PROCEEDINGS, 49th Workshop on Geothermal Reservoir Engineering
Stanford University, Stanford, California, February 12-14, 2024
SGP-TR-227

Well Temperature and Pressure Profiling Using Machine Learning

Jainul TRIVEDI

New LJ Institute of Engineering and Technology, India

jainultrivedi11111@gmail.com

Keywords: Geothermal Energy, Machine Learning, Temperature

ABSTRACT

The ability of wells to preserve the zonal isolation of geologic formations and avoid fluid (native or injected) transfer between those formations can be referred to as well integrity. The most often noted physical characteristics in boreholes are temperature and pressure. It is discussed how pressure well testing and temperature well testing differ and are comparable. This paper's major objective is to use machine learning to profile the well's temperature and pressure based on various variables. A good profiling of well temperature and pressure is done through the use of different elements during well testing, including thermal conductivity, formal temperature, and contact resistance. A method has been established for calculating the thermal conductivity of the formation, the beginning temperature, the skin factor, and the thermal resistance of the contact. The model used in this study therefore exhibits excellent agreement with the field collected data. The results of this study can therefore be used to more accurately compute the wellbore temperature and pressure parameters in challenging well settings.

1. INTRODUCTION

The thermal energy produced and stored in the Earth's crust is known as geothermal energy. The mantle rises as a result of certain rocks melting due to the extreme heat and pressure (as they grow lighter with the heat). These molten rocks that originated in the crust of the Earth are forced upward and become trapped in areas known as "hot spots." Steam is produced when subterranean water comes into contact with the hot point. This hot water-formed area occasionally finds surface exits. Hot springs are what happen when this hot water shoots out of one of these outlets. Because nuclear fusion occurs continuously, the temperature at the center of the Earth is almost constant, matching that of the Sun. Above all, geothermal energy is a clean, renewable source of electricity. There is a limited number of ideal places for geothermal power plants on Earth, thus the amount of energy that can be produced using this method isn't infinite. The possibility for surface instability is the primary environmental issue associated with geothermal power facilities. The soil atop geothermal reservoirs may occasionally gradually drop over time as a result of the plants' removal of water and steam from those reservoirs. To lessen the chance of land subsidence, the majority of geothermal facilities, however, re-inject spent water into the ground using an injection well. Increased earthquakes are another issue that might occur while geothermal power facilities are operating.

The highest oscillation of the in-ground temperature happens at the earth's surface and is determined by the daily fluctuation of solar irradiance and ambient air temperature. As the depth rises, this oscillation becomes less intense. The primary factor influencing the in-ground temperature's cyclical fluctuation is the meteorological parameters' cyclical change. A number of studies that have documented in-ground temperature profiles at different depths have discovered that at a certain depth, the temperature's oscillation attenuates and becomes constant. The soil surface conditions have a significant influence on the in-ground temperature value. Given that the cost of drilling is frequently the greatest expenditure in deep geothermal energy projects, pore pressure prediction is a well-developed critical discipline for well planning in the petroleum business. This suggests a similar relevance for deep geothermal wells.Seventy percent of all deep geothermal wells drilled have had their drilling issues linked to pore pressure examined in order to compare the influence of pore pressure and its forecast; two deep geothermal projects are provided as more thorough examples. As a result, one-third of all drilled wells had pore pressure-related drilling issues, which led to multiple side trips and an estimated 40% decrease in drilling rate. This emphasizes how crucial accurate pore pressure prediction is to bring down the cost of deep geothermal drilling in overpressured environments.

