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Natural State Modeling for a Geothermal System using Artificial Intelligence

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Abstract: ***Natural state modelling of a geothermal system is the process of adjusting uncertain reservoir parameters until an acceptable match with the measured field data is achieved. Complexity and insufficient knowledge of reservoir characteristics make this process time-consuming with a high computational cost. This study aims to examine the application of Artificial Intelligence (AI) to improve the time and efforts required for completing a successful natural state modelling. A synthetic 2D model of a vapor-dominated geothermal system is built using TOUGH2-EOS1, and was used as the subject and ground truth of natural state matching. An AI model was created to perform natural state modelling, and play a role as a prototype for full-field reservoir simulation that runs in a few seconds.***

Keywords: geothermal, natural state, artificial intelligence, neural network

1. Introduction

The natural state of a geothermal system represents the conditions where the system has not been exploited. A natural state model of a geothermal system then refers to the mathematical representation of the physical behavior of the system before exploitation [1]. In the mathematical representation, we set up a computer model that approximately the permeability structure, heat inputs that represent magma chambers underlying the reservoir at correct locations, and fluid inputs of a real reservoir.

A successful computer model is the one that will nearly duplicate the behavior of the geothermal system before exploitation. The model should account for all significant physical processes that take place in the system. Some of the processes include mass transport, conductive and convective heat transfer, boiling, and condensation [2]. The objectives of natural state modelling are: (i) to develop a conceptual model, (ii) to measure the natural mass and heat moving in the system, and (iii) to serve as a basis for modelling studies of the system when it is being exploited.

The purpose of the work described here was to examine the application of Artificial Intelligence (AI) to improve the time and efforts required for completing a successful natural state modelling for a geothermal system.

A synthetic 2D model of a vapor-dominated geothermal system is built using TOUGH2-EOS1 [3] and was used as the subject and ground truth of natural state matching. Then, natural state modelling was carried out using an AI model that was developed in Python. The AI model plays a role as a prototype for full-field reservoir simulation that runs in a few seconds.

2. Methodology

Simulation Model

A synthetic 2D model of a vapor-dominated geothermal system is constructed using TOUGH2-EOS1 which has dimensions of 5000 m × 50 m with a 2000 m depth. This model was built is a typical vapor-dominated system, since the reservoir is governed by impermeable rocks [4]. The model domain is divided into 25 grids in the x-direction and one grid in the y-direction with 25 layers, as shown in Figure 1. The grid size is 200 m × 50 m × 80 m for all grid blocks.

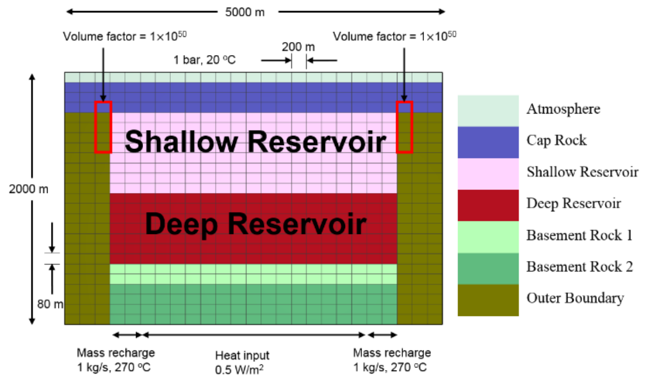

Figure 1: Two-dimensional model of a vapor-dominated geothermal system.

Seven types of rock material were assigned in the model as summarized in Table 1. The properties of rock type are based on the Darajat geothermal field (Indonesia) because it is a typical vapor-dominated geothermal system [5]. These rock materials represent atmosphere layer, caprock, reservoir, impermeable boundary, and basement rock.

For all rock types, the rock density of 2650 kg/m^3 and the specific heat of 1000 J/(kg K) are used. The capillary pressure effect is neglected. The porous medium approach is utilized in the whole domain. Relative permeability of Grant's curves [6] is used with residual liquid saturation (S_{lr}) and residual gas saturation (S_{gr}) of 0.3 and 0.05, respectively.

The thickness of reservoir domain is 1200 m which lay down at depth between 320 m to 520 m. It consists of a shallow reservoir (320 m to 960 m) and deep reservoir (960 m to 1520 m). The caprock layer overlies the reservoir with 240 m thick. The atmospheric condition of 1 bar and 20 °C is specified at the top layer. Conductive heat flux of 0.5

W/m^2 is given at the bottom of the model. High-temperature water of 270 °C at a flow rate of 1 kg/s recharges the reservoir from two locations at the bottom layer.

To maintain a hydrostatic condition at the lateral boundary, we assigned an infinitely large volume (volume factor of 1 × 10^{50}) in some grids at the lateral boundary of the reservoir (grids within the red boxes in Figure 1). After setting up the model, it was run for one million years to reach a reasonable steady state. This long simulation time is required to achieve a natural state condition of a geothermal system.

Table 1: Rock properties assigned for the 2D model

Material name	Color	ϕ (-)	k (m^2)	C (W/m K)
Atmosphere		0.9	1×10^{-12}	2.5
Caprock		0.05	8×10^{-18}	0.2
Shallow reservoir		0.1	5×10^{-14}	2.5
Deep reservoir		0.1	1×10^{-14}	2.5
Basement rock 1		0.06	1×10^{-15}	2.5
Basement rock 2		0.03	5×10^{-16}	2.5
Outer boundary		0.01	5×10^{-17}	2.5

Artificial Neural Network

Artificial Neural Network (ANN) is an algorithm that was originally motivated by the goal of having machines that can mimic the brain [7]. Figure 2 illustrates the input, hidden and output layers and their connections in the Artificial Neural Network (ANN) algorithm.

The results from the simulation were then used to generate a spatio-temporal database that involves static and dynamic reservoir characteristics. Static data refers to the reservoir properties that are not changing through time, such as permeability and porosity. Dynamic data refer to variable parameters that are altering over time, such as the distribution of pressure, temperature, and vapor saturation.

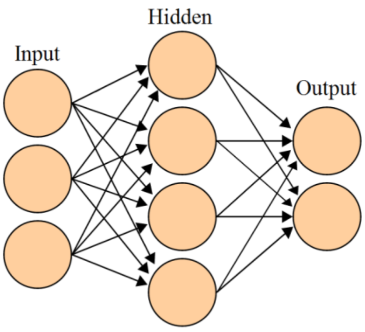

Figure 2: A scheme of an artificial neural network

3. Results and Discussion

The simulation was assumed reach natural state condition for natural state modeling in 50,000 years. The highest pressure is found in the grid just above the mass recharge point, see Figure 3. This makes the fluid flowing upward from the recharge point to the reservoir domain. The resulting pressure in the steady-state is about 200 bar at the bottom layer.

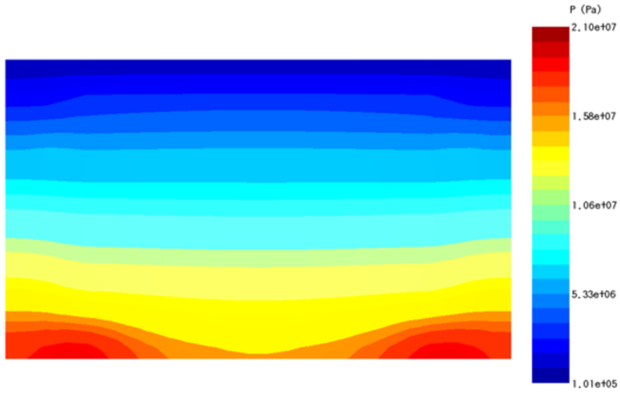

Figure 3: Pressure distribution undernatural state

The high-temperature zone is formed in the center of the bottom layer, see Figure 4. The temperature at the margin of the lateral boundary of the upper part of the reservoir seems to be constant because we set an infinitely large volume. If a well is allocated at 500 m from the center of the model (see A in Figure 4), there is a decrease of temperature at a depth between 600 m to 900 m and then an increase again with depth.

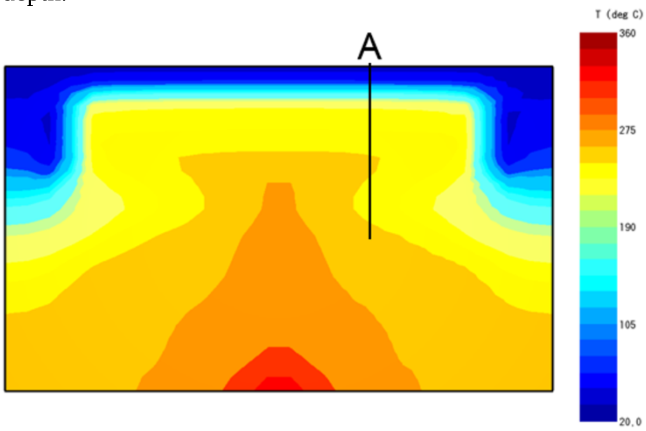

Figure 4: Temperature distribution undernatural state

A thin vapor-dominated zone is formed at depths from 300 m to 350 m in the shallow zone of the reservoir (Figure 5), just below the caprock. The vapor saturation in that zone is in the range of 0.6 to 0.8. On the other hand, liquid water occupies most of the other zones in the model domain.

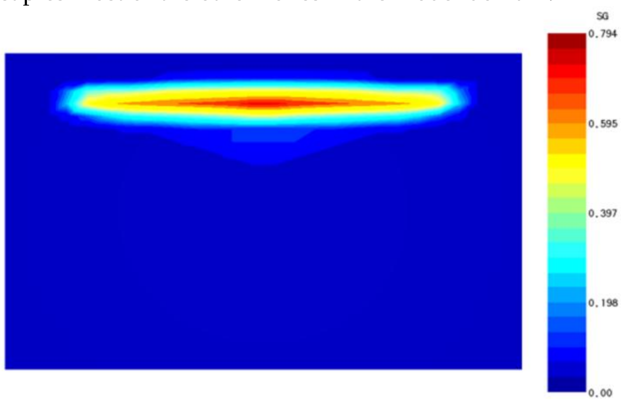

Figure 5: Vapor saturation distribution undernatural state

Then, we generate a dataset by running a series of simulation with changing reservoir parameter, i.e., heat influx, porosity, and permeability to obtain the simulation output, namely, temperature and vapor saturation. Figure 6 shows the design of ANN architecture with 3 inputs (heat influx, porosity, and permeability), 3 neurons, and 2 outputs (temperature and vapor saturation).

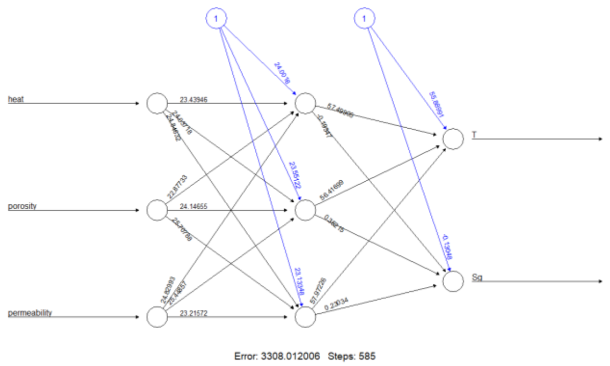

Figure 6: ANN architecture with 3 inputs, 3 neurons, and 2 outputs

Table 2 shows that the results have a relatively good agreement for the temperature prediction. However, the vapor saturation prediction has a poor prediction, with relative squared errors of 0.642. This means the ANN architecture should be modified, for example by adding neurons and normalizing the input data before training.

Table 2: Results metric from the ANN model

Output	*rmse*	*rse*	mae
Temperature	13.178	0.893	9.607
Vapor Saturation	0.281	0.642	0.216

4. Conclusion

A synthetic 2D model of a vapor-dominated geothermal system has been constructed using TOUGH2-EOS1. The simulation results show that a thin vapor-dominated zone, in the range of 0.6 – 0.8, is formed at depths from 300 m to 350 m, whereas the liquid water occupies most of the other zones in the model domain. The ANN model is generated by involving three different processes, i.e., training, calibration, and testing, by using the database generated from the simulation results. The elapsed time to perform those processes is negligible compared to the reservoir simulation run-time.

The ANN can predict the temperature distribution quite well, yet, poor in predicting the vapor saturation. To improve its performance, the ANN architecture should redesign, such as, adding the inputs and neurons or normalize the input before training. In addition, the other ANN models for time series modeling should be considered, such as, radial basis function (RBF), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN).

This study recommends to include more reservoir parameters as inputs and implement other types of neural networks, e.g., radial basis function (RBF), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN).

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