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Utilizing Downhole Drilling Dynamic Data to Characterize Geomechanics of Enhanced Geothermal Reservoirs at FORGE

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ABSTRACT

Successful development and operations of an Enhanced Geothermal System (EGS) requires a thorough understanding of subsurface characterization with reasonable estimates of the geomechanical characteristics of the formations, including rock properties and in-situ stresses. Typically, these essential parameters are estimated in 1-D from well logs or seismic. However, these approaches are undermined by the absence of data, oversimplified empirical methods, or insufficient spatial resolution necessary for subsurface purposes. Our solution to this data challenge is Drilling Dynamic Geomechanics (DDG) technology that utilizes downhole drilling dynamics data to calculate continuous 1-D profiles of the principal stresses. Using bit vibration data measured while drilling and Electronic Drilling Recorder (EDR) data routinely measured at surface is low cost and uses readily available data, imposing no additional time for data acquisition. Downhole drilling dynamics data is available along the entire well length and provides higher resolution estimates of stresses than well logs. A supervised machine learning methodology guided by physics considerations and aided by targeted signal processing techniques is implemented to extract in-situ stresses from input data. The result provides high resolution geomechanical models and wellbore stability without logs from the surface to total depth, rock property and stress profiles along the horizontals which are useful for optimizing stimulation and completion designs and mitigating casing deformation, and real-time geomechanics and wellbore stability analysis.

DDG was applied to the FORGE Well 16A78_32 dataset to understand how the workflow works on high temperature geothermal reservoirs and provide useful geomechanical insight for EGS. The results show that DDG was able to reasonably predict the rock properties and stresses with around 90% accuracy. The temperature effect seems to be captured by vibration data and the technology works in high temperature reservoirs. Therefore, DDG can be used to characterize and develop the connected and complex fracture networks critical to EGS reservoirs for optimal production.

1. INTRODUCTION

To ensure safe and cost-effective subsurface operations, knowledge of the state of stress is essential. Specifically, in geothermal development operations, characterizing the in-situ stress state in the complex reservoirs and cap rocks is critical for safe storage of CO2 and minimizing environmental hazards related to fluid leakage and induced seismicity. Also, the integrity of the borehole is directly dependent on the 3D stress profile along the well trajectory and appropriate design of the drilling and stimulation operations. In-situ stresses are notoriously difficult to determine.

The currently available methodologies for stress estimation are heavily dependent on well logs such as density, sonic, porosity, etc. These inferences are based on simplified models or correlations which generally result in stress profiles with a large range of uncertainties and requirement to be calibrated against expensive field tests such as Extended Leak-off Test (XLOT), minifrac, and Diagnostic Fracture Injection Test (DFIT). The required logs are rarely available in horizontal wells where understanding the lateral changes in the state of stress is very important. Also, seismic data that cover a larger volume of subsurface formations are not of sufficient in spatial resolution for the required subsurface characterization, especially for carbon storage purposes. These limitations and shortcomings identify an essential requirement for new sources of data for stress evaluations, which provide higher resolution data with more substantial spatial coverage.

During drilling, a large volume of data is generated either on the rig or by downhole Logging While Drilling (LWD) and Measurement While Drilling (MWD) tools, and other sensors in the Bottom-hole Assembly (BHA) (Bowler et al., 2016). However, due to a lack of robust interpretation schemes, these data have not been used to understand geomechanical characteristics of the formations, including rock properties and in-situ stresses. The exception is rudimentary Mechanical Specific Energy (MSE) calculations; however, MSE analysis samples only part of the complete data set that is generated during drilling operations (Pastorek et al., 2019). The drill bit is the first BHA component meeting and interacting with the formation, thereby generating rock property data. With the recent advancements in LWD and MWD, high-scanning-rate data can be collected near the bit, and interpretation of these data, in combination with standard MSE procedures, may enable creating profiles of rock properties and in-situ stresses. Previous experimental and analytical studies have provided invaluable information about the dynamic system response arising from the bit-rock interaction (Detournay & Defourny, 1992). Since the bit-rock interface laws encapsulate information about all processes induced by the bit during drilling, the effects attributed to the bit, rock properties, and stresses can be differentiated through modeling. Despite encouraging results, no significant investigations have been carried out to relate these valuable data to the subsurface state of stress.

The fundamental basis of this technology is to determine geomechanical properties of formations using proprietary algorithms to post-process and interpret drilling dynamics data. To achieve this, we used advanced signal processing and machine learning methodologies to identify and extract the signals that carry information about rocks and the stress field.

2. BACKGROUND

Building a reliable geomechanical model is the foundation for any subsurface studies including drilling optimization, wellbore stability, hydraulic fracturing, reservoir management, Enhanced Geothermal Systems (EGS), and so on. The total principal in-situ stresses, reservoir pressure, and rock mechanical properties are the primary components of such geomechanical models. Inaccurate estimation of subsurface stresses has been identified as one of the main uncertainties in subsurface projects. Failure to construct reasonably accurate geomechanical models costs the industry billions of dollars annually due to wellbore collapse, poor performance of reservoirs, cap-rock integrity issues, as well as inappropriate well placement and completion design. Non-productive time caused by geomechanically-related problems during drilling operations can translate into significant cost. According to many published reports, articles, and papers (e.g., Rahman, 2018; Scanlan et al., 2018), unsatisfactory well completions and frac designs can significantly contribute to underperformance of reservoirs. Successful EGS development and production rely on accurate knowledge of the subsurface state of stress and its evolution during and after injection to guarantee efficient fracture networks. In-situ stresses, characteristics of the reservoir and the adjacent formations, and presence of conductive natural fractures (also dependent on the stress field) are factors controlling the success of a connected fracture network in an EGS. Good understanding of the stress field (i.e., magnitude and orientation) in EGS reservoirs can lead to substantial improvement in the ability to develop and monitor an efficient fracture network. Also, knowledge of the stress field is essential for defining operational limits to avoid over-pressurizing the reservoir or inducing unintended fractures and induced seismicity.

