according to [6]. The first stage is the linear section of elastic deformation (II), in which a decrease in θ coefficient is observed. The next stage III is parabolic and occurs when the Beckofen-Consider condition is reached, the coefficient θ at this stage decreases to zero. The transition to stage IV is accompanied by a small linear segment, but the general character of the curve remains parabolic and the strain-hardening coefficient at this segment remains close to zero. Stages V and VI are absent, which can be attributed to the deformation characteristic of the material. At the final stage VII the coefficient θ drops to negative values, which is caused by low ductility of the alloy. Neck thickness during deformation process remains practically constant, so in the last stage the material sharply loosens, which leads to its destruction.

It is found that Mg-Y-Nd alloy in extruded state has higher mechanical characteristics than in recrystallized state. Under static tension, the deformation behavior of Mg-Y-Nd alloy in extruded and recrystallised states has a common pattern in terms of different relative elongation. The severe plastic deformation method is more efficient in the extruded state.

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OIL PRODUCTION RATE PREDICTION AFTER TREATMENT OPERATIONS USING MACHINE-LEARNING TECHNIQUES

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The biggest part of the modern oil fields has poor filtration properties, so the energy industry needs new solutions in different spheres to reach economic efficiency in the process of oil extraction. One of the most widespread methods to produce hydrocarbons from tight reservoirs or facial zone with low permeability (for example, deep marine depositional environment: lobe deposit) is applying multistage hydraulic fracturing (HF) on horizontal wells.

Drilling a well and conducting workovers are connected with a high degree of risk and costs thousands of dollars so it requires precise engineering calculations. There are several semi-empirical equations to evaluate productivity index, starting liquid and oil rates, water cut, and other well performance indicators. Despite all of these formulas using understandable mathematical models of fluid flow in a reservoir, they include highly uncertain parameters such as drainage area, permeability, or supply contour radius.

These parameters could be estimated by well test analysis, however, it is expensive and takes dozens of hours to conduct. In our research, we have investigated the machine-learning method in order to reduceing the uncertainty of oil production rate forecast after HF.

The main hypothesis is that a trained regression model based on gradient boosting algorithm is able to predict oil production rate after treatment operations without application of analytical equations. For this purpose, the general workflow was developed and it includes the followings: data preparation, tuning hyperparameters and training of the model, validation on the evaluation data, making forecast based on training data and interpretation of model performance.

As a result, the proposed approach provides time saving in routine reservoir engineering task in conjunction with high-precision oil rate prediction and low uncertainty. Methodology is based on a gradient boosting algorithm and regression problem solving. The latter is related to mathematical method for estimating the relationship between dependent variables and independent variables in order to find the link. The former is key and tool for solving regression problem to find optimal solution.

Gradient boosting is based on decision trees where each branch represents the outcome of regression. There are many techniques such as XGBoost, Random Forest, etc. However, based on the previous experience [3], CatBoost is chosen as the main tool for solving regression problem.

First of all, a machine-learning model has been trained. To receive a good performance of the model and avoid overfitting, the main aspects should be taken into account: applicable loss-function, hyperparameters tuning and cross-validation. Traditionally, RMSE (*Root Mean Square Error*) metric is applied as loss-function (Fig.1) that controls training and quality assessment of regression model [2]

Fig. 1. Typical loss-function for training model process

Loss-function aims to global minimum and the lower value the highest quality and prediction ability of model will be [1]. Since the performance of the model is controlled by the behavior of loss-function, there are regulating hyperparameters. The creation of regression model is not completed without tuning. This procedure includes selecting hyperparameters such as a number of threes, learning rate, etc., in order to avoid overfitting. Partially, training efficiency is affected by the variance of the dataset. So, cross-validation is applied in order to estimate the impact of data splitting on the training process. When training is completed, it is necessary to evaluate the model ability to forecast. For this purpose, coefficient of determination (R^2) is introduced. It shows how much variance of the observed variable can be explained using the constructed model, i.e. the value of the coefficient of determination indicates the share (in percent) of changes due to the influence of factor features in the total variability of the effective feature.

Secondly, it is required to explain the nature of the data. For our experiment, the main parameters of the technical side and reservoir characteristics are collected from real fields. Table 1 demonstrates the names of features and their relationship by using the Pearson correlation matrix (Fig.2). The specificity of the proposed algorithm is characterized by the fact that features should not strongly correlate to each other to avoid overfitting [4]. So, the analysis of the covariance matrix allows excluding oil viscosity (*Visc*) and well pressure drop (*dP*) from data.

Table

Name of features in dataset

Parameter	Description
L	Length of horizontal section
N	Number of stages
H_{pay}	Reservoir thickness
P_{res}	Reservoir pressure
Visc	Oil viscosity
Az	Azimuth
M_{prop}	Propant agent mass
X_f	Half length of the fracture
H	Height fracture
W	Width fracture
BHP	Bottom Hole Pressure
Perm	Permeability
dp	Well Pressure Drop

