# Application of the Committee Machine Method to Forecast an Increase in the USD/RUB Exchange Rate Volatility

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**Abstract**

In the article is studied problems of the committee machine method application to forecast weeks, in which there is a high possibility of an increase in the USD/RUB exchange rate volatility. All calculations were done on a data from financial markets for the period of April 2009 till September 2018.

## 1 Introduction

Currency exchange rates play a great role in the international market affairs, because they to a great extent define competitiveness of each national economy. Russia has mostly resource-based economy and, consequently, any change in the rouble currency exchange rate have a great influence on GDP, because most of the national revenues come in form of foreign currency. Nowadays rouble exists in a period of high volatility, which started in 2014 year with imposition of economic sanctions, fall in oil prices and refuse of the Central Bank of Russian Federation to continue its support of rouble currency exchange rate (it is known as a switch to free-floating exchange rates). Such state of affairs significantly increased financial risks of Russian economy and each citizen of Russian Federation. At another point of view this period opened ample opportunities for traders of financial instruments.

## 2 Methodology of the research

As a part of the trading technologies there are many strategies based on the different forecasting methods. To use any method first of all there is a need to define what is predicted.

### 2.1 Description of the research problem and applied forecasting method

In terms of trading activities, it is commonly known that to earn money there must be predicted direction in which prices on a certain financial instrument will move. But this is only part of the truth, because by using of option strategies it is possible to earn just by a correct prediction of a price movement power (volutility) with no difference if it would be downward or upward.

As part of option strategies traders need to forecast an increase in the volatility by some methods. With development of computer technologies and free access to market data one of the most popular group of methods to solve most of the trading problems has become a quantitive analysis which use different mathematical models to forecast future market prices. In the context of this article there is examined the operation and use of the committee machine method as a part of the quantitive analysis.

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### 2.1.1 Options in the purchasing of volatility

Option is a derivative financial instrument (contract) in which purchaser of an option acquires the right, and the seller of the option undertakes obligation to buy (call-option) or sell (put-option) a certain asset in the future according to a price (strike) stipulated by contract. Using a combination of options, a trader can make a purchase of a volatility, for this purpose an option-put is purchased with a strike below the current market price and an option-call with a strike above the current market price. So, in a case of a strong market movement, the execution of one of the contracts will be able to cover all the costs for the purchase of both options and bring a great profit.

### 2.1.2 The committee machine method

The committee machine method makes it possible to get some generalized decision in contradictory situations, when there is no unambiguous decision. The committee machine method may be used in case, if there are a set of observations with a group of parameters for each observation. Inside the set of all observations can be distinguished a subset which can be divided into 2 classes. So, committee machine will need to solve a problem how by training on the subset with a known division into classes, distinguish division into classes for a subset with unknown division into classes.

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 members, which votes for the decision individually. The final single decision is based on all individual decisions combined by using of a committee machine logic. There are 3 main committee machine logics: majority, unanimity and seniority logics (hereinafter for brevity sake, consequently CM, CU, CS). In accordance with names, CM is a committee machine where a decision is accepted if a majority of committee members votes for this decision; in the CU case a decision is accepted only if all committee members votes for this decision; CS requires different committee members to have different weights which reflects their power in the voting process, a decision is accepted if it collects enough total weights through the votes of the committee members.

From a mathematical point of view, the committee machine method is a linear discriminant combination. 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.

At another point the committee member in geometric interpretation is just a line in a dimension of 2 parameters, or a plane in a dimension of 3 parameters. With further increase in number of parameters geometric interpretation is more difficult because human mind has difficulties trying to imagine more than 3-dimensional space. However, to show how this method works it is enough to study an example in a 2-dimensional space, with understanding that the same logic works for a space with more dimensions. One of the simplest geometric example of the CM of 3 committee members for 2 parameters is shown in Figure 1.

