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Optimization of Production and Injection of Geothermal Fields: A Machine Learning Approach

Ali Baser[1], Serhat Kucuk[1], Onder Saracoglu[1], Erdinc Senturk[2], and Serhat Akın[1]

[1]Middle East Technical University, Petroleum and Natural Gas Engineering Department, Ankara, Turkey

[2]Zorlu Energy Group, Zorlu Plaza, Avcılar, Istanbul, Turkey

alibaser@metu.edu.tr, kserhat@metu.edu.tr, ondersar@metu.edu.tr, erdinc.senturk@zorlu.com, serhat@metu.edu.tr

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ABSTRACT

Optimizing field injection and production requires a calibrated numerical model, typically consisting of thousands of grid blocks. Optimization carried out using such a model usually takes a very long time. If the numerical model is replaced by an accurate proxy model, run-time can be significantly reduced. A numerical model has been developed using TOUGH2 to optimize the production of Kızıldere geothermal field. A proxy model developed in Python is used to optimize the production and injection of the field. The results are compared with the TOUGH2 model. The proxy model results are consistent with the field model. This approach significantly reduces time and effort.

1. INTRODUCTION

Turkey is located in the eastern part of Alpine-Himalayan orogenic belt. As a result of tectonic activities, the region has many young grabens, a great number of faults and extensive volcanism, which are some of the most important parameters enabling the existence of a geothermal field. Since the earth's crust is thinner under grabens, geothermal fields may occur along these grabens just like the east-west trending Büyük Menderes Graben. The graben hosts many high enthalpy geothermal fields of Turkey.

With the completion of the first well at a depth of 540 m in 1968, the first geothermal field of Turkey was discovered in Kızıldere with a temperature of 198°C and the first commercial scale geothermal power plant of Turkey was built in Kızıldere in 1984 (Şimşek et al., 2009). After being operated for 24 years by Turkish Electricity Generation Co. Inc., Kızıldere Geothermal Field had undergone privatization in September 1, 2008. Zorlu Energy acquired the operational rights of the license area, including the power plant, for 30 years. New production and reinjection wells were drilled as a part of Kızıldere Phase-II and Phase-III development plans and the total capacity of the Kızıldere Geothermal Field has reached 260 MW, making the field one of the most important geothermal energy locations of the world.

Kızıldere geothermal field is located between Denizli and Aydın provinces, in the eastern part of the Büyük Menderes Graben, between the Buldan and Babadağ Horsts (Figure 1). Currently, more than 80 wells are operational (both production and injection) in the field, some of them are reaching more than 3500 meters depth. Although the characteristics of the reservoir are well-known to some extent, decline of the reservoir pressure is an issue in the field. The ratio of produced and reinjected fluid, the location and depth of the wells influence the rate of pressure decline.

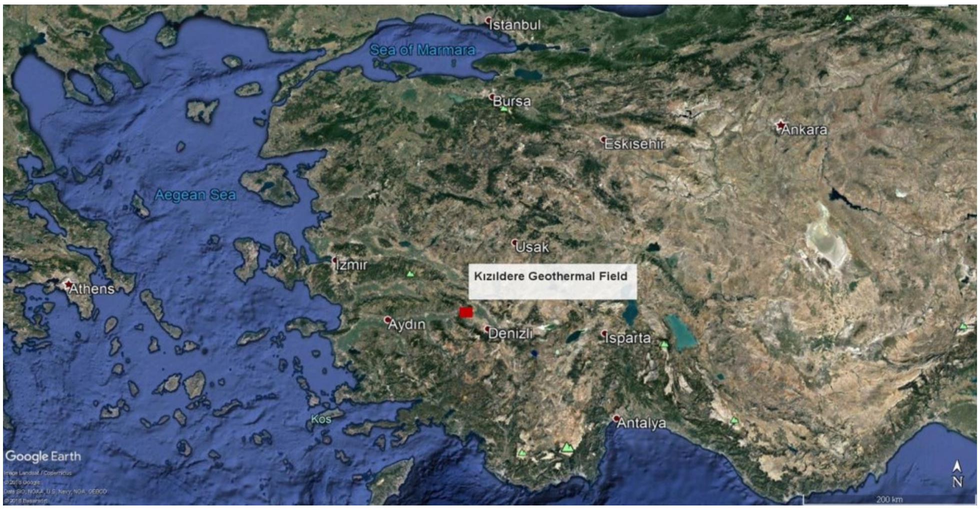

Figure 1: Location of Kızıldere Geothermal Field.

