Subsurface Characterization and Machine Learning Predictions at Brady Hot Springs

Preprint

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Subsurface Characterization and Machine Learning Predictions at Brady Hot Springs

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ABSTRACT

Subsurface data analysis, reservoir modeling, and machine learning (ML) techniques have been applied to the Brady Hot Springs (BHS) geothermal field in Nevada, USA to further characterize the subsurface and assist with optimizing reservoir management. Hundreds of reservoir simulations have been conducted in TETRAD-G and CMG STARS to explore different injection and production fluid flow rates and allocations and to develop a training data set for ML. This process included simulating the historical injection and production since 1979 and prediction of future performance through 2040. ML networks were created and trained using TensorFlow based on multilayer perceptron, long short-term memory, and convolutional neural network architectures. These networks took as input selected flow rates, injection temperatures, and historical field operation data and produced estimates of future production temperatures. This approach was first successfully tested on a simplified single-fracture doublet system, followed by the application to the BHS reservoir. Using an initial BHS data set with 37 simulated scenarios, the trained and validated network predicted the production temperature for six production wells with the mean absolute percentage error of less than 8%. In a complementary analysis effort, the principal component analysis applied to 13 BHS geological parameters revealed that vertical fracture permeability shows the strongest correlation with fault density and fault intersection density. A new BHS reservoir model was developed considering the fault intersection density as proxy for permeability. This new reservoir model helps to explore under-exploited zones in the reservoir. A data gathering plan to obtain additional subsurface data was developed; it includes temperature surveying for three idle injection wells at which the reservoir simulations indicate high bottom-hole temperatures. The collected data assist with calibrating the reservoir model. Data gathering activities are planned for the first quarter of 2021.

1. INTRODUCTION

Many geothermal fields around the world show a gradual decline in reservoir temperature and pressure, resulting in a decrease of heat and/or power production over time. Proper reservoir management can limit the reservoir performance decline and optimize the system over its lifetime. Reservoir management strategies include optimal fluid allocation across existing injection and production wells and drilling of new wells at optimal locations. Reservoir simulations can guide reservoir management strategies; however, given the vast number of configurations possible, reservoir simulations can only cover a small subset of possible options. Machine learning (ML) techniques are applied in this work to the Brady Hot Springs (BHS) geothermal project to improve reservoir management decisions, guide additional data collection activities, and accelerate subsurface model updates. Our main long-term objective is to use ML to find an optimal flow allocation across multiple injection and production wells to maximize the energy extracted over the next 20 years at BHS.

The ML efforts described in this paper were inspired by the recent work on applying ML to oil and gas industry problems (Nwachukwu, 2018; Hegde and Gray, 2017; Memon et al., 2014). These studies show that it is possible to train neural networks that can accurately predict parameters of interest by capturing complex, non-linear relations among various metrics in multi-well reservoir systems. The current work evaluates the ability of these techniques that would help solve optimization problems for geothermal power plants and leverage time series forecasting methods that are proven to be efficient and accurate (Brownlee, 2018). Specifically, this work evaluates the multilayer perceptron (MLP; also referred to as artificial neural networks) (Gardner and Dorling, 1998), long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997), and convolutional neural network (CNN) (LeCun, Bengio, and Hinton, 2015) architectures. The results demonstrate these networks can predict future production temperatures well—for both simpler and more complex systems being modeled. Initial results show the MLP and CNN networks slightly outperform LSTM networks in terms of prediction accuracy, although this outcome may change with additional training or when more training data become available.

This paper documents the research and modeling efforts during the first year of this project, which includes the development of reservoir models for BHS and generation of ML training data (Section 2), application of ML techniques for time series forecasting (Section 3), development of an updated BHS reservoir model based on the principal component analysis (Section 4), and development of a data gathering plan to further characterize the BHS reservoir and assist with improvement of the BHS reservoir model and ML predictions (Section 5).

2. BHS RESERVOIR SIMULATIONS

BHS reservoir simulations were set up and run in TETRAD-G (Shook and Faulder, 1991) and CMG STARS (Computer Modelling Group Ltd., 2019) to generate a training data set for the ML algorithms. Both models are a three-dimensional (3D) numerical thermo-hydraulic (TH) dual-porosity reservoir model, consisting of roughly 20,000 grid elements. The model includes an initial temperature and pressure distribution, about 40 injection and production wells (including surface fumaroles at the top and fluid sources at the bottom of the reservoir), historical injection and production data since 1979, and representation of a major flow path in the reservoir connecting injection and production wells. Constant temperature at top and bottom and constant pressure aquifers on the four sides are included as boundary condition. Simulations consist of two parts: (1) the historical data are first simulated from 1979 to today; (2) future production temperatures and pressures are predicted through 2040 for different reservoir operation conditions which become part of the training data set for the ML algorithms. A screenshot of the CMG reservoir model and initial temperature is provided in Figure 1.

