PROCEEDINGS, 50th Workshop on Geothermal Reservoir Engineering
Stanford University, Stanford, California, February 10-12, 2025
SGP-TR-229

Evaluation of Drilling Performance at The Geysers with Machine Learning Methods Using Geologic Data

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Keywords: Machine learning, The Geysers, drilling performance, PDC bits

ABSTRACT

A recent well, GDC-36, was drilled in The Geysers Geothermal Field served in a Department of Energy-industry to demonstrate improved drilling performance with polycrystalline diamond compact (PDC) bits. Both PDC and roller cone drill bits were used to drill this well. Key challenges encountered during drilling included lost circulation in the mud-drilled section, and bit damage interfacial severity in the deeper, air-drilled section. The objective of this study is to evaluate the drilling performance in relation to the local geological characteristics using machine learning methods. By applying K-clustering to the sonic log data, we were able to identify areas correlated with measured lost circulation. Also, the boundaries defined by clustering of the mineralogical and lithological data from the mud logs correlate well with interfacial severity during drilling. A random forest model was employed to build correlation between drilling data and rock strength. The confined compressive strength (CCS) of the rock in the training of the machine learning model was inferred from the dipole sonic log. The R-squared of the testing data is 0.78, and the RMSE (Root Mean Squared Error) is 0.06. The trained model was used to forecast rock strength for the section where sonic log data are not available. CCS could also be inferred from mud logs provided the relationship between mineralogy and rock strength is established through core testing data.

1. INTRODUCTION

Drilling is a major contributor to the overall cost of geothermal power development. Co-funded by U.S. Department of Energy (DOE), a recent well was drilled in The Geysers Geothermal Field to demonstrate the possibility of improving drilling performance with polycrystalline diamond compact (PDC) bits (So et al., 2024). The objective of this paper is to evaluate the drilling performance in relation to the geological characteristics encountered in the well. Among other factors, drilling performance is related to the mechanical properties of the rock, including the bulk matrix, lithology interfaces present in situ, and natural fractures or veins. Key challenges encountered during drilling include lost circulation in the mud-drilled section, and bit damage due to interfacial severity in the deeper, air-drilled section. To fully understand these challenges, it is essential to assess the mechanical properties of the rock formations encountered during the drilling. However, a direct measurement of the mechanical properties is difficult. Even for this research well, petrophysical data are limited, and there are only dipole sonic and image logs for the shallower mud-drilled section (12.25” hole from approximately 2,400 to 3,300 feet MD). For the deeper section (8.5” hole, steam reservoir) drilled with air, the only geologic data comes from mud logs of the finely pulverized rock cuttings, providing mineralogy and lithology information, indirect assessments of infilled fractures, as well as occurrences of drilling breaks and steam entries indicative of open fractures.

In this study, machine learning techniques were employed to establish correlations between drilling and geologic data. Firstly, unsupervised machine learning, specifically K-clustering methods, was applied to the sonic log and the mud log to identify critical zones associated with drilling issues. Secondly, supervised machine learning models (e.g. Random Forest) were used to build correlations between drilling data and rock strength.

2. DATA COLLECTION AND PREPROCESSING

Substantial data were collected during the drilling of GDC-36, including drilling parameters recorded at 1-sec frequency, dipole sonic log, mud logging, and image logs. This combined dataset was used to train the machine learning models.

The drilling parameters of well GDC-36 including standpipe pressure, surface torque, weight on bit, and ROP (rate of penetration) are shown in Figure 1. Both PDC and roller cone bits were used in this well. Drilling operations began with mud drilling from the surface to a measured depth (MD) of 3,346 feet. Then, from 3,346 feet MD to the total depth (TD) of 9,220 feet, air drilling was utilized. The hole diameter from 2,452 feet MD to 3,334 feet MD is 12.25 inches, while from 3,334 feet MD to the total depth, the diameter is reduced to 8.5 inches. As shown in Figure 1, the standpipe pressure and weight on bit for mud drilling are understandably larger than those for air drilling. For most cases, the standpipe pressure, and surface torque for PDC bits are larger than those for roller cone bits. Weight on bit shows more variability in the PDC runs compared with the roller cone runs, reflecting experimentation and optimization efforts during the PDC runs. However, the ROP for PDC bits was mostly much larger than for the roller cone bits.