In order to address this issue, a numerical model of the field was constructed with TOUGH2 numerical simulator (Kucuk et al,. 2020). EOS2 fluid property module of TOUGH2 (which handles water-CO_2 mixtures) was used, since the field contains significant amount of CO_2, which has considerable effects on the reservoir performance. PetrasSim is used as the graphical interface to the TOUGH2 numerical simulator. It is a helpful tool for pre-processing and post-processing of data, as well as visualization of the simulation parameters.

The model was calibrated with existing static and dynamic p-T data as well as pressure observation data obtained from observation wells located at differing locations in the well field. The average difference between the observed and the simulated data was 3.8% and 5.6%, respectively for static pressure and static temperature profiles of more than 50 wells. After the validation of the numerical model, it was used to assess the current situation of the field and to propose optimum reinjection/production strategy with the existing wells. According to Kucuk et al. (2020), the optimum scenario for Kızıldere Geothermal Field is to shift the reinjection water from the eastern and north-western shallow wells to the deeper wells located at the southern and eastern boundaries, which allows significant increase of the production rates and pressure support.

The procedure for finding the optimum scenario for a geothermal field can be really time consuming due to its trial and error nature. This issue can be addressed by developing a proxy model, which significantly decreases computation time if a successful calibration is possible. The aim of this study is to showcase an approach to create a proxy model in order to perform numerous and very time-consuming simulations to be used in production and injection optimization in a very short time.

2. METHODOLOGY

In order to create a proxy model to be used in optimization calculations, a training data set needs to be built for the proxy. This data set is built using the numerical model and a specific simulation methodology. The data should encompass the area and at the same time, the range of the values needed for the simulation must be comprehensive and attainable in reasonable time frames. To fulfill both conditions, being encompassing and reasonable, eight different regions (Figure 2) have been selected in the numerical model. These regions are selected according to their depth and proximity to geological features such as producing formations and faults. Region "a" includes shallow Phase-1 production wells of the field. Region "b", "c1" and "c2" are composed of Phase-2, Phase-3.1 and Phase-3.2 production wells respectively. Region "i1" represents the injection wells located on eastern part of the field and most of them are shallow. On the other hand, wells in region "i2" are relatively deeper. Regions "i3" and "i4" includes injection wells located on the western part of the field; where "i3" represents the deeper injection wells, "i4" represents the shallow ones.

Since there are a total of 8 regions, the possible scenarios had to be calculated as x^8, where x denotes the number of different coefficients for production and injection rates. Assigning two different production and injection coefficients as ratios to each region (i.e. 0.7 and 1.3), $2^8 = 256$ possible scenarios had to be performed to create the dataset for training the proxy model. For example, in one of 256 scenarios, production rates for the wells in region "a" are multiplied by 1.3 while reinjection rates in "i4" region are multiplied by 0.7.

A custom visual basic code has been written to create the input files for 256 different TOUGH2 simulations. The program imports the PetraSim well data file and manipulates the flow rates accordingly. Next, another script runs TOUGH2 simulations by loading the input files for each scenario.

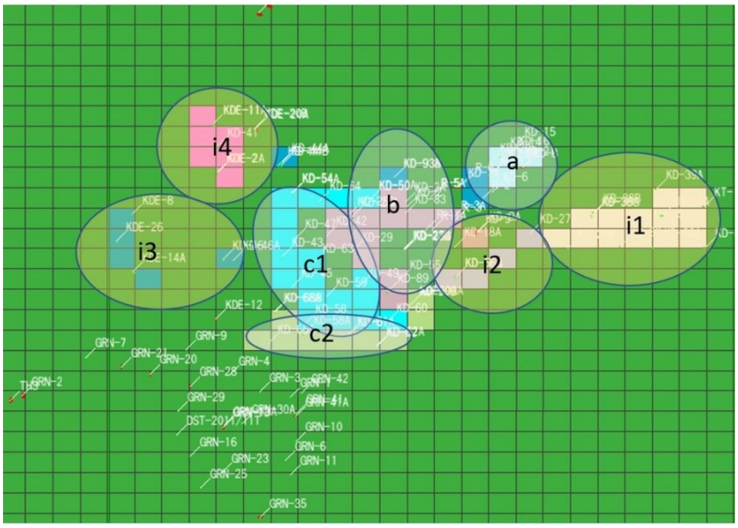

Figure 2: Selected regions to be manipulated by coefficients.

After completing the TOUGH2 simulations, in order to build the training datasets for the proxy, the sample space had to be determined mainly by considering the cells corresponding to the $9^{5/8"}$ casing depth. A comprehensive representation of the field was attained by selecting the cells encompassing production and injections fields (Figure 3). A total of 36 different cells have been selected as sample points. Then, temperature and pressure values collected from these sample points for each scenario are written into a file. Next, collected data were reorganized in a randomly manner in order to be used as training and testing datasets. Resulting dataset is composed of 200 instances and test dataset has 56 instances for each of 36 sample cells. Using these datasets, a multilayer perceptron has been trained as a proxy model.

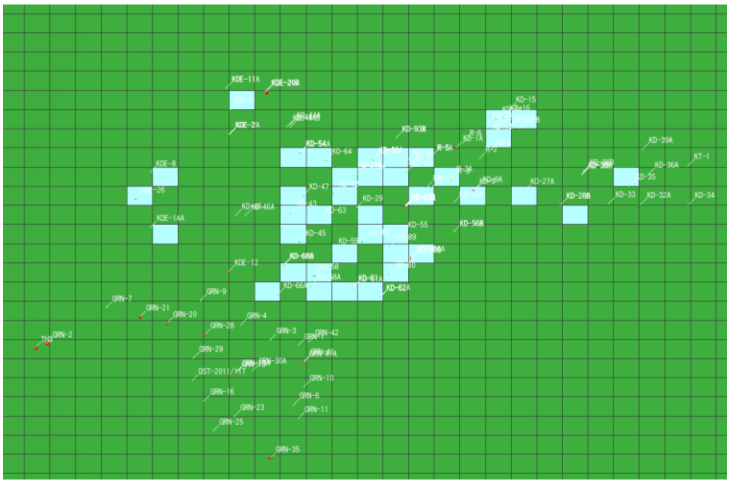

Figure 3: Sample cells.

Perceptron is a unit which takes a vector of real value inputs, calculates a linear combination of these inputs and produces an output depending on an activation function (Mitchell, 1997). By combining perceptrons in a layered fashion, neural networks are constructed. A type of neural network in which data flows in one way only, from input layers to output layers is called feedforward network. Multilayer perceptrons are also feedforward neural networks with hidden layers which would not be seen by any input or output layers directly (Hawkin, 2014).

The structure of the multilayer perceptron used for training the proxy model involves an input layer x of 73 different flow rates of wells, two hidden layers n and m with 37 and 18 nodes respectively, lastly an output layer with a single node (Figure 4). Sigmoid function has been used as the activation function for all nodes.

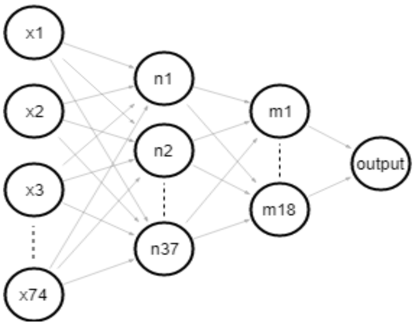

Figure 4: Multilayer perceptron diagram.

After training the multilayer perceptron on the training data set with 10-fold cross validation, root mean squared error remained below 0.35 and R^2 (coefficient of determination, best possible score is 1) remained above 0.9993 for all cases, which proves excellent correlation between the proxy model and the simulation. Table 1 shows a sample data from the test set and its corresponding prediction. Figure 5 shows the general relation of predicted values from proxy model vs actual values from simulation model.

