according to the conditions of applicability chosen. The decision rule factors are given in *Table 6*.

Given the high correlation of the studied currency pairs and oil, it is of certain interest to add a binary parameter to the currency pairs that takes the value of +1, if the oil price from 10:15am to 20:45 increased the previous day, and the value of –1, if it fell. *Table 7* presents the results of classification of the majority committee of three experts with six parameters for the selected currency pairs.

Table 7 shows that the majority committee of three experts for six parameters gives the result of more than 50 percent in both the learning and validation sets. For CAD/USD and EUR/RUB, it is impossible to note any significant changes, because for the 2nd class, the result

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has remained less than 50 percent (the maximum result is 43 percent).

However, the quality of the model for USD/RUB shows a significant improvement with the minimum result difference for both classes. For the learning set, the difference of the results between the 1st and 2nd classes is 5.88 percent, and for the validation set, it is 1.72 percent only. Accordingly, taking into account the fact that USD/RUB has the greatest correlation with oil, it is possible to make an assumption about improving the quality of the model when adding some parameters to it that have a high correlation with the available parameters.

Despite the satisfactory results concerning USD/RUB, it is still early to talk about the applicability of the results obtained as a trading strategy, because the validation set result is 52.73 percent only, which is just slightly more than the trading results without any strategy (the success probability is 50 percent).

Therefore, given the increase in the quality of the model of five committee experts for USD/RUB, it is of certain interest to try to improve the result obtained by increasing the number of committee experts. For comparison, we make calculations for other currency pairs. The results of calculations of the indicated model are presented in *Table 8*.

Based on the results presented in *Table 8*, it is possible to note the improvement of results on all currency pairs in comparison with similar results from *Table 7*. However, as before in CAD/USD and EUR/RUB, despite the high results in the learning set, the results in the validation set do not meet all the requirements of the quality of the model.

But the results for USD/RUB pair, which, with five parameters, has already shown satisfactory results, could get improved considerably through adding just one parameter more. The final result compared to the similar result from *Table 6* has increased by 3.72 percent for the learning set, and by 7.27 percent for the validation set. The difference between the results in the learning and validation sets is 4.31 percent only, which helps draw a conclusion of the model's stability.

Moreover, the quality requirement for the distribution of results between the two classes, which became higher compared to the previous results, is now met (the minimum result is 55.69 percent, whereas previously, it was 51.85 percent). The decision rule factors are given in *Table 9*.

So, we have two decision rules that meet the chosen criteria of applicability as a trading strategy.

However, given the binary specificity of the prediction that takes on the value of either the movement of quotes up or down, it is natural that the problem of risk associated with absolute price change comes to light.

For example, a decision rule can give ten correct predictions about the price change by 0.1 percent, but it will suffice to have one wrong prediction with a change of 1 percent to lose all profits. Therefore, in order to make sure that these strategies really work, that is they are able to bring profit, it is necessary to calculate the theoretical profitability of the strategy for the calculated period. The chart shows the profitability of the strategies taking into account a simple investment of funds, that is in case the invested funds are not replenished.

As may be seen in *Fig. 2*, the Brent strategy shows a much faster increase in profitability compared to USD/RUB. The May 23, 2017 difference between the strategies' profitability was 113.71 percent. At the same time, the chart shows that the USD/RUB strategy for the whole period under study is more stable in comparison with the less long and strong periods of profitability declining. This result largely reflects the specifics of the financial assets, as within the period under study, oil is more volatile than the USD/RUB currency pair.

However, these results were calculated for the period the decision rule was created. This does not allow to say about the stability of the strategy under changing market conditions.

For more thorough study of the decision rules, we try to check their results for the previous periods, since 2010.

To begin with, let us consider the results of voting of the decision rules on USD/RUB and Brent oil for the specified period, presented in *Table 10*.

Based on *Table 10* data, it is possible to say about stability of the USD/RUB decision rule to changes of market conditions. For all the years reviewed, the aggregated results for both the sets (J) had a success rate above 50 percent. The criteria of applicability for the individual sets (J_1 and J_2) correspond to the results for 2012 and 2014, but the minimum result is 46.32 percent, which is slightly different from the target condition (not less than 50 percent).

For Brent oil, the results on J comply with the applicability conditions for 2010, 2011, and 2013 only. The condition for J_1 and J_2 is not met in any considered year. The final result for USD/RUB for the five years only slightly does not meet the conditions of applicability (J_1 < 50% by 0.25 percent), whereas for Brent oil, the discrepancy on this condition is 16 percent.

In connection with the results obtained, it is of certain interest to check the theoretical profitability in the new period under consideration without taking into account the training period. *Fig. 3* presents these results.

According to *Fig. 3*, it is possible to say that, as well as in *Fig. 1*, Brent oil considerably surpasses USD/RUB as to profitability, despite much stronger prognostic results from *Table 10*.

