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# Development of a comprehensive methodology for the forecast of effectiveness of geological and technical measures based on machine learning algorithms

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**Abstract**. The main part of hydrocarbon production in Russia is represented by old oil and gas producing regions. Such areas are characterized by a significant decrease in well productivity due to high water cut and faster production of the most productive facilities. An important role for such deposits is played by stabilization of production and increase of mobile reserves by improving the development system. This is facilitated by various geological and technical measures.

Today, an urgent problem is to increase the reliability of the forecast of technological and economic efficiency when planning various geological and technical measures. This is due to the difficulty in selecting candidate wells under the conditions of the old stock, the large volume of planned activities, the reduction in the profitability of measures, the lack of a comprehensive methodology for assessing the potential of wells for the short and long term.

Currently, there are several methods to evaluate the effectiveness of geological and technical measures: forecast based on geological and field analysis, statistical forecast, machine learning, hydrodynamic modeling. However, each of them has its own shortcomings and assumptions. The authors propose a methodology for predicting the effectiveness of geological and technical measures, which allows one to combine the main methods at different stages of evaluating the effectiveness and to predict the increase in fluid and oil production rates, additional production, changes in the dynamics of reservoir pressure and the rate of watering of well production.

**Keywords**: geological and technical measures, efficiency forecast, machine learning, mathematical statistics, hydrodynamic modeling, geological and physical parameters

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## Analysis of the effectiveness of the main workover actions in carbonate reservoirs of the Perm Territory fields

The Perm Territory is an old oil-producing region, as a result of which oil fields are characterized by high depletion of reserves, involvement in the development of heterogeneous reservoirs with low fluid storage capacity properties, as well as deposits with high-viscosity oils. Development of fields in difficult geological and technological conditions of operation of carbonate reservoirs, as a rule, is carried out with low annual rates of reserves recovery (no more than 2.5%) and with low oil recovery factor (ORF) (no more than 35%) (Voevodkin et al., 2014).

At the fields of the Perm Territory, starting from the 70s, the methods of production intensification (PI) and enhanced oil recovery (EOR) are being increasingly introduced every year. Even with a high economic effect of a certain technology, it is necessary to use and implement all types of PI and EOR methods in order to maintain facilities at the required level for oil production. Moreover, each technology demonstrates success in certain geological, physical and technological conditions (Putilov et al., 2020).

The most successful methods of oil production intensification and enhanced oil recovery for carbonate objects of the Perm Territory fields are recognized as acid hydraulic fracturing (acid fracturing), acid

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treatment (AT), radial drilling (RD), drilling perforation (DP), reperforation (RP) and additional reperforation & completion (RPC) (Ilyushin et al., 2015; Kochnev et al., 2018).

Figure 1 shows a comparison of the efficiency of technologies for the analyzed period (2006–2019) for vertical wells in terms of the average additional production per well and the average daily production increase.

Figure 2 shows a comparison of the average duration of the effect from workover actions. The effective period is the time of the well operating with an increase in the oil production rate caused by workover actions, until the oil production rate decreases to the base value.

Analysis of Figures 1–2 shows that the highest additional production and average daily increment are characteristic of acid fracturing, but this technology has significant disadvantages: high cost; the risk of fracture breakthrough into a water-cut reservoir; the use of a large volume of chemical reagents leads to complex work on the disposal of contaminants. In addition, when hydraulic fracturing (hydraulic fracturing), the technical requirements for candidate wells are high, which seriously limits the use of this technology, especially on the old well stock. The rest of the considered technologies are less demanding for the selection of candidate wells and less costly. Radial drilling technology based on the average increment in additional oil production (additional oil production through the well until the oil production rate drops to the base value) from geological and technical measures defers only to acid fracturing, and in terms of time of economic effect is the best one.

Radial drilling technology is one of the main for the Chernushinskaya (25%), Osinskaya (24%) and Nozhovskaya (34%) groups of fields in the Perm Territory. The analysis of the effectiveness of geological and technical measures for various carbonate objects of the Perm Territory fields is described in the works (Ilyushin et al., 2015; Kochnev et al., 2018). Evaluation of the effectiveness of radial drilling technology was carried out in (Galkin et al., 2019).

