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Recent Applications of Data Science in Geothermal Reservoir Management

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ABSTRACT

Data Science has provided geothermal reservoir managers with new avenues for making energy production from this resource more sustainable, accurate, and efficient in recent years. The focus of this review paper is to examine recent data science use and development, specifically using machine learning (ML) and big data analytics. New artificial intelligence (AI) tools offer incredible opportunities for field operators to incorporate this technology into their older equipment, ranging from drilling to monitoring operations. With continuous data generation from geothermal reservoirs, operators can utilize AI tools to improve decision-making, optimize resource extraction, and improve reservoir monitoring. Due to a large amount of variability in the ranges of permeability, porosity, and fluid distribution, reservoir characterization and modeling have had a great deal of uncertainty. By applying ML techniques to the geological and geophysical data, one can create the most representative hydrocarbon static model of each reservoir. By combining them with traditional reservoir simulation methods, reservoir engineers would work with more reliable tools for understanding reservoir behavior, history matching, and optimizing the production strategies of those reservoirs. Moreover, by combining big data and numerous datasets (production logs, well tests, or numerical simulation), physics-informed machine learning (PIML) can be utilized to determine the dynamic behavior and identify the potential unseen risks of geothermal reservoir management. Additionally, the real time monitoring and predictive maintenance of geothermal reservoir operation are two other benefits of data science, where Internet of Things (IoT)-enabled sensors and AI driven models allow operators to continue monitoring key parameters of the operation, where normally the environmental temperature, pressure, stress, and salinity are greater. Anomaly detection, predicting equipment failure, bottleneck detection, program optimization, reducing downtime, extending the life of reservoir infrastructure, and minimizing operational costs, etc., are some examples of how data science can aid in the traditional operation of geothermal reservoirs and improve the overall efficiency of geothermal energy production. This review addresses multiple aspects of the integration of data science and reservoir management strategies, focusing primarily on the geothermal industry. Data science, including AI, ML, and big data analytics, can provide the geothermal field operators and researchers with the ability to apply AI capabilities to their daily routines. Some examples of how geothermal energy can be enhanced as part of the renewable energy matrix through data-driven modeling techniques include improving decision-making, enhancing resource management, achieving sustainability goals, and identifying bottlenecks.

1. INTRODUCTION

The global movement toward reducing greenhouse gas emissions and controlling the carbon footprint has become increasingly prominent over the past few years, and geothermal energy has emerged as one of the possible alternative energy resources. Due to the fluctuations of other energy sources, such as wind farms or underground hydrogen storage (UHS), geothermal energy can serve as a reliable source that aids in regulating grid stability with a lower carbon footprint when compared to fossil fuels. As depicted in Figure 1, the natural heat source of the Earth, which is located in the subsurface layers, can be employed in various industrial processes in the form of direct heating or converted to electrical energy.

In addition to geological challenges, effective resource management of geothermal reservoirs also faces operational challenges, such as high temperatures and extreme pressures, as well as complex subsurface chemistry and structures. Therefore, there is a need for significant modeling and technological improvements to address these challenges. Traditionally, the capital expenditures associated with the implementation of a successful geothermal reservoir project were high due to exploration, drilling, and infrastructure development, especially in areas that are difficult to access because of geological settings and locations. Compared to traditional oil and gas operations, the components required for the design, construction, and operation of geothermal reservoirs must withstand elevated temperatures. With the emergence of Industry 4.0 technologies, data science, and AI models, the development of geothermal reservoirs has accelerated due to process modeling, real-time monitoring, and optimization. These tools can reduce operational costs of geothermal systems and increase their efficiencies by facilitating predictive maintenance, optimal placement of wells, and understanding the behavior of reservoirs. Through the application of these technologies in geothermal systems, reservoir management has improved significantly, allowing operators to overcome the long-standing obstacles of the geothermal sector and contribute to the widespread adoption of geothermal energy as a mainstream renewable resource (Santos et al. 2022, Kumar et al. 2023, Rohit et al, 2023, Temizel et al., 2024).

This study reviews the current state-of-the-art in AI, ML, and digital analytics for geothermal reservoir management. The research conducts a detailed evaluation of AI/ML tools and models as well as their critical elements, which assess several AI/ML applications deployed in geothermal projects across the world based on the research of Yerima et al. (2024), Kumar et al. (2022), and Santos et al. (2022).

The focus of this study is to investigate Enhanced Geothermal Systems (EGS) to show that artificial stimulation techniques combined with abandoned oil and gas well reuse. Additional benefits include the decreased methane release and geothermal energy production from current oil and gas facilities as enhance geothermal resources. The study evaluated Physics-Informed Machine Learning (PIML) frameworks and data-driven methodologies.

By analyzing of the recent advances, this review paper provides a broad perspective of how data science is (1) revolutionizing geothermal resource management, (2) increasing the feasibility of geothermal energy, and (3) contributing to a sustainable global energy transition.

Figure 1, depicts a typical hydrothermal energy system. Hydrothermal energy systems typically consist of a geothermal reservoir, the recharge zone, and the conduit zones. In many hydrothermal energy systems, a cold superficial fluid is pumped into the reservoir in the area of the high-temperature zone and the hot fluid produced is returned to the surface.

