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*New Approaches*

# DEVELOPMENT OF OIL FIELDS USING SCIENCE ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

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**Abstract.** Since artificial intelligence has become increasingly prevalent in the oil industry, it is relevant to this study since it is being used for exploration, development, production, field design, and management planning to improve decision-making, reduce costs, and speed up production. For establishing relationships between complex non-linear datasets, machine learning has proved superior to regression methods in petroleum engineering when it comes to high-dimensional data prediction errors, processing power, and memory. In this article, machine learning is compared with conventional statistical models of oil and gas engineering for determining and predicting reservoir pressure values in the development of oil fields. The effectiveness and potential of machine learning to determine reservoir pressure values was analysed. Using non-parametric multivariate model that link well performance over time, a new method is proposed for predicting reservoir pressure using machine learning. According to the proposed method, the predicted reservoir pressure correlates well with values measured by hydrodynamic studies of wells based on the dynamics of indicators describing well performance. Machine learning method based on random forest algorithm tends to provide better prediction reliability for reservoir pressure than linear regression method (absolute deviation: 0.86; relative deviation: 6.8%).

*Keywords:* Machine learning; Oil fields; Reservoir pressure; Prediction; Non-parametric

## 1. Introduction

In many parts of the world, hydrocarbon fields are currently in the final stages of development. For these hydrocarbon fields, operational control of development parameters and a comprehensive study of productive formations are required (Yu et al. 2018; Smirnov & Al-Obaidi 2008; McGlade 2012). The reservoir pressure is one of the most important indicators of development, which is determined primarily by hydrodynamic studies of wells (well testing). Accurate reservoir pressure prediction has a wide range of applications in the oil industry, especially in optimizing continuous field production, quantifying reservoir productivity, adjusting oil production costs, and evaluating workovers (Al-Obaidi, Kamensky & Hofmann 2010; N. Chithra et al. 2013; Song, Fuquan et al. 2023). Well-test methods are mainly used in oilfield businesses to determine the energy state of the reservoir in zones of the well drainage, as prescribed by the guidelines. The main disadvantage is the need to stop the well, in some cases for a very long time, which leads to the so-called shortfalls in oil production. Considering the time difference between studies, comparing reservoir pressures across all wells seems impossible because all wells cannot be shut down simultaneously in field conditions (Tan, J. et al. 2021; Romanov & Zolnikova 2008).

In the conditions of modern oil production, an urgent task is the widespread use of digital technologies to solve various problems of oil and gas production (Giovanni, F. 2018; Haouel & Nemeslaki 2023; Al-Obaidi 2016). Their solution complicates the need to take into account the influence of geological and technological indicators on the development of oil and gas fields. As a matter of fact, even well-studied development targets are characterized by a wide range of reservoir parameters and technological indicators, which significantly complicates the use of digital technologies to address urgent production problems (Su, J., Yao, S., & Liu, H. 2022; Li, G. et al. 2019). Thus, it appears appropriate to investigate how probabilistic analysis and machine learning can contribute to solving these problems.

As artificial intelligence becomes more prevalent in the oil industry, it is used for exploration, development, production, field engineering, and management planning to reduce costs and speed up decision-making. Machine learning has gained a lot of popularity in establishing relationships between complex non-linear datasets. This type of machine learning algorithm has demonstrated its superiority over regression methods in petroleum engineering in terms of high-dimensional data prediction errors, processing power, and memory (Daniel Asante Otchere et al. 2021; Wang, J. et al. 2022; Al-Obaidi, Patkin & Guliaeva 2003). This results in faster decision-making, which invariably saves money, time and equipment. For an improved and more accurate reservoir characterization process, which is robust to anticipated or unexpected changes, the level of accuracy must be high (Fernandes, Corchado & Marreiros 2022; Steven, Bernd & Petros 2020).