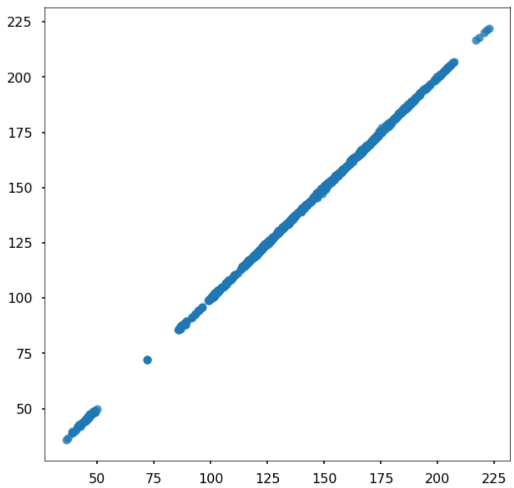

Figure 5: Predicted vs actual values for test data.

By validating the accuracy of the proxy model, production and injection optimization process could be started. While working with the actual numerical model, because of time constraints, only two flow rate coefficients (0.7 and 1.3) were chosen to limit the number of required runs to be performed. With the presence of the proxy model, such constraints are no longer applicable and seven different flow rate coefficients were implemented (0.6, 0.8, 0.9, 1, 1.1, 1.2 and 1.4). Introducing these flow rate coefficients would result in 7^8=5764801 different possible scenarios, which could be predicted with the proxy model; however, most of those scenarios involves unreasonable injection rates. In order to focus on more practical scenarios, ratio of injection and production amounts were calculated. Due to evaporation and losses during operations, injection rates more than 75% of production is very unlikely. Also, injection rates below 65% production would not be feasible for a long-term pressure support. Because of these reasons only the scenarios with injection/production rates between 0.65 and 0.75 are chosen. These constraints filtered the possible scenarios to 1044195. To see the flexibility of the proxy model, randomly selected 19 scenarios from the list were run using the TOUGH2 code. The comparison of randomly selected predictions and simulation results can be seen in Table 2.

Table 1: Sample of predicted vs actual values.

Instance #	Predicted Pressure 1 (bar)	Actual Pressure 1 (bar)	Error	abs. error %	Predicted Temp 1 (°C)	Actual Temp 1 (°C)	Error	abs. error %
1	44.67	44.69	0.02	0.04%	182.86	182.83	0.03	0.02%
2	38.73	38.74	0.01	0.02%	183.23	183.21	0.02	0.01%
3	46.98	47.06	0.08	0.17%	183.15	183.13	0.02	0.01%
4	47.29	47.47	0.18	0.37%	182.59	182.59	0.00	0.00%
5	43.36	42.88	0.48	1.11%	182.30	182.29	0.01	0.01%
6	46.30	46.29	0.01	0.03%	183.08	183.09	0.01	0.01%
7	39.54	38.85	0.69	1.75%	182.79	182.80	0.01	0.01%
8	43.24	43.31	0.07	0.16%	182.93	182.96	0.03	0.02%
9	47.91	48.34	0.43	0.90%	183.27	183.24	0.03	0.02%
10	45.25	45.25	0.00	0.01%	182.90	182.93	0.03	0.02%
11	42.66	42.02	0.64	1.51%	182.19	182.18	0.01	0.01%
12	38.88	38.92	0.04	0.10%	183.01	183.01	0.00	0.00%
13	36.47	36.89	0.42	1.14%	183.01	183.04	0.03	0.02%
14	46.62	46.68	0.06	0.14%	182.52	182.54	0.02	0.01%
15	35.88	36.39	0.51	1.43%	182.90	182.92	0.02	0.01%
16	43.27	43.50	0.23	0.54%	182.99	183.00	0.01	0.01%
17	46.30	46.05	0.25	0.54%	182.59	182.59	0.00	0.00%
18	44.89	44.93	0.04	0.09%	182.99	183.00	0.01	0.01%
19	41.87	41.57	0.30	0.71%	183.08	183.08	0.00	0.00%
20	47.05	46.80	0.25	0.54%	182.19	182.19	0.00	0.00%
21	44.94	44.84	0.10	0.21%	182.62	182.63	0.01	0.01%
22	45.20	45.10	0.10	0.22%	182.41	182.39	0.02	0.01%
23	44.91	44.85	0.06	0.13%	183.01	183.01	0.00	0.00%
24	44.31	44.02	0.29	0.67%	182.66	182.68	0.02	0.01%
25	42.18	41.81	0.37	0.87%	182.52	182.54	0.02	0.01%
26	41.54	41.22	0.32	0.76%	182.30	182.29	0.01	0.01%
		average=	0.02			average=	0.03	

Table 2: Random proxy test results vs simulation results.

Actual total pressure(bar)	Predicted total pressure(bar)	abs error	abs error %
5,047.43	5045.72	1.71	0.034%
4,191.94	4215.04	23.10	0.551%
4,326.66	4324.35	2.31	0.053%
4,205.00	4217.98	12.98	0.309%
4,304.48	4293.9	10.58	0.246%
4,423.28	4392.77	30.51	0.690%
4,362.11	4361.28	0.83	0.019%
4,557.64	4551.7	5.94	0.130%
4,660.97	4639.87	21.10	0.453%
4,365.51	4375.31	9.80	0.225%
3,985.60	3981.11	4.49	0.113%
4,691.27	4678.4	12.87	0.274%
4,497.27	4492.98	4.29	0.095%
4,411.83	4406.74	5.09	0.115%
4,379.84	4376.77	3.07	0.070%
4,364.78	4362.5	2.28	0.052%
4,189.36	4209.31	19.95	0.476%
4,183.20	4211.46	28.26	0.676%
4,226.00	4238.91	12.91	0.305%

3. RESULTS

With the results of 1044195 different scenarios, a table with total pressure of the field and total production is created. Using this table, the graph given in Figure 6 is constructed. This graph can be used as a decision surface for finding optimal production and injection flow rates. Top right corner of the graph can be considered as the highest possible production from the field with minimum pressure loss in the reservoir. At a given pressure level, the scenario with the highest production rate can be found by drawing a vertical line from the desired pressure value, intersecting the diagonal line. Similarly, the highest pressure support for a desired production rate can be found by drawing a horizontal line from that production level until intersecting the diagonal line. Typically, the highest performing scenarios involve, decreasing the injection rates from the shallow injection wells (i1 and i4), and diverting their fluid to the regions i2 and i3 which contains deeper injection wells.