Usually, stress measurement procedures consist of perturbing an in-situ equilibrium state by inducing deformation or applying pressure to generate a fracture and observing rock deformation or evaluating a pressure signature. When the perturbation is an applied or induced deformation, stresses are back calculated from these deformations (Ljunggren et al., 2003). Alternatively, small scale hydraulic fracturing is a standard method for inferring the minimum in-situ principal stress. Total principal stresses are frequently aligned with the vertical stress (Sv), the minimum horizontal stress (Shmin), and the maximum horizontal stress (SHmax) on the presumption of a relaxed basin and/or minimal tectonic history. Sv can be calculated by integrating a density log over depth. Shmin is typically interpreted from the results of any hydraulic fracturing test; e.g. Extended Leak-off Test (XLOT), minifrac, Diagnostic Fracture Injection Test (DFIT), and primary hydraulic fracturing treatments. However, for inferring SHmax, except for openhole situations with favorably aligned wellbores, no consistent and reliable measurement methods are available. While approximations or ranges of SHmax can be made from evaluating breakouts, stress polygons, and breakdown pressure, reliability remains poor. Since SHmax has a major effect on all subsurface activities, a reliable technique to estimate the full state of stress (all principal stresses) from other sources of information remains a priority. The development of such a technique is expected to have significant impact on successful storage siting, operation, and long-term integrity.

Back calculation of SHmax from borehole breakout geometry (Leeman, 1964; Haimson & Lee,1995; Zoback et al., 1985) is widely used in the oil and gas industry. However, this protocol is based on several assumptions (e.g. elasticity, plane strain, isotropy, homogeneity, etc.) that jeopardize its applicability in many rock types (e.g. shale, mudstone, claystone, unconsolidated sandstones, coals, salts, and any fractured or anisotropic formations). This analysis protocol may not be applicable in many inelastic and anisotropic unconventional reservoirs. Even in the cases where targeted formations nearly meet the assumed conditions (such as very brittle and isotropic shale), breakout analysis must still be used with caution since breakout-like geometries may be caused by factors that are not directly related to the near-wellbore stresses (Ljunggren et al., 2003). Concerning the state-of-the-art, few significant developments have been recently reported. Exceptions include some attempts to improve or combine already existing methods such as borehole deformation, core deformation, core disking, hydraulic fracturing and evaluating anisotropy of acoustic wave velocities. These attempts are often derivatives of scientific drilling projects (e.g. KTB - Germany, SAFOD - California, Chelungpu fault -Taiwan etc.) which have the luxury of extensive and detailed data availability. (Haimson & Chang, 2002; Zoback et al., 2003; Hickman & Zoback, 2004; Boness & Zoback, 2006; Haimson et al., 2010; Lin et al., 2010; Zhang & Roegiers, 2010). However, this is usually not the case in actual, commercial operations. In addition, most of the abovementioned methodologies only provide stress estimation at one specific depth, however, what is required for geomechanical modeling is a continuous profile of stresses along the wellbores.

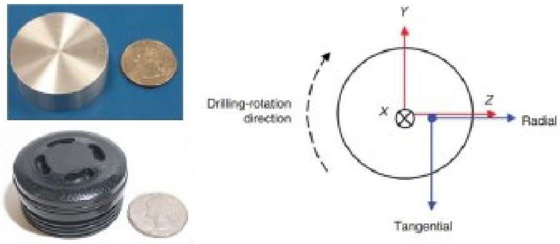
Despite significant efforts in estimating in-situ stresses using geophysical methods (velocity processing), almost universally, these calculations are erroneous due to application of oversimplified models of the in-situ geologic domain (uniaxial strain, supplementary differential tectonic stresses, etc.). About a decade ago, Schlumberger introduced the Sonic Scanner logging tool that uses cross-dipole, multi-spaced-monopole, and axial-azimuthal measurements (Sinha et al., 2008). Other service companies have also introduced similar products. These devices have been designed to estimate the magnitude and orientation of SHmax using an underlying theory based on acoustoelastic response of rock. However, the method did not become popular due to cost and lack of definitive proof of concept. Ito et al. (2016) integrated hydraulic fracturing with deformation of core samples and developed a downhole tool for stress determination called the Deep Rock Stress Tester (DRST). This technique requires drilling a small diameter hole and taking oriented core which is quite costly, while still suffering from unrealistic assumptions of rock behavior. The tool is applicable at pressures up to 4,350 psi and temperature up to 100°C.

Our review of existing techniques for stress estimation in boreholes concluded that there is currently no single technique for reliable determination of the complete state of in-situ stress.

Over the past decade, extensive experimental and analytical studies have been carried out to understand the fundamentals of tool-rock interaction during drilling. This has provided unique capabilities to explore the nature of this interface and to study the dynamic system response arising from the interaction between bits, BHAs, drill string, and the rock. As a result of these investigations, bit-rock interface "laws" for drag bits (PDC), roller-cones (with and without percussive action) and diamond bits have been developed and validated with laboratory drilling experiments. These relationships have been partially validated by analysis of field data (Detournay & Defourny, 1992). Since these bit-rock interface laws or models encapsulate information about all processes induced by the bit during drilling, the effects attributed to the bit (state of wear and geometry) and to the rock (stiffness, strength, abrasivity and hardness) can be differentiated through model parameters. A relevant question is whether the model can be used to assess dynamic response. Challenges include: 1. window length (one revolution of the bit); 2. frequency band (pass-band filter); and 3. acceleration to displacement calculation, RPM-dependent (surface vs. downhole); 4. stochastic nature of acceleration data, RMS.