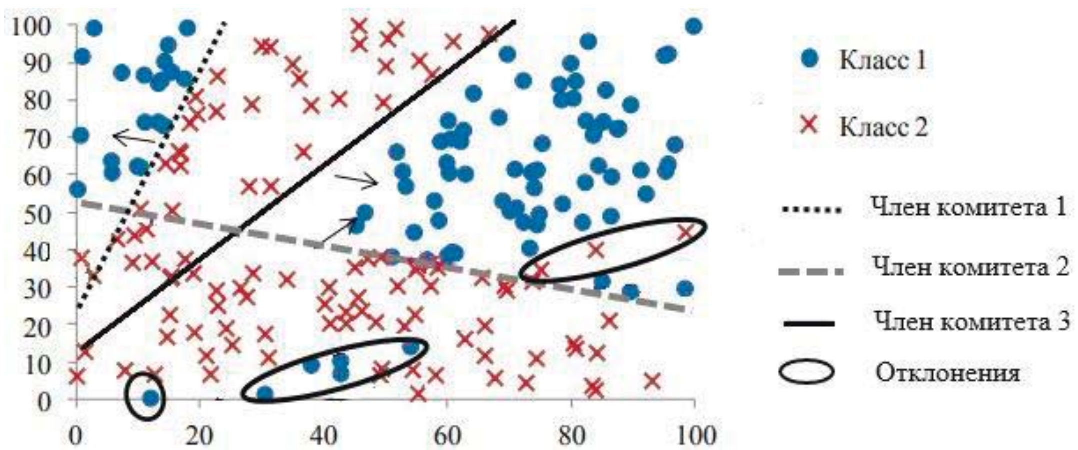


Figure 1: An example of the majority committee machine of the three members for two parameters

Figure 1 shows how the majority committee machine classify some samples into two classes. The arrows show the direction of voting of each committee member, and the oval curves circle classification errors.

### 2.1.3 The committee machine mathematic model

In accordance with Figure 1 there is shown that committee members don't classify perfectly and there are some classification errors. Consequently, the committee machine method solves a problem of how to find such combination of the experts that a number of deviations for each class will be minimum. The mathematic representation of the committee machine is a simple linear programming model with minimization by Chebyshev approximation (minimax).

$$\sum_{i \in I} (p_{ij} * x_i^t) + b^t - L * z_j^t \le -\varepsilon \quad j \in J_1, t \in T \quad (1)$$

$$\sum_{i \in I} (p_{ij} * x_i^t) + b^t + L * z_j^t \ge \varepsilon \quad j \in J_2, t \in T \quad (2)$$

$$\sum_{t \in T} (z_j^t * V^t) \le m + sv * d_j \quad j \in J_1 \quad (3)$$

$$\sum_{t \in T} (z_j^t * V^t) \le sv - m - 1 + sv * d_j \quad j \in J_2 \quad (4)$$

$$\sum_{j \in J_1} d_j \le K_1 * ch \quad (5)$$

$$\sum_{j \in J_2} d_j \le K_2 * ch \quad (6)$$

Objective function: min $ch$ (7)

, where $J_1$ and $J_2$ are the sets to be divided;

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

*I* is the set of observation parameters;

*T* is the set of the committee members;

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

$K_1$ and $K_2$ are number of observation in $J_1$ and $J_2$ consequently;

$p_{ij}$ is an *i-th* parameter of *j-th* observation (constants);

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

$b^t$ are the absolute terms of hyperplane (decision variable);

*L* is the gillion used for the conditions fulfillment rigor (constant);

$\varepsilon$ is a very small number used for the rigid restrictions (constant);

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

$d_j$ is the Boolean variable to fixate the computation error;

$n$ is a number of the committee members;

$V^t$ is the fixated weights for each committee member ($sv = \sum_{t \in T} V^t$);

*m* is a minority (a variable in a range: $0 <= m <= sv - 1$);

*ch is* a Chebyshev approximation (minimax) variable.