The use of machine learning methods is becoming increasingly prevalent in many industries, including oil and gas (Tariq, Z. et al. 2021; You, L. et al. 2018; Al-Obaidi & Khalaf 2019; Le Van & Chon 2017). There is a tremendous amount of digital information being processed by oil companies around the world, and the amount of data is growing each year. The quality of their processing and interpretation is the basis for making effective design and management decisions. In this regard, the adaptation of machine learning methods to the oil and gas industry in order to create automated systems for monitoring the parameters of oil field operation has great potential (Saeed, Masoud & Adel 2023; A. Choubineh et al. 2017; Wang, X.L. 2017).

So, for example, some oil and gas companies use machine learning technologies to identify the causes of failures in the operation of electric centrifugal pumps and also identify several priority areas for themselves using these methods – searching for analogue objects, restoring historical operational data, processing research data in real-time, etc. When generating a large amount of technological information, it seems possible to use methods based on the collection, systematization, processing and interpretation of data presented in the form of digital arrays.

An approach to predicting reservoir pressure is discussed in (Galkin, Ponomareva & Martyushev 2020; Al-Obaidi & Khalaf 2023), which utilizes multilevel probabilistic-statistical models. The use of the developed multidimensional mathematical models makes it possible to determine reservoir pressure in any period of wells operation without shutting them down for testing. It should be noted that the presented models should not be considered as an alternative to hydrodynamic studies. Their use is advisable for express assessment of reservoir pressure or when it is impossible to stop the well for testing due to technological reasons.

It appears that this technique can be applied to other hydrocarbon fields not only in Russia or China but around the world, since it is the most reliable and adapted among the ones known. Moreover, taking into account the experience of its application, we are exploring machine learning methods for determining reservoir pressure values in real-time and for the reproduction of the historical work of the well.

## 2. Methodology and materials

The following types of problems can be solved using machine learning methods:

1. Regression – prediction of a specific number based on an array of features or characteristics (Palmer 2009; Emeke 2019; S. Tou, 1988);
2. Classification – determination of the category of an object of study by the quantity and quality of its signs or characteristics (Pan, Deng & Lee 2020; Valkó & John Lee 2010; Al-Obaidi & Chang 2023);
3. Clustering – combining objects into groups according to a common feature (Anifowosea, Labadina & Abdulraheem 2015; Sancho et al. 2022; Patel, Kalpesh & Rohit Patwardhan 2019);
4. Dimensionality reduction – compression of the array of object characteristics to a smaller number of features (Sorek et al. 2017; Galkin et al. 2005; Hofmann, Al-Obaidi & Hussein 2022).

As part of the oil and gas field development analysis, these tasks are ubiquitous; they involve controlling the energy state of the development object, through which formation pressure is measured. Since the described approaches have not been used previously to determine formation pressure in oil fields of the studied region, it is important to investigate their applicability and explore future prospects for their development.

*2.1 Initial data for reservoir pressure assessment and forecasting*

One of the promising oil fields in the studied territory (object Bb) was chosen as the object of study. The initial data for building models were used from three other oil fields (objects Bb) in the studied territory, which are characterized by a significant life cycle of operation and the volume of field information. These fields are well-studied and have a sufficient number of actual reservoir pressure measurements. Basic information about the development of these fields is given in Table 1.

**Table 1.** Oil fields information used in building initial models

| *Parameter* | *Field* | | |
|---|---|---|---|
| | *1* | *2* | *3* |
| *Number of wells* | *112* | *48* | *68* |
| *Number of wells tests* | *349* | *212* | *231* |
| *Initial reservoir pressure, MPa* | *21,2* | *23,4* | *22,5* |
| *Current reservoir pressure, MPa* | *11,1* | *9,5* | *7,2* |

*2.2. Machine learning models*

Explaining machine learning models is always an important research topic (Elkatatny, Tariq & Mahmoud 2016; Salem, Yakoot & Mahmoud 2022; Al-Obaidi 2016). Simple machine learning models like linear regression and decision trees are easy to understand and explain. For linear regression, the contribution of each variable is determined by the sign and value of its coefficient. Decision trees can be interpreted by visualizing the internal nodes and branches. However, complex non-linear machine learning methods such as support vector regression, random forests, and deep neural networks are difficult to understand, even though they always provide higher fidelity than simpler machine learning methods.

Two methods were used to estimate and predict reservoir pressure: multiple linear regression and "random forest regression". The random forest machine learning method has been widely used in many areas and is great for solving various kinds of problems (Mehran Rahimi & Mohammad Riahi 2022; Liang Xue et al., 2021; Hofmann, M., Al-Obaidi, S. H. & Hussein, K.F. 2022). This machine learning algorithm was first proposed by American mathematicians Leo Breiman and Adele Cutler and is one of the few universal algorithms. Its versatility lies in the fact that it is suitable for solving problems of classification, regression, clustering, searching for anomalies, etc. Basically, a "random regression forest" is a set of decision trees in which, when solving the regression problem, their answers are averaged, which is suitable for calculating the reservoir pressure parameter.

The random forest model is described by the following characteristics:

1. The number of decision trees – the quality of the result depends on this factor, however, with an increase in the number of trees, the setup time and model operation also increases;
2. Maximum decision tree depth – Increasing this factor will improve the quality of the preparing, however, shallow decision trees are recommended when solving problems with heavy noise (outliers);
3. Maximum number of decision tree nodes (width) – Choosing this parameter must take into account the possibility of preparing the model with a small tree depth;
4. The maximum number of features of one decision tree – With an increase in this factor, the time to build a forest increases and the trees become monotonous; for regression problems, it is n/3, where n is the number of trees.

These characteristics are adapted to solve the problems of reproducing and predicting formation pressure values.

**3. Results and discussion**

*3.1. Reservoir pressure prediction using machine learning methods*

In the first stage, pre-processing and structuring of field data (fluid flow rate; operating factor; bottom-hole pressure; initial reservoir pressure) is necessary. A computer program “Square” has been created to automate the analysis of field data and build mathematical models, the algorithms of which are based on the methods described above.

To verify the reliability of the developed models, historical measurements of reservoir pressure were reproduced using the probabilistic-statistical model of multiple linear regression and the method of machine learning “random regression forest”.

The multiple linear regression equation was obtained by the least squares method and has the following form:

$$P_{r(t)} = 0.7548P_{r(t-1)} + 0.0131\frac{(Q_{f(t)}-Q_{f(t-1)})}{Q_{f(t)}} + 0.207P_{wf(t)} - 0.00001T + 1.2851$$

Where $P_{r(t)}$ – predicted reservoir pressure; $P_{r(t-1)}$ - reservoir pressure preceding the forecast;

$\frac{(Q_{f(t)}-Q_{f(t-1)})}{Q_{f(t)}}$ - fluid rate growth rate (hereinafter $Tq$) relative to the previous well test;

$Q_{f(t)}$ – fluid flow rate per day (in a monthly average); $P_{wf(t)}$ – the current bottom-hole pressure; $T$ – Well operation time.

Using the p-test to assess the significance of the coefficients of the linear regression equation, the following results were obtained (Table 2).

**Table 2.** Coefficients of the linear regression method and their significance

| *Parameter* | *p-criterion* |
|---|---|
| *Free member* | *0,000** |
| $P_{r(t-1)}$ | *0,000** |
| $T_q$ | *0,005** |
| $P_{wf(t)}$ | *0,000** |
| $T$ | *0,000** |

As a result of calculations, the average absolute deviation of the model on the input data was calculated, which amounted to 0.821 MPa, with $R^2$=0.757.

The following parameters were used to build the random regression forest model:

– The number of trees is 200;

– The maximum depth is 5;

– Three features are the maximum number of features in one tree.

After training the "random forest" model, the coefficients of the significance of the factors were calculated. The significance of a factor in a "random forest" is determined by its cumulative importance for each decision tree, i.e., by the measure of the reduction in Gini heterogeneity (Table 3). The average absolute deviation on the input data of the "random forest" model was 0.812 MPa.