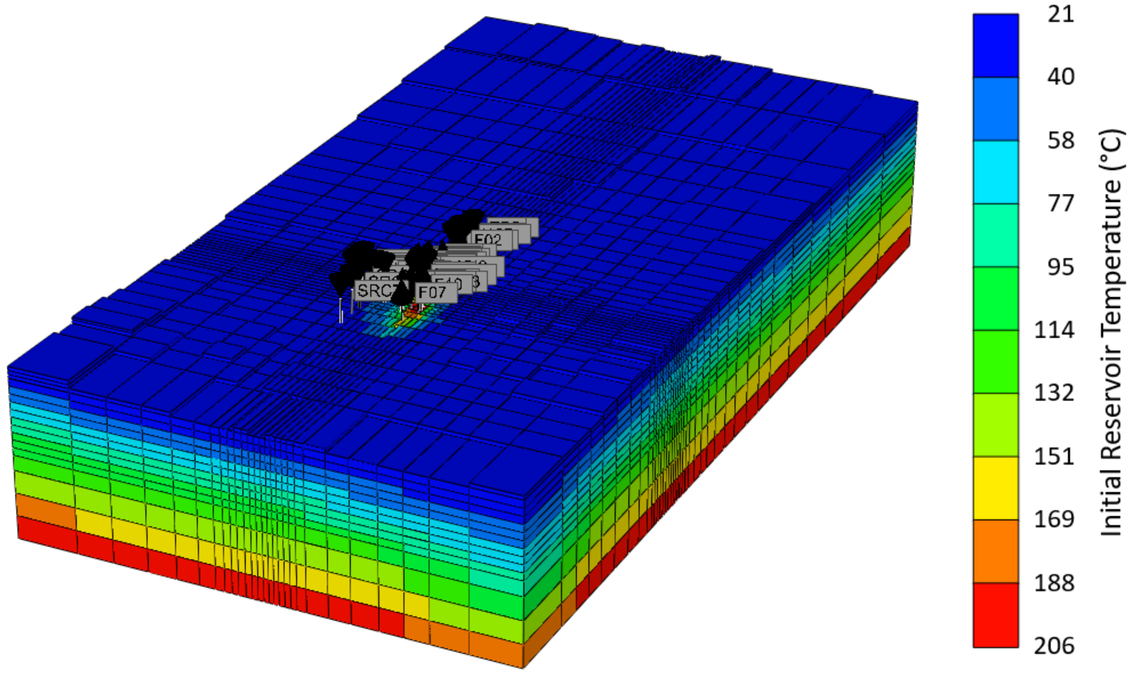

Figure 1: CMG numerical reservoir model of Brady Hot Springs with initial temperature distribution. The model dimensions are approximately 18 km × 10 km × 3.5 km. Wells are concentrated near zone with elevated shallow temperature.

The TETRAD-G model was provided by Ormat and results in good comparison with historical data measured in the field (mean absolute error between 4.4°C and 16.4°C for six production wells). A MATLAB script was developed to automatically generate TETRAD-G inputs and process its results. The TETRAD-G model was converted to a CMG STARS model to allow for use of its built-in ML capabilities. An excellent match in injection and production flow rates and pressures was obtained between the TETRAD-G and CMG STARS model. However, the production temperature profiles—while following the same trends—deviated by about +/-5°C on average. Further refining of the CMG STARS model is planned in the second budget year to try to obtain a better match to the TETRAD-G temperature output and historical data.

Prior to running the BHS model, simulations were performed for a simple single-fracture system with one injection and one production well replicating the Song et al. (2018) model. This simplified model was used to test our ML approach of time series forecasting with different ML algorithms. Training data were generated with the simulators CMG STARS, TOUGH2-CSM (Winterfeld et al., 2019), and the analytical equation for a single fracture with two-dimensional heat transfer (Gringarten et al., 1975; Song et al., 2018).