Figure 1 shows an example of downhole sensors for high frequency drilling vibration measurements and the type of signals obtained.

Some encouraging results internally achieved by Petrolern LLC have indicated the need for robust and efficient routines to process and prepare actual drilling data for diagnostic analyses. The proposed project will utilize the developed know-how and competency in fundamentals of drilling mechanics, signal processing, and data analytics to develop algorithms for post-processing and interpretation of drilling data to provide reliable estimations of rock properties and in situ stress.



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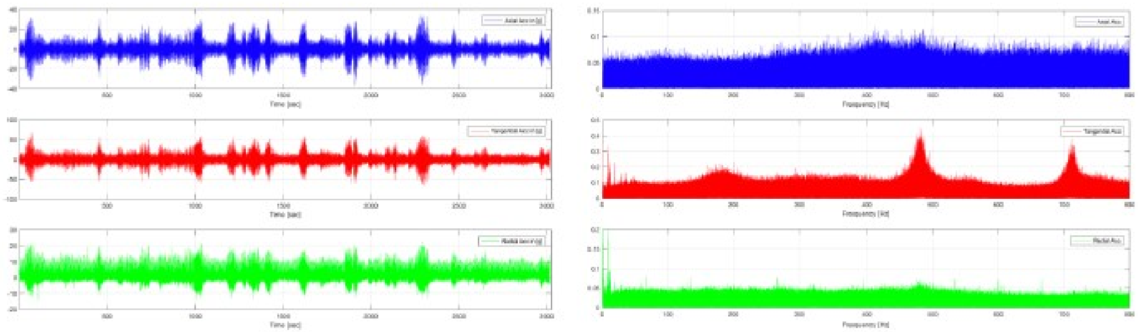

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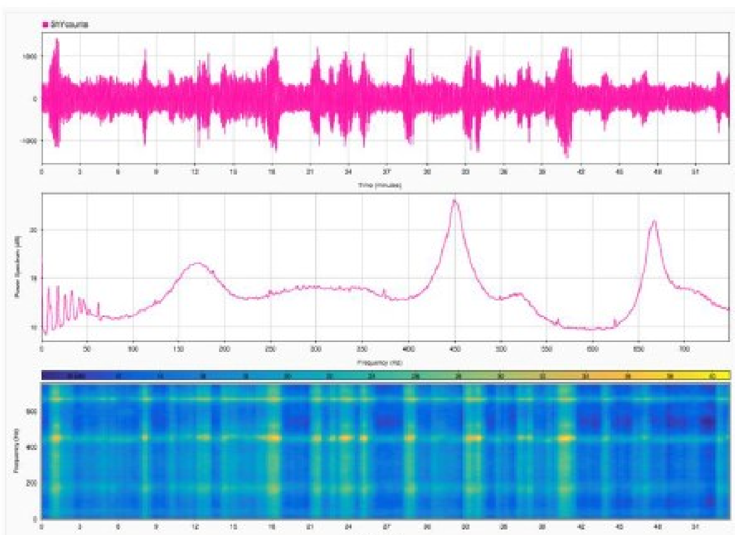

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Figure 1. (a) Alpha sensor for vibration measurements (left, Jones et al., 2016) and schematic of sensor-coordinate system looking downhole (right, Bowler et al., 2016); (b) Examples of time domain (left) versus frequency domain (right) vibration data; (c) Tangential components.

3. METHODS

The primary objective of this project was to prove that the principal in-situ stresses along the borehole can be estimated from drilling dynamics data for EGS at a reasonable accuracy. As there is currently neither theoretical nor empirical frameworks directly relating the stresses and downhole drill-bit vibration measurements, a supervised machine learning methodology guided by physical considerations and aided by targeted signal processing techniques was implemented. The data considered for the model input included three-axis accelerometer data measured near the bit at a high sampling rate, Gamma Ray (GR) log, and routinely measured surface drilling parameters (EDR, Electronic Data Recorder data) including surface weight-on-bit, RPM, torque, and rate-of-penetration. The outputs of the model were selected to be the vertical stress (Sv), and the minimum and maximum horizontal stresses (Sh and SH, respectively).

The approach used developed a novel workflow by combining analytical methods with advanced signal processing and machine learning algorithms. Two main approaches were used to estimate the stresses from the vibration data. First, we consider the traditional regression analysis to better understand the data and to perform the preprocessing steps such as denoising (Fig. 2), outlier detection and model selection tasks. However, this approach is usually only reliable for stationary data and cannot, in its basic form, account for the dynamics of a time series data. To address these shortcomings, we investigate the application of the Recurrent Neural Networks (RNNs) for estimating the stress signal. In both cases we view the problem as a supervised learning task; assuming we have access to the training data with correctly estimated stress signal.

