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Recent Trends in Artificial Intelligence for Subsurface Geothermal Applications

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ABSTRACT

This paper presents a review of the trends in applying artificial intelligence (AI) for the drilling and subsurface aspects of the geothermal industry. The applications over the past twenty years (from 2001 to 2021) were reviewed to understand what AI algorithms are being applied, the kind of problems being addressed with AI, and where there might be opportunities to use AI in the geothermal industry. The study showed that there has been a steady increase in the application of AI in the geothermal industry over the past 20 years. Particularly, years 2020 and 2021 saw a significant rise in AI publications within the geothermal industry. Several domains for subsurface geothermal energy were reviewed, and it was found that reservoir engineering and characterization had the most significant applications of AI in the geothermal industry. This study shows that there is an opportunity to leverage recent AI algorithms to improve and expand the application of AI in domains such as drilling and exploration, where risk and cost reductions are needed.

1. INTRODUCTION

The past decades have experienced a surge in artificial intelligence (AI) applications across several industries. The AI Index shows that the field of AI is more active than ever before, with increased investment in that research area, thus leading to a dramatic increase in AI publications in the past 20 years (Vincent, 2017). However, the investment in AI for energy exploitation has been minimal, resulting in fewer publications carried out in the industry and usually attributed to a strong dependence on physics-based modeling (Zhang et al., 2021). Studies have shown an impressive application of AI in the oil and gas sector, notably a study conducted by Li et al. (2021), where AI trends in the oil and gas sector were observed to exhibit exponential growth over a few decades when observing the publication count (Figure 1). The geothermal industry has similarities with the oil and gas industry regarding technical challenges, risks, and domains. The geothermal energy sector has gained interest over the past decades due to clean, renewable, and sustainable energy demands. Despite the numerous benefits of geothermal energy, such as being a low carbon-emitting resource and all-year availability, the exploitation of geothermal resources has been challenging due to the complex geologic and engineering problems associated with harnessing this type of resource. Traditionally, expert knowledge has been highly dependent on identifying areas for geothermal exploration and subsurface characterization. However, as we enter frontiers in geothermal energy, such as enhanced geothermal systems, and explore regions with significant uncertainties and complex subsurface characteristics, we need to investigate approaches that will reduce the risks and costs of geothermal exploration and development. The oil and gas industry has utilized AI to reduce risk and costs in most of its processes (Pandey et al., 2017; Holditch, 2013). Hence, the objective of our study is to identify if artificial intelligence has been used to perform similar tasks in the geothermal industry, what the trend has been over the past twenty years, and what opportunities exist for further application of AI in the geothermal industry.