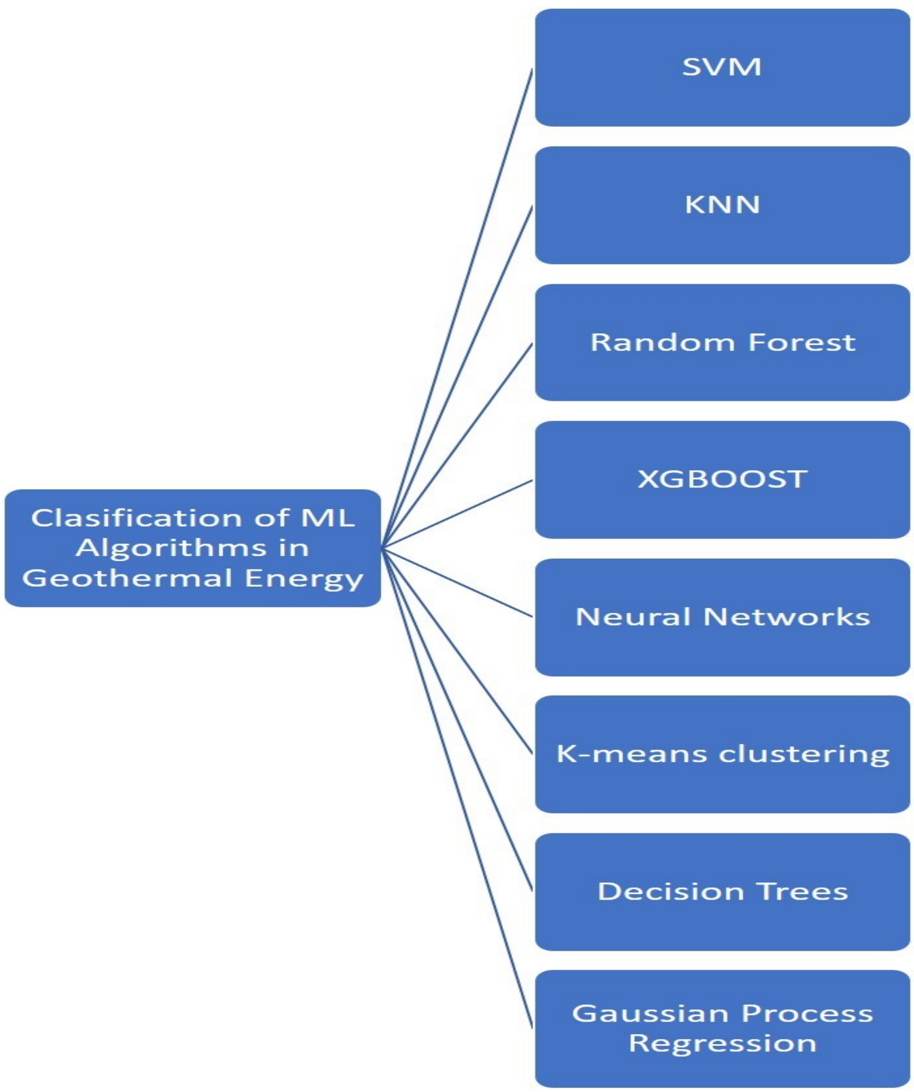
For deep-water gas well production designs, an accurate wellbore temperature forecast is crucial. Forecasting the temperature along the wellbore is possible with this model. Computer programming is used to plot temperature response type curves and examine temperature effect variables after a study on the coupling of the reservoir model and wellbore temperature model is conducted. Many models have been developed for the purpose of profiling well temperature and pressure. These include the Wellbore Pressure Model in Deep-water Drilling and the Transient Heat Transfer Models of the Wellbore in Deep-water Drilling, among many more. The assessment and management of geothermal resources are only two of the many areas where downhole pressure prediction is essential. Gauges are used to measure pressure in the past. A sophisticated non-invasive real-time sensing device that can get beyond many of the drawbacks of conventional gauges is called distributed fiber optics sensing (DFOS). Numerous downhole sensing applications can benefit from the use of fiber optic sensors because of their insensitivity to electromagnetic noise, resistance to corrosion, tolerance to high pressure and temperature, and lack of need for electronics along the optical route.

In geothermal zones, machine learning is a viable method for making predictions. Of all the machine learning techniques, only the GBRT algorithm has been shown to be effective in predicting GHF; nevertheless, it requires a substantial amount of well-selected data. For subsurface temperature prediction, XGBoost and Random Forest produce the best results in terms of accuracy. The most often used machine learning approach across all subsurface geothermal industrial sectors seems to be neural networks, both in machine learning and deep learning. The primary issues that would need to be resolved, though, are making sure that data is available to researchers, preparing the data for machine learning, and educating experts and students in the geothermal business about artificial intelligence as it relates to the energy sector.