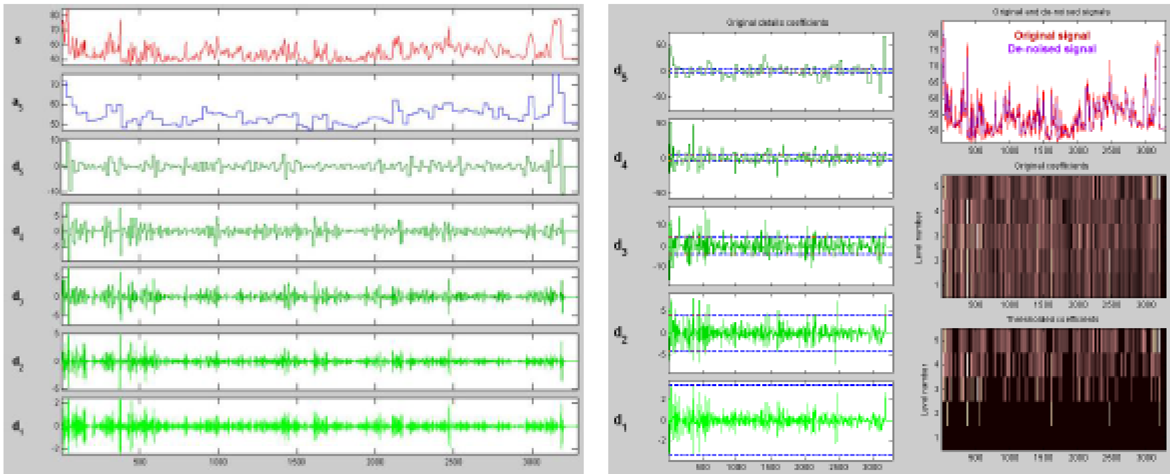

Figure 2. Sonic log decomposition in five levels using bior wavelet (right); Sonic log denoising using Elena threshold and optimum signal energy (left).

3.1 Data Preprocessing

Naively applying a regression analysis to estimate a dependent variable (stress signal) from a time series data may result in poor model fitting and generalization. Various analysis and techniques can be employed to pre-process each feature of input space in order to remove the noise and unwanted outliers. After normalizing each feature to a standard form (e.g. zero mean, unit variance), we use the wavelet analysis to detect and remove the noise caused by sensor issues or background vibrations in the environment. In the past, we have successfully applied the wavelet analysis (See Fig. 2) to remove noise from sonic log data. This analysis can also be used to decompose the signal into more informative frequency bounds which can be added to the model as supplementary derivative features as well. In addition to the denoising, we will also consider the effects of temporal correlation between consecutive readings of each feature. While individual features may be non-stationary, the regression model assumes the residual signal to be stationery and deviance from this assumption invalidates the model and subsequent analysis. Further, in time series analysis, a similar trend between an independent and the dependent variable can result in an invalid analysis. Spurious regression (Granger, 1974) is one such case that shows how two completely unrelated series with the same trend may cause an inflated significance testing result. Removing the temporal correlation can be a remedy in such cases (Figure 3).