3. MACHINE LEARNING FOR IMPROVING GEOTHERMAL RESERVOIR MANAGEMENT

Our approach is based on training neural networks and using them to predict future values of well characteristics. The ML approaches we have selected were implemented using TensorFlow (Abadi et al., 2016) and were applied to learning the relations among temperature time series and historical reservoir data, future well flow rates, and future injection temperatures. Three different neural network architectures were applied and evaluated: MLP, LSTM, and CNN. These networks were first tested on a simple single-fracture geothermal system with one injection well and one production well, for which an analytical solution can be obtained (Song et al., 2018). Initial testing showed that incorporating physical parameters that would be readily available to geothermal operators, such as injection temperature and mass flow, yielded more accurate predictions than using a pure time series forecasting approach. Therefore, future production temperatures are predicted based on historical production temperature, injection temperature, and well injection mass flow rate. In this single-fracture modeling problem, we augmented the temperature training sequences of length N=12 (tunable parameter) with the signal from two additional channels (see Figure 2a)—injection temperature and injection mass flow (both variables are controlled by the geothermal reservoir operators). The time series in these two channels are aligned based on timestamps (Nwachukwu, 2018). It is also worth noting that single-step predictions are turned into sequences of predictions (e.g., for an entire year) by following the “adding forecasting output (AFO)” scheme (in contrast to the “adding actual output (AAO)” scheme), as discussed in the context of artificial neural networks applied to power plant modeling (Prieto, 2001).

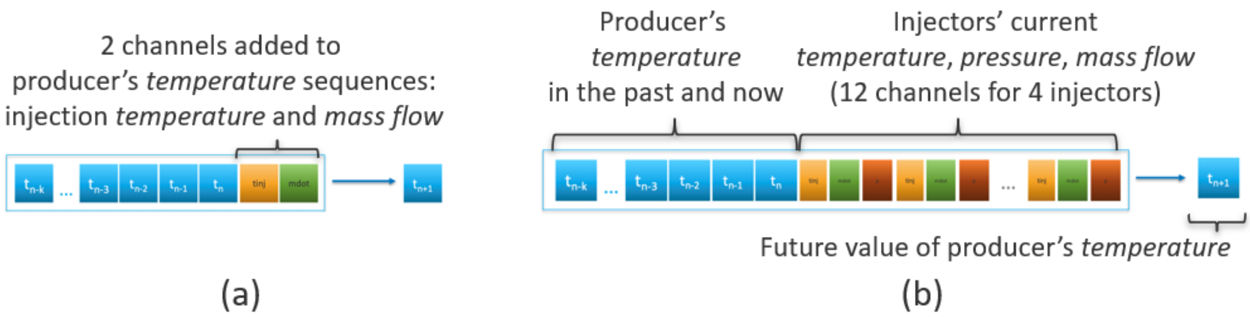

Figure 2: Machine learning algorithms for time series prediction were developed for a simple single-fracture doublet system (a), and for BHS model with four active injector wells and six active production wells (b).

80 temperature trajectories were generated based on the data produced by the analytical solution that is available for this system (Song et al., 2018). Of these trajectories, 52 were used for training (65%), eight for validation (10%), and 20 for testing (25%), according to the three-fold split typically used in ML studies. Figure 3 illustrates the evaluation results we have obtained for LSTM: the plots show both the predicted values and the true values (coming from the subset for testing) for 20 scenarios. A good match between these values is characterized by the relatively low values of the mean absolute percentage error (MAPE) metric, in the range between 1.69% and 20.73%, with most of the values being only several percent.