## Basic methods for forecasting the effectiveness of workover measures

Today, one of the main methods for predicting the effectiveness of workover measures is the mathematical modeling on a hydrodynamic model (Kravchenko et al., 2018; Sayfutdinov et al., 2018; Repina et al., 2018). The advantages of this method include the possibility of a comprehensive assessment of geological and technical measures in conditions of the mutual influence of all wells on the oil production process, as well as taking into account the geological characteristics of the reservoir. Simulation can be performed in a variety of simulators.

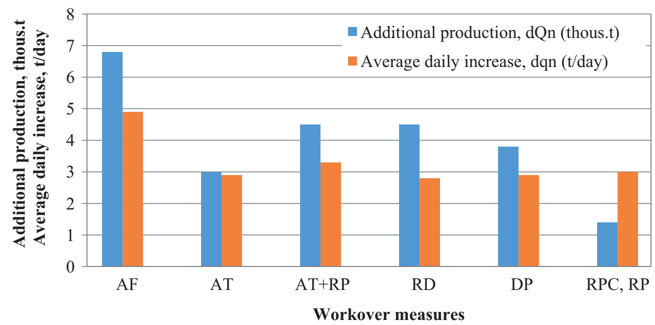


*Fig. 1. Comparison of workover measures in terms of efficiency. Acid fracturing – acid hydraulic fracturing, AT – acid treatment, RP – reperforation, RD – radial drilling, DP – drilling perforation, RPC – reperforation and completion.*

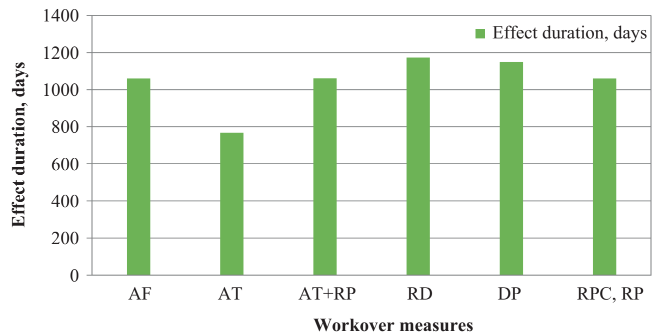


*Fig. 2. Comparison of workover measures in terms of effect duration*

The main software systems for Russian oil and gas companies are Tempest, Eclipse, T-Navigator.

In geological and hydrodynamic modeling, it is important to take into account the subjectivity of the adaptation of the model and the way of the workover actions modeling, which significantly affects the predictive characteristics of the model (Olenchikov, Kruglikova, 2008; Kolbikov et al., 2018; Lyu et al., 2014). The large time and cost of hydrodynamic modeling determines the need for its use mainly for the design of high-cost workover measures (drilling horizontal wells and sidetracks) (Andronov, 2019).

The methodological recommendations (Polukeev et al., 2018) describe a method for predicting the increase in flow rate from geological and technical measures through the specific productivity factor, which is based on a comparison of analogs and fluid flow rate forecast. The calculation of the production rate increase using this method is simple and prompt in the presence of a developed base of measures, but its accuracy is often not great. The calculation does not take into account the complex of geological and technological parameters, but only the specific productivity factor and its components are considered. The approach is currently the main one for the LUKOIL group of companies. Detailed "manual" analysis of wells based on geological field analysis using analytical and statistical methods takes a lot of time and is subjective.

The development of digital technologies provides significant potential for the application of machine learning technologies in the oil and gas industry (Koroteev et al., 2014). These are various methods such as neural networks, decision trees, random forest algorithm, cluster analysis. Among the advantages of machine learning methods for specialists designing geological and technical measures, one can note the possibility of promptly obtaining satisfactory forecasts and the absence of requirements for hydrodynamic modeling skills. In general, the main advantages of using machine learning technologies are: accuracy, automation, speed, customization, scalability (Andronov, 2019).

The main disadvantages are: lack of clear forecasting algorithms, lack of physical justification, low interpretability of the results obtained (Pichugin et al., 2013; Azbuhanov et al., 2019).

Also, various methods of mathematical statistics are used to predict the effectiveness of geological and technical measures. The work (Galkin et al., 2019) notes the successful application of the methods, however, there are drawbacks: the need for manual search and analysis of "outliers", the use of a set of various statistical methods for data preparation.

