ISSN 2712-8008
Volume / Том 25 №1 2025
Journal Homepage: http://vestnik.pstu.ru/geo/

Perm Journal of Petroleum and Mining Engineering

GEOLOGY, PROSPECTING, EXPLORATION AND EXPLOITATION OF OIL AND GAS FIELDS

UDC 622.276
Article / Статья

Application of Machine Learning Algorithms for Enhanced Modeling of a Carbonate Reef Reservoir

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Применение алгоритмов машинного обучения для совершенствования моделирования карбонатного рифового резервуара

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Received / Получена: 30.09.2024. Accepted / Принята: 05.12.2024. Published / Опубликована: 24.02.2025

Keywords:
carbonate reservoir, waterflood system, high-permeability intervals, machine learning, random forest, gradient bousting, support vector method, sensitivity analysis.

The development and modeling of carbonate reservoirs with complex structure is an actual task. In conditions of high heterogeneity of reservoir properties due to the peculiarities of formation, frequent change of sedimentation cycles and the presence of diagenetic transformations, there is a high degree of uncertainty in the modeling process and, as a consequence, in the forecast of development indicators. Underestimation of the influence of diagenetic processes on changes in filtration-capacitance properties can have a critical impact on the organization and management of the waterflood system. When studying the geological structure of the Alpha field, intervals of highly permeable reservoirs (up to 18 Darcies) were identified. This study proposes an approach to identify such intervals in order to refine the dynamic model of the field based on machine learning methods. The paper compares the following algorithms: gradient bousting, random forest and support vector method. Based on the results of the study, the optimal algorithms were identified that allow predicting high permeability intervals with a high degree of accuracy. To improve model adaptation to the field development history, it is suggested to use a model trained on core and geophysical well survey data. To take into account the risks associated with highly permeable intervals, when drilling new wells, it is recommended to use a model trained only on geophysical well tests. In this paper, sensitivity analysis was performed when specifying properties for highly permeable intervals - absolute permeability and relative phase permeabilities. The permeability cube of the dynamic model was updated, the model was adapted and calculations on waterflood system optimization were performed. Based on the predictive analysis on the model with highly permeable intervals, a number of measures were proposed to optimize the development system to reduce the risk of water breakthrough in highly permeable intervals. According to the results of the forecast calculations, these measures will provide additional 750 thousand m^3 of oil.

Ключевые слова:
карбонатный резервуар, система заводнения, высокопроницаемые интервалы, машинное обучение, случайный лес, градиентный бустинг, метод опорных векторов, анализ чувствительности.

Разработка и моделирование карбонатных резервуаров сложного строения является актуальной задачей. В условиях высокой неоднородности свойств коллектора, обусловленной особенностями формирования, частой сменой циклов осадконакопления и наличием диагенетических преобразований, возникает высокая степень неопределенности в процессе моделирования и, как следствие, прогноза показателей разработки. Недоучет влияния диагенетических процессов на изменение фильтрационно-емкостных свойств может оказать критическое влияние на организацию и управление системой заводнения. При изучении геологического строения месторождения Альфа выявлены интервалы высокопроницаемых коллекторов (до 18 Дарси). В рамках данного исследования предложен подход выделения подобных интервалов с целью уточнения динамической модели месторождения на основе методов машинного обучения. В работе проведено сравнение следующих алгоритмов: градиентный бустинг, случайный лес и метод опорных векторов. По результатам исследования выявлены оптимальные алгоритмы, позволяющие с высокой степенью точности прогнозировать интервалы высокой проницаемости. Для улучшения адаптации модели по истории разработки месторождения предлагается использовать модель, обученную по данным керна и геофизических исследований скважин. Для учета рисков, связанных с высокопроницаемыми интервалами, при бурении новых скважин рекомендуется использовать модель, обученную только по геофизическим исследованиям скважин. В работе выполнен анализ чувствительности при задании свойств для высокопроницаемых интервалов – абсолютная проницаемость и относительные фазовые проницаемости. Выполнено обновление куба проницаемости динамической модели, адаптация модели и расчеты по оптимизации системы заводнения. На основе прогнозного анализа на модели с высокопроницаемыми интервалами предложен ряд мер по оптимизации системы разработки для снижения рисков прорыва воды в высокопроницаемых интервалах. По результатам прогнозных расчетов эти меры позволят дополнительно получить 750 тыс. $м^3$ нефти.

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Please cite this article in English as:
Krivoschekov S.N., Kochnev A.A., Putilov I.S., Shirinkin D.O., Botalov A.N., Ozhgibesov E.S., Chalova P.O. Application of machine learning algorithms for enhanced modeling of a carbonate reef reservoir. *Perm Journal of Petroleum and Mining Engineering*, 2025, vol.25, no.1, pp. 9-20. DOI: 10.15593/2712-8008/2025.1.2

Просьба ссылаться на эту статью в русскоязычных источниках следующим образом:
Применение алгоритмов машинного обучения для совершенствования моделирования карбонатного рифового резервуара / С.Н. Кривощеков, А.А. Кочнев, И.С. Путилов, Д.О. Ширинкин, А.Н. Боталов, Е.С. Ожгибесов, П.О. Чалова // Недропользование. – 2025. – Т.25, №1. – С. 9–20. DOI: 10.15593/2712-8008/2025.1.2

Introduction

Carbonate reef reservoirs are characterized as a complex geological structure including caverns, fractures, and widespread secondary alterations. Lithologic and facies heterogeneity in such reservoirs is caused by the feautures of their formation, frequent changes in sediment accumulation cycles and the diagenetic transformations. The most commonly encountered secondary transformations include the fractures formation, leaching, dolomitization, and recrystallization. These processes are crucial in determining the capacitive and filtration properties [1, 2].

The processes occur with varying degrees of intensity and can significantly affect the field development. Cementation, dolomitization, and leaching directly influence changes in porosity and permeability [3, 4]. The formation of secondary caverns and fractures contributes to a considerable improvement of reservoir properties and increases well productivity, however, on the other hand, these processes often cause the premature water breakthroughs [5-8]. Underestimating these processes, especially leaching, can be critical in waterflooding processes and managing water cut [9-11]. The influence of leaching and fracturing on waterflooding efficiency is described in paper [12]. Another important task is to take diagenetic changes into account when creating static and dynamic models of the field and assessing the reserves [13]. The work proposes a methodology for constructing a permeability cube considering cavernosity based on the calculation of secondary porosity using density and neutron logging data, as well as geostatistical modeling. This methodology has successfully reproduced the development history of the field on the model. In work [14], the approach based on the integration of multiscale data (seismic, core, fracture model) is described. Then, an automatic algorithm is proposed that enables the creation of complex carbonate reservoir models. In paper [15], highly permeable intervals is studied and modeled. They were selected according to core data (permeability > 350 mD) and well logging. The modeling results allowed us to reproduce the development history considering the influence of waterflooding. The authors [16] point out the relevance of identifying and modeling highly permeable intervals. The connectivity of highly permeable bodies is one of the most important parameters, which can be determined by using an integrated approach considering the core sampling data, thin rock section, geophysical well logging and production data. A strong correlation is noted between electrical logging methods and highly permeable intervals.

In research [17] it is emphasized that permeability modeling in carbonate reservoirs of complex structure is a challenging task. A method based on machine learning techniques (clustering) has been proposed for predicting highly permeable zones.

Machine learning technologies are being actively implemented in the oil and gas industry to solve many different problems. The technologies enable the automation of routine processes, reduce the subjectivity of the human factor and facilitate the implicit relationships between parameters. Today, technologies are being introduced at all stages of a project, from geological exploration and development to the recovery and transportation of products [18–21].

Machine learning is widely used to forecast reservoir properties by integrating geophysical well surveys and seismic exploration results [22, 23]. Forecasting the reservoir properties and petrophysical types is one of the most important tasks [24, 25].

Table 1

Reservoir properties

Layer	Parameter	Average	Median	Min.	Max.
D_3fm_1(el1)	k, mD	86.05	7.55	0.1	9058.2
	φ, %	7.5	6.95	0.4	21.2
D_3fm_1(el3)	k, mD	128	2.75	0.1	18143
	φ, %	6.45	6.15	0.9	29.6

In work [26], the potential application of algorithms for assessing the saturation characteristics of layers is described. The gradient boosting algorithm has been successfully used to identify facies based on logging curves [27]. A number of studies describe the possibility of using machine learning for lithologic distinction based on logging results [28, 29] and for correlating borehole sections [30].

Many studies are focused on developing methodologies for the classification of carbonate reservoirs using machine learning methods [31, 32].

A number of works are aimed at forecasting permeability, including carbonate reservoirs [33]. The importance of reliable permeability forecast in the context of high reservoir heterogeneity is emphasized. In the work [34], the use of a graph-based clustering algorithm with several variants is proposed for permeability prediction based on well logging data.

In this paper, a comparative analysis of classification algorithms for predicting highly permeable intervals will be performed. Based on the classification results for the wells, intervals with abnormally high permeability will be identified. Subsequently, interpolation will be performed over the cube volume.

Multivariate modeling will be performed for the obtained intervals to assess the sensitivity of parameters on the quality of model adaptation. Based on the modeling results, the forecast of technological indicators will be performed and solutions for optimizing injection considering highly permeable intervals will be proposed.

Geology

The object of the study is the Alpha field located within the Timan-Pechora province.

The oil-bearing capacity of the Alpha field is associated with the Lower Famennian reef complexes, formed sequentially on top of each other during one Zadonsky Sequence and three Yeletsky Sequences of reef-building. The oil-bearing reservoirs include both carbonate sediments of the reef facies and backreef shelf sediments.

The lithologic description of the productive interval is based on the core sample obtained from drilling twelve wells. The reef structure sediments are represented by limestones and secondary medium-grained dolomites with relics of detrital-algal limestones, which are secondarily clotted and lump-like, consisting of biogenic material. The backreef shelf deposits are composed of gray, dark gray, and light brown microbial-detrital limestones that are finely cryptocrystallined and dolomitized, with inclusions of argillites (up to 15 %).

The reservoir properties are presented in Table 1.

The carbonate reservoir is characterized by a complex type of void space, which consists of intergranular, cavernous and fractured voids. The formation of the void space is highly influenced by various secondary changes in rocks. The high degree of secondary transformations of limestones can lead to the formation of highly productive interlayers with anomalous properties, referred to as highly permeable intervals – supercollectors.