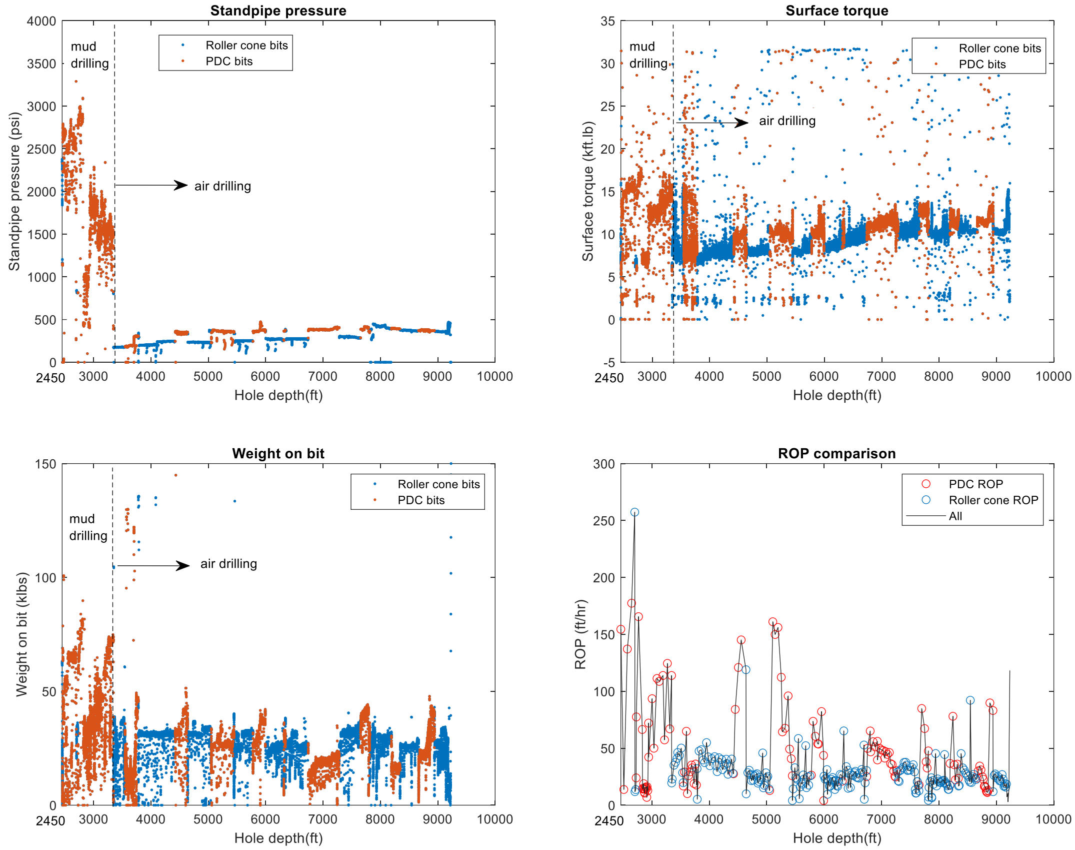


Figure 1: Drilling parameters for well GDC-36.

Before casing was installed, a dipole sonic log was conducted in the 12.25" hole from 2,452 to 3,303 ft MD (refer to Figure 2). The cuttings circulated to the surface were also analyzed. A section of the mud log is shown in Figure 3, which includes information related to the lithology and mineralogy.

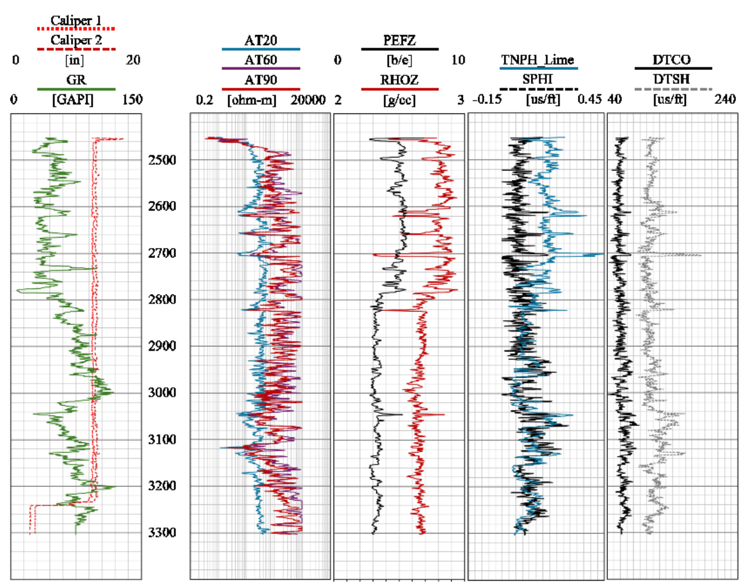


Figure 2: Slowness of sonic logs for well GDC-36.