## Development of a comprehensive methodology for predicting the effectiveness of workover measures

To improve the reliability of forecasting, an approach is proposed for combining methods at different stages of forecasting, which consists of four main stages.

1. Creation of a database on geological and technical measures and the corresponding geological and physical parameters.

For a comprehensive forecast of the effectiveness of geological and technical measures, it is necessary to take into account the influence of both geological and technological parameters. Therefore, at this stage, it is necessary to create a consolidated database, including wells on which geological and technical measures were carried out, as well as the results of geophysical, hydrodynamic and other studies on these wells.

2. Identification of the parameters that have the greatest impact on the potential for additional production for each workover measures by using the methods of mathematical analysis.

To ensure a high-quality forecast, it is necessary to understand what parameters determine the effectiveness of the technology in various geological and physical conditions. To identify these parameters, it is proposed to use one-factor and multivariate mathematical analysis.

3. Construction of regression models based on the identified parameters to predict the increase in liquid/oil production using machine learning methods.

At this stage, machine learning models are built to predict the increase in liquid/oil production rate.

4. Forecasting the potential of additional production by entering the results of machine learning into the hydrodynamic model.

To obtain a long-term forecast, it is necessary to take into account the mutual influence of wells, therefore, it is proposed to integrate mathematical models with a geological and hydrodynamic model (HDM).

In this work, the methodology has been tested using the example of radial drilling technology.

## Identification of parameters affecting the efficiency of radial drilling technology

At the first stage, a consolidated database was created for all wells with measures taken for radial drilling for the period from 2006 to 2019 in the Perm Territory and the corresponding parameters. The database includes the geological and physical characteristics of the reservoir adopted at the fields when calculating reserves; the results of hydrodynamic studies of wells before carrying out measures for RD; the well log interpretation results, oil and liquid production rates before RD, data on perforation intervals, data on previous well interventions. As a result, to assess the effectiveness of radial drilling measures, the analysis took into account data on 590 wells in 40 oil fields and with 36 parameters.

At the second stage, the impact of the geological and physical parameters of the object on the performance indicators of geological and technical measures was assessed. The following parameters were chosen as efficiency indicators: average daily increase in oil production rate (t/day), additional production (thousand tons), maximum flow rate after geological and technical measures (t/day), duration of the effect (days).

Initially, a univariate analysis was performed. The assessment of the influence of parameters on performance indicators was carried out using the Student's t-test. The essence of the method is to test the hypothesis that the mean values are equal (1):

$$t_p = \frac{|X_1 - X_2|}{\sqrt{\frac{1}{n_1} + \frac{1}{n_2}\left(\frac{(n_1-1)S_1^2+(n_2-1)S_2^2}{n_1+n_2-2}\right)}} \tag{1}$$

where $X_1$, $X_2$ – respectively, the average values of the sample indicators; $S_{12}$, $S_{22}$ – variances of sample indicators.

The difference in mean values is considered statistically significant if $t_p > t_t$, where $t_p$ is the calculated value of the criterion, and $t_t$ is the tabular value of the t criterion. The $t_t$ values are determined depending on the amount of compared data and the significance level ($p = 0.05$), if the significance level is less than 5%, then the samples are different with a probability of more than 95%. The results of calculating the Student's test are presented in Table 1. Values with an attainable

| **Additional oil production, t** | **< 2000** | **> 2000** | **t-test** | **p** | **$N_1$** | **$N_2$** |
|---|---|---|---|---|---|---|
| Porosity $K_p$, % | 12,4 | 12,8 | -1,64 | *0,10* | 96 | 93 |
| Oil viscosity $\mu$, mPa*s | 24,9 | 32,0 | -1,76 | *0,08* | 96 | 93 |
| Oil density $\varrho_o$, g/cm$^3$ | 0,87 | 0,89 | -2,06 | **0,04** | 96 | 93 |
| Bottom hole pressure $P_{bot}$, MPa | 5,22 | 6,29 | -2,57 | **0,01** | 56 | 75 |
| Saturation pressure $P_{sat}$, MPa | 10,32 | 10,21 | 0,33 | 0,74 | 56 | 75 |
| Skin factor S, un. | -3,52 | -2,03 | -2,82 | **0,01** | 56 | 75 |
| Oil-saturated thickness $h_{sat}$, m | 8,47 | 9,32 | -1,85 | *0,07* | 96 | 92 |
| **Average daily increase, t/day** | **< 3** | **>3** | **t-test** | **p** | **$N_1$** | **$N_2$** |
| Porosity $K_p$, % | 12,32 | 12,94 | -2,59 | **0,01** | 102 | 87 |
| Oil viscosity $\mu$, mPa*s | 25,38 | 32,04 | -1,65 | *0,10* | 102 | 87 |
| Oil density $\varrho_o$, г/см$^3$ | 0,87 | 0,89 | -1,90 | *0,06* | 102 | 87 |
| Specific interlayer thickness $h_{int}$, m | 2,09 | 1,66 | 2,08 | **0,04** | 97 | 76 |
| Reservoir pressure $P_{res}$, MPa | 11,95 | 13,29 | -2,65 | **0,01** | 71 | 60 |
| Bottom hole pressure $P_{bot}$, MPa | 5,28 | 6,49 | -2,95 | **0,00** | 71 | 60 |
| S, un. | -3,16 | -2,09 | -2,01 | **0,05** | 71 | 60 |
| **Effect duration from RD, day** | **< 900** | **>900** | **t-test** | **p** | **$N_1$** | **$N_2$** |
| Oil flow rate before workover $q_o$, t/day | 3,47 | 2,89 | 2,01 | **0,05** | 98 | 91 |
| Skin factor S, un. | -3,66 | -1,83 | -3,52 | **0,00** | 60 | 71 |
| **Max oil flow rate after RD, t/day** | **< 10** | **> 10** | **t-test** | **p** | **$N_1$** | **$N_2$** |
| Oil flow rate before workover $q_o$, t/day | 2,33 | 4,00 | -6,27 | **0,00** | 92 | 97 |
| Water cut W,% | 21,50 | 16,86 | 2,24 | 0,03 | 87 | 96 |
| **Ad. oil flow rate in 1 year after RD, t/day** | **< 5** | **> 5** | **t-test** | **p** | **$N_1$** | **$N_2$** |
| Total reservoir thickness $H_t$, m | 21,26 | 24,53 | -1,99 | **0,05** | 93 | 96 |
| Porosity $K_p$, % | 12,39 | 12,81 | -1,71 | *0,09* | 93 | 96 |
| Oil density $\varrho_o$, g/cm$^3$ | 0,87 | 0,89 | -2,71 | **0,01** | 93 | 96 |
| Volumetric ratio *b*, un. fr. | 1,09 | 1,06 | 2,65 | **0,01** | 93 | 96 |
| Gas content G, m$^3$/m$^3$ | 41,81 | 31,55 | 2,31 | **0,02** | 93 | 96 |
| Skin factor S, un. | -3,50 | -2,05 | -2,73 | **0,01** | 56 | 75 |
| Total thickness $H_{total}$, m | 22,23 | 25,27 | -1,85 | *0,07* | 93 | 95 |

*Tab. 1. Influence of geological and physical parameters on the efficiency of RD for wells of the Tournaisian facilities of the Perm Territory fields*

significance level p below 0.05 are highlighted in bold type for indicators, at which, with a probability of more than 95%, one can argue about differences in the considered samples. In this case, the studied parameter has a statistically significant (non-random) effect on the differences in indicators in the samples. Values with p in the range from 0.05 to 0.10 are italicized, for which the influence also exists, but somewhat lower.

Greater additional production and average daily growth after RD are characterized by deposits with higher oil viscosity and density, which are more characterized by the formation of stagnant zones in low-permeability zones of the reservoir. It is also more preferable to use RB under conditions of significant energy potential of the reservoir ($P_{res}$, $P_{bh}$) and with a higher porosity of the reservoir. The conditions of large specific interlayer thicknesses, total and oil-saturated thicknesses also generally positively affect the efficiency of the RD. The increase in oil production in the first year after RD is influenced by the effective thickness, reservoir storage capacity, oil density, volumetric ratio and gas saturation.

