

OPTIMIZATION OF RE-INJECTION IN LOW TEMPERATURE GEOTHERMAL RESERVOIRS USING NEURAL NETWORK AND KRIGING PROXIES

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ABSTRACT

Re-injection of produced geothermal water for pressure support is a common practice in geothermal field management. The location selection of the re-injection well and the rate of injection is a challenging subject for geothermal reservoir engineers. The goal of optimization for this type of problem is usually to find one or more combinations of geothermal re-injection well locations that will maximize the production and the pressure support at minimum cost and minimum enthalpy decrease. Although the number of well combinations is potentially infinite, it has been customary to pre-specify a grid of potentially good well locations and then formulate the search to locate the most time- or cost-effective subset of those locations that meets production goals. Typically, a knowledge base of representative solutions is developed using a simulator. Then an artificial neural network to predict selected outcomes is trained and tested. In the next step well combinations and injection rates of these wells to predict outcomes with a given number of injection wells are generated. On the other hand, knowledge base of representative solutions may be kriged to generate an optimization surface which then be used to select new optimal search directions. In this study, neural network proxy and kriging proxies for fast re-injection location evaluations are compared using low temperature Kizilcahamam, Turkey geothermal field. The results show that neural network proxy method is faster and more accurate than kriging proxy. It is observed that accuracy of kriging proxy optimization method depends on accuracy of variogram analysis. Moreover, kriging proxy optimization may not result in global optimum.

INTRODUCTION

One of the methods used in geothermal reservoir management is to reinject geothermal fluid back into the reservoir. Initially started as a disposal method, reinjection has become a common practice for increasing the amount of energy that can be recovered from a geothermal reservoir (Goyal, 1999;

Axelsson and Dong, 1998). Several parameters need to be considered for a successful reinjection process (Stefansson, 1997):

1. Disposal of waste fluid
2. Cost
3. Reservoir temperature (thermal breakthrough)
4. Reservoir pressure or production decline
5. Temperature of injected fluid
6. Silica scaling
7. Location of reinjection wells
8. Chemistry changes in reservoir fluid
9. Recovery of injected fluid
10. Subsidence

The proper selection of reinjection location is perhaps the most important factor affecting the success of the reinjection and it has long been a controversial subject in the geothermal literature. There are differing opinions regarding the location selection from injecting outside the field (Einarsson et al, 1975) which is the most common reinjection configuration (Stefansson, 1997) to injection some fraction of the waste water near the center of the reservoir (Bodvarsson and Stefansson, 1988). Yet another reinjection strategy is to consider production and injection wells are interchangeable and that they are distributed uniformly in the field (James, 1979). A ramification of intermixed reinjection model is to interchange the injection and production wells at different parts of the reservoir for different times (Stefansson, 1986). Sigurdsson et al (1995) concluded that the peripheral injection is better if the maximum thermal sweep is of greater importance than pressure maintenance.

Simulation-optimization, a term that refers to the coupling of models to optimization drivers, has received extensive attention in the petroleum literature (Johnson and Rogers, 2001). The goal of optimization for this type of problem is usually to find one or more combinations of injection well locations that will maximize the production at minimum cost. Although the number of well combinations is potentially infinite, it has been customary to pre-specify a simulation grid of

potentially good well locations and then formulate the search to locate the most time- or cost-effective subset of those locations that meets production goals. Nonlinear optimization algorithms extend from genetic algorithm and hybrid versions of genetic algorithm (Guyaguler, 2002) to artificial neural networks (Centilmen et al, 1999 McNichol et al, 2001).

Formal optimization strategies normally evaluate hundreds or even thousands of scenarios in the course of searching for the optimal solution to a given management question. This process is extremely time-consuming when numeric simulators of the subsurface are used to predict the efficacy of a scenario. One solution is to use a mathematical proxy or surrogate such as trained artificial neural networks (ANNs) to stand in for the simulator during the course of searches directed by some optimization technique such as the genetic algorithm (GA) or simulated annealing (SA). The networks are trained from a representative sample of simulations, which forms a re-useable knowledge base of information for addressing many different management questions. On the other hand, knowledge base of representative solutions may be kriged to generate an optimization surface which then be used to select new optimal search directions. Previously kriging has been used in a similar fashion by Pan and Horne, Aanonsen et al and Guyaguler et al. Kriging is an algorithm based on the theory of regionalized variables and can be used as a multidimensional interpolation and extrapolation algorithm. Kriging estimates are exact at data locations (i.e. they honor the data), which is a very favorable property.