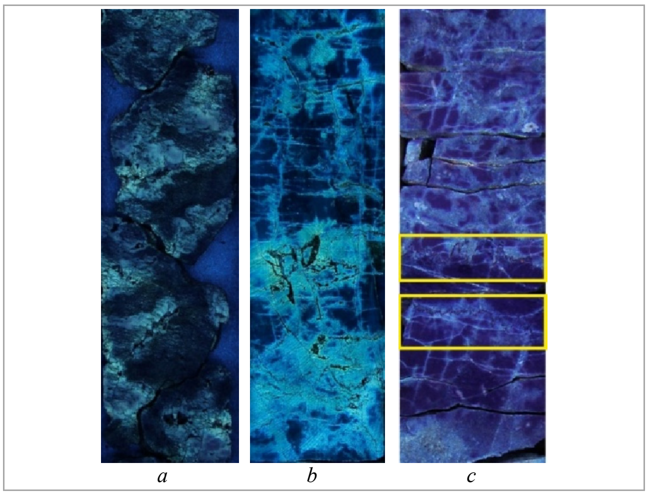


Fig. 1. Types of cavernous voids in the Alpha deposit:
a – caverns; *b* – carstified fractures;
c – carstified stylolite seams (with yellow)

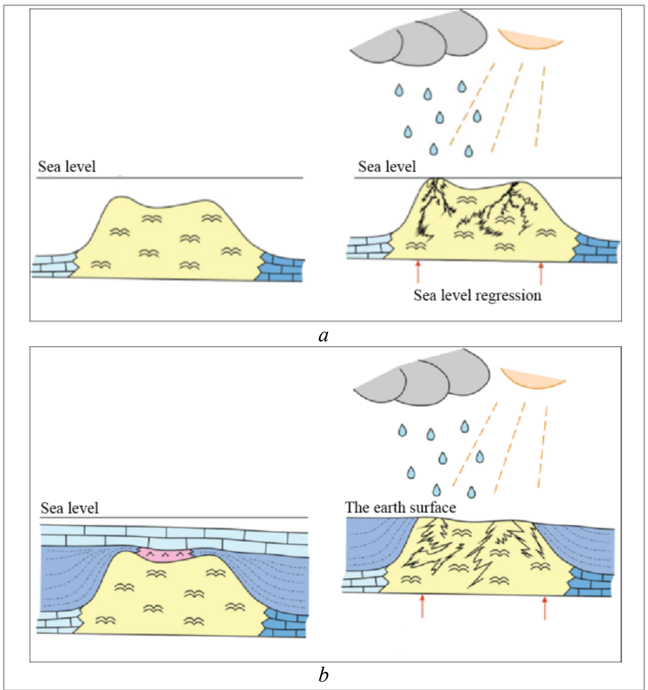


Fig. 2. Mechanisms of karst processes formation:
a – during sea level regression; *b* – during erosion of overlying sediments

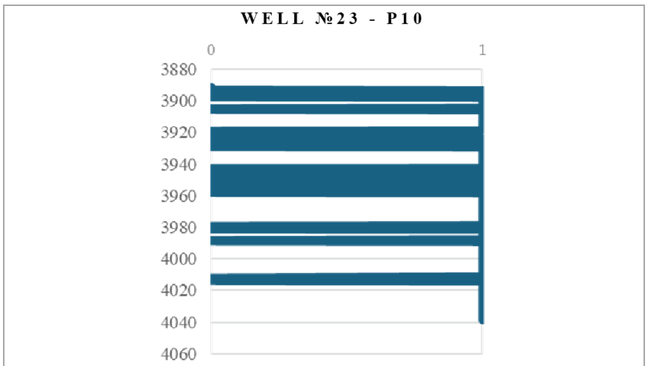


Fig. 3. Supercollector intervals
for well No. 23. Implementation of P10

The leaching process in carbonate rocks is one of the dominant factors of void space transformation. During the study of core samples, it was found that the rifogenic rocks of the Lower Famennian age in the Alpha field have a complex void structure both laterally and vertically. The complexity is caused by the significant distribution of caverns, karst fractures and stylolite seams within the rocks (Fig. 1), as well as the replacement of reef-forming limestones by secondary dolomites.

The processes of dissolution and replacement under surface or near-surface conditions could have played a key role in the formation of karst voids and secondary dolomites.

In this context, two theories of karst voids formation have been proposed. The first theory suggests that microbial limestones accumulated on the shallow shelf and were repeatedly exposed at different intervals of the Famennian time as a result of sea level lowering. Red, reddish-pink and reddish-brown inclusions were found in the core of the reefogenic Zadon-Yeletsky sediments, which may indicate the presence of iron oxides in the rocks. These oxides are indicators of oxidative conditions and arid climate. These compounds could have been transported by freshwater in the form of colloids and solutions, accumulating on the reef body. Meteoric waters may have played a crucial role in the formation of karst voids within the reefogenic rocks of the Alpha reservoir (Fig. 2).

According to the second theory, karst voids could have formed as a result of rock dissolution by atmospheric waters infiltrating through the rocks during erosional processes that likely occurred at a later stage. This is supported by the presence of an unconformity higher up the stratigraphic section between the Upper Devonian and Lower Carboniferous deposits, where the rocks of the Tournaisian Stage are completely eroded, while those of the Famennian Stage are partially eroded. This phenomenon is associated with the formation of the modern basin structure under conditions of tectonic compression within the fold system (see Fig. 2).

Materials and Methods

The initial data for the study includes well logging curves for eight wells, core and thin sections, and results of flowmetric tests. In work [35] analysis and integration of different-scale studies were performed. According to the results of the analysis, highly permeable intervals were identified with probabilities of P90, P50, and P10. The results of identifying the intervals were used as data labeling for training the model in the present work.

The research methods involve statistical data analysis and the use of machine learning algorithms to identify highly permeable intervals, as well as the application of reservoir dynamic modeling approaches.

Highly permeable intervals marked as target variables for classification were selected. The models were trained on two different datasets: core study results combined with logging data; and logging data alone. The core study results included rock porosity and permeability. The logging data included curves that have the highest correlation with the core permeability values: porosity coefficient curves determined by acoustic (KPA), density (KPD), and neutron (KPN) methods, as well as the effective porosity coefficient defined by nuclear magnetic logging (CMFF); permeability coefficient curves defined using nuclear magnetic resonance based on the SDR model (KSDR), as well as permeability coefficients calculated using the Timur-Coates model (KTIM); the curve representing the oil saturation fraction of the total void volume (FOIL);

Table 2

Comparison of algorithm metrics (training on core and logging data)

Metric/ algorithm	Gradient Boosting	Random forest	Support Vector Machine
Accuracy	0.98	0.97	0.96
Precision	0.99	1	0.97
Recall	0.96	0.91	0.91
F1 Score	0.97	0.95	0.94
ROC AUC	1	1	0.98

Table 3

Comparison of algorithm metrics (training on logging data)

Metric/ algorithm	Gradient Boosting	Random forest	Support Vector Machine
Accuracy	0.97	0.97	0.97
Precision	1	1	0.98
Recall	0.9	0.9	0.91
F1 Score	0.95	0.95	0.95
ROC AUC	0.97	0.97	0.97

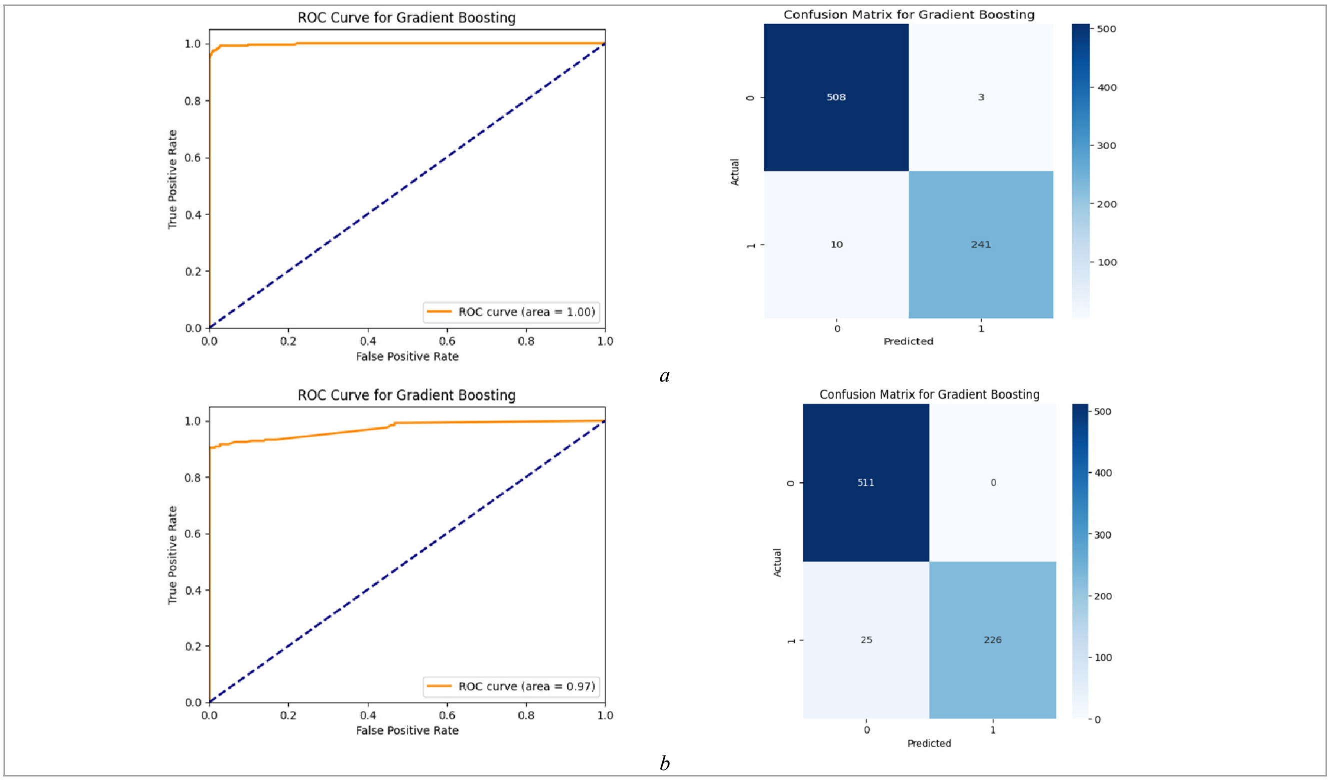


Fig. 4. ROC-curve and confusion matrices for P10 implementation:
a – training on core and logging data; *b* – training on logging data

and fracture density from FMI data. The dataset includes core and logging study results for eight wells in the Alpha field.

