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Reproduction of Reservoir Pressure in Oil Field Development: Prospects and Problems of Using Methods Machine Learning

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Abstract. Currently, models based on the application of artificial intelligence methods are actively developed and applied in solving a variety of problems, including in the practice of petroleum engineering. Evaluation of the accuracy and reliability of the developed models is usually reduced to defining standard statistical criteria, while the developers do not always use a separate examination sample. This article presents the results of the study, which are reduced to multivariate testing of the neural network model previously developed by the authors to determine the dynamic reservoir pressure in the selection zones of oil wells. The model is characterized by a number of advantageous characteristics, including minimal requirements for the amount of initial data, which determines its relevance and practical demand. However, the closed nature of computational algorithms related to the "black box" category does not allow us to reasonably formulate the conditions and criteria for applying the model, the reliability of the retro- and prospective forecast of the reservoir pressure. Three oil deposits of one field with different geological and physical conditions were selected as the object of study. The availability of a large number of actual reservoir pressure determinations by means of hydrodynamic well testing at the field allowed testing the model under a variety of scenarios, for each of which the forecast error was estimated and analyzed. As a result, high estimates of the model for retro- and prospective reservoir pressure reproduction were confirmed. It was found that forecast errors are reduced to zero in the presence of a large number of actual reservoir pressure determinations. However, to perform the calculation for each well, a single measurement for the entire history is sufficient. It was found that a sharp change in the well flow rate should also be accompanied by an actual determination of reservoir pressure with the entry of the obtained value into the model. In the absence of even a single reservoir pressure measurement for the wells, the model reliably reproduces its value using the kriging procedure used in the algorithms.

Keywords: machine learning, artificial intelligence, reservoir pressure, oil well, forecast

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Introduction

Continuous formation pressure control is one of the main elements of hydrocarbon field development monitor system. Availability of authentic information regarding formation pressure is crucial when solving various tasks of petroleum engineering. For instance, the necessity for using formation pressure for the material balance method in estimation hydrocarbon resources is shown in research work (Levitina et al., 2023). Authors (Zong et al., 2023) use formation pressure dynamic data for studying the legitimacy of water infusion of productive reservoirs. Formation pressure is used for monitoring interaction between productive objects of multilayered hydrocarbon field in the research work (Jia et al., 2021).

Meanwhile formation pressure, which is one of the most important characteristics of the energy state of the reservoir, is determined quite rarely in practice because of insufficient regularity of well tests in relation to high duration of the pressure restoration and the necessity for the stopping of the well (Martyushev et al., 2023;

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Martyushev et al., 2021). The prognosis of needed duration of well's stopping sought-for obtaining high-quality pressure recovery curve (PRC curve) is a relevant task that currently does not have a universal solution as the process is quite complex, its legitimacies are defined by combination of different factors. For example, in the research work (Nigametyanova, Ishkin, 2024) authors conclude that the type of well completion influences pressure recovery duration.

A new direction devoted to the potential of reducing the durability of research. For instance, authors of scientific research (Savchenko et al., 2023) suggest registering pressure dynamic at the beginning of the electric-centrifugal pump during technologic stops of wells and defining some parameters on that basis. Other authors (Khankishieva, 2023) propose similar conclusions, however, made for oil well pumps. Methods of interpretation of the well tests after brief perturbing effect of the reservoir is presented in other scientific work (Gadilshina et al., 2023).

In other cases, quality of received research data does not let resolve tasks authentically, including formation pressure definition, even when the durability of well stoppings is sufficient. Thus, authors of work (Akhmetdinow et al., 2024) introduce the phase segregation after well stopping process data which impacts final pressure recovery curve and its processing results. In the article (Sergeev et al., 2019) data regarding lack of processing radiant flow section on many PRC graphs which also reduces quality of researched material and specifies the necessity of developing other ways of their interpretation.

In that case, development of indirect methods of formation pressure definition that either does not require well stopping for study or minimizes the durability is a relevant task.

Common methods of formation pressure prognosis lean on physical models in the first place. Such models are based on rock mechanics and liquid dynamics that include a broad range of appropriate parameters (Cao et al., 2024; Deng et al., 2024; Li et al., 2024; Shi et al., 2024; Kanin et al., 2025). However, application of these methods suggests the availability of big number of parameters, including empirical ones, which may lead to inaccuracies of sough-for parameter prognosis, especially on difficult geophysical conditions.

