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OPTIMIZATION OF REINJECTION IN GEOTHERMAL RESERVOIRS

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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 temperature 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. To achieve this goal neural network technology is proposed. First, a knowledge base of representative solutions for a geothermal field located in Turkey was developed using a simulator. Then artificial neural networks to predict selected outcomes was 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 were generated.

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.

Artificial Neural Networks

Within recent years there has been a steady increase in the application of neural network modeling in engineering. ANNs have been used to address some of the fundamental problems, as well as specific ones that conventional computing has been unable to solve, in particular when engineering data for design, interpretations, and calculations have been less than adequate. Also with the recent strong advances in pattern recognition, classification of noisy data, nonlinear feature detection, market forecasting and process modeling, neural network technology is very well suited for solving problems in the petroleum industry. Within the last five years, work has been published covering the successful and potential application of ANNs in different areas of the geosciences (Yilmaz *et al*, 2002).

Neural computing is an alternative to programmed computing which is a mathematical model inspired by biological models. This computing system is made up of a number of artificial neurons and a huge number of interconnections between them. According to the structure of the connections, we identify different classes of network architectures (Figure 1).

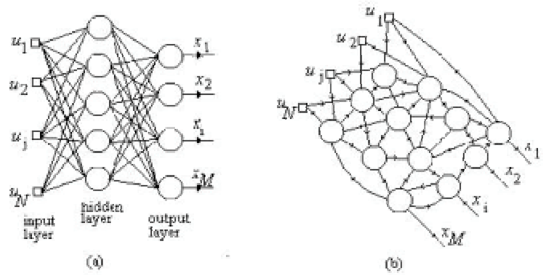

Figure1. a) Layered feed-forward neural network, b) Non-layered recurrent neural network

In feed-forward neural networks, the neurons are organized in the form of layers. The neurons in a layer get input from the previous layer and feed their output to the next layer. In this kind of networks connections to the neurons in the same or previous layers are not permitted. The last layer of neurons is called the output layer (right column) and the layers between the input and output layers are called the hidden layers. The input layer (left column) is made up of special input neurons, transmitting only the applied external input to their outputs. In a network if there is only the layer of input nodes and a single layer of neurons constituting the output layer then they are called single layer network. If there are one or more hidden layers (middle column), such networks are called multilayer networks. The structures, in which connections to the neurons of the same layer or to the previous layers are allowed, are called recurrent networks.

The lines represent weighted connections (i.e., a scaling factor) between processing elements. The performance of a network as shown in Figure 1 is measured in terms of a desired signal and an error criterion. The output of the network is compared with a desired response to produce an error. An algorithm called back-propagation (Haykin, 1994) is used to adjust the weights a small amount at a time in a way that reduces the error. The network is trained by repeating this process many times. The goal of the training is to reach an optimal solution based on the performance measurement.

In order to tackle the optimum reinjection location selection for a given geothermal field, an alternative solution approach using the power of back-propagation artificial neural networks (ANN) is proposed. First, the training of the ANN with simulator generated data for a geothermal field is presented. Then using the ANN optimum reinjection location, depth and rate for the given conditions are obtained. Advantages and disadvantages of the proposed method are discussed using a case study. It was observed that the proposed technique provided satisfactory results.

METHODOLOGY

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).

In this study, STARS thermal simulator (CMG, 2002) was used. Dual porosity simulation model was calibrated using historical production, temperature and pressure data from Kizildere geothermal field, Turkey (Yeltekin *et al*, 2002). The developed simulation model (Table 1) consisted of 8x12x6 rectangular grids (Fig. 1) with equal areal dimensions (60x60 m). The depth of the blocks (Fig. 2) matched the depth of the producing reservoir (Igdecik formation) divided into five equal parts. The last *z* block was thick (5000 m) and was supported by a thermal aquifer. The developed simulation model is in accord with hydrogeological models (Satman and Serpen, 2000; Dominco, 1974) that consider infiltration of meteoric water into deeper sections of the Earth and up-flow of it after heating. Sample pressure and temperature history matches for wells KD-6, KD-13 and KD-20 are provided in Figures 3 through 5. The permeability data initially derived from well test analysis (Kappa, 2001) was modified to achieve a reasonable match (Fig. 6). The initial and final temperature and pressure distributions at the end of 14 years of history match are given in Fig. 7 and 8 respectively.

