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HORIZONTAL WELL PRESSURE PREDICTION APPLYING MACHINE-LEARNING MODEL

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Predicting pressure parameters is an important prerequisite for successful field development. Accurate prediction of pressure behavior is essential for drilling plans, enhanced oil and gas recovery programmes and reservoir development strategies. Knowledge of these parameters greatly increases the chances of successful and efficient production. It also helps to make the economic model more accurate and predictable [1].

The most common approach to determining well pressure worldwide is the diffusivity equation [2]. The diffusivity equation relates the pressure and time, radius. This equation is based on material balance and Darcy's law [5]. According to this equation, the main factors affecting the fluid pressure are viscosity of liquid, permeability, porosity, total compressibility, wellbore radius, radial distance from well, time [6]. It is considered to use time and radius in a dimensionless form. The well design must also be taken into account [1]. It becomes a difficult task to evaluate all the above factors in the process of field development, as there is a constant change in formation energy (pressure, aquifer), deterioration of bottomhole zone (skin factor), decrease in phase permeability due to flooding of the near-wellbore zone, the influence of relative phase permeability (RPP), formation fluid properties (PVT), and reservoir heterogeneity in general.

Nowadays, there are various methods of well pressure prediction. Nevertheless, they have different accuracy and take different amounts of time. The mathematical approach is the fastest, but on the other hand, it has the lowest level of accuracy and a number of assumptions. At the same time, the method of using simulators is more accurate than the mathematical method, but it requires large time expenditures. In order to determine the well pressure a large amount of information about the field is needed, which introduces its uncertainty in the final prediction. The essence of the method lies in the use of software packages that allow, using the law diffusivity equation and geological information, to iteratively calculate well pressure. This approach allows to replace complex analytical formulas with numerical calculations: the solution based on simplification (approximation) by simpler expressions [1]. Simulators are the most accurate possible way to predict well pressure, which helps to estimate the production profile. They allow evaluating the uncertainty and risks of further development. However, at the same time, it requires many calculations and a large amount of time to create these profiles. To ensure the accuracy of the simulator and the speed of mathematical calculations, it is proposed to use machine learning. This approach will identify the patterns and analytical formulae embedded in the simulator, which will allow further use of this model for rapid production and risk assessment in general [1].

In recent years, attempts have been made to apply machine learning and AI in oil and gas area. For example, in drilling [9], geophysics [8], reservoir engineering [7]. This method is not only easy to implement, but also can capture the complex relationship between input and output datasets. This approach is based more on data analysis, interaction and correlation of system parameters rather than physical processes.

The main purpose of this paper is the development of a machine-learning model to quantify well pressure based on geological properties at different time steps. The object of the research is stock of horizontal wells in a gas condensate field in Western Siberia.

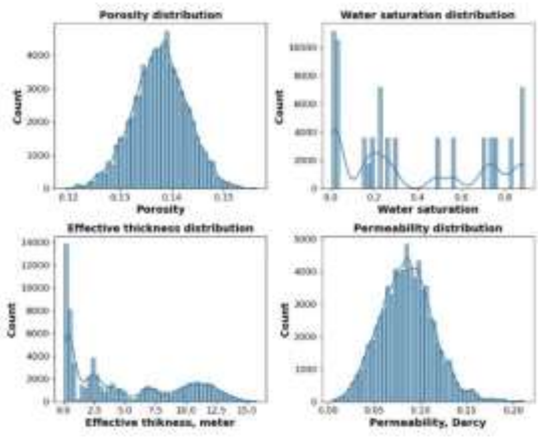

Fig. 1. Distribution of geological properties

At first, 300 iterations of hydrodynamic modeling in the simulator were carried out. An initial data set with the following parameters was collected: time step, porosity, permeability, initial water saturation, reservoir thickness, bottomhole pressure at the wellbore area. In addition, a distribution was obtained for the geological data in order to assess the nature of the density distribution of the input parameters (see Fig. 1). The correlation evaluation between the independent and dependent variables considered was analyzed. This research of correlation coefficients shows that all attributes correlate with wellbore zone pressure for a horizontal well. It was decided not to exclude features as this information allows the model to train better and produce a more accurate result. Exploratory Data Analysis (EDA) helps to save time and improve quality of future machine learning (ML) model. In the data there were not NaN (Not available) values and zero values