In the conditions of the modern stage of petroleum engineering development, methods based on statistical processing of big amount of accumulated data which distinguishes factual definitions of prognosed parameters. Research results regarding statistical models of formation pressure definition for oil producing wells of one of Perm Krai oil fields are shown in the research study (Ponomareva et al., 2022). Authors have developed a series of multiple linear regression equations that let calculate the value of formation pressure according to geological and technological indicators. Understanding of computational algorithms and an opportunity to analyze them in order to develop regularities of prognosed value behavior (formation pressure) are undeniable advantages of models which was demonstrated by the authors for the conditions of the concerned field. It is also important to state that although models have sufficiently high statistical assessments, their practical use and production is limited due to harsh requirements of input data which should correspond to actual range of training set to the full. For instance, one of the most significant features, that appear in the first places of regression equations, is such indicator as producing life of well after putting into operation. The training set included the data regarding the exploitation of wells in the range of five years, thus it is not recommended to carry out estimations in appliance with the model for bigger work period. In addition, excluding the indicator from the model leads to substantial decline of its statistical assessments which are coefficient of determination, level of concern and standard error of estimate.

In the conditions of modern methods of mass data processing development, new methods of defining various geological and technological parameters, including formation pressure, got application based on using methods of artificial intelligence (AI) (Karsakov et al., 2025; Davoodi et al., 2025; Nie et al., 2025). For instance, authors of the article (Tang et al., 2022) demonstrate high success of formation pressure prognosis with complex use of two methods of computer-assisted instruction. In the research study (Harp et al., 2021) authors demonstrate high assessments of formation pressure prognosis model which feature is complexing computer-assisted instruction method and physical (analuytical) permeable medium fluid flow model. Article authors (Martyushev et al., 2021; Zakharov et al., 2022) describe formation pressure definition model also based on usage of neural network. Materials of factual formation pressure definition regarding significant quantity of oil producing wells as well as their exploitation indicators were used when training it. The developed model demonstrates high prognostic ability at retrospective and perspective modelling of dynamical formation pressure in recovery zones of oil producing wells. Minimal amount of necessary input data its advantage is also considered its advantage.

The most common computer-assisted instruction models include support vector regression (SVR), multilayer perception (MLP), extreme gradient boosting (XGBoost) and networks with long short-term memory (LSTM). These models demonstrate predominantly high prognostic ability in comparison to traditional methods of formation pressure prognosis (Zhang et al., 2022; Kanin et al., 2024; Peters et al., 2024; Zhang et al., 2024; Wang et al., 2025; Xi et al., 2025). Still, computer-assisted instruction methods have their limits such as responsiveness to quality and quantity of data and limited ability to reproduce spatiotemporal dynamical characteristics (Campos et al., 2024; Soromotin et al., 2025). Although development of deep computer-assisted instruction methods allows to eliminate a number of issues, their abilities do not let describe processes inherent for complex geological systems in the dynamic of their development. In the research (Kuznetsova et al., 2023) authors, confirming general high efficiency of the model, mark out the probability of receiving invalid data in some individual cases.

Studying computational algorithm of most models based on computer-assisted instruction methods usage is complex and not always explicit procedure. In almost every case, developers of such models, when analyzing them, restrict themselves with assessing standard statistical parameters – correlation coefficients between the calculated and actual values of the modeled parameter, including usage of independent test sets, standard error, etc. (Yu et al., 2020; Pwavodi et al., 2023; Zong et al., 2023; Kalem et al., 2024; Shao et al., 2024). Oftentimes, even developers cannot fully prognose its behavior for changing conditions of studied process. However, general propagation and use of computer-assisted instruction methods for the purposes of solving different tasks specifies the necessity for their analysis and research.

Thereby, it is effectually to study not the system on the whole, but its reaction to the changing conditions which would allow to broaden the knowledge of the model based on computer-assisted instruction, its abilities and limitations, which this article is dedicated to. Conducting such studies is relevant not only in the context of studying specific concerned model, but also for the development of general direction of usage of artificial intelligence methods and computer-assisted instruction methods for solving tasks of petroleum engineering.

Thereby, the aim of this research is to study the efficiency of the model developed by a group of authors for various geological and geophysical conditions based on the usage od computer-assisted instruction methods, created in order to reproduce dynamical formation pressure in recovery zones of oil producing wells. Within this research various tasks are being resolved: 1) performing calculations of formation pressure in retrospective and perspective periods with the help of developed model and comparing it with actual measurements; 2) performing calculations of formation pressure with the help of the developed model when successively removing actual measurements; 3) assessment of the formation pressure prognosis ability with the help of the developed model when only one actual measurement is available; 4) the study of prognostic ability of the developed model.

Materials and methods

The researched model of the retrospective and perspective dynamical formation pressure prognosis in the recovery zones of oil producing wells, made as a specialized software (Martyushev et al., 2023). As an input data, it uses information regarding average monthly liquid, oil and water flow rate and the operating factor for all the wells that have ever been in use at the development site under consideration. The period if perspective prognosis, chosen by experts, right now is 12 months and could be prolonged through training and adjusting the model in the future. Thorough description of the model, the history of its creation and training is introduced in the research study (Zakharov et al., 2022).