Table 1. Simulation model properties

Property	***Value***
Fracture spacing	20 m.
Shape factor	Gilman - Kazemi
Fracture relative permeability	Power law n = 2.8
Matrix permeability	1 md.
Fracture porosity	0.08

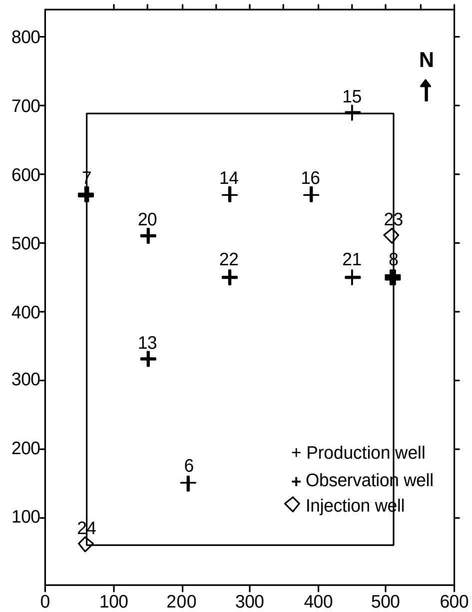

Figure 1. Reservoir model grid diagram

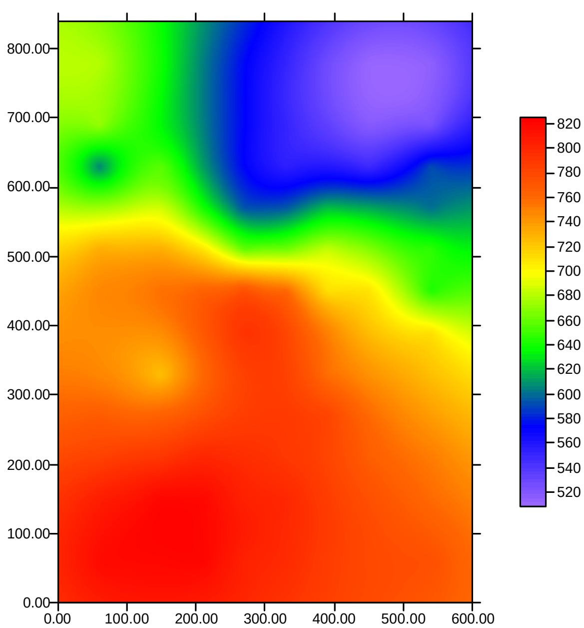

Figure 2. Grid tops (m) distribution for the producing layer.

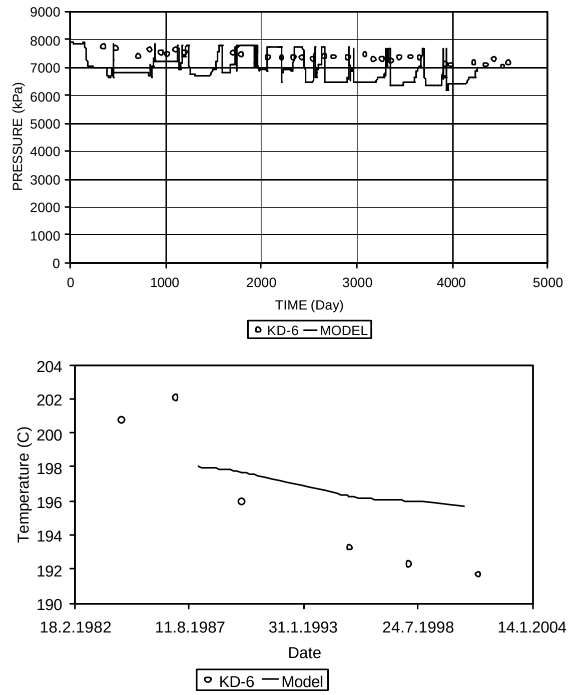

Figure 3. Pressure (top) and temperature (bottom) match for well KD-6.