Moreover, USD/RUB shows extremely low results for the whole period. They do not exceed 16 percent, taking periodically some negative values of profitability even. From mid-July 2014, the profitability starts plummeting. The December 31, 2014 loss on USD/RUB would be 21.46 percent, and as to Brent, it would be –2.66 percent.

The marked drop in yield can be linked to the beginning of a sharp fall in oil prices, which also had a significant impact on the USD/RUB rate. The low profitability for the whole period of time until July 2014 allows to draw the following conclusions.

First, the chosen strategy works best for the assets possessing high volatility, as Brent oil at a low prognostic ability, yielded to USD/RUB, has considerably outstripped it by profitability.

Second, given the fact that on the learning set with a higher prognostic capacity, the profitability is significantly higher (*Fig. 1* and *2*), it seems logical to make an adjustment to the 2nd condition of the admissibility of the decision rule as a trading strategy. For this purpose, it is to be said that the final classification should have at least 60 percent of success.

Conclusion

The use of a committee decision for forecasting the direction of exchange rate movements is permissible and yields acceptable results in real trading. Based on the calculations, we show that the selected number of committee experts has a significant impact on the quality of models. Also, to improve the quality of models, it is good to take into account not only the parameters directly related to the financial instrument, but, if possible, consider the parameters with indirect influence.

In this paper, the price of Brent crude oil is an example of such a parameter, as we analyze the currencies having the expressed correlation with oil.

The results of this work are empirically deduced conditions of applicability of the decision rule as a trading strategy.

Two decision rules corresponding to the selected conditions for Brent oil and USD/RUB are created. As to Brent oil, the final result is 63.19 percent of correct predictions in the test set and 63.64 percent in the validation set. As to USD/RUB, the final result is 64.31 percent of correct predictions in the test set and 60 percent in the validation set.

During the review of the decision rules on historical data for the period from January 7, 2010 to December 31, 2014, it was shown that these decision rules do not have absolute universality, because the prognostic ability has decreased in comparison with the learning and validation sets.

A positive point, which allows to say about the prospects of further research, is the fact that the USD/RUB pair, in general, retain the acceptable results (very close to the selected conditions of applicability).

It should be noted that due to the continuous changes in the market environment, to use the committee machine method as a trading strategy, it is necessary to update the learning set and make the model actualized periodically.

Also, we note that the study used the quotations on financial instruments only, without taking into account many important factors, such as the trading volume and open interest, which are also included in the field of technical analysis of financial markets.

Moreover, fundamental factors, including regular macroeconomic data, can be taken into account to improve the accuracy of the model.

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https://doi.org/10.24891/df.23.1.108

Table 1

The method of calculating the relative change in price

Parameter	Description of calculation method
p_{1j}	(Rate on 10:15 yesterday / Rate on 20:45 the day before yesterday) – 1
p_{2j}	(Rate on 11:45 yesterday / Rate on 10:15 yesterday) – 1
p_{3j}	(Rate on US Exchange opening yesterday + 15 minutes / Rate on 11:45 yesterday) – 1
p_{4j}	(Rate on 20:45 yesterday / Rate on US Exchange opening yesterday + 15 minutes) – 1
p_{5j}	(Rate on 10:15 today / Rate on 20:45 yesterday) – 1

Source: Authoring

Table 2

Correlation between currency pairs and Brent crude oil

Oil	CAD/USD	EUR/RUB	USD/RUB
Brent crude oil	69.55%	−86.28%	−90.65%

Source: Authoring

Table 3

The number of observations for each class of learning and validation datasets

Assets	Learning dataset		Validation dataset	
	J_1	J_2	J_1	J_2
CAD/USD	281	229	32	23
EUR/RUB	275	235	32	23
USD/RUB	255	255	28	27
Brent crude oil	264	246	29	26

Source: Authoring

Table 4

Classification of the majority committee of three experts for five parameters

Assets	Learning dataset			Validation dataset		
	J_1	J_2	J	J_1	J_2	J
CAD/USD	90.75	27.95	62.55	96.88	17.39	63.64
EUR/RUB	86.91	32.34	61.76	90.63	21.74	61.82
USD/RUB	40.78	76.86	58.82	14.29	77.78	45.45
Brent crude oil	83.96	20.22	54.73	96.55	3.85	52.73

Source: Authoring

Table 5

Classification of the majority committee of five experts for five parameters

Assets	Learning dataset			Validation dataset		
	J_1	J_2	J	J_1	J_2	J
CAD/USD	69.97	45.24	58.94	56.25	34.78	47.27
EUR/RUB	78.83	43.41	62.65	71.88	34.78	56.36
USD/RUB	76.08	50.98	63.53	64.29	33.33	49.09
Brent crude oil	51.84	73.72	63.19	75.86	50	63.64

