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The Fluid Temperature Prediction with Hydro-geochemical Indicators Using A Deep Learning Model: A Case Study Western Anatolia (Turkey)

Fusun S. Tut Haklidir[1], Mehmet Haklidir[2]

[1] Istanbul Bilgi University, Department of Energy Systems Engineering, Eyüp Istanbul-Turkey

[2] Istanbul Technical University, Control and Automation Engineering Department, Maslak Istanbul-Turkey,

fusun.tut@bilgi.edu.tr, mhaklidir@itu.edu.tr

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Abstract

Using geothermal fluids are beneficial however, it requires extensively exploration studies before drilling operations in a region. Geothermal drilling are complex and quite expensive operations that the costs may reach to 2.9 million USD for 1500-2500 m in Western Anatolia (Turkey) conditions. Because of the high operational costs, exploration phase of the geothermal projects is of great importance to reduce project costs. Evaluation of existing earth sciences data, detailed geology studies, mapping and some geochemical studies such as using geothermometers can provide important information to reach geothermal reservoir in a geothermal field. Nowadays, developing technology may give a chance to predict geothermal reservoir temperatures with less cost at geothermal fields. The hydro-geochemistry data quality is quite critical to predict reservoir temperature during the exploration phase.

Machine learning is a technique of data analytics, teaching computers to learn from previous experience. Machine learning algorithms use computational methods to learn required information directly from data and these methods adaptively enhance their performance by increasing the number of samples or learning information available. One of the important applications of machine learning is prediction of a result. Deep learning is a subset of machine learning that attempt to learn at various levels, corresponding to various levels of abstraction. It is generally used for abstract useful data information.

In this study, we developed a Deep Neural Network (DNN) model, to predict the geothermal fluid temperatures based on hydro-geochemistry data from Western Anatolia (Turkey). This is early stage study for the reservoir prediction and emphasize to data quality also. A comparative study of traditional machine learning algorithms has been performed to benchmark the performance of DNN predictions.

1. Introduction

Early stages of geothermal project development have significant financial risk. Most of the time, geothermal exploration requires literature survey, additional geological, geophysical and geochemistry studies for a potential geothermal field. After the detailed field survey, geothermal exploration drilling operation starts and resource exploration and drilling operations can equal to 42 % of total project costs for a geothermal power development project (Jennejohn, 2009). The success of drilling operation directly depends on initial exploration studies and the data collecting and gathering are quite important to find correct drilling location in the field. The exploration phase methodologies are also quite important to reach required reservoir conditions after the drilling operation. Fluid characterization, reservoir characteristics are critical to determination of design parameters for the selection of power cycle at high temperature systems.

Prediction of geothermal fluid temperature in a reservoir is critical issue among all exploration studies. If there are a few geothermal springs or shallow wells, it is possible to use geothermometers, which are using prediction of reservoir temperature based on hydro-geochemical characterization (such as Na^+, K^+, Mg^{2+}, SiO_2) of thermal waters before a drilling operation in a geothermal system (Arnorsson, 1975). These indicators may show water-rock interaction in deep and high temperature conditions at geothermal reservoirs. Cation and silica geothermometers are widely used to predict for geothermal reservoir prediction during the exploration phase at geothermal project development (Haklidir Tut, 2013). However, data quality is quite important

Deep learning (DL) is one of the approaches to machine learning (ML). Machine learning is a methodology by which the outcomes can be predicted based on a model prepared by training it on input data and its output behavior. Using deep learning for geothermal energy and geosciences is a new approach for now. There are a few studies on ML approaches for geothermal reservoirs (Tian and Horne, 2019; Li et al., 2017).

Principally, a performance comparison of the machine learning algorithms has been carried out and the results have been presented. In this study, more than 60 natural thermal springs are selected to create the data set, which represent different geothermal systems relatively high, medium and low temperatures in Western Anatolia (Turkey).

2. FLUID CHARACTERIZATION IN WESTERN ANATOLIA

Western Anatolian Graben Systems have both good reservoir potentials and fluid carrier properties by tectonic activities for geothermal systems. There are many low and low-medium temperature thermal springs can be seen along the large graben systems such as; the Büyük Menderes, the Gediz, the Simav and the Küçük Menderes Grabens. The highest reservoir temperatures are recorded over than 210 °C at west and east flanks of the Büyük Menderes Graben and southwest of the Gediz Graben in Western Anatolia. Almost all discovered high temperature geothermal reservoirs are identified as water-dominated with high noncondensable gases (98-99 %CO_2) (Haizlip Robinson et al., 2013).

In Kızıldere and Germencik geothermal systems, geothermal fluids indicate intense water-rock interaction due to high temperature and pressure conditions. High temperature geothermal fluids have higher Na^+, K^+, and Cl^- ion concentrations (Fig.1a). Alaşehir geothermal system shows high water-rock interaction however, it may reflect not deep feeding like Kızıldere and Germencik systems. Low-and medium low temperature other thermal waters have been observed at immature part of the Giggenbach Na-K-Mg diagram (Figure 1b).

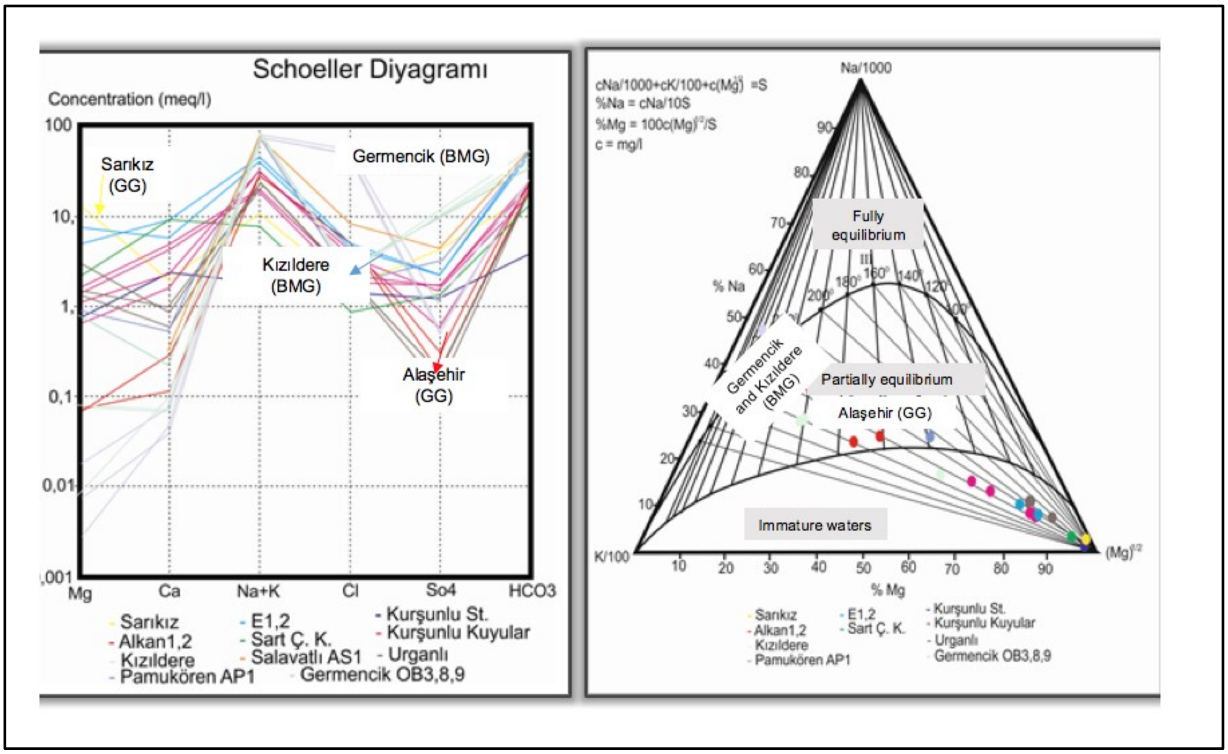


Figure 1a: Schoeller diagram of fluids for a few geothermal systems in Western Anatolia

1b: Na-K-Mg triangle for geothermal fluids at different geothermal systems in Western Anatolia (Haklıdır Tut et al., 2014)

3. METHODOLOGY

In this study more than 60 thermal springs at different temperatures are selected for the preparing of data set for the region by different references. These thermal springs are located along the different large graben systems in Western Anatolia and they categorized as high, medium and low temperature geothermal fluids. The categorization is accepted as Low temperature indicates to 20-40 °C, Medium temperature indicates to 40-60 °C while, the High shows more than 60 °C.

Some critical hydro-geochemical indicators are selected for the study that may indicate water-rock interaction effect at depth for the selected waters. These indicators consist of temperature of waters, pH and electrical conductivity values, Na^+, K^+, B_{total}, Cl^- ions and SiO_2 concentrations for each spring.

A comparative study of existing set of machine learning algorithms has been realized for the study. The machine learning models have been constructed based on the training dataset and have been verified with a test dataset. In this regression approach, the results obtained have been compared with the actual results as a numerical value.

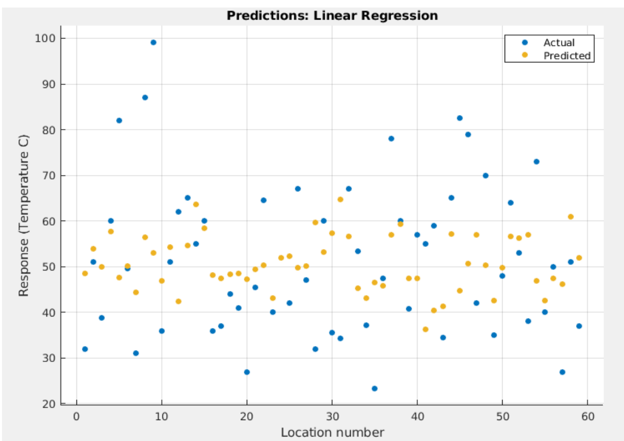
In this study, 3 data sets have been prepared for training, testing and ground truth data as part of the study approach. 16 set analysis of thermal springs are selected as test data. Ground truth data includes the required information of correct the fluid temperature for each location in the testing data list.

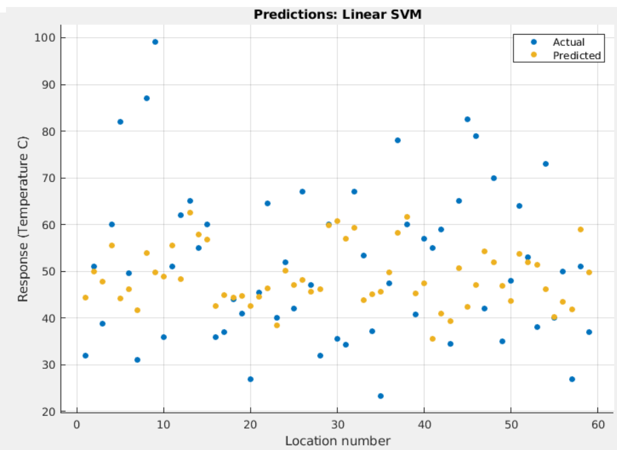
4. RESULTS AND DISCUSSION

4.1 GEOTHERMAL FLUID TEMPERATURE PREDICTION BY USING REGRESSION

Training and evaluation of machine learning models have been carried out using the regression approach. The results include the graphs showing the relation between predicted fluid temperature and actual geothermal fluids temperature for the training data.

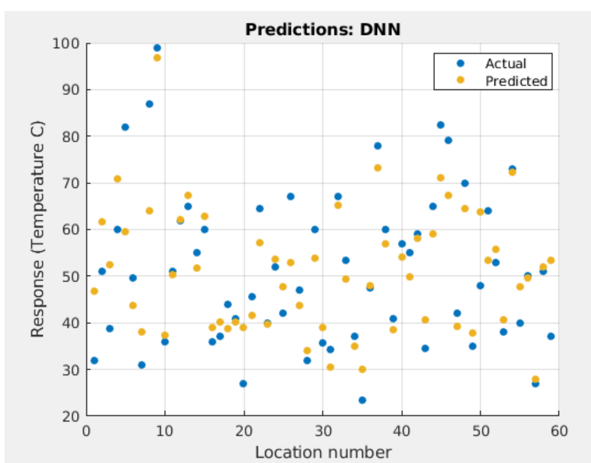
Fig. 2a, b,c include the location number against geothermal fluid temperatures plots for the 3 regression algorithms under consideration, covering both the predicted and the actual temperature values. The variation between predicted and actual reservoir temperatures have been depicted in these graphics. If actual and predicted points coincide, it indicates maximum accuracy.





a. Linear Regression

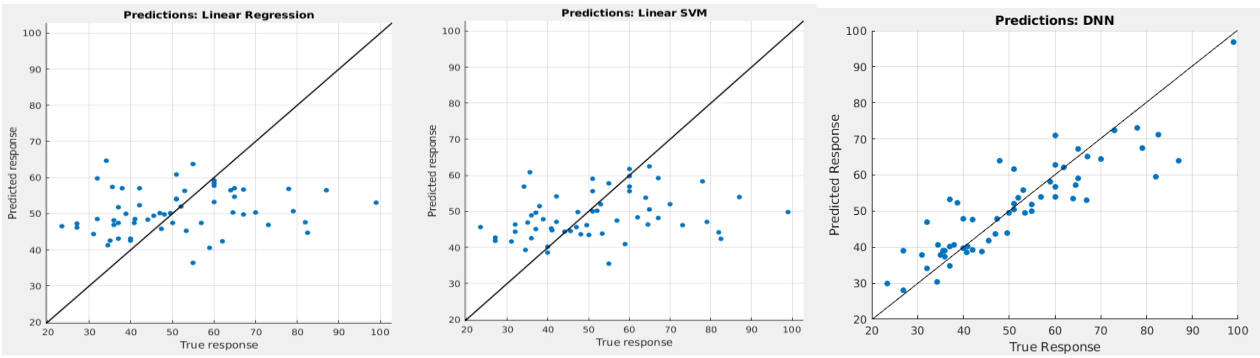
b. Linear SVM



c. DNN

Figure 2a, b, c: Response Plots - Visualisation of Location vs. Fluid Temperatures covering both predicted and actual values for the models by Linear Regression, Linear SVM and DNN

In Fig.3 a, b, c the variation of the actual fluid temperatures from the predicted of the training dataset have been plotted in the form of a regression line. The plots of performance of both of algorithms are included. For the most accurate algorithm, maximum points would be on the regression line.



a.Linear Regression b.Linear SVM c. DNN

Figure 3a, b, c: Visualization of the predicted fluid temperatures vs. actual values for Linear Regression, Linear SVM and DNN

RMSE and MAE values for the training of the models have been presented in Table 1.

Table 1: RMSE and MAE Values for Linear Regression, Linear SVM and DNN models

	Linear Regression	Linear SVM	DNN
RMSE (Root Mean Square Error)	18.73	16.95	9.64
MAE (Mean Absolute Error)	15.91	15.36	7.70

Linear Regression, Linear SVM and DNN models have been tested using the test dataset. The results include the graphs showing the relation between the predicted fluid temperatures and the actual fluid temperatures for the test data. The results have been given in Table 2. RMSE and MAE values for these models have been presented in Table 3.

Table 2: Measured (Actual) and Predicted Fluid Temperatures

Sample ID	Location	Actual (Real) Temperature (°C)	Prediction (Linear Regression)	Prediction (Linear SVM)	Prediction (DNN)
1	Aydın	40.5	40.5	36.3	41.6
2	Aydın	38.2	49.6	46.8	41.5
3	Balıkesir	51.0	54.8	52.9	51.7
4	Balıkesir	58.0	54.9	52.9	57.3
5	Denizli	72.0	58.3	58.3	81.3
6	Denizli	55.5	55.1	61.8	45.4
7	Balıkesir	34.0	50.4	48.6	43.2
8	Balıkesir	27.0	45.9	41.7	37.8
9	Balıkesir	28.8	49.4	45.4	39.0
10	Balıkesir	33.0	49.1	44.5	36.9
11	İzmir	62.0	56.1	54.9	64.2
12	İzmir	86.0	68.9	72.5	72.5
13	İzmir	65.0	48.4	43.8	40.2
14	Manisa	55.0	45.3	43.0	41.5
15	Çanakkale	60.0	55.6	52.0	53.1
16	Bursa	36.0	49.8	46.9	52.8

Table 3: RMSE and MAE Values for test data by using Linear Regression, Linear SVM and LSTM models

	Linear Regression	Linear SVM	DNN
RMSE (Root Mean Square Error)	12.65	11.70	10.71
MAE (Mean Absolute Error)	10.75	10.61	8.56

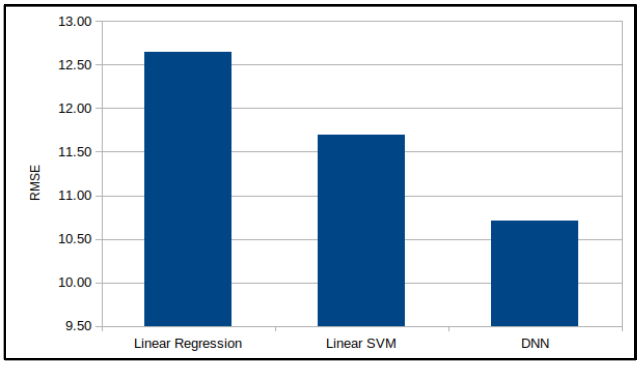


Figure 4: Visualisation of Root Mean Square Error Values for Linear Regression, Linear SVM and DNN models

The main objective is to obtain lowest RMSE Value the algorithm having. Based on the results, DNN algorithm generates the least error (Table 1 and Table 3). In the study, neither linear regression nor linear SVM algorithms provide satisfactory results for the low and high temperature prediction. However, some anomalies are detected at the results which may evaluated unexpected based on the chemistry of geothermal fluids such as 6, 9, 16 sample ID numbered which are categorized as Low in dataset. DNN algorithm gives more accurate values especially for the High temperature fluids which temperature higher than 60 °C.

5. Conclusion

In this study, natural thermal springs at different temperatures are used to create the dataset which belong to different geothermal systems in Western Anatolia (Turkey). More than 60 thermal springs are selected for training set and 16 set analysis of them are selected for the test data. A limited hydro-geochemical dataset has been used because lack of reliable open data in the study area. It is accepted that all given data set in the data set is correct when making temperature estimates in the study. As the quality and number of data increases, the accuracy of the estimates is expected to increase.

A performance comparison of machine learning methods tried to perform on data set. Both regression and classification approaches has been used in this study. The different algorithms were applied to the same data to reach consistent comparison of results for each used approach. In regression approach, neither the Linear Regression nor the linear SVM algorithms give satisfactory results for the low and the high temperature prediction for the fluids. DNN algorithm gives more accurate values especially for the High temperature fluids which temperature higher than 60 °C.

It is expected that working with more qualified data may give more effective results for a geothermal system. It is thought that these results may provide a new approach for the exploration phase in a geothermal field in near future. Hydro-geochemical indicators of geothermal systems may be used to more widely for the exploration phase and they may be correlated with geothermometers in a geothermal field. It is possible to use Machine Learning methods to predict reservoir temperatures from surface temperatures before the decision of a new drilling operation. Both old geological well logs, reservoir levels and temperature data can also be used for this approach.

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