Gradient boosting, random forest and support vector method are chosen as machine learning algorithms. Using these algorithms is conditioned by their high degree of successful application in various fields, including the reservoir properties forecast [36–38].

To assess the models quality, confusion matrices were constructed, and standard metrics for assessing classification models were calculated: Accuracy, Recall, Precision, F1-score, and ROC-AUC. These classification quality metrics are used to assess the effectiveness and performance of classification algorithms. They provide insights into how effectively the model can distinguish between objects of different classes [39–43].

The distribution of highly permeable intervals in the interwell space was based on mathematical methods of geostatistics, which are embedded in the stochastic indicator modeling tools in the RMS 13.1.1 software from AspenTech company. The module for stochastic distribution of parameters in the volume is called Petrophysical Modeling and is based on variogram analysis. For a more accurate distribution, the total cube of secondary carbonate changes was used as a trend, specifically the sum of fracturing, leaching, dolomitization, and recrystallization.

At the next stage, a multivariate modeling and statistical analysis approach was adopted to assess the influence of supercollector parameters on the hydrodynamic model adaptation results.

To obtain the permeability distribution in the supercollector intervals, the hydraulic flow unit (FZI) calculation technique was applied [44]. Core samples were classified using the DRT method [45] based on a designated formula (1) to isolate samples with similar filtration characteristics after applying the formula (2).

$$FZI = \frac{0{,}0314\sqrt{\dfrac{k}{\varphi}}}{\dfrac{\varphi}{1-\varphi}}, \qquad (1)$$

where k – permeability coefficient, mD; φ – porosity coefficient, unit fractions.

$$DRT = 2\ln\left(FZI\right) + 10{,}6. \qquad (2)$$

Subsequently, three options for categorizing core samples based on their filtration characteristics were proposed, and the best option was determined using the Student's t-test, based on the average values comparison of different samples (3).

$$t = \frac{M_1 - M_2}{\sqrt{m_1^2 + m_2^2}}, \qquad (3)$$

where M_1 is the arithmetic mean of the first compared category; M_2 is the arithmetic mean of the second compared category; m_1 is the standard error of the first arithmetic mean; m_2 is the standard error of the second arithmetic mean.

Then, a history matching and forecasting of the development indicators were carried out. The analysis of the obtained results was performed and optimization measures were proposed.

Results

At the first stage, the forecast of highly permeable intervals was carried out, identified with a probability of P10 [35]. Such identification allows for maintaining the best balance in the sample with the ratio of super collector to regular collector. Fig. 3 below shows an example of well No. 23 with selected super collector intervals. For this well, the largest number of super collector intervals has been identified.

The results of the calculations are presented in Tables 2 and 3, and the metrics were assessed on test samples.

The best metric values are observed for the gradient boosting algorithm. This algorithm, with a high degree of accuracy, allows forecasting the presence of super collector intervals both for the dataset that includes core and logging data, and for the logging data alone.

Fig. 4 shows the ROC-curve graphs and confusion matrices for the selected optimal algorithms.

The prediction of intervals with P10 probability was performed due to the most balanced sample and demonstrated high accuracy of the obtained model.

At the next stage, a predictive model was built to identify the super collector with a P50 estimation that best reflects the filtration processes in the reservoir [35]. Fig. 5 shows an example for well No. 23 with selected super collector intervals.

The computational results are presented in Tables 4, 5, with metrics assessed on test samples.

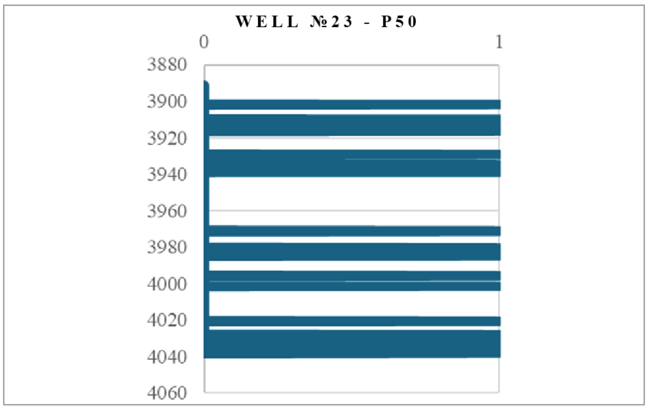


Fig. 5. Super collector intervals for well No. 23. Implementation of P50

Table 4

Comparison of algorithm metrics (training on core and logging data)

Metric/ algorithm	Gradient Boosting	Random forest	Support Vector Machine
Accuracy	0.99	0.98	0.98
Precision	0.92	0.71	0.5
Recall	0.69	0.31	0.25
F1 Score	0.79	0.43	0.33
ROC AUC	0.98	0.95	0.96

Table 5

Comparison of algorithm metrics (training on logging data)

Metric/ algorithm	Gradient Boosting	Random forest	Support Vector Machine
Accuracy	0.99	0.99	0.98
Precision	1	1	0.67
Recall	0.44	0.56	0.38
F1 Score	0.61	0.72	0.48
ROC AUC	0.84	0.85	0.94

The best metric values are observed for the gradient boosting algorithm when using a set of core and logging data. This algorithm, with a high degree of accuracy, allows for the prediction of super collector intervals. However, when the model is trained only on logging data, the Recall and F1 Score metrics significantly decrease. For this case, the random forest algorithm proves to be more effective.

Fig. 6 shows the ROC-curve graphs and confusion matrices for the selected optimal algorithms.

Fig. 6 indicates that the predictive model for the training variant on core and logging data is applicable for classification, while the variant trained only on logging data shows insufficient effectiveness in predicting the super collector. Additionally, there is a notable sample imbalance, which leads to a training and prediction imbalance in favor of the standard collector.

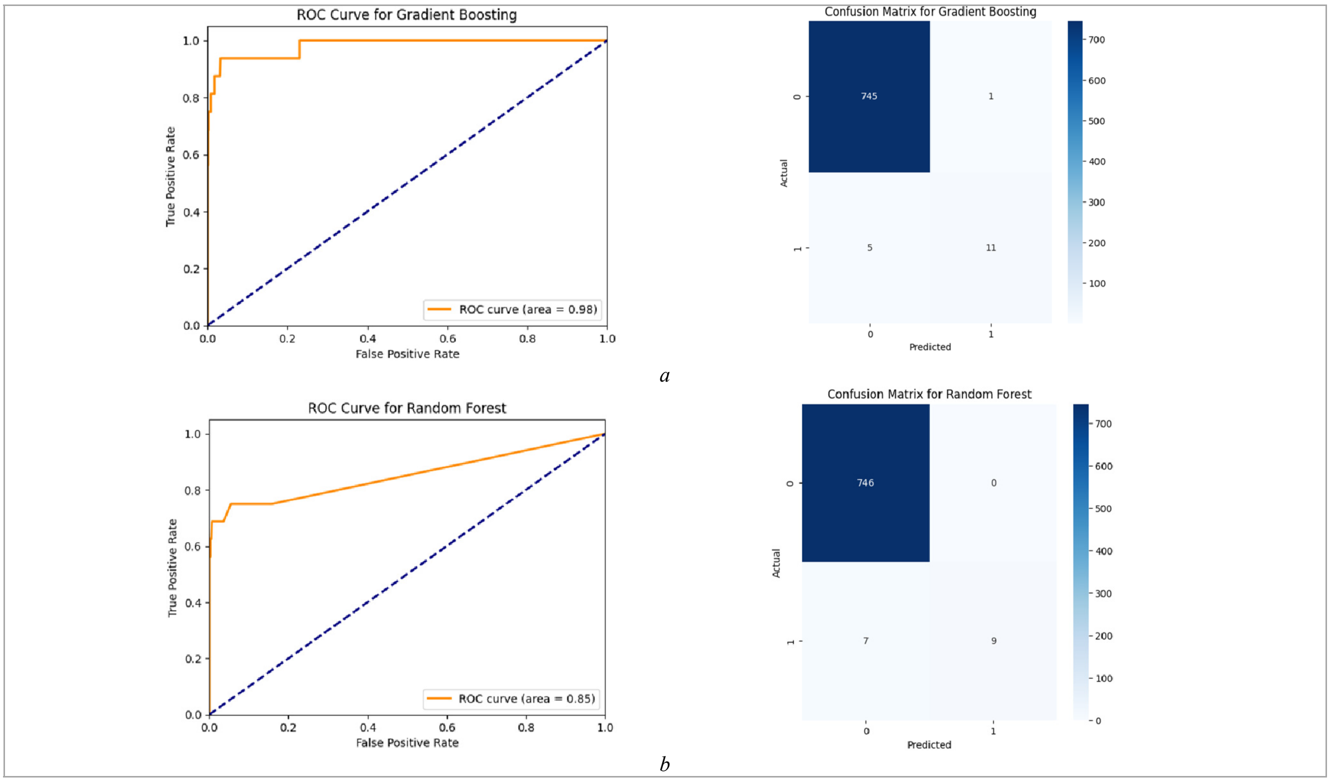


Fig. 6. ROC-curve and confusion matrices for P50 implementation: *a* – training on core and logging data; *b* – training on logging data

Using the model trained on core and logging data (option P50) is proposed for predicting the super collector as part of the model adaptation task. The model trained on logging data (option R10) will be used to assess the risks associated with the super collector when drilling new wells. According to the results of logging studies conducted prior to perforation, the model will allow predicting all possible intervals of the super collector, and in the case of injection wells, consider the option of refraining from perforating highly permeable intervals.

Further, using stochastic methods of geologic parameters distribution in three-dimensional space, interpolation of super collector intervals was performed in the interwell space. To ensure the most accurate distribution and alignment with the reservoir geology, the total cube of secondary transformation development was used as a trend (Fig. 7).

As a result, a three-dimensional dataset of super collector development within the reservoir volume was obtained and used for further research (Fig. 8).

At the next stage, the approaches for transition from a discrete cube of super collector development intervals to a distribution of absolute permeability were developed, which will subsequently be used for calculations in the hydrodynamic model. It was decided to distribute permeability in the standard collector intervals by the standard way according to the petrophysical relationship between permeability and porosity identified in all standard-sized core samples (Fig. 9). In the highly permeable intervals (super collectors) various methods were used to set the permeability. After, each option was calculated in the hydrodynamic model, and the convergence of actual development indicators during the reproduction of its history was compared to assess the extent of influence on calculation results when using different approaches for setting permeability.