The input data is used as an individual file with a .txt format (Fig. 1). It is considered standard and is uploaded from hydrodynamical reservoir model which minimizes time expenditures for the preparatory process and the

HFORM	WELL	'DD/MMM/YYYY'	QOIL	QWAT	QLIQ	QGAS	WEFA	BHP	THP
HTAB									
	1	01/DEC/2013	92.3900	0.0808	92.4708	1.3935	0.6452	0.00000	0.0000
	1	01/JAN/2014	90.3273	0.0887	90.4160	0.7302	0.9892	0.00000	0.0000
	1	01/FEB/2014	87.1116	0.0822	87.1939	0.9647	0.9970	0.00000	0.0000
	1	01/MAR/2014	88.4815	0.4197	88.9011	0.5344	1.0000	0.00000	0.0000
	1	01/APR/2014	84.3995	1.0431	85.4426	3.1440	1.0000	0.00000	0.0000
	1	01/MAY/2014	82.7936	1.0157	83.8093	3.3172	0.8777	0.00000	0.0000
	1	01/JUN/2014	78.3135	0.9604	79.2739	3.3526	0.5903	0.00000	0.0000
	1	01/JUL/2014	84.5230	0.5294	85.0524	3.0766	1.0000	0.00000	0.0000
	1	01/AUG/2014	82.2252	0.5151	82.7403	2.8596	0.9852	0.00000	0.0000
	1	01/SEP/2014	77.9945	0.4819	78.4763	6.2620	1.0000	0.00000	0.0000
	1	01/OCT/2014	69.9625	0.1406	70.1031	3.4159	0.8387	148.59330	177.1356
	1	01/NOV/2014	64.0032	0.1219	64.1251	3.2409	1.0000	0.00000	0.0000
	1	01/DEC/2014	90.2650	0.2140	90.4790	3.6638	1.0000	0.00000	0.0000
	1	01/JAN/2015	70.3000	1.1540	71.4539	2.3147	0.9960	0.00000	0.0000
	1	01/FEB/2015	69.7044	3.5411	73.2455	3.2628	1.0000	0.00000	0.0000
	1	01/MAR/2015	55.6461	1.5699	57.2160	2.5810	0.9960	0.00000	0.0000
	1	01/APR/2015	35.2334	0.5929	35.8263	1.8543	0.7458	150.34660	173.8022

Fig. 1. The illustration of the file content with input data. Well – the number of the well; DD/MMM/YYYY – date, month and year; Qoil – oil extraction (monthly), th.t.; Qwat – water extraction (monthly), thous.m^3; Qliq – liquid extraction (monthly), thous.m^3; Qgas – gas extraction (monthly), million m^3; WEFA – well operation coefficient; BHP – formation pressure (actual), atm, THP – formation pressure (prognosed), atm.

probability of errors that accompanies their by-hand entry.

The data regarding bottom hole pressure (column "BHP") of wells is not used when performing calculations, however, its entry is foreseen by the program functionality with the aim of following visualization and expert analysis of the user.

It is necessary to point out the issue regarding definition of optimal amount of actual formation pressure definition (with well tests) for accurate performance of the model. Technically, the data about actual formation pressure definition is not necessary when performing calculations. In that case, if such estimations are missing, calculation of the model formation pressure value will be performed based on the kriging procedure – special interpolation of the calculation results for the neighboring wells. The ability of kriging procedure realization is ensured through executing simultaneous modeling for the whole development object (reservoir) and considering spatial layout of the coordinates of wells. However, accuracy and authenticity of the modeling results may turn out to be unacceptable in case of lack of actual formation pressure definition. The goal of responsiveness assessment of the model to the availability of actual formation pressure and its discretization will be explored in course of this research. Moreover, the tasks regarding assessment of prognosis ability of the model in retro- and perspective reproduction of formation pressure will be set during the research.

Multivariable modeling with following comparison of the prognosed and actual formation pressure value would be used as a main instrument of solving set tasks. In this case, the research object should possess a big number of actual formation pressure definition. It is also expedient to carry out calculations applied to various geological and physical conditions which is also necessary to take into consideration when choosing the research object. This article would study one of oil fields in northern part of Perm Krai with three reservoirs with different geophysical features in their structure as a main study object in appliance with set requirements.

Operating well stock of the field includes 54 wells as well as 18 wells of object D_3fm+C_1t, 22 wells of object C_1bb and 14 wells of object C_2b. Considerable number of high-information well test with the use of deep measuring equipment will be performed on the wells which allows to use formation pressure, determined during its implementation, as reference value.

Results

Calculations are performed for all of the development object on the basis of the neural network model. Formation pressure values for all the operation period of each well in increments of one month as well as perspective value prognosis for 12 months with corresponding increments are the results of the calculations. The results are shown in a graph form, done individually for every well of the field. Graphs from Fig. 2, made for the representative wells of each object in a module service Data Stream Analytics for retrospective (red line) and perspective (purple line) period of one year are introduced as an example. Actual formation pressure values for the dates of well tests are plotted on the graphs which allows to estimate the prognosis accuracy based on visual analysis beforehand.