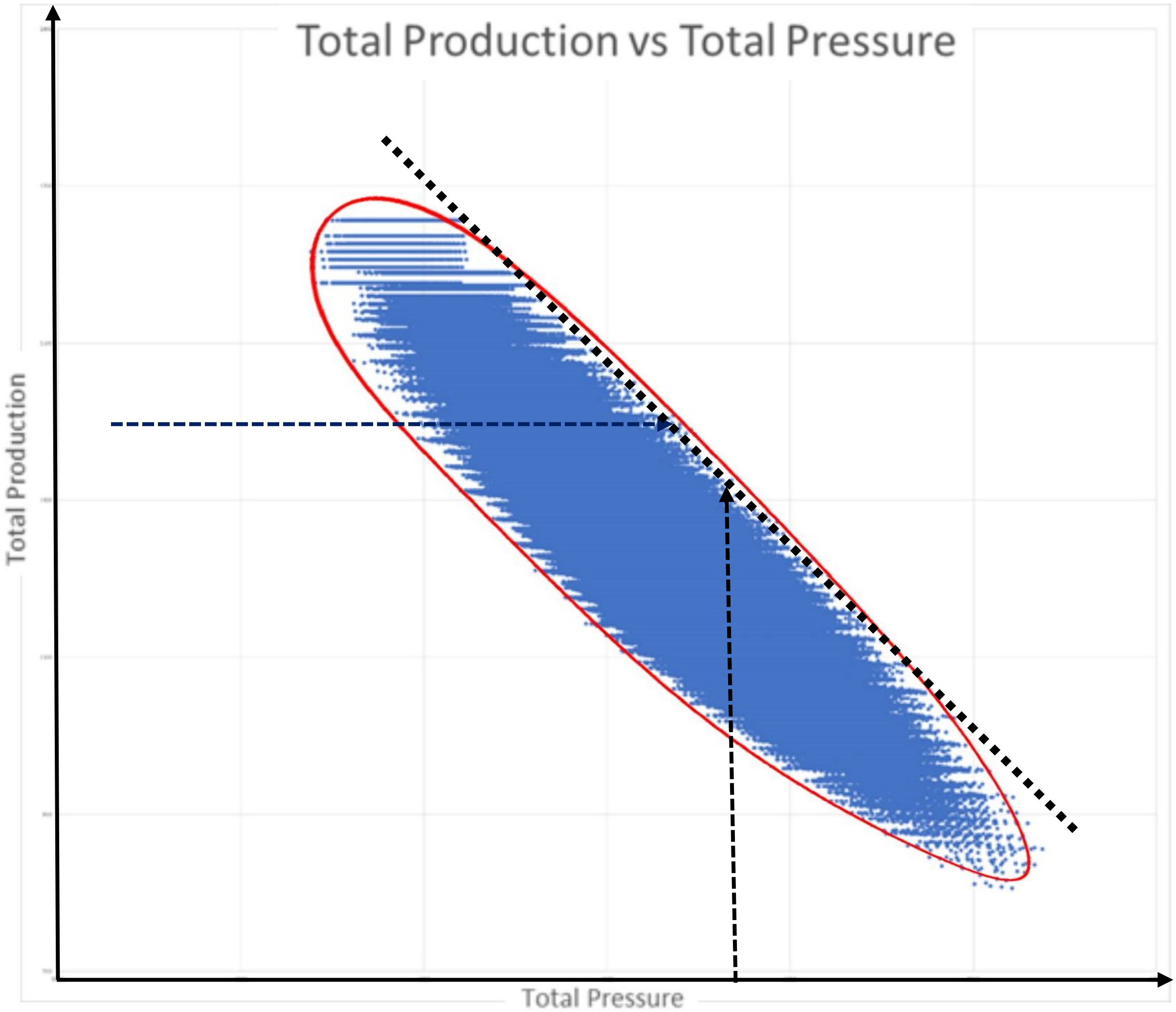

Figure 6: Total production vs total pressure of scenarios (decision surface).

