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Uncertainty Quantification of a Real Low-Enthalpy Geