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A Predictive Model of Wellbore Performance in Presence of Carbon Dioxide in Kizildere Geothermal Field

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ABSTRACT

Typically, geothermal wellbore model is used to predict the production performance of wells using a wellbore simulator based on flow tests. An iterative procedure is used to calibrate NCG content. In this study, a predictive modelling approach harnessing the power of machine learning is proposed. Several deep well data in Kizildere Geothermal Field have been used to calibrate the model. The results are compared to flowmeter data attached to a mini separator. It has been observed that flowmeter NCG results are consistent with predictive modelling results in most of the wells. Since NCG measurements with mini separator are challenging, it is possible to predict NCG values for the wells without actual measurements at the wellsite.

1. INTRODUCTION

There are several geothermal systems throughout the world which contain more than 1% non-condensable gas (NCG) by weight dissolved in the liquid phase and there are multiple systems in active graben areas in the western part of Turkey (Haizlip et al., 2013). As cited in (Haizlip et al., 2016), most geothermal systems in the western part of Turkey are characterized by fluid temperatures (150°C to 240°C), liquid-dominated, high in NCG (more than 1% by weight in the reservoir) (Aksoy, 2015, Haizlip et al., 2013), low to moderate salinity and hosted in marine and lacustrine carbonate, marbles, meta carbonates and calc-schist reservoirs (Simsek, 1985, Yilmazer et al., 2010). Calcite is the dominant carbonate mineral in most of these rocks.

The first commercial scale geothermal power plant of Turkey was built in Kizildere Field in 1984. The total capacity of the Kizildere Geothermal Field has reached 260 MW. The plant is located between Denizli and Aydin provinces, at the eastern part of the Buyuk Menderes Graben, which is between the Buldan and Babadag Horsts. Menderes metamorphics which mainly consist of augen gneisses, schists, quartzite, micaschists and marbles form the basement rocks (Karamanderesi, 2013).

Although the Kizildere resource has a reasonably high enthalpy, it presents very high concentrations of NCG consisting of mainly carbon dioxide in the reservoir. CO_2 content in the produced water is 2-3% range by weight (even higher in some cases) (Satman et al.,2016). The partial pressure exerted by CO_2 is a significant source of fluid uplift in the wellbore.

Presence of high CO_2 in geothermal fields may cause some operational and environmental issues. For this reason, Horizon 2020 Research and Innovation programme contributes to the Geothermal Emission Control (GECO) Project. The project will advance the provision of cleaner and cost-effective geothermal energy across Europe and the World with reduced emissions of carbon and sulphur. The core of this project is the application of an innovative technology, recently developed and successfully demonstrated at a pilot-scale in Iceland, which can limit the emissions from geothermal plants by condensing and re-injecting gases in the subsurface, or turning them into commercial products. GECO aims to increase public acceptance and generalise this novel approach. To that end, the re-injection method will be applied in four distinct geothermal systems in four European countries: 1) a high temperature basaltic reservoir in Iceland; 2) a high temperature gneiss reservoir in Italy; 3) a high temperature metamorphic reservoir in Turkey and 4) a low temperature sedimentary reservoir in Germany.

As a result, monitoring the CO_2 content of the produced fluid is of a great importance in Kizildere Geothermal Field. Considering the number of production wells in the field, these measurements can be time consuming. In order to develop an effective way of CO_2 measurements a machine learning approach has been utilized.

2. METHODOLOGY

Two methods of CO_2 wt% evaluations are described in following sections which are CO_2 wt% calculation with Wellbore Simulator and NCG Measurement with Mini Separator and Flowmeter, respectively.

2.1 CO_2 Calculation with Wellbore Simulator

The pressure drop related with two-phase fluid transport in geothermal wells represent the effects of friction, acceleration and the elevation change. The simulator treats the steady flow of liquid water and steam through the wellbore including the parameters that describes the well deviation, formation temperature distribution with depth and effective thermal conductivity. For the wellbores with two-phase flow at the bottom of the well, the fluid state is determined by specifying bottom hole flowing pressure, flowing enthalpy, salinity, and gas content in the reservoir (Garg et al., 2005).

The downhole pressure and temperature profiles in the cased portion of flowing wells have been simulated using a steady-flow wellbore model and CO_2 content has been evaluated. Static temperature and pressures required to calibrate the model are acquired from Kizildere numerical model. Details of this numerical model are reported elsewhere (Kucuk et al, 2020).