For a comprehensive assessment of the impact of indicators (multivariate analysis), linear discriminant analysis was used. The most important indicator of efficiency is the increase in the flow rate of oil and liquid after workover measures. In this case, a set of parameters was identified that affects the increase in oil (2) and liquid (3) flow rates after RD. As a result of calculations, the following linear discriminant functions (Z) were obtained, which maximally separate the samples by the average value of the increase in production.

To increase the oil production rate (at R = 0.60):

$$Z = -0.218 \cdot q_o + 10.314 \cdot K_s - 0.061 \cdot K_{calc} - 0.00633 \cdot \mu_o + 0.176 \cdot \varsigma_{ch} + 0.00556 \cdot \chi - 0.762 \cdot h_i + 0.0013 \cdot S - 3.41. \quad (2)$$

To increase the liquid flow rate (at R = 0.79):

$$Z = -0.39 \cdot q_l + 0.27 \cdot P_{res} - 0.102 \cdot h_{oit} + 0.26 \cdot \phi + 0.069 \cdot S - 6.48 \quad (3)$$

where $q_o$ – oil production rate before RD, t/day; $q_l$ – liquid flow rate before RD, m$^3$/day; $h_i$ – oil-saturated thickness, m; $\phi$ – porosity,%; $K_s$ – net-to-gross sand ratio; $K_{calc}$ – coefficient of dissection; $\mu_o$ – oil viscosity in reservoir conditions, mPa*s; $\varrho_o$ – oil density in reservoir conditions, g/cm$^3$; $\chi$ – piezoconductivity, cm$^2$*s; $P_{res}$ – reservoir pressure, MPa; $h_{oit}$ is the average thickness of a single oil-saturated interlayer, m (the average thickness of a single oil-saturated interlayer was calculated as the ratio of $h_i$ to the number of oil-saturated interlayers); S – well skin factor; $\varsigma_{ch}$ – $h_i$, m/number of radial channels.

As a result of multivariate analysis, it was revealed that the increase in oil production rate is affected by the following set of parameters: oil production rate prior to RD, net sand coefficient, compartmentalization, oil viscosity, channel density, piezoconductivity, average thickness of a single oil-saturated interlayer and skin factor.

The increase in fluid flow rate is most influenced by a set of parameters: fluid flow rate to RD, reservoir pressure, oil-saturated thickness, porosity, skin factor.

The identified parameters are used to build computing learning models.

## Forecast of the increase in fluid flow rate after workover measures

At this stage, the forecast of the increase in fluid flow rate was made using machine learning methods. Artificial neural networks are chosen as the first method. Neural networks are a mathematical model built on the principle of biological neural networks and allow solving problems of regression, clustering and data analysis (Voronovsky et al., 1997; Tsaregorodtsev, 2008). As a result, networks with different architectures were built, which quite reliably allow predicting the increase in fluid flow rate (R – from 0.77 to 0.86). For further forecasting, a network with a simpler architecture was chosen – a multilayer perceptron: 17 neurons on the input layer, 1 hidden layer with 5 neurons and 1 neuron on the output layer, the neuron activation function is logistic, the error function is the sum of squares. When training this network, sufficiently high correlation coefficients were achieved, both on the training sample, and on the test and control (Figure 3a).

The second method for calculating the increase in oil production after RD is the support vector machine (SVM). SVM is a class of supervised learning algorithms used for classification and regression analysis problems. As a result of the calculations, several classifying dividing lines are constructed, of which only one corresponds to the optimal dividing (Tsaregorodtsev, 2008). Figure 3b shows the results of model calculations for the training and test samples, respectively.

For comparison, the increase in fluid flow rate was calculated using linear discriminant analysis (LDA). The method solves the problems of classification, not regression, however, in the calculations, a transition to a probabilistic assessment is possible, and through probability it becomes possible to predict an increase in production rate (Figure 4) (Galkin et al., 2019).

The result of training in this case is somewhat worse (R = 0.77–0.72), but the advantage of the method is that in the process of building a model it is possible to verify its physicality. That is, the signs of the linear discriminant function and the parameters should not contradict the physical meaning. When building a neural network or a support vector model, there is no way to track the physicality of the coefficients in the model, which is one of the main disadvantages of the method.