### 2.2 Parameter set and classification feature of the committee machine model

#### 2.2.1 Financial market parameters

In context of this research there was chosen to analyze a Moscow Exchange (MOEX) market data on prices of financial instrument which reflect USD/RUB currency exchange rate (hereinafter for brevity sake USD/RUB). These are USDRUB_TOM price, its trading volume (hereinafter for brevity sake VTOM), trading volume of financial instrument USDRUB_TOD[1] (hereinafter for brevity sake $V_{TOD}$) and trading volume on USD/RUB currency exchange rate (hereinafter for brevity sake USD/RUB) futures (hereinafter for brevity sake $V_{FORTS}$) on the MOEX FORTS derivative market. In addition, there is studied changes in currency exchange rates of AUD/USD, USD/CAD, BRL/USD and prices of Brent crude oil, because their performance have a strong connection with USD/RUB. In Table 1 is described parameters name and their calculation methodology.

Table 1: Description of the model parameters

| № | Parameter name | Calculation methodology |
|---|---|---|
| 1 | Weekly USD/RUB volatility | $P1 = \frac{\text{Max. USD/RUB}}{\text{Min. USD/RUB}} - 1$ |
| 2 | P1 change from last week with a cumulative total [2] | $P2_n = \frac{\text{P1 of week n}}{\text{P1 of week (n−1)}} - 1$ |
| 3 | The change in the total trading volume of the USD/RUB (V) on the currency and derivatives markets of the MOEX since last week with a cumulative total | $V = V_{TOM} + V_{TOD} + V_{FORTS}$<br>$P3_n = \frac{\text{V of week n}}{\text{V of week (n−1)}}$ |
| 4 | How many times $V_{TOM}$ , more than $V_{TOD}$ | $V_{TOM} / V_{TOD}$ |
| 5 | How many times $V_{TOM}$ , more than $V_{FORTS}$ | $V_{TOM} / V_{FORTS}$ |
| 6 | Weekly AUD/USD volatility | $P6 = \frac{\text{Max.AUD/USD}}{\text{Min.AUD/USD}} - 1$ |
| 7 | P6 change from last week with a cumulative total | $P7_n = \frac{\text{P6 of week n}}{\text{P6 of week (n−1)}} - 1$ |
| 8 | Weekly USD/CAD rate volatility | $P8 = \frac{\text{Max.USD/CAD}}{\text{Min.USD/CAD}} - 1$ |
| 9 | P8 change from last week with a cumulative total | $P9_n = \frac{\text{P8 of week n}}{\text{P8 of week (n−1)}} - 1$ |
| 10 | Weekly BRL/USD rate volatility | $P10 = \frac{\text{Max.BRL/USD}}{\text{Min.BRL/USD}} - 1$ |
| 11 | P10 change from last week with a cumulative total | $P10_n = \frac{\text{P10 of week n}}{\text{P10 of week (n−1)}} - 1$ |
| 12 | Weekly Brent crude oil price volatility | $P10 = \frac{\text{Max.BRL/USD}}{\text{Min.BRL/USD}} - 1$ |
| 13 | P12 change from last week with a cumulative total | $P13_n = \frac{\text{P13 of week n}}{\text{P13 of week (n−1)}} - 1$ |
| 14 | Brent trading volume ($V_{Brent}$) change from last week with a cumulative total | $P14_n = \frac{V_{Brent}\text{ of week n}}{V_{Brent}\text{ of week (n−1)}} - 1$ |

[1] Both TOM and TOD reflect USD/RUB, but for TOD, the settlement date is the same as the transaction date, and for TOM, the settlement date is the next day.

[2] Under the cumulative total, we will keep in mind that if the direction of a volatility change coincides with the direction of a volatility change of the last week ($P_n * P_{(n-1)} > 0$), then we add the previous values to the current value ($P_n + P_{n-1}$)

### 2.2.2 Classification feature

The period from April 2009 to September 2018 was chosen for research. This period covers market changes that occurred after the financial crisis of 2008 year, since the market has changed drastically since that time, and the crisis period has been a runout, where standard patterns no longer work. Accordingly, in the period under review, observations related to the weeks before a high USD/RUB volatility period were highlighted. In terms of this research by weeks before a high USD/RUB volatility period will be regarded the following 2 situations:

1. If the maximum rate change relative to the closing of the week within the next 2 weeks exceeds 2%, and within 4 weeks it is no less than 1.5 times stronger than that fixed within 2 weeks if direction of price movement in both cases is the same.
2. If the maximum rate change within the next 4 weeks exceeds 8% and direction of price movement within the next 2 weeks is the same.

