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Wellbore Instability Prediction by Geomechanical Behavioral Modeling in Zilaie Oil Field

Amin Tohidi[1]*, Arash Ebrahim Abadi[2] and Atefeh Musavi[3]

1. Department of Geotechnics, Islamic Azad University, Central Tehran branch, Tehran, Iran

2. Department of Petroleum, Mining and Material Engineering, Islamic Azad University, Central Tehran branch, Tehran, Iran

3. Cyberspace Research Institute, Shahid Beheshti University, Tehran, Iran

Abstract
Wellbore instability is a critical problem during oil and gas reservoirs' drilling and production phase, for which analytical, numerical, experimental, and field methods have been widely discussed. Because of the limitations of the mentioned techniques for predicting the different types of wellbore failures, the problem is still open. Although well logs provide a great source of big data for instability prediction, data-mining techniques have not matured in this domain. This paper explains how an AI-based method can be applied to instability detection/prediction. Unlike other data mining studies in this field, we proposed a systematic approach that can be traceable by the readers. We used several classification algorithms (e.g., Bayesian network, SVM) and found that the C5 decision tree algorithm has the best precision. We show the effectiveness of the method by applying the method to a dataset with about 30,000 records of wellbore logs, getting an accuracy of 91.5%.

Keywords: *wellbore stability; well log; Data mining; AI prediction*

Introduction
The wellbore instability has multiple mechanical, chemical, thermal, operational, and hybrid sources. Also, instability may occur during either the drilling or production phase. Mechanical instabilities arise when changes in the induced effective stress exceed the strength of the rock. Such changes may be the results of drilling or production from a reservoir. Chemical interaction between mud and rock formation, the difference in temperature between drilling fluid and formation, and the vibration of drill string can cause chemical, thermal, and dynamic instabilities, respectively [1-3].
Wellbore instability has become more important in recent decades due to drilling in unconventional reservoirs, high-pressure, high-temperature (HPHT) formations, and deviated and horizontal drilling. For example, the need for drilling a horizontal well with multiple hydraulic fractures to produce gas from shale formation is accompanied by more geomechanical problems [4-8].
Wellbore instability studies may have analytical, numerical, experimental, or field approaches. In either analytical or numerical methods, wellbore instability is determined by comparing the estimated induced stresses around a wellbore in elastic, poroelastic, and plastic medium with appropriate failure criteria such as Mohr-Coulomb or Hoke-Brown. The estimated induced stress is achieved by solving a set of equilibrium, continuity, constitutive, and Darcy flow equations performed by analytical or numerical (e.g., FEM, FDM, and DEM) methods. Though common in the industry, these approaches have no sound and complete results. The use of several simplified assumptions (e.g., homogeneity, isotropy, and axial symmetry) in analytical and the dependency of numerical modeling on the input parameters are the main drawbacks of these methods respectively [9-14].
Experimental approaches often determine the magnitude of failure load by simulating the naïve instability conditions in the lab. It is performed by applying far-field stresses and pore pressure with hydraulic jacks to a pre-built tiny model of the wellbore [15-18]. The most reliable procedure to diagnose wellbore instability is the field method. These approaches analyze different types of well logs to detect failure. Ultrasonic logs (e.g., UBI), Image logs (e.g., FMS and FMI), and caliper logs are examples of such logs. Despite this, one should note that

**Corresponding author:* Amin Tohidi, *Department of Geotechnics, Islamic Azad University, Central Tehran branch, Tehran, Iran*
E-mail addresses: a.tohidi@iauctb.ac.ir
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these approaches are not able to detect the instability before its occurrence [19-21].

Recently, few works have used the data-mining approach for the prediction/detection of wellbore instabilities. These studies, however, have a weak foundation of artificial intelligence and poor usage of data-mining algorithms, which may cause unreliable outcomes. Considering the above-noted shortcomings in the existing approaches, in this paper, a data-mining-based method has been proposed for predicting wellbore instability with the application of the systematic procedure that should be used in any AI-based study.