A corresponding graphical comparison of actual and modeled data has been made in order to assess the accuracy of retrospective formation pressure reproduction of all wells of operating reservoirs fund (Fig. 3).

When comparing modeled and actual formation pressure definitions, shown on the correlation filed of Fig. 3, it must be addressed that the studied neural network model allows to accurately make retrospective prognosis of formation pressure for all three development objects with different geophysical features. The points are closely and evenly grouped along the imaginary lines with a monic incline and the correlation coefficient between calculated and actual values exceed the number r = 0,9 in all the cases.

As it appears from the data introduced in Figs. 2 and 3, the ability of reproducing formation pressure of the model is relatively high for all three development objects. However, a proper number of well tests with definition of actual formation pressure value was performed on wells, which probably contributes to the improvement of working conditions of the model.

№	Parameter	Reservoir implications (for the object)		
		D_3fm+C_1t	C_1bb	C_2b
1	Type of reservoir	carbonate	sandstone	carbonate
2	Reservoir oil viscosity, mPa*s	2.46	2.53	17.5
3	Solution gas-oil ratio, m^3/t	68.1	66.5	21.3
4	Porosity (fraction)	0.08	0.17	0.14
5	Permeability coefficient, μm²	0.002	0.402	0.042

Table 1. A brief geophysical characterization of the field

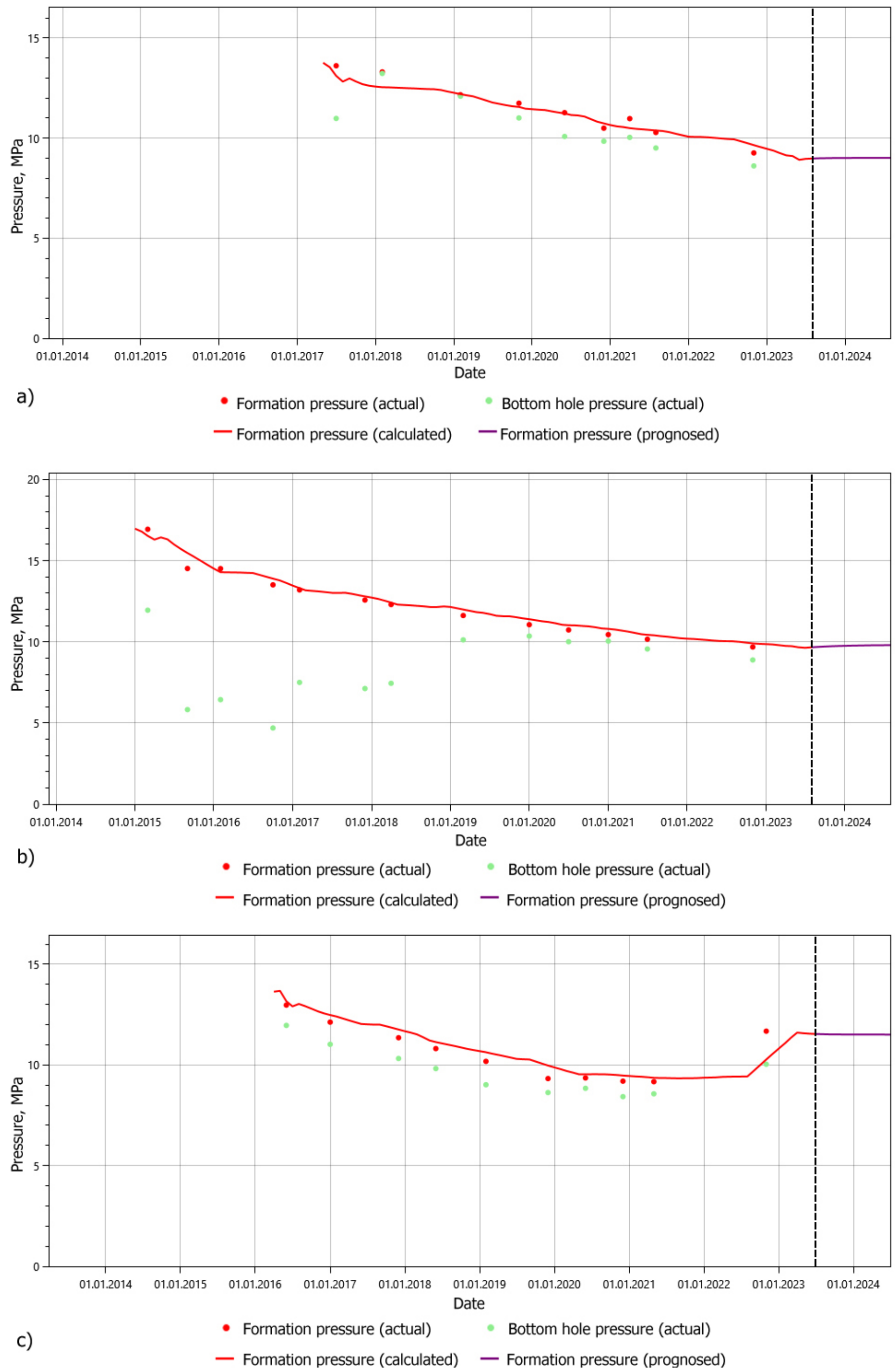

Fig. 2. Graphical comparison of modeled and actual formation pressure definitions: an example for the well of the carbonate object D_3fm+C_1t (a); an example for the well of the terrigenous object C_1bb (b); an example for the well of the carbonate object C_2b (c)