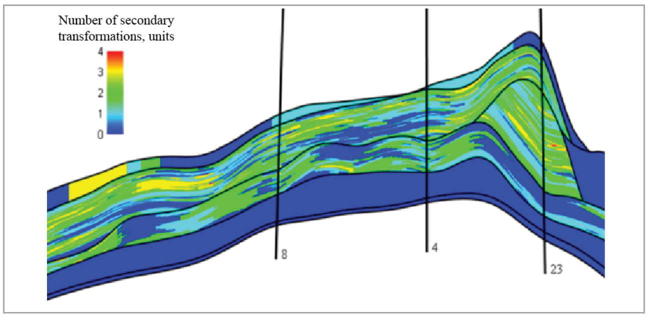


Fig. 7. The total cube section of secondary development transformations in the reservoir volume

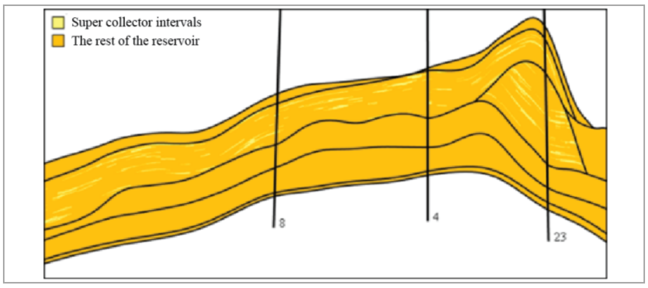


Fig. 8. Cross-section of the final development cube of the supercollector within the reservoir volume, based on the P50 model

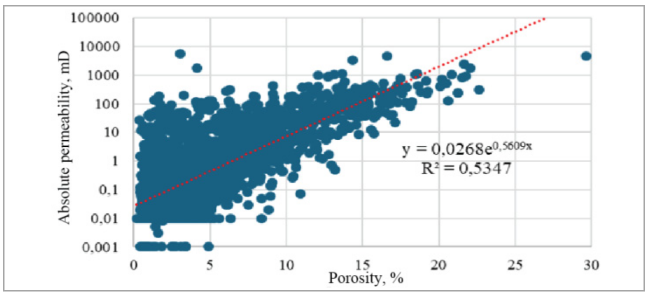


Fig. 9. Standard petrophysical "permeability-porosity" dependence for all standard-sized core samples

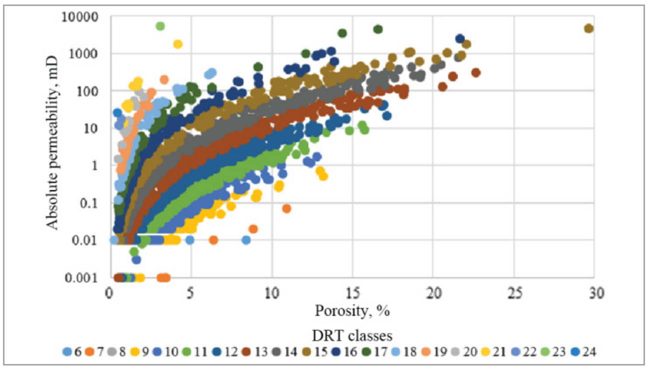


Fig. 10. Classification of DRT core images

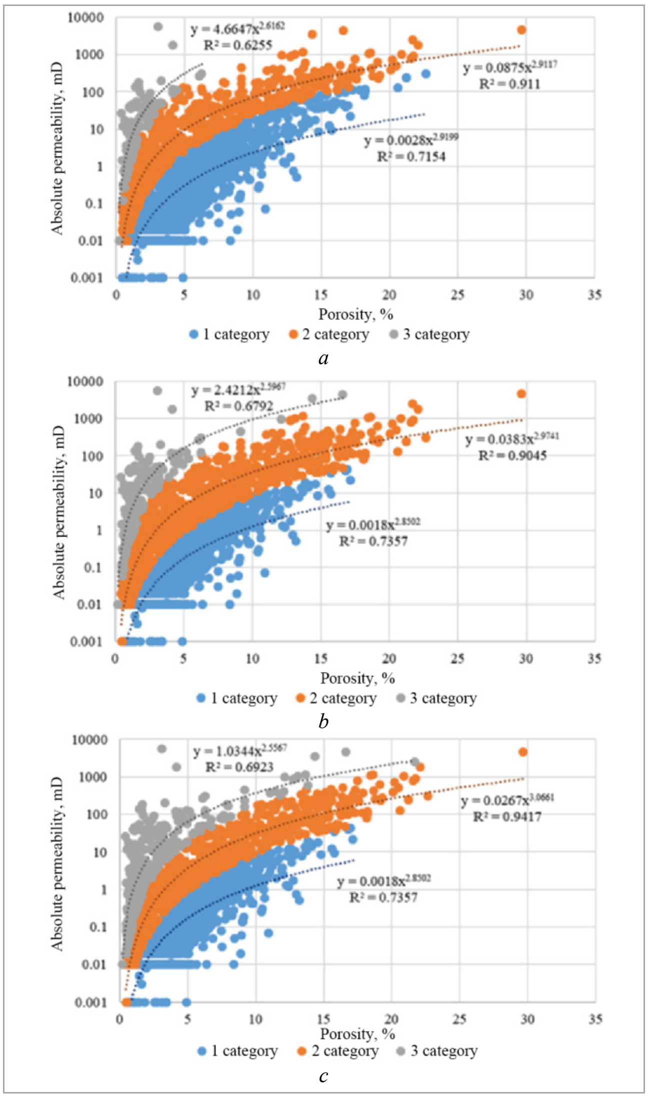


Fig. 11. Variants of new petrophysical dependences:
a – 1st option; *b* – 2nd option; *c* – 3rd option

Table 6

Comparison of Student's *t*-test for permeability in different classification options of core samples

Category	Average 1	Average 2	*t*-criterion	*p*-value
1st option				
1st–2nd	3.75	78.06	-8.78	0.000000
2nd–3rd	78.06	102.16	-0.63	0.526388
2nd option				
1st–2nd	0.84	49.66	-7.72	0.000000
2nd–3rd	49.66	126.86	-3.05	0.002346
3rd option				
1st–2nd	0.84	44.98	**-7.48**	**0.000000**
2nd–3rd	44.98	108.49	**-3.12**	**0.001874**

The following methods are chosen to determine the permeability in the super collector intervals:

– by one number corresponding to the maximum value determined from standard core samples;

– by one number corresponding to the maximum value determined from full-sized core samples;

– through refined petrophysical "permeability – porosity" dependences obtained by petrophysical analysis;

– through the standard petrophysical "permeability – porosity" dependence determined from all standard-sized core samples (see Fig. 7).

The DRT petrotyping approach was used to clarify the petrophysical dependence. For this purpose, the value of FZI (1) was calculated for each core sample. After that, the core samples were classified into different petrotypes according to the DRT classification using formula (2) (see Fig. 10).

Next, based on the DRT classes, the core samples were grouped in various ways into three scale classes in order to obtain petrophysical dependences that describe a sufficient range of core studies for the hydrodynamic model.

While exploring variations of DRT classes with different qualities of filtration and reservoir properties, a decision was made to focus on three categories that are characterized by the highest coefficients:

– 1st option: 1st category – 6th–13th DRT classes; 2nd category – 14th–17th DRT classes; 3rd category – 18–24th DRT classes (Fig. 11, *a*);

– 2nd option: 1st category – 6th–12th DRT classes; 2nd category – 13th–16th DRT classes; 3rd category – 17–24th DRT classes (Fig. 11, *b*);

– 3rd option: 1st category – 6th–12th DRT classes; 2nd category – 13th–15th DRT classes; 3rd category – 16–24th DRT classes (Fig. 11, *c*).

To determine the final distribution of core samples across categories, Student's *t*-test was calculated to identify the best classification in terms of porosity and permeability differentiation (Tables 6, 7).

As a result of comparing Student's *t*-test values a decision was made to use the 3rd option for distributing core samples into categories with the corresponding petrophysical dependences of "permeability – porosity" in further research.

In the next step, the final permeability cubes were calculated for each method of permeability setting in the super collector intervals. The average values for the super collector are presented in Table 8.

Subsequently, the obtained permeability distributions were loaded into the hydrodynamic model and the field development history was reproduced to compare the convergence between calculated and actual operation indicators. For more correct determination of reservoir potential at different permeability variants, calculations were carried out with limitation of wells by actual bottomhole pressure. The calculation results are presented after one iteration (Figs. 12, 13, Table 9).

In Figs. 12, 13 it can be observed that during the reproduction of the development history, the method of permeability setting in the super collector based on the petrophysical dependence for the third category demonstrates the best convergence with the historical trend. Therefore, the implementation of absolute permeability distribution will be used for further calculations.

Table 7

Comparison of Student's *t*-test for porosity under different options for classifying core samples

Category	Average 1	Average 2	*t*-criterion	*p*-value
		1st option		
1st–2nd	4.90	5.24	-1.83	0.067618
2nd–3rd	5.24	1.60	7.17	0.000000
		2nd option		
1st–2nd	4.67	5.51	-4.65	0.000003
2nd–3rd	5.51	2.06	8.57	0.000000
		3rd option		
1st–2nd	4.67	5.78	**-5.95**	**0.000000**
2nd–3rd	5.78	2.70	**9.58**	**0.000000**

Table 8

Average values for the super collector

Permeability setting method	Average value for super collector, mD	Average value for the whole model, mD
Maximum value for standard core samples	5.574	296.2
Maximum value for full-sized core samples	11.544	598.2
Petrophysical dependence for the 1st category	1.4	14.2
Petrophysical dependence for the 2nd category	40.1	15.1
Petrophysical dependence for the 3rd category	970.9	37.6
Standard petrophysical dependence	35.6	14.8

The high impact of different permeability setting methods on the dynamics of oil and fluid production in the super collector is noted. Thus, the difference between maximum and minimum accumulated liquid production was 19,690.7 thousand m^3, which is equal to 91.5 % of the actual production. The difference between maximum and minimum oil production amounted to 15,060.5 thousand meters^3, which is equal to 76.2 % of actual production. The water cut at the end of 2023 ranges from 10 to 46 % with the actual water cut of 11 %.