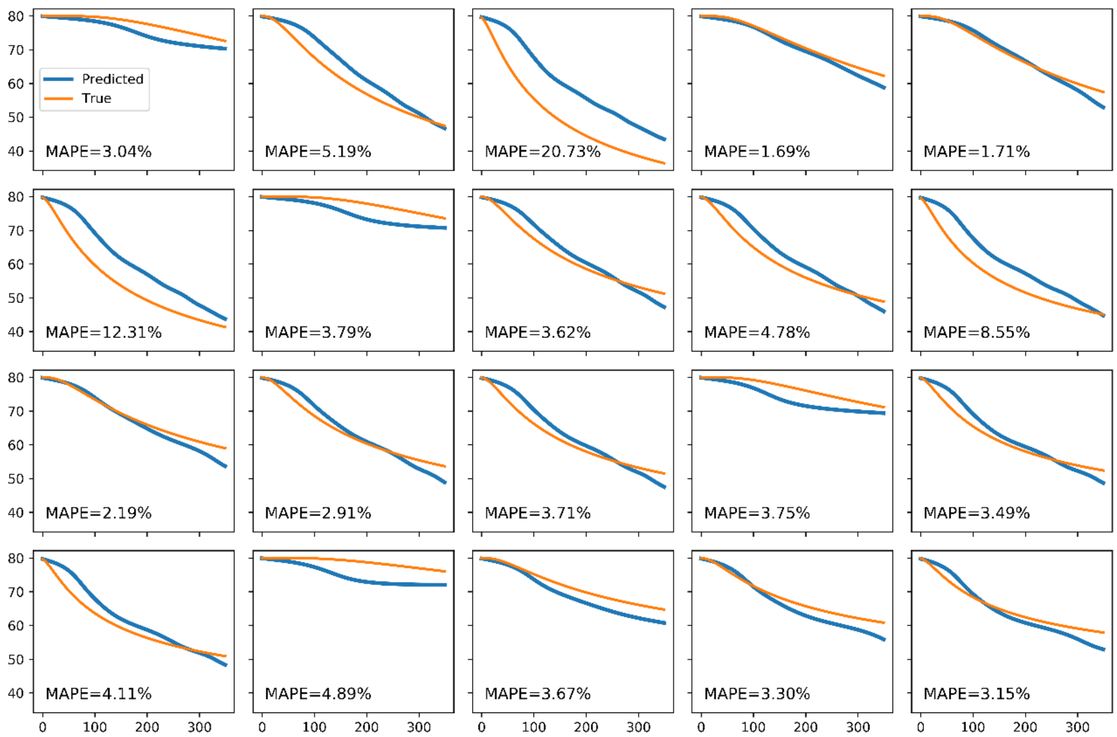

Figure 3: Examples of the temperature trajectories predicted using LSTM networks for the single-fracture doublet system and MAPE values characterizing the accuracy of these predictions. X-axis: number of days since the beginning of learning and prediction. Y-axis: production well temperatures (in °C).

In addition to showing these individual trajectories, we present Figure 4, where we depict the results obtained using all three types of selected neural networks, along with the average MAPE values. The plots demonstrate good overall predictive power of these networks applied to the single-fracture problem, with the MLP performing best and yielding results with the MAPE of 3.99%, averaged across the studied test trajectories.

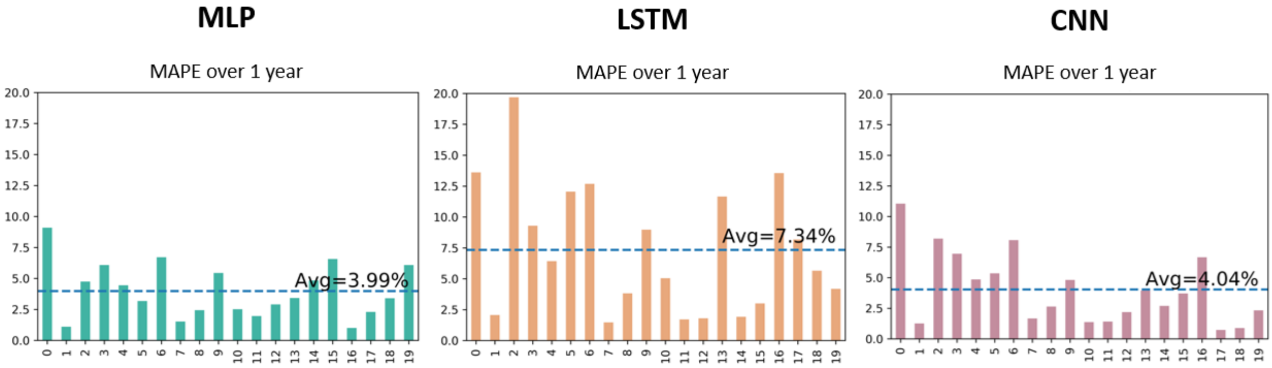

Figure 4: MAPE values for temperature predictions in the single-fracture doublet system; evaluation results are shown for 3 network architectures being studied (MLP, LSTM, CNN). All these architectures produced accurate predictions, with 3.99%–7.34% relative errors (judged by the averaged MAPE values) between the predicted and true result in twenty scenarios. X-axis: test scenario's number. Y-axis: MAPE (in %).

Our long-term objective is to use ML to find an optimal flow allocation across multiple injection and production wells to maximize the energy extracted during a significant period of time (e.g., 20 years). The immediate goal pursued in the current work is to evaluate if ML can accurately predict time series simulation data. After training and evaluating neural networks for the single-fracture doublet system and seeing satisfying results in the form of accurate predictions, we applied the same methodology to the BHS simulation data, as schematically shown in Figure 2b. Instead of two additional channels used previously, the training sequences in this training problem had twelve additional channels: temperature, pressure, and mass flow rate for each of the four injector wells.