## Forecast of additional oil production from workover measures

In the process of predicting the effectiveness of geological and technical measures, it is important to

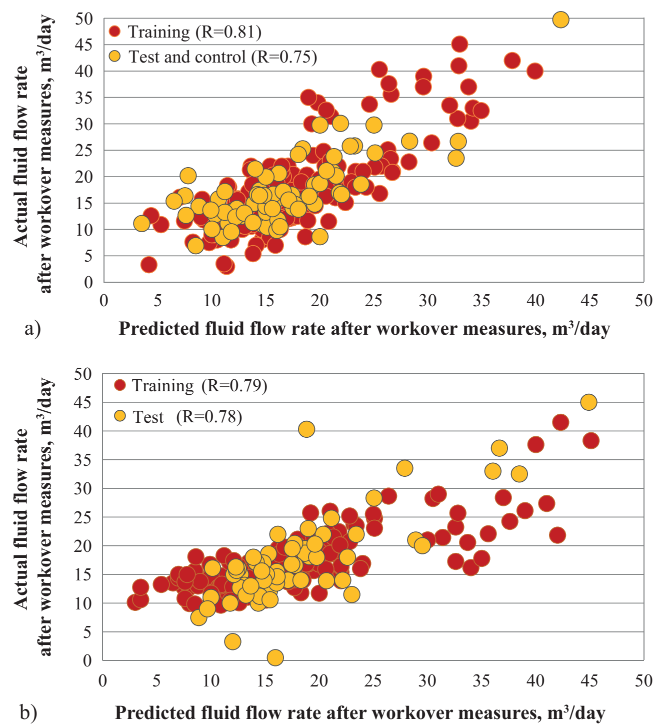


*Fig. 3. Comparison of actual and predicted values of fluid flow rate after workover measures: a) neural networks; b) SVM method.*

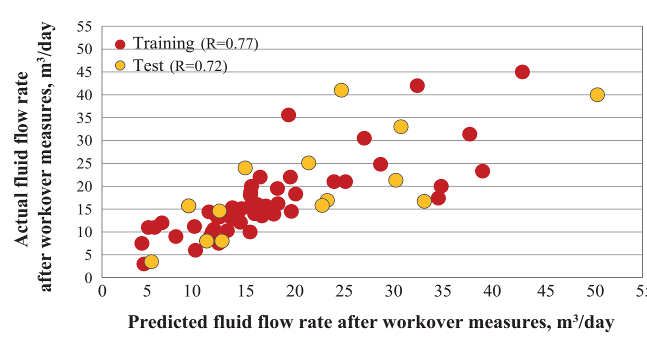


*Fig. 4. Comparison of actual and forecast values. Discriminant analysis.*

assess the potential for additional production. When using only statistical models, changes in the physical and pressure conditions of the reservoir during the forecast period are not taken into account, which does not allow for an assessment of production in the long term. Statistical models are able to predict only for current conditions and for one well, without taking into account mutual influence and interference.

The integration of statistical models and hydrodynamic modeling opens up opportunities for planning workover measures in the long term, that is, taking into account changes in reservoir conditions during development. In addition, the integration approach allows one to take into account the geological structure of the reservoir, namely, the variability of properties in the reservoir volume and the rate of water breakthrough after the event, depending on the hydrodynamic connectivity of the reservoir and the rate of the front of oil displacement by water.

In this work, two algorithms have been developed to predict liquid flow rate and additional oil production after the event: 1) integration of a mathematical model obtained using a neural network and hydrodynamic modeling; 2) integration of a multidimensional model obtained using LDA and hydrodynamic modeling.

The algorithm for calculating additional production using neural networks is as follows:

1. Determination of candidate wells and the date of the event;
2. Calculation of the increase in fluid flow rate using a trained neural network;
3. Entering fluid flow rate values into the hydrodynamic simulator, taking into account the increment from geological and technical measures for the candidate well;
4. Launching the calculation of the HDM;
5. Assessment of the potential for an increase in oil production rate, additional production for the forecast period, the nature of the rate of water cut and the dynamics of reservoir pressure.

To integrate a multidimensional statistical model for calculating the liquid flow rate obtained using linear discriminant analysis, a Python script has been developed that allows taking into account the obtained dependencies in the Roxar Tempest More hydrodynamic simulator.