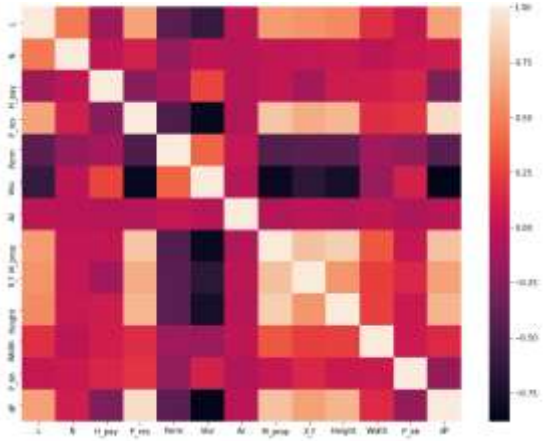

Fig. 2. Names of features in dataset

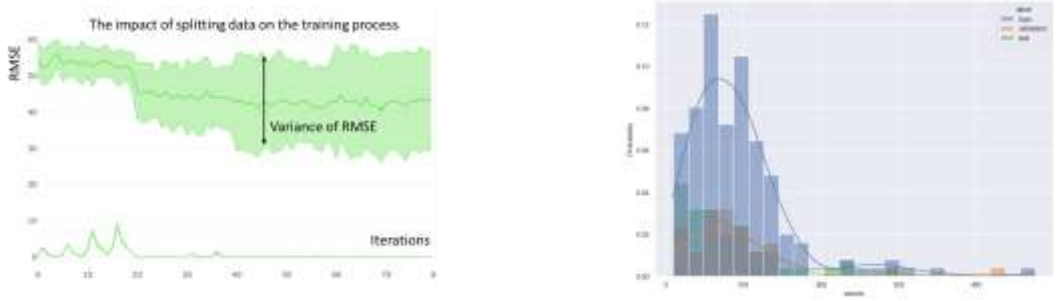

Fig. 3. Cross-validation and target value distribution for training, evaluating and testing data

Finally, results are obtained. The figure (Fig.4) demonstrates a cross-plot where the correlation between predicted and true values of oil rate after HF is presented for tested dataset (R^2 = 0.86). Obviously, the regression model has a high prediction ability. Additionally, the model has low aleatoric uncertainty if the predicted value lies in the range from 5 to 50 and from 200 to 300. It means that forecast of low and high oil rates looks better than middle values.

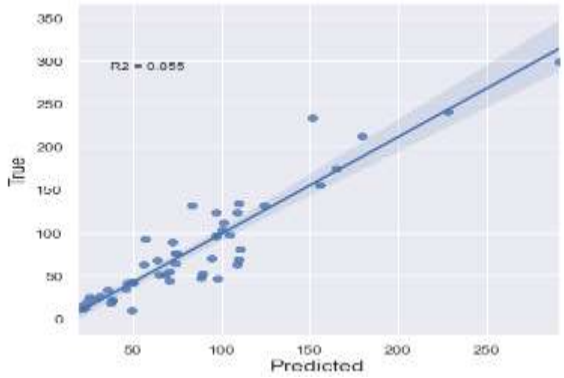

Fig. 4. Cross plot of predicted and true values

The following conclusion is made as a result of this study:

- The regression model for flow rate prediction was created by CatBoostRegressor algorithm;
- Input parameters allow to reach the high predictive ability of the model;
- Performance of model is sufficient: RMSE (test) = 0.86;
- Based on the trained model the computational time for the forecast is less than 1 minute;
- Applicability of proposed solution can be translated into routine reservoir engineer tasks.

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SURFACTANT TYPES AND CLASSIFICATION IN CHEMICAL ENHANCED OIL RECOVERY (CEOR)

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For the first time, the use of surfactants as an additive in oil reservoir flooding was used in the USA in the 40s of the 20th centuries. According to the nature of hydrophilic head groups, surfactants are majorly divided into four classes: anionic, cationic, zwitterionic, and nonionic surfactants (Fig. 1). Anionic surfactant is the most commonly used type, containing sulfate (-O-SO_3^-), sulfonate (SO_3^-), or carboxylate (-COO^-) groups, though usually in association with an alkaline metal (Na^+ or K^+) cation. The sulfate surfactant has a better tolerance to salinity for both monovalent and divalent cations, but can be easily decomposed at temperature higher than 60 °C. On the other hand, surfactants containing sulfonate groups are tolerated to high temperature, but sensitive to high salinity and easily precipitate at high divalent cation concentrations. The most commonly used surfactants for CEOR are sulfonate surfactants, which were produced either by direct sulfonation of aromatic groups in refinery streams or crude oils, or by organic synthesis of alkyl/aryl sulfonates. Petroleum sulfonate, synthetic alkyl/aryl sulfonate, internal olefin sulfonate (IOS), alpha olefin sulfonate (AOS), and alkoxy sulfonates have been evaluated for CEOR applications. Equilibrium adsorption for the alkyl aryl sulfonate surfactant was 3.5 mg/m^2, whereas its ethoxylated counterpart demonstrated lower adsorption of 0.8 mg/m2 on calcite. Under water-wet conditions, changing the surface redox potential from an oxidized to a reduced state decreased the C14−16 AOS adsorption level by 40%, to ~0.3 mg/g on Berea sandstone cores [1, 2]. At a concentration of 3000 ppm of IOS, increasing the pH from 8.24 to 9.57 decreased surfactant adsorption from 0.760 to 0.161 meq/100 g of rock. Adsorption of C15−18 IOS onto two pure minerals (calcite and quartz) are about the same ~1.1 mg/g, and the adsorption capacity of shales depends on the mineral composition, ranging from 7.0 to 1.7 mg/g. Typically, cationic surfactants are quaternary ammonium compounds (QAC), with the positive charge on the N atom. Nonetheless, cationic surfactants are more expensive than anionic surfactants. Zwitterionic surfactant contains