Although these proxies are very easy and fast, they often require an initial investment in computation for calibration purposes. The magnitude of this initial computational investment is unclear. Also the calibration points, that are used to calibrate the proxy, are chosen synchronously; that is, the choice of a particular point to be simulated is independent of the others even though in real life the choice of later experiments would be based on the experience of earlier observations. In this study, neural network proxy and kriging proxies for fast re-injection location evaluations are compared using low temperature Kizilcahamam, Turkey geothermal field. Initial investment of computation for each proxy method is evaluated for speed and accuracy.

KIZILCAHAMAM FIELD

Kizilcahamam geothermal field is located 70km far from Ankara (Fig. 1). The geothermal fluid, produced with an average temperature of 74–86°C (Gevrek, I, 2000) and flowrate of 80 l/s is used in 2500 house district heating, in thermal hotels (Başkent University

Thermal Hotel, Asya Thermal Resorts, Ab-1 Hayat and municipality hotels), in district facilities by using heat exchangers (Kaya, 2005). Used geothermal water is reinjected to the reservoir with a flowrate of 40 l/s at a temperature of approximately 42°C in a shallow and a deep reinjector. A total of 6 production and 2 reinjector wells are currently present in the field (Fig. 2). Deep reinjector well (KHD-1) is used as a production well during winters. All production wells use pumps at depths between 50 and 66 meters (Table 1)..

Table 1. Producing and injecting well properties.

Name of the Well	Well Depth (m)	Flow rate (l/s)	Well head temperature (°C)	Dynamic Level (m)	Pump depth (m)
MTA-1(re-injection)	179	40	42	0	0
MTA-2	310	30	76	120	65
KHD-1(re-injection)	1556	15	42	0	0
İHL-1	590	20	76	25	65
İHL-2	670	40	74	30	66
İHL-3	673	20	79	20	57
FETHIBEY	592	20	76	25	65
Asya Finans	600	20	65	25	50

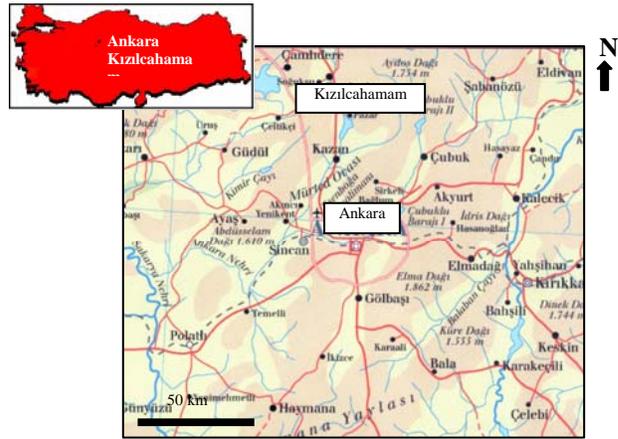


Figure. 1. Kizilcahamam geothermal field location map.

Geology

Geological, geochemical and geophysical studies have been previously carried out by Tatli (1975), Ongur (1976), Kocak (1977), Demiroer (1985), Gurer and Celik (1987), Gevrek and Aydin (1988), Ozbek (1988) and Gulec (1994). The Kizilcahamam area is located within the Tertiary-aged Galatian Volcanic Province that consists of autoclastic and

pyroclastic deposits (Gevrek, 2000). Stratigraphic units (approximately 1800 m) from the bottom to the top are as follows: 1. Basaltic lava flows (Paleocene); 2. Pyroclastic deposits consisting of tuffs and agglomerates (Miocene); 3. Undifferentiated lava flows ranging in composition from andesitic, basaltic, trachyandesitic to dacitic (Miocene); 4. Debris flows (Quaternary) (see KHD-1 stratigraphic section in Fig. 4). The basement beneath the province consists of Paleozoic schists and Permo-Triassic limestones. The Lower Cretaceous limestone and Upper flysch facies and limestone lie over the Paleozoic basement, and are overlain by the Galatian Volcanic Province. The volcanic activity is believed to have started at the end of the Upper Cretaceous, but reached its climax during the Miocene age (Gevrek, 2000). Gravity faults, which strike dominantly in the ENE–WSW direction, are observed in the district. The Kızılcahamam fault, which passes through the town has approximately an E–W direction and is 2250 m in length (Fig. 3).

comparison to the waters sampled from the localities outside the town center. The Kızılcahamam geothermal water has a pH of approximately 7.2. It contains bicarbonate, chlorite, sodium, carbon dioxide and arsenic. The water is suitable for balneology and Kızılcahamam thermal water has solution mineral value of 250mg/l. The chemical classification is; bicarbonate (67.18%), chlorite (19.22%), sodium (82.64%), arsenic (0.34 mg/l) and carbon dioxide (283.4 mg/l). Metaboric acid (18.95 mg/l) and fluorite (1.96 mg/l) also exist (Kaya, 2005). The variations in the temperature and the chemical composition of the waters can be accounted for by a combination of processes including mixing between cold-shallow and hot-deep waters, boiling either before or after mixing, steam heating and conductive cooling. The chemical geothermometers, silica-enthalpy and enthalpy-chloride mixing models suggest a reservoir temperature of 124–190°C for the Kızılcahamam region, and a maximum of 71% deep, hot component for the thermal waters (Gulec, 1994).