The developed mathematical models of the increase in fluid flow rate from workover measures are entered into the program code of the script. The variables of the mathematical model refer to the vectors of the values of the simulation model. The script takes into account the static indicators (thickness, compartmentalization, net-to-gross sand ratio, porosity, permeability, fluid properties, etc.) entered in a tabular form in the simulator, and the dynamic performance of the well read by the script at the time of forecasting (reservoir and bottomhole pressure, current flow rate liquid, water cut). As a result, this makes it possible to obtain a forecast of the increase in the liquid flow rate from the event at any time, and then to assess the technological efficiency of the event in the long term.

Thus, when using LDA, the algorithm for predicting additional production can be summarized as follows:

1. Determination of the candidate well and the date of the event;
2. Entering static parameters for the well into the hydrodynamic simulator (net oil pay, porosity, skin factor, etc.) in tabular form;
3. Launching the calculation of the HDM;
4. Determination of the dynamic parameters of the well (current reservoir pressure, current fluid flow rate) on the date of the event in automatic mode using a script;
5. Calculation of the increase in fluid flow rate from geological and technical measures according to the previously obtained LDA dependencies in automatic mode using a script.

According to formula (4), a linear discriminant function is calculated, which maximally separates objects into groups of more and less promising workover measures (the boundary value of the increase in fluid flow rate is 8 m$^3$/day). In this formula, the script reads the parameters of fluid flow rate ($q_l$) and reservoir pressure ($P_{res}$) from the hydrodynamic model at the time of the forecast. The parameters of the oil-saturated thickness ($h_i$), porosity coefficient ($\phi$) and skin factor (S) are entered in a tabular form:

$$Z = -0.39 \cdot q_l + 0.27 \cdot P_{res} - 0.1 \cdot h_i + 0.26 \cdot \phi + 0.07 \cdot S - 6.48. \quad (4)$$

According to the formula (5), the probability of attributing workover measures to a promising class is calculated (an increase in fluid flow rate of more than 8 m$^3$/day):

$$P(Z) = -0.015 \cdot (Z)^3 + 0.021 \cdot (Z)^2 + 0.34 \cdot (Z) + 0.47. \quad (5)$$

According to the formula (6), the value of the increase in fluid flow rate is calculated:

$$\Delta q_l = 12.35 \cdot (P(Z)) + 3.82. \quad (6)$$

6. Calculation of further dynamics of technological parameters of the well in the hydrodynamic model and determination of additional oil production.

As a result, by integrating the LDA model and geological and hydrodynamic modeling, it is possible to calculate the increase in the flow rate of liquid and oil from workover measures in an automatic mode. It should also be noted that geological and hydrodynamic modeling makes it possible to assess additional oil production from geological and technical measures, the dynamics of reservoir pressure and water cut rates after workover, and well interference (Figures 5–6).

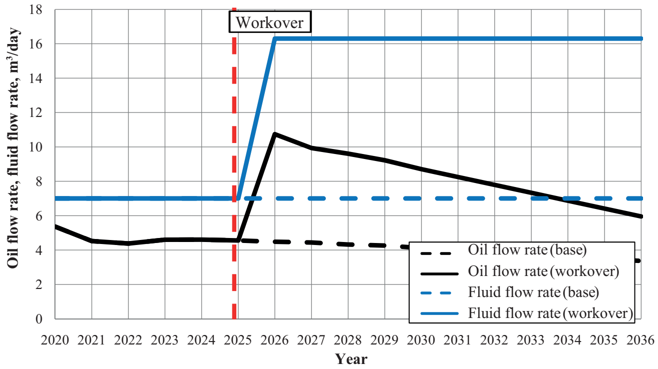


*Fig. 5. Assessment of the effect of workover measures using the proposed method*

