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Prediction of Hydrodynamic Parameters of the State of the Bottomhole Zone of Wells Using Machine Learning Methods

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The relevance of the development of a methodology for the operational assessment of the bottom-hole formation zone (the permeability of the bottom-hole formation zone and the skin factor) is primarily due to economic considerations, since existing approaches to its definition based on hydrodynamic studies lead to shortages and increased risks of failure to ensure the output of the well. In this regard, the use of modern methods of working with big data, such as deep learning of artificial neural networks, will ensure monitoring of the condition of the bottom-hole zone of the well formation without stopping them for hydrodynamic tests, which will reduce losses for oil production enterprises. It will allow for operational analysis for effective and timely application of intensification technologies, enhanced oil recovery. The authors analyzed the existing methods for determining the bottom-hole characteristics of the formation and machine learning approaches in the direction of solving this problem. The article presents a methodology for the operational assessment of the state of the bottom-hole formation zone: the permeability of the near bottomhole zone (NBHZ) and the skin factor using artificial neural network training approaches based on geological, operational data and the results of interpretation of hydrodynamic studies on the example of sandstones of oil fields in the Perm Region. A fully connected neural network was used to predict the NBHZ permeability. The article presents the results of testing various neural network architectures: the number of layers and neurons in layers with the choice of the best one. Some techniques were used to prevent over-training of models. The author's methodology for assessing the skin factor of wells is proposed using a comprehensive analysis of the constructed statistical models and training models of artificial neural networks to solve the regression problem. In future studies, it is planned to use recurrent and convolutional neural networks to study the dynamic components of the formation of the bottom-hole formation zone and create an integrated approach to solve the problem.

Keywords: sandstone reservoir, bottom-hole formation zone, permeability, skin factor, machine learning, neural network

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1. Introduction

A significant portion of the remaining resources of oil and gas fields are concentrated in complex reservoirs, the permeability and porosity of which are generally low or ultra-low (Kantaatmadja et al., 2019; Alghazal et al., 2020; He et al., 2022), which causes additional filtration resistance when filtering hydrocarbons. The state of the bottomhole formation zone (BHZ) in reservoirs of this type plays an important role in the movement of fluids from the formation to the well. In this work, we will consider such parameters as the permeability of the reservoir zone and the skin factor, on which the productivity of production and injectivity of injection wells, the success of stimulation methods and methods of increasing oil recovery depend (Byrne, Mcphee, 2012; Gouda, Attia, 2022).

In real formation conditions, deterioration of the condition of the bottomhole zone of a well can be caused by exposure to clay mud when drilling a productive formation, flushing of the bottomhole with various process fluids (water, acid, steam, etc.), clogging of formation voids with reaction products, deposition of organic substances, etc. (Al-Obaidi, 2016; Yang et al., 2023; Dvoynikov et al., 2024). Today, various approaches are known that allow one to evaluate and

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predict the skin factor in various geological and physical conditions. For example, the mathematical model of the skin factor presented in (Mahmoudi et al., 2016) takes into account formation damage and flow convergence. The work (Xie, 2015) performed a finite element analysis and studied the influence of the length of the slot holes and their structure on the filtration of fluid flow, as well as on the skin factor. The authors (Sivagnanam et al., 2017) in their work used CFD (Computational Fluid Dynamics) – a *k*–ε-model of turbulence, built on the basis of a modified Darcy's law, which takes into account inertial effects. Studies (Dong et al., 2018; Abobaker et al., 2021) proposed mathematical models of the skin factor of inclined wells in anisotropic reservoirs. Most models based on optimization of the Hawkins skin factor equation consider the radius of the damage zone in the direction from the "toe" to the "root" of the wellbore as a constant, linear and parabolic distribution. The work (Wang et al., 2023) optimized the skin factor model, assuming that the distribution of the damage zone along the horizontal wellbore has a parabolic decreasing shape. As the cement content increases, the rock can gradually turn into chemogenic rock, which can worsen the permeability properties of the reservoir and gradually turn it into unproductive rock, since this creates a surface layer in the wellbore zone (Al-Obaidi, Khalaf, 2018; Abdulaziz et al., 2022). The work (Khairullin et al., 2016) considers an approach based on the simultaneous use of data on changes in pressure and temperature at the bottom of the well with subsequent quantitative assessment of formation parameters and skin factor values. The authors (Kubota, Gioria, 2022; Gomaa et al., 2022) proposed an original solution for using regression models based on retrospective values of bottomhole pressure and fluid production to estimate the skin factor during well shutdowns for research. In these works, using various approaches, the influence of geological and technological parameters on the skin factor was studied, the determination of which is of fundamental importance for assessing the success of intensification measures.