**Table 3.** The factors of the Random Forest method

| *Factor* | *Significance coefficient* |
|---|---|
| $P_{r(t-1)}$ | *0,815158* |
| $T_q$ | *0,023523* |
| $P_{wf(t)}$ | *0,132228* |
| $T$ | *0,029091* |

For the methods described above, the performance of the models was evaluated using a cross-validation approach. In this approach, the sample is divided into equal parts, then each part is sequentially excluded (deferred sample), and a model is built using the remaining data. The error value of the delayed sample is then checked. As a result of this test, the standard deviation for the linear regression model was 1.071 ± 0.14 MPa, and for the "random forest" model was 1.018 ± 0.17 MPa. In case no of the models has previously been "trained" on the input data, these values indicate the stability of the models, which means a good chance of getting a reliable result.

To assess the reliability of the linear regression method and the "random forest" method, the dependences of the actual (1553 measurements) and calculated reservoir pressure measurements were plotted (Figs. 1, 2).

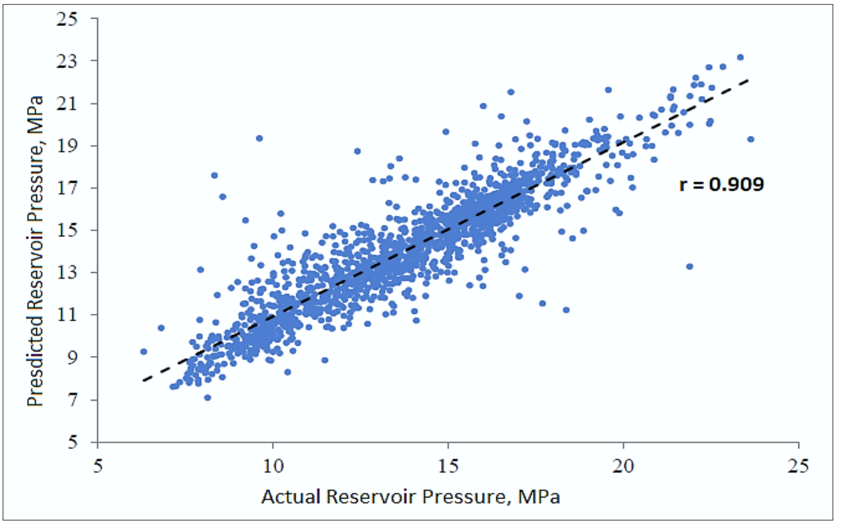


**Figure 1.** Linear regression correlation between actual and calculated reservoir pressure values

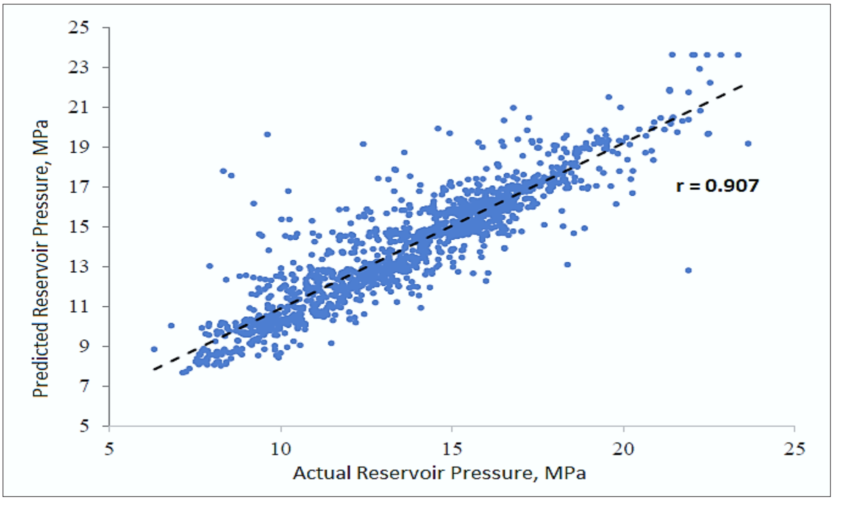


**Figure 2.** Correlation between actual and calculated reservoir pressures using the "random forest" method

By analyzing the presented graphs, it can be concluded that in both cases, the calculated reservoir pressure parameters have a "dense" distribution with actual measurements, which indicates a good convergence of the results in general. The deviations resulting from using linear regression and "random forest" for the entire sample under study are presented in Table 4.