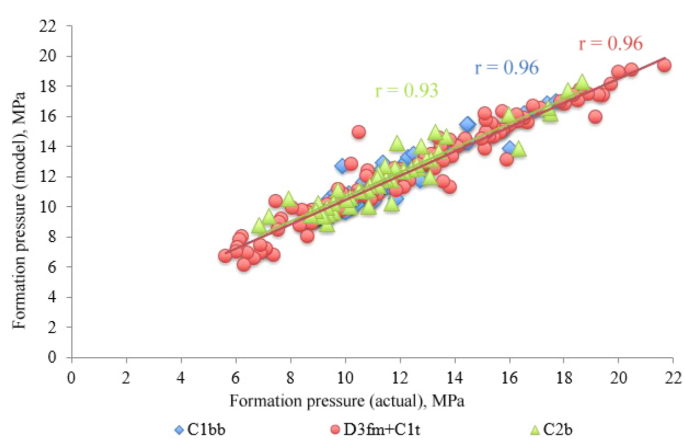

Fig. 3. Comparison of modeled and actual formation pressure definitions differentially for the development object

In that case, research regarding accuracy assessment when gradually deleting actual measurements has been done later on. Moreover, two scenarios were considered: deleting either one of the final (scenario 1) or one of the first (scenario 2) actual definitions.

Five well tests with defining actual formation pressure have been performed on the concerned well. As the study went on, five calculations were made during which the model reproduced formation pressure when deleting final actual formation pressure value (scenario 1.1), two final values (scenario 1.2), etc., until all five actual definitions have been deleted. Calculations regarding the second scenario were done analogically. Results assessment done with graphical comparison of predicted and actual formation pressure dynamic in the course of operating period of the well (Figs. 4, 5). Both graphs also illustrate the basic variant that demonstrates calculation results made when all actual formation pressure value was included in the model.

Moreover, an error which represents deviation value of the pressure was calculated for each scenario (Figs. 6, 7).

As it appears from the analysis of the data introduced in Figs. 4–7, the researched neural network model has different responsiveness towards the amount of actual formation pressure definition used as input data. There was far less computation error when realizing scenario 2. The scenario that suggests usage of only one actual formation pressure definition demonstrates extremely low assessments. In other words, despite technical abilities to perform the computing operation, the quality of prognosis is low which highlights the necessity of solving tasks regarding optimization of input data quantity. It is also notable that low realization error of scenarios 1.5 and 2.5 for which is typical to lack the information about actual formation pressure definition as input data and the calculations are based on using the kriging procedure in the mathematical tool.

Scenario 2.3 has been chosen as the most optimal one. It suggests the availability of two actual formation pressure definitions for the November of 2019 and the May of 2021 and they have error less than 1 MPa.

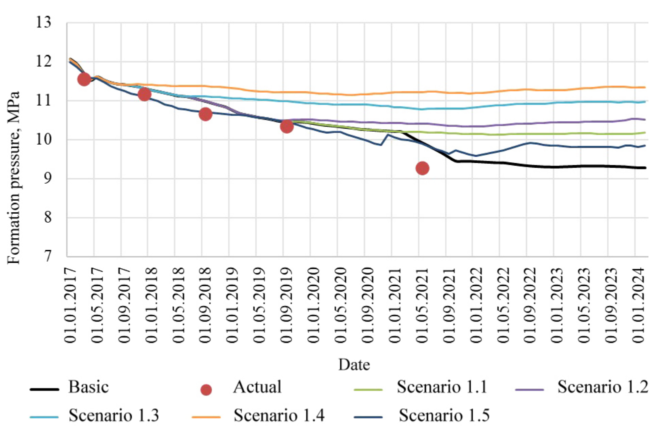

Fig. 4. The research results of the prognostic ability of the neural network model with consistent deleting of final values of one of the wells (scenario 1)

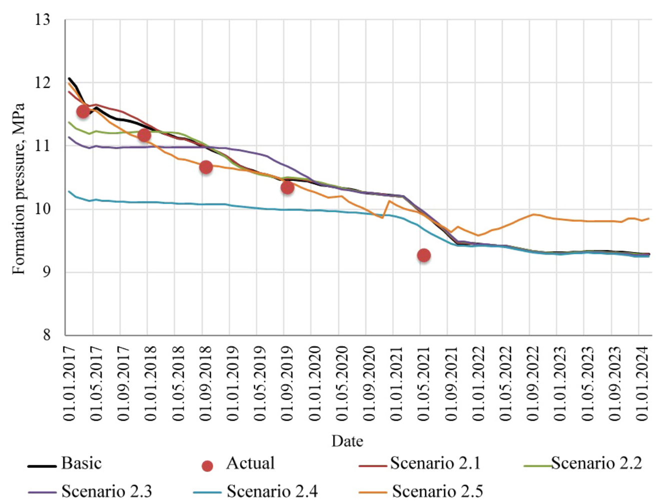

Fig. 5. The research results of the prognostic ability of the neural network model with decimation of actual definitions of one of the wells (scenario 2)