Permeability prediction is one of the current researches in oil and gas industry (Zhou et al., 2024; Wang et al., 2024). To date, there is a small amount of published work on the application of machine learning methods to solve the problem of uncertainty in predicting BHZ permeability (Bennis, Torres-Verdín, 2019; Eriavbe, Okene, 2019; Singh et al., 2020; Bennis, Torres-Verdín, 2023; Rashid et al., 2023; Pei et al., 2024). The most adapted and frequently used method of artificial intelligence (AI) technologies for predicting reservoir properties based on well logging data are neural networks and fuzzy logic (Dong et al., 2023). These methods estimate and predict reservoir parameters more accurately and reliably compared to traditional methods (Matinkia et al., 2023). However, the use of machine learning algorithms to interpret geophysical survey data to obtain reservoir characteristics is complicated by problems of subjectivity of interpretation (Negara et al., 2016; Aygun et al., 2023; Liu et al., 2023). Artificial intelligence is used to predict permeability using the calculated HFU (Hydraulic Flow Units) parameter (Bahaloo et al., 2023). The results show that AI with HFU gives a good estimate of permeability (Alobaidi, 2016). In a study by (Hameed, Hamd-Allah, 2023), permeability predicted by an AI model more accurately described the well's operating history. In (Liu et al., 2020; Zakharov et al., 2022), the feasibility and accuracy of automated interpretation of pressure build-up curves to determine near-wellbore reservoir characteristics using a convolutional neural network was assessed. It has also been noted that permeability calculations using reservoir simulation methods are greatly affected by uncertainty in the interpretation of reservoir thickness (Bist et al., 2023; Li et al., 2023).

Assessing and predicting the permeability of the bottomhole zone of wells and the skin factor are a primary task, the solution of which will allow a more reasonable approach to the selection of technological operating modes, methods for intensifying well production and increasing oil recovery. However, at present, little attention is paid to this; to make various kinds of decisions, the permeability of the remote zone of the formation (RFZ), which is determined according to the data of hydrodynamic testing of wells (well testing), is used to make various kinds of decisions.

The purpose of this article is to improve and adapt machine learning methods based on historical data from the development of hydrocarbon fields to assess and predict such parameters of the state of the near-wellbore formation zone as skin factor and BHZ permeability.

2. Materials and methods

Data from 486 hydrodynamic studies of production wells were used (real names of fields and well locations are not indicated due to the confidentiality of this information), processed in the KAPPA Workstation software product (Saphir module) with determination of the skin factor (S) and RFZ permeability (k_{RFZ}). 39 indicator diagrams with determination of the skin factor and permeability of the near-wellbore formation zone (k_{BHZ}) were interpreted.

The following parameters were used to predict k_{BHZ} values:

P_{wf} – bottomhole pressure of well flowing, MPa;
P_{res} – reservoir pressure, MPa;
P_{sat} – saturation pressure of oil with gas, MPa;
Q – liquid flow rate, m³/day;
h – effective thickness of the formation, m;
GOR – gas-oil ratio, m³/t;
W – water cut, %;
m – porosity, %;
$R_k = \frac{Q}{(P_{res}-P_{wf})\cdot h}, \frac{m^2}{day\cdot MPa},$ – calculated coefficient of specific well productivity to improve the accuracy of the model;
S – skin factor.