**Table 4.** Absolute and relative deviations resulting from the application of linear regression and random forest methods

| *Method* | *Absolute deviation from the actual measurement (average), MPa* | *Relative deviation from the actual measurement (average),%* |
|---|---|---|
| *Linear regression* | *0,87* | *6,9* |
| *Random forest* | *0,86* | *6,8* |

Thus, it can be noted that the methods of linear regression and "random forest" have an equal minimum deviation of the predicted reservoir pressure values from the actual ones, which indicates the effectiveness and prospects of using these methods.

Given the "heterogeneity" of the sample and the large amount of data, it is necessary to compare the results well by well. For this purpose, graphs were constructed for comparing the results of actual and calculated values of reservoir pressure (Fig. 3 – 5). The choice of wells for demonstrating the obtained data was made in such a way as to reflect the most complete picture of the applicability of the methods used.

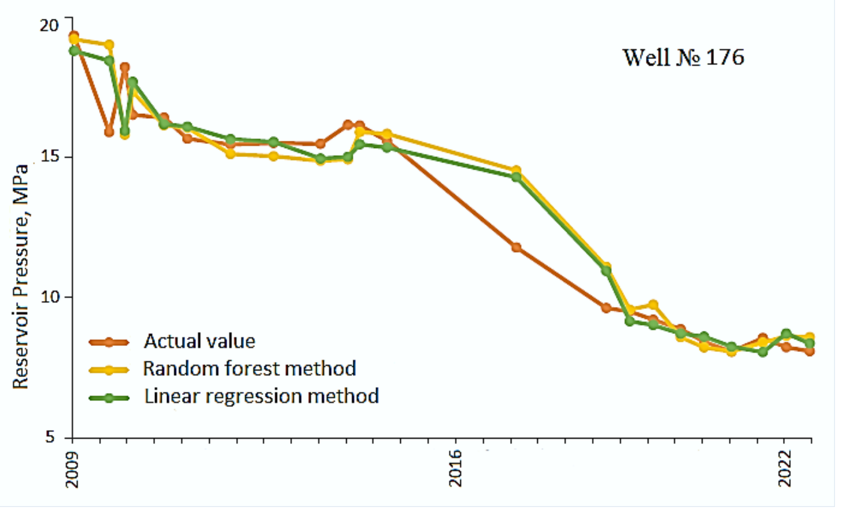


**Figure 3.** Calculated and actual reservoir pressure values for well 176

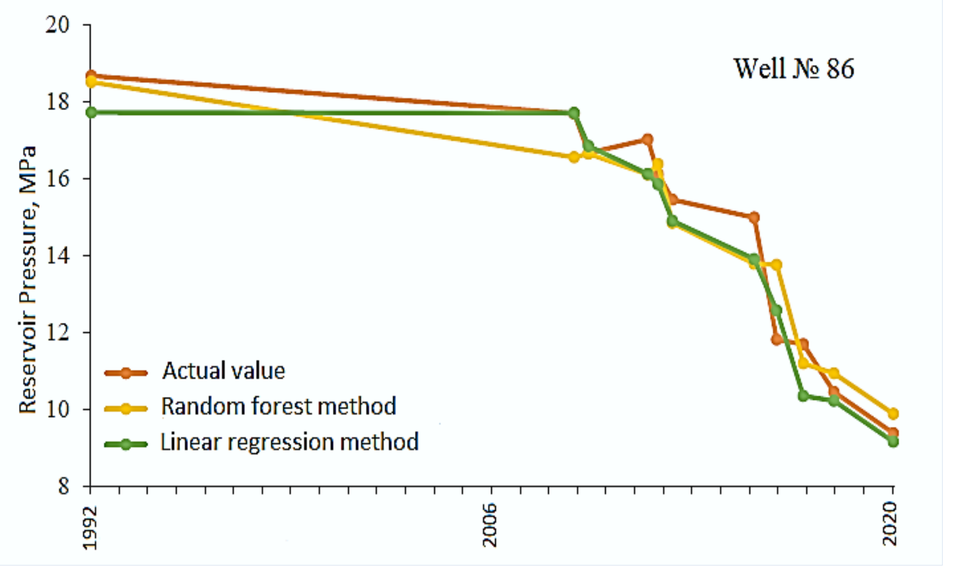


**Figure 4.** Calculated and actual reservoir pressure values for well 86

Analyzing the presented graphs of comparison of actual and calculated values of reservoir pressure, we can conclude that both methods show good convergence with historical data when solving the problem of reproducing the "falling" dynamics of the studied parameter. However, in some cases, the random forest method shows better convergence. So, for example, in wells 167 and 86, the general reservoir pressure trend is modelled closer to the fact by this method. Particular attention should be paid to calculating the last reservoir pressure measurement since it is most important in predicting this parameter. It is evident from the high degree of convergence of this point that the mathematical model accurately reflects the current energy state of the wells and the development object. As a result, the random forest method also shows better convergence than linear regression. Nevertheless, none of the studied methods could simulate sharp changes in reservoir pressure for well 56 (Fig. 5). In this regard, it is necessary to refine the methodology for monitoring the energy state of the reservoir, taking into account the experience gained.