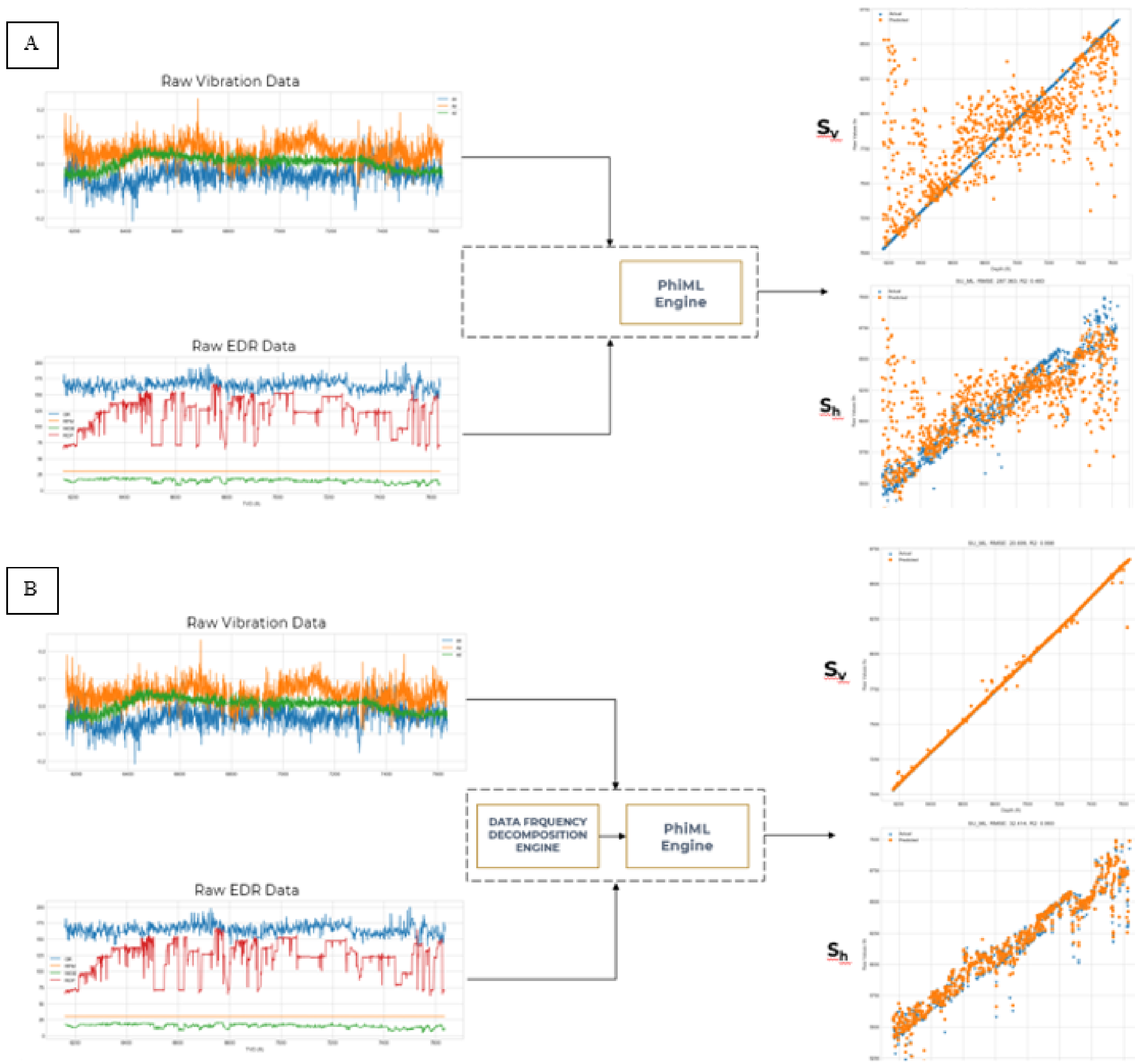

Figure 3. Development progress (A) without signal processing and (B) with signal processing.

3.2 Feature Selection

Feature selection is one of the core concepts of machine learning that hugely impacts the performance of the model. This process consists of two main steps: 1. adding new features derived from the raw data; 2. removing the undesired features from the final selection. In the first step, we attempt to extract more relevant features from the raw data. For a typical numerical dataset that belongs to a time series, this may include the current mean and variance of the input feature as wells as frequency information. In this regard, the data can be augmented with Short Time Fourier Transform (STFT) to add relevant frequency information to the time series data. Our previous works on processing well logs information signifies the importance of such information in learning the characteristics of the vibration data (Soroush et al., 2011, 2012, 2013). Learning from the meticulously augmented feature vectors is usually much faster and does not require complex learning models. The next step after augmenting the feature vectors is to select a subset of important features. There are three main criteria that we need to consider: 1. feature significance; 2. avoiding collinearity; 3. model selection penalties:

1. Failing to remove insignificant features from the feature vectors has many consequences. It will make the learning slower and adds unnecessary complexity to the learning. Further, it increases the possibility of overfitting by increasing the number of parameters of the model. One of the simplest ways to estimate the significance of each feature is to use the linear regression analysis. In this analysis we are mainly interested in assessing the p-value for the null hypothesis (indicating that the feature is not useful). We can filter the feature vectors by keeping only those features above a certain confidence level (e.g. 0.05).

2. Collinearity is more crucial than the significance testing. This problem arises when two or more features are linearly dependent on each other. The existence of such correlation among features makes most of the machine learning algorithm unstable and will generate faulty and inaccurate models. There are various statistical approaches to detect and remove colinear features. The simplest approach is to estimate the correlation matrix. Using this analysis, those features that are correlated significantly (i.e., correlation coefficient close to 1) are considered colinear. This method, however, cannot find all possible complex multicollinearity cases and there may be a need for further analysis. For example, we may use Variance Inflation Factor (VIF) analysis which measures the inflation in the variances of the parameter estimates due to collinearities that exist among the predictors. It is a measure of how much the variance of an estimated regression coefficient is "inflated" by the existence of correlation among the predictor variables in the model.

3. Poor generalization due to over-fitting is one of the main problems of machine learning approaches. This is particularly evident in scenarios where the dimension of feature space compared to the number of samples is large. Additionally, employing ensemble learning techniques such as boosting techniques as well as neural network-based approaches which increase the number of parameters of the model makes such a problem more prevalent. One of the main techniques to alleviate this is to consider some penalty in learning to encourage models with the lowest number of parameters. Intuitively, if by removing one of the features, the performance of the model for the training dataset does not change considerably, then removing that feature may increase the generalization performance of the model which is always a desirable feature. One of the most well-known techniques to compare models with different numbers of parameters (different number of features) is to use Bayesian Information Criteria (BIC) or similarly Akaike Information Criteria (AIC). These two approaches add a penalty to the models based on the number of parameters in the model which makes it possible to quantitively compare the overall log-likelihood of the two models.

3.3 Estimating Stresses via Regression Analysis

Regression models are some of the most fundamental techniques in machine learning. In the most basic form, linear regression model explains a dependent variable y via a linear combination of the independent predictor signals xi, i.e.,

$$y=\beta 0+\beta 1x1+\cdots+\beta nxn+ \epsilon$$

where ϵ is an additive noise and is assumed to be a white Gaussian noise. Despite its simplicity, this model is widely used as a baseline and as a tool for analytical study of the independent variables and to understand the significance of the input features. In the following, we address some of the main aspects of the data processing as part of the regression model analysis. We use the linear regression analysis to study the feature space and for the model selection. Despite its simplicity and the linearity assumption, this model usually performs reasonably well and has good generalization performance. We will, however, consider more sophisticated models such as regression trees to achieve more accurate estimates. Basic linear regression is a global method that assumes one single linear formula for the whole space of features. However, most of the relation between features are not perfectly linear. Further, finding a generalized nonlinear relation for large space of features is not practical and can be employed only under certain strong assumptions. An alternative is to sub-divide (partition) the space into smaller regions where the interactions are more manageable. These regions can be recursively divided until the smallest of regions can be faithfully explained by a linear model. The dividing forms a tree where we start from the root and divide each node by asking a question similar to "is feature xi greater than 1.5?". There are various algorithms based on this core idea of recursive splitting of feature space. One of the ways different decision tree algorithms differ is the way this splitting is carried out. The mostly adopted criteria for splitting are the Gini Index and the Information gain. The number of splits and the depth of the decision trees are two important hyper parameters of these models which also controls the tradeoff between model accuracy and generalization performance. Instead of using only one decision tree, we can use an ensemble of multiple different models. The final prediction then can be carried out by the averaging the prediction of the individual models. In general, ensemble learning can significantly outperform the typical single decision tree approaches. However, most of these techniques suffer from the over-fitting problem. As such, in practice these ensemble learning techniques (e.g., gradient boosting, bootstrap aggregating) should be applied with special care and in scenarios where the size of the training data is very large compared to the feature size. Random Forest (Ho, 1995) is an ensemble learning technique which alleviates the over-fitting issue and usually offers excellent generalization performance. In this approach multiple decision trees are constructed at training time and the mean (or the mode) of the individual predictions is reported as the output of the ensemble method. In this method, at each candidate splitting within each tree model, a randomly selected subset of feature space is used. This trick has proven to be very effective and the resulting models are usually robust to the overfitting problem. We propose to investigate the various regression analysis and to compare the effectiveness and their generalization quality for estimating the stress signals.