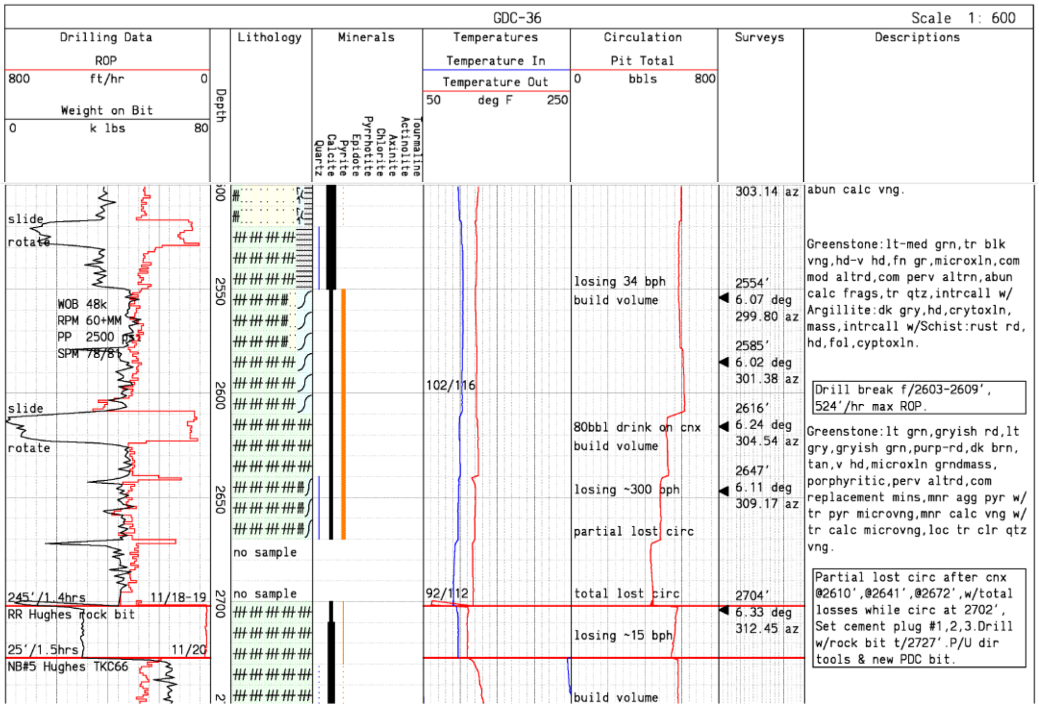


Figure 3: A section of mud log for well GDC-36.

3. MACHINE LEARNING METHODOLOGY

3.1 K-clustering of the sonic log data to correlate with significant mud loss

K-clustering, an unsupervised machine learning method, can be used to classify the data into different categories. Here K-clustering method is applied to sonic log data to identify the zone with significant mud loss. Figure 4 shows the results of K-clustering from the sonic log run in well GDC-36. For the K-clustering, the input features include DTCO (compressive wave slowness), DTSH_FAST (fast shear wave slowness), DTSH_SLOW (slow shear wave slowness), GR_EDTC (gamma ray), and RHOZ (density). Figure 4 only shows the DTCO vs. depth in different categories as defined by the K-clustering for visualization. Clearly, the red category correlates with the locations of no mud returns (complete mud loss), which further correspond to large DTCO indicating smaller Young's modulus and the likelihood of fractures.

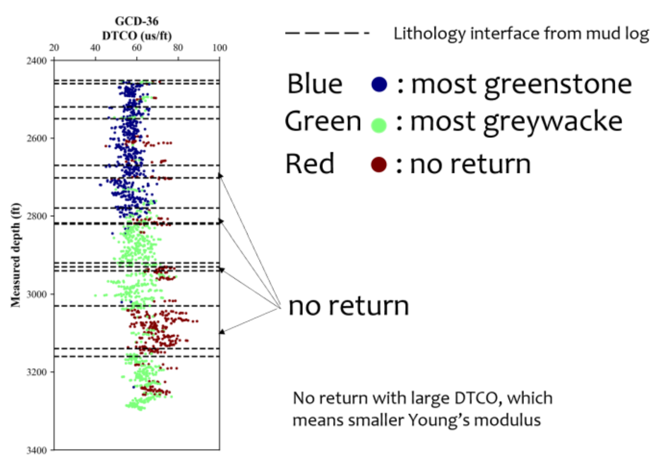


Figure 4: DTCO vs. MD for the different categories obtained from K-clustering of the sonic log data for well GDC-36.

3.2 Supervised machine learning to infer rock strength from drilling data

In this section, we aimed to build a machine learning model that can predict the rock strength from the drilling data. For the model training, the rock strength can be estimated from the sonic log and the mineralogy from the mud log. The goal is to use the trained ML (machine learning) model to predict rock strength when logging data is not available. Additional core testing is being carried out on an offset well.

3.2.1 UCS/CCS inferred from sonic log and mud log

Bit performance can be related to rock strength, particularly the so-called confined compressive strength (CCS) (Caicedo et al. 2005). UCS (unconfined compressive strength) and the internal friction angle can be grossly inferred from the sonic log, although there are many different correlations for doing so. Phelan et al. (2022) estimated the CCS (confined compressive strength) from sonic logs for geothermal wells at Utah FORGE, calibrated by laboratory core testing results. However, the rock types at The Geysers are greenstone/argillite and graywacke, which are substantially different from the granite and gneiss at Utah FORGE. Without ground truth, the same empirical formula from Phelan et al. (2022) is used to calculate the CCS and UCS for well GDC-36 (refer to Figure 5). The estimated UCS is between about 10,000 and 30,000 psi. This needs to be further calibrated by the core testing results from an offset well at The Geysers.