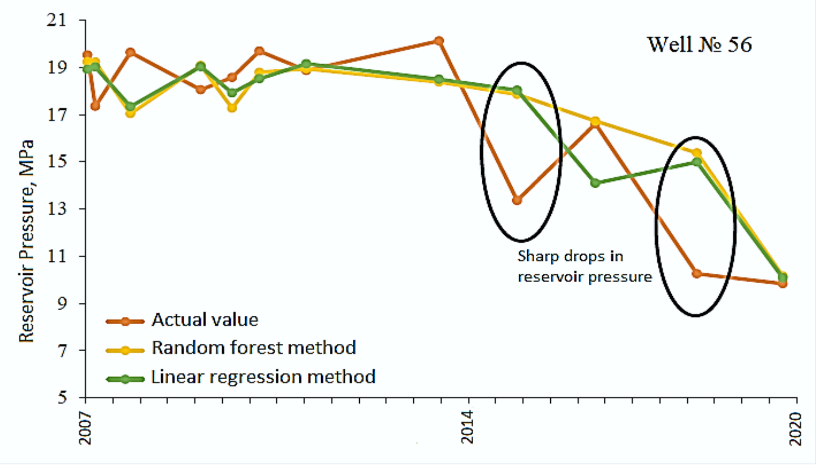


**Figure 5.** Calculated and actual reservoir pressure values for well 56

Generally, both methods have shown good results in reproducing the actual values of the reservoir pressure parameter and can be used by experts to evaluate "outliers" in the received data in order to resolve production issues. As well as additional training on the "random forest" model, other machine learning methods should be evaluated for solving the problem, including expanding the set of factors to more accurately model reservoir pressure.

## 4. Conclusions

In the oil industry, there has been an accumulation of too much information over the years, so machine learning algorithms capable of handling multivariate and complex data are preferred over empirical correlations and linear regression models. The presented study proposes a new method for reservoir pressure prediction using machine learning, based on a non-parametric multivariate model that links well performance over time. Based on the proposed method, reservoir pressures are predicted by taking into account the dynamics of indicators characterizing well operation. The predicted reservoir pressure has a good correlation with well-test values ($r = 0.909$ for linear regression & $r = 0.907$ for random forest). In the study, random forest machine learning provided a better reservoir pressure prediction accuracy than linear regression (absolute deviation: 0.86; relative deviation: 6.8%). In addition, the proposed method avoids the tedious procedure of coefficient calibration compared to methods based on parametric transformations.

Based on the calculated value of reservoir pressure, using machine learning, it is possible to determine the mode of development of the reservoir at the moment, design a system for maintaining reservoir pressure in advance or evaluate its effectiveness, and also reasonably make further rational decisions on the development of oil fields.

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