To establish individual patterns of formation of the permeability of the bottom-hole zone of the formation (phase for oil), a sample was used, previously ranked by permeability k_{BHZ} from maximum to minimum values. After ranking, a stepwise modeling procedure was performed using multiple linear regression. This process is described in detail in (Galkin et al., 2021; Ponomareva et al., 2022), so this article outlines only its main stages. At the first stage, a model is built using the first three rows of the table with a data sample (n = 3), then the second model with a data sample (n = 4), etc.

Fig. 1 shows that a sharp decrease in the multiple correlation coefficient (R^2) occurs when the BHZ permeability is less than 1 μm². Despite the relatively large R^2 value on the full data set (0.812), the model has a large standard error of the mean – 0.191 μm².

Models built for different BHZ permeability ranges are presented in Fig. 2 and in Table 1. Statistical performance characteristics are also calculated for each model. According to the analysis of the coefficients of determination, the accuracy of the models and the

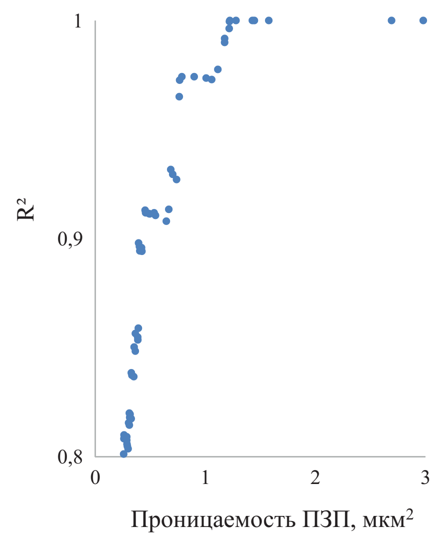

Fig. 1. Multiple correlation coefficient (R^2) at different BHZ permeability ranges

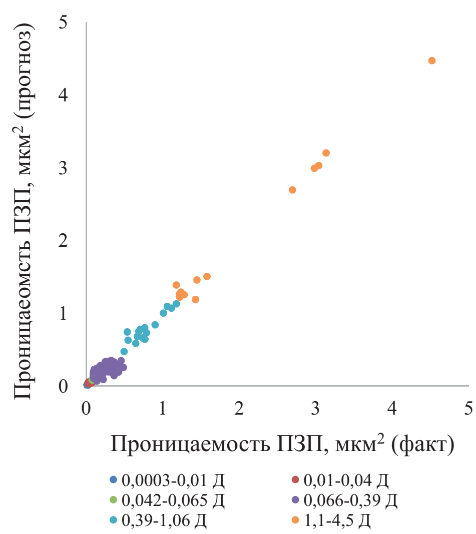

Fig. 2. Scatterplot of predicted and actual BHZ permeability values (ranking by BHZ permeability)

BHZ permeability range, μm²	Regression model
1.1–4.5	$k_{BHZ} = -21.813 - 0.017R_k + 0.017W + 0.137S + 0.03Q - 0.418h - 3.243P_{res} + 1.976P_{sat} + 3.179P_{заб} + 0.041m - 0.034GOR$ R^2: 0.429; 0.767; 0.961; 0.971; 0.986; 0.989; 0.989; 0.995; 0.998; 0.999
0.39–1.06	$k_{BHZ} = 0.777 - 0.014R_k + 0.0002W - 0.019GOR + 0.194P_{sat} - 0.748P_{res} + 0.721P_{wf} + 0.019S + 0.017Q - 0.07h + 0.003m$ R^2: 0.268; 0.372; 0.377; 0.417; 0.435; 0.519; 0.697; 0.702; 0.795; 0.797
0.066–0.39	$k_{BHZ} = 0.556 + 0.014R_k + 0.001W - 0.022P_{sat} - 0.007m + 0.001Q - 0.003h - 0.009P_{res} + 0.009P_{wf} + 0.001S$ R^2: 0.365; 0.436; 0.441; 0.457; 0.469; 0.475; 0.488; 0.504; 0.507
0.042–0.065	$k_{BHZ} = -0.119 + 0.011P_{sat} + 0.001m - 0.001P_{wf} + 0.004R_k - 0.001h - 0.0002S$ R^2: 0.149; 0.212; 0.273; 0.372; 0.471; 0.498
0.01–0.04	$k_{BHZ} = 0.016 + 0.013R_k + 0.0001W + 0.001P_{res} - 0.0003h - 0.0004S$ R^2: 0.204; 0.390; 0.475; 0.510; 0.532
0.0003–0.01	$k_{BHZ} = -0.002 + 0.018R_k + 0.0002P_{res} + 0.00002W$ R^2: 0.569; 0.665; 0.697