Secondly, machine-learning models, gradient boosting (GB), was developed to predict the well pressure. By situating geology in the input data, will make this model more versatile, physics based. The one must take into consideration the time step, which will make it possible to make a forecast not only of the starting rate of flow rate, but also to estimate its further change. Halving Search (Halving Search) with cross-validation was used to find the optimal hyperparameters. A portion of the data is used for model development (training sample) and the remaining data is used as a check on the predictive ability of the model (validation sample). The best algorithm was selected by comparing the behavior on the test and training data. Gradient boosting is a highly efficient and widely used machine-learning algorithm [3]. GB consists of using the combination of basic algorithms (usually simplified) into a single system. It is trained sequentially (which is different from runaway techniques). Each new iteration attempts to compute the variance of an already trained model on the training sample. By creating such an ensemble of models, it is possible to obtain minimum variance in the output. In general, different algorithms can be used as a base algorithm. As a rule, gradient boosting performs well when working with decision trees [4]. The function for optimizing gradient boosting can look like in following expression:

$$L(t) = \sum_{i=1}^{n} l(y_i, \hat{y}(x_i)^{t-1} + f_t(x_i) + \Omega(f_t))$$

where $L(t)$ – optimization function, $l(g(t))$ – loss function, $y_i, \hat{y}(x_i)^{t-1}$ – the value of the i-th element of the training sample and the sum of the values of the first t basis functions respectively (in our case trees) ,x_i – set of features of the i-th element of the training sample, f_t – the function we want to train (in our case, a tree) at step t, $f_t(x_i)$ – value of the model at the i-th element of the training sample, $\Omega(f_t)$ – regularization function (does not allow the model to be overfitted).

Finally, we got best set of hyperparameters by Half Search CV is to enumerate combinations of hyperparameters (pre-defined set). The essence of the method is to reduce the initial sample to the n-th number of elements (n is set by the user) and further evaluation of combinations of hyperparameters of this sample. After that, the sample is increased by k times, and the number of hyperparameter combinations is reduced by k times (candidates with the worst error rate are removed). This is how a half grid search is performed. As a result, one best candidate remains, and it will be the best set of hyperparameters for a given machine-learning model. This approach saves time, with little loss in accuracy. The best hyperparameters are following: learning_rate = 0.1, n_estimators = 3000, max_depth = 10.

A cross plot of the well pressure predicted by the simulator and the machine-learning model and the error values are shown in Fig. 2. This figure shows the performance of the model on both the training sample and the test sample.

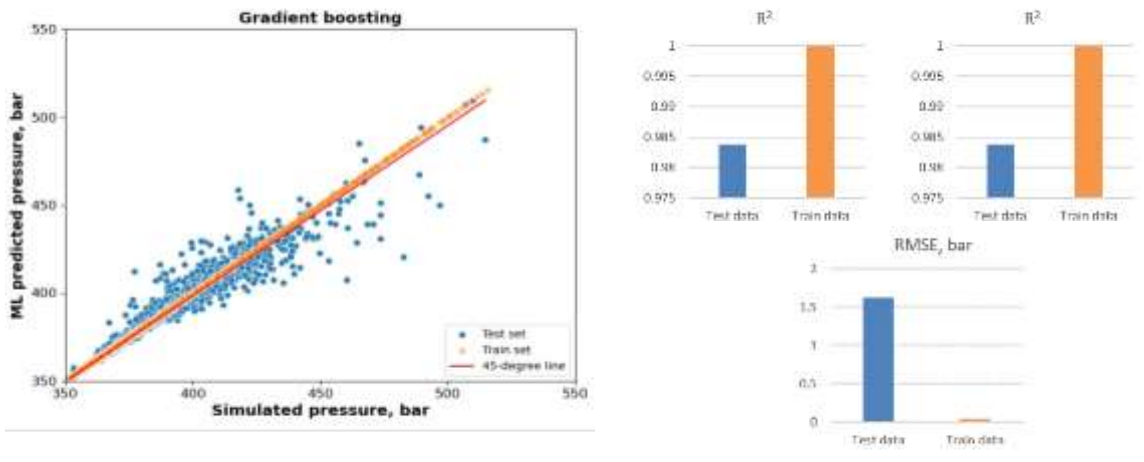

Fig. 2. Comparison of prediction results achieved by GB model developed

As a conclusion, in this study, the well pressure was predicted by applying gradient boosting ML models. The model requires geological parameters (porosity, permeability, effective thickness, saturation). 300 iterations of hydrodynamic calculations were performed to create an initial data set for further model development and validation. The best result was the gradient boosting model with following error values: RMSE = 1,61 bar, R^2= 0,984 %, MAPE = 0,1 %.