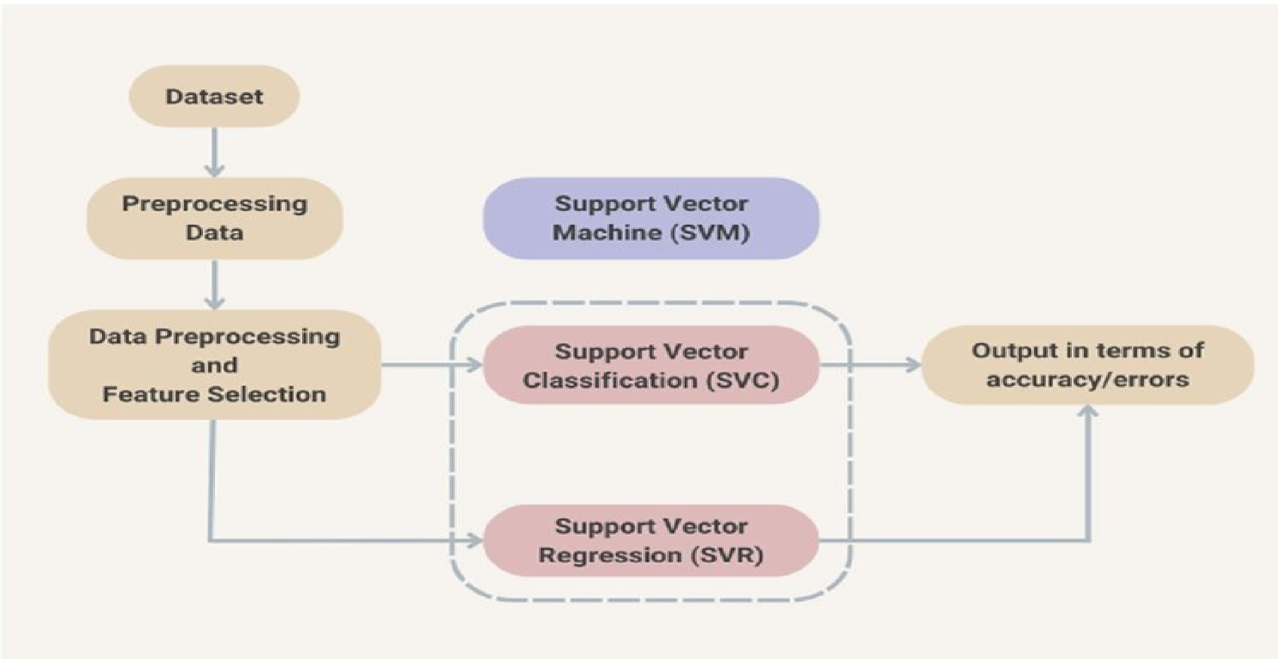
2. CLASSIFICATION OF VARIOUS ML ALGORITHMS IN WELL TEMPERATURE AND PRESSURE PROFILING IN GEOTHERMAL ENERGY

2.1 INTRODUCTION

It is crucial to comprehend how the wellbore's temperature and pressure characteristics vary with the well's depth when producing high-temperature and high-pressure gas wells. A wellbore temperature and pressure prediction model was established that took into account the influence of high-temperature and high-pressure gas wells on the temperature and pressure of the wellbore under the coupling of fluid velocity, density, and Joule–Thomson effect. This was based on the conservation of fluid energy, momentum, and mass in the wellbore. After that, we could measure the pressure and temperature in the wellbore along its depth. In geothermal energy, well temperature and pressure profiling is done using algorithms like Random Forest, Support Vector Machine, XGBoost model based on a decision tree, and many more. Encouraging public discourse and fostering a better environment will benefit from diction. The oil and gas industry has made extensive use of machine learning (ML) in recent years. Due to its exceptional capacity to handle nonlinear situations, it has been demonstrated to be more effective than traditional statistical approaches.