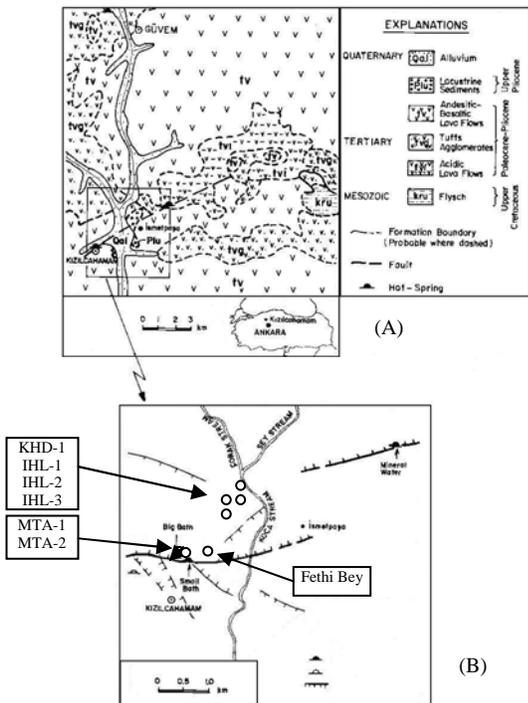


Figure 2. (A) Geological map of Kızılcahamam area (Erol, 1955), (B) Location of wells in Kızılcahamam Geothermal Field (Revised from Özbek, 1988).

Chemical Properties of Geothermal Fluid

Thermal waters issuing through the Tertiary aged volcanics in the Kızılcahamam geothermal area are all alkali-bicarbonate waters with temperatures ranging from 28°C to 86°C. The waters from the town center have the highest temperature and an intermediate total dissolved solid content, in

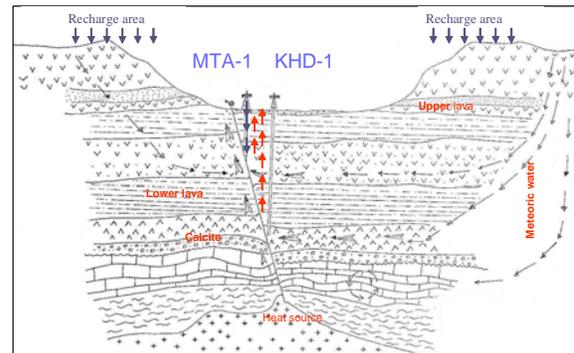


Figure 3. Conceptual model of Kızılcahamam geothermal field.

SIMULATION MODEL

In this study, STARS thermal simulator (CMG, 2007) was used. Dual porosity simulation model was calibrated using historical production, temperature and pressure data from Kızılcahamam geothermal field, Turkey (Kaya, 2005). The developed simulation model consisted of cartesian grids (Fig. 4) with equal dimensions (50x50x50 m). The depth of the blocks matched the depth of the producing reservoir divided into 33 equal parts. The last z block was thick (10000 m) and was supported by a weak thermal aquifer. The developed simulation model is in accord with hydrogeological model that consider infiltration of meteoric water into deeper sections of the Earth and up-flow of it after heating (Fig. 3). Matrix permeability (1 md) and porosity (0.01%) was constant in all grid blocks. Likewise, initial fracture permeability (1 Darcy) and porosity (5%) was taken as constant. Fracture relative permeabilities was power law functions of the corresponding saturations with an exponent of 2.8. Gilman-Kazemi shape

factor was used for handling fracture-matrix transfer. Fracture intensity near Fethibey well was relatively low (4x4x4 m matrix blocks) compared to rest of the field (2x2x2 m matrix blocks). Sample pressure and temperature history matches for well KHD-1, in Fig. 5. Fig. 4 shows native state model temperatures.

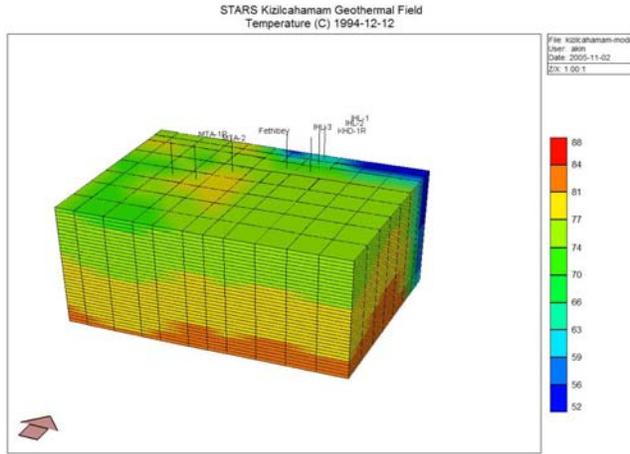


Figure. 4. Native state model temperatures.

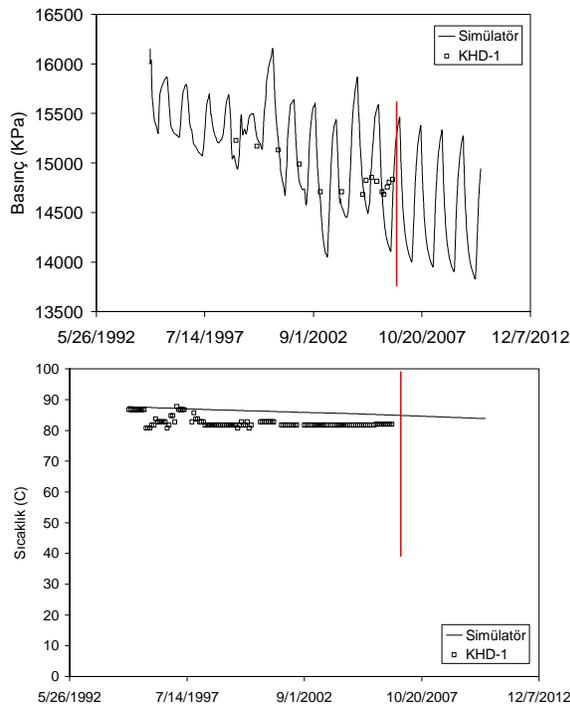


Figure. 5. Pressure (top) and temperature (bottom) matches for KHD-1.

RESULTS AND DISCUSSIONS

ANN Proxy

A knowledge base of 99 simulations sampling possible injection locations at three different depths covering whole field was generated using the final simulation model by opening an injection well in

empty grids with a reinjection temperature of 40°C. Same seasonal production-reinjection strategy was used in the prediction period. The maximum flow rate was selected based on operating company's pumping capacity. The knowledgebase data consisted of dimensionless pressure and enthalpy data of the production and observation wells at the end of simulation period corresponding to 5 years of reinjection. While obtaining non-dimensional parameters maximum pressure and enthalpy data observed in the field was used. An alternative is to use the last observed pressure and temperature. Then using this knowledgebase several different back propagation ANN's were trained. During the training process for determining the weights, some simulation data should be withheld for later verification of network accuracy. These data are often referred to as test or validation data. Once the weights have been determined through back propagation, the test data were used as network inputs for determining the network's accuracy in predicting unprocessed data sets. The quality or goodness of training was judged based on the closeness of the prediction of the remaining "testing" data (i.e. simulated injection data that was not used for training). Approximately 10% of the data was kept for testing. This process was repeated for various networks and the network with the highest accuracy was used as the model. Rather than randomly selecting the initial weight matrix, previously generated successful matrices were used at the start. This feature decreased the iterations approximately 30% and also guaranteed training of a "good" network (Yimaz et al, 2002). Several networks with varying degree of complexity have been trained. A double hidden layer network composed of 25 hidden nodes at each layer resulted in the lowest error among the single and double layer networks tried. Although use of more than a single layer can lead to a very large number of local minima and make the training extremely difficult (Hornik et al; 1989) this network resulted in the best error.

The results obtained are given in Fig. 6. In these plots ANN enthalpy and pressure outputs are scaled with maximum values and then averaged by dividing to total number of wells to find a representative number (dimensionless decrease per well) for the corresponding reinjection location. Thus, high values of this number (hot colors like red) correspond to relatively small decreases of the corresponding parameter (i.e. enthalpy or pressure). It was observed that deep reinjection results in approximately 1% lower enthalpy compared to shallow reinjection. On the other hand pressure response is relatively complex such that there is no direct relationship with depth and pressure change.

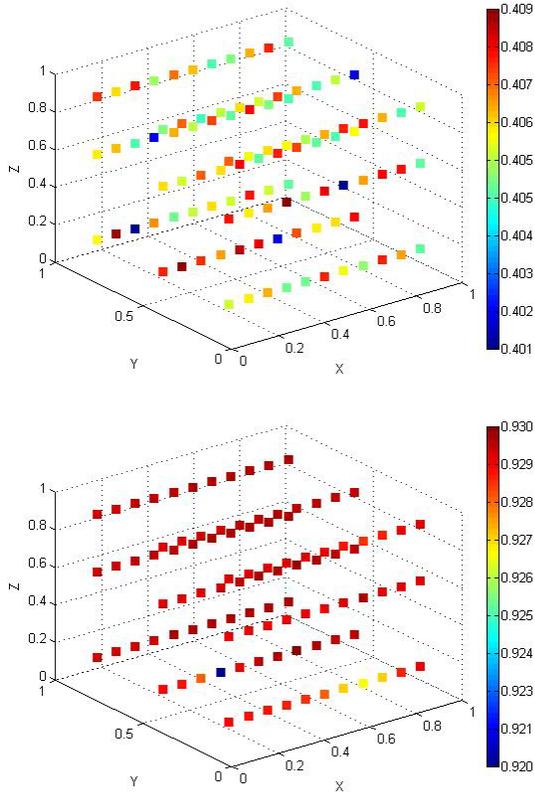


Figure 6. Dimensionless pressure (top) and enthalpy (bottom) responses at different locations.

The rapid estimates of enthalpy and pressure data provided by the ANN were fed into calculations where minimum temperature decrease – maximum pressure support is sought, which in turn were used by a search algorithm to evaluate the effectiveness of different injection well locations and injection rates. Dimensionless volumetric plots (Fig. 7) were generated for evaluating the optimum reinjection location. Deep and shallow reinjection contrast is clear such that deep reinjection results in faster cooling compared to shallow reinjection. Injection into middle section of the reservoir near to the west boundary where a fault is present results in relatively small pressure and enthalpy loss. However, for pressure maintenance deeper sections of the reservoir must be selected for reinjection.

A sensitivity study was carried out to evaluate the efficiency of ANN proxy. To achieve this goal the number of test data was increased from 10 to 66 points. As the number of test data points increased the average residual error decreased from 2.62% to 0.08%. Likewise keeping number of test data at 10% of training data it was observed that as the number of training data points decreased from 99 to 50 average residual error increased from 2.62% to

4.54%. These results show that for accurate results the number of training and test data points must be kept as high as possible. Although not shown here the use of ANN proxy resulted in similar optimization results (i.e. boundaries of low and high dimensionless pressure and enthalpy in the reservoir volume did not change significantly).

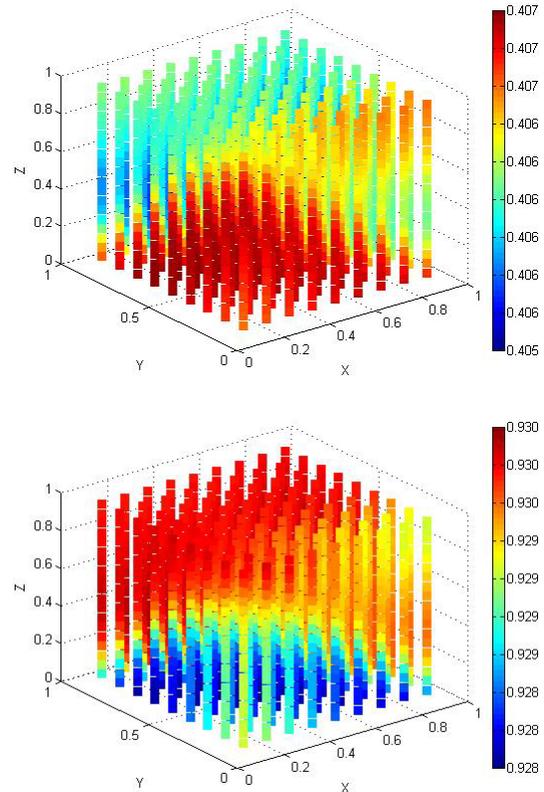


Figure 7. Volumetric dimensionless pressure (top) and enthalpy (bottom) responses generated by ANN proxy at different locations.

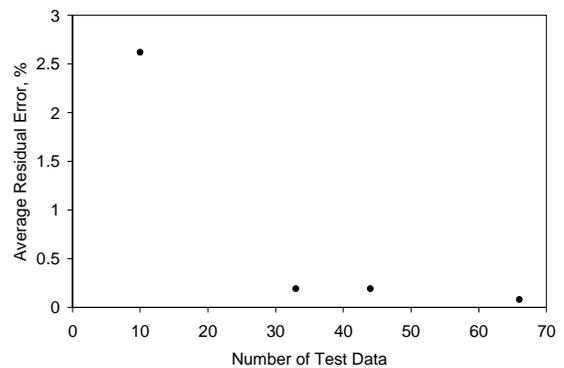


Figure 8. ANN test data sensitivity.

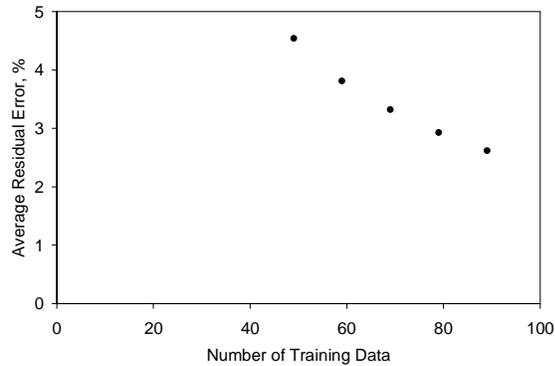


Figure. 9. ANN training data sensitivity.

Kriging Proxy

Ordinary kriging was used in this study since there is no prior information about the mean. A variogram was fit to capture the correlation between evaluated points. The power variogram was chosen as it provided better fit after some experimentation with different variogram types. Figure 10 shows the optimization surfaces obtained at the top, middle and bottom sections of the reservoir using the same data set that was used in ANN proxy runs. In these plots as in the case of ANN proxy, enthalpy and pressure outputs are scaled with maximum values and then averaged by dividing to total number of wells to find a representative number (dimensionless decrease per well) for the corresponding reinjection location. It was observed that similar to ANN proxy middle and deeper sections of the reservoir except for the north of the reservoir are better for pressure support; however west sections of the reservoir regardless of depth must be preferred for reinjection to obtain minimum enthalpy change. Thus the results are somewhat different than the ones obtained with the ANN proxy.

A sensitivity study was carried out to analyze the response of kriging proxy to the use of number of points used in variogram modeling. It was observed that as the number of points used in variogram modeling decreased variogram model parameters changed significantly. The nugget value was affected more than the power value. As the number of data points used to generate variograms and thus the surfaces decreased the results changed significantly (Fig. 10 through 12). For example when 66 data points was used the optimum pressure support location shifted to south east of the reservoir regardless of the reinjection depth. Likewise as the number of data points was further reduced to 33, resemblance of the optimization surfaces with the ones generated with 99 points were completely gone. Furthermore, the surfaces were geometrically simpler.

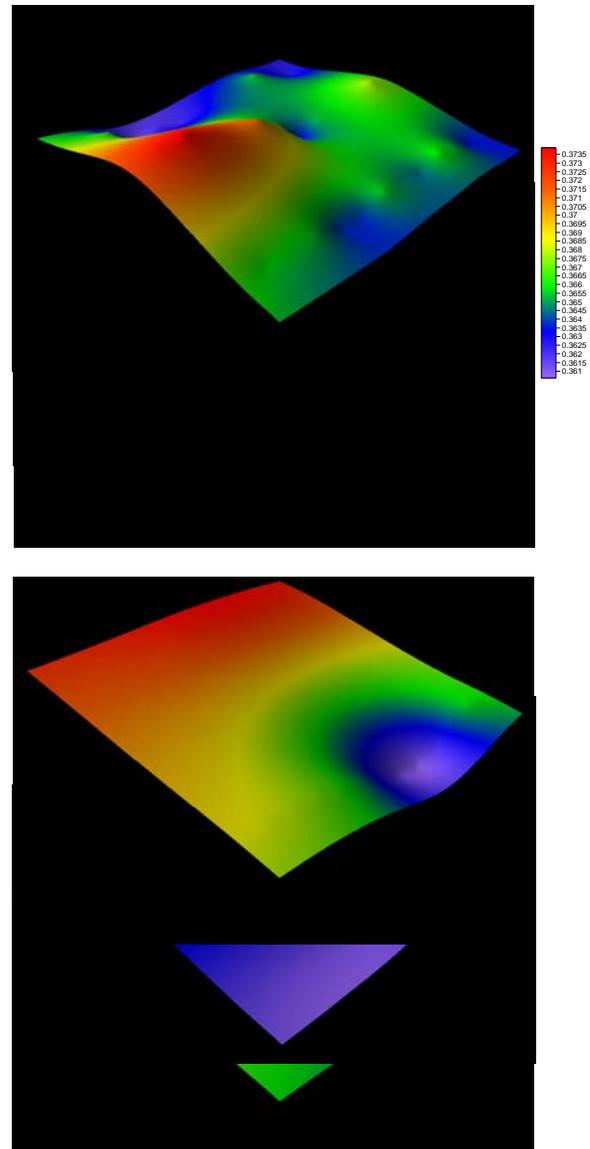


Figure. 10. Volumetric dimensionless pressure (top) and enthalpy (bottom) responses generated by kriging proxy at different locations using 99 data points.