Table 1. Multivariate regression models for different ranges of BHZ permeability. Note: P_{wf} – bottomhole pressure, MPa; P_{res} – reservoir pressure, MPa; P_{sat} – saturation pressure, MPa; Q – liquid flow rate, m³/day; h – effective thickness of the formation, m; GOR – gas-oil ratio, m³/t; W – water cut, %; m – porosity, %; R_k – specific well productivity; S – skin factor

influence of features decreases with a decrease in the permeability range.

The next step is to predict k_{BHZ} based on training a fully connected neural network with different layer configurations. Additional calculation parameters have been added as additional features for training a fully connected neural network:

P_{wf}/P_{res} – ratio of bottomhole pressure to reservoir pressure;

P_{wf}/P_{sat} – ratio of bottomhole pressure to saturation pressure.

To implement the algorithms, we used the open Keras library, written in Python and providing interaction with artificial neural networks (https://keras.io/). The learning model is designed to stop at early epochs (iterations) when the error on the validation data set stops improving or begins to deteriorate to prevent overfitting and optimize its generalization ability. This technique is implemented by periodically computing the error on the validation dataset after each training epoch. If the error stops decreasing or begins to increase within a given number of epochs, model training stops and the best model obtained up to that point is returned. The activation function ReLu on the output layer is a linear activation function.

We tested architectures with different numbers of layers (from 1 to 4) and number of neurons (50, 100, 150, 200). The best model with 4 layers of 100 neurons each was selected. The model architecture and set of input data for predicting BHZ permeability are presented in Fig. 3.

To predict the skin factor S, additional calculation parameters have been added to the original database:

k_{BHZ}^{T} – median value of BHZ permeability of all historical interpretation data for the well;

k_{RFZ}^{T} – median value of RFZ permeability of all historical interpretation data for the well;

$k_{BHZ}^{T} / k_{RFZ}^{T}$ – ratio of the median BHZ value to the median RFZ value.

k_{BHZ}^{av} – average value of BHZ permeability of all historical interpretation data for the well;

k_{RFZ}^{av} – average value of RFZ permeability of all historical interpretation data for the well;

$k_{BHZ}^{av} / k_{RFZ}^{av}$ – ratio of the average BHZ value to the average RFZ value.

The proposed methodology for estimating S consists of preliminary prediction of the BHZ permeability (Fig. 3) with subsequent adjustment of the median value of the BHZ permeability of the well and, as a consequence, the ratio of the median values of the BHZ and RFZ permeabilities as one of the main initial parameters for the skin forecasting neural network model factor (Fig. 4).

Architectures with different numbers of layers (from 1 to 4) and neurons (50, 100, 150, 200) were tested. The best model with 4 layers of 100 neurons each was selected, as for BHZ permeability. Dropout layers have been added as an additional measure to prevent overfitting. This technique randomly turns off neurons in layers and improves generalization ability. The architecture of the model and the set of initial data for predicting the skin factor are presented in Fig. 4.

Figures 5 and 6 show scatterplots of skin factor and permeability ratio; skin factor and the ratio of median permeability values RFZ/BHZ for the entire operating life for each well. When using median values, the R^2 coefficient decreased from 0.834 to 0.425.