3.4 Estimating Stresses via Recurrent Neural Networks

In the previous analysis we mostly ignored the dynamics of the signal and assumed that at each timestamp the dependent variable is explained by the to the independent features at that time. However, before further analysis, it is not clear if this simplifying assumption is valid. While there are traditional statistical approaches for learning the dynamics of the model and incorporating past sequences in the time-series forecasting (e.g., Auto Regressive Moving Average-ARMA, Seasonal ARMA, etc.) these models are usually mathematically complex and work under certain conditions. In recent years, Recurrent Neural Networks (RNNs) have shown to outperform the standard statistical approaches in variety of the time series analysis including speech recognition (Graves, 2013). At a very high level, an RNN cell provides a neural mechanism for learning autoregressive models with an impressive flexibility. There are variety of designs for these recurrent cells, for example Vanilla RNN, Long Short-Term Memory (LSTM) and multidimensional RNNs. LSTM cells are very efficient and can learn long correspondences due to their gated design.

Despite their superior performance compared to the traditional statistical approach, they have some shortcomings. For example, unlike the linear regression, it is not easy to estimate the confidence level for RNN predictions or to estimate the significance of each feature analytically. One way to address this is to employ the ensemble learning paradigm. We can construct several different RNN models and perform voting (e.g, averaging). One way to design multiple models is to use different training data for each model. It is also possible to use an approach similar to the Random Forest and to select subsets of the features randomly in each model and then use the aggregate model for the prediction. In addition to the confidence testing, this can also alleviate the over-fitting problem which is usually the weak point of neural approaches. In time series analysis and especially when the sample rate is high enough, it can be beneficial to incorporate the frequency information in the time series forecasting as well. In the feature selection we briefly addressed the possibility of adding frequency information as part of the input features. RNNs on the other hand, allows us to incorporate this side information more systematically. This can be accomplished using a 2D grid LSTM (Fig. 4.c) which process the data sequentially in two directions of time and frequency. This Time-Frequency LSTM (TF-LSTM) (Graves, 2007; Sainath, 2016) makes it possible to incorporate the frequency information into the prediction model.

The full technology architecture outlined in this section is shown in Figure 3.

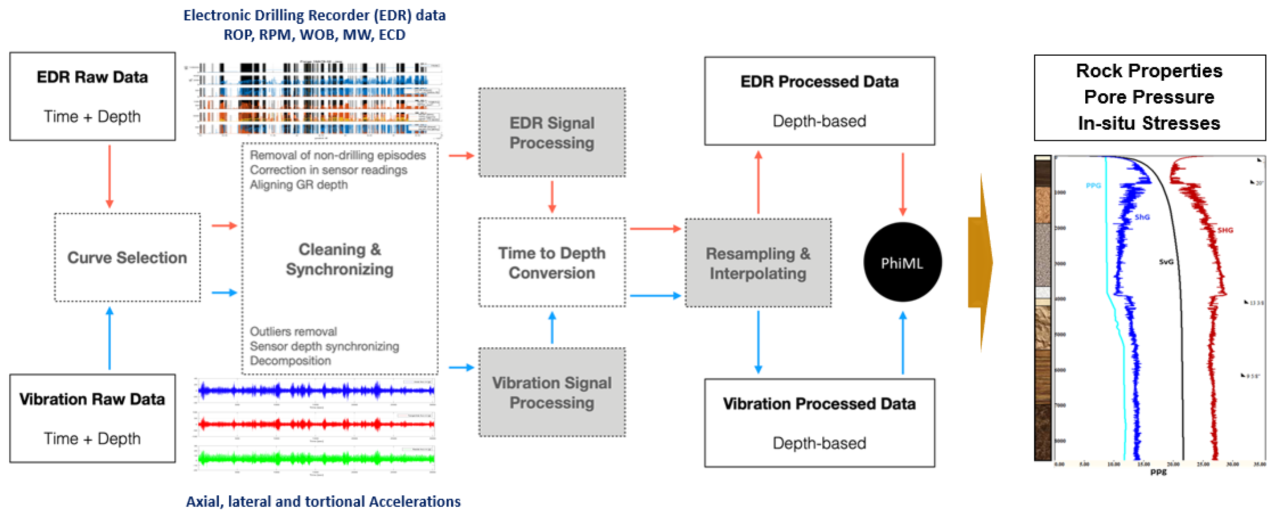

Figure 4. Technology architecture used in this methodology.