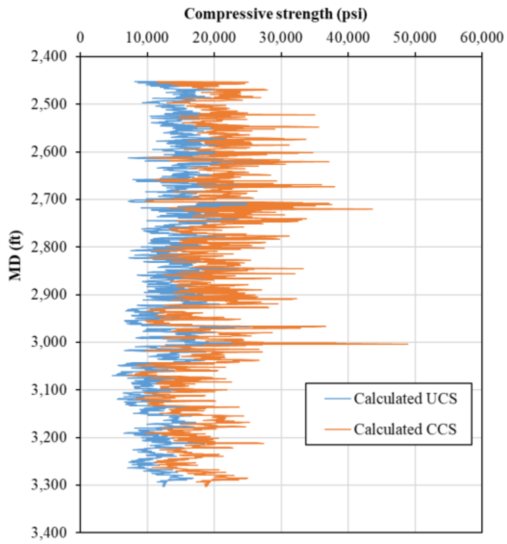


Figure 5: Estimation of the UCS and CCS from sonic log data in well GDC-36

The UCS can also be grossly inferred from mineralogic components. The mud log from GDC-36 provides mineralogic composition, as shown in Figure 3. Chen et al. (2023) estimated the UCS of sandstone from the quartz and clay contents. However, the formula in Chen et al. (2023) is based on sandstone, and hence cannot directly be used for greenstone or greywacke. By increasing the base strength, a new formula that matches results inferred from the sonic log can be written as:

$$UCS = 70.5 + 114.51\ \mathrm{Qz} - 44.97\ \mathrm{Clay}$$

where the UCS unit is MPa. The calculated UCS using this formula is shown in Figure 6, together with those inferred from sonic log. Although, the UCS inferred from mineral components from mud log is coarse, it can provide continuous data along the well at low cost. As a precaution, predictions of UCS either from the sonic log or from mineralogy needs to be calibrated by ongoing laboratory core testing. Moreover, the CCS is difficult to estimate from the mineralogy alone because the relationship between the internal friction angle and the mineral components is missing. We will need to build a correlation between the internal friction angle and the mineral components using laboratory core testing.

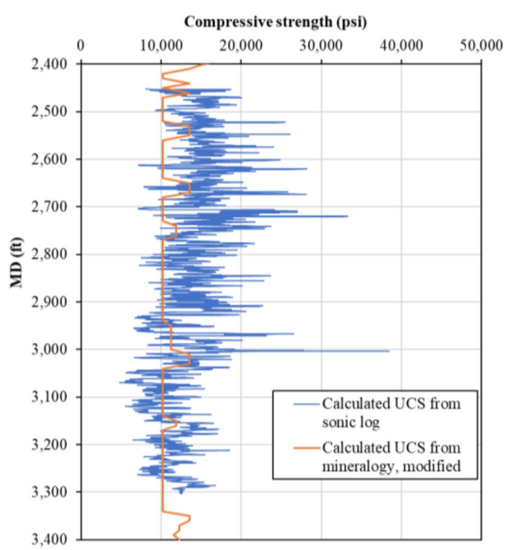


Figure 6: UCS inferred from sonic log and mineralogy information in mud log from GDC-36.

Figure 7 is a comparison of downhole MSE (mechanical specific energy, derived from the 1-second drilling data per Dupriest and Noynaert, 2024) with the CCS calculated using the sonic log. The downhole MSE starts to deviate from the CCS at 3,050 ft MD, which is consistent with the location of significant mud loss, as shown in Figure 4.

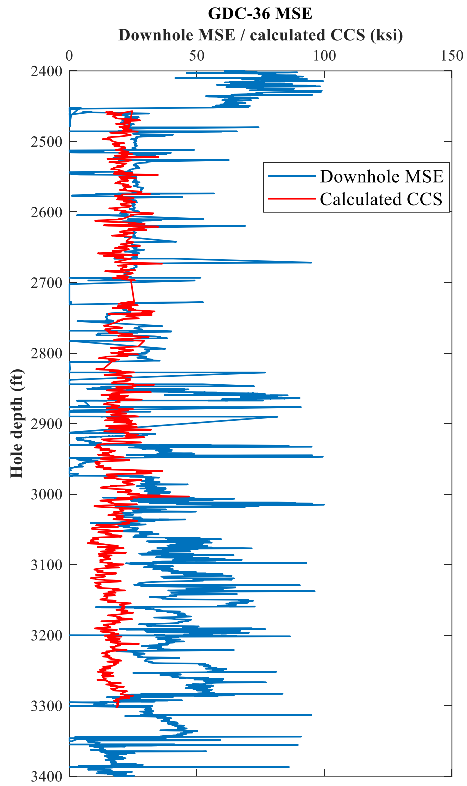


Figure 7: Comparison of downhole MSE and estimated CCS from sonic log.

3.2.2 ML model training and prediction performance

Machine learning model was used to build a correlation between drilling data and the CCS (inferred from sonic log) in the mud drilling section from 2,400 ft MD to 3,300 ft MD in well GDC-36. The correlation coefficient for the drilling parameters and CCS is shown in Figure 8. Not surprisingly, rate of penetration (ROP) has a higher correlation coefficient with other drilling parameters, e.g. standpipe pressure, surface torque, weight on bit, and differential pressure. In contrast, CCS has low correlation coefficient with most of the drilling parameters, among which the relative significant ones are hole depth (-0.28), and differential pressure (-0.17). The parameter pairs that have high correlation coefficients are 1) total pump output and bit RPM, 2) surface rotary and bit RPM, 3) sandpipe pressure and ROP. The parameters/features that are chosen for the machine learning model training are listed in Table 1. The data were preprocessed by removing outliers, and the final range of the parameters is also shown in Table 1.