Reservoir simulations using CMG STARS and TETRAD-G were conducted to generate over 100 cases with different flow configurations for training of the neural networks. The geological model, the number injection wells (four), and the number of production wells (six) were kept constant. Production temperatures for the six producers are predicted based on chosen injection and production flow rates, injection temperatures, and injection pressures. Similar to the previously described training efforts, we split an initial set of 37 cases selected for learning into 24 cases for training (65%), three for validation (10%), and 10 for testing (25%). Figure 5 illustrates the predicted production temperatures for one of the BHS wells (10 test cases) and the corresponding simulation data (marked as "True") used for assessing prediction accuracy. The MAPE ranged from 0.17% to 3.92%, showing excellent accuracy.

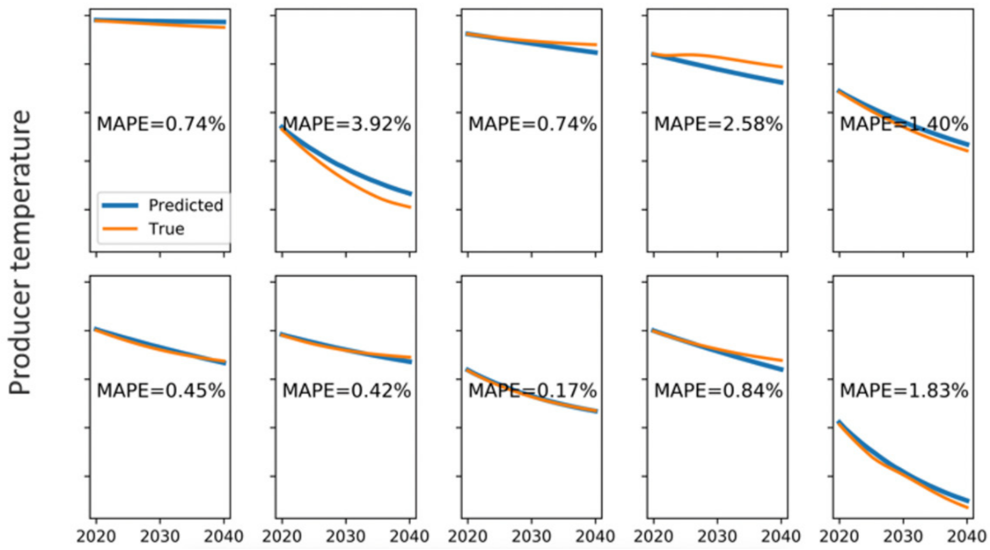

Figure 5: Examples of temperature trajectories predicted from 2020–2040, for a BHS producer well. X-axis: time. Y-axis: selected producer well's temperature (numbers are removed per industry partner requirements).

As shown in Figure 6, averaged over all 10 test cases, the best trained networks that are based on MLP and LSTM architectures (the best-performing and the worst-performing architectures based on the results from Figure 4) are able to predict the six production well temperature trajectories with MAPE under 8% for all configurations, and with the averages for MAPE at 1% (MLP) and around 2.5% (LSTM). While we believe it is possible to further train these networks, which we plan to pursue as we incorporate more data into the training, these initial results have demonstrated commendable accuracy. As part of future work, we will also extend the training and our analysis to the production-well pressure time series. Once both temperature and pressure data can be predicted, we will be able to pursue accurately predicting important reservoir-wide characteristics such as the energy and exergy being produced.

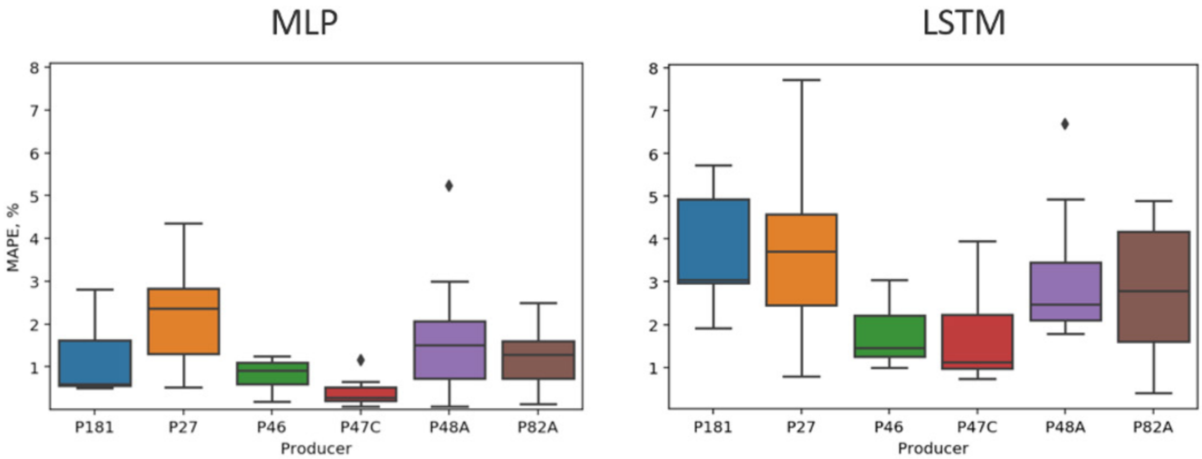

Figure 6: MAPE values for prediction of temperatures of six production wells at BHS. Results are shown for the ten best-performing MLP and LSTM networks. The average MAPE for the MLP networks is on the order of 1%, while for the LSTM networks, it is around 2.5%.