Our method builds a behavioral model of the wellbore based on a set of three types of input features. First are parameters directly extracted from the logs (e.g., hole size, CGR[1], NPHI[2], and RHOB[3]). The second type of input feature is those embedded in a 1-D geomechanical model of a wellbore (e.g., friction angle, pore pressure, poison ratio). Finally, the third type is related to the mineral volume of a formation (e.g., shale and limestone volume) measured from the initial logs.

We have implemented a prototype for our method using a dataset with about 30,000 records of 19 parameters gathered from seven oil wells in southwest Iran. We have provided labels (stable/unstable) for the records based on image and caliper logs.

Different models are used, and the final learned model is a C5 decision tree that can detect better mechanical, chemical, and dynamic instabilities in the test set with an accuracy of 91.5%.

In the rest of this paper, we first review the related works 2 and The proposed data-mining-based technique is presented, and discusses the implementation and evaluation of the proposed detection technique. We discuss several related issues in the discussion and conclusion sections.

Related Works

The data mining approach stands for many ways to predict complex behavior. For example, machine- learning is a modified version of AI methods and both subsets of data mining. As mentioned earlier, wellbore instability is a complex problem due to various causes such as mechanical, chemical, dynamic, creep, natural fracture, etc. Hence, data-mining techniques are a reasonable approach for predicting this event [22].

A lot of research used data mining to predict wellbore incidents. Nautiyal et al. used a modified ML algorithm and added input features such as formation type and geomechanical stresses to predict stuck pipe in A well [24]. Rocha Vargas et al. use image processing and machine learning to predict wellbore instability from caving images. They use shape, edge definition, color, and size of caving as input parameters [23].

Noshi et al. reviewed the application of the Machin learning algorithm in the oil and gas industry and said that the new algorithm can process a large amount of data [24].

The use of data-mining models in the domain of wellbore stability has been limited to some elementary use of artificial neural network (ANN) classification. Jahanbakhshi and Keshavarz studied the wellbore instability with the ANNs method [25]. They elaborated on several instability sources which are overlooked by the conventional methods. For example, conventional approaches do not consider the bedding plane and natural fracture in the formation. However, they do not clarify the input parameters fed into the ANN model.

Jahanbakhshi et al. applied the ANN method to analyze lost circulation in a similar study. They used either geomechanical or non-geomechanical parameters and showed that a model with only geomechanical input parameters could get accurate results [26]. The data set in both of the studies was very small (less than 260 records).

Alkinani et al. also developed a new classification for lost circulation materials to select the right LCM based on the type of losses and application. The method presents a flowchart to select LCM materials based on seepage, partial, severe, and complete loss [4].

Lin et al. used both PCA and LDA algorithms to find the linear relationship and reduce the dimensionality of the dataset and conclude that these reduction methods cause an unacceptable decrease in the accuracy for both ANN and SVM models [5]. Okpo et al. use the ANN model to study wellbore instability using 10 features [27]. Mohamadian et al. applied machine learning to predict the poisons ratio and maximum horizontal stress and then decide about casing collapse [28].

The mentioned data-mining approaches do not follow a systematic procedure required for the AI methods to be reliable. As for the results, one may find no description of the data set and the result accuracy (or similar evaluation measures) in the mentioned papers.

Materials and Methods

In this section, we have elaborated our idea, which is a data-mining-based detection of the wellbore instabilities. To do so, we first summarize our method in overview Section. We would mention the detailed description of the wellbore behavioral features used by our method in the input data Section.

Overview

Classification is a data-mining function that can determine the label defined for data records based on the values of the input features. Hence, having a large set of data records about stable wellbores and different unstable situations, one will use classification to learn an intelligent model through a supervised learning phase. This model can further predict the occurrence of learned instabilities.

Like any other knowledge discovery technique, the classification should be performed through a well-defined set of steps necessary to provide reliable results. Fig. 1 shows an overall view of the proposed method. As the figure suggests, these steps, as mentioned by Hann et al. [29], should be done through a preprocessing phase, including data cleaning, integration, selection, and transformation. After this phase, the learning phase can be performed by deploying Like any other knowledge discovery technique, the classification should be performed through a well-defined set of steps necessary to provide reliable results.