4. RESULTS

This technology was applied to the FORGE Utah (DOE-sponsored Frontier Observatory for Research in Geothermal Energy, Utah) project Well 16A(78)-32. The data from this well was collected from the Department of Energy's Geothermal Data Repository (GDR). Well 16A(78)-32 was selected for this study because it had downhole vibration data and geomechanics data. The workflow described previously was used to build a 1-well model by separating some of the data for blind testing in the machine learning algorithm. This test was the first geothermal application used with this methodology. Limitations of this data included that there was no raw, or high frequency, vibration data. Only processed data was available. This hinders the best model performance but still provides good performance within the scope of the project. Another limitation is that no cross-validation for depth alignment which means an assumption that all data is aligned properly was used in this study.

The goal here is to demonstrate the benefits using downhole drilling dynamic data for geothermal drilling applications. The developed customized AI-based model (ML/DL model) was used to predict in-situ geomechanics from the drilling dynamics data of well 16A(78)-32. These properties included in-situ stresses, pore pressure, and rock properties.

The initial dataset used included a mixture of time-based data from EDR and vibration data sets and depth-based geomechanics logs. The initial data is cleaned and signal processing is applied through the workflow, and then the ML/DL model is applied to get the geomechanical characteristics including elastic properties (Young modulus and Poisson's ratio), strength properties (compressive strength, tensile strength, cohesion, and friction angle), stress magnitudes (vertical and horizontal stress gradients, minimum horizontal stress, and maximum horizontal stress), and porosity (Figure 5-7).

Initial results of using the neural network algorithm show that the actual and predicted yield about 90% accuracy for a majority of the determined output properties. The elastic rock properties (Young's Modulus and Poison's Ratio) average a R2 value around 0.90, the strength rock properties around 0.85-0.90, and the stress values have an R2 between 0.85-0.96 (Figure 5, 6, 7). The RMSE value is the error value for each of these parameters. In this case study, all RMSE values are small relative to the corresponding parameter. Several modeling profiles were tested to determine the best fit, and grid parameterization was used to determine the best model.

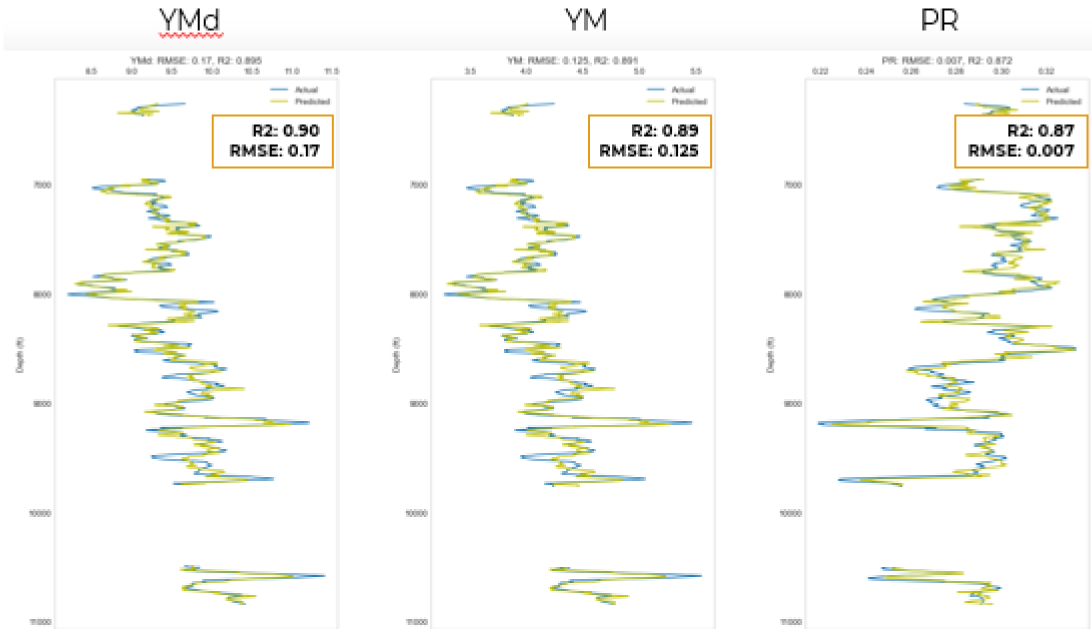

Figure 5. Output measurements for rock property predictions. YMd = differential Young's Modulus, YM = Young's Modulus, PR = Poison's Ratio. Blue is the actual data, Green is the predicted data from the ML/DL algorithm.