Source: Authoring

Table 6

The coefficients of decision rule for Brent crude oil

t	x_1^t	x_2^t	x_3^t	x_4^t	x_5^t	b^t
1	0.143	−1.321	0.692	4.286	1	0.026
2	3.42	−1.154	−1.078	1.263	1	−0.012
3	−3.252	−2.339	2.342	−1.788	−1	0.09
4	−1.055	−2.08	−0.14	−1.794	1	−0.026
5	0.626	−0.399	−0.425	−0.251	−1	−0.016

Source: Authoring

Table 7

Classification of the majority committee of three experts for six parameters

Assets	Learning dataset			Validation dataset		
	J_1	J_2	J	J_1	J_2	J
CAD/USD	93.95	27.07	59.27	96.88	21.74	65.45
EUR/RUB	78.91	42.13	57.45	62.5	39.13	52.73
USD/RUB	57.65	63.53	60.59	53.57	51.85	52.73

Source: Authoring

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Table 8

Classification of the majority committee of five experts for six parameters

Assets	Learning dataset			Validation dataset		
	J_1	J_2	J	J_1	J_2	J
CAD/USD	95.37	27.07	64.71	93.75	0	54.55
EUR/RUB	69.09	62.13	65.88	53.13	34.78	45.45
USD/RUB	55.69	72.94	64.31	57.14	62.96	60

Source: Authoring

Table 9

The coefficients of decision rule for USD/RUB

t	x_1^t	x_2^t	x_3^t	x_4^t	x_5^t	b^t
1	129.015	−102.942	11.836	5.316	−0.639	−1
2	145.826	−380.49	−121.69	−143.466	−39.39	1
3	−38.392	387.635	22.057	8.109	65.28	1
4	−135.653	191.393	37.203	219.293	39.313	1
5	−38.574	−127.759	−53.782	−58.133	−104.635	−1

Source: Authoring

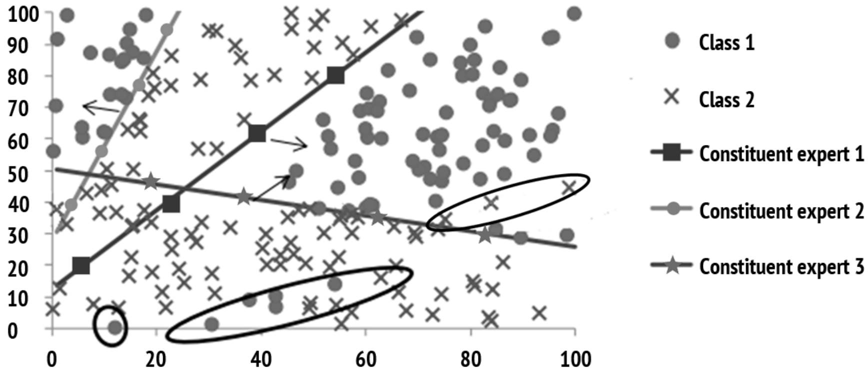
Table 10

The results of voting of the committee experts for decision rules on USD/RUB and Brent crude oil (2010 to 2014)

Year	USD/RUB			Brent crude oil		
	J_1	J_2	J	J_1	J_2	J
2010	48.04	60.34	54.59	62.04	43.64	52.75
2011	46.32	58.65	51.67	61.48	41.53	51.67
2012	54.23	59.81	56.63	67.83	30.6	47.79
2013	47.06	61.9	54.69	78.81	33.07	55.1
2014	53.19	57.53	55.83	72.22	21.93	48.33
Total for 5 years	49.75	59.6	54.7	68.59	34	51.09