3. Results

A fully connected neural network was used to predict BHZ permeability. Figures 7 and 8 show scatterplots of the training and test samples. The average absolute error on the test sample is 0.024 μm² with R^2 = 0.986.

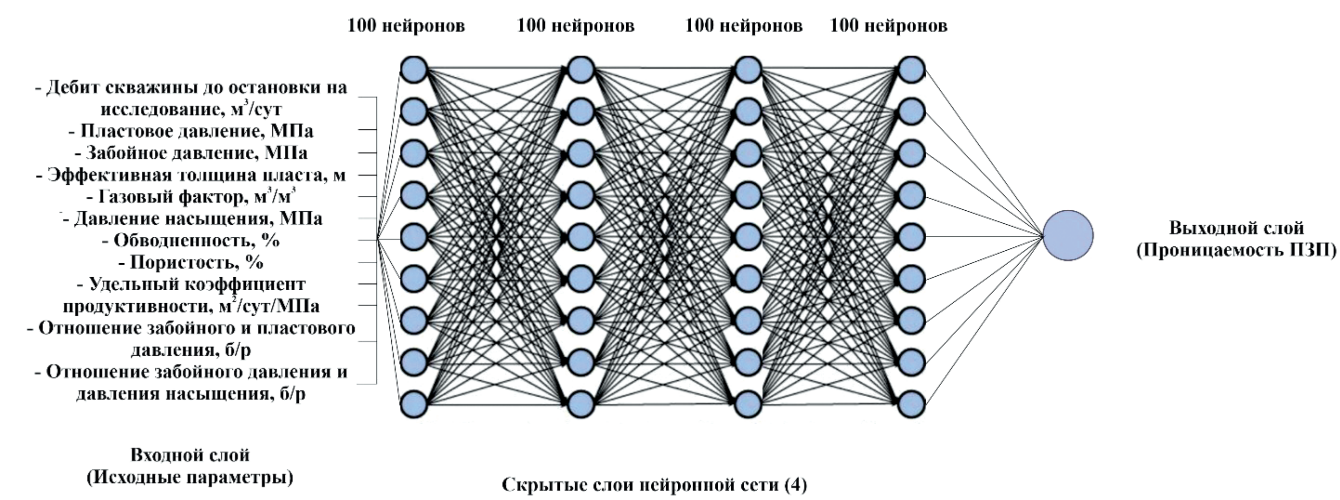

Fig. 3. Architecture of a fully connected neural network for predicting the permeability of the near-wellbore formation zone