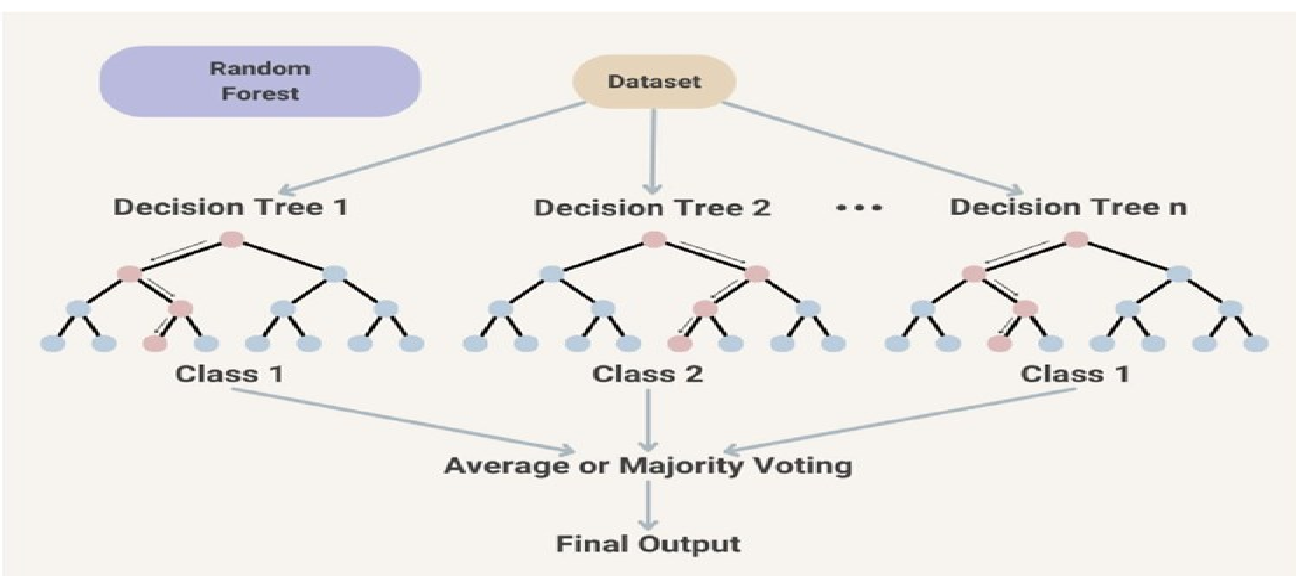


2.2 SVM



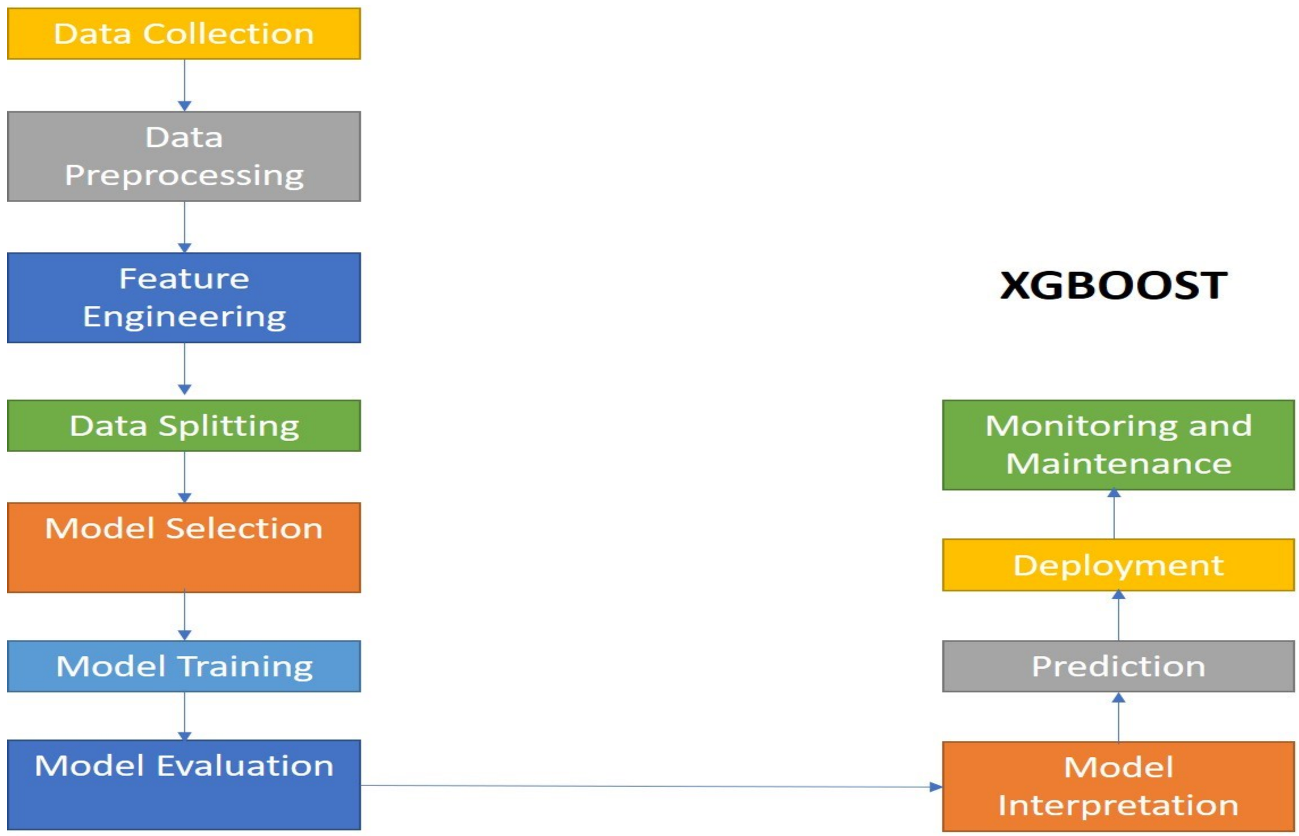
In the case of linearly separable data, the optimum separating hyperplane theory served as the foundation for the development of the SVM machine learning algorithm. The SVM approach was invented and developed entirely on the basis of the Structural Risk Minimization concept. An approach that may be used for small-scale samples is the support vector machine (SVM) technique, which operates on the notion of structural minimization as opposed to empirical risk minimization. Right now, researchers employ the SVM approach to address a wide range of support vector prediction issues, such as projecting short-term power loads, managing human resources, and estimating mineral resources. While it supports vector regression in real-time forecasting applications, its use to predict temperature is currently rather tiny and domestic.