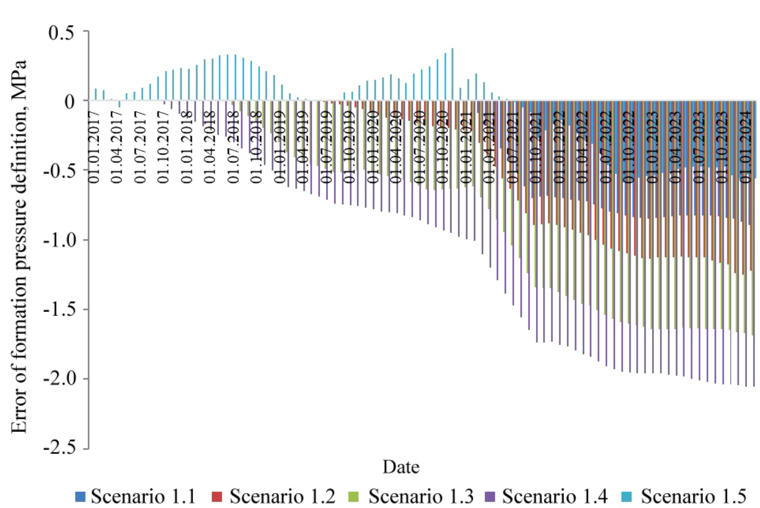

Fig. 6. Graphical projection of error of formation pressure definition compared to the basic variant (scenario 1)

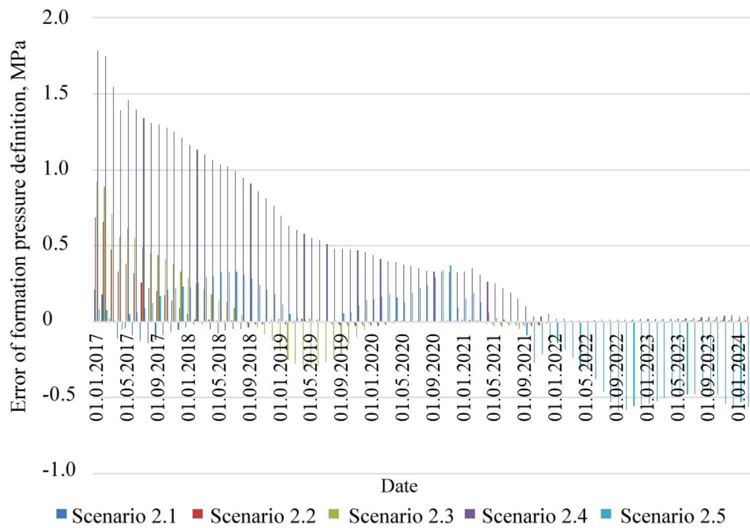

Fig. 7. Graphical projection of error of formation pressure definition compared to the basic variant (scenario 2)

Mentioned dates are highlighted on the graph of well operation (Fig. 8) from which the fact of their correspondence with the period of pronounced change of character of liquid rate which, in its turn, can be specified by the change of filtration conditions in the drainage area, due to performing some geotechnical activities.

The research regarding perspective prognostic abilities of the neural network model has also been done according to two scenarios. The first scenario used input data about the January of 2022 (all data of 2022–2024 period excluded) for its calculations and further actual formation pressure definition used in assessment of calculated parameters. In second scenario realization, only actual formation pressure definitions in the period of 2022-2024 have been excluded, but the model used information about all well flow rates for the whole mentioned period. That is, the difference between scenarios only lies in availability or unavailability of information regarding flow rates in the prognosed period. Scenario 1 appeared to be closer to actual conditions of perspective modelling.