1. Corrected Gamma Ray
2. Neutron Prosity
3. Density Log

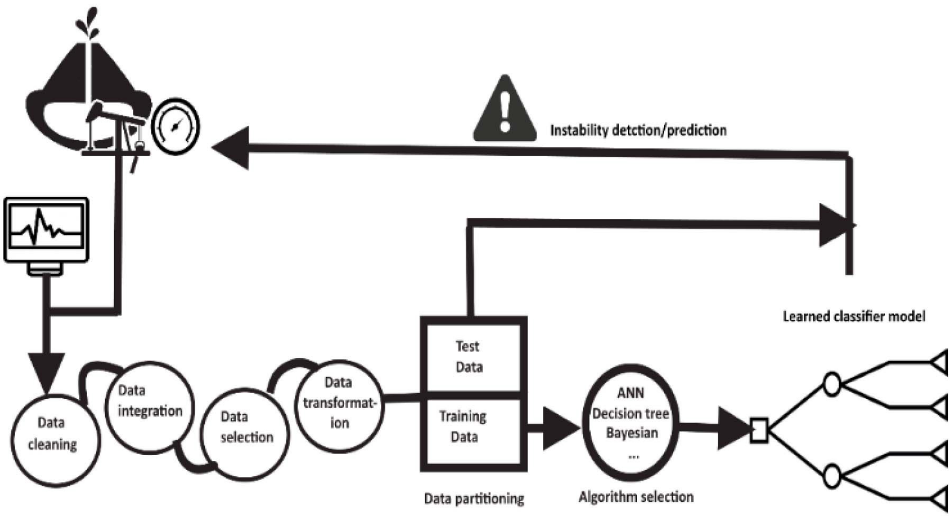

Fig. 1 An overall view of the proposed data-mining-based method for wellbore instability detection.

Fig. 1 shows an overall view of the proposed method. As the figure suggests, these steps, as mentioned by Hann et al. [29], should be done through a preprocessing phase, including data cleaning, integration, selection, and transformation. After this phase, the learning phase can be performed by deploying classification techniques..The model, achieved through the learning phase, is then used to predict instabilities through the test phase. In what follows, we will discuss each step in detail.

The Input Data

We have used 19 features as the input of our proposed method. As noted in introduction, our method uses three input data sources. Some features are directly read from the field. These include depth, bit size, CGR, NPHI, Pmw, and RHOB. Some other features come from the mechanical earth model (e.g., static young modulus, friction angle, and poison ratio). In addition, to cover chemical instabilities, some other formation information (e.g., volume of shale, dolomite, limestone) is among the input parameters. The summary of these features is shown in Table 1. Since our method uses the supervised learning algorithm, we should provide labels for the records.

Data Preprocessing Phase

Data cleaning is the first step for preprocessing data to remove missed or error-prone values. Log data that are received from the field might include multiple such errors. Hence, it is important to identify and clean the probable noisy data.

Discrepancy detection is an overall name for techniques for determining errors in the input data. It may perform the process based on the existing knowledge about the domain of features. After this initial data auditing, we should correct false values.

Alternating the data with constants, most probable values, and measures of central tendency (e.g., mean/median) are well-known data cleaning methods.

Since multiple data sources (e.g., logs provided for different disciplines) exist, we should identify probable redundant features in the data integration step.

For example, the values may have been recorded by different standards and formats, which should be corrected. Data selection is the most important effort in the preprocessing phase[1]. The in-hand dataset often has multiple to many features. The parameters' high dimensionality may confuse the analysis and interpretation. There are multiple ways to determine which features are the most relevant to the initial problem (wellbore instability in our case), referred to as feature selection methods. An important question is which feature selection method is appropriate for our case.

Measuring the correlation between the features is one the most well-known methods to find the association level between different features. Such a feature selection technique results in features that are a subset of the initial features.

Some other data reduction techniques result in a new set of features achieved by combining the initial features. PCA analysis is one of the most well-known examples of such techniques, which transform data to a new coordinate system for the greatest variances among features [30]. These coordinates linearly combined initial features. While PCA analysis can cause better modeling performance for high-dimensional data, it can decrease the interpretability of the predictions made by the model. For example, with wellbore stability, PCA analysis may eradicate the power of modification of controllable features. In addition, the PCA analysis has assumed linear relationships between features, which should be considered for usage.