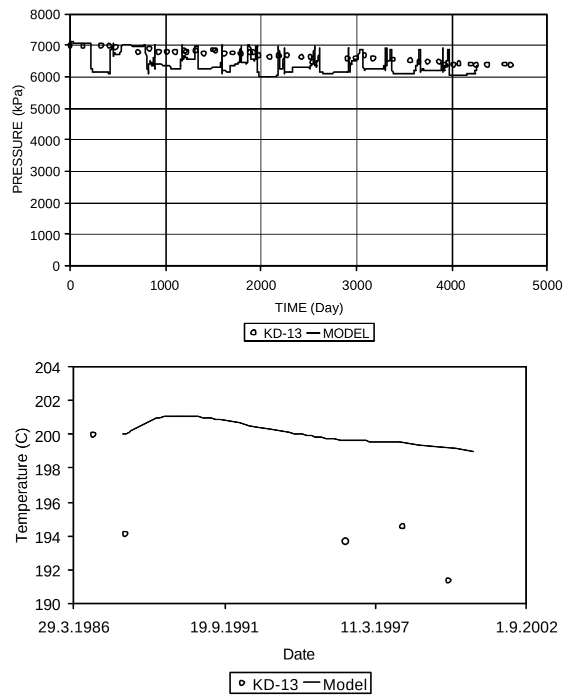

Figure 4. Pressure (top) and temperature (bottom) match for well KD-13.

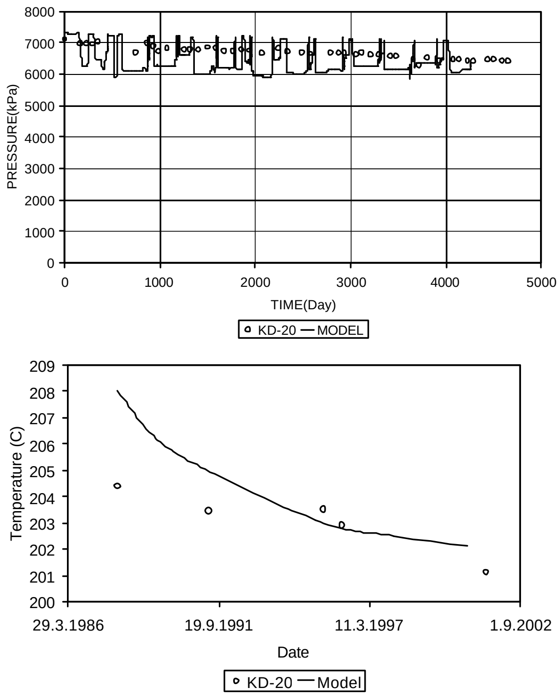

Figure 5. Pressure (top) and temperature (bottom) match for well KD-13.

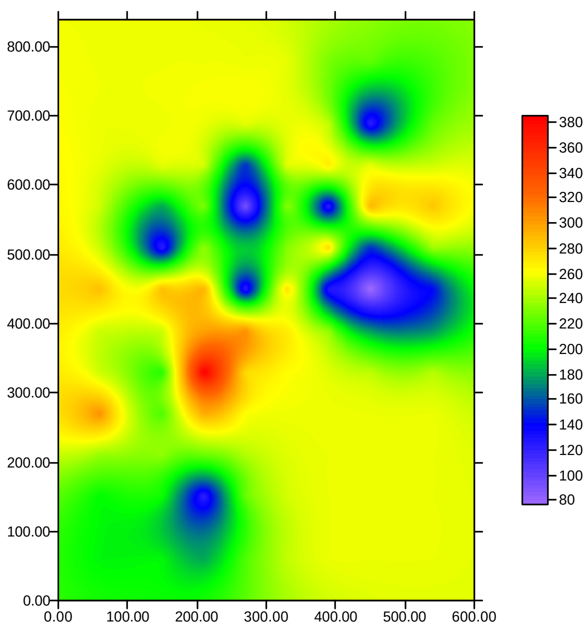

Figure 6. Permeability (md) distribution.

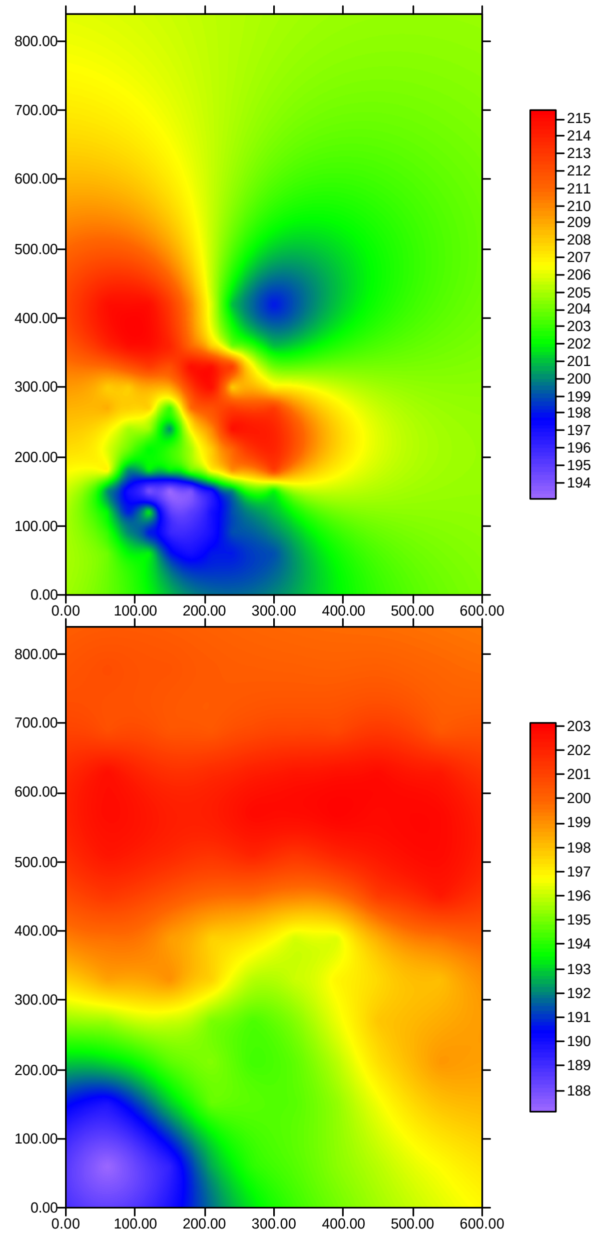

Figure 7. Temperature (°C) distribution. Initial - 01/01/1988 (top), final - 01/09/2002 (bottom)