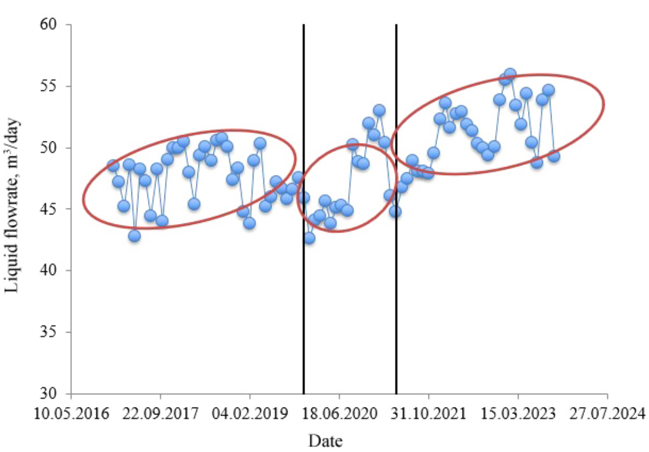

Fig. 8. The dynamic of liquid flowrate of the well – research object

Described scenarios were realized for eight wells in all of which were performed well tests in observed time. Comparison between modeled and calculated formation pressure, also the errors in their definition, are graphically illustrated in Figs. 9–10. With that, the deviation value from the actual value of modeled formation pressure definition has been chosen as an error.

Discussion

The outlined above research was made with an objective to study the workability of the model, developed by a group of authors and created to reproduce dynamical formation pressure in recovery zones of oil producing wells. The model is trained on actual field data from a long-term history of hydrocarbon production in the considered area, complied into a significant digital database. In the period of the production of the model, its accuracy assessment has been done by the set of the simplest statistical parameters only (nominal and absolute error prognosis) which did not let fully formulate the conditions of its effective use. Labour intensity and analysis vagueness of the computing algorithm, typical of complex models based on computer-assisted instruction methods usage, also did not allow to solve considered task which caused the necessity to performed research, outlined above.

The done researches reposed in multivariable model testing for different input data set. In that case, a solid choice of objects which also should be marked by maximum amount of actual prognosed parameter (formation pressure in this context) became an important step.

During multivariable testing, some special features of the studied formation pressure definition model functioning have been estimated. Technically, only one actual formation pressure definition in the whole history of operation of each well is minimally needed for the

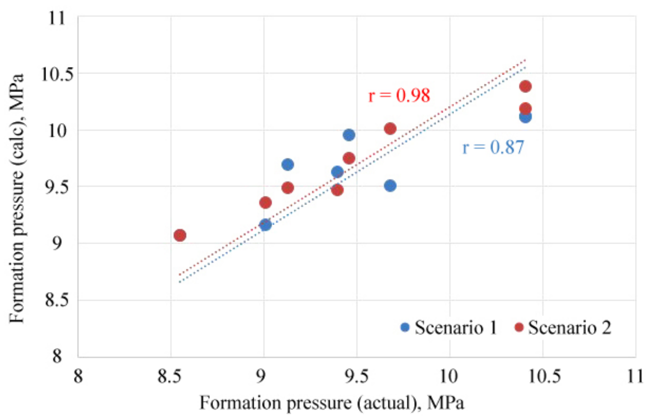

Fig. 9. The comparison of calculated and actual formation pressure values with perspective modeling

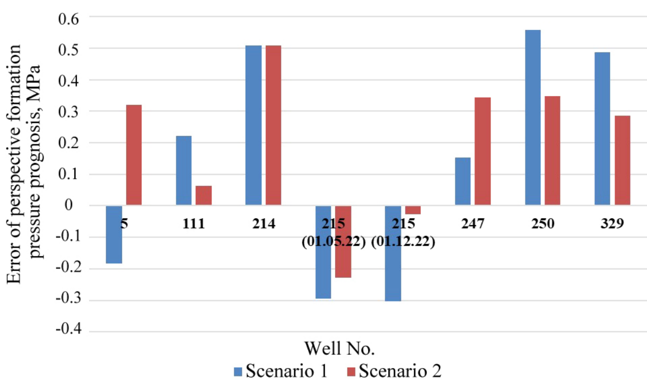

Fig. 10. Graphical projection of error of perspective formation pressure prognosis compared to actual values. The results of well 215 are introduced for different dates if research carry-out

calculation performance. However, increase of actual formation pressure definition number gradually upgrades the accuracy of the model. Moreover, the availability of big amount of well tests is impossible in some occasions due to economical and technological reasons, also it states the question regarding the necessity of retrospective formation pressure modelling. Eventually, an estimation of balance between the amount of actual formation pressure definition and accuracy of model prognosis is viable. The multivariable testing, made with this objective, has demonstrated the advantages of scenario 2.3 for which is typical to use two actual formation pressure definition in periods, marked by the evident change of filtration conditions during which a sharp change in rate of production of wells happens.

On the whole, a number of important conclusions has been received during the analysis of the results of the multivariable testing of the model. Thus, the model cannot fully prognose the value of formation pressure when filtration conditions change, for instance, hooking up previously unused reservoir sections when performing geotechnical actions etc.

It is also necessary to note that a single actual formation pressure sample, which is technically enough for calculation performances, does not provide high accuracy of modeled and actual formation pressure definitions.

The following conclusion is quite logical. The exclusion of actual samples in any operating period of wells causes synchronized degradation of reproductive ability if the model at the same time. On account of that, a recommendation, regarding the performance of well tests at even flow, is followed.