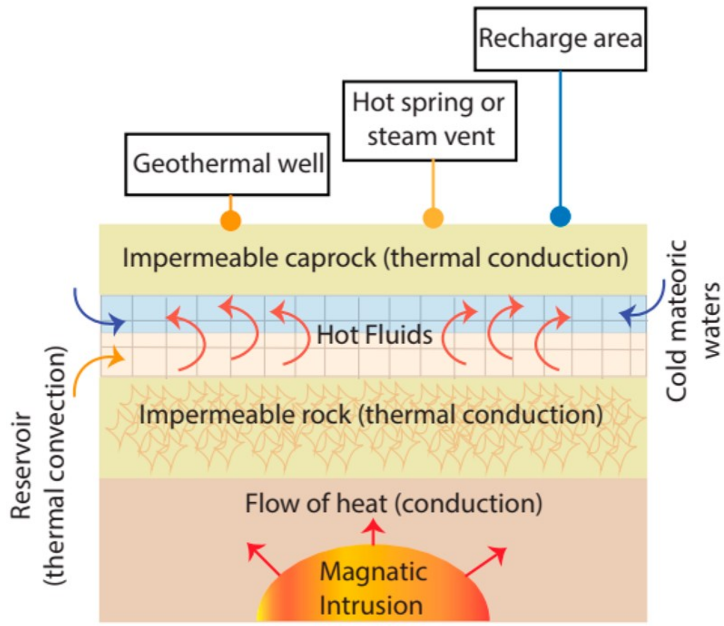

Figure 1. Illustration of an ideal geothermal system. From (Kumar et al. 2022).

Figure 2 presents the different ways that the heat exchange can be arranged with heat pump systems. Part (A) represents an air exchange for either heating or cooling a building using the heat pump; whereas Part (B) illustrates a ground source heat exchange system where the heat from the ground is used as the exchange medium for the heat pump. The heat exchange process is far more effective when utilizing the ground compared to the air because a steady temperature exists beneath the earth's surface making it ideal for buildings regardless of how stable the subsurface temperatures are. Therefore, the comparison clearly indicates the superiority of ground-source heat exchange systems in providing an even temperature due to the minimal influence of ambient air temperature changes (Kumar et al. 2022).

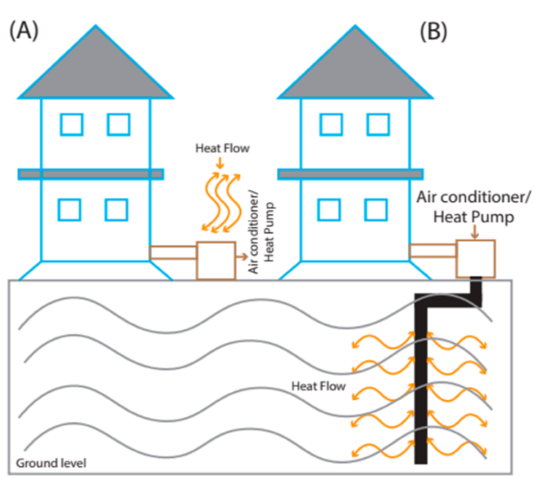

Figure 2. (A) Schematic of the heat-exchange arrangement for a heat pump system that heats or cools using air exchange. (B) Heat-exchange arrangement for a heat pump system that uses the ground rather than air to exchange heat (Kumar et al. 2022).

Figure 3 is a representation of a ground source heat pump system. Ground source heat pump systems absorb thermal energy from the Earth and transfer that energy to a liquid flowing in a closed-loop system. The system includes an evaporator, an expansion valve, a compressor, a condenser, and a heat exchanger. After the absorbed geothermal heat has been transferred to the buildings using a heat exchanger (Kumar et al. 2022), the process cycle can continue with another absorption of geothermal thermal energy.

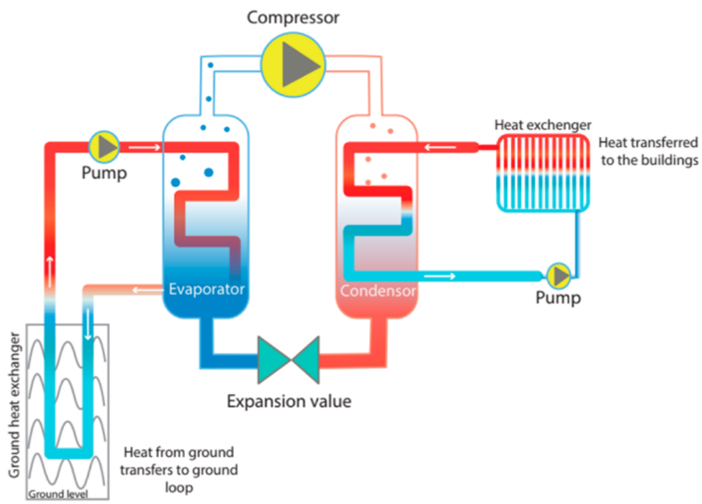

Figure 3. **Schematic of a ground source heat pump for district heating (Kumar et al. 2022).**

To develop innovative and efficient solutions for managing geothermal reservoirs, Kumar et al. 2022 evaluates how data science and AI can assist with the many challenges of managing geothermal reservoirs. The authors reported that these results can be achieved through four main approaches which included (1) enhanced reservoir characterization, (2) real-time monitoring integration, (3) thermodynamic cycle optimization and (4) predictive maintenance capabilities. Additionally, the study incorporates the current state-of-the-art and practical demonstrations of digitalization of geothermal systems to illustrate the potential for digitalization of geothermal systems.

The study conducted by Yerima et al. (2024), as well as Yan et al. (2024), have shown that EGS enable geothermal resource exploration in areas, which were previously considered non-geothermal. In order to explore and understand the induced seismicity and production operation associated with EGS technology, researchers utilize a combination of the EGS technology along with PIML based frameworks in order to model the fluid-rock interaction and fracture behavior precisely. PIML is an effective tool for EGS technology due to its ability to simulate complex geothermal systems with limited computational resources allowing for real time monitoring of geothermal systems and rapid response to changes made to the system. The PIML framework helps operators achieve their highest geothermal energy production through improved stimulation and extraction techniques.

Geothermal energy is gaining popularity due to its increasing use as a renewable source of energy. However, geothermal systems contain numerous complexities that are still being overcome by the use of new digital technologies, such as AI and ML. Traditional methods for managing geothermal systems have been successful but can rarely operate at optimal levels as a result of the uncertainty associated with the geology of subsurface environments in geothermal systems. This includes extremely high temperatures, variable pressure conditions, and complex fracture networks. Advances in data science and the implementation of Industry 4.0 technologies have allowed the geothermal industry to apply digital technologies to support real time decision making, enhance operational efficiencies, and reduce the negative environmental impacts of geothermal development. AI & ML based applications, such as reservoir characterization and predictive maintenance have created numerous improvements in resource management, and longer productive lives for geothermal fields.

The following section demonstrates how AI & ML application in geothermal reservoir management creates opportunities for sustainable and cost-effective resource management in geothermal industries world-wide. These applications demonstrate how AI based solutions will provide geothermal operations with a means to meet their sustainability goals by optimizing the resource management within the geothermal operation and reducing the costs of operating. This analysis of the applications demonstrates how data science will provide geothermal managers with environmentally responsible, reactive systems for the management of geothermal energy production.

2. RESERVOIR CHARACTERISTICS AND MODELING

Due to its role in defining subsurface characteristics such as porosity and permeability, and saturation of fluids which affect the ease of resource production, that reservoir characterization forms a basis for all geothermal resource management activities. The study of Esiri et al. (2024), demonstrates that combining geostatistics and petrophysics into a single approach will enable accurate reservoir characterization, which will result in reservoir models that show both the spatial variability and uncertainties in the reservoir properties. Building on this research, Ibekwe et al. (2019), provide evidence of how integrating geological data with both geophysical and engineering measurements can be used to produce reservoir models of sufficient detail to enable the selection of optimal well drilling sites and extractive techniques for the production of hydrocarbons.

Aydin and Temizel (2022) went one-step further by documenting numerous geothermal reservoir characterization methods available at various stages of a project. The authors showed that seismic surveys combined with pressure transient testing and tracer tests and numerical reservoir simulation produce separate data sets, which help determine geothermal reservoir conditions. Scientists use seismic data to develop fault network and fracture maps, which function as vital pathways for geothermal reservoir fluid movement.

Tracer tests are particularly valuable for assessing fluid connectivity between injection and production wells, thus allowing for targeted and efficient management of geothermal fluids. Numerical reservoir simulations integrate these data sources to produce a model that predicts the response of the reservoir under various production scenarios (Figure 4).

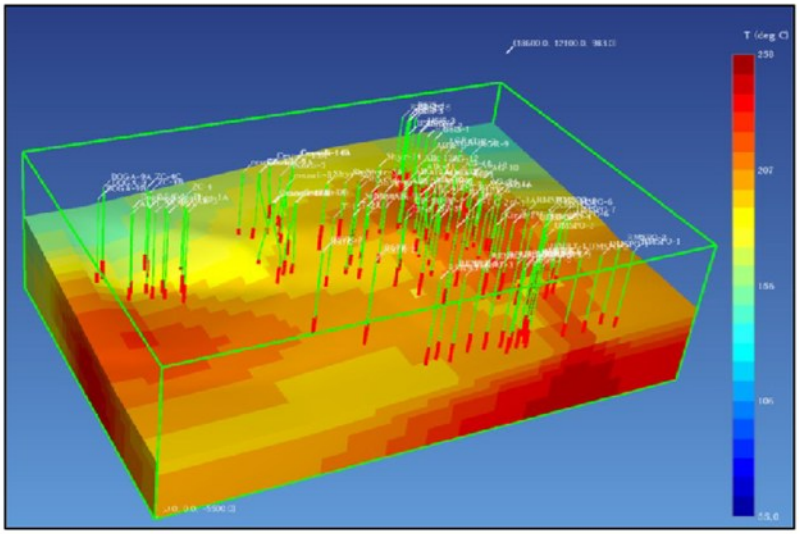

Figure 4. Numerical reservoir simulation of Alaşehir field. From (Aydin and Akin, 2022).

Horne (1982) provides an overview of the international experiences of reinjecting water into fractured geothermal reservoirs. Horne outlines the advantages and disadvantages of water reinjection for the purposes of maintaining reservoir pressure, increasing energy recovery, and removing geothermal waste fluids. The reinjection of water into a fractured reservoir system is a very complicated procedure and will require careful planning and management to prevent problems associated with thermal breakthroughs and lower-quality steam being produced in the production wells.

Three principal concerns are evident from the experiences reported at numerous geothermal operations world-wide, namely, (1) the impact of reinjection on permeability changes within the reservoir, (2) the pathways traveled by the injected water as indicated by tracer studies, and (3) the thermal and hydraulic impacts of reinjection on both the injection wells and the surrounding production wells. In addition to demonstrating the varied results obtained at different operations (e.g., Wairakei/Broadlands, New Zealand; Otake/Hatchobaru, Japan), the field studies illustrate that the tracer studies indicate the ability of reinjected water to travel considerable distances in fractured systems to cause early thermal interference with production wells. Furthermore, maintaining long-term injectivity has proven difficult in many cases, primarily because of precipitation of minerals such as silica that block pore spaces in the reservoir. The study emphasizes the need for site-specific and well-defined reinjection strategies that account for the specific conditions of each geothermal reservoir. The reinjection strategy can vary depending upon the temperature of the injected fluids, the rate of injection, and the location of the injection wells relative to the production wells to minimize or eliminate rapid thermal breakthroughs. By balancing the positive effects of maintaining pressure levels and recovering energy, while also minimizing the negative effects of decreased energy production due to early cooling effects in production zones, such strategies will allow geothermal operators to efficiently produce geothermal energy with minimal environmental impacts (Horne, 1982).

Geologists and engineers have been able to create highly accurate and well-defined models of the geothermal reservoir at Iceland's Nesjavellir field utilizing neural network-based AI, which analyzed multiple large data sets of geological and geophysical information. These predictive models provide highly detailed predictions of the physical and fluid properties of rocks as well as significant improvements to the location accuracy of the geothermal production wells and the fluid flow predictions, therefore decreasing the operational risks associated with the geothermal operation (Aljubran and Horne, 2024). Therefore, geothermal operators will be able to use these types of analytical tools to increase their understanding and management of their complex subsurface systems with a greater level of accuracy, and thus provide an even more cost effective and environmental friendly way of producing geothermal energy (Aljubran and Horne, 2024; Gudmundsdottir and Horne, 2018).

Aljubran and Horne (2024) used a physics-informed graph neural network based on a physics-informed data-driven spatial interpolation algorithm to generate three-dimensional temperature-at-depth maps for the contiguous United States. The model was designed to approximate the three-dimensional heat conduction equation by making simultaneous predictions of the subsurface temperature, thermal conductivity and surface heat flow. To enhance the model's predictive performance, the authors included a variety of physical inputs beyond bottom-hole temperature measurements. These additional inputs included depth, latitude and longitude, elevation, sediment thickness, magnetic anomaly, gravity anomaly, gamma ray flux from radioactive materials, seismic activity, and electric conductivity.

The variety of the datasets used in this project permitted a physically reasonable representation of how geological and geophysical factors could influence subsurface temperature. Additionally, the physics-informed nature of the neural network models ensured that the predictive results would be consistent with the physical laws from which they were derived; therefore, further confidence was generated about the reliability of the model. The model demonstrated excellent accuracy, with a mean absolute error of almost five degrees Celsius in temperature prediction, indicating that the model was effective in accurately mapping subsurface temperatures. The ability to map subsurface temperatures effectively is critical to many applications including geothermal energy exploration and environmental studies (Aljubran and Horne, 2024).

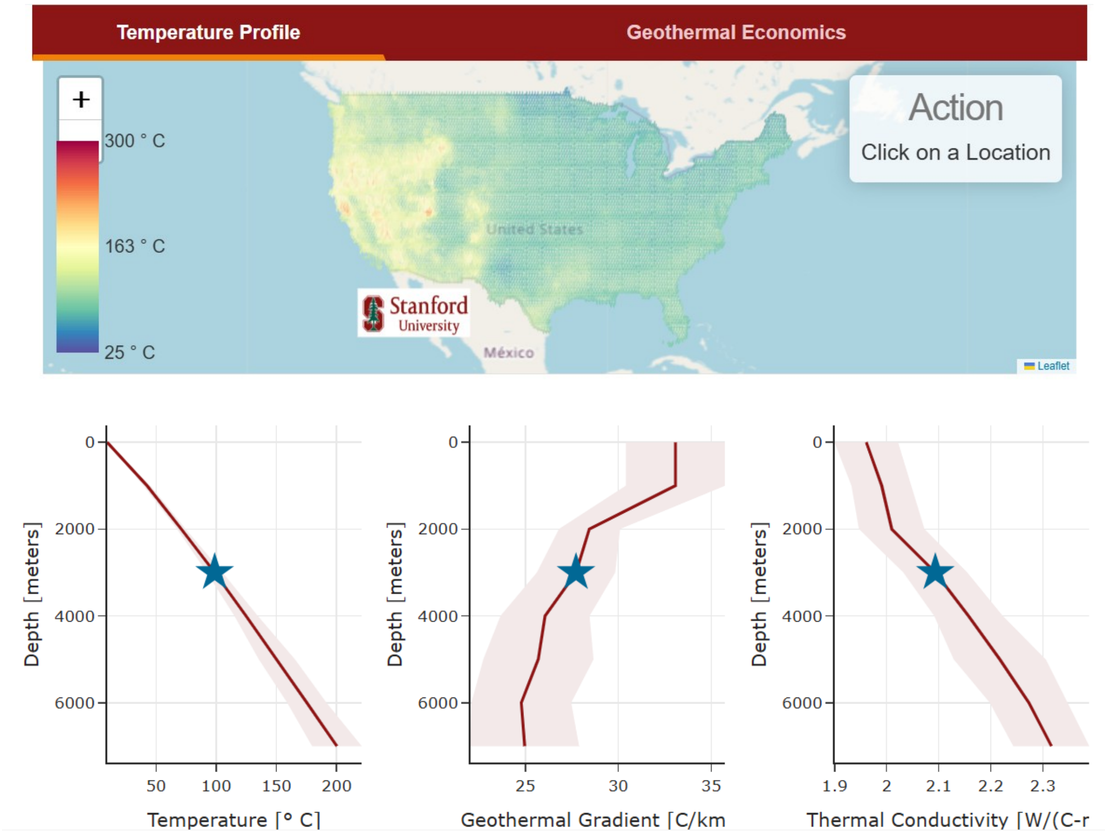

Figure 5. Temperature profile map for the contiguous United States developed using a physics-informed graph neural network model by Aljubran and Horne. The map displays temperature distribution at depth across various locations, while the accompanying plots show depth-dependent profiles for temperature, geothermal gradient, and thermal conductivity (Aljubran and Horne, 2024).

It is also very important to understand how geothermal fluids are distributed throughout a reservoir in order to extract the geothermal resource in an efficient and sustainable way. To do so, the operator needs to have knowledge about the distribution of the geothermal fluids through-out the entire reservoir. The use of advanced AI models is currently allowing operators to be able to more accurately forecast the behavior and movement of the geothermal fluids within the reservoir and with that information they will be able to make better choices for the management of their resources. The use of AI to forecast the distribution of geothermal fluids within a geothermal reservoir will be discussed as well as the future uses of AI in optimizing the extraction of the resource and ensuring the health of the geothermal reservoir over time.

3. PREDICTING FLUID DISTRIBUTION USING AI

AI models enable operators to improve their knowledge about fluid distribution patterns in the Larderello Italy geothermal reservoir. The AI models are able to analyze and process a significant amount of historical production data in order to generate detailed maps showing where the geothermal fluids (hot water and/or steam) are distributed throughout the reservoir. Using AI models to map out the distribution of the geothermal fluids enables field operators to make more informed decisions on how to allocate the geothermal resources. Operators can increase geothermal field operation time and decrease withdrawal problems by using optimized extraction rates which maintain reservoir pressure equilibrium (Temizel et al. 2024). Machine learning can be used to evaluate the effects of induced microseismic activity, which may pose potential risks to nearby residents (McClure and Horne, 2010).

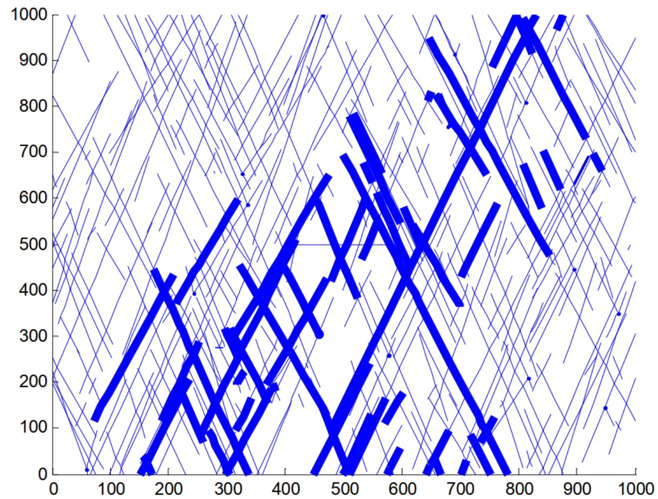

Figure 6. Permeability of fractures after hydraulic stimulation. Thick lines are fractures stimulated while thin lines are fractures that were not stimulated. From (McClure and Horne, 2010).

Discrete fracture network models allow for the simulation of reservoir processes and are capable of representing stochastic fracture networks and reducing the computational cost of heat conduction.

Stress perturbations created by slip in individual fractures contribute to localized permeability bottlenecks, resulting in heterogeneous permeability. McClure and Horne (2010) proposed methods to mitigate seismic effects of EGS operations. The methods include decreasing injection pressures gradually through time and initiating production immediately after injection.

Tauhara, a geothermal field, is located in New Zealand and demonstrates the ability of big data analytics to assist in optimizing geothermal field development and operations by utilizing big data analytics for integrating multiple types of data including; Thermal data, seismic data, hydrological data and operational data. By providing a complete picture of the subsurface through the utilization of big data analytics and also providing the ability to adjust the extraction strategy as needed based on current subsurface conditions this provides a basis for informed decision making regarding optimum heat extraction rates and extending the lifespan of the reservoir (Kumar et al. 2022).

Morra et al. (2020) outlined how the rapid production of massive datasets by geodynamic models presents a significant challenge to data processing, and stated that ML can enhance model resolution, and therefore the accuracy of model-derived predictions. This was a part of their studies on the numerical approaches used in geodynamics, and on the use of big data, high-performance computing (HPC), and ML to improve geodynamic problem resolution.

Deep learning models can be utilized for seismic data analyses. Meanwhile the hybrid ML/numerical models are sutible for improving computational speed for geophysical analysis, and an educational requirement to train geoscientists with the skills to manage the increasingly complex nature of earth system models; these are a few examples of the many applications of ML presented in Morra et al. (2020).

In Indonesia's Wayang Windu geothermal field, the IoT-based sensors were installed so that the monitoring of key parameters associated with the reservoirs (temperature, pressure and flow rates), can be done continuously and in real-time. By deploying AI system to enhance the performance of the sensors; predictive maintenance models can be used to proactively identify any potential problems with equipment operations, anomaly detection or failures. An example of how this technology works is through ML algorithms analyzing sensor data to predict when an equipment item such as a pump or valve needs to have maintenance performed on it before it fails. This results in (1) minimized downtime, (2) reduced maintenance costs, and (3) ensured continuation of power generation by maintaining optimum operating conditions and prolonging the life of the reservoir infrastructure (Rohit et al. 2023).

Moreover, monitoring temperature and pressure profiles are critical to the evaluate the health and productivity of geothermal reservoirs. ML models were developed to analyze extensive sensor data collected in Kenya's Olkaria geothermal field to produce accurate temperature and pressure maps of the subsurface environment. The maps enable operators to identify areas of high geothermal productivity and identify potential risks, such as pressure buildup that can cause safety concerns. Temperature and pressure maps also guide resource allocation, enabling operators to target extraction activities to the most productive areas of the reservoir, increasing both efficiency and sustainability (Gilbert et al. 2023).

Understanding the properties of fractured networks in geothermal reservoirs is fundamental because they affect the permeability of the reservoir. Convolutional Neural Networks (CNNs) were applied to seismic data in California's Geysers geothermal field to determine the geometry and connectivity of the fracture networks present in the geothermal reservoir. Accurate determination of fracture networks enables operators to place wells to maximize fluid flow and energy extraction, particularly in reservoirs where fractures serve as the primary conduit for fluid movement. Therefore, accurate fracture network analysis can benefit both resource recovery and operational safety in these reservoirs (Puthur, 2023).

Yang et al. (2024) introduced a Long Short-Term Memory (LSTM) Fully Convolutional Network (FCN) architecture for fracture characterization in subsurface reservoirs. The characterization of fractures is very closely related to the downhole temperature distribution caused by the coupled behavior of fluid flow and heat transfer in fractured systems. High-resolution Distributed Temperature Sensing (DTS) data contain valuable spatiotemporal information, and therefore constitute a good candidate for fracture distribution inversion. While traditional knowledge-based inverse methods require predefined mappings and process cases to be treated individually, this machine learning method enables automatic learning of mapping relationships directly from the data, and thus efficiently manages multiple cases simultaneously. Yang et al. (2024) aim to develop a deep learning model for accurate fracture identification in all the operational phases of the geothermal reservoir (injection, warmback, static) and to investigate the complex relationship between fracture characteristics and temperature distributions, and to determine fracture flow rates using DTS profiles, and hence to assist in optimizing the design and control of the reservoir.

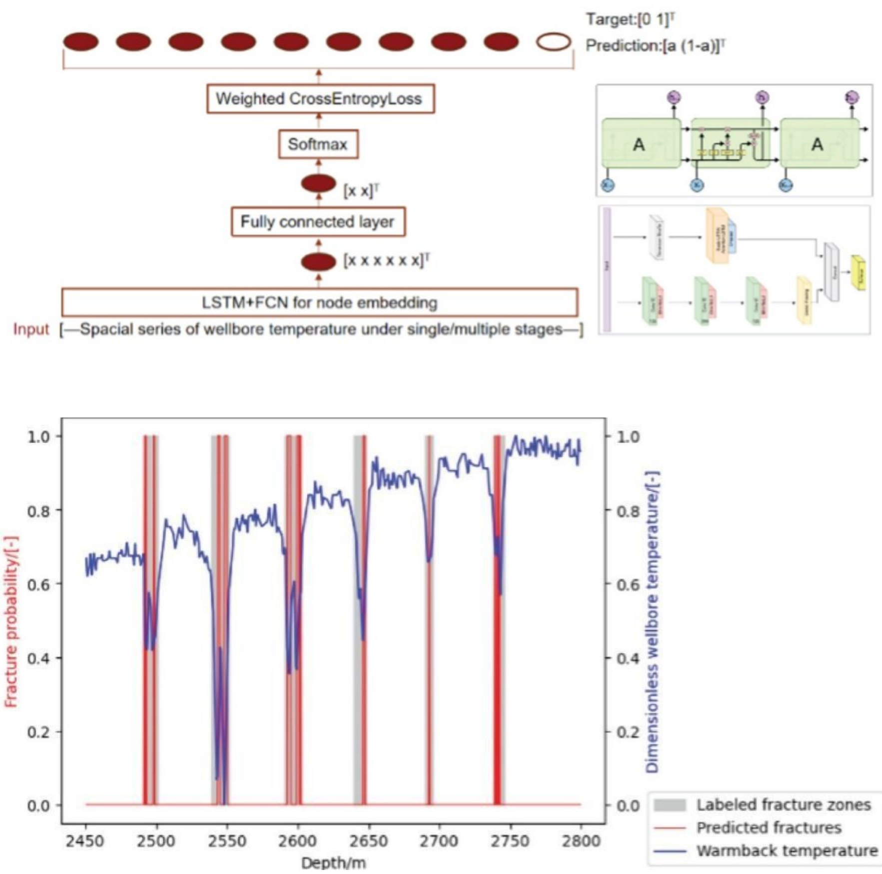

Figure 7. The LSTM fully convolutional network architecture for fracture characterization (Yang et al.,2024).

4.PRODUCTION FORECASTING

Production forecasting is one of the most common uses of AI in geothermal energy. AI enables geothermal operations to model historical reservoir conditions and therefore forecast future trends in production. At Iceland's Reykjanes field, AI models combine a number of factors to model future output of the field, including current production rates; temperature gradient data; and pressure data. With the predictive models developed from this data, operators can schedule drilling activities and allocate resources as well as develop long-term development strategies to extract energy from the geothermal reservoir. Accurate forecasting of production also supports operators in maintaining stable production levels over time to meet both short-term and long-term requirements of the electric grid and to provide a predictable basis for resource allocation and financial planning (Nooshiri et al. 2022).

5.THERMAL BREAK THROUGH PREDICTION

At Mexico's Cerro Prieto geothermal field, AI has been utilized to predict thermal breakthrough events where cooler (or colder) water from adjacent aquifers enter into the geothermal reservoir and lower the temperature of the fluids being produced. Thermal breakthroughs are critical to manage in order to preserve as much energy as possible in the geothermal reservoir, and therefore thermal breakthroughs should be predicted when possible. To predict thermal breakthroughs, AI models analyze the temperature, flow rate and geological data associated with the reservoir and identify the areas in the reservoir that will likely undergo thermal breakthrough. When these areas are identified, operators can implement a number of preventative actions to reduce the potential impact of thermal breakthrough on the geothermal reservoir, including reducing pressures and/or flow rates through the affected zones of the reservoir (Barbier, 2002).

6. ANOMALIES IN RESERVOIR PERFORMANCE

Machine learning models were applied to the Mak-Ban field located in the Philippines to identify anomalies in reservoir performance. Machine learning models apply mathematical algorithms to operational data to determine how actual performance differs from expected performance. Anomalies may include unanticipated decreases in temperature and/or flow rates in the reservoir. The early detection of such anomalies enables operators to investigate the cause of the anomaly prior to it becoming a major problem and to take corrective action to limit the disruption to reservoir operation and to protect the long-term. By planning ahead for the future productivity of the reservoir, this type of proactive approach to reservoir management will ultimately enhance the overall success of reservoir management and provide sufficient quantities of electricity to meet customer demands (Sarmiento et al., 2007).

The Kızıldere geothermal field in Turkiye underwent (AI) analysis of seismic data which revealed information about the geothermal reservoir's internal structure and its boundaries. Analyzing seismic data is difficult due to the complexity of subsurface formations; however, AI can evaluate large amounts of seismic data and identify the seismic patterns that define the internal structure of the geothermal reservoir (Aydin and Akin, 2022).

Operators can use their knowledge of geothermal reservoir spatial patterns to pick well positions which reduce drilling expenses while they achieve the highest possible geothermal resource recovery from the field for better geothermal field development efficiency (Meneghini et al. 2024).

The Oguni geothermal field in Japan employed reinforcement learning to determine the best flow rates through analysis of current temperature and pressure data. Reinforcement learning enables the system to learn through experience and adjust to changing reservoir conditions in search of an equilibrium point between flow rate and reservoir condition that results in long term, steady state production while maintaining reservoir pressure at acceptable levels. Continuously making adjustments to flow rates based on changes in reservoir conditions, this method maximizes the production of geothermal energy by maximizing the time frame of the useful life of the geothermal reservoir and increasing the total amount of energy removed from the reservoir (Horne, 1982).

7. SOME OTHER APPLICATIONs

7.1. Reservoir Depletion Monitoring

The Salton Sea field in California utilizes predictive modeling to determine reservoir depletion rates allowing the operator to monitor changes in reservoir pressure and fluid levels as a function of time. Using this information, the operator is able to plan long-term production levels. Additionally, the operator is able to develop strategies to minimize production decline using supplemental fluid injection and/or changing flow rates based upon the operator's knowledge of the reservoir depletion rates (Taylor, 2007).

7.2. Injection Well Optimization

The Dixie Valley field in Nevada uses AI algorithms to boost injection well performance by using AI to find the best operating points for pressure and flow rates. The operation of geothermal energy requires injection wells to maintain reservoir pressure but high injection speeds lead to two major problems, which result in temperature decreases in the reservoir and ground shaking occurrences. AI models process reservoir property information with fluid characteristics and pressure readings to determine optimal injection methods which maintain reservoir pressure while minimizing environmental impacts during long-term geothermal power plant operations (Sullera and Horne, 2001; Juliusson and Horne, 2013).

7.3. Temperature Gradient Modeling

Using ML models, temperature gradient maps of the subsurface have been created for Iceland's Hellisheidi geothermal field. To generate visual representations of temperature gradient patterns in the geothermal reservoir, the ML models processed geology data and well log information and thermal measurement results. The operator requires temperature gradient knowledge because it allows them to direct resources toward the most lucrative thermal energy sections of the reservoir while they can identify potential threats from cooler areas, which could affect geothermal power production. The operator develops methods to prevent thermal energy leakage through temperature gradient analysis (Nooshiri, al. 2022).

7.4. Risk Assessment Modeling

The Hengill field in Iceland uses AI-based risk assessment models to determine the seismic and operational threats, which occur during geothermal energy production. The models utilize historical data related to seismic activity, subsurface conditions and extraction rates to predict possible hazards, such as induced seismic events. Operators can reduce unexpected incidents by identifying and measuring risks which allows them to develop safety protocols and adjust operational parameters (Nooshiri et al. 2022).