2.3 **Random Forest**



When it comes to categorization, we're trying to divide up our data into classes by applying judgment calls. When they are used in regression, we are trying to do something similar, but we are predicting a value rather than a class. We first choose a choice that will divide up our data at the top of the tree, or the root node. This process continues down the tree until there are no more splits possible, which is often indicated by the maximum depth of the tree or by the minimum number of samples per end node (leaf node). Reservoirs' hierarchical qualities, which result in unique domain features in their logging curves, are a result of geological development and can help rebuild logging curves for unknown wells. Machine learning (ML) methods have been utilized in a number of studies recently to rebuild logging curves without taking domain variables into account, which may be the reason for the algorithms' subpar results. An unknown well logging curve may be produced using a random-forest-adaptive-domain-clustering (RF-ADC) model since breaking down raw data into domain data can optimize an anticipated variance and hence increase the accuracy and resilience of ML prediction models. Using domain data, the random forest (RF) technique may be used to produce unknown well logging curves.

2.4 **XGBoost**



The machine learning package XGBoost, or Extreme Gradient Boosting, is distributed and scalable, using gradient-boosted decision trees (GBDT). It is the top machine learning package for issues including regression, classification, and ranking, and it offers parallel tree training. supervised machine learning, decision trees, ensemble learning, and gradient boosting are the machine learning ideas and techniques that XGBoost initially grasps and expands upon.OneAPI-powered software accelerations are available to Intel CPU users via XGBoost, which doesn't need code modifications. Optimal performance for your current hardware is achieved through software adjustments. As a result, there is less latency during inference and quicker iterations throughout development and training. When compared to traditional methods, temperature prediction has greatly improved with the use of state-of-the-art deep learning and machine learning algorithms. When processing large data sets in predicting scenarios where substantial quantities of previous temperature records might be employed, these unique strategies are applicable. The ensemble learning model XGBoost is likewise based on regression trees. Contrary to random forests, XGBoost constructs complimentary trees for prediction rather than averaging many separate trees, allowing for vastly varied functional connections. Applicability of XGBoost is more difficult and computationally expensive than RF models since it depends on several hyperparameters. A strong potential model for this investigation is XGBoost, which shown outstanding results in a number of machine learning contests.

3. USE CASES

3.1 SVM

Well temperature and well profile in the oil and gas sector are two sectors where Support Vector Machines (SVM) are applied as adaptable machine learning models. Five possible SVM use cases in this situation are as follows:

Anomaly Identification in Temperature Profiles: Support Vector machines (SVMs) may be utilized to identify irregularities or discrepancies in temperature profiles inside a well. The SVM can recognize aberrant fluctuations or anomalies, pointing to possible problems like fluid migration or equipment breakdown, by being trained on normal temperature patterns.

Identification of Formations: Using temperature and pressure profiles, SVMs may help distinguish between various geological formations. The Support Vector Machine (SVM) may be trained on known data from different formations to categorize fresh profiles into the appropriate formations. This can help with subsurface structure knowledge and geological investigation.

Predictive maintenance: By examining temperature patterns and data profiles, SVMs can forecast when equipment will break down or require repair. The SVM can predict possible breakdowns and perform preventive maintenance to save expensive downtime by identifying patterns of temperature changes that occur before equipment failures.

Drilling Parameter Optimization: By examining past data and connecting it to productive drilling results, SVMs may optimize drilling parameters including depth, pressure, and temperature. This aids in maximizing productivity and lowering hazards throughout the drilling process by enabling educated decision-making.

Well Classification and Categorization: SVMs are capable of classifying wells according to their temperature and profile attributes, so dividing them into distinct types or classes. Decisions about production tactics, the distribution of resources, and the identification of well-to-well parallels and contrasts for improved management can all be aided by this categorization.

These use examples demonstrate how SVMs may be used in the field of well temperature and profiling, offering the oil and gas sector insightful information, predictive powers, and decision assistance.

3.2 Random forest

In the oil and gas sector, Random Forest is an additional potent machine learning technique that is used for data profiling and well temperature analysis. In this situation, Random Forest may be used in the following five scenarios:

Feature Importance and Selection: Random Forest may be used to ascertain which features in temperature and profile datasets have the most influence. It aids in determining which variables have the most effects on temperature fluctuations and well behavior by weighing the significance of various parameters (such as pressure, depth, and thermal conductivity).

Diagnosis and Fault Detection: abnormalities in well temperature profiles may be efficiently identified using Random Forest models. With the use of training on past data including known fault cases (such as leaks and blockages), it is able to correctly identify and diagnose problems in real-time data, facilitating prompt maintenance and intervention.

Prognosis of Formation Features: By utilizing temperature and profile information, Random Forest models are able to forecast formation features. By means of training on established formations and the characteristics linked with them, the model is able to forecast the characteristics of novel formations found during exploration or drilling, helping to advance geological knowledge.

