EARTH SCIENCES

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INNOVATIVE APPROACH TO DIAGNOSTICS OF WELL INTEGRITY USING MACHINE LEARNING

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Abstract

The paper considers a method for determination of production casing string integrity using machine learning algorithms. Under conditions of late stage of field development and high water cut of produced fluid, timely diagnostics of leaky production casing becomes an urgent problem. Traditional methods based on well logging often fail to promptly detect casing leaks, which leads to economic losses and environmental risks.

The authors propose a new method based on water chemistry analysis, well age, number of well repairs, well production performance and well design. These features are processed and analyzed using machine learning model to obtain a real-time decision on leak presence. The paper presents the results of application of different machine learning algorithms such as decision tree, random forest, CatBoost and LightGBM. The best results have been obtained using LightGBM, with F1-score metric of 0.764.

The paper also analyzes the impact of different features on model predictions using SHAP analysis. Finally, the advantages of the proposed workflow are discussed, such as reduction of decision-making time and improved efficiency of production casing leak detection, which in turn improve the economic performance and reduce environmental risks.

Keywords: production casing leak, study, water compositional analysis, machine learning, evaluation of features impact.

Currently, the majority of fields are at the late stage of development, with many wells experiencing high water cut and operational failures [1]. In this regard, the problem of timely identification of troublesome wells and possible solutions is quite acute. To date, the most popular method for well integrity evaluation is well logging [2-6].

Figure 1 shows the distribution of conducted production casing integrity studies by areas of N field for the period from 2000 to 2022, based on 23715 studies. The studies have covered mostly the largest areas of N field: EO-13, EO-1 and EO-4. The least number of studies have been conducted in EO-18, EO-12 and EO-21. On the average, 1129 studies were performed from 2000 to 2022.

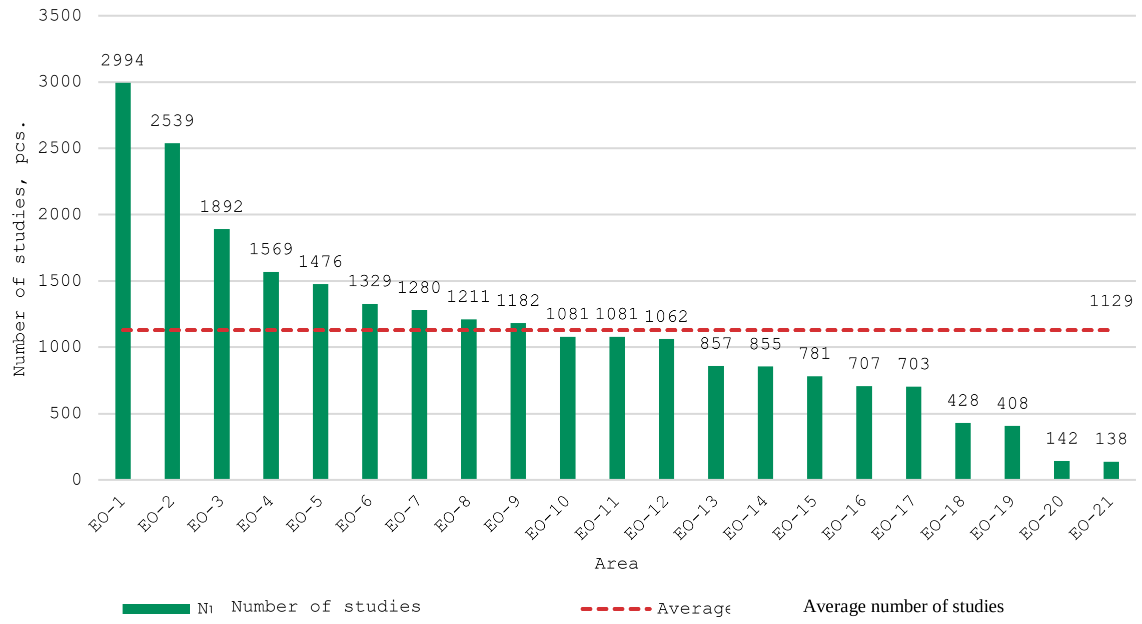

Figure 1 - Area-wise distribution of conducted production casing integrity studies

The next step provides for evaluation of the efficiency of conducted studies by areas of N field (Figure 2). The efficiency of production casing leak detection is defined as the ratio of the number of studies indicating casing integrity failures to the total number of studies performed.