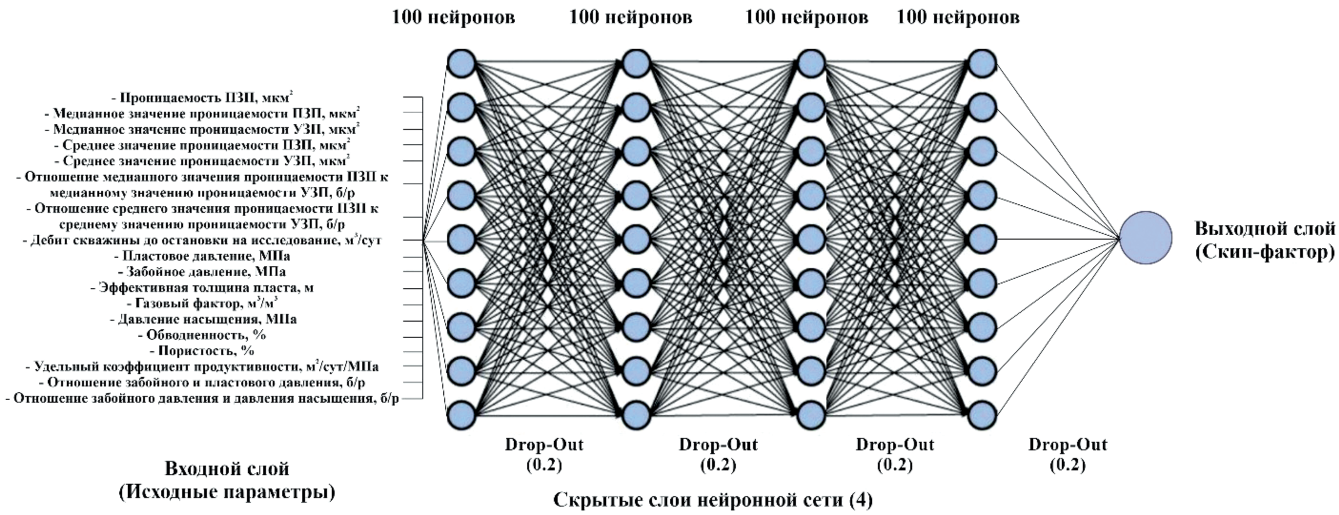

Fig. 4. Architecture of a fully connected neural network for skin factor prediction

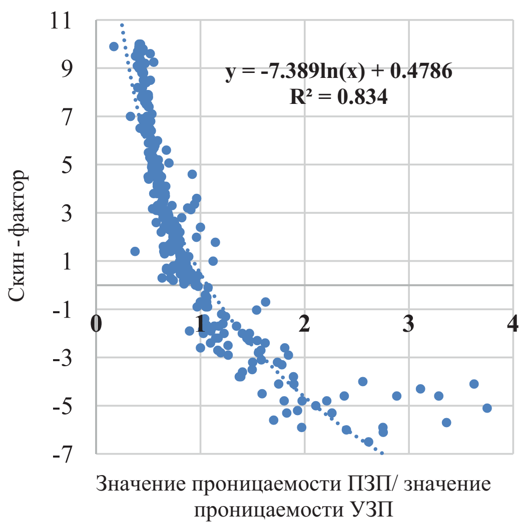

Fig. 5. Scatter diagram of the skin factor from the ratio of permeability BHZ to RFZ

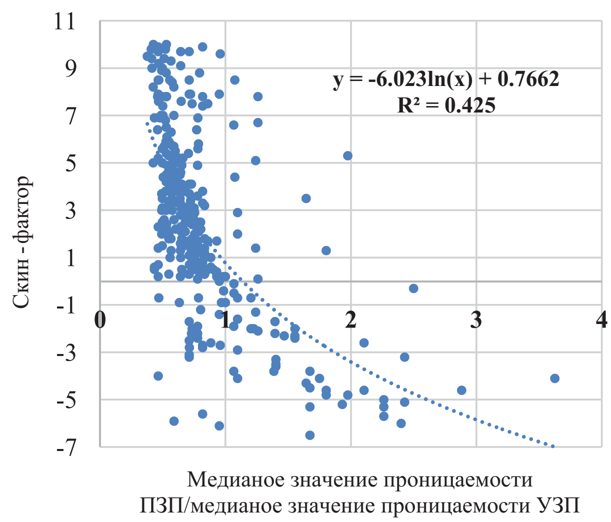

Fig. 6. Scatter diagram of the skin factor versus the ratio of the median permeability values of BHZ to RFZ

At the next stage, the dependence of the loss function on the number of epochs for the skin factor model was plotted, shown in Fig. 9.

Figure 9 shows that the neural network model for predicting the skin factor can be trained, there is no retraining. The average absolute error on the test sample is 1.8 (R^2 = 0.644). The epoch of a neural network is considered to be the passage of a complete set of data through the neural network. During each epoch, the system receives input data, passes through the layers, calculates the error, and adjusts the weights using a backpropagation algorithm. The neural network loss function is used to measure the difference between the predicted and actual values. The purpose of the loss function is to minimize the error. In our case, the root mean square error is used as a loss function. A fully connected neural network was used to predict the skin