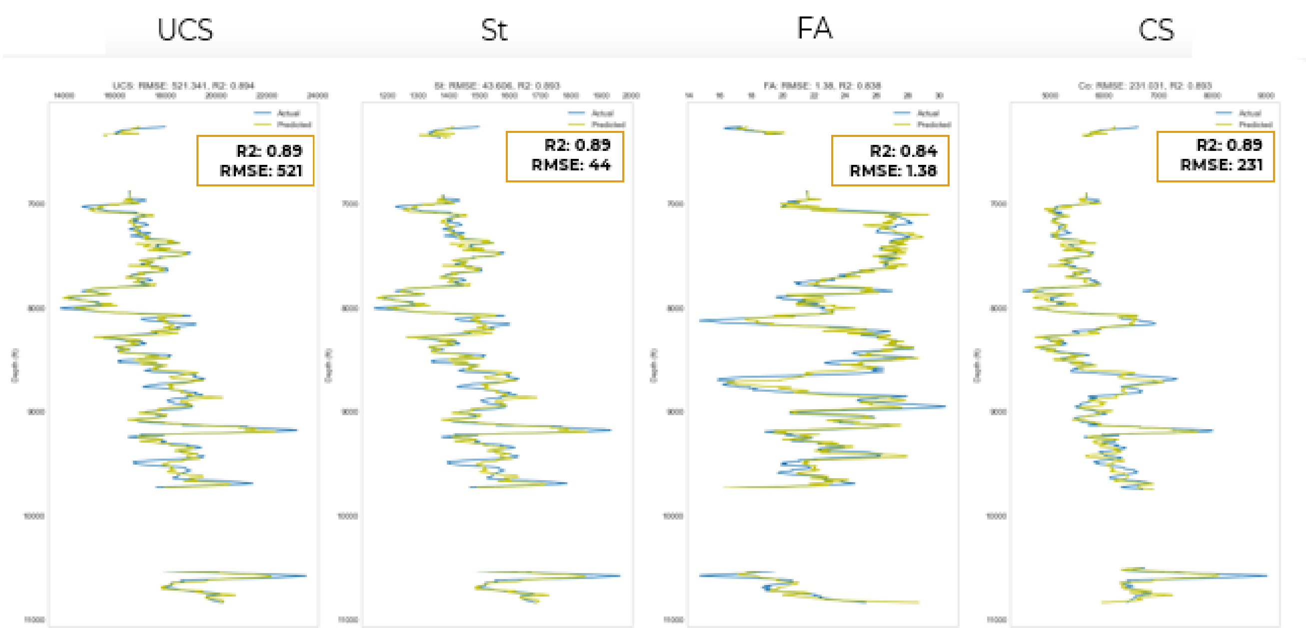

Figure 6. Output measurements for strength property predictions. UCS = compressive strength, St = tensile strength, FA = friction angle, Co = cohesion. Blue is the actual data, Green is the predicted data from the ML/DL algorithm.

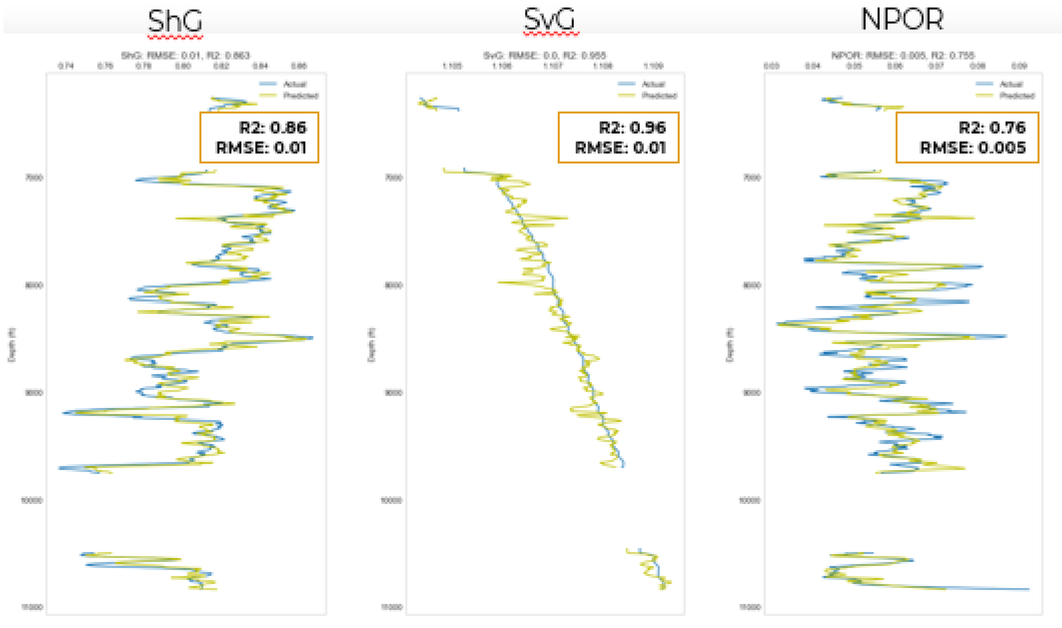

Figure 7. Output measurements for stress property predictions. ShG = horizontal stress gradient, SvG = vertical stress gradient, NPOR = porosity. Blue is the actual data, Green is the predicted data from the ML/DL algorithm.

5. CONCLUSIONS

In this project, the FORGE drilling dynamics dataset was analyzed for well 16A(78)-32. The vibration data collected and used in this project was not original and were filtered. Therefore the results were based on filtered data. Regardless, the technology was able to reasonably predict the rock properties and stresses within around 90% accuracy.

This is the first application of DDG on a geothermal project. Any temperature effects seem to not affect the accuracy of the vibration data and we saw no discrepancies with analyzing at higher temperatures. The technology works in high temperature reservoirs as well as other lower temperature settings. DDG provides petrophysical and geomechanical data that can be acquired from near-bit measurements that can characterize the reservoir and improve the drilling process. In this way, it provides significant information for reservoir characterization and completion design without additional data collection from the drill bit. The *in-situ* stresses and rock strength properties are of great value because these provide a baseline for the confined compressive strength required to the mechanical specific energy that is related to the efficiency in drilling. With this baseline, it is then of use to understand if there is a deviation and an indication of problems during drilling.

Two main industry challenges are addressed with DDG: drilling performance and reservoir characterization. DDG provides insight to what is going on at the bit and assesses dysfunction. The data gathered also provides understanding of the mechanics of the reservoir and fracture density which are key components to characterizing geothermal reservoirs. DDG assists in reservoir characterization by measuring the mechanical and petrophysical properties of the intact material and by inferring some characteristics of the natural fractures. Future work includes blind testing selected depth intervals in the wellbore and looking at defining other parameters with the same technique.

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