The data were split to 80% as training and 20% as testing. The random forest method was chosen. The performance of the ML model is shown in Figure 9. The R-squared of the testing data is 0.78, and RMSE is 0.06. The four important features for predicting CCS are hole depth, standpipe pressure, differential pressure, and ROP.

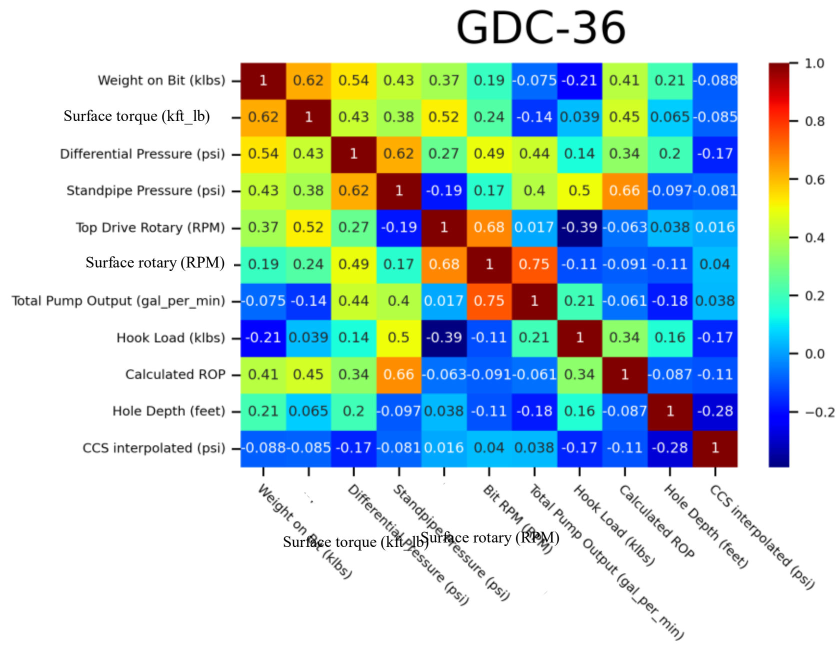
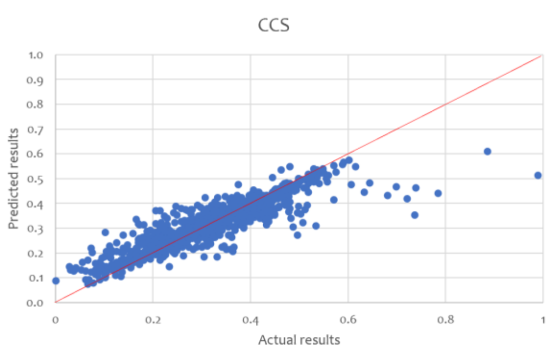


Figure 8: Correlation coefficient heat map for drilling parameters and CCS of GDC-36.

Table 1: Parameters used in the machine learning model to predict CCS.

Machine learning parameter	Min value	Max value
MD (ft)	2478	3303
Weight on bit (klb)	0	100.8
Standpipe pressure (psi)	0	3604
Differential pressure (psi)	-1846	1716
Surface rotary (RPM)	0	99
Surface torque (kft·lb)	0	31.5
ROP (ft/hr)	1	329
CCS (psi)	7086	46875

Criteria	Train	Test
R-squared	0.97	0.78
RMSE	0.02	0.06



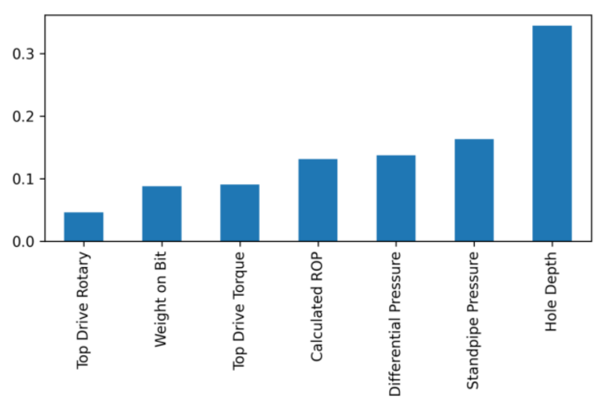


Figure 9: Performance of the ML model in prediction of CCS for GDC-36.

The trained ML model was then used to predict the CCS in the air-drilled section where sonic log data are not available. The results are shown in Figure 10. Note this prediction should be used cautiously because the model was trained in the mud-drilled section. Once the correlation between the mineral components and the CCS is established from core testing results, the CCS predicted by the ML model (trained by sonic log data) can be compared with those inferred from the mud logging.