Drilling Practice Optimization: By examining temperature, pressure, and other pertinent data, Random Forest can optimize drilling procedures. By directing decision-making during the drilling process, it may forecast the ideal drilling parameters or circumstances based on previous trends, increasing efficiency and lowering costs.

Sorting Different Kinds of Wells: Using features from profile data and temperature, Random Forest can sort various kinds of wells. It assists in classifying wells into several groups or classes, such as production, injection, or exploratory wells, enabling more focused and specialized approaches to the management of these various well kinds.

These use examples show how Random Forest algorithms may be used in the oil and gas sector to profile and analyze well temperature data in order to extract insightful information, forecast results, and support decision-making.

3.3 XGBOOST

The oil and gas sector finds that XGBoost, an enhanced gradient boosting technique, is also very helpful for profiling data and well temperature analysis. Five possible use cases for XGBoost in this situation are as follows:

Transient Event Detection: XGBoost is capable of detecting sudden variations in well temperature or profile data. It can identify abrupt changes that can point to anomalies or significant events by learning from past patterns, allowing for quick research or action.

Temperature Trend Prediction: XGBoost models are capable of predicting temperature changes inside individual wells. The system helps with proactive decision-making by accurately predicting future temperature fluctuations by utilizing past temperature data together with other pertinent criteria.

Production rate optimization: XGBoost uses temperature analysis and data profiling to optimize production rates. It may provide recommendations for the best production rates based on historical data, enabling modifications that optimize production efficiency while taking formation features, temperature, pressure, and other aspects into account.

Downhole Conditions Prediction: Using temperature and profiler data as inputs, XGBoost models are able to forecast the downhole conditions. It is able to predict circumstances like fluid flow or pressure changes by training on known downhole scenarios and related data, which helps with risk assessment and mitigation plans.

Determine Correlations Among Parameters: In well temperature and profiling datasets, XGBoost may identify intricate relationships between different parameters. Insights for better well management techniques may be gained from seeing how various parameters (such as temperature, depth, and fluid composition) interact and impact one another.

The aforementioned use cases showcase the adaptability of XGBoost in terms of deriving practical insights, forecasting, and supporting decision-making procedures concerning well temperature and profile analysis within the petroleum sector.

4. FUTURE SCOPE

Machine learning offers enormous promise for improving temperature and pressure profiles in geothermal energy:

Improved Resource Characterization:

Predictive Modeling: ML algorithms can evaluate geological data to anticipate subsurface temperature and pressure patterns, assisting in site selection and resource evaluation.

Feature Extraction: Algorithms can extract patterns from complicated data sets, detecting relationships between various geological characteristics and possible energy reserves.

Real-Time Monitoring and Optimization:

Sensor Data Analysis: ML can process real-time data from sensors put in geothermal wells, identifying abnormalities and anticipating changes in pressure and temperature.

Control Systems: ML models can optimize control mechanisms for drilling and resource extraction, altering activities for efficiency and safety.

Enhanced efficiency and cost savings:

Drilling Technique Optimization: ML algorithms can assess previous drilling data to optimize drilling procedures, lowering well construction costs and time.

Predictive Maintenance: Machine Learning can predict equipment failures or maintenance requirements, reducing downtime and boosting overall operational efficiency.

Risk Mitigation and Decision Support:

Risk Assessment: Machine learning models can analyze risks connected with geothermal projects by taking into account a variety of criteria such as geological conditions, environmental effect, and economic feasibility.

Decision-Making Aids: Decision support systems driven by machine learning (ML) may help stakeholders make educated decisions based on predictive analytics and simulations.

Connection to Renewable Energy Systems:

Hybrid System Optimization: ML can optimize the integration of geothermal energy with other renewable sources, regulating power production variations and guaranteeing grid stability.

Advances in machine learning algorithms, combined with a greater emphasis on sustainable energy sources, will likely pave the way for more efficient and effective geothermal energy utilization in the future, optimizing temperature and pressure profiling in wells for enhanced energy production.

5. CHALLENGES

Machine learning in well temperature and pressure profiling for geothermal energy confronts numerous challenges:

Data Availability and Quality:

Limited Data: Geothermal exploration frequently depends on limited and sparse data, making it difficult to train effective machine learning models.

Data Heterogeneity: Combining varied data sources (geological, temperature, pressure, etc.) with varying forms and quality can be complicated and may influence model accuracy.

Black-Box Models:

Interpretability and Trust: Some sophisticated machine learning models lack interpretability, making it difficult to grasp how they arrive at specific forecasts or recommendations, which is vital for stakeholders in key decision-making processes.

Trust and Validation: Building trust in ML models for decision-making necessitates rigorous validation, particularly in businesses with demanding safety and reliability norms, such as energy generation.