As a general comment the use of kriging proxy is somewhat slower compared to ANN proxy. The main reason for this is trial and error process involved in variogram modeling which complicates the analysis. Note that it is possible to obtain similar optimization surfaces with different variogram models; however, variogram model (power law variograms) was not changed during the analyses in order to minimize possible interpretation errors.

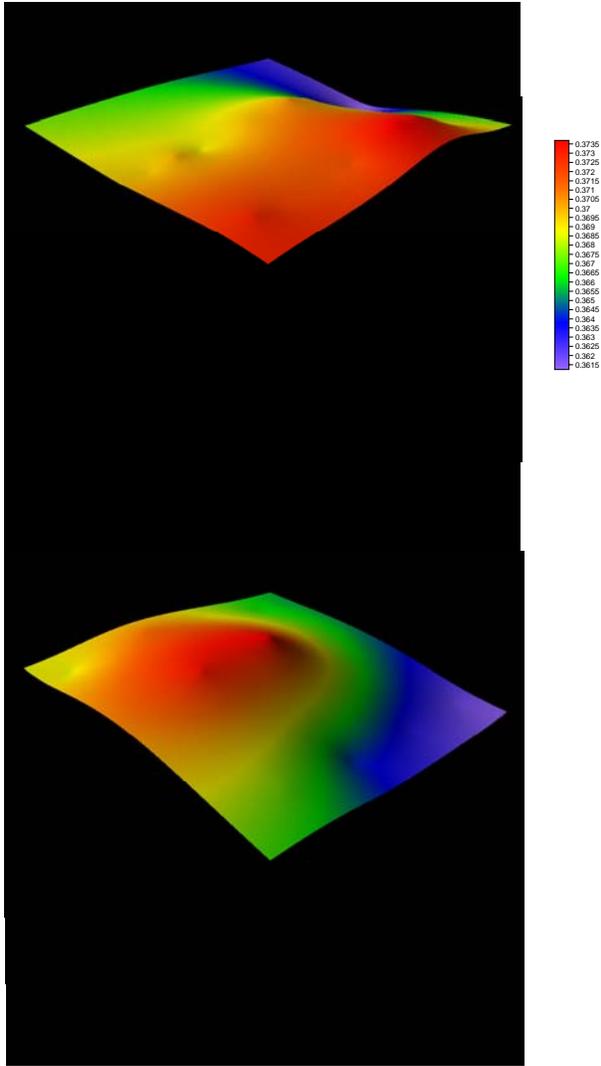


Figure. 11. Volumetric dimensionless pressure (top) and enthalpy (bottom) responses generated by kriging proxy at different locations using 66 data points.

One other complicating issue was the use of different data sets to obtain variogram fits. To analyze this issue different data sets were generated by randomly removing data points from the master set generated with 99 points. Figure 13 shows the surfaces obtained using two different data sets with 66 points. As can be see optimum reinjection locations for both pressure and enthalpy support has changed significantly. This shows that kriging proxy function must be used with extensive care.

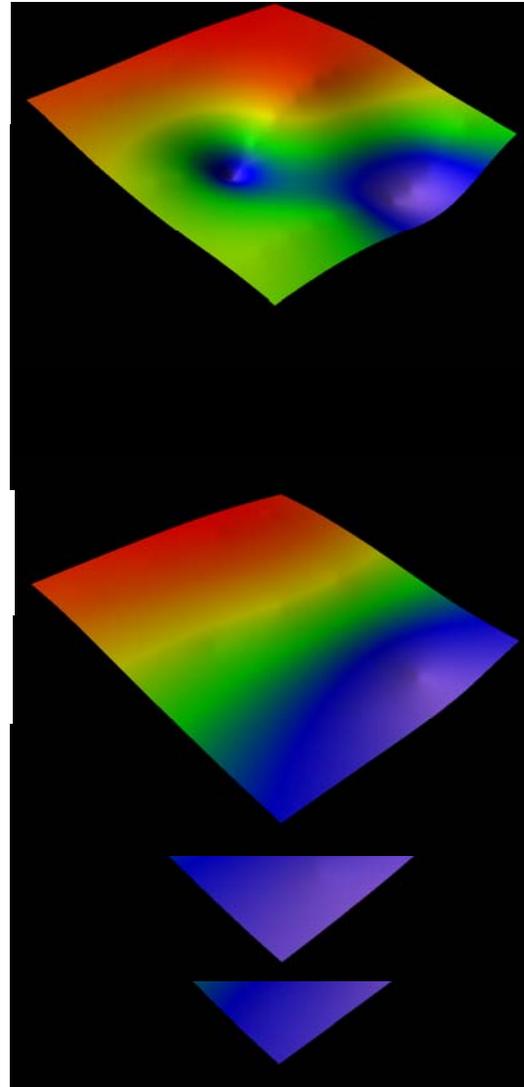


Figure. 12. Volumetric dimensionless pressure (top) and enthalpy (bottom) responses generated by kriging proxy at different locations using 33 data points.

DISCUSSION

Application of proxies could be carried out in three different ways (Johnson and Rogers, 2000):

1. Simulation stepping search: full model used to evaluate the objective function each time;
2. Proxy stepping search: Deep look work as example: pre-trained proxies (i.e. ANN or kriging proxy) step through searches, validation at the end of the search;
3. Proxy-guided, simulation stepping search: proxies impact the search, giving it speed and higher range of guessing at the best search directions, but full simulation used during the search, not at just the beginning and the end.

In this study only simulation stepping search has been evaluated. No one search architecture will solve all problems. If the problem is straightforward (such as the relatively homogeneous reservoir presented in this paper) traditional simulation-stepping techniques may work. With more complexity some combination of proxies and heuristic methods will make more sense. One may decide on either a proxy-stepping, pay up front with simulations to train proxies, or a hybrid proxy guided, simulation stepping search that trains the proxies as the search proceeds, never straying far from the full model simulation. The latter is more a pay-as-you-go simulation investment and employs strengths of the proxies without full reliance on them (Johnson and Rogers, 2000).

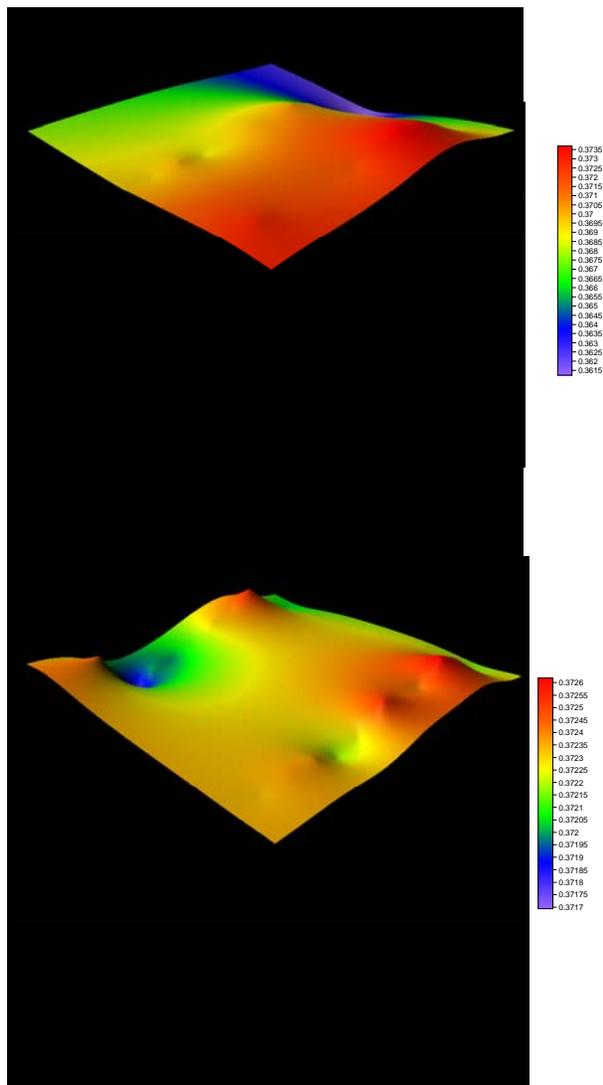


Figure. 13. Volumetric dimensionless pressure (top) responses generated by kriging proxy at different locations using different datasets with 66 points.

CONCLUSIONS

ANN and kriging proxy techniques for optimization of reinjection well placement were studied for a low temperature geothermal reservoir. The following conclusions were drawn:

1. It was observed that the use ANN and kriging proxy functions produced quantitatively different optimization surfaces.
2. The number of data points used to generate variograms may change the results significantly with the use of kriging proxy functions.
3. The use of different data points may result in different variogram models and thus the optimization surface may change significantly.
4. Kriging proxy is slower than ANN proxy.

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