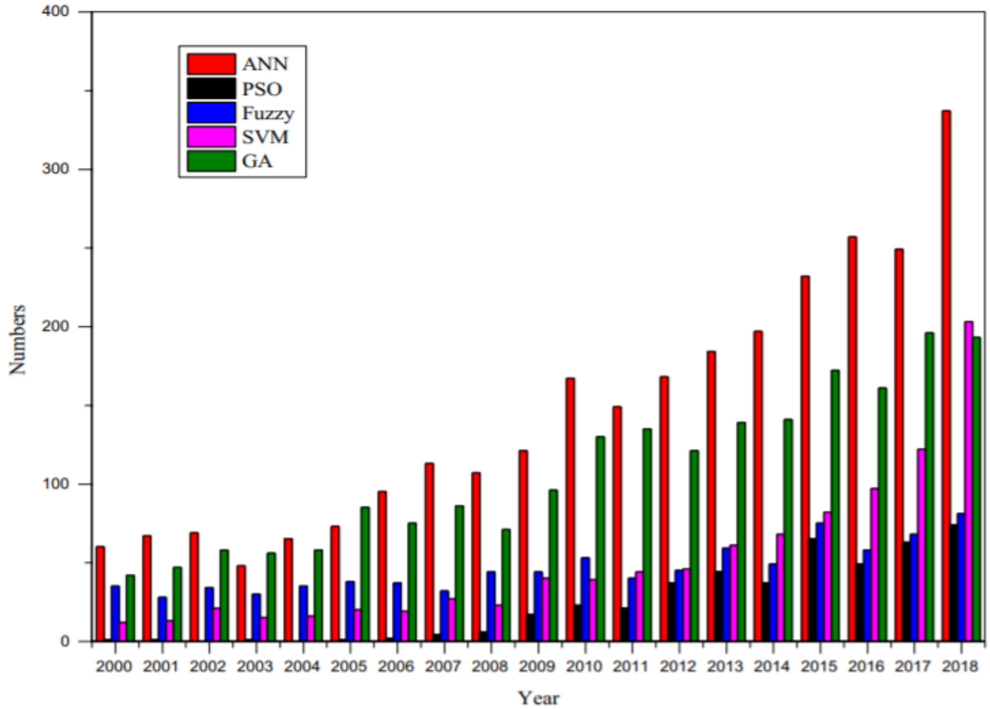

Figure 1: Research trends of AI application in the Oil and Gas sector (after Li et al. 2021).

2. METHODOLOGY

The assessment of the application and trends of AI methods in subsurface geothermal was carried out by first selecting two sources containing research on AI in geothermal energy: 1) the International Geothermal Association (IGA) database, which was accessed through the Stanford University geothermal search engine, and 2) Google Scholar search engine and database. A Python routine was developed to extract the required data for the analysis. A total of 23,661 papers were collected from the two databases with specific keywords: 'artificial intelligence', 'machine learning', 'deep learning', 'statistical learning', 'supervised learning', 'unsupervised learning', and 'neural network'. The extensive data collected was screened to 287 papers of application of AI in the geothermal industry, and then manually filtered to 98 data to ensure that the utilized data samples analyzed were relevant applications of AI methods in subsurface geothermal.

A categorization of the different AI methods implemented in the reviewed research was defined to analyze the cleaned-up data. In the context of this paper, the different AI methods were categorized into machine learning (ML) and deep learning (DL). ML is an AI method that trains history data to develop efficient models capable of learning from the trained data. It is broadly divided into two types: supervised learning and unsupervised learning. Supervised learning algorithms train on independent features and learn a mapping to a target variable. On the other hand, unsupervised learning algorithms utilize only the independent features to derive patterns without the need for a target variable. We identified several ML techniques that have been implemented in subsurface geothermal, which include random forest (RF), support vector machine (SVM), gradient boosting (GB), k-nearest neighbors (kNN), and shallow multilayer perceptrons (MLP), which are categorized under supervised learning. Algorithms such as principal component analysis (PCA), k-Means, and hierarchical clustering are under the unsupervised learning category. DL is a subdivision of ML (Figure 2) that extends the ML framework to involve highly nonlinear and complex functions with significantly higher degrees of expressiveness given various structures of data. These are neural networks that utilize multiple hidden layers to enable deeper learning. Deep multilayer perceptron (MLP), Convolution neural networks (CNN), recurrent neural networks (RNN), and autoencoders are some DL algorithms that have been utilized for subsurface geothermal energy and will be analyzed based on the data we collected.