Complexity of Geological Systems:

Complexity and Variability in Geological Systems: Because geological formations are exceedingly complex and varied, it is difficult to build models that correctly reflect these intricate systems.

Non-Linear interactions: Understanding the non-linear interactions between various geological and subsurface elements is critical, but it presents a barrier in building reliable prediction models.

Limited Understanding of Geothermal Systems:

Uncertain Parameters: The underlying environment and behavior of geothermal systems might have unclear characteristics, making accurate modeling difficult.

Temporal and spatial dynamics: Geothermal systems display dynamic changes across time and space, which can be challenging to describe.

Environmental and regulatory factors:

Regulatory Compliance: It is critical to follow environmental rules and safety requirements. These limitations must be considered by ML models in order for their suggestions to be compliant.

Environmental Impact Assessment: Evaluating the environmental impact of drilling and energy extraction necessitates rigorous planning and decision-making.

Integration with Traditional Methods:

Hybrid Approaches:

Integration with Traditional Methods: Using machine learning in conjunction with traditional geothermal exploration and drilling technologies necessitates careful coordination and adaptation to industry procedures.

To overcome these obstacles, domain experts, data scientists, and stakeholders must work together to improve data collection, improve model interpretability, account for geological complexity, and assure regulatory compliance. Advances in machine learning approaches suited for geothermal energy, as well as a better knowledge of subsurface dynamics, will assist in addressing these obstacles and realizing the full promise of machine learning in this industry.

6. CONCLUSION

Finally, incorporating machine learning (ML) approaches into well temperature and pressure profiling for geothermal energy offers enormous promise and potential. Several major insights come from this domain, however:

Possibilities and Benefits:

Improved Predictive Capabilities: Machine learning allows for more accurate forecasts of subsurface conditions, which aids in resource appraisal and appropriate well location.

Real-Time Monitoring and Control: Machine learning offers continuous monitoring, allowing for adaptive control systems that optimize processes while minimizing hazards.

Efficiency and cost reduction: Optimizations in drilling methods and predictive maintenance driven by machine learning offer significant cost savings and better operational efficiency.

Problems and Considerations:

Data Complexity: The paucity and variability of data provide hurdles in building viable ML models for geothermal research.

Interpretability and Complexity Trade-off: Striking a balance between model complexity and interpretability is critical, especially in businesses where transparency and trust are key.

Geological Complexity: Because of their diversity and complicated linkages, modeling intricate geological systems remains a problem.

Future Plans:

Data Enhancement: Improve model accuracy and dependability by gathering high-quality, varied datasets.

Interdisciplinary Collaboration: Collaborative efforts between specialists, data scientists, and stakeholders are critical for generating strong, interpretable models that are aligned with industry goals.

Regulatory Compliance and Environmental effect: Integrating regulatory compliance and environmental effect assessment into ML models is crucial for long-term geothermal energy production.

Action Steps:

Continued Research: Further investigation of specialized ML algorithms for geothermal energy, as well as breakthroughs in data gathering approaches, are required for development.

application and Validation: Thorough testing, validation, and real-world application of ML models are required to demonstrate their effectiveness and acquire industry trust and adoption.

In conclusion, while machine learning has enormous potential for optimizing well temperature and pressure profiling for geothermal energy, addressing data challenges, ensuring interpretability, understanding geological complexities, and aligning with regulatory frameworks are critical for realizing these opportunities. Collaborative research and continuing efforts will be critical in improving this subject and supporting the sustainable use of geothermal resources.

7. REFERENCES

Al-Rbeawi, S. (2017). Analysis of pressure behaviors and flow regimes of naturally and hydraulically fractured unconventional gas reservoirs using multi-linear flow regimes approach. *Journal of Natural Gas Science and Engineering*, *45*, 637–658. https://doi.org/10.1016/j.jngse.2017.06.026

Baker, H. A., & Salih, I. S. (2019). Skin and Reservoir Pressure Profiling Utilizing Production Logging. *IOP Conference Series: Materials Science and Engineering*, *579*(1). https://doi.org/10.1088/1757-899X/579/1/012040

Cinco-Ley, H., & Samaniego, F. (1981). TRANSIENT PRESSURE ANALYSIS FOR FRACTURED WELLS. *JPT, Journal of Petroleum Technology*, *33*(9), 1749–1766. https://doi.org/10.2118/7490-PA

Gringarten, A. C., Ramey, H. J., & Raghavan. R. (1974). UNSTEADY-STATE PRESSURE DISTRIBUTIONS CREATED BY A WELL WITH A SINGLE INFINITE-CONDUCTIVITY VERTICAL FRACTURE. *Soc Pet Eng AIME J*, *14*(4), 347–360. https://doi.org/10.2118/4051-pa