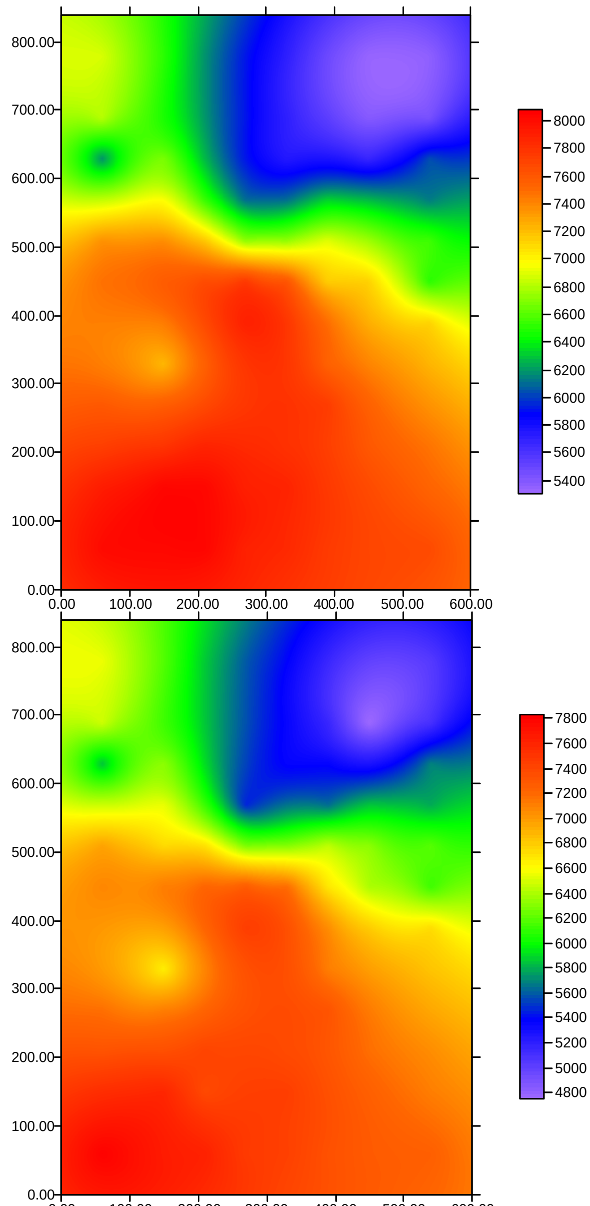

Figure 8. Pressure (kPa) distribution. Initial-01/01/1988 (top), final-01/09/2002 (bottom)

RESULTS AND DISCUSSIONS

A knowledge base of 126 simulations sampling 85 possible injection locations and three different rates (2500, 3750, 4911 m^3/day) was generated using the final simulation model by opening an injection well at each empty grid block skipping one grid block in a chessboard fashion at 10 years after the commencement of injection at 150°C. The maximum flow rate was selected based on operating company's pump capacity. The knowledgebase data consisted of pressure and temperature data of the production and observation wells at different time steps. As a general observation for high injection rate (4911 m^3/day) overall temperature decrease was less pronounced (usually less than 4°C per grid block) with corner injections; however, pressure drop was the highest (more than 130 kPa per grid block). On the other hand, injections near the center of the field resulted in better pressure support (less than 117 kPa per grid block) but cooling was somewhat more (about 5 and 6 °C per grid block). These observations were valid also for the lower injection rates; however, the magnitudes of the pressure drop and the temperature decrease were somewhat less.

Then using this knowledgebase several different 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). 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 with no success. A two hidden layer network composed of 4 and 13 hidden nodes 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 rapid estimates of temperature 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. Several dimensionless surface plots (see for example figures 9 and 10) were generated for evaluating the optimum reinjection location. In these plots ANN temperature 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 injection location. Thus, high values of this number (hot colors like red) correspond to relatively small

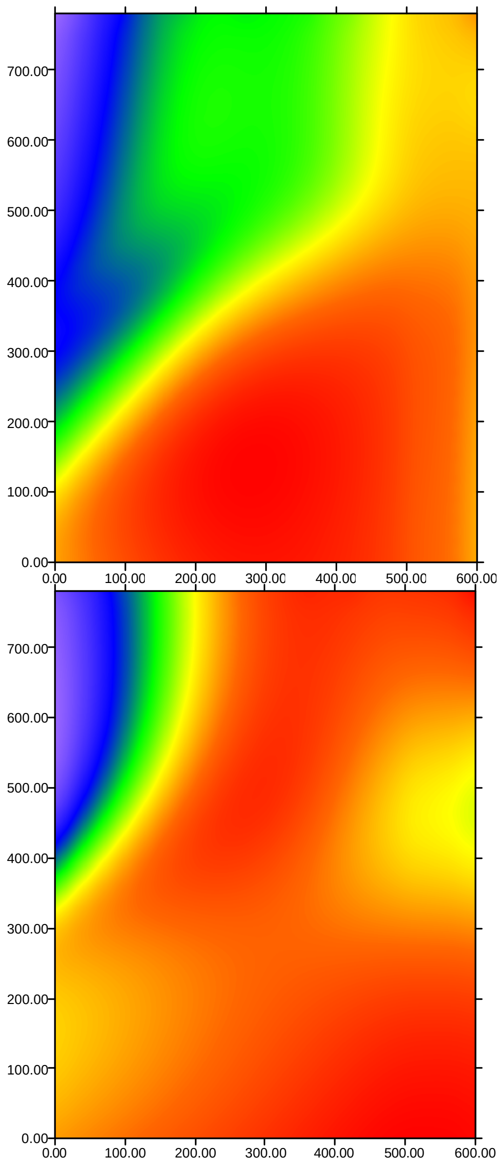

Figure 9. ANN dimensionless pressure decrease per well (top) and ANN dimensionless temperature decrease per well (bottom) plots for high injection rate (4911 m^3/day).

decreases of the corresponding parameter (i.e. temperature or pressure).