An ability if perspective prognosis of formation pressure value in a length of 12 months is one of the advantages of the studied model. Such task is relatively relevant for petroleum engineering practice which explained the viability of researching the accuracy if perspective prognosis. With this this aim, historical input data regarding the objects has been reduced by two years. The prognosed values for the eight wells with actual formation pressure definitions have an error of less than 0,6 MPa in the excluded period, which proves high reproductive ability of the model with a perspective of 12 months. It is also notable that a calculation error should be compared to the value of depression per formation, for example. Thus, such parameter, on average, has essentially great value for the conditions of concerned region.

It is also necessary to point out high assessments of the reproductive ability of the model, significant for the scenarios with the full exclusion of actual formation pressure definition in which the calculation is carried out based on the kriging procedure. However, this variant is suitable only for individual (singular) wells because the computing algorithms are based on the usage of the prognosis results of the neihbouring wells. Thereby, the modeling results regarding neighbouring wells should be fully accurate. Besides, the kriging procedure can be used as an instrument for the validation of the backbone network of wells for the formation pressure value control.

The authors of the article think that the developed model of dynamical formation pressure reproduction in the recovery zones of oil producing wells is not the alternative of the well tests, its functionality comes down to deepening the analysis of the energy state of the field and the perspective prognosis.

The scenario seems perspective when regular well tests are performed on the valid backbone network of wells and the calculations regarding the rest fund are performed with the use of the developed model.

The introduced research should not be considered comprehensive as it does not give the answers regarding the special aspects of the usage of the developed model based on computer-assisted instruction methods use.

The relevancy of both continuation of the calculating experiments outlined above and general replication of the way of deep study of such model when solving engineering tasks does not raise any doubts.

Conclusion

The done research, which consisted of multivariable testing of the neural network model, allowed to receive a set of conclusions, that characterized the studied model, and formulate conditions for its effective usage.

The model is characterized by high retro- and perspective prognostic ability when defining dynamical formation pressure in the recovery zones of oil producing wells. Moreover, the number of actual definitions of the prognosed parameter gradually increases the accuracy of modelling.

The availability of just one actual definition of the formation pressure value in each well for the whole operating period is enough for calculation performance. However, the change in filtration conditions of the recovery zone can lead to the decrease of prognostic ability of the model. In this case, sharp changes flowrate, caused by, for example, geotechnic actions for the given or neighbouring wells, is viable to accompany with actual formation pressure definitions with writing the value into the neural network model.

The described research does not fully expand on all of the special features of the model and it could be continued both as a direction of increasing the number of solved tasks and through choosing other research objects which is quire relevant for similar computing algorithms, that are widespread nowadays. Overall, it is viable to do such researches for all models which mathematical tool is based on usage of artificial intelligence and computer-assisted instruction methods which would allow to assess them objectively, highlight the conditions of the effective use, fixate possible limitations.

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Воспроизведение пластового давления при разработке нефтяных месторождений: перспективы и проблемы использования методов машинного обучения

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В настоящее время модели, основанные на применении методов искусственного интеллекта, активно разрабатываются и применяются при решении самых различных задач, в том числе в практике нефтяного инжиниринга. Оценка точности и достоверности разработанных моделей сводится, как правило, к определению стандартных статистических критериев, при этом не всегда разработчиками используется отдельная валидационная выборка. В настоящей статье приводятся результаты исследования, в котором описывается многовариантное тестирование модели, ранее разработанной авторами с целью определения динамического пластового давления в зонах отбора нефтедобывающих скважин. Модель основана на применении методов машинного обучения и характеризуется рядом преимущественных характеристик, в том числе минимальными требованиями к количеству исходных данных, что обуславливает ее актуальность и практическую востребованность. Высокой сходимости расчетных и фактических значений прогнозируемого параметра удалось добиться за счет усложнения модели, что затрудняет ее интерпретацию и не позволяет обоснованно сформулировать условия и критерии практического применения. В качестве объекта исследования выбраны три залежи нефти одного месторождения с различающимися геолого-физическими условиями. Наличие большого количества фактических определений пластового давления посредством гидродинамических исследований скважин на месторождении позволило провести тестирование модели по самым различным сценариям, для каждого из которых оценивалась и анализировалась ошибка прогноза. В результате подтверждены высокие статистические оценки прогностической способности модели при ретро- и перспективном воспроизведении пластового давления. Установлено, что ошибки прогнозирования стремятся к нулю при наличии большого количества фактических определений величины пластового давления. Однако для проведения вычисления по каждой скважине достаточным является наличие единичного замера за всю историю. Установлено, что резкое изменение дебита скважины также должно сопровождаться фактическим определением пластового давления с занесением полученной величины в модель. В случае отсутствия по отдельным скважинам даже единичного замера пластового давления модель достоверно воспроизводит его величину посредством используемой в алгоритмах процедуры кригинга при наличии замеров по соседним скважинам.

Ключевые слова: машинное обучение, искусственный интеллект, пластовое давление, нефтедобывающая скважина, прогноз

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