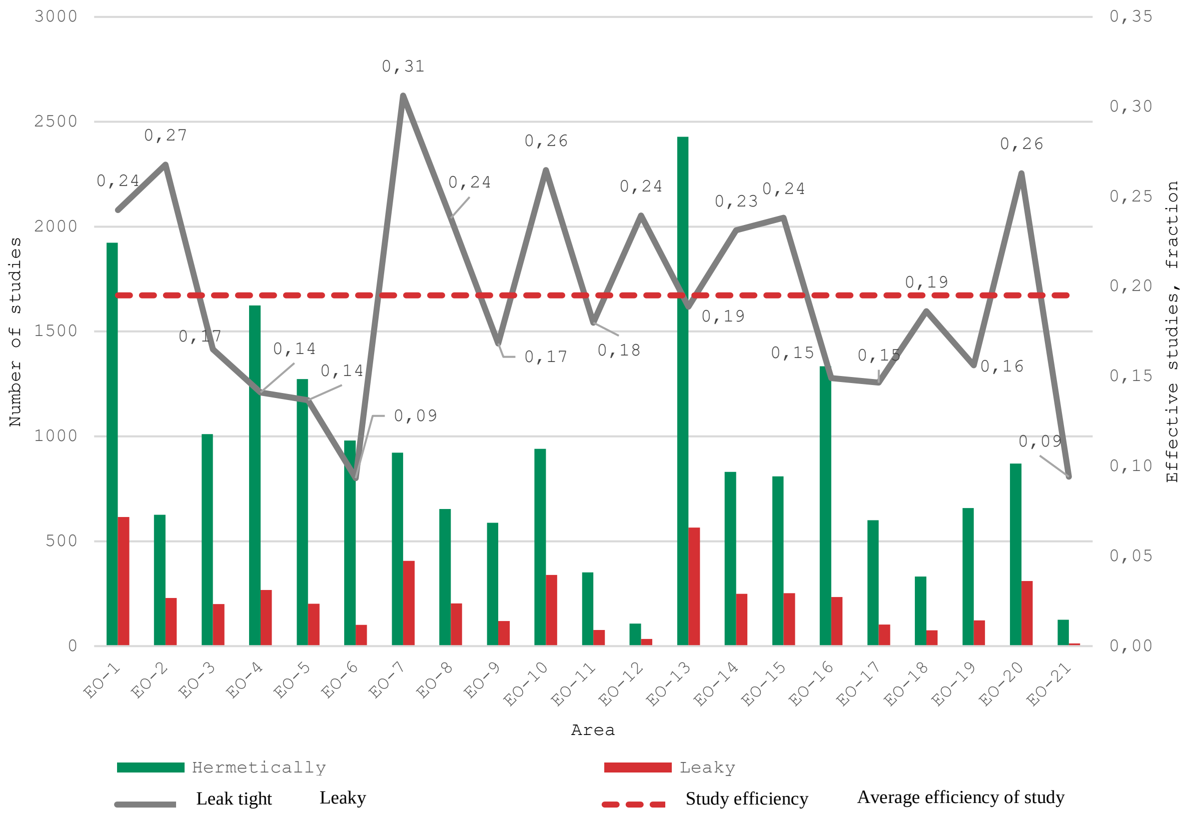

Figure 2 - Efficiency of conducted studies by areas of N field

Average efficiency of conducted production casing integrity studies is estimated at 0.195. The best efficiency is observed for EO-7, EO-2 and EO-10, reaching as high as 0.31, 0.27 and 0.26, respectively. The lowest efficiency is observed for EO-4, EO-5, EO-21 and EO-6, being as low as 0.14, 0.14, 0.09 and 0.09, respectively.

The above statistics suggests that a new method for production casing leak detection should be developed to increase the share of confirmation studies.

So far, the simplest and most effective method for detection of production casing failure relies on chemical analysis of downhole water sample composition. Nevertheless, this method does not always enable identification of water composition variations on-the-fly. It often takes 70 days or more to detect the leaks.

Thus, the main disadvantage of modern casing leak detection methods implies addressing an already existing problem. In this paper, a new approach to this problem is proposed and machine-learning-model based module is created to proactively predict casing leaks. This model uses data analytics andalgorithms to predict casing integrity failure risk.

Comprehensive operations aimed at step-wise problem solving were preceded by the analysis of casing leak causes. The authors identified three maingroups of causes: poor cementing quality, metal wear and metal corrosion. The main consequences of casing leaks include water cut increase, environmental pollution, non-productive injection, as well as failure to achieve target economic results [7-10].

Water chemistry, well design details, well performance, well age at the time of study, and number of tripping operations and leak test cycles were identified as leak detection criteria, whose dependencies were used as model basis.

Traditionally, the industry has accepted basic approaches to identification of the features indicative of abnormal water composition; particularly, analysis of Cl/Ca ratio (Figure 3).

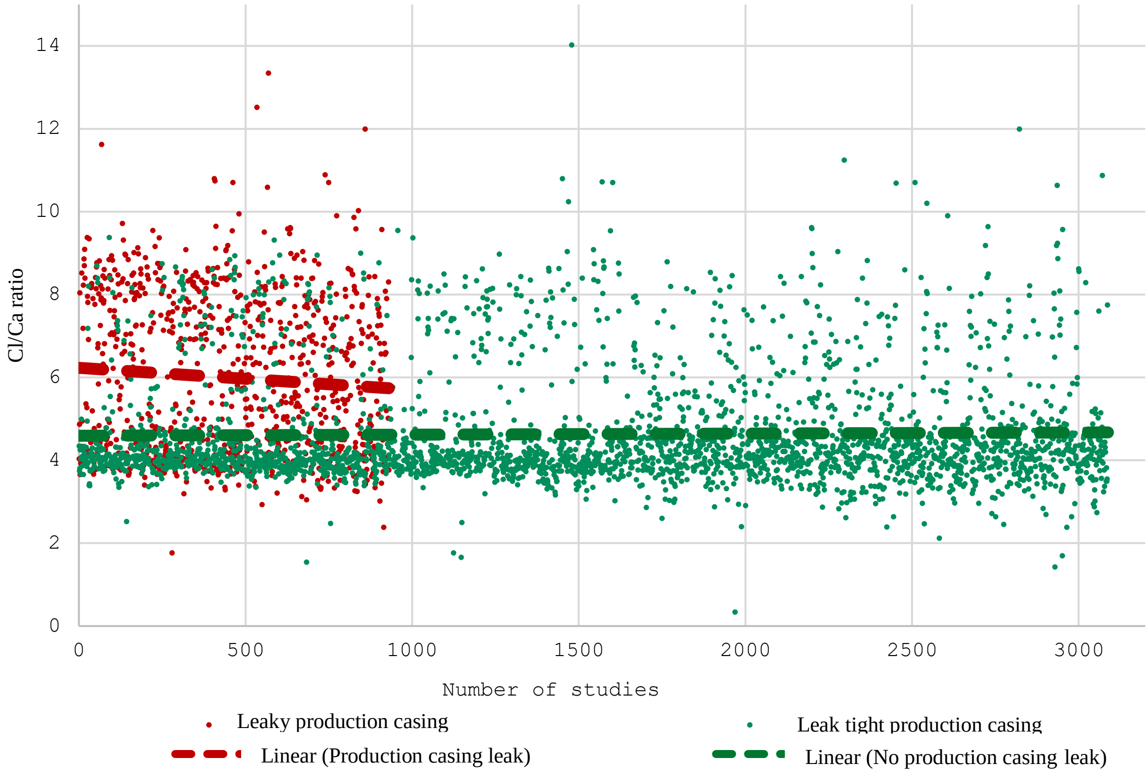

Figure 3 – Cl/Ca ratio

According to the analysis of more than 4 thousand cases, including 930 cases with leaky production casing and 3086 with leak tight production casing, it can be noted that should casing leak occur, the Cl/Ca ratio reaches 6, on the average, compared to 4.6 for leak tight production casing case.