When two extreme injection rates are considered, high injection rate results in better pressure support especially at the southeast of the reservoir. The overall pressure decrease is considerably less than that of the low injection rate. On the other hand, when low injection rate is preferred, the reservoir cools faster. If maximum enthalpy is the overall objective then lower injection rates need to be selected (see Fig. 10). In all cases bottom low quadrant or southeast of the reservoir seems to be the ideal location for reinjection. This location also hosts a fault named as southern fault zone and connects to another geothermal reservoir namely Tekkehamam region located approximately 4 km from the nearest well in the area.

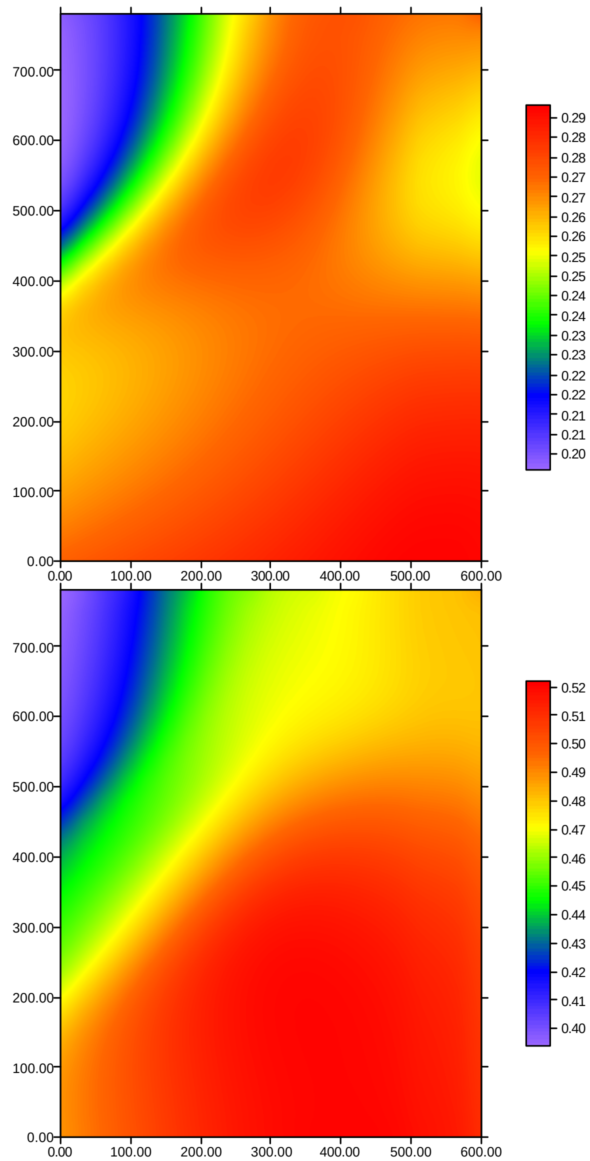

Figure 10. ANN dimensionless pressure decrease per well (top) and ANN dimensionless temperature decrease per well (bottom) plots for low injection rate (2500 m^3/day).

CONCLUSIONS

Optimization of reinjection well placement and reinjection rate by simulation-optimization via artificial neural networks is proposed. The use of the developed technology is demonstrated through a water dominated geothermal field located in Turkey. The performance of the reinjection location is evaluated by means of dimensionless temperature and pressure drop per well plots obtained for the whole field. With these plots it is possible to pinpoint locations that will result in maximum pressure or maximum enthalpy support. For the water dominated geothermal system studied here, the best reinjection location is the southeast of the reservoir.

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