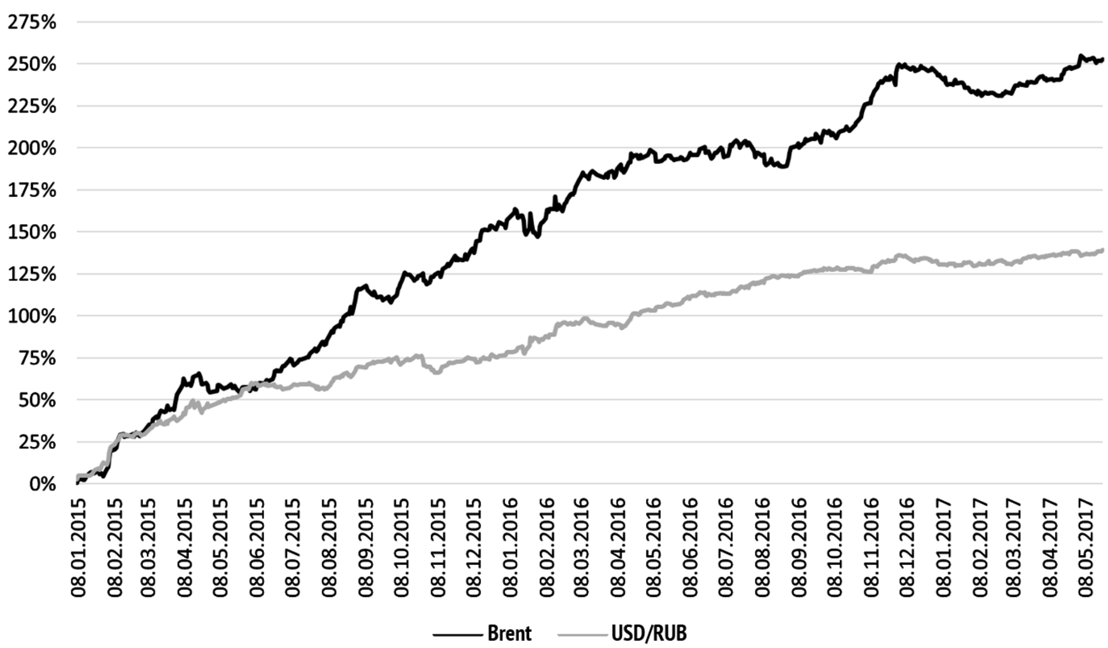
Source: Authoring

Figure 1
The majority committee of three experts for two parameters: An example



Source: [16]

Figure 2
A chart of profitability on strategies for Brent crude oil and USD/RUB (January 8, 2015 to May 23, 2017)

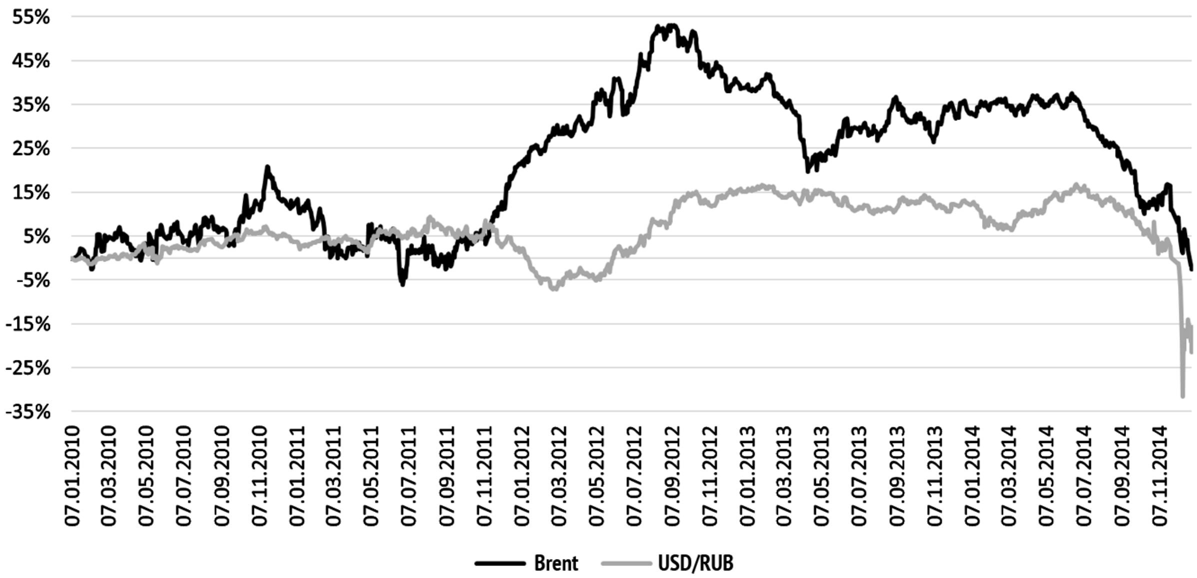


Note. Dates are given in the DD/MM/YY format.

Source: Authoring

Please cite this article as: Akberdina V.V., Chernavin N.P., Chernavin F.P. Application of the Committee Machine Method to Forecast the Movement of Exchange Rates and Oil Prices. *Digest Finance*, 2018, vol. 23, iss. 1, pp. 108–120.
https://doi.org/10.24891/df.23.1.108

Figure 3
A chart of profitability on strategies for Brent crude oil and USD/RUB (January 7, 2010 to December 31, 2014)



Note. Dates are given in the DD/MM/YY format.

Source: Authoring

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Conflict-of-interest notification

We, the authors of this article, bindingly and explicitly declare of the partial and total lack of actual or potential conflict of interest with any other third party whatsoever, which may arise as a result of the publication of this article. This statement relates to the study, data collection and interpretation, writing and preparation of the article, and the decision to submit the manuscript for publication.

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https://doi.org/10.24891/df.23.1.108