These rules were empirically compiled by the authors based on the logic of an option trading strategy. As was mentioned, an option is a future contract, which means that it is not enough to understand just the fact that the value of the asset should change drastically, but also take the time factor into account, because by the time the volatility will increase, the contract may already be expired. Accordingly, based on this logic, it is introduced that the change in value should occur abruptly (by more than 2%) within 2 weeks or gradually, but very strongly (by more than 8%) within 4 weeks.

Below in Figure 2 is presented USD/RUB chart, which is based on the weekly data of the closing price for the period from 06.04.2009 to 07.09.2018, where weeks which agree to the rules described before are highlighted. The chart timeline axe is presented in the format “MM.YY”.

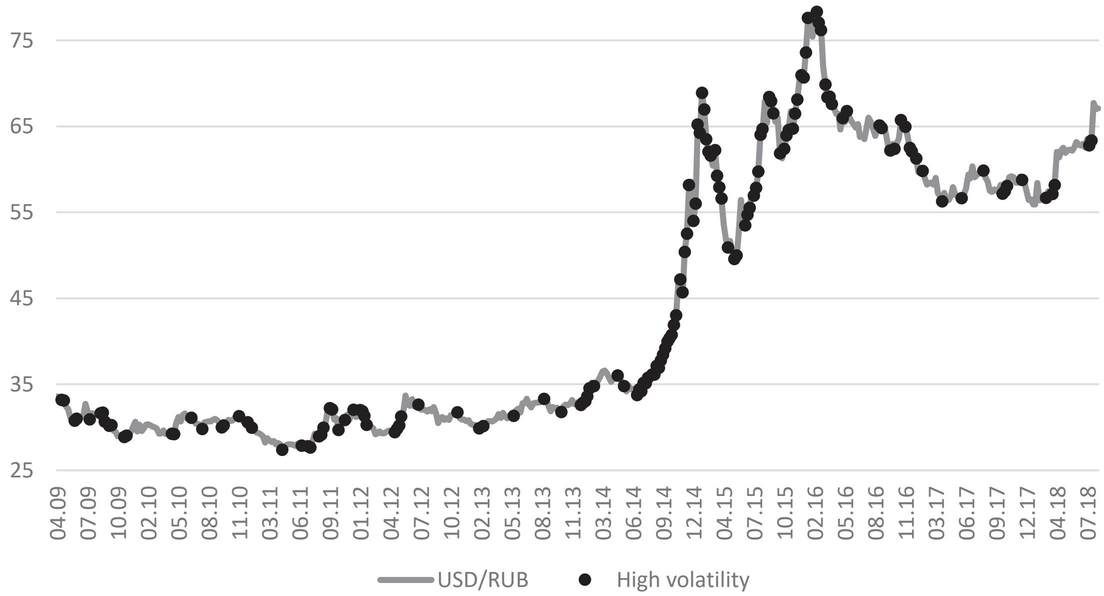


Figure 2: The periods of high USD/RUB volatility in accord with authors’ rules

In Figure 2 out of 514 observations, 148 observations were selected according to the rules for selecting the high USD/RUB volatility periods. By studying the chart, you can see that most of the points formed in the period from June 2014 to January 2015. In this period, almost each of the weeks was selected, which turns the entire given period into information noise for the model. Accordingly, since we are interested in the moments of trend change, and not just confirmation of the current trend, we will try to introduce an additional rule, according to which, week is not highlighted if in the previous 3 weeks there has been already highlighted week. With the introduction of this additional rule, the chart will take the form as in Figure 3.

