Calculation filtration coefficient using regression models

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Abstract

Uranium nuclear disintegration is one of the cleanest ways to meet the growing demand for energy. The uranium needed for power plants is mainly produced by two methods in approximately equal volumes: in quarries (underground and open) and leaching on-site (ISL). Effective use of ISL requires, among other things, the correct determination of the filtration characteristics of the accommodating rocks. In Kazakhstan, this calculation is still based on methods developed more than 50 years ago, and in some cases there is inaccurate results. At the sa uranium mining, machine learning, regression model, filtration characteristics.me time, knowledge of filtration characteristics is necessary to count extracted reserves, predicting the dynamics of production, calculating the optimal number of wells, etc. This article describes the method for calculating the coefficient of filtering of rudinal rocks using machine learning. The proposed method is based on nonlinear regression models. It also allows you to estimate the filtration properties of breeds in the process of technological acidification, where the existing method is not applicable. The proposed method is applicable to about half the uranium produced in the world and allows us to significantly (by 22% -70%) to increase the accuracy of determining the filtering coefficient and, accordingly, increase the accuracy of the estimated reserves and economic indicators of production processes.

Keywords: uranium mining, machine learning, regression model, filtration characteristics.

1 Introduction

According to the World Nuclear Association, in 2018, the largest uranium mining companies produced 86% of the world's total uranium production [1,2], of which NAC Kazatomprom JSC accounted for 21%. Companies use two main mining methods: open pit (underground and open-pit), which accounted for 45.9% of the production, and in-situ leaching (ISL), which accounts for 48.3% of the world's uranium production. Approximately 5.8% of uranium is mined as a byproduct, such as in gold mining [3]. In Kazakhstan uranium production is carried out by the in-situ leaching (ISL) method. In this method, uranium is extracted through a network of pumping and injection wells through which a leaching solution circulates. An important characteristic for planning uranium mining is the filtration properties of the host rock. Filtration properties of rocks have a significant impact on the mineral composition of both the surface soil layer and rocks that lie at a depth of tens and hundreds of meters. Knowledge of filtration properties in the form of filtration coefficient allows to plan the volume of ore extraction. The currently used methodology for calculating the filtration properties of wells for uranium mining by in-situ leaching is based on a system of rules that take into account only one geophysical parameter (apparent resistivity- AR). However, this methodology is not applicable in the case of a failure to record CW or distortion of values under the influence of acid, which is widely used in uranium mining. At the same time, other geophysical parameters can be used to calculate the filtration coefficient, the use of which can improve the accuracy of the calculation. Multiple parameters in the presence of actual measurements can be accounted for by using machine learning models (MLM) [4, 5]. MLM is widely used to solve the tasks geological mapping [6], lithology classification [7,8], stratigraphy [9].

2 Methodological steps

The methodological scheme of the study consists of the following steps:

- Data collection and preprocessing. This step is necessary to form a set of input variables and to select the target variable.
- Application of machine learning methods in two experiments.

a) Experiment 1: ANN-based regression model based on data from exploratory wells of the Budennovskoye field.

b) Experiment 2. Regression models based on ANN and Extreme Gradient Boosting (XGBoost [10]) use data from the Inkai field.

Verification of results using root mean square error (RMSE), coefficient of determination (R^2), Pearson correlation coefficient R.

3 Results

According to the current methodology [11], the parameters of the rock filtration properties and the actual value of the filtration coefficient (K_f) were identified at the exploration drilling stage. Subsequently, the obtained parameters were used to calculate the filtration properties of the technological wells. Correct calculation of K_f affects the estimation of recoverable reserves and parameters of the production process. Based on the results of the experiments, a two-stage scheme for determining filtration coefficients in the fields of Kazakhstan using machine-learning models was proposed [12].

In the first stage, machine learning models were tuned using data from exploratory wells. A hybrid model is formed from the tuned models, which use the MLM for acidified well sections, where the input data are spontaneous polarization potential (SP) (XGBoost (SP)). For non-acidified sections, the apparent resistance logging (AR) and lithological code set by the expert (LC) data were used (XGBoost (AR, LC)).

Because technogenic acidification intervals are found only in production wells, they are not present in the dataset generated from exploration wells. Therefore, it is impossible to directly teach the correct predictions K_f for acidified intervals. Because of the poor quality of SP curve recording, adding it as an input regression parameter usually slightly worsens the accuracy.

However, in acidified well sections, the AR curve is too distorted, and the lithological code only indicates the acidification interval (not the actual rock type). Moreover, this distortion is dependent on the lithological composition of the rocks and the amount of acid. Therefore, the only option in this case is to use the SP, even though it has low accuracy.

During the training on data from exploration wells, only intervals with a thickness of 0.5 m were used for comparison with data from hydrogeological studies, which led to a high RMSE value. In the technological well data, lithologic intervals were mainly more than 2 m thick, so the result of the approved methodology was relatively good (in wells without acidified intervals, almost comparable with regression models). Based on this, we can draw the following conclusions.

1. Regression models work well for all intervals, while the current methodology is only suitable for intervals greater than 1.5-2m.
2. The current methodology is not applicable to wells containing acidified intervals.
3. Hybrid can be applied to wells containing acidified intervals.

4 Conclusion.

The extraction of uranium by the method of underground borehole leaching requires a fairly accurate determination of the lithological composition and filtration properties of ore-bearing rocks. The mineral composition of the surface layer of soil, as well as rocks at a depth of tens and hundreds of meters depends on the filtration properties of the ore rocks. The methodology used in Kazakhstan for assessing the filtration properties is based on the fact that at the stage of exploratory drilling, parameters are determined, which are subsequently used to calculate the filtration properties of technological wells. However, the existing technique gives an inaccurate result, and in the zones of technological acidification, which make up to 40% of all considered data, it cannot be used. Inaccuracies in determining the filtration coefficient lead to errors in the production process and inaccurate calculation of recoverable reserves.

To overcome the shortcomings of the existing approach, the paper proposes a method for calculating the filtration coefficient based on the use of regression models. The proposed model receives electrical logging data as an input, and the calculated filter coefficient as an output. To improve the quality of the model, it is made hybrid, that is, it is formed from two models. For non-acidified areas, a model is used in which the input variables consist of AR and LC. For acidic areas, a model is used whose input variables consist of SP data.

The analysis shows that the proposed method gives a significantly lower mean square error in determining the filtration coefficient, better (by 70%) correlates with the flow rates of wells, with the actual values of the filtration coefficient (by 27%) is applicable for small intervals and, in addition, can be used to calculate filtration coefficient in acidification zones.

5 Acknowledgment.

This research was funded by the Science Committee of the Ministry of Education and Science of the Republic of Kazakhstan (Grants: No. BR10965172), Integrated Infrastructure Operational Program for the project: Systemic Public Research Infrastructure – Biobank for Cancer and Rare diseases, ITMS: 313011AFG5, co-financed by the European Regional Development Fund, ERASMUS+ ACeSYRI: Advanced Centre for PhD Students and Young Researchers in Informatics reg.no. 610166-EPP-1-2019-1-SK-EPPKA2-CBHE-JP.

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