The matching consists of systematically altering CO_2 content and the P and T of feed (i.e. reservoir) formation until a satisfactory match is obtained. Dynamic pressure and temperature match for a well in Kizildere Geothermal Field for different dates in 2018 are shown in Figure 1 and 2. They all match with great accuracy. CO_2 wt% have been calculated as 3.8% and 3.2% in February and December 2018 for this well, respectively.

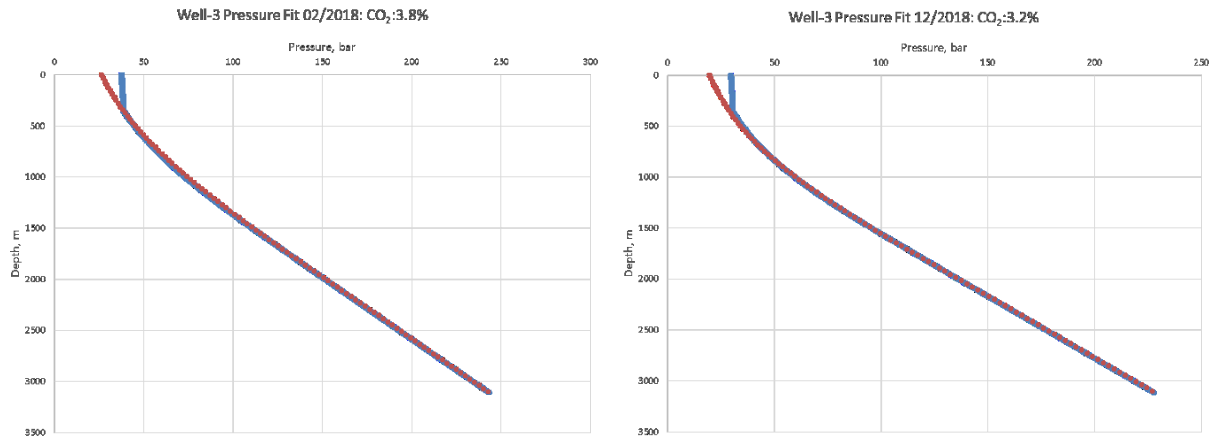


Figure-1: Dynamic Pressure Match for Well-3: February and December 2018.

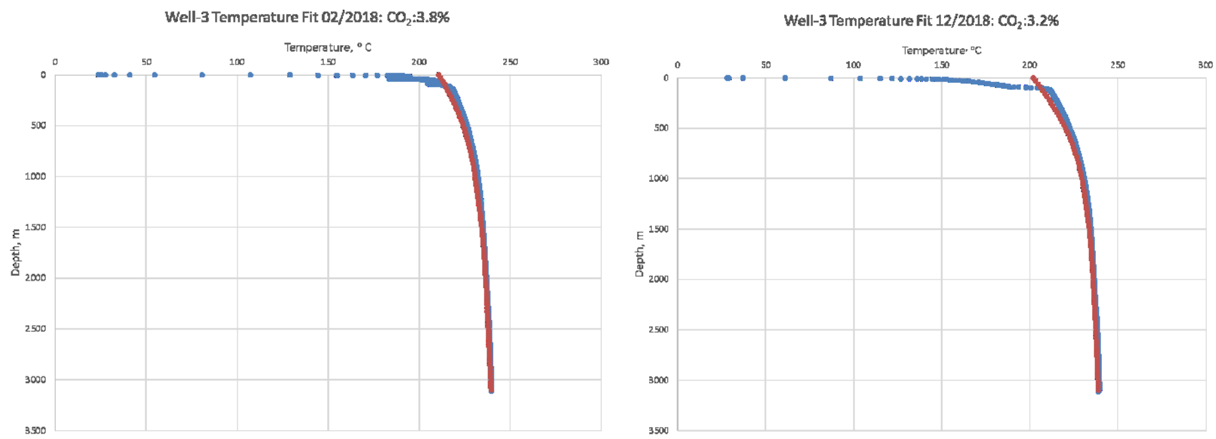


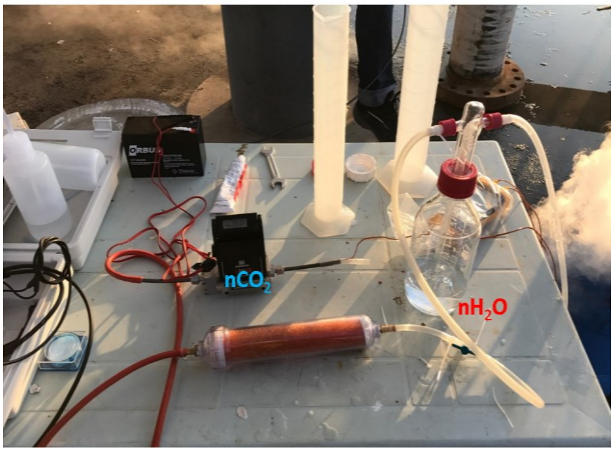
Figure 2: Dynamic Temperature Match for Well-3: February and December 2018.

2.2 CO_2 Measurement with Flowmeter

The geothermal fluid is in the liquid phase in the reservoir of Kizildere Geothermal Field. As the geothermal water rises in the well, with the decrease of the pressure on the fluid, steam and the dissolved gases like CO_2 pass into the gas phase. When the geothermal fluid reaches to the surface of the well, it consists of steam, water and non-condensable gas components under surface production conditions. In order to determine the characteristics of each phase, separators and condensers at the well heads are used (Figure 3-a).

In this method, the gas coming from gas outlet of the mini separator and passes through the condenser. Steam then condenses through the condenser. Hence, the non-condensable gases consisting mainly carbon dioxide and water (condensed steam) are separated. The water is accumulated in the gas washing bottle whereas carbon dioxide gas is passed through flowmeter simultaneously (Figure 3-b). The mass of carbon dioxide gas is measured using the Sierra brand 822-S model mass flowmeter. In the gas flow meter, the gas is passed through a special chamber and the mass or volumetric flow rates are calculated with heat transfer equations that uses temperature difference between two distinct detectors. The amounts of accumulated water in the gas washing bottle and the amount of CO_2 measured by flowmeter are proportionated each other.

(a)



(b)

Figure 3: In situ CO_2 measurements and equipments in Kizildere field. CO_2 and steam are separated by using mini separator and condenser (a). nCO_2/nH_2O is determined via flowmeter and gas wash bottle.

CO_2 measurements are collected on monthly basis from the wells in Kizildere Geothermal Field. CO_2 wt% from wellbore model and flowmeter measurements are compared in Table 1. Although the results are close to each other, it should be noted that CO_2 measurements may give wrong results due to slug or intermittent flow in the well. Ideally, such measurements should be carried out when there is bubbly flow or dispersed flow.

Table 1: CO_2 wt% comparison Wellbore Model vs. Flowmeter

Well	CO_2 wt% from Wellbore Model		CO_2 wt% from Flowmeter	
Well-1	3.5 (Feb-18)	3.2 (Dec-18)	3.3 (Feb-18)	2.8 (Dec-18)
Well-2	1.7 (Aug-17)	0.6 (Jul-18)	1.5 (Aug-17)	0.6 (Jul-18)
Well-3	3.8 (Feb-18)	3.2 (Dec-18)	4.0 (Feb-18)	3.0 (Dec-18)
Well-4	3.2 (Feb-18)	2.8 (Dec-18)	3.9 (Feb-18)	2.8 (Dec-18)
Well-5	3.8 (Feb-18)	3.0 (Dec-18)	4.4 (Feb-18)	3.0 (Dec-18)

2.3 CO_2 Prediction with Machine Learning

In this study, 210 CO_2 measured data from the wells in the field in 2018 on monthly basis have been used for the training dataset.

On the well basis; number of days on production, CO_2 wt% (in the reservoir), flow rate, well flowline temperature and pressure, closed $9^{5/8}$ in. casing depths and the regions data have been used as the training dataset in machine learning algorithms. In order to define the regions, the field has been divided into 28 grids (Figure 4) and the wells which belong to these grids have been defined accordingly.

Figure 4: Regions used in Machine Learning.

Different machine learning algorithms have been tested and the following three gave successful results for the available data;

- **Random Forest:** Random forest is a popular method that can be used to build predictive models for both classification and regression problems. It is a combination of tree predictors such that each tree depends on the values of a random vector sampled independently. It can also perform dimensional reduction methods which detect outlier values, treat missing values and other steps of data exploration as well. It is known as an ensemble way of learning as a group of weak models that are combined to form a much powerful model. For the classification of new object based attributes, every one of the trees represents a classification. This presentation is also known as ‘voting’ for the class. The forest is then given a choice to choose the classification with the most votes (Sullivan, 2017). Some random forests which are reported in the literature have consistently lower generalization error than others (Breiman, 2001).

- **Decision Tree:** Decision tree is a range of conditions and actions depicted as nodes and the branches of the tree which link the premises with conclusions. It is a classifier expressed as a recursive partition of the instance space and it consists of nodes that form a rooted tree, which means that it is a directed tree with a node called “root” that has no incoming edges. All other nodes have exactly one incoming edge. A node with outgoing edges is called an internal node and all other nodes are called leaves. In a decision tree, each internal node splits the instance space into two or more sub-spaces according to a certain discrete function of the input attributes values (Rokach and Maimon, 2005).

- **Kstar:** The K* algorithm uses entropy as a distance measure, as a stronger approximation to handling symbolic, real-valued attributes, missing values and it is an instance-based learner which uses such an evaluation (Martínez-López et al.,2016).

Total number of instances used in the training dataset are 210 and 10 for the test dataset. A 10-fold cross-validation method has been used to ensure that the training data is not over fitted.

3. RESULTS

Correlation coefficient, mean absolute error, root mean squared error, relative absolute error, root relative squared errors and the number of instances values for the training and test dataset are presented in Table 2 and 3. Root mean squared errors (RMSE) for the training dataset as per Random Forest, Decision Tree and Kstar machine learning algorithms are 0.5182, 0.5719 and 0.5158 and for the test dataset they are 0.0987, 0.2178 and 0.2721, respectively. Random Forest algorithm has the lowest RMSE for both training and test datasets. Actual and predicted CO_2 wt% results have been compared in Table 4 and Figure 5, 6, 7 and 8. All three machine learning algorithms give successful results; however, Random Forest algorithm gave the best predicted results.

Table 2: Training dataset results

Summary	Random Forest	Decision Tree	Kstar
Correlation coefficient	0.9464	0.9311	0.9452
Mean absolute error	0.3067	0.3674	0.2845
Root mean squared error	0.5182	0.5719	0.5158
Relative absolute error	23.39%	28.03%	21.70%
Root relative squared error	32.88%	36.28%	32.72%
Total Number of Instances	200	200	200

Table 3: Test dataset results

Summary	Random Forest	Decision Tree	Kstar
Correlation coefficient	0.9969	0.9880	0.9806
Mean absolute error	0.0766	0.1788	0.2080
Root mean squared error	0.0987	0.2178	0.2721
Total Number of Instances	10	10	10

Table 4: Test dataset results- actual vs. predicted CO_2 wt%

	Random Forest				Decision Tree				Kstar			
inst#	actual CO_2 wt%	predicted CO_2 wt%	error	abs. error %	actual CO_2 wt%	predicted CO_2 wt%	error	abs. error %	actual CO_2 wt%	predicted CO_2 wt%	error	abs. error %
1	4.33	4.21	-0.12	2.70	4.33	4.34	0.01	0.28	4.33	4.52	0.19	4.41
2	0.60	0.66	0.06	10.50	0.60	0.61	0.01	2.00	0.60	0.65	0.05	7.67
3	3.38	3.24	-0.14	4.20	3.38	3.19	-0.19	5.62	3.38	3.16	-0.22	6.63
4	2.79	2.80	0.01	0.39	2.79	3.23	0.44	15.77	2.79	3.17	0.38	13.51
5	0.60	0.65	0.05	8.17	0.60	0.65	0.05	9.00	0.60	0.60	0.00	0.17
6	3.20	3.39	0.19	5.84	3.20	3.41	0.21	6.56	3.20	3.15	-0.05	1.69
7	3.08	3.05	-0.03	1.10	3.08	3.22	0.14	4.55	3.08	3.04	-0.04	1.40
8	2.98	2.98	0.00	0.07	2.98	3.22	0.24	8.05	2.98	2.55	-0.43	14.30
9	1.10	0.96	-0.14	13.09	1.10	0.86	-0.24	21.64	1.10	0.92	-0.18	16.18
10	1.58	1.60	0.02	1.08	1.58	1.33	-0.25	16.01	1.58	1.04	-0.54	34.11

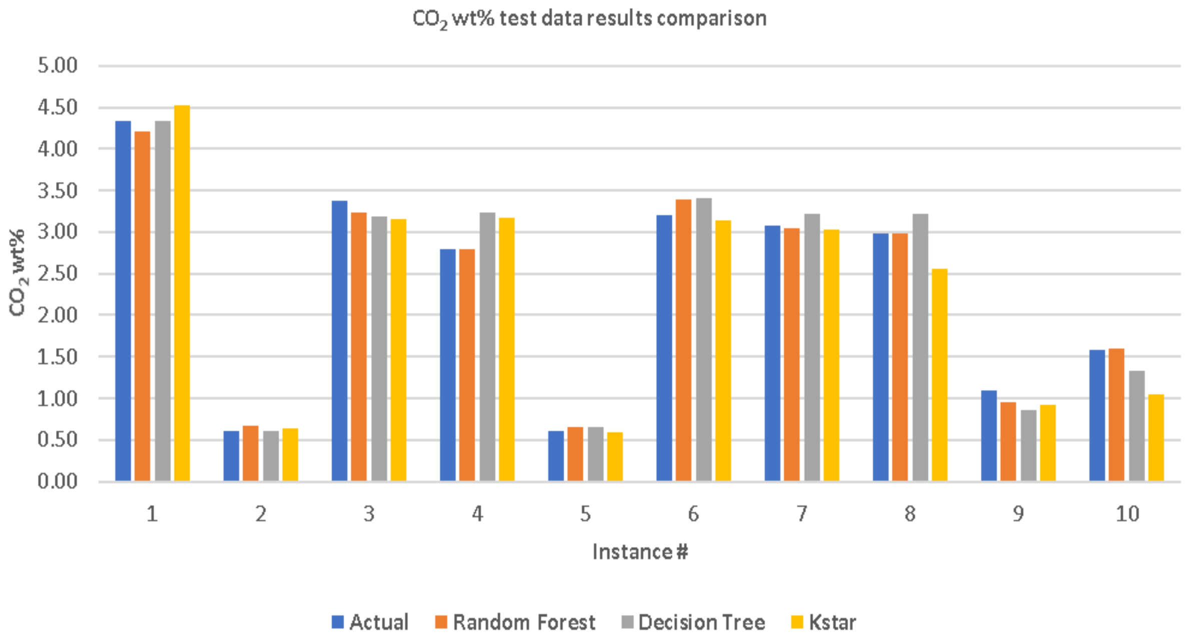


Figure 5: CO_2 wt% test data results comparison.

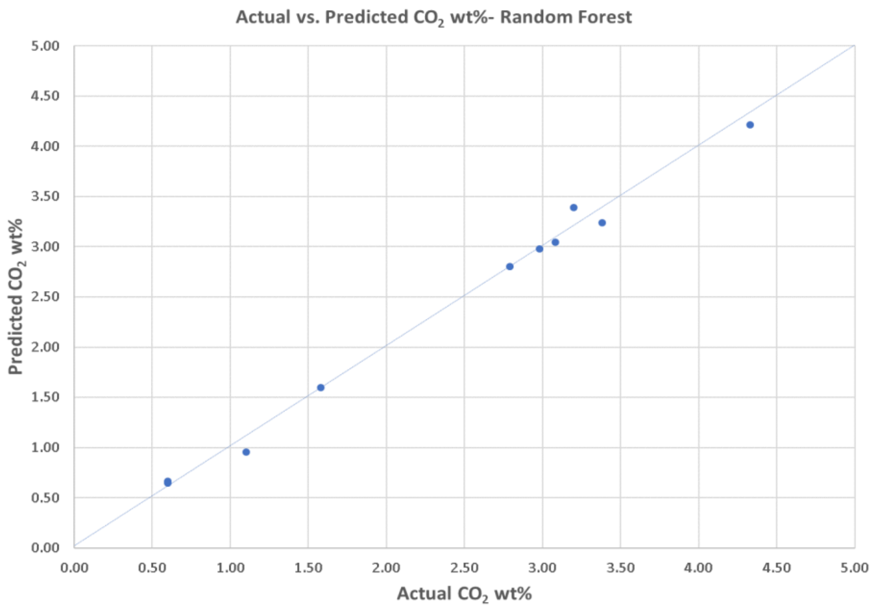


Figure 6: Actual vs. predicted CO_2 wt% comparison for Random Forest Algorithm.

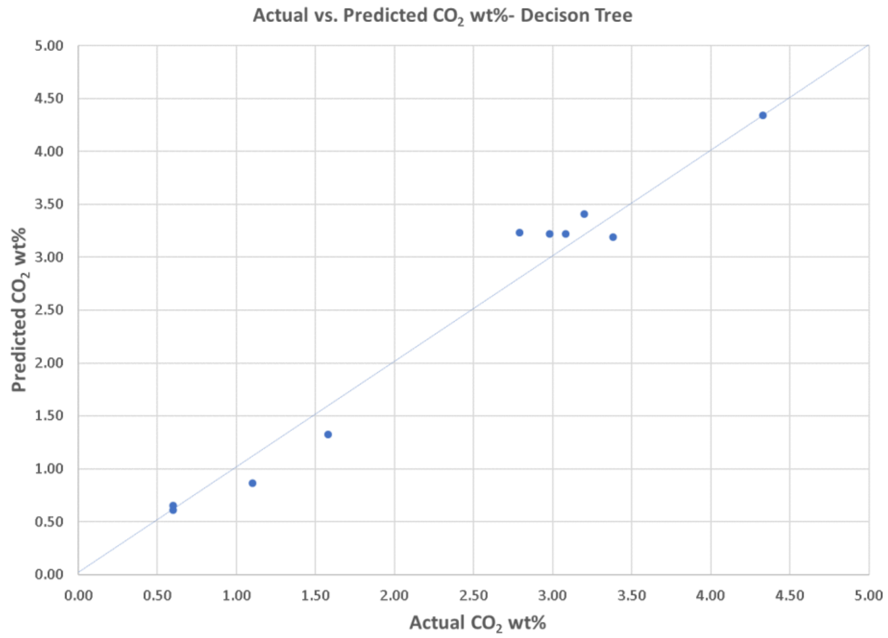


Figure 7: Actual vs. predicted CO_2 wt% comparison for Decision Tree Algorithm.

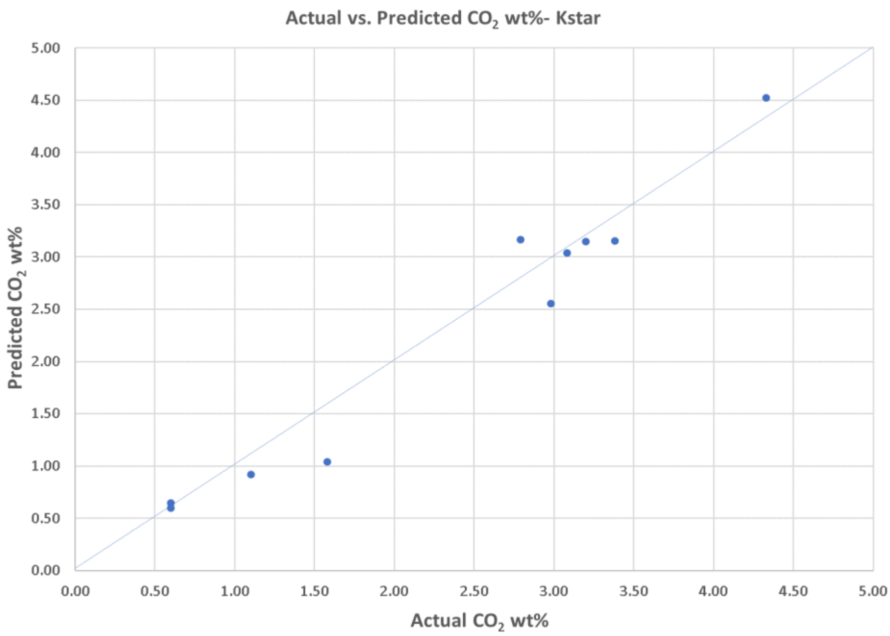


Figure 8: Actual vs. predicted CO_2 wt% comparison for Kstar Algorithm.

The results show that Random Forest algorithm successfully represents the CO_2 behavior of Kizildere production wells at different times. The developed predictive model gives successful results regardless of distance to major geological features such as faults and changing reservoir conditions as a function of time showing the success of the model. The developed predictive model can be used to model production from deep Menderes metamorphics (i.e. Marble); however, with additional data it can be used to predict behavior of shallower production wells. In this regard, this model is representative of Phase II and Phase III production wells.

4. CONCLUSION

In this study, CO_2 wt% measurements from the wells in Kizildere Geothermal Field, which have been taken on monthly basis in 2018 were used to create the datasets to for machine learning algorithms. A total of 210 datasets are selected for training data and 10 datasets are selected for the test data. As per the RMSE values for the machine algorithms used, Random Forest algorithm gave the best and successful results for the predicted CO_2 wt%; however, these results can be improved if more data is provided. Since CO_2 wt% measurements are taken on monthly basis, with this approach more CO_2 wt% data can be provided for better well monitoring without actual measurement at the wellsite. It should be noted that this study is only valid for Kizildere Geothermal Field; however, this approach can easily be applied to other geothermal fields. With this method more frequent CO_2 wt% data can be provided without actual wellsite measurement which leads cost savings to the companies.

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