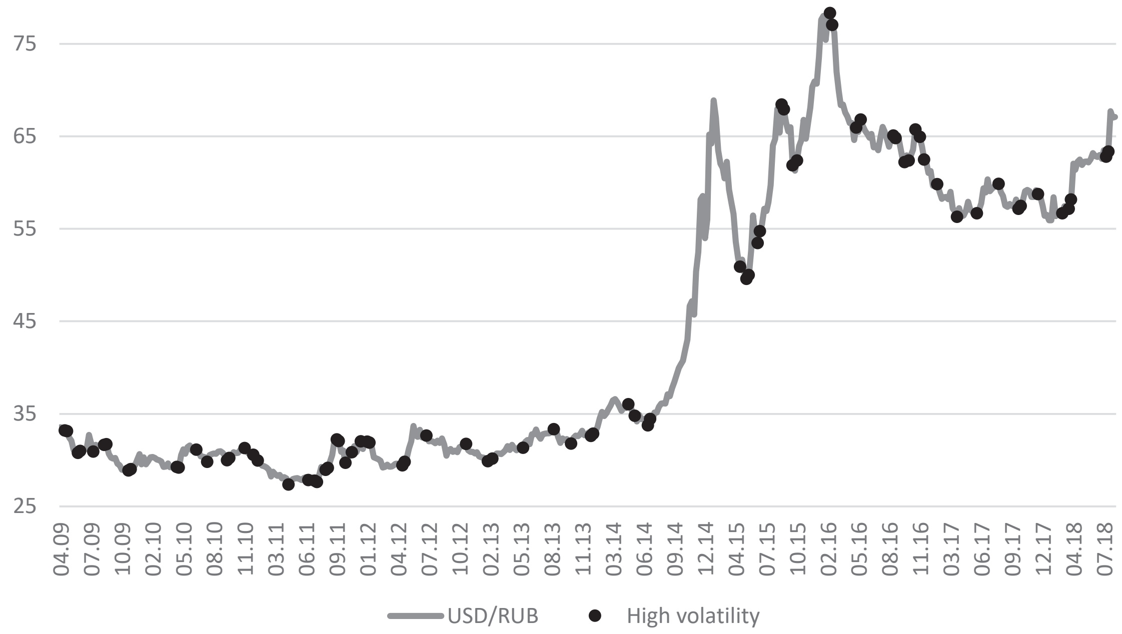


Figure 3: The periods of high USD/RUB volatility in accord with the additional rule

As can be seen in Figure 3 the number of the highlighted weeks are much smaller. There are only 83 weeks chosen as the moments before high volatile period.

## 3 The classification results

While the mathematical model and dataset parameters are chosen there can be calculated classification decision rules for the trading strategies.

### 3.1 The classification results for different committee machine types

Before calculation may be started there must be distinguished training and test datasets. A training dataset is a set of the samples which our mathematical model will try to optimize, while samples from a test dataset are not included, and give an opportunity to test the results without risk of model overtraining. Consequently, the entire period under research was divided into training and test datasets, as shown in Table 2.

Table 2: Description of training and test datasets

| Dataset | Period | The number of weeks | | |
|---|---|---|---|---|
| | | $J_1$ | $J_2$ | $J$ |
| Training | April 2009 – December 2017 | 403 | 78 | 481 |
| Test | January 2018 – September 2018 | 30 | 5 | 35 |
| Total | April 2009 – September 2018 | 431 | 83 | 514 |

On the basis of the compiled datasets, calculations were made by the committee machine method with constructions of the committees from 3 to 6 committee members. The corresponding calculation results are presented in Table 3, where in the column "Committee type" a number is used to indicate a number of the committee members.

Table 3: The results of classification with the different committee machine types (% correct recognition)

| Committee type | Training dataset | | Test dataset | |
|---|---|---|---|---|
| | $J_1$ | $J_2$ | $J_1$ | $J_2$ |
| CU 3 | 79.4% | 76.9% | 73,3% | 40.0% |
| CU 4 | 78.9% | 75.6% | 73,3% | 20.0% |
| CS 4 | 73.4% | 70.5% | 70,0% | 40.0% |
| CU 5 | 82.4% | 82.1% | 73,3% | 40.0% |
| CS 5 | 79.2% | 80.8% | 60,0% | 40.0% |
| CU 6 | 83.1% | 83.3% | 76,7% | 40.0% |
| CS 6 | 84.1% | 84.6% | 63,3% | 40.0% |

Based on the results in Table 3, it may be stated that satisfactory results were obtained on the training dataset. At the same time, it is clear that the CU shows the results better than the CS, which indicates that the model of unanimity logic is more applicable for the separation of this dataset. Despite the fact that with an increase in the number of the committee members up to 6, can be seen an improvement in the results on the training dataset for CS to more than 84% correctly recognized weeks, however, on the test sample, the results are much worse than for CU. Such a fact is a sign of the model overtraining, and hence the senselessness of further increasing of the committee members number.

Moreover, for further support idea of the unanimity logic advantages in classification of compiled datasets it is worth noting first of all that there is no example of CM, because in every case mathematic model has found better result by applying CU. And in addition, for a committee of 3 committee members, the model with precedence logic was eventually reduced to CU ($m = 0$) and therefore CS for 3 members was not given.

### 3.2 The analysis of the classification result for the specific committee machine

By analyzing the results, at first glance, we can say that the result for J2 is not satisfactory, but if you look at the results based on the trading problem, then the result has a real analytical value. To begin with, we will once again research the chart given earlier, but specifically for the test dataset period as presented in Figure 4.

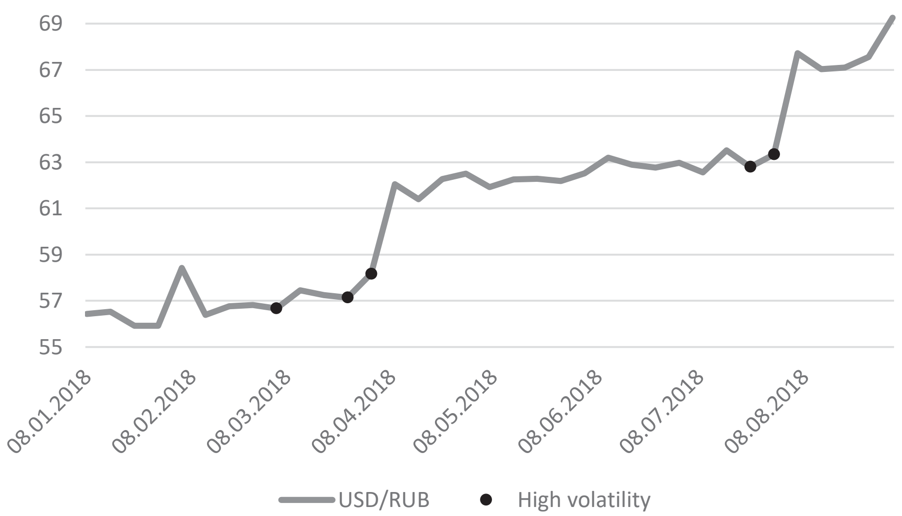


Figure 4: USD/RUB chart for the test dataset with high volatility periods highlighted

The chart shows that the 2 most important movements in the course volatility during 2018 occurred in the beginning of April and August. Accordingly, we can assume that the rule is satisfactory according to $J_2$ of the test dataset, if it can recognize at least one week for each period of high volatility. Of all the calculated committee machines, this condition is satisfied only by an unanimity committee of 5 committee members, which out of 5 weeks in $J_2$ recognized 2, one for each period. The following Table 4 presents the coefficients of hyperplanes calculated for this committee.

Table 4: The coefficients of decision rule for CU of 5 committee members

| Parameters | Coefficients of the committee machine | | | | |
|---|---|---|---|---|---|
| | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_5$ |
| $p_1$ | -1 | -1 | 1 | -1 | -1 |
| $p_2$ | -363,5 | 1,1 | -3,1 | -3,2 | 2,4 |
| $p_3$ | -803,2 | 0,6 | -0,1 | 1,4 | -4,1 |
| $p_4$ | 1814,4 | -7,4 | 0,5 | -1,1 | 3,1 |
| $p_5$ | 145,7 | 0,3 | 0,1 | -4,7 | -7,7 |
| $p_6$ | 469,7 | -1,8 | -2,5 | -4,0 | 3,6 |
| $p_7$ | 1195,7 | 3,7 | 2,2 | -1,4 | 5,5 |
| $p_8$ | -1361,5 | 5,1 | 4,5 | 3,1 | -1,6 |
| $p_9$ | 1189,8 | -7,2 | -3,4 | -3,8 | -6,0 |
| $p_{10}$ | 40,3 | 0,0 | 0,6 | -0,8 | 1,2 |
| $p_{11}$ | -1614,0 | 1,5 | -7,8 | 2,9 | -2,0 |
| $p_{12}$ | 329,4 | -0,1 | -0,6 | 0,5 | -0,9 |
| $p_{13}$ | -79,3 | 0,1 | -0,4 | -0,4 | -0,9 |
| $p_{14}$ | 19,1 | 0,0 | -0,1 | -0,1 | 0,2 |
| b | -10367,7 | 12,9 | -13,3 | 4,1 | -19,7 |