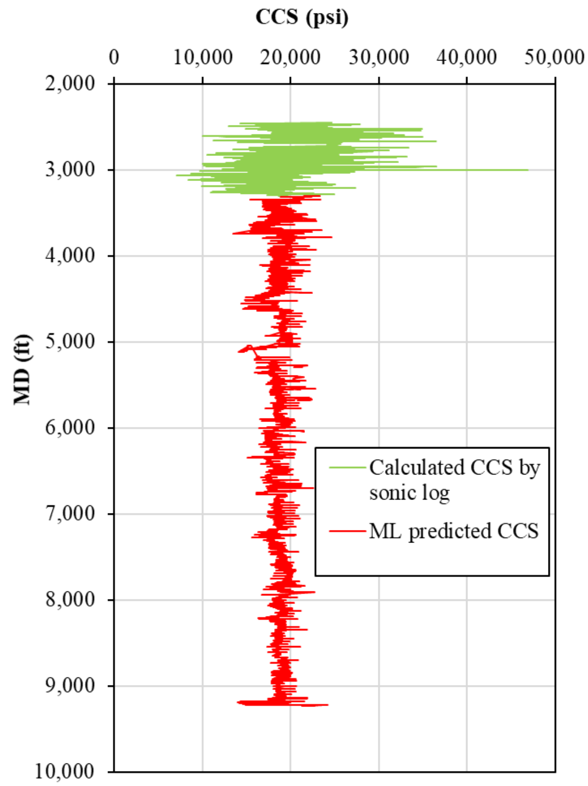


Figure 10: Prediction of CCS in the 8.5" hole (air drilling) using the machine learning model trained by the section of 12.25" hole.

3.3 K-clustering for the mud log data and correlation with interface severity

K-clustering methods were also employed to classify the mud log data and correlate with interfacial severity encountered during drilling. The mud log contains information from both lithology and mineralogy. K-clustering of both mineralogy and lithology was conducted for GDC-36 and two offset wells.

3.3.1 GDC-36

Three clusters were identified for both lithology and mineralogy. The clustering results for GDC-36 are shown in Figure 11. For mineralogy, the red represents a low quartz content, a medium amount of calcite, and a low amount of chlorite; the green represents a medium amount of quartz, a low amount of calcite, and a medium amount of chlorite; the blue represents a high amount of quartz, a low amount of calcite, and a medium amount of chlorite. Higher quartz indicates higher rock strength, which is consistent with the rock type. For lithology classification, the red represents argillite/serpentine/greenstone, the green represents greywacke, and the blue represents felsite.

The horizontal red dashed lines in Figure 11 represent the locations of interfacial severity, which are also the locations of the end for each PDC bit run. The end of each bit run is when the bit failed presumably due to the interfacial severity (personal communication with Sam Noynaert). As is shown in the figure, the interfacial severity correlates well with the boundaries of the different clusters of mineralogy or lithology. Most of the interfacial severities align with the mineralogy cluster boundaries, with the remainder being very close. However, this is not the case for the lithology cluster boundaries. Four interfacial severities - at 5,447 ft, 5,993 ft, 6,342 ft, and 8,855 ft - clearly do not correspond to any lithology cluster boundaries. When lithology differs, mineralogy often changes accordingly. However, even when the lithology remains the same, mineralogy can vary due to fractures filled with different minerals within the bulk rock.

From the point of view of physics, the interfacial severity resulting in bit failure is either from lithologic interfaces that have abrupt change of mechanical properties in the rocks above and below or due to presence of fractures. The K-clustering methods can effectively distinguish between these two types of interfacial severities: lithological interfaces and fracture interfaces. Locations with only mineralogical changes, but consistent lithology, indicate that the interfacial severity is caused by fractures. In contrast, locations with changes in both mineralogy and lithology signify a lithological interface that separates different rock types. For GDC-36, four interfacial severities are attributed to lithological interfaces, while another four are caused by fractures.