7.5. Geochemical Data Integration

The Sarulla field in Indonesia uses geochemical data, which includes fluid composition and minerals together with operational data to enhance its monitoring and decision-making capabilities. Geochemical data helps scientists understand the reservoir's chemical composition, which enables them to predict how fluid composition will change and impact both equipment and reservoir operations. The combination of geochemical information with operational data produces better predictive model accuracy because it minimizes operational problems which result from scaling or corrosion issues (Putra et al. 2020; Agustia et al. 2023).

7.6. Well Interference Prediction

The Unterhaching field in Germany employs ML models to predict well interference which occurs when neighboring wells produce operational issues that impact each other. The models use spatial data about well locations and production amounts to forecast the degree of well interference. The operator can use the results to find the best positions for wells which will reduce well interference problems and lead to higher total extraction rates and maximum geothermal field productivity (Drews, et al. 2022).

7.7. Machine Vision for Drilling Operations

Machine vision technology now operates in Italy's Campi Flegrei field to track drilling activities in real-time while detecting any upcoming issues which might include drill-bit deterioration or path variations from scheduled routes. The machine vision algorithms process video data from the drilling site to identify potential equipment failures and dangerous conditions through their analysis of video data. Machine vision technology allows operators to identify issues when they first occur which results in improved operational safety and reduced equipment downtime and lower drilling costs (Somma, et al. 2021).

7.8. Enhanced Connectivity Modeling

The researchers at Nevada's Steamboat Springs field used enhanced connectivity modeling to study how fractures connect throughout the geothermal reservoir. The AI models analyzed seismic and geological data to create an exact model of fracture networks, which scientists used to study fluid movement patterns and predict how the reservoir would react. By optimizing the connectivity between fractures, operators can increase the efficiency of fluid flow and extract more energy from the geothermal resource, and therefore, support more sustainable geothermal energy production (Siler, et al. 2021).

7.9. Reservoir Pressure Control

At the Tiwi field in the Philippines, AI-based pressure monitoring systems were implemented to control the well-head pressures at the wells, to optimize the extraction of the geothermal resource while limiting the over-pressurization of the reservoir. The machine learning algorithms analyze pressure data from multiple wells to find the best real-time operating parameters which protect both people and equipment and maximize production output. The method produces better energy results while safeguarding the reservoir from high-pressure extraction so it reduces the chances of dangerous occurrences (Sarmiento, et al. 2007).

8. CONCLUSIONS

The implementation of AI and ML and data science in geothermal reservoir management through geothermal resource optimization has brought a new approach to geothermal resource development.

The geothermal reservoir environment presents numerous complexities (e.g., high temperatures, varying pressure, irregular distribution of fluids, and intricate fracture networks) that have made it difficult to apply traditional methods of geothermal management. Therefore, to characterize the reservoir effectively, to predict the distribution of fluids, to understand the fracture network and to optimize the entire system, there are now innovative solutions available in the form of AI and ML that can address the previously mentioned challenges.

The research demonstrated several operational AI/ML applications, which operate at geothermal fields across the world to demonstrate the full spectrum of digital solutions used in real-world field operations. Examples of these applications include (but are not limited to) the application of neural networks at Iceland's Nesjavellir field to predict porosity and permeability of the reservoir, and the enhanced connectivity modeling at Nevada's Steamboat Springs field. The applications demonstrate that AI/ML technology produces new information, which regular methods fail to detect. The applications use AI/ML capabilities to process extensive data collections, which help them understand underground processes and forecast operational results and develop extraction methods that boost geothermal resource efficiency and reservoir operational duration.

One of the largest advances in the past few years is in the realm of predictive maintenance and real-time monitoring. As seen in Indonesia's Wayang Windu field, IoT enabled sensors and AI driven analytics have allowed for predictive maintenance of critical infrastructure, greatly reducing downtime and saving money. Additionally, big data analytics, such as those employed in New Zealand's Tauhara field, have proven to be extremely beneficial in optimizing the field wide operations of the geothermal facility by combining different types of data (thermal, seismic, and hydrologic) to gain a complete understanding of the subsurface conditions and to make informed decisions regarding the extraction strategy.   The examples demonstrate how AI and ML technology improves geothermal reservoir management yet various challenges continue to affect the system. To deploy AI and ML successfully, access to high-quality and large quantities of data is required, and the availability of data can limit the accuracy of the models. The deployment of AI and ML systems needs stakeholders to merge their expertise for successful digital tool integration into current operational systems. The geothermal industry needs to solve two main environmental and regulatory problems which stem from using data-driven technologies during EGS operations that produce induced seismicity and threaten subsurface integrity.

The geothermal energy industry will see AI and ML technologies play a growing role, which will help renewable energy adoption through better geothermal operation sustainability and efficiency and safety. The geothermal industry faces various obstacles, which AI and ML solutions have started to solve through their ability to analyze reservoir data, perform predictive maintenance, optimize fluid circulation rates, and evaluate potential dangers. The combination of digitalization and data science progress will create new opportunities for geothermal energy because it will link digital systems to current geothermal operational systems. Geothermal energy requires researchers to work with industry partners who will create a dependable renewable power system based on resilience.

Future studies should include more realistic fracture network models, and 3-D models to improve the ability to apply the results of modeling techniques to actual EGS operations.

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