Finally, data transformation is the last preprocessing step, including normalization, discretization, or smoothing of the values.

Training and Testing Phase

We should divide the data set into train and test sets such that both sets should include sufficient records of different types of instabilities. However, this can be challenging for wellbore stability detection because instabilities are rare compared to stable cases. Hence, the class distributions are different, and the classifier cannot infer information about such rare cases. There are different techniques for solving this challenge, often called the class imbalance problem [31]. Some techniques work at the data level to compensate for the small number of instances for the minority class (e.g., unstable records) in a data set.

1. The selection (reduction) can be applied on either of the number of input features or the data records. However, data record reduction is meaning-less in our special case.

Table 1. The input features of our proposed method (MEM stands for Mechanical Earth model).

Feature name	Description	Feature source
Depth	Depth measured from the surface of the well (m)	logs
Bit Size	Diameter of the Drill bit (Inch).	logs
CGR	Display the content of potassium and thorium as represented by shale and clay (API).	logs
Static Young Modulus(E_{static})	Represent the deformation behavior of formation (GPa)	MEM
Friction angle	Represent the strength of the rock based on Mohr-Coulomb failure criteria (deg).	MEM
NPHI	Neutron Porosity for porosity calculation of rock (API).	Logs
P_{MW}	must exert enough hydrostatic pressure greater than pore and collapse pressure and less than the tensile strength of rock(MPa).	logs
Pore pressure	Pore pressures are the fluid pressures in the pore spaces in the porous formations (MPa).	MEM
Poisson Ratio (ν)	the phenomenon in which a material tends to expand in directions perpendicular to the direction of compression that represents the deformation behavior of rocks.	MEM
RHOB	The rock's density is used to calculate vertical stress and rock properties.	Logs
Vertical Stress (S_v)	the in situ stress represents the weight of the overburden	MEM
Maximum Horizontal Stress (S_H)	An important parameter for drilling optimization and wellbore stability	MEM
Minimum Horizontal Stress (S_h)	Measure in the field with hydraulic fracture, we extract from poroelastic relation.	MEM
Unconfined Compressive Strength (UCS)	Show stress-strain behavior of rock and failure load under zero horizontal stresses condition(MPa).	MEM
Tensile Strength of rock (T_0)	The failure load of rock is due to tensile load(MPa).	MEM
Volume of dolomite	common rock-forming mineral. It is a calcium magnesium carbonate with $CaMg(CO_3)_2$ (%) chemical composition.	Petro physic Analyses
Volume of limestone	Limestone is a sedimentary rock composed primarily of calcium carbonate ($CaCO_3$) in the form of the mineral calcite (%).	Petro physic Analyses
Volume of shale	Shale is a clay-rich heterogeneous rock that contains a variable content of clay minerals (mostly illite, kaolinite, chlorite, and montmorillonite) and organic matter (%).	Petro physic Analyses
Volume of sandstone	Sandstone is a clastic sedimentary rock composed mainly of sand-sized mineral particles or rock fragments (%).	Petro physic Analyses

Over-sampling methods [32] are such techniques that create synthetic records based on the existing unstable cases. Another approach is to help the classifier at the algorithm level to find more focus on the minority class. Bagging (i.e., aggregating results of some parallel models) and boosting (i.e., higher weights to more important instances) are techniques that decide about a record based on multiple classifiers built at the training phase. The final choice is reinforcing the classifier using higher misclassification costs for instability records.
Different classification techniques exist (e.g., SVM and neural networks). To find the best algorithm, one can analyze them to find the best for a special problem. Decision tree classifiers (e.g., CART and CHAID) are well-known data-mining techniques that are non-parametric (i.e., do not make strong assumptions about the form of the mapping function (f) that maps input variables X to output variables Y), hence can fit complicated relations between our features. Though less known in the oil and gas research domain, unlike artificial neural networks, they also result in more interpretable classifiers. Hence, we have used the C5 decision tree as the classification technique. In addition, decision trees include an implicit feature selection procedure to find the feature with the highest splitting criterion at each branching decision. In this paper, we have used C5 classification techniques that support multiple advanced options (e.g., boosting and winnowing) for better instability detection.