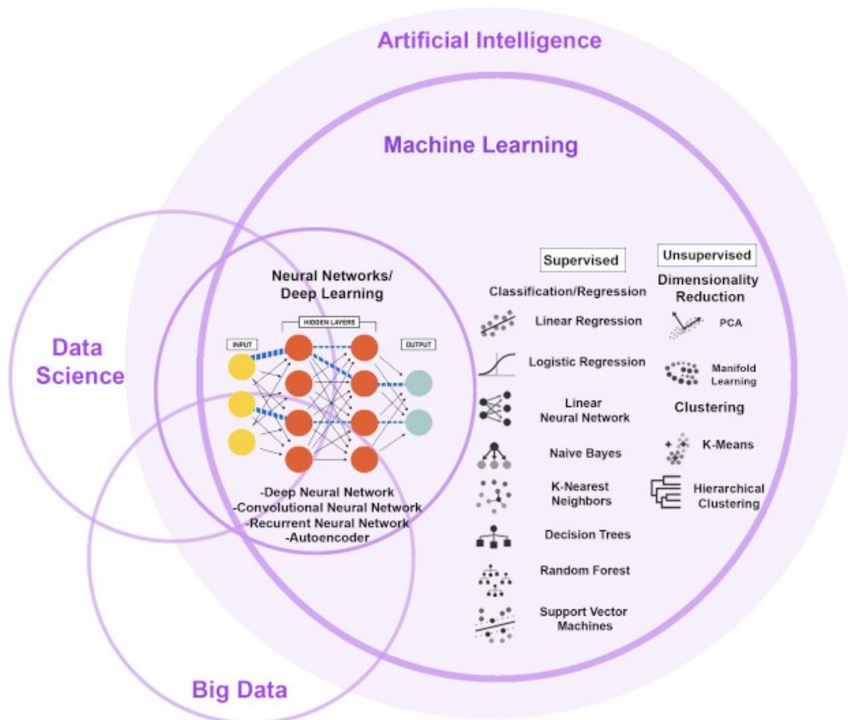

Figure 2: Venn diagram on the relationship between artificial intelligence, data science, and big data. Also displayed are common machine learning and deep learning algorithms.

3. RESULTS AND DISCUSSION

The categorized dataset was first analyzed based on the titles used in the different reviewed publications to identify possible research areas and major keywords researched in subsurface geothermal. A word cloud was generated, as shown in Figure 3, where the size of the word reflects how frequently it has appeared in the titles of the referenced publications. It was observed, from Figure 3, that the majority of research conducted was related to exploration, reservoir characterization, and reservoir engineering. In exploration, it has been applied in specific applications such as fracture characterization, fault identification, seismic and microseismic characterization. Also, AI has been used popularly in drilling to predict the rate of penetration (ROP). Other popular applications evident from the figure below include reservoir temperature prediction, porosity prediction, geochemical and hydrochemical properties prediction, and production and injection rates prediction. It was also observed that the majority of the AI in geothermal industry research conducted was carried out in some countries where geothermal exploitation is commonplace, e.g., Anatolia in Turkey and Nevada, United States.

Figure 3: Word cloud of retrieved subsurface geothermal articles.

Analyzing the 98 publications obtained from the data collection process illustrates that the first decade from 2002 experienced a limited volume of research studies in subsurface geothermal AI applications. On the contrary, the past five years show exponential growth in the number of AI publications in geothermal energy, as seen in Figure 4. It is also evident that most of these articles are journal research publications. Similar trends were observed in Figure 5, which illustrates the trends of ML and DL application in the different geothermal domains showing an exponential increase in the implementation of ML and DL methods in the past five years. It was also observed that there has been a considerably limited volume of research publications on the application of DL algorithms until the past two years. Furthermore, recent studies have shown increased adoption of CNN and RNN in particular, seen in Figure 6.

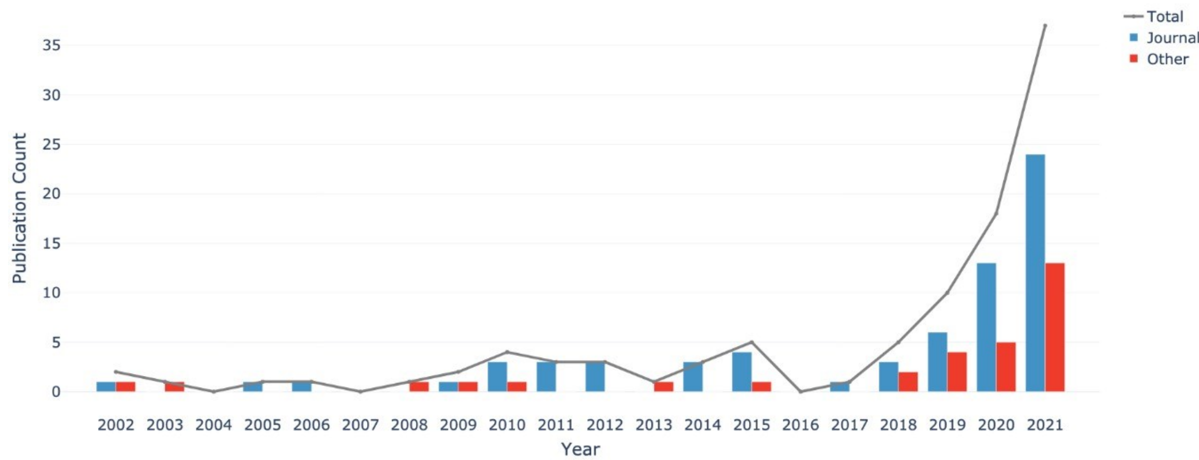

Figure 4: Journal and non-journal publication on AI methods in subsurface geothermal energy over 20 years.

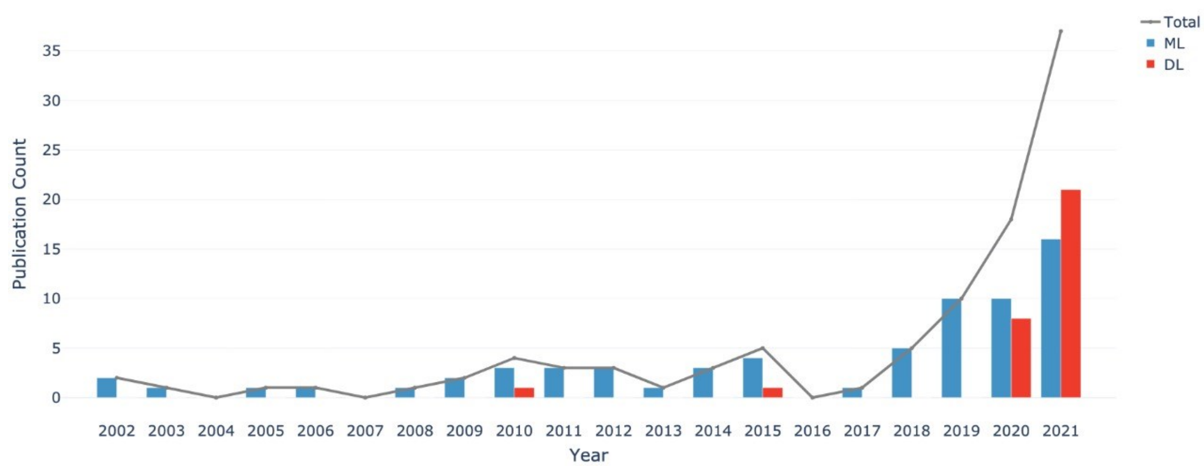

Figure 5: Trends of machine learning and deep learning methods in subsurface geothermal energy over 20 years.

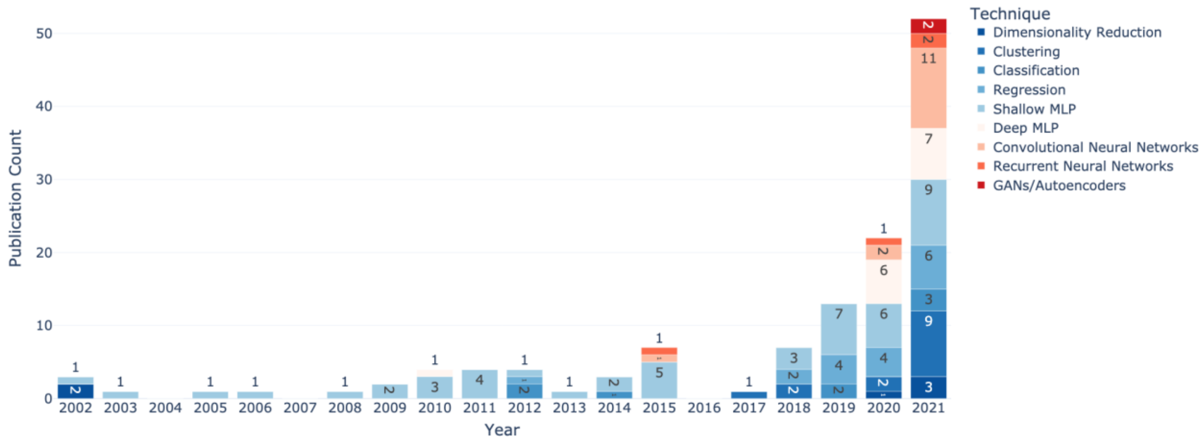

Figure 6: Detailed applications of artificial intelligence algorithms in subsurface geothermal energy over the past twenty years.

3.1 Artificial Intelligence in Subsurface Geothermal Development

The development of subsurface geothermal resources is associated with high technical risk due to the significant uncertainties encountered at the early stages of resource identification and verification. Risk diminishes only after drilling confirms the presence of a commercial resource. Cole et al. (2017) presented some information indicating that exploration, permitting, and drilling costs, which occur at the early stages of geothermal resource development, comprise about one-third of the capital for an average 50-megawatt (MW) geothermal plant. Considering that big data are available from previous exploration and drilling activities, the predictive power of AI models could potentially reduce the uncertainties and risks associated with geothermal development. In order to evaluate where AI has been applied in subsurface geothermal, we identified the geothermal domains most relevant to the publications collected in this study. Figure 7 illustrates the different research domains of subsurface geothermal energy with respect to the various AI techniques implemented that were reviewed. From Figure 7, we observed that reservoir characterization, reservoir engineering, and exploration were the areas with the most applications of AI. Drilling, which is an area that contributes to high costs of geothermal resource development, had relatively fewer applications of AI. This domain has opportunities for further application of AI techniques.

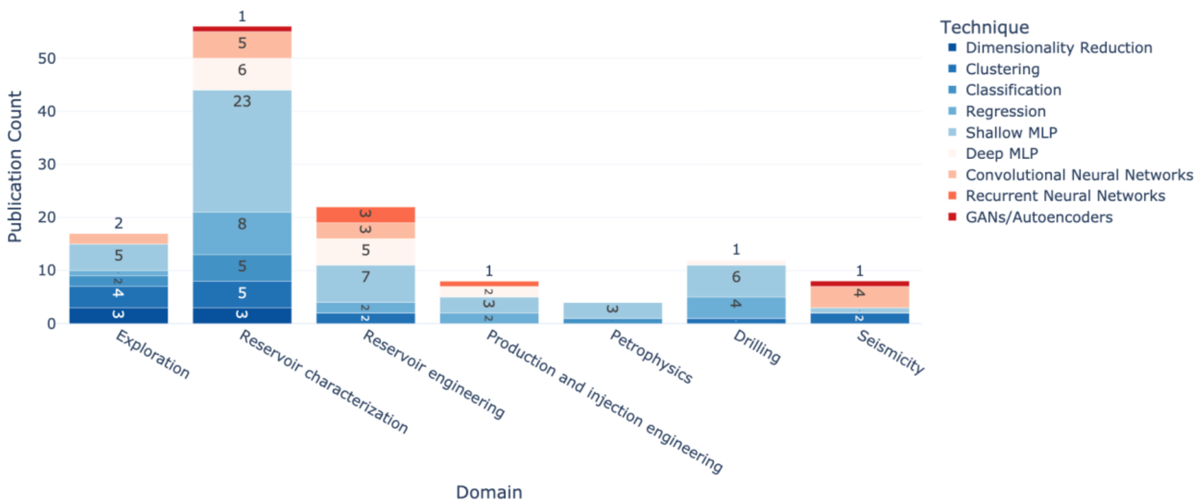

Figure 7: Reviewed domains of Subsurface Geothermal.

In subsurface geothermal development, the different AI methods described have been applied to reduce the high risk of uncertainty, the cost of geothermal exploration, and the optimization of geothermal operation. The optimization of geothermal exploration is pertinent as it guides the decision-making required for investment in geothermal resource exploitation. Several studies have been carried out in applying AI methods in geothermal exploration, such as a study conducted by Perozzi, Guglielmetti, and Moscariello (2021), which focused on the quantitative interpretation of the existing seismic lines of the Canton of Geneva by applying machine learning techniques. The aim of their work was to demonstrate how these quantitative techniques can be applied to fault detection, seismic facies interpretation, and automatically identify lithofacies based on well-log measurements. They used a fault detection algorithm and k-means unsupervised clustering algorithm. Their results showed that the implementation of k-means clustering is an additional tool that could help improve the knowledge and characterize a geothermal reservoir, thus reducing the subsurface uncertainty, if and only if they are applied together with a domain specialist such as experienced geologists and geophysicists.

Petrophysical rock properties are essential for characterizing the subsurface geothermal resources and are utilized in reservoir modeling, which is key to assessing the viability of the resource and its economic feasibility. Due to the complexities of geothermal resources and the limited information of these properties the implementation of AI methods has helped reduce these uncertainties. Kiran & Salehi (2020) assessed the relationship between petrophysical and operational parameters in geothermal wells. They used unsupervised ML algorithms coupled with digital filtering techniques to filter the well logs, which were used as inputs. They tested different ML algorithms such as kNN, GB, decision tree (DT), and RF classifiers to predict lost circulation zones using well logs. Of the four, RF showed the highest accuracy, while DT classifiers showed the lowest accuracy.

Höhn et al. (2020) presented the application of ML techniques in optimizing drilling rates which consequently minimizes the financial risk associated with increased drilling time in geothermal resource exploitation. The authors utilized two supervised machine learning techniques: RF and GB techniques, to predict the ROP. The results were evaluated, and the RF model recorded a high performance. Priyangga and Ruliandi (2018) utilized surface drilling data such as ROP, weight on bit (WOB), rotation (RPM), hydraulic horsepower per square inch (HSI), and torque as train features in the development of an ANN model that predicts drill bit grade.

Beckers et al. (2021) evaluated the performances of three neural network architectures: Multilayer perceptron (MLP), LSTM, and CNN for time series forecasting of future injection temperatures. The resulting assessment highlights the benefits of the application of MLP in the prediction of temperature as it recorded the least mean absolute percentage error. Ariturk (2018) utilized data from the K-field in Turkey to predict missing production data and future production flow rates. The author utilized an MLP with 50 neurons in the hidden layer to first predict the missing flow rates in the production data using well pressure and temperatures, valve positions, and bottom-hole pressures and then predicted the future flow rates of the production wells.

Gudmundsdottir and Horne (2018, 2021) used both unsupervised and supervised ML algorithms to quantify the connectivity between wells using synthetic injection and production data. Suzuki et al. (2021) trained an SVM model to predict permeability distribution from pressure and temperature measurements. Zheng et al. (2021) developed a neural network characterizing small-scale fractures using seismic data. Vivas and Salehi (2021) proposed a machine learning methodology to predict thermal conductivity using real-time surface geothermal drilling data such as ROP, WOB, RPM, SPP, torque, and flow rate. The authors applied several machine learning techniques such as DT, RF, kNN, and deep MLP, with the kNN model having the best performance for the real-time prediction of thermal conductivity.

Okoroafor et al. (2021) used CNN to predict the depths and temperatures of feed zones, average reservoir pressure and its associated depth, from temperature and pressure logs. Their training error was 0.9%, their validation error was 2%, and their test error was 7%. They demonstrated how CNN can be valuable for training and testing spatial data, and building an AI model that could aid in temperature and pressure log interpretation.

4. CONCLUSIONS

The application of AI methods in subsurface geothermal has been exponential over the last 20 years, with expectations for more research implementation of DL in the coming years. Three domains have significantly adopted AI methods to reduce risks or improve reservoir performance: reservoir characterization, reservoir engineering, and exploration. Finally, the review of AI trends in subsurface geothermal has shown that there exist gaps across different domains, such as drilling and seismicity, where the implementation of AI could significantly reduce associated risks and costs.

NOMENCLATURE

AI	Artificial Intelligence
ANN	Artificial Neural Network
DL	Deep Learning
CNN	Convolutional Neural Network
GB	Gradient Boosting
kNN	k-Nearest Neighbor
IGA	International Geothermal Association
LSTM	Long-Short Term Memory
ML	Machine Learning
MLP	Multilayer Perceptron

PCA	Principal Component Analysis
RF	Random Forest
ROP	Rotation of Penetration
RPM	Revolution per Minute
SPP	Standard Pipe Pressure
SVM	Support Vector Machine
WOB	Weight on Bit

REFERENCES

Ariturk, M. (2018). Optimizing the Production and Injection Wells Flow Rates in Geothermal Field Using Artificial Intelligence. Morgantown, West Virginia: The Research Repository @ WVU.

Beckers, K., Duplyakin, D., Martin, M., Johnston, H., & Siler, D. (2021). Subsurface Characterization and Machine Learning Predictions at Brady Hot Springs. 46th Workshop on Geothermal Reservoir Engineering, Stanford University. Stanford, California: Stanford University.

Cole, P., Young, K., Doke, C., Duncan, N. & Eustes, B. 2017. Geothermal Drilling: A Baseline Study of Nonproductive Time Related to Lost Circulation. Proceedings, 42nd Workshop on Geothermal Reservoir Engineering, Stanford University, Stanford, California, February 13-15, 2017 SGP-TR-212.

Gudmundsdottir, H., & Horne, R. (2018). Reservoir Characterization and Prediction Modeling Using Statistical Techniques. 43rd Workshop on Geothermal Reservoir Engineering, Stanford University. California: Stanford University.

Gudmundsdottir, H., & Horne, R. (2021). Inferring Interwell Connectivity in Fractured Geothermal Reservoirs Using Neural Networks. World Geothermal Congress. Reykjavik, Iceland: World Geothermal Congress.

Höhn, P., Odebrett, F., Paz, C., & Oppelt, J. (2020). Case Study ROP Modeling Using Random Forest Regression and Gradient Boosting in the Hanover Region in Germany. Proceedings of the ASME 2020 39th International Conference on Ocean, Offshore and Arctic Engineering. 11. VirtuaL, Online: ASME. doi:https://doi.org/10.1115/OMAE2020-18677

Holditch, S. A. (2013). Unconventional oil and gas resource development–Let's do it right. Journal of Unconventional Oil and Gas Resources, 1, 2-8.

Kiran, R., & Salehi, S. (2020). Assessing the relation between petrophysical and operational parameters in geothermal wells: a machine learning approach. Proceedings, forty-fifth workshop on geothermal reservoir engineering (p. 10). Stanford University.

Li, H., Yu, H., Cao, N., Tian, H., & Cheng, S. (2021). Applications of artificial intelligence in oil and gas development. Archives of Computational Methods in Engineering, 28(3), 937-949.

Liu, Y., Ling, W., Young, R., Cladouhos, T.T., Zia, J., and Jafarpour, B. (2021). Deep Learning for Prediction and Fault Detection in Geothermal Operations. 46th Workshop on Geothermal Reservoir Engineering, Stanford University, Stanford, California.

Muhammad, A., Kabir, K., & Alli, A. (2019). Machine learning model for improving single flash geothermal energy production: A case of Indonesia. 7th Indonesia International Geothermal Convention & Exhibition (IIGCE), Jakarta, Indonesia.

Okoroafor, R., Pollack, A., Murphy, J., & Horne, R. (2021) Engineer Level Automated Interpretation of Geothermal Well Logs Using Convolutional Neural Networks. In AGU Fall Meeting 2021. AGU.

Pandey, R. K., Kakati, H., & Mandal, A. (2017). Thermodynamic modeling of equilibrium conditions of CH4/CO2/N2 clathrate hydrate in presence of aqueous solution of sodium chloride inhibitor. Petroleum Science and Technology, 35(10), 947-954.

Perozzi, L., Guglielmetti, L., & Moscariello, A. (2021). Geothermal Reservoir Characterization Using Seismic and Machine Learning - A Case Study from the Geneva Basin. World Geothermal Congress 2020+1. Reykjavik, Iceland. Retrieved from https://pangea.stanford.edu/ERE/db/WGC/papers/WGC/2020/32007.pdf

Priyangga, H. Y., & Ruliandi, D. (2018). Application of pattern recognition and classification using artificial neural networks in geothermal operation. Stanford University.

Suzuki, A., Konno, M., Watanabe, K., Inoue, K., Onodera, S., Ishizaki, J., & Hashida, T. (2021). Machine Learning for Input Parameter Estimation in Geothermal Reservoir Modeling. World Geothermal Congress. Reykjavik, Iceland: World Geothermal Congress.

Vincent, J. (2017). Artificial intelligence isn't as clever as we think, but that doesn't stop it being a threat. Retrieved from The Verge: https://www.theverge.com/2017/12/1/16723238/ai-artificial-intelligence-progress-index. (accessed 17 January 2022).

Vivas, C., & Salehi, S. Real-Time Model for Thermal Conductivity Prediction in Geothermal Wells Using Surface Drilling Data: A Machine Learning Approach.

Zhang, D., Mishra, S., Brynjolfsson, E., Etchemendy, J., Ganguli, D., Grosz, B., . . . Perrault, R. (2021). The AI Index 2021 Annual Report. Stanford, CA: AI Index Steering Committee, Human-Centered AI Institute, Stanford University.

Zheng, Y., Li, J., Lin, R., Hu, H., Gao, K., & Huang, L. (2021). Physics-Guided Machine Learning Approach to Characterizing Small-Scale Fractures in Geothermal Fields. 46th Workshop on Geothermal Reservoir Engineering, Stanford University. California: Stanford University.