However, this analysis is labor-intensive and requires an on-site specialist to review each potentially leaking well. Large number of wells reduce the speed of decision making significantly. Also, this is just one approach to leaky well detection. Such approaches are numerous, while determination of concentration ratios over the entire range of water components is time-consuming and costly.

For the first time ever, a system predicting casing leaks based on analysis of more than 20 input parameters has been developed. For this purpose, necessary field data pool was generated, followed by data processing and loading into the model for training. Several machine learning algorithms such as decision tree, random forest, CatBoost, LGBM, etc. were tested during training. According to training and testing, the best results in terms of F1-score parameter have been obtained by LGBMClassifier gradient boosting, with 0.764 (Figure 4).

Figure 4 - Model quality metrics with class balance

For the purposes of data interpretation and understanding of features impact on overall model prediction, a SHAP analysis of LightGBM machine learning model was performed.

Figure 5 shows a horizontal bar chart representing the degree of importance of different features on model prediction outcomes. The features are arranged in descending order of importance. The length of the horizontal line of a feature is proportional to total importance of this feature. The longer the horizontal line, the greater the contribution of this feature to model predictions.

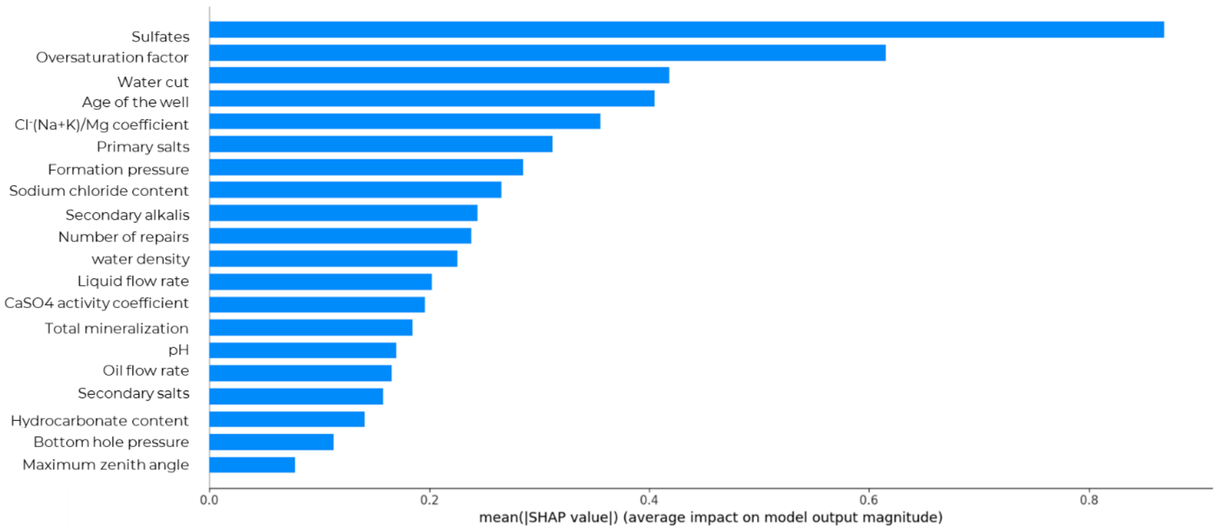

Figure 5 – Degree of feature importance for model predictions

As seen in Figure 5, the following features are mostly responsible for leak occurrence according to LightGBM model: sulfate content, oversaturation factor, produced fluid water cut, age of the well at the time of study, as well as the hydrochemical coefficient Cl^- (Na+K)/Mg.

Below, the more specific cases are considered. Figure 6 (a) shows a case, when LightGBM model indicates well leak event. Casing leak probability reached as high as 95%. Referring to Figure 6 (b), features with positive values cover a substantial area of the bar chart.

The function indicative of casing leak probability has the values in the range from -5.53 (0.4% leak probability) to 4.32 (98.68% leak probability). The boundary value of the function corresponding to class change is -0.3322. In the case shown in Figure 6 (a), the function value was 2.97.