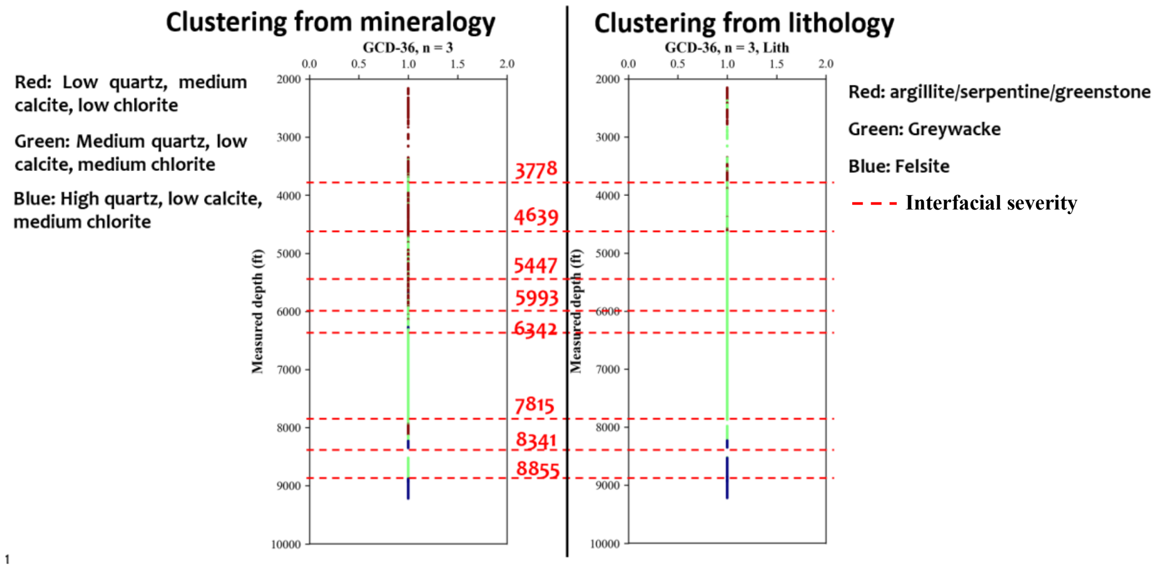


Figure 11: K-clustering of mineralogy and lithology from mud log for well GDC-36, and the correlation with interfacial severity.

<u>3.3.2 Offset wells</u>

A similar K-clustering process was also applied to two subsequent offset wells that have recently used PDC bits in The Geysers. The results are shown in Figures 12 and 13. The interfacial severities for both of these wells correlate with lithologic or mineralogic boundaries/interface, providing additional support for our hypothesis.

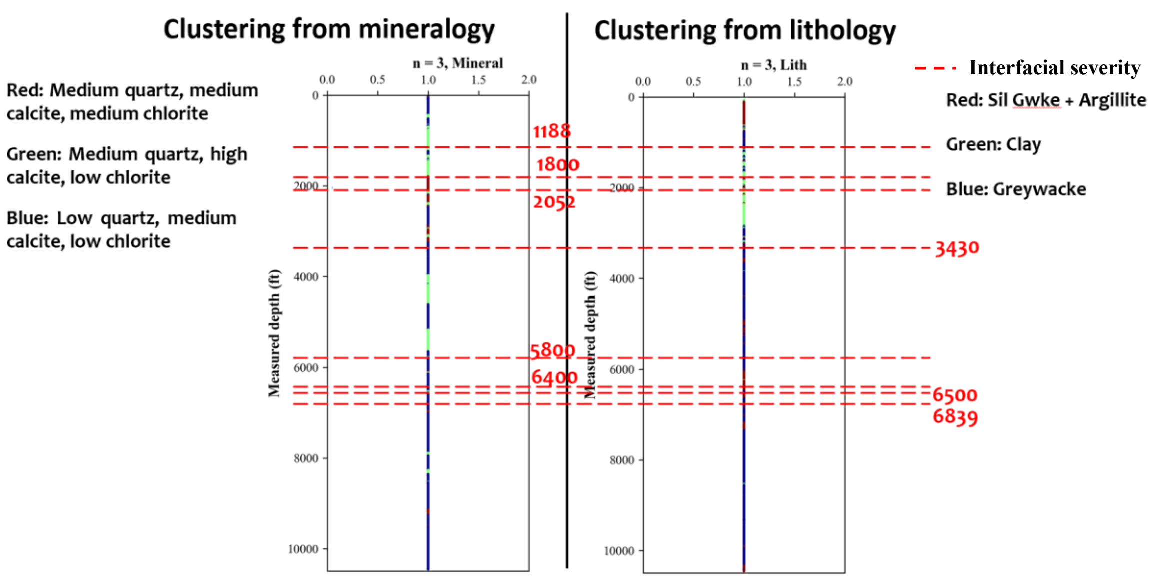


Figure 12: K-clustering of mineralogy and lithology from mud log for well offset well A, and the correlation with interfacial severity.

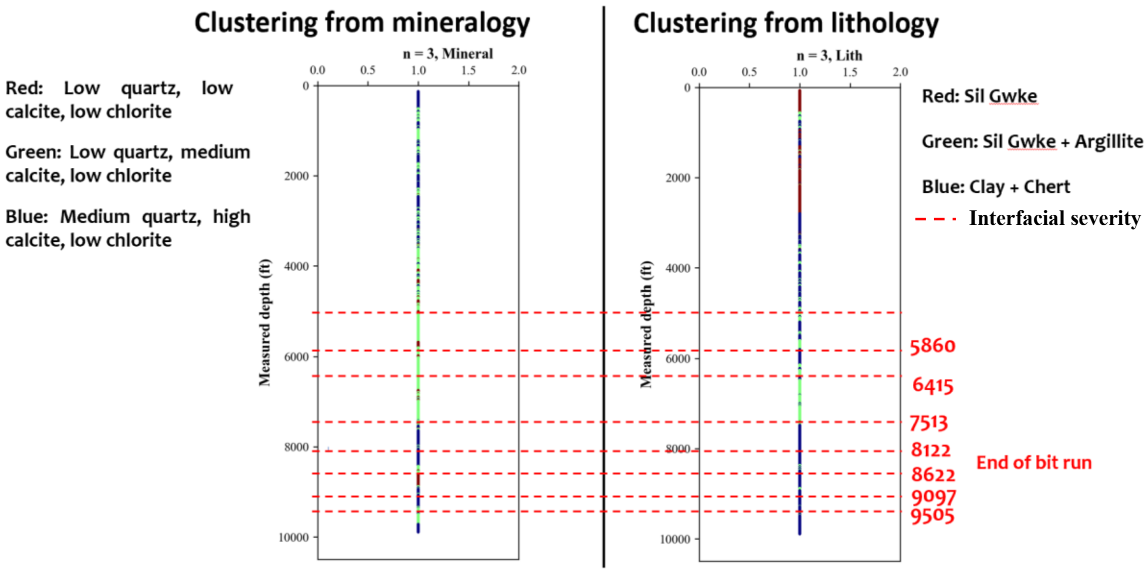


Figure 13: K-clustering of mineralogy and lithology from mud log for well offset well B, and the correlation with interfacial severity.