4. UPDATED BHS RESERVOIR MODEL USING PRINCIPAL COMPONENT ANALYSIS

Using principal component analysis, we compared geologic factors from a 3D geologic map to vertical fracture permeability (zfrac) from the Ormat BHS reservoir model. Thirteen geologic factors were considered, including fault density, fault intersection density, modeled stress change (Siler et al., 2018), slip tendency, dilation tendency, curvature of faults, distance from faults, distance from contacts, thickness of stratigraphy, and 3D temperature (Siler et al., 2016). Principal component analysis revealed that five principal components represent over 80% of the variability in the data. A heat map was developed to visualize correlation between variables (see Figure 7 with warm colors corresponding to high correlation). The vertical fracture permeability has highest correlation with fault density and fault intersection density.

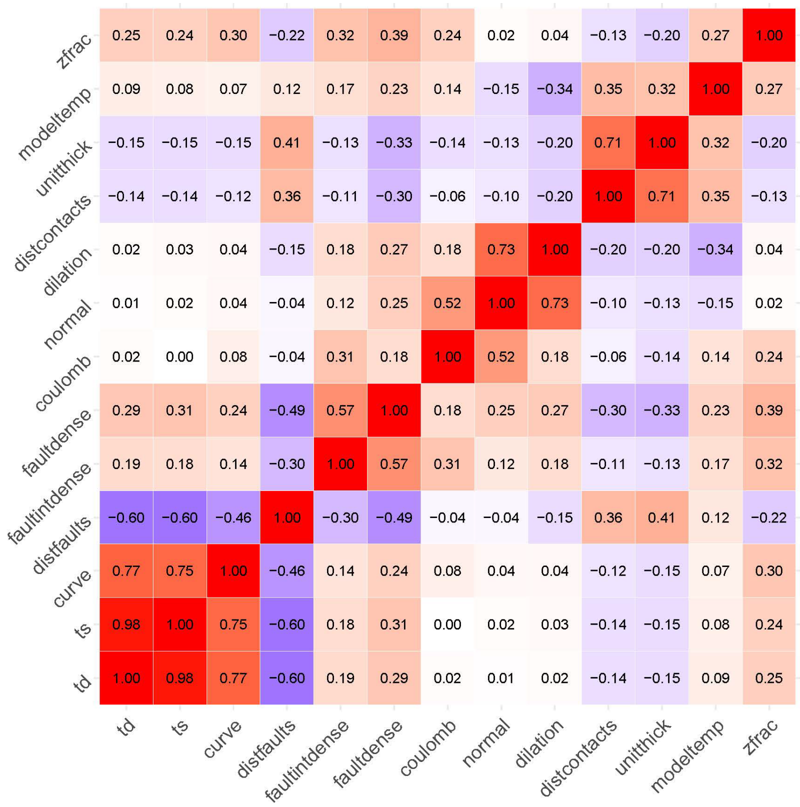

Figure 7: Correlation heatmap between 13 geologic variables. Warm colors indicate high correlation between variables. Fracture permeability has highest correlation with fault density and fault intersection density.

Figure 8 shows zones of high permeability (red blocks) overlaying zones with high fault intersection density (warm colors). Using the fault density and static stress state of faults as proxies to predict spatial distribution of reservoir permeability, a new reservoir model was developed to explore potentially under-exploited regions in the field for future production (given that producing zones require high permeability). Simulations using this updated model will be conducted in the second budget year.