Results and Discussion

We introduce the dataset gathered for evaluating the proposed instability detection method in implementation and evaluation. After reviewing preprocessing and feature selection, we test the proposed method.

Dataset

We have obtained the dataset used in this research from logs of seven Iranian wellbores. It includes over 29000 records of the wells' stable and unstable conditions (4% of the records). The dataset consists of labeled records to show instabilities. We have provided the labels from the caliper and image log. The instability occurred if the bit size and diameter read from the caliper log were markedly different. Also, the symmetrical dark line in the image log represents a breakout and tensile fracture in the well, and the unsymmetrical dark line stands for a scratch of the wellbore wall with the boring tool.

Data Preprocessing Phase

Before the preprocessing phase, we applied quality control to all data. It means that if the data is out of range, at first, the reason determined to change it. For unknown reasons, use empirical correlations between trusted and out-of-range data. If there aren't suitable empirical correlations, use data mining techniques to replace data with appropriate ones.

Feature Selection

Although the C5 classification technique uses an embedded feature selection procedure, in this section, we perform a feature selection to show the effectiveness of our features. Since most of our features have a quite normal distribution (Fig. 2), we have used the Pearson Correlation Coefficient (PCC), which is more effective for normal probability distributions.

With our features, the FCC can show the independence of the failure with any individual feature. Fig. 3 shows the PCC values computed for breakout and induced tensile fracture. As Fig. 3 suggests, vertical stress, bit size, Caliper log, pore pressure, static Young modulus, and tensile strength are the most important features common between both mentioned failures.

These results are consistent with engineering judgment because the bit size is the most important factor in wellbore stability, so the wellbore instability increases by increasing the bit size.

Also, the friction angle, UCS, and To are strength parameters that increase by the wellbore stability.