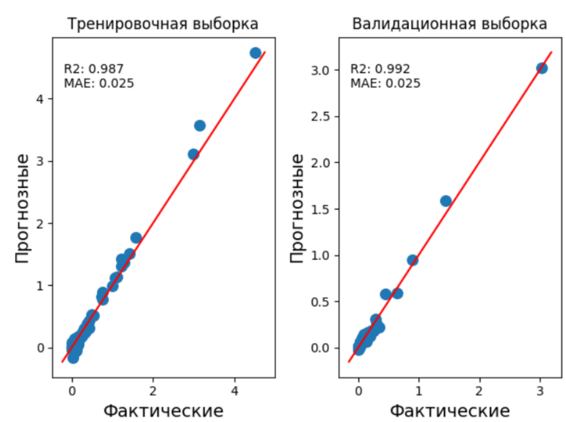

Fig. 7. Scatterplots of BHZ permeability on training and validation samples

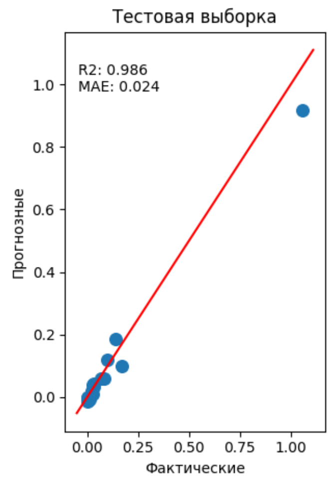

Fig. 8. Scatterplot of BHZ permeability on test sample

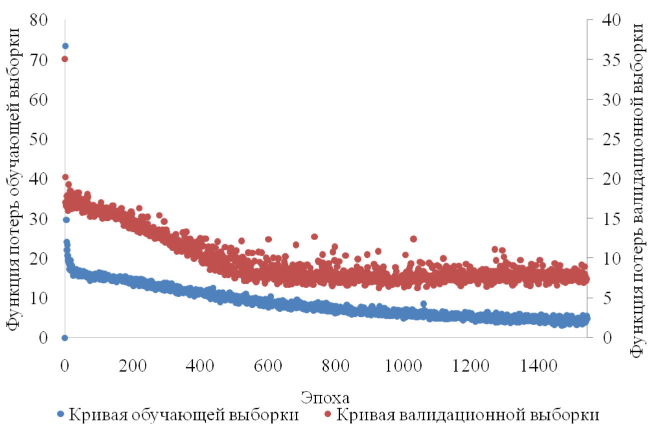

Fig. 9. Learning curves of training and validation samples of the skin factor model

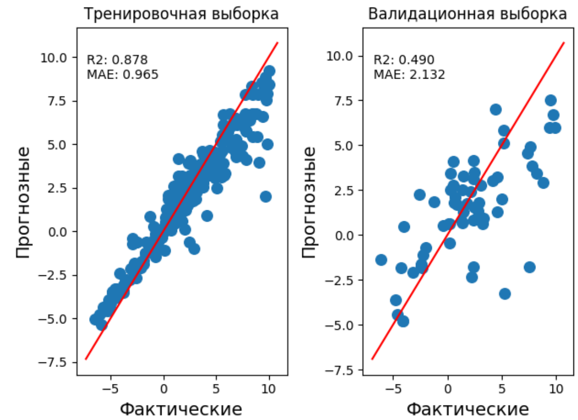

Fig. 10. Scatter diagrams of the skin factor on training and validation samples

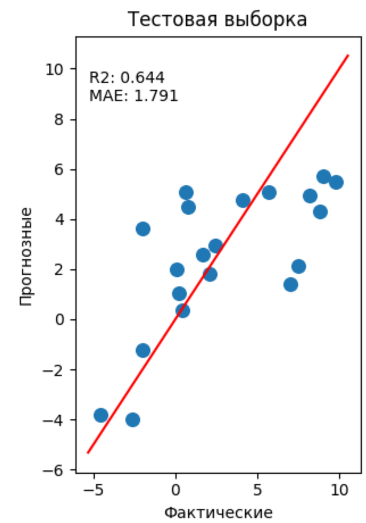

Fig. 11. Scatter diagram of the skin factor on the test sample

factor. Figures 10 and 11 show scatterplots for the training and validation sets.