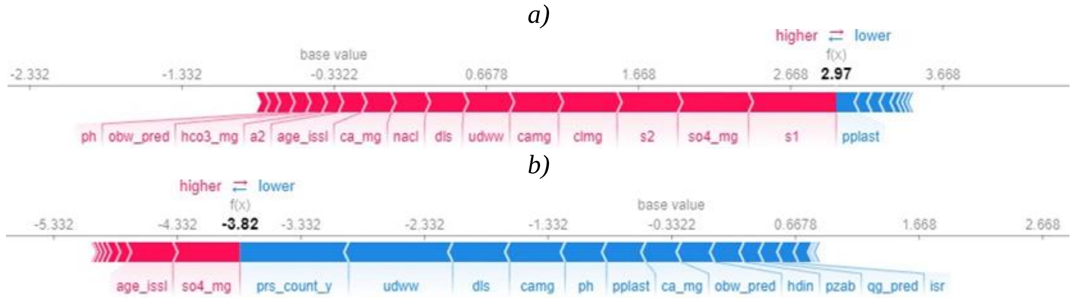

Figure 6 - Evaluation of the impact of factors on prediction for the case of leaky casing (a) and for the case of leak tight casing (b)

Table 1 details the numerical values of the features that contribute most to model prediction, and weighted sum of the features that increase or decrease the prediction of positive class, i.e., the probability of casing integrity failure.

Table 1

Evaluation of parameter impact on prediction

Case	Parameter	Weight in prediction, fractions	Sum of positive weights	Sum of negative weights
Leaky casing	Primary salts	0.577	3.8	-0.5
	Sulfates	0.464		
	Secondary salts	0.399		
	Chlorine-magnesium	0.385		
	Calcium-magnesium	0.321		
Leak tight casing	Number of repairs	-0.879	1.2	-4.6
	Water density	-0.841		
	Well curvature	-0.46		
	Calcium-magnesium	-0.45		
	pH	-0.334		

In Figure 6 (b), an opposite pattern is observed. Casing leak probability predicted by LightGBM model is 2%. Features that increase the negative prediction class, i.e. indicate casing integrity, predominate. The most influential features and values thereof are also presented in Table 1. Feature value indicative of casing leak event was -3.82.

Prediction process workflow is illustrated in Figure 7. The first step entails selection of production site with wells to be subject to casing integrity analysis or a list of target wells may be loaded individually. Then, data are uploaded from corporate database in real time, followed by data validation and generation of new features. Processed data are introduced into machine learning model to generate a prediction and then the result is returned back to the user in Excel file format.

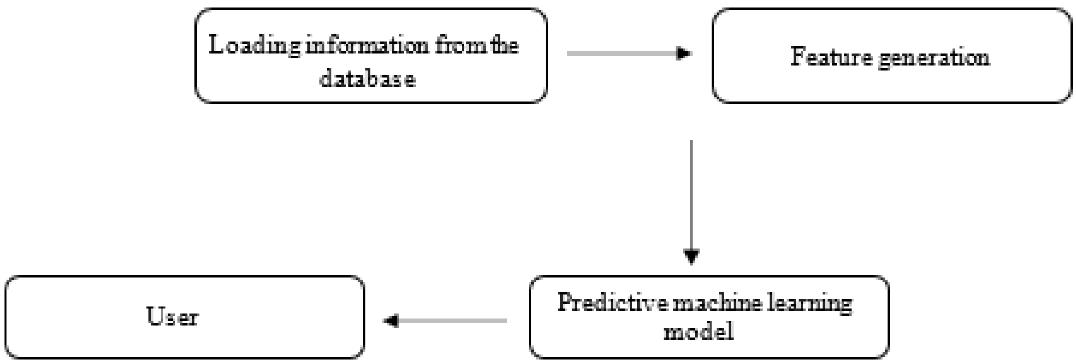

Figure 7 – Casing integrity prediction workflow

Thus, the authors have considered various indirect methods for production casing leak detection, such as determination of the ratio of produced fluid components, the use of correlation matrix, and machine learning models. The present research resulted in the method for production casing leak detection, as well as an indirect method for diagnostics and prediction of production casing fatigue severity and casing leak risk.

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