In previous calculations, average trends of relative phase permeabilities (RPP) were used for the whole core cloud (Fig. 14). At the next stage, the impact of the RPP curve shape on the hydrodynamic model calculations is assessed, using maximum and minimum trends for comparison.

The results of comparing the influence of the RPP curves shape in the hydrodynamic model when reproducing the development history are shown in Figs. 15–17 and Table 10.

Figs. 15–17 show that the RPP curves shape has a lesser influence on the calculation results compared to absolute permeability. Specifically, the range of variation in cumulative liquid production was 4.3 % relative to the average trend, the range of variation in cumulative oil production was 2.9 %, and water cut varied between 15 % and 19%. It is worth noting that by using the RPP with the maximum trend in the super collector intervals, it was possible to reduce the deviation in cumulative liquid production from 2.5 to 0.5 % and in cumulative oil production from 0.8 to 0.5 %. Therefore, this form of the RPP curve will be used for predicting calculations. Additionally, the use of the RPP curve with the maximum trend allows for a more conservative risk assessments of premature water breakthrough.

Due to the presence of highly permeable intervals and the strong mutual influence between production and injection wells, the results of the forecast calculations show breakthrough nature of the water cut, which emphasizes the need for planning additional geological and technical measures (GTM) to regulate the watering in wells of the field. The model created with standard methods does not capture these effects.

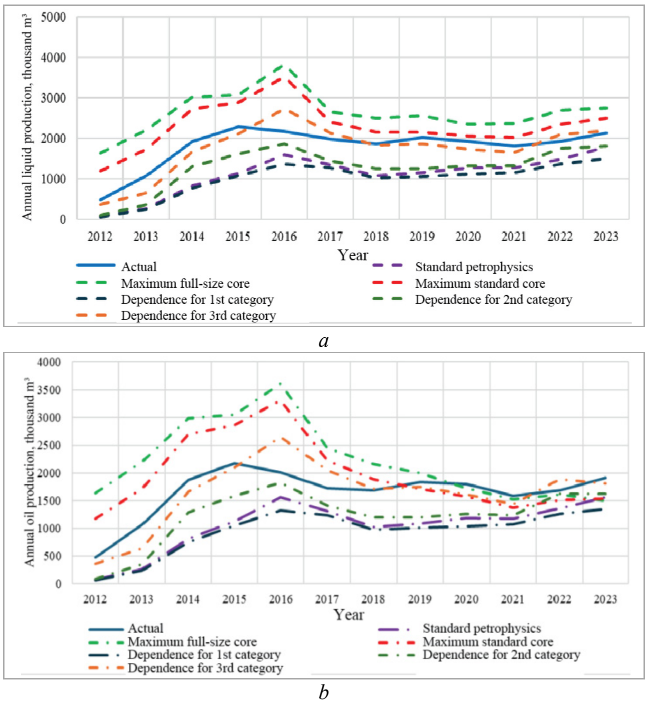


Fig. 12. Comparison of liquid (*a*) and oil (*b*) production dynamics under different permeability distribution options in the super collector when reproducing the development history in the hydrodynamic model

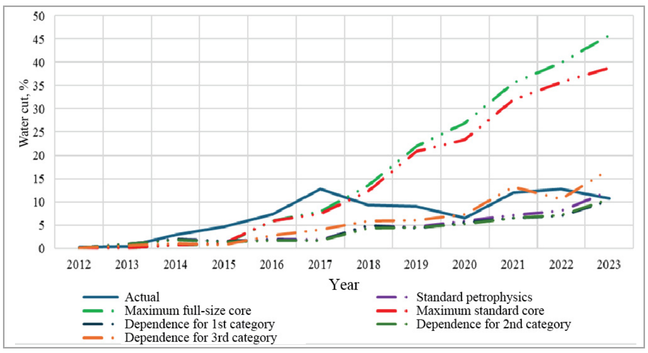


Fig. 13. Comparison of water cut change dynamics under different permeability distribution options in the super collector when reproducing the development history in the hydrodynamic model

Table 9

Comparison of accumulated indicators at different options of permeability distribution in a super collector when reproducing the development history in a hydrodynamic model

Method of permeability setting	Cumulative liquid production, th. m^3	Cumulative oil production, th. m^3	Deviation of cumulative liquid production from actual, %	Deviation of cumulative oil production from actual, %
Maximum value for standard core samples	31,586.6	26,401.9	-46.8	-33.5
Maximum value for full-sized core samples	27,612.5	23,533.0	-28.3	-19.0
Petrophysical dependence for the 1st category	11,895.8	11,341.5	44.7	42.6
Petrophysical dependence for the 2nd category	15,318.8	14,633.0	28.8	26.0
Petrophysical dependence for the 3rd category	**20,974.3**	**19,622.4**	**2.5**	**0.8**
Standard petrophysical dependence	13,184.7	12,491.6	38.7	36.8
Actual	21,516.3	19,773.1		

Table 10

Comparison of cumulative performance at different RPP in a super collector when reproducing the development history in a hydrodynamic model

Method of permeability setting	Cumulative liquid production, th. m^3	Cumulative oil production, th. m^3	Deviation of cumulative liquid production from actual, %	Deviation of cumulative oil production from actual, %
Petrophysical dependence for the 3rd category (average trend)	20,974.3	19,622.4	2.5	0.8
Maximum RPP trend	**21,398.8**	**19,874.1**	**0.5**	**-0.5**
Minimum RPP trend	20,505.8	19,313.2	4.7	2.3
Actual	21,516.3	19,773.1		

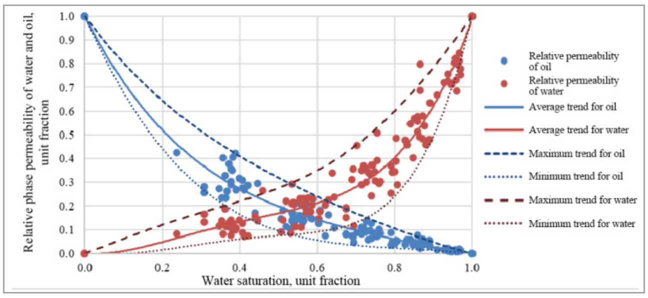


Fig. 14. Relative phase permeabilities for oil and water

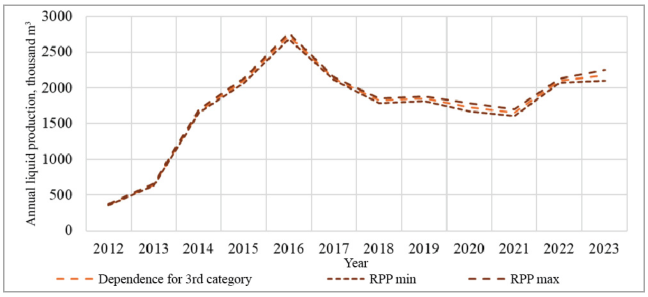


Fig. 15. Comparison of RPP curves shape influence in the hydrodynamic model on the liquid production dynamics

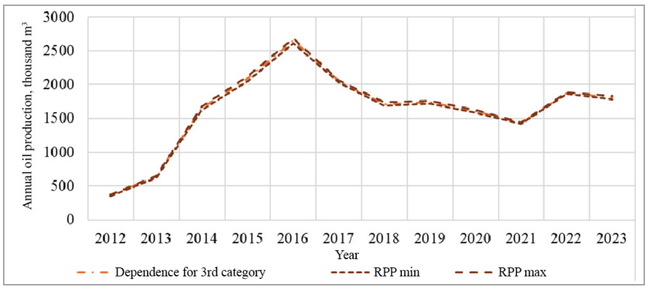


Fig. 16. Comparison of RPP curves shape influence in the hydrodynamic model on oil production dynamics

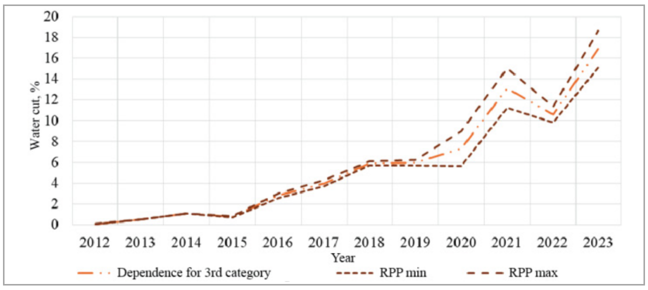


Fig. 17. Comparison of RPP curves shape influence in the hydrodynamic model on water cut dynamics

Analyzing the reservoir development system of the field, a set of measures was proposed to reduce the risks of premature water breakthroughs in production wells. It included performing repair and isolation works on wells with high water cut dynamics, carrying out re-perforation operations on a number of production wells in intervals not characterized by water breakthrough in the zones of secondary changes, etc.

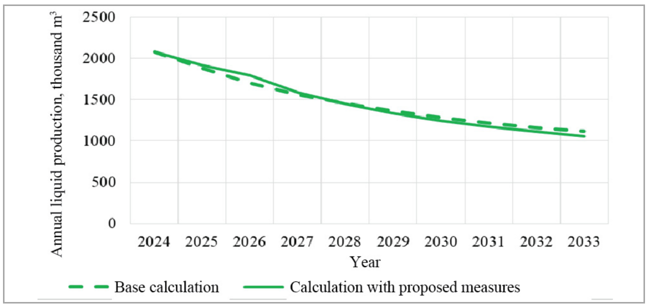
The results of forecast calculations are shown in Fig. 18 and Table 11.

In Fig. 18 and Table 11, it can be observed that as a result of the methodology for identifying and distributing super collectors in the geological-hydrodynamic model, as well as proposing various geological and technological measures aimed at correcting the current development system in the context of super collector intervals, it was possible to achieve a 10 % reduction in product water cut by 2034 and to increase oil production by 750,000 m^3, which, in turn, leads to an increase in the operation profitability.