3.3.3 Summary

Tables 2 and 3 summarize mineralogic and lithologic categories of the three wells considered, as defined by the K-clustering techniques. From the point of view of lithology, GDC-36 is different from the other two offset wells. At the deepest section of GDC-36, there is felsite, which is not encountered in the two other wells.

For offset wells A and B, the lithology classification needs more than one lithology characteristic to distinguish from others. This is achieved by using the K-clustering method, which helps to define "lithology interfaces". For example, in Well B, "Sil Graywacke + Argillite" is different from "Sil Graywacke".

The mineralogy is largely represented by three minerals: quartz, calcite, and chlorite. The difference between these three minerals for the three categories for well GDC-36 is more prominent. The boundaries of categories for mineralogy are not necessarily aligned with those for lithology.

Table 2: Summary of the lithology categories defined by K-clustering for the three wells investigated.

Well	Color	Dominant factor
GDC-36	Red	Greenstone
	Green	Sil Graywacke
	Blue	Felsite
Well A	Red	Sil Graywacke + Argillite
	Green	Clay
	Blue	Sil Graywacke
Well B	Red	Sil Graywacke
	Green	Sil Graywacke + Argillite
	Blue	Clay + Chert

Table 3: Summary of the mineralogy categories defined by K-clustering for the three wells investigated.

Well	Color	Dominant factor
GDC-36	Red	Low quartz, medium calcite, low chlorite
	Green	Medium quartz, low calcite, medium chlorite
	Blue	High quartz, low calcite, medium chlorite
Well A	Red	Medium quartz, medium calcite, medium chlorite
	Green	Medium quartz, high calcite, low chlorite
	Blue	Low quartz, medium calcite, low chlorite
Well B	Red	Low quartz, low calcite, low chlorite
	Green	Low quartz, medium calcite, low chlorite
	Blue	Medium quartz, high calcite, low chlorite

4. CONCLUSIONS AND FUTURE WORK

Machine learning methods are used to evaluate the drilling performance – mud loss, interfacial severity, relationship between drilling and rock strength - of the wells drilled with PDC bits at The Geysers. The data in the analyses include drilling data, sonic logging data, and mud logs. The machine learning methods include K-clustering (unsupervised machine learning) and random forest (supervised machine learning).

For well GDC-36, both roller cone and PDC bits were used. Although larger standpipe pressure, surface torque, and weight on bit were applied during drilling with PDC bits, they also resulted in higher ROP than roller cone bits.

By clustering the sonic log data, we were able to identify areas correlated with measured lost circulation, while clustering mineralogical and lithological data from the mud logs helped locate zones of interfacial severity. The K-clustering methods can effectively distinguish between the two types of interfacial severities: lithological interfaces and fracture interfaces. This technique was also applied to other offset wells, helping to identify fractures and lithological interfaces within the reservoir. In the long run, it will be ideal to do real-time scanning of the cuttings to provide real-time data which can help monitor lithologic or mineralogic change, so that we can take action to appropriately run through the interface and avoid bit failure. X-ray diffraction (XRD) testing of core being tested from another offset will help us to understand the types of mineralogy or lithology interfaces.

A random forest model was used to build a correlation between drilling data and CCS of the rock. For the model training, CCS was inferred from the sonic log data. The estimated CCS needs to be further calibrated by ongoing laboratory core testing. The R-squared of the testing data is 0.78, and the RMSE is 0.06. The trained machine learning model was used to predict the CCS in the 8.5" hole drilled with air.

Rock mechanical properties including CCS can also be inferred from mineralogy from the mud log. However, the relationship between CCS and mineralogy is not established. To address this, laboratory testing, including UCS tests, triaxial compression tests, and XRD mineralogy analysis, are being conducted on cores from an offset well at The Geysers. The advantage of using mud logging instead of a sonic log to calculate CCS is that mud logs are typically available for each well, while sonic logging is expensive and prone to failure in high-temperature environments. If a continuous mechanical properties profile can be inferred using data acquired from mud logging, there will be abundant data to train the machine learning model, and wireline logging might be foregone in subsequent wells. With abundant data available for model training, this approach holds significant potential for improving drilling efficiency and predicting subsurface conditions in The Geysers geothermal play.

ACKNOWLEDGEMENTS

Funding for this work was provided by the U.S. DOE under grant DE-EE0010445. The team would also like to thank the Calpine Geysers Power Company management for supporting this effort.

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