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EFFECT OF WELL DESIGN AND GEOLOGICAL FEATURES ON «FISHBONE» WELL PERFORMANCE (FIELD X CASE STUDY)

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Fields with low porosity and permeability values, complex geological structure and high degree of uncertainty are the main share of all discovered reserves. Such field could be successfully developed only with implementation of modern techniques and non-standard methods.

These methods include the use of multilateral wells with long horizontal sections. They allow to increase the oil saturated area which is involved into development process. One of such design which consists of main horizontal wellbore and a few sidetracks is called «Fishbone» wells. Such constructions are used in situations when long horizontal sections with following multistage hydraulic fracturing are not applicable (risks of water coning or breakthrough of gas). There are lot of design factors which controls «Fishbone» well performance – length of horizontal section and sidetracks, angle between them, spacing between sidetracks.

The other significant role in field development planning geological features and sedimentary environment play. The value of average Net-to-Gross ratio (NTG), type of sand bodies, their scale, space distribution and connectivity have to be taken into account before production starts.

In the frames of this work performance of «Fishbone» well for different designs will be assessed in the reservoir with high degree of heterogeneity (with using synthetical model of a Field X). Effectivity of «Fishbone» construction will be compared with multilateral assemblies and base horizontal wells. Impact of each design features and reservoir characteristics will be evaluated and some recommendations about «Fishbone» design applicability could be formulated.

«Fishbone» well consists of one main wellbore and a few sidetracks. Such design requires less volume of drilling operations in comparison with drilling separate horizontal wells, allow to increase conformance of oil saturated rocks. According to reviewed resources, growth of drilling cost in value by 130 percent gives extra production up to 200–300 % [3].

The common design of «Fishbone» well is presented on Figure 1.

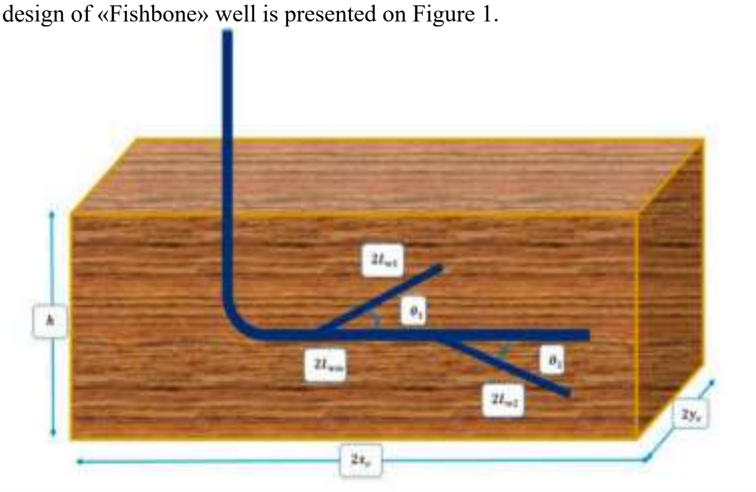

Fig. 1. «Fishbone» well [1]

Such configuration allows to achieve the following goals and tasks:

- Decrease drilling. It happens due to lower time required for tripping and drilling operations.
- Provide a way to involve isolated and unprofitable reservoir bodies into production.
- Produce oil from parts of reservoir with low poroperm properties and high degree of compartmentalization.
- Same production level can be achieved at lower drawdown due to higher Productivity Index (avoid/decrease possibility of development troubles such as water coning).

Distribution of sand bodies plays a crucial impact on each well design performance.

Reservoir conductivity describes connection of sand bodies with each other and with production/injection wells. If high connectivity is achieved with lower NTG value (plot of Connectivity as a function of NTG) – bigger part of reserves is involved in water flooding and development process, more reservoir bodies are connected and can transmit fluid (Fig. 2).