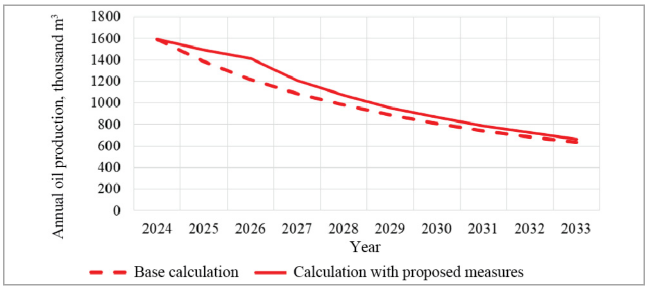
Table 11

Comparison of accumulated indicators over a 10-year forecast period under the basic development system and with additional measures aimed at interaction with the super collector

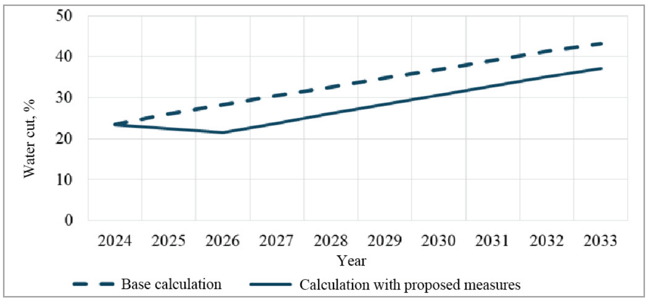
Method of permeability setting	Cumulative liquid production, th. m^3	Cumulative oil production, th. m^3	Water cut, %
Basic calculation	14,820.6	10,018.7	43.2
Calculation with proposed measures	**14,762.6**	**10,768.8**	**37.2**
Additional fluid production / change in water cut	–58	+750.1	-10



a



b



c

Fig. 18. Comparison of oil production dynamics (*a–c*) in the forecast under the basic development system and considering additional measures aimed at interaction with the super collector

Conclusion

The study proposes an approach for identifying highly permeable intervals based on machine learning algorithms. The most accurate algorithm for predicting the intervals is gradient boosting. To improve the model adaptation by development history data, a model trained on logging and core data (P50 implementation) is proposed for predicting highly permeable intervals. To account for risks, associated with highly permeable intervals when drilling new wells, it is recommended to use a model trained only on logging data (P10 implementation). Based on the analysis of logging data prior to perforation, the model can predict all possible super collector intervals. In the case of an injection well, it may serve as a basis for avoiding the perforation of highly permeable intervals.

Modeling of highly permeable intervals was carried out within the reservoir volume, with multiple variant forecasting conducted to refine the properties of model sections corresponding to highly permeable zones. The approach involved analysis of DRT core samples classification in combination with Student's *t*-criterion to determine the petrophysical dependence that best describes the correlation between porosity and permeability of super collector zones. After adjusting the model by development history data, the differences in cumulative liquid production were 2.5 %, while differences in cumulative oil production were 0.8 %. It was found that the absolute permeability of the super collector is the most significant parameter in model adaptation, whereas the relative permeability curves contribute minimally to the adaptation results. The application of relative permeability curves with maximum trend in the super collector intervals reduced the deviation of cumulative liquid production from 2.5 to 0.5 %, and cumulative oil production – from 0.8 to 0.5 %. Thus, the most conservative relative permeability curve was used for forecasting. Its influence was minimal due to the low current water cut of the field (less than 11 %), but at later stages of development the influence of the curve may become more significant.

Based on the predictive model analysis with highly permeable intervals, a series of measures are proposed to reduce the risks of water breakthrough in the intervals. According to forecasts, these measures will allow for an additional oil recovery of 750,000 m^3.

The approach presented in this study allows us to analyze and manage the development of a complex carbonate reservoir considering secondary changes in reservoir properties. It significantly improves the geologic accuracy of the history matching process and enables the forecasting of potential water breakthroughs due to the presence of the super collector.

References

1. Janjuhah H.T., Salim A.M.A., Ghosh D., Wahid A. Diagenetic process and their effect on reservoir quality in Miocene carbonate reservoir Offshore, Sarawak, Malaysia. *In Proceedings of the International Conference on Integrated Petroleum Engineering and Geosciences*. Singapore, 2016. DOI: 10.1007/978-981-10-3650-7_48
2. Farzaneh S.A., Dehghan A.A., Lakzaie A. Using diagenetic processes in facies modeling of a carbonate reservoir. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 2013, no. 35 (6), pp. 516-528. DOI: 10.1080/15567036.2010.504946
3. Riabokon E., Turbakov M., Kozhevnikov E., Poplygin V., Guzev M. Study of the influence of nonlinear dynamic loads on elastic modulus of carbonate reservoir rocks. *Energies*, 2021, vol. 14, no. 24. DOI 10.3390/en14248559
4. Huang Q., Liu W., Zhang Y., Shi S., Wang K. Progress of research on dolomitization and dolomite reservoir. *Advances in Earth Science*, 2015, no. 30 (5), 539 p. DOI: 10.11867/j.issn.1001-8166.2015.05.0539
5. Xu Z.X., Li S.Y., Li B.F., Chen D.Q., Liu Z.Y., Li Z.M. A review of development methods and EOR technologies for carbonate reservoirs. *Petroleum Science*, 2020, no. 17, pp. 990-1013. DOI: 10.1007/s12182-020-00467-5.
6. Shcherbakov A.A., Khizhniak G.P., Galkin V.I. Otsenka effektivnosti meropriiatii po intensifikatsii dobychi nefti (na primere mestorozhdenii Solikamskoi depressii) [Effectiveness evaluation of oil production stimulation measures (on the example of the Solikamsk depression fields)]. *Geologiia, geofizika i razrabotka neftianykh i gazovykh mestorozhdenii*, 2019, no. 2, pp. 70-73. DOI: 10.30713/2413-5011-2019-2-70-73
7. Erofeev A.A., Ponomareva I.N., Turbakov M.S. Otsenka uslovii primeneniia metodov obrabotki krivykh vosstanovleniia davleniia skvazhin v karbonatnykh kollektorakh [Evaluation of the application conditions for methods of processing well pressure recovery curves in carbonate reservoirs]. *Inzhener-neftianik*, 2011, no. 3, pp. 12-15.
8. Yang B., He J., Lyu D., Tang H., Zhang J., Li X., Zhao J. Production optimization for water flooding in fractured-vuggy carbonate reservoir-From laboratory physical model to reservoir operation. *Journal of Petroleum Science and Engineering*, 2020, no. 184, 106520 p. DOI: 10.1016/j.petrol.2019.106520

9. Zhao M., Xin X., Yu G., Hu R., Gong Y. Mechanistic Study and Optimization of High Water Cut Phase Management Strategies in Fracture-Vuggy Carbonate Reservoirs with Bottom Water. *Processes*, 2023, no. 11, 3135 p. DOI: 10.3390/pr11113135

10. Mahmood S., Salazar P., Zhao X., Pointing M., Sayed A. Waterflooding in giant carbonate reservoir; successes and challenges. *In Proceedings of the Abu Dhabi International Petroleum Exhibition and Conference*. Abu Dhabi, UAE, 2017. DOI: 10.2118/188532-MS

11. Su Z., Gao S., Li Z., Li T., Kang N. Integrated Waterflooding Effect Evaluation Methodology for Carbonate Fractured-Vuggy Reservoirs Based on the Unascertained Measure-Mahalanobis Distance Theory. *Processes*, 2024, no. 12, 274 p. DOI: 10.3390/pr12020274

12. Jiao F. Practice and knowledge of volumetric development of deep fractured-vuggy carbonate reservoirs in Tarim basin NW China. *Petroleum Exploration and Development*, 2019, no. 46 (3), pp. 576-582. DOI: 10.1016/S1876-3804(19)60037-6

13. Dehghani K., Edwards K.A., Harris P.M. Modeling of waterflood in a vuggy carbonate reservoir. *In Proceedings of the SPE Annual Technical Conference and Exhibition*, San Antonio, Texas, 1997. DOI: 10.2118/38567-MS

14. Cho Y. Stochastic discrete fracture network modeling in shale reservoirs via integration of seismic attributes and petrophysical data. *Interpretation*, 2021, no. 9 (4), pp. SG47-SG58. DOI: 10.1190/INT-2020-0210.1

15. Brantferger K.M., Kompanik G.S., Al-Jenaibi H.M., Dodge W.S., Patel H. Impact and lessons of using high permeability streaks in history matching a giant offshore Middle East carbonate reservoir. *In Proceedings of the Abu Dhabi International Petroleum Exhibition and Conference*. Abu Dhabi, United Arab Emirates, 2012. DOI: 10.2118/161426-MS

16. Poli E., Maza C., Virgone A., Gisquet F., Fraisse C., Cecile P. High Permeability Streaks Characterisations in Middle East Carbonate. *In Proceedings of the International Petroleum Technology Conference*. Doha, Qatar, 2009. DOI: 10.2523/IPTC-13385-ABSTRACT

17. Manish Kumar S., Humberto P., Obeida E.J., Houcine B.J., Chakib K.K., Hussein M. Using Machine Learning to Capture High-Permeability Streaks in Reservoir Models. *In Proceedings of the ADIPEC*. Abu Dhabi, UAE, 2022. DOI: 10.2118/211661-MS

18. Tariq Z., Aljawad M.S., Hasan A., Murtaza M., Mohammed E., El Husseiny A., Alarifi S., M. Mahmoud, A. Abdulraheem A systematic review of data science and machine learning applications to the oil and gas industry. *Journal of Petroleum Exploration and Production Technology*, 2021, no. 11, pp. 4339-4374. DOI: 10.1007/s13202-021-01302-2

19. Choubey S., Karmakar G.P. Artificial intelligence techniques and their application in oil and gas industry. *Artificial Intelligence Review*, 2021, no. 54 (5), pp. 3665-3683. DOI: 10.1007/s10462-020-09935-1

20. Aljameel S.S., Alomari D.M., Alismail S., Khawaher F., Alkhudhair A.A., Aljubran F., Alzannan R.M. An Anomaly Detection Model for Oil and Gas Pipelines Using Machine Learning. *Computation*, 2022, no. 10, 138 p. DOI: 10.3390/computation10080138

21. Sircar A., Yadav K., Rayavarapu K., Bist N., Oza H. Application of machine learning and artificial intelligence in oil and gas industry. *Petroleum Research*, 2021, no. 6 (4), pp. 379-391. DOI: 10.1016/j.ptlrs.2021.05.009

22. Zhao L., Zou C., Chen Y., Shen W., Wang Y., Chen H., Geng J. Fluid and lithofacies prediction based on integration of well-log data and seismic inversion: A machine-learning approach. *Geophysics*, 2021, no. 86 (4), pp. M151-M165. DOI: 10.1190/geo2020-0521.1