Li, Y., Wang, S., Zhao, J., Jiang, Y., & Zhai, R. (2011). Pressure decline analysis of horizontal well after multiple stage fracturing. *Proceedings - 2011 International Conference on Computational and Information Sciences, ICCIS 2011*, 611–615. https://doi.org/10.1109/ICCIS.2011.201

Pouladi, B., Bour, O., Longuevergne, L., de La Bernardie, J., & Simon, N. (2021). Modelling borehole flows from Distributed Temperature Sensing data to monitor groundwater dynamics in fractured media. *Journal of Hydrology*, *598*. https://doi.org/10.1016/j.jhydrol.2021.126450

Wang, L., Wang, X., Li, J., & Wang, J. (2013). Simulation of Pressure Transient Behavior for Asymmetrically Finite-Conductivity Fractured Wells in Coal Reservoirs. *Transport in Porous Media*, *97*(3), 353–372. https://doi.org/10.1007/s11242-013-0128-z

Zhang, Q., Wang, B., Chen, W., Wang, W., & Zeng, F. (2021). Pressure transient analysis of vertically fractured wells with multi-wing complex fractures. In *Petroleum Science and Technology* (Vol. 39, Issues 9–10, pp. 323–350). Bellwether Publishing, Ltd. https://doi.org/10.1080/10916466.2021.1895836 Zongxiao, R., Xiaodong, W., Dandan, L., Rui, R., Wei, G., Zhiming, C., Jiaming, Z., Xiaojun, W., Heng, Z., & Zhaoguang, T. (2016). Semi-analytical model of the transient pressure behavior of complex fracture networks in tight oil reservoirs. *Journal of Natural Gas Science and Engineering*, *35*, 497–508. https://doi.org/10.1016/j.jngse.2016.09.006

l-Rbeawi, S. (2017). Analysis of pressure behaviors and flow regimes of naturally and hydraulically fractured unconventional gas reservoirs using multi-linear flow regimes approach. *Journal of Natural Gas Science and Engineering*, *45*, 637–658. https://doi.org/10.1016/j.jngse.2017.06.026

Baker, H. A., & Salih, I. S. (2019). Skin and Reservoir Pressure Profiling Utilizing Production Logging. *IOP Conference Series: Materials Science and Engineering*, *579*(1). https://doi.org/10.1088/1757-899X/579/1/012040

Cinco-Ley, H., & Samaniego, F. (1981). TRANSIENT PRESSURE ANALYSIS FOR FRACTURED WELLS. *JPT, Journal of Petroleum Technology*, *33*(9), 1749–1766. https://doi.org/10.2118/7490-PA

Gringarten, A. C., Ramey, H. J., & Raghavan. R. (1974). UNSTEADY-STATE PRESSURE DISTRIBUTIONS CREATED BY A WELL WITH A SINGLE INFINITE-CONDUCTIVITY VERTICAL FRACTURE. *Soc Pet Eng AIME J*, *14*(4), 347–360. https://doi.org/10.2118/4051-pa

Li, Y., Wang, S., Zhao, J., Jiang, Y., & Zhai, R. (2011). Pressure decline analysis of horizontal well after multiple stage fracturing. *Proceedings - 2011 International Conference on Computational and Information Sciences, ICCIS 2011*, 611–615. https://doi.org/10.1109/ICCIS.2011.201

Pouladi, B., Bour, O., Longuevergne, L., de La Bernardie, J., & Simon, N. (2021). Modelling borehole flows from Distributed Temperature Sensing data to monitor groundwater dynamics in fractured media. *Journal of Hydrology*, *598*. https://doi.org/10.1016/j.jhydrol.2021.126450

Wang, L., Wang, X., Li, J., & Wang, J. (2013). Simulation of Pressure Transient Behavior for Asymmetrically Finite-Conductivity Fractured Wells in Coal Reservoirs. *Transport in Porous Media*, *97*(3), 353–372. https://doi.org/10.1007/s11242-013-0128-z

Zhang, Q., Wang, B., Chen, W., Wang, W., & Zeng, F. (2021). Pressure transient analysis of vertically fractured wells with multi-wing complex fractures. In *Petroleum Science and Technology* (Vol. 39, Issues 9–10, pp. 323–350). Bellwether Publishing, Ltd. https://doi.org/10.1080/10916466.2021.1895836

Zongxiao, R., Xiaodong, W., Dandan, L., Rui, R., Wei, G., Zhiming, C., Jiaming, Z., Xiaojun, W., Heng, Z., & Zhaoguang, T. (2016). Semi-analytical model of the transient pressure behavior of complex fracture networks in tight oil reservoirs. *Journal of Natural Gas Science and Engineering*, *35*, 497–508. https://doi.org/10.1016/j.jngse.2016.09.006