Proceedings World Geothermal Congress 2020+1
Reykjavik, Iceland, April - October 2021

The Reservoir Temperature Prediction Using Hydrogeochemical Indicators By Machine Learning: Western Anatolia (Turkey) Case

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Keywords: Machine learning, deep learning, hydrogeochemistry, geothermal, geothermal exploration

ABSTRACT

Although geothermal fluids can be used with different purposes, it requires expensive detailed exploration studies for a region. These geothermal exploration studies mainly consist of geology, geophysics and geochemistry disciplines, to understand location, dimension, possible capacity and temperature of the source before a drilling operation. Geothermal drilling operations are also complex and quite expensive, the costs may change by 1.8-2.9 million USD for 1500-2500 m in Western Anatolia (Turkey). Because of the high operational costs, the exploration phase of the geothermal projects is of great importance to reduce project costs. Evaluation of existing earth sciences data, detailed geologic studies, mapping and some geochemical studies, such as using geothermometry, can provide important information to reach geothermal reservoir in a geothermal field. Nowadays, developing technology may give a chance to predict geothermal reservoir temperatures in geothermal fields.

Machine learning (ML) is a data analytics technology that teaches computers to learn from ML algorithms and use computational methods to learn information directly from data. These methods adaptively improve their performance as the number of samples or information available for learning increases. The technology addressed to many study areas such as science, marketing, and engineering.

In this study, a deep learning classifier has been developed to classify the predicted geothermal reservoir temperatures based on the hydro-geochemistry data. We defined three main categories for the geothermal reservoir temperatures to classify our data; low (50-89 °C), medium (90-150 °C) and high (> 150 °C). To compare the prediction performance of our proposed deep learning classifier, two traditional classification approaches were used, k-nearest neighbors (KNN) and linear support vector machines (SVM). They have been performed and the results have been presented. The results have been presented as categories and the models have been compared with their accuracy in this study. The performance comparison showed that our deep learning model achieved better prediction performance than traditional machine learning techniques.

1. INTRODUCTION

Geothermal sources can be used with different purposes and power production, heating and cooling applications are of great importance among renewable energy systems in the modern world. Although geothermal energy is a good option, with independent meteorological conditions and low emissions, geothermal investments are risky and have uncertainties during the exploration stage.

At the development stage of a geothermal project, finding geothermal potential is the first important step by conducting geological, geophysical and geochemical surveys in a licensed area. Geothermal exploration studies start withthe data gathering and determination of the heat source, possible reservoir, cap rocks, and main fault zones before the drilling operation. In most of the geothermal systems, geothermal fluids are required. Temperature, permeability, volume of the reservoir, and multi-reservoir possibilities in the system need to be investigated by the earth scientists (Witter et al., 2019). The detailed subsurface studies will be helpful to prepare a possible geothermal drilling program and minimize the risks and reduce the drilling operation costs. During the drilling operations, collecting rock samples, following the alterations (Uzun and Haklıdır Tut, 2012).

Intelligence systems can be used for different purposes in various topics such as engineering, finance, medicine and energy. These systems use existing data, give a chance to predict some specific issues regarding the study areas, and provide an optimization and control of a system (Mata et al., 2018; Weiss and Indurkhya, 1995).

Reservoir temperature is one of the important determinations for the design criteria of a geothermal system. If the reservoir temperature is predicted based on the scientific data in the exploration phase, it may help the investment decision for a geothermal field. Kaloginou et al., 2012 and Porkhial et al., 2015 have studied geothermal maps of temperature for different depths, by artificial neural networks and modeling and predicting of geothermal reservoirs by intelligence systems.

Machine learning (ML) methods focus on the development of the computer programs and data are used for the learning procedure. End of the learning period, the methods present what they learnt and relationships of the given data and the algorithms of ML are generally classified as supervised and unsupervised learning (Fig.1). In this study, supervised ML algorithms have been applied to the selected hydrogeochemical parameters to predict geothermal reservoir temperatures.

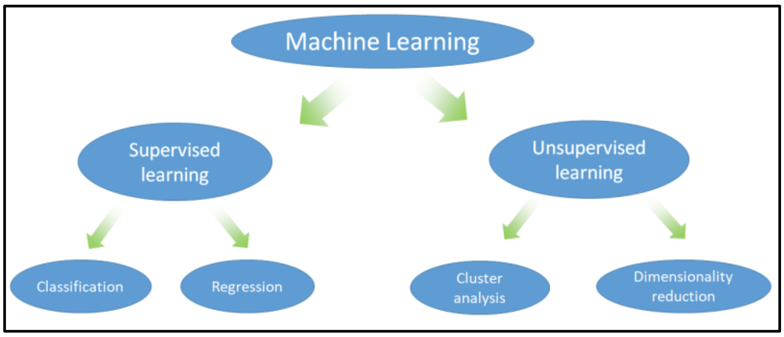


Fig.1 Machine learning methods (http://www.diegocalvo.es/en/machine-learning-supervised-unsupervised/)

2. THE IMPORTANCE OF HYDROGEOCHEMISTRY IN GEOTHERMAL EXPLORATION STUDIES

Geothermal well drilling operations are complex, long and expensive. Especially deep drilling, the costs may change 1.8-2.9 million USD for 1500-2500 m for geothermal reservoir exploration in Western Anatolia (Turkey). Even for an experienced drilling team, the operation is risky and is mostly under uncertain conditions at depth. For this reason, the success of the drilling during the development phase is often quite critical for the continuation of the project. Possible well locations are determined following a long survey on a map, this is why geothermal exploration requires extensive research in a field.

Geothermal exploration studies are of great importance to develop a geothermal project. The evaluation of existing geological, geophysical, geochemical data and previous drilling information constitute the first stage of geothermal survey in a field. Detailed information has been provided from field observation by collecting rock samples, water samples, and additional geophysical surveys such as gravity, magnetic, seismic, well logging, and magneto-telluric. After all geological and geophysical studies are completed, the detailed geological map, which includes possible fault systems, is prepared to find correct new well locations. Geochemistry and hydrochemistry attempts to approach reservoir temperature and fluid type, while reservoir dimension and permeability of the reservoir rocks tries to understand the target location. Reservoir temperature is one of the most critical parameters for the project aim. The reservoir temperature, fluid type and flow rates of the fluid at each well are of great importance to geothermal power projects, they directly affect the project budget if one of them fails to expectations in the project.

The reservoir temperatures could be calculated by different geothermometers, which is based on the hydrochemistry of the fluids. Different mineral and cations such as silica, Na-K, Na-K-Mg, gas or isotope geothermometers, under different reservoir condition expectations can be used to calculate reservoir temperatures. These studies help to predict the reservoir temperatures if there are any natural springs or existing geochemical data around the project area. Different researchers have proposed various geothermometers and as a new development. A few researchers have proposed to improve the existing calculation methods by artificial neural networks (Can, 2002; Diaz-Gonzalez et al., 2008). All geothermometer results can be compared to measured reservoir temperature after drilling operations and the most suitable geothermometer calculation can be defined for the next geothermal well in the area.

Haklıdır Tut and Haklıdır; 2019 proposed to a new approach to present hydrochemical indicators such as; silica, boron, chloride and fluid temperature relationship in geothermal fields. As a next step, the researchers try to predict the reservoir temperatures based on these hydrochemical indicators by supervised learning, which is a category of machine learning.

2.1 Basic Methodology and Dataset of the Study

In this study, a total of 74 thermal waters in Western Anatolia are used to calculation of reservoir temperatures. 15 of them are selected as test data, while the rest of them are identified as training data. After selection of the samples, detailed physical and chemical analysis are provided from different references. Some critical parameters such as pH, electrical conductivity, Na^+, K^+, B_{total}, Cl^- ions, and SiO_2 concentrations, which indicate water-rock interaction and deep recharge are selected for the study. Ground truth data contains real temperature values for each location in the test data.

Classification method is applied to the training data and 3 possible predicted classes are categorized as low (50-89 °C), medium (90-150 °C) and high (>150 °C). SVM (support vector machine), KNN (k-nearest neighborhood) and DNN (deep learning algorithms) are used to comparison of currency of the reservoir temperatures in the study area.

3. MAIN RESERVOIR CHARACTERISTICS OF WESTERN ANATOLIA GEOTHERMAL SYSTEMS

There are low, medium and high temperature geothermal sources in Western Anatolia. In the large graben systems, medium and high temperature geothermal systems have been observed. Geothermal power and heat production can be mostly provided along these graben systems (Fig.2; Haklıdır et al., 2014).

Geothermal power production is provided from temperatures between 170°C to more than 260 °C, these temperatures are found along the Büyük Menderes Graben (BMG), Gediz Graben (GG) systems in Western Anatolia. The installed capacity is around 1.5 GWe and the power cycle selections have been changed such as flash, multi-flash, advanced, and ORC-binary based on the reservoir temperatures (Haklıdır Tut and Balaban Özen, 2019).

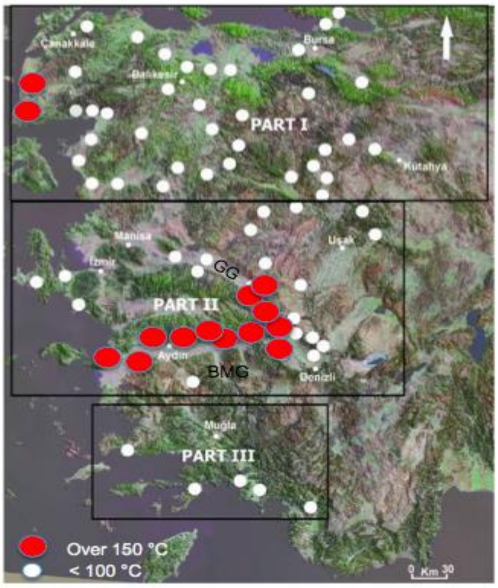
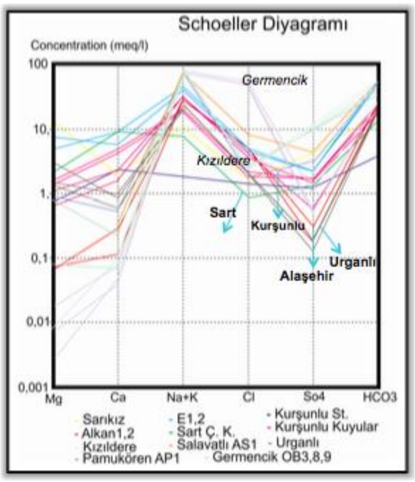


Fig.2 Geothermal sources in Western Anatolia

Geothermal waters show different characterization based on the reservoir rocks, water-rock interaction duration, water mixing and sea intrusion effects in Western Anatolia. For example, Germencik (Aydın) show marine sediments effects (paleo-sea) in the reservoir which cause high Cl^- and boron ion concentrations, whereas other geothermal systems have lower Cl^- concentrations in the study area (Fig.3). Tuzla (Çanakkale) geothermal system shows sea intrusion effects with high Cl^- concentrations in the reservoir (Baba et al., 2015). Stable isotope results indicate water-rock interactions (Fig.4).



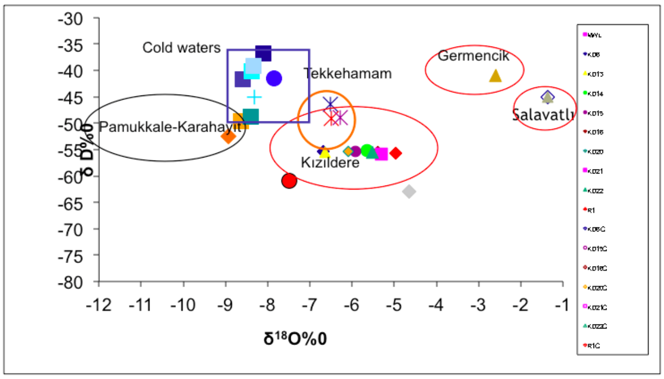
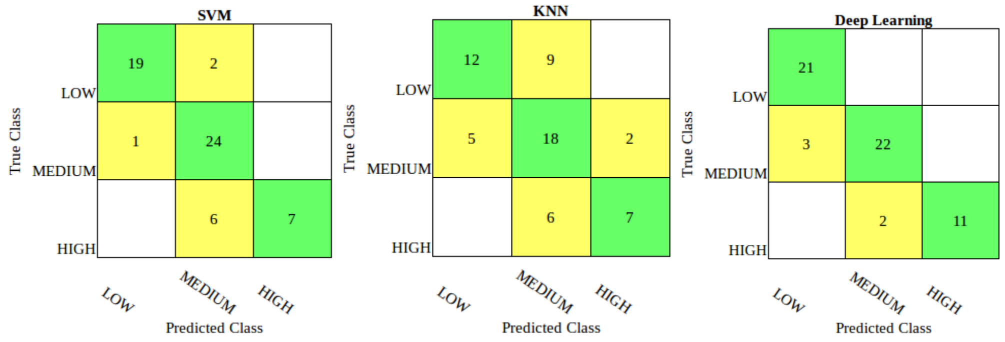


Fig.3 (Left) Geothermal water types in Western Anatolia and cold waters along BMG (Haklıdır et al., 2014)
Fig.4(Right) D-^{18}O isotope compositions of geothermal waters (Haklıdır Tut et al., 2012)

4. GEOTHERMAL RESERVOIR TEMPERATURE PREDICTION USING HYDROGEOCHEMISTRY BY MACHINE LEARNING

In this study, a deep learning classifier has been developed to classify predicted geothermal reservoir temperatures based on the hydrogeochemical data. We defined three main categories for the geothermal reservoir temperatures to classify our data: Low (50-89 °C), medium (90-150 °C) and high (> 150 °C). To compare the prediction performance of our proposed deep learning classifier, two traditional classification approaches, KNN and SVM, are implemented. They have been performed and the results have been presented.

Training and assessment of the machine learning models by using classification approach have been carried out. A confusion matrix is a method to summarize the performance of an algorithm for classification. The confusion matrices for the 3 classification methods, tables were used to describe the performance of the classifiers, seen in Fig. 5a, b, c.



a) SVM **b) KNN** **c) Deep Learning**

Figure 5a, b, c Confusion Matrices for SVM, KNN and Deep Learning methods

In this study, there were 3 possible predicted classes: "Low", "Medium", and "High". The classification models made a total of 59 predictions (25 low temperatures, 21 medium temperatures and 13 high temperatures). SVM classifier predicted 19 low temperatures and 2 medium temperatures of actual 21 low temperatures in reality. It predicted 24 of 25 medium temperatures and 6 of 13 high temperatures correctly (Fig. 5a). The KNN classifier predicted 9 of 21 low temperatures and 7 of 13 high temperatures correctly. KNN predicted 18 medium temperatures, 5 low temperatures and 2 high temperatures of actual 25 medium temperatures in reality (Fig. 5b). Deep learning method predicted all low temperatures correctly. It also predicted 22 of 25 medium temperatures and 11 of 13 high temperatures correctly (Fig. 5c).

The accuracy of classification is the ratio of correct predictions to total predictions. The accuracy of the classification methods have been given in Table 3.

Table 1. Accuracy of the classification methods

Classification Method	SVM	KNN	Deep Learning
Accuracy	83,20%	67,40%	92,60%

Comparison of the accuracy performance of these 3 models shows that the most accuracy is provided by Deep Learning algorithm with 92.6 % for the study.

Three classification models have been tested using test dataset with 15 testing data. The results have been given in Table 2.

Table 2. Classification models for the reservoir temperature prediction

Sample ID	Location	Temperature (C)	Reservoir Temperature Class	Prediction (SVM)	Prediction (KNN)	Prediction (Deep Learning)
Sample 1	Aydın	97	MEDIUM	MEDIUM	MEDIUM	MEDIUM
Sample 2	Balıkesir	92	MEDIUM	MEDIUM	MEDIUM	MEDIUM
Sample 3	Balıkesir	83	LOW	MEDIUM	MEDIUM	LOW
Sample 4	Balıkesir	53	LOW	LOW	MEDIUM	LOW
Sample 5	Bursa	94	MEDIUM	MEDIUM	MEDIUM	MEDIUM
Sample 6	Bursa	96	MEDIUM	MEDIUM	MEDIUM	MEDIUM
Sample 7	Çanakkale	103	MEDIUM	MEDIUM	MEDIUM	MEDIUM
Sample 8	Denizli	164	HIGH	HIGH	HIGH	HIGH
Sample 9	Denizli	156	HIGH	HIGH	MEDIUM	HIGH
Sample 10	Manisa	83	LOW	MEDIUM	MEDIUM	LOW
Sample 11	Denizli	183	HIGH	HIGH	HIGH	HIGH
Sample 12	Denizli	225	HIGH	HIGH	HIGH	HIGH
Sample 13	Denizli	208	HIGH	HIGH	HIGH	HIGH
Sample 14	Denizli	201	HIGH	HIGH	HIGH	HIGH
Sample 15	Denizli	207	HIGH	HIGH	HIGH	HIGH

The SVM model correctly predicted the reservoir temperature class of 13 out of 15 test locations. The reservoir temperature class of Sample 3, which is at the end of the low class limit with 83 °C, is to be medium. The reservoir temperature class of Sample 10 which temperature is 83 °C was predicted as medium incorrectly. The reservoir temperature class of all 7 high temperature locations in the test data was estimated correctly.

The KNN model incorrectly predicts the reservoir temperature class for Sample 4 and Sample 10 like as the SVM model. However, the predicted reservoir temperature class of Sample 9, which is at the beginning of the high-class limit with 153 °C, to be medium and made a significant prediction error.

The Deep Learning model correctly predicted the reservoir temperature class of all 15 test locations.

6.CONCLUSION

Reservoir temperature prediction is a part of geothermal exploration studies. It is possible to calculate by different type geothermometers. In this study, the existing hydro-geochemical data used to predict reservoir temperatures in Western Anatolia geothermal systems by Classification method of ML. SVM, KNN and DNN algorithms were evaluated on the same data for a consistent comparison of results for each approach.

Based on the results, the deep learning classifier, which has % 92.60 accuracy, correctly predicted the reservoir temperature class of all 15 test locations. The performance comparison showed that our deep learning classifier achieved better prediction performance than traditional machine learning techniques.

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