23. Zou C., Zhao L., Chen Y., Wang Y. Machine learning based fluids and lithofacies prediction based on the integration of well logging data and seismic inversion. *In Proceedings of the SEG 2020 Workshop: 2nd SEG Borehole Geophysics*, 2020. DOI: 2020.10.1190/bhgp2020-32.1

24. Talebkeikhah M., Sadeghtabaghi Z., Shabani M. A comparison of machine learning approaches for prediction of permeability using well log data in the hydrocarbon reservoirs. *Journal of Human, Earth, and Future*, 2021, no. 2, pp. 82-99. DOI: 10.28991/HEF-2021-02-02-01

25. Wood D.A. Predicting porosity, permeability and water saturation applying an optimized nearest-neighbour, machine-learning and data-mining network of well-log data. *Journal of Petroleum Science and Engineering*, 2020, no. 184, 106587 p. DOI: 10.1016/j.petrol.2019.106587

26. Miah M.I., Zendehboudi S., Ahmed S. Log data-driven model and feature ranking for water saturation prediction using machine learning approach. *Journal of Petroleum Science and Engineering*, 2020, no. 194, 107291 p. DOI: 10.1016/j.petrol.2020.107291

27. Bestagini P., Lipari V., Tubaro S. A machine learning approach to facies classification using well logs. *In Proceedings of the SEG International Exposition and Annual Meeting*. Houston, Texas, 2017. DOI: 10.1190/segam2017-17729805.1

28. Salehi S.M., Honarvar B. Automatic identification of formation iithology from well log data: a machine learning approach. *Journal of Petroleum Science Research* 2014, no. 3, pp. 73-82. DOI: 10.14355/jpsr.2014.0302.04

29. Meshalkin Y., Shakirov A., Orlov D., Koroteev D. Well-Logging based lithology prediction using Machine Learning. *Data Science in Oil & Gas*, 2020, no. 2020 (1), pp. 1-5. DOI: 10.3997/2214-4609.202054010

30. Brazell S., Bayeh A.C., Ashby M., Burton D. A machine-learning-based approach to assistive well-log correlation. *Petrophysics*, 2019, no. 60 (4), pp. 469-479. DOI: 10.30632/PJV60N4-2019a1

31. Hussain M., Liu S., Ashraf U., Ali M., Hussain W., Ali N., Anees A. Application of Machine Learning for Lithofacies Prediction and Cluster Analysis Approach to Identify Rock Type. *Energies*, 2022, no. 15, 4501 p. DOI: 10.3390/en15124501

32. Kantaatmadja B., Kasim F., Zainudin W.N.S., Elsebakhi E., Jr E., Ali A. Permeability Prediction Using Rock-Typing, Flow Zone Indicator and Machine Learning Techniques in a Brownfield Offshore Malaysia. *In Proceedings of the International Petroleum Technology Conference, Virtual*, 2021. DOI: 10.2523/IPTC-21436-MS

33. Al Khalifah H., Glover P.W.J., Lorinczi P. Permeability prediction and diagenesis in tight carbonates using machine learning techniques. *Marine and Petroleum Geology*, 2020, no. 112, 104096 p. DOI: 10.1016/j.marpetgeo.2019.104096

34. Alameedy U.S., Almomen A.T., Abd N. Evaluating machine learning techniques for carbonate formation permeability prediction using well log data. *The Iraqi Geological Journal*, 2023, no. 56, pp. 175-187. DOI: 10.46717/igj.56.1D.14ms-2023-4-23

35. Shirinkin D., Kochnev A., Krivoshchekov S., Putilov I., Botalov A., Kozyrev N., Ozhgibesov E. High Permeability Streak Identification and Modelling Approach for Carbonate Reef Reservoir. *Energies*, 2024, no. 17, 236 p. DOI: 10.3390/en17010236

36. Otchere D., Ganat T., Ojero J., Tackie-Otoo B.N., Taki M. Application of gradient boosting regression model for the evaluation of feature selection techniques in improving reservoir characterisation predictions. *Journal of Petroleum Science and Engineering*, 2022, No. 208, 109244 p. DOI: 10.1016/j.petrol.2021.109244

37. Abbas M.A., Al-Mudhafar W.J., Wood D.A. Improving permeability prediction in carbonate reservoirs through gradient boosting hyperparameter tuning. *Earth Science Informatics*, 2023, no. 16 (4), pp. 3417-3432. DOI: 10.1007/s12145-023-01099-0

38. Rahimi M., Riahi M.A. Reservoir facies classification based on random forest and geostatistics methods in an offshore oilfield. *Journal of Applied Geophysics*, 2022, no. 201, 104640 p. DOI: 10.1016/j.jappgeo.2022.104640

39. Amagada P.U. An Inferable Machine Learning Approach for Reservoir Lithology Characterization Using Drilling Data. *In Proceedings of the SPE Annual Technical Conference and Exhibition*. San Antonio, Texas, USA, 2023. DOI: 10.2118/217485-STU

40. Liu W., Chen Z., Hu Y., Xu L. A systematic machine learning method for reservoir identification and production prediction. *Petroleum Science*, 2023, no. 20 (1), pp. 295-308. DOI: 10.1016/j.petsci.2022.09.002

41. Li W., Hu W., Abubakar A. Machine learning and data analytics for geoscience applications - Introduction. *Geophysics*, 2020, no. 85 (4), pp. WAi-WAii. DOI: 10.1190/geo2020-0518-spseintro.1

42. Nti I.K., Quarcoo J.A., Aning J., Fosu G.K. A mini-review of machine learning in big data analytics: Applications, challenges, and prospects. *Big Data Mining and Analytics*, 2022, no. 5 (2), pp. 81-97. DOI: 10.26599/BDMA.2021.9020028

43. Maganathan T., Senthilkumar S., Balakrishnan V. Machine learning and data analytics for environmental science: a Review, Prospects and Challenges. *IOP Conference Series: Materials Science and Engineering*, 2020, no. 955 (1), 012107 p. DOI: 10.1088/1757-899X/955/1/012107

44. Amaefule J.O., Altunbay M., Tiab D., Kersey D., Keelan D. Enhanced Reservoir Description: Using Core and Log Data to identify Hydraulic (Flow) Units and Predict Permeability in Uncored Intervals/Wells. *In Proceedings of the SPE Annual Technical Conference and Exhibition*. Houston, Texas, 1993. DOI: 10.2118/26436-MS

45. Garrouch A.A., Al-Sultan A.A. Exploring the link between the flow zone indicator and key open-hole log measurements: An application of dimensional analysis. *Petroleum geoscience*, 2019, no. 25, pp. 219-234. DOI: 10.1144/petgeo2018-035

Библиографический список

1. Diagenetic process and their effect on reservoir quality in Miocene carbonate reservoir Offshore, Sarawak, Malaysia / H.T. Janjuhah, A.M.A. Salim, D. Ghosh, A. Wahid // In Proceedings of the International Conference on Integrated Petroleum Engineering and Geosciences. – Singapore, 2016. DOI: 10.1007/978-981-10-3650-7_48

2. Farzaneh, S.A. Using diagenetic processes in facies modeling of a carbonate reservoir / S.A. Farzaneh, A.A. Dehghan, A. Lakzaie // Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. – 2013. – No. 35 (6). – P. 516–528. DOI: 10.1080/15567036.2010.504946

3. Study of the influence of nonlinear dynamic loads on elastic modulus of carbonate reservoir rocks / E. Riabokon, M. Turbakov, E. Kozhevnikov, V. Poplygin, M. Guzev // Energies. – 2021. – Vol. 14, no. 24. DOI 10.3390/en14248559

4. Progress of research on dolomitization and dolomite reservoir / Q. Huang, W. Liu, Y. Zhang, S. Shi, K. Wang // Advances in Earth Science. – 2015. – No. 30 (5). – P. 539. DOI: 10.11867/j.issn.1001-8166.2015.05.0539

5. A review of development methods and EOR technologies for carbonate reservoirs / Z.X. Xu., S.Y. Li, B.F. Li, D.Q. Chen, Z.Y. Liu, Z.M. Li // Petroleum Science. – 2020. – No. 17. – P. 990–1013. DOI: 10.1007/s12182-020-00467-5.

6. Щербаков, А.А. Оценка эффективности мероприятий по интенсификации добычи нефти (на примере месторождений Соликамской депрессии) / А.А. Щербаков, Г.П. Хижняк, В.И. Галкин // Геология, геофизика и разработка нефтяных и газовых месторождений. – 2019. – № 2. – С. 70–73. DOI: 10.30713/2413-5011-2019-2-70-73

7. Ерофеев, А.А. Оценка условий применения методов обработки кривых восстановления давления скважин в карбонатных коллекторах / А.А. Ерофеев, И.Н. Пономарева, М.С. Турбаков // Инженер-нефтяник. – 2011. – № 3. – С. 12–15.

8. Production optimization for water flooding in fractured-vuggy carbonate reservoir–From laboratory physical model to reservoir operation / B. Yang, J. He, D. Lyu, H. Tang, J. Zhang, X. Li, J. Zhao // Journal of Petroleum Science and Engineering. – 2020. – No. 184. – P. 106520. DOI: 10.1016/j.petrol.2019.106520

9. Mechanistic Study and Optimization of High Water Cut Phase Management Strategies in Fracture-Vuggy Carbonate Reservoirs with Bottom Water / M. Zhao, X. Xin, G. Yu, R. Hu, Y. Gong // Processes. – 2023. – No. 11. – P. 3135. DOI: 10.3390/pr11113135

10. Waterflooding in giant carbonate reservoir; successes and challenges / S. Mahmood, P. Salazar, X. Zhao, M. Pointing, A. Sayed // In Proceedings of the Abu Dhabi International Petroleum Exhibition and Conference. – Abu Dhabi, UAE, 2017. DOI: 10.2118/188532-MS