The considered approaches and methods are the first stage of creating a comprehensive system for assessing the state of the bottomhole formation zone based on significant field data (Big Data) obtained during the development of oil and gas facilities.

The results of the obtained studies indicate a good predictive ability of BHZ permeability based on well productivity. Higher estimates of forecasting accuracy were obtained using a fully connected artificial neural network than using a multiple linear regression model. The average absolute error on the test sample is 0.024 μm^2; for multiple linear regression it is 0.190 μm^2. The coefficient of determination R^2 of the predicted and actual values of BHZ permeability on the test sample is 0.986.

A methodology for estimating the skin factor of a well is proposed. Note that the accuracy of determining the skin factor using this method depends on the uncertainty of RFZ permeability, the quality of hydrodynamic data and their interpretation. The neural network model for predicting the skin factor can be trained, there is no retraining. The average absolute error on the test set is 1.8. The coefficient of determination R^2 of the predicted and actual values of the skin factor is 0.644, for multiple linear regression it is 0.427.

4. Conclusion

The paper proposes a methodology for rapid assessment of the state of the BHZ based on historical data from the development of the object: geological and operational information, as well as the results of interpretation of hydrodynamic studies. Based on these data, the following artificial neural network models were built to predict the parameters of the bottomhole formation zone:

1) BHZ permeability prediction model based on neural network training: the average absolute error on the test sample is 0.024 μm^2, for multiple linear regression it is 0.190 μm^2; the coefficient of determination R^2 of the predicted and actual values of BHZ permeability on the test sample is 0.986.

2) skin factor prediction model based on neural network training: the average absolute error on the test sample is 1.8; the coefficient of determination R^2 of the predicted and actual values of the skin factor is 0.644, for multiple linear regression it is 0.427.

BHZ permeability is determined quite accurately based on well productivity characteristics. The approach proposed in the work for determining the skin factor is complicated by the accuracy of well test interpretation. In future studies, it is planned to use recurrent and convolutional neural networks to study the dynamic components of the formation of the bottomhole formation zone and create an integrated approach to solve the problem.

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Прогнозирование гидродинамических параметров состояния призабойной зоны скважин с помощью методов машинного обучения

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Актуальность разработки методики оперативной оценки призабойной зоны пласта (проницаемости призабойной зоны пласта и скин-фактора) обусловлена в первую очередь экономическими причинами, поскольку существующие подходы к ее определению, основанные на проведении гидродинамических исследований, ведут к недоборам нефти и повышению рисков необеспечения вывода скважины на режим. Современные методы работы с большими данными, например глубокое обучение искусственных нейронных сетей, позволяют осуществлять контроль за состоянием призабойной зоны пласта (ПЗП) скважин без их остановки на гидродинамические исследования, что сократит убытки у предприятий, осуществляющих добычу нефти, с одной стороны, и позволит проводить оперативный анализ для эффективного и своевременного применения технологий интенсификации, повышения нефтеотдачи пласта, с другой. В работе проанализированы существующие методы по определению призабойных характеристик пласта и подходов машинного обучения. Предложена методика для оперативной оценки состояния призабойной зоны пласта: проницаемости ПЗП и скин-фактора – с помощью обучения искусственных нейронных сетей на геологических и эксплуатационных данных и результатах интерпретации гидродинамических исследований на примере терригенных объектов нефтяных месторождений. Представлены результаты тестирования различных архитектур нейронных сетей для прогнозирования проницаемости ПЗП: количества слоев и нейронов в них с выбором наилучшей. Использованы технические приемы для предотвращения переобучения моделей. Предложена авторская методика по оценке скин-фактора скважин с помощью комплексного анализа построенных статистических моделей и моделей обучения искусственных нейронных сетей для решения задачи регрессии.

Ключевые слова: терригенный коллектор, призабойная зона пласта, проницаемость, скин-фактор, машинное обучение, нейронная сеть

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