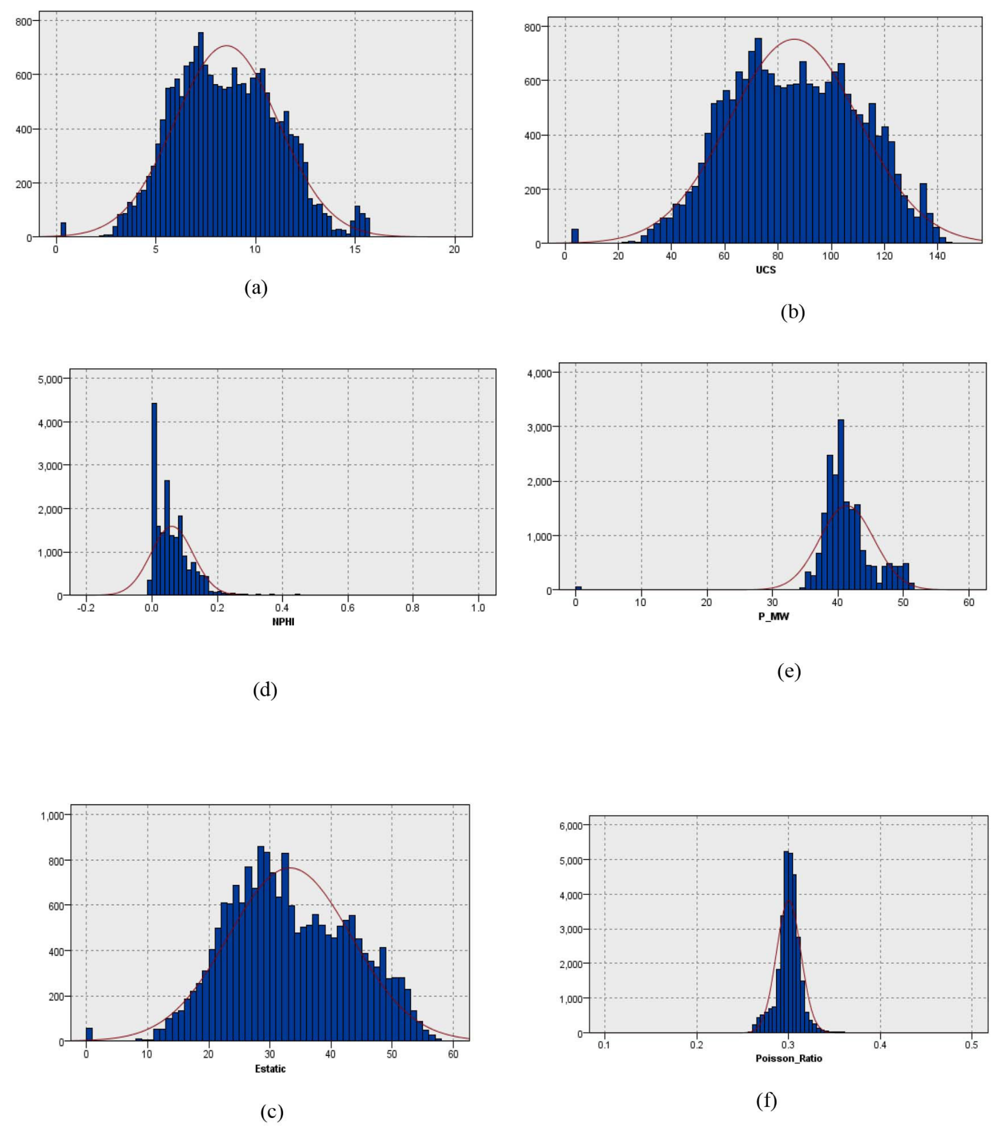

Fig 2. The observed distribution for different initial features compared to the normal distribution (drawn line) is shown for Tensile strength (a), Unconfined compressive strength (b), Static Young modules (c), Neutron porosity (d), Mud pressure (e), and Poisson ratio (f).

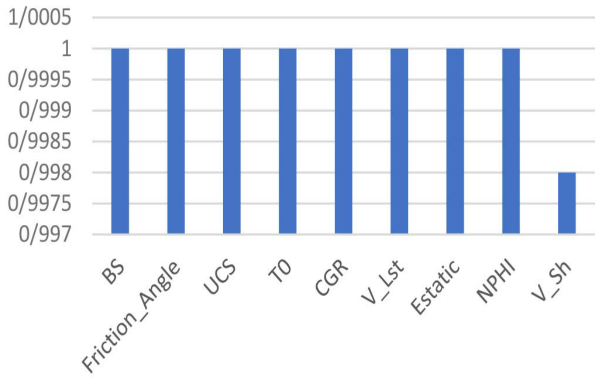

Fig 3. Pearson correlation coefficient of the most important features correlated with the wellbore instabilities.

```
Rule 1 - estimated accuracy 85.41% [boost 97.9%]
        BS <= 8.499 [ Mode: 0 ]
               T0 <= 3.148 [ Mode: 1 ] => 1.0
               T0 > 3.148 [ Mode: 0 ]
                       RHOB <= 2,031 [ Mode: 1 ] => 1.0
                       RHOB > 2,031 [ Mode: 0 ]
                               P_MW <= 45.200 [ Mode: 0 ]
                                       Friction_Angle <= 48.371 [ Mode: 0 ] => 0.0
                                       Friction_Angle > 48.371 [ Mode: 0 ]
                                               NPHI <= 0.031 [ Mode: 0 ] => 0.0
                                               NPHI > 0.031 [ Mode: 1 ] => 1.0
                               P_MW > 45.200 [ Mode: 0 ]
                                       Poisson_Ratio <= 0.315 [ Mode: 0 ] => 0.0
                                       Poisson_Ratio > 0.315 [ Mode: 1 ] => 1.0
        BS > 8.499 [ Mode: 1 ]
          ...
```

Fig. 4 A partial view of the first rule of the C5 decision tree.

Evaluation

To investigate the effectiveness of the proposed detection scheme, we trained and tested 100 different machine learning models, including different classification techniques (i.e., SVM, Bayesian network, decision trees, etc.) with different configuration parameters. Table 2 shows the initial results of best-achieved classifiers.