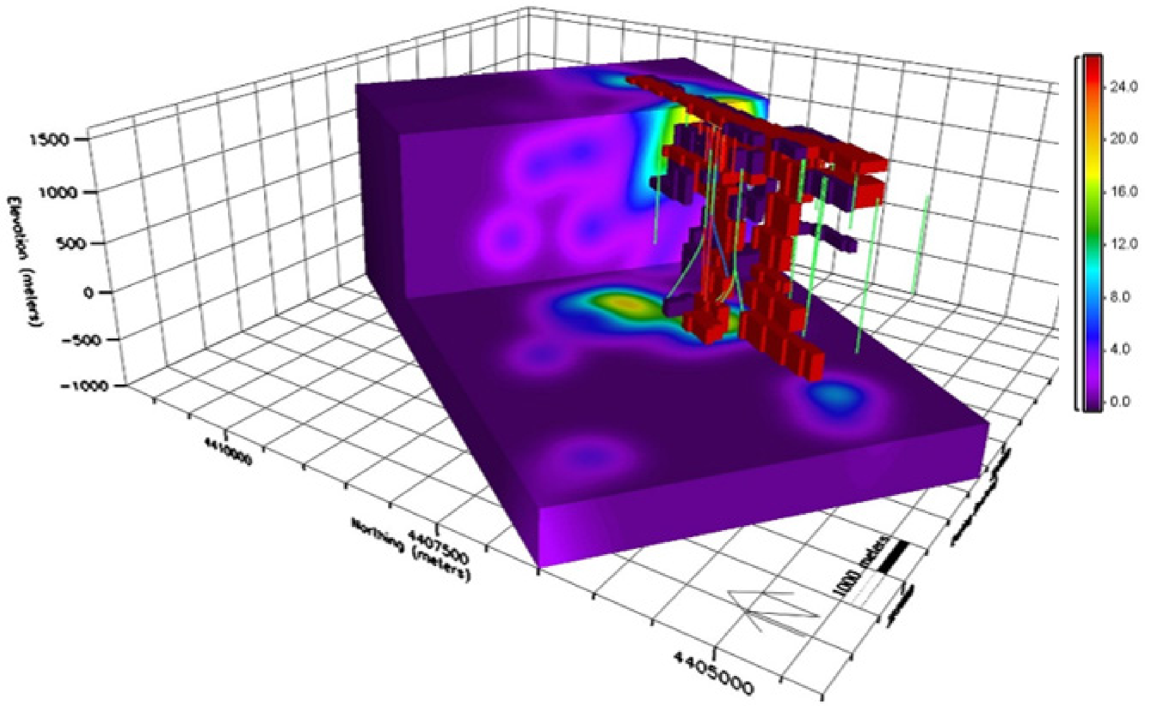

Figure 8: Vertical fracture permeability from Ormat reservoir model (red cuboids indicate high permeability; purple cuboids indicate moderate permeability) overlain on fault intersection density (warm colors indicate high fault density) indicate strong correlation between these variables. Green lines represent wells. Analysis suggests promising zones in reservoir are currently under-developed.

5. DATA GATHERING PLAN

A data gathering plan has been developed to obtain new subsurface data for further characterizing the BHS subsurface. The data gathering activities are scheduled for the second quarter of the second budget period. The data gathering plan focuses on temperature surveying of wells 18A-1, MGI-1, and MGI-2. These wells are former injection wells that have been sitting idle for several years. The reservoir model indicates good near-wellbore permeability at these well locations. Reservoir simulations using TETRAD-G and CMG STARS suggest the bottom-hole temperature in each well has increased steadily and is currently sufficiently high for the well to be considered as a producer. Temperature surveying will confirm (or deny) these temperature predictions and provide down-hole data points for further calibrating of the reservoir model.