It is worth noting that the feature of the classification problem is the ambiguity of the selected classification feature, since the choice of moments of increased volatility can be built according to the different criteria. Consequently, the above indicated results do not fully reflect the effectiveness of the committee machine. Therefore, for empirical understanding, it is worthwhile to consider the results obtained on the USD/RUB chart, as presented below in Figure 5.

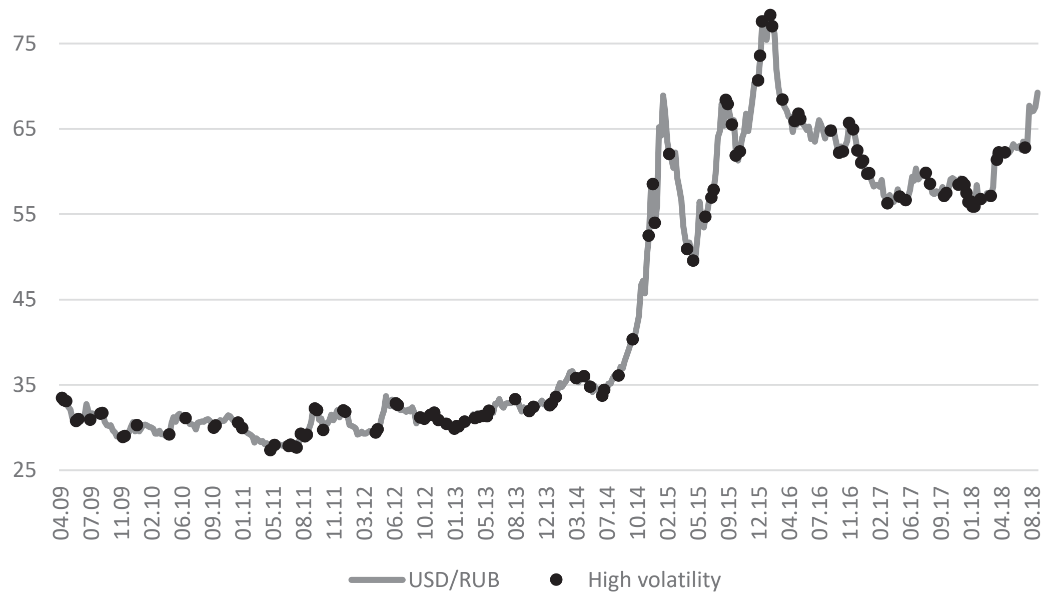


Figure 5: Results of CU of 5 committee members on USD/RUB chart

The chart shows that this decision rule in most cases correctly predicts moments of increasing volatility, with the exception of some periods. For example, in October 2012 to May 2013 for a long time there was no significant volatility of the USD/RUB rate, but the decisive rule mistakenly recognized many weeks in this period as highly volatile. In authors' point of view, it is possible to solve this problem and improve decision rule by introducing an additional parameter which would reflect the average USD/RUB volatility over a long period, so that the model can recognize such periods.

So, as a result of this research there was formed a decisive rule for predicting the growth of the USD/RUB volatility, which can be used as a part of the trading option strategies. There is still a way to significantly improve results by addition of better parameters, determine an optimal classification feature and removing of non-informative parameters and weeks from dataset. These improvements will be researched in the further authors' works on this theme.

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