Table 2 Best achieved classifiers (without misclassification cost)

Classifier model	accuracy	Number of used fields
CHAID 1	99.24	7
C5	99.9	5
Neural Net	76.41	20

Although the models were accurate, we have found unacceptable false negatives in the results. Hence, we have added the misclassification cost (i.e., false negative cost=30) to the settings. In this new setting, C5 trees have the best accuracies and fewer false positives. We used cross-validation with k=10. We have used an adaptive boosting technology embedded in the C5 workflow to provide the required model sensitivity to such instability occurrences. The behavioral model for the breakout failure prediction is a decision tree with 40 levels. We can see the tree as 10 rules, each has dozens of sub-rules.

Due to the space limit, it is impossible to embed the full decision tree in the manuscript, but the tree is available by Predictive Model Markup Language (PMML) on [33]. Such a PMML model makes it possible to exchange and reuse the achieved model for further usage.

Fig. 4 shows a partial view of the first rule of the C5 tree. The rule has an accuracy of 85.41%, and another set of rules compensates for the error.

According to rules in very weak rocks, the UCS and tensile strength are very low, the instability predicted by the algorithm. As the figure suggests, the rule begins with an initial condition on the BS (i.e., whether it is lower than 8.5). When the bit size is lower than 8.5 inches, and the tensile strength of the rock is lower than 3.148 Mpa, the breakdown occurs in the well shown in the figure. It can also show the importance of this feature from the model's viewpoint.

The model built by a data-mining technique can be evaluated using multiple metrics. It is important to choose appropriate metrics by realization of what they measure, their application, and their probable bias. We can realize these measures.

by the use of the so-called binary contingency table The most accepted measure for the classification model is accuracy, defined as the number of correct predictions (Tp+Tn) to the total number of predictions (Tn+Tp+Fp+Fn). Table 3 shows how false positives and negatives should be considered about the data labels and predicted labels.

Table 3 Explanation of false positives/negatives.

Label/predicted	-	+
-	True negative	False positive
+	False-negative	True positive

Another important measure is the Area Under Curve (AUC), which is the value for the area under the receiver operating characteristic curve. The curve plots the true positive rate (Tp/P) against the false positive rate (Fp/N). We can interpret the value as the probability that a classifier will rank a randomly chosen positive instance" (wellbore failure in our case) "higher than a randomly chosen negative one" (normal situation) [34]. Table 4 shows the characteristics of the achieved models based on the mentioned measures.

As the table suggests, the final C5 tree can detect instabilities with an accuracy of 91.5%. The model has used 19 features to build a model that can be seen as a decision tree with 10 fundamental rules and a maximum depth of 104 levels.

It is worthwhile to note that there is another group of sensitivity measures, including recall (Tp/P) and precision (Tp/(Tp+Fp)). These measures originally used in information retrieval cover only the positive cases and hence cannot be used solely in the context of our model evaluation. According to Table 2, another important result is the zero false negative. That means no instability occurred, and the model cannot predict them. But false positive equals 10%, which means the model is conservative in predicting wellbore instability.

Although the proposed technique can detect instabilities, we did not use it to detect the instability sources (i.e., mechanical, chemical, thermal, dynamic, or hybrid). We believe that by having a larger dataset with more records for wellbore failures with different sources, one can also use the method for determining the source.

Table 4 Achieved results of the two classifiers used for instability detection.

	ModelAccuracy	False positive	False-negative	Area under curve	Number of used features
Result	91.5	10	0	0.93	17

Like any other data-mining technique and especially non-parametric ones, inappropriate use of our proposed method may cause an over-fitted (i.e., a model that picked up noises or random fluctuations in the training data and learned these as data parameters) or under-fitted models (i.e., a model cannot adequately capture the underlying structure of the data). Using a secondary global pruning for the tree and cross-validation (as was used by our method) can mitigate such probable shortcomings.

Conclusions

In this manuscript, we have used a data mining classification technique for the detection/prediction of wellbore instabilities based on a set of 19 features. These features can be read from the field or achieved by a post-process calculation on field logs. Our features can detect mechanical, chemical, and dynamic wellbore instabilities. The effectiveness of our method is shown by gathering a dataset with about 30,000 records, in which our final C5 decision tree classifier determines the instability cases with an accuracy of 91.5%.

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