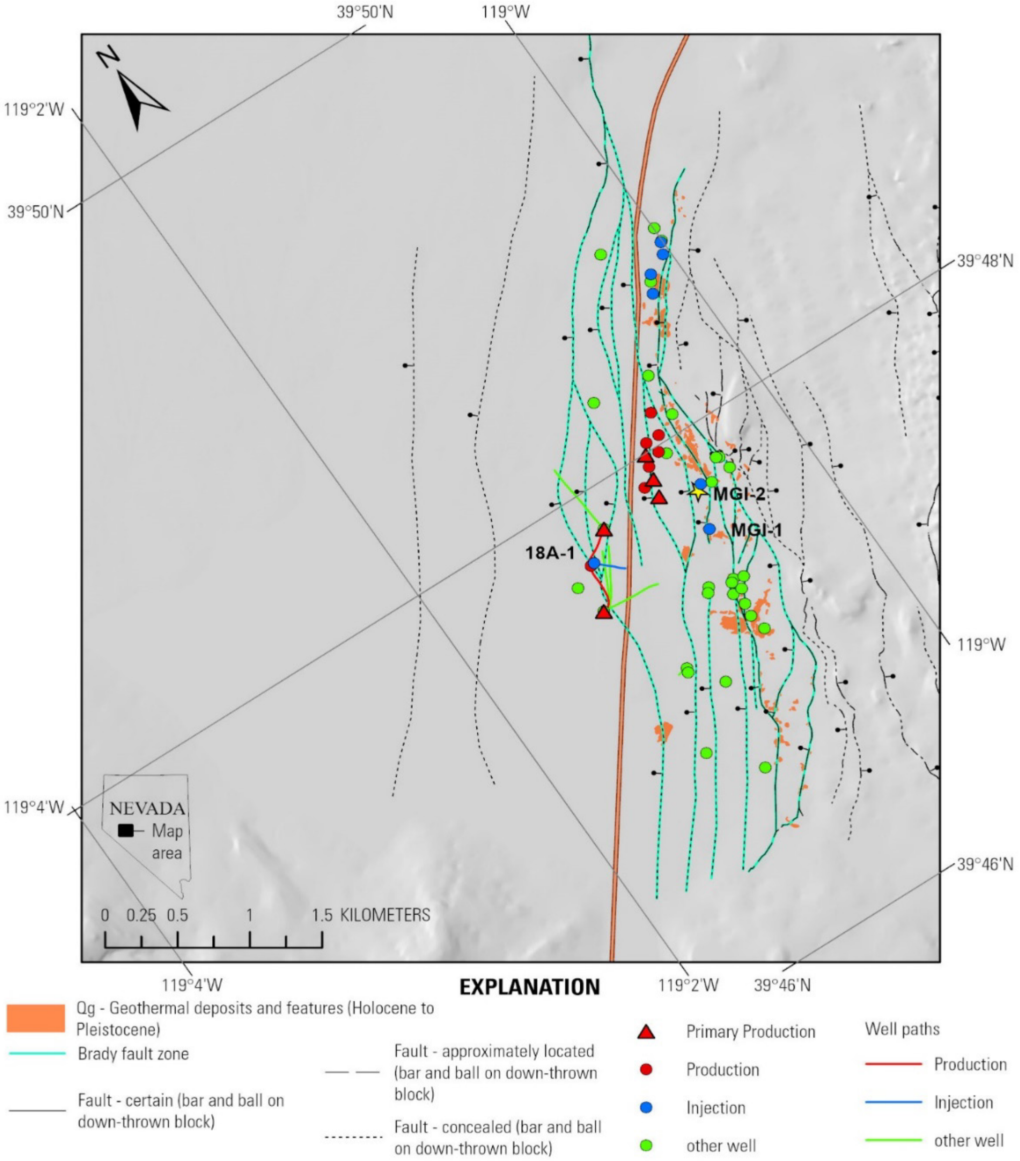

Figure 9: Data gathering plan developed for Fiscal Year 21 includes temperature surveying of three idle wells (18A-1, MGI-1, and MGI-2), which look promising for future production.

6. CONCLUSIONS AND FUTURE WORK

The current project seeks to use machine learning to find an optimal flow allocation across multiple injection and production wells in the Brady Hot Springs (BHS) geothermal field to maximize energy extracted over future decades. This paper summarizes the research performed during the first budget period of our project and the results we have gathered while working on subsurface characterization and ML predictions at the BHS geothermal field near Fernley, Nevada, USA. To guide reservoir management at this field, ML models were developed for time series prediction of future production temperatures in the time interval between 2020 and 2040 based on injection and production flow allocations and historic reservoir data. The models were based on MLP, LSTM, and CNN machine learning architectures. The reservoir simulations in TETRAD-G and CMG STARS for the BHS field were conducted to generate data sets for training, validation, and testing of the ML models. Using an initial data set of 37 simulated scenarios, we have obtained temperature predictions with mean absolute percentage error of 1% for the MLP and 2.5% for the LSTM (averaged over the six currently active production wells at BHS). We are currently extending this training to include prediction of pressure values as well as field-wide energy and exergy production estimates. To better understand the BHS subsurface, a principal component analysis was performed on 13 geological variables at BHS. This analysis revealed that fault density and fault intersection density show the strongest correlation with fracture permeability, which is a critical parameter in finding suitable production zones. Using the fault density and static stress state of faults as proxies for permeability, a new BHS reservoir model was developed to assist with targeting zones for new wells that could potentially produce from the under-exploited areas in the field. Simulations using this updated model will be conducted in the second budget year. A data gathering plan was developed for obtaining additional subsurface data for reservoir model calibration and for ground truthing of promising areas for future production. The plan includes temperature surveying for three previously used yet currently idle injector wells, for which the reservoir models predict bottom-hole temperatures that are suitable for production. The data gathering activities are scheduled for the first quarter of 2021. At the end of this project, we plan to share with our industry partner all of the developed software artifacts used for prediction.

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