11. Integrated Waterflooding Effect Evaluation Methodology for Carbonate Fractured-Vuggy Reservoirs Based on the Unascertained Measure–Mahalanobis Distance Theory / Z. Su, S. Gao, Z. Li, T. Li, N. Kang // Processes. – 2024. – No. 12. – P. 274. DOI: 10.3390/pr12020274
12. Jiao, F. Practice and knowledge of volumetric development of deep fractured-vuggy carbonate reservoirs in Tarim basin NW China / F. Jiao // Petroleum Exploration and Development, – 2019. – No. 46 (3). – P. 576–582. DOI: 10.1016/S1876-3804(19)60037-6
13. Dehghani, K. Modeling of waterflood in a vuggy carbonate reservoir / K. Dehghani, K.A. Edwards, P.M. Harris // In Proceedings of the SPE Annual Technical Conference and Exhibition. – San Antonio, Texas, 1997. DOI: 10.2118/38567-MS
14. Cho, Y. Stochastic discrete fracture network modeling in shale reservoirs via integration of seismic attributes and petrophysical data / Y. Cho // Interpretation. – 2021. – No. 9 (4). – P. SG47–SG58. DOI: 10.1190/INT-2020-0210.1
15. Impact and lessons of using high permeability streaks in history matching a giant offshore Middle East carbonate reservoir / K.M. Brantferger, G.S. Kompanik, H.M. Al-Jenaibi, W.S. Dodge, H. Patel // In Proceedings of the Abu Dhabi International Petroleum Exhibition and Conference. – Abu Dhabi, United Arab Emirates, 2012. DOI: 10.2118/161426-MS
16. High Permeability Streaks Characterisations in Middle East Carbonate / E. Poli, C. Maza, A. Virgone, F. Gisquet, C. Fraisse, P. Cecile // In Proceedings of the International Petroleum Technology Conference. – Doha, Qatar, 2009. DOI: 10.2523/IPTC-13385-ABSTRACT
17. Using Machine Learning to Capture High-Permeability Streaks in Reservoir Models / S. Manish Kumar, P. Humberto, E.J. Obeida, B.J. Houcine, K.K. Chakib, M. Hussein // In Proceedings of the ADIPEC. – Abu Dhabi, UAE, 2022. DOI: 10.2118/211661-MS
18. A systematic review of data science and machine learning applications to the oil and gas industry / Z. Tariq, M.S. Aljawad, A. Hasan, M. Murtaza, E. Mohammed, A. El Husseiny, S. Alarifi, M. Mahmoud, A. Abdulraheem // Journal of Petroleum Exploration and Production Technology. – 2021. – No. 11. – P. 4339–4374. DOI: 10.1007/s13202-021-01302-2
19. Choubey, S. Artificial intelligence techniques and their application in oil and gas industry / S. Choubey, G.P. Karmakar // Artificial Intelligence Review. – 2021. – No. 54 (5). – P. 3665–3683. DOI: 10.1007/s10462-020-09935-1
20. An Anomaly Detection Model for Oil and Gas Pipelines Using Machine Learning / S.S. Aljameel, D.M. Alomari, S. Alismail, F. Khawaher, A.A. Alkhudhair, F. Aljubran, R.M. Alzannan // Computation. – 2022. – No. 10. – P. 138. DOI: 10.3390/computation10080138
21. Application of machine learning and artificial intelligence in oil and gas industry / A. Sircar, K. Yadav, K. Rayavarapu, N. Bist, H. Oza // Petroleum Research. – 2021. – No. 6 (4). – P. 379–391. DOI: 10.1016/j.ptlrs.2021.05.009
22. Fluid and lithofacies prediction based on integration of well-log data and seismic inversion: A machine-learning approach / L. Zhao, C.Zou, Y. Chen, W. Shen, Y. Wang, H. Chen, J. Geng // Geophysics. – 2021. – No. 86 (4). – P. M151–M165. DOI: 10.1190/geo2020-0521.1
23. Machine learning based fluids and lithofacies prediction based on the integration of well logging data and seismic inversion / C. Zou, L. Zhao, Y. Chen, Y. Wang // In Proceedings of the SEG 2020 Workshop: 2nd SEG Borehole Geophysics. – 2020. DOI: 2020.10.1190/bhgp2020-32.1
24. Talebkeikhah, M. A comparison of machine learning approaches for prediction of permeability using well log data in the hydrocarbon reservoirs / M. Talebkeikhah, Z. Sadeghtabaghi, M. Shabani // Journal of Human, Earth, and Future. – 2021. – No. 2. – P. 82–99. DOI: 10.28991/HEF-2021-02-02-01
25. Wood, D.A. Predicting porosity, permeability and water saturation applying an optimized nearest-neighbour, machine-learning and data-mining network of well-log data / D.A. Wood // Journal of Petroleum Science and Engineering. – 2020. – No. 184. – P. 106587. DOI: 10.1016/j.petrol.2019.106587
26. Miah, M.I. Log data-driven model and feature ranking for water saturation prediction using machine learning approach / M.I. Miah, S. Zendehboudi, S. Ahmed // Journal of Petroleum Science and Engineering. – 2020. – No. 194. – P. 107291. DOI: 10.1016/j.petrol.2020.107291
27. Bestagini, P. A machine learning approach to facies classification using well logs / P. Bestagini, V. Lipari, S. Tubaro // In Proceedings of the SEG International Exposition and Annual Meeting. – Houston, Texas, 2017. DOI: 10.1190/segam2017-17729805.1
28. Salehi, S.M. Automatic identification of formation iithology from well log data: a machine learning approach / S.M. Salehi, B. Honarvar // Journal of Petroleum Science Research. – 2014. – No. 3. – P. 73–82. DOI: 10.14355/jpsr.2014.0302.04
29. Well-Logging based lithology prediction using Machine Learning / Y. Meshalkin, A. Shakirov, D. Orlov, D. Koroteev // Data Science in Oil & Gas. – 2020. – No. 2020 (1). – P. 1–5. DOI: 10.3997/2214-4609.202054010
30. A machine-learning-based approach to assistive well-log correlation / S. Brazell, A.C. Bayeh, M. Ashby, D. Burton // Petrophysics. – 2019. – No. 60 (4). – P. 469–479. DOI: 10.30632/PJV60N4-2019a1
31. Application of Machine Learning for Lithofacies Prediction and Cluster Analysis Approach to Identify Rock Type / M. Hussain, S. Liu, U. Ashraf, M. Ali, W. Hussain, N. Ali, A. Anees // Energies. – 2022. – No. 15. – P. 4501. DOI: 10.3390/en15124501
32. Permeability Prediction Using Rock-Typing, Flow Zone Indicator and Machine Learning Techniques in a Brownfield Offshore Malaysia / B. Kantaatmadja, F. Kasim, W.N.S. Zainudin, E. Elsebakhi, E. Jr, A. Ali // In Proceedings of the International Petroleum Technology Conference, Virtual. – 2021. DOI: 10.2523/IPTC-21436-MS
33. Al Khalifah, H. Permeability prediction and diagenesis in tight carbonates using machine learning techniques / H. Al Khalifah, P.W.J. Glover, P. Lorinczi // Marine and Petroleum Geology. – 2020. – No. 112. – P. 104096. DOI: 10.1016/j.marpetgeo.2019.104096
34. Alameedy, U.S. Evaluating machine learning techniques for carbonate formation permeability prediction using well log data / U.S. Alameedy, A.T. Almomen, N. Abd // The Iraqi Geological Journal. – 2023. – No. 56. – P. 175–187. DOI: 10.46717/igj.56.1D.14ms-2023-4-23
35. High Permeability Streak Identification and Modelling Approach for Carbonate Reef Reservoir / D. Shirinkin, A. Kochnev, S. Krivoshchekov, I. Putilov, A. Botalov, N. Kozyrev, E. Ozhgibesov // Energies. – 2024. – No. 17. – P. 236. DOI: 10.3390/en17010236
36. Application of gradient boosting regression model for the evaluation of feature selection techniques in improving reservoir characterisation predictions / D. Otchere, T. Ganat, J. Ojero, B.N. Tackie-Otoo, M. Taki // Journal of Petroleum Science and Engineering. – 2022. – No. 208. – P. 109244. DOI: 10.1016/j.petrol.2021.109244
37. Abbas, M.A. Improving permeability prediction in carbonate reservoirs through gradient boosting hyperparameter tuning / M.A. Abbas, W.J. Al-Mudhafar, D.A. Wood // Earth Science Informatics. – 2023. – No. 16 (4). – P. 3417–3432. DOI: 10.1007/s12145-023-01099-0
38. Rahimi, M. Reservoir facies classification based on random forest and geostatistics methods in an offshore oilfield / M. Rahimi, M.A. Riahi // Journal of Applied Geophysics. – 2022. – No. 201. – P. 104640. DOI: 10.1016/j.jappgeo.2022.104640
39. Amagada, P.U. An Inferable Machine Learning Approach for Reservoir Lithology Characterization Using Drilling Data / P.U. Amagada // In Proceedings of the SPE Annual Technical Conference and Exhibition. – San Antonio, Texas, USA, 2023. DOI: 10.2118/217485-STU
40. A systematic machine learning method for reservoir identification and production prediction / W. Liu, Z. Chen, Y. Hu, L. Xu // Petroleum Science. – 2023. – No. 20 (1). – P. 295–308. DOI: 10.1016/j.petsci.2022.09.002
41. Li, W. Machine learning and data analytics for geoscience applications—Introduction / W. Li, W. Hu, A. Abubakar // Geophysics. – 2020. – No. 85 (4). – P. WAi–WAii. DOI: 10.1190/geo2020-0518-spseintro.1
42. A mini-review of machine learning in big data analytics: Applications, challenges, and prospects / I.K. Nti, J.A. Quarcoo, J. Aning, G.K. Fosu // Big Data Mining and Analytics. – 2022. – No. 5 (2). – P. 81–97. DOI: 10.26599/BDMA.2021.9020028
43. Maganathan T., Senthilkumar S., Balakrishnan V. Machine learning and data analytics for environmental science: a Review, Prospects and Challenges / T. Maganathan, S. Senthilkumar, V. Balakrishnan // IOP Conference Series: Materials Science and Engineering. – 2020. – No. 955 (1). – P. 012107. DOI: 10.1088/1757-899X/955/1/012107
44. Enhanced Reservoir Description: Using Core and Log Data to identify Hydraulic (Flow) Units and Predict Permeability in Uncored Intervals/Wells / J.O. Amaefule, M. Altunbay, D. Tiab, D. Kersey, D. Keelan // In Proceedings of the SPE Annual Technical Conference and Exhibition. – Houston, Texas, 1993. DOI: 10.2118/26436-MS
45. Garrouch, A.A. Exploring the link between the flow zone indicator and key open-hole log measurements: An application of dimensional analysis / A.A. Garrouch, A.A. Al-Sultan // Petroleum geoscience. – 2019. – No. 25. – P. 219–234. DOI: 10.1144/petgeo2018-035

Funding. The study was carried out under the Russian Science Foundation grant No. 22-17-00111.
Conflict of interest. The authors declare no conflict of interest.
The authors' contribution is equivalent.