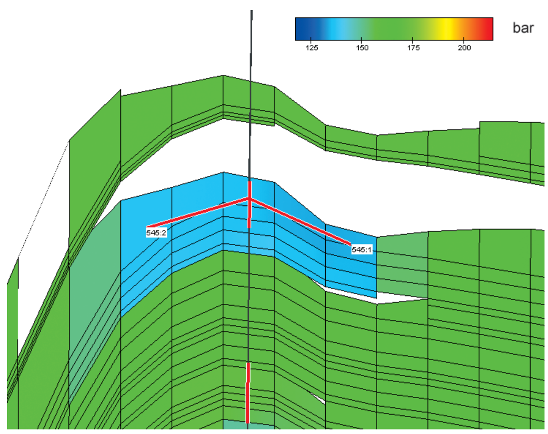


*Fig. 6. Assessment of changes in reservoir pressure after workover measures*

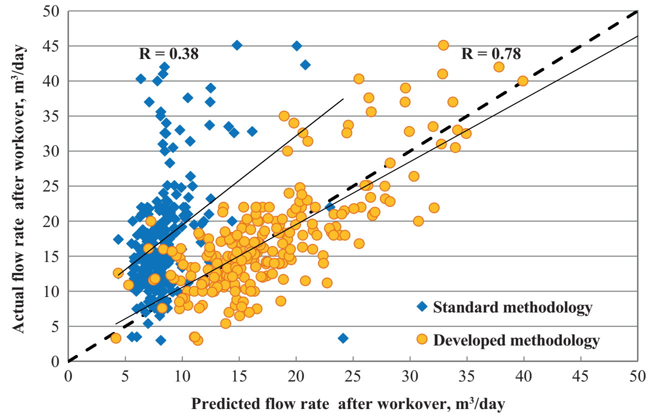


*Fig. 7. Comparison of the forecast accuracy of the standard methodology and the developed methodology for predicting the increase in fluid flow rate after RB*

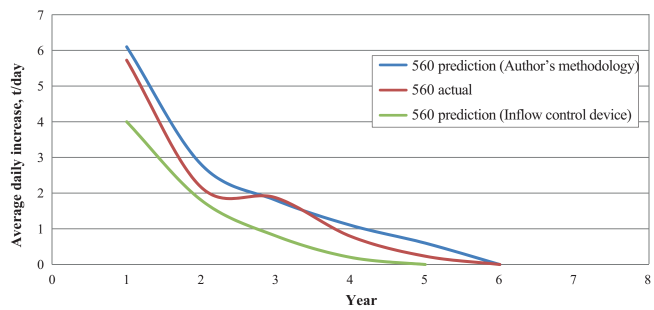


*Fig. 8. Comparison of the forecast of the standard methodology and the developed methodology with the actual data of the average daily increase in oil production by years*

## Results

The developed methodological approach includes a combination of several methods for predicting the increase in the flow rate of liquid, oil and additional production. The combination of statistical and mathematical forecasting methods can significantly increase the predictive reliability of the effects from geological and technical measures. As part of the study, a script has been developed that automatically calculates the effects of radial drilling, which significantly reduces time costs and enables quick assessment of the measure effectiveness.

As a result of the implementation of the methodology, using the example of radial drilling technology, it was possible to increase the predicted reliability of the increase in fluid flow rate, as well as the assessment of additional production (Figures 7–8).

Figure 8 shows a comparison of the results of the forecast of the average daily increase in oil production versus the actual data according to the existing and proprietary methodology. Based on the analysis, it can be seen that the existing methodology significantly underestimates the effect of the workover event relative to the actual effect, both in terms of additional oil production (32%) and in terms of the effect duration. Due to the underestimation of the potential of the candidate well, there is a possibility of abandoning the event and, as a consequence, a decrease in the final oil recovery factor and the efficiency of development in general.

The proprietary methodology repeats with greater accuracy the actual effect of the workover event, although it showed a somewhat overestimated result, while the deviation in additional oil production does not exceed 5%. The combination of statistical and hydrodynamic modeling makes it possible to reduce uncertainties and reduce the shortcomings of existing techniques by combining methods at different stages of forecasting. To refine the machine learning models, the parameters used are physically substantiated using statistical analysis (Student's t-test, linear discriminant analysis). To reduce the time of recording events in the hydrodynamic model and reduce the uncertainties associated with the method of modeling various workover measures on the hydrodynamic model, a developed script is used that allows you to quickly enter data into geological and hydrodynamic models, as well as calculate the increase in fluid flow rate taking into account machine learning models that take physical and technological parameters. The script allows calculation of the effect in automatic mode, thereby reducing the time spent by 2.5 work hour or even more.

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