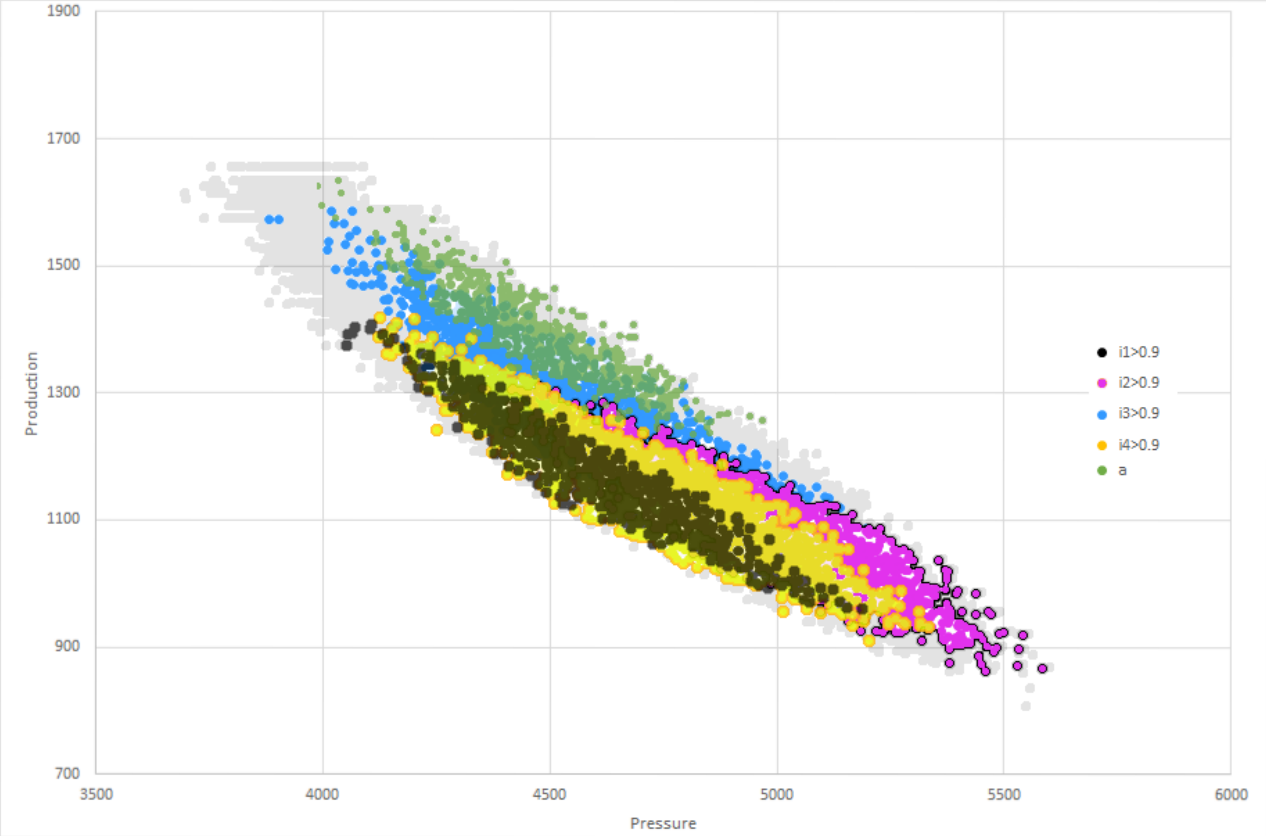

Figure 7: Decision surface, different scenarios plotted.

Figure 7 is a summary of the resulting decision surface:

- Black points represent the scenarios where the flowrate coefficient of region i1 is kept above 0.9 while all other injection regions have the coefficients below 0.9. This combination results in one of the worst performances, with low production rates and high pressure decline for the field. This proves the importance of deeper injections.
- Yellow points represent the scenarios where the flowrate coefficient of region i4 is kept above 0.9 while all other injection regions have the coefficients below 0.9. This combination also proves to be lacking in performance and shows the value of deeper injections.
- Magenta points represent the scenarios where the flowrate coefficient of region i2 is kept above 0.9 while all other injection regions have the coefficients below 0.9. This combination reaches optimum values of production and pressure under specific production rates.
- Blue points represent the scenarios where the flowrate coefficient of region i3 kept above 0.9 while all other injection regions have the coefficients below 0.9. This combination also reaches optimum values of production and pressure under specific production rates with a wider range in general.
- Combining blue and magenta schemas resulted in the Green schema. Green points represent the scenarios with the flowrate coefficient <0.9 for i1 and i4, while this coefficient is>1.1 for i2 and i3. Thus, this scenarios limit reinjection in shallow regions and divert this flow to deeper reinjection regions. This schema results in higher production rates while keeping the pressure of the field high.

4. CONCLUSION

Optimizing the production and injection strategy using conventional simulation approach usually involves trial and error procedures which could be immensely time consuming. By introducing a machine learning based solution to the existing workflow, the optimization could be performed much faster. This approach also expands the workspace of possible production/injection scenarios, and gives reservoir engineers a broader vision. Since very high correlation and accuracy has been attained by the proxy model the graph that was constructed as a result of this work could also be used to create a cost function which includes the economic aspects of optimization such as the procurement costs of the pumps that might be needed for heavy injection scenarios and such.

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REFERENCES

Hawkin. (2014). Intriguing properties of neural networks, Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, Rob Fergus. In *arXiv preprint*. https://doi.org/978-0131471399

Mitchell, T. M. (1997). *Machine Learning*. McGraw-Hill Science.

Kucuk, S., Baser, A., Saracoglu, O., Senturk, E., and Akın, S.: Reinjection Optimization of Kızıldere Geothermal Field for Sustainable Reservoir Pressure Management, Proceedings, World Geothermal Congress 2020, Reykjavik, Iceland (2020).

Simsek, S., Parlaktuna, M., and Akin, S.: Data Gathering and Evaluation of Kızıldere Geothermal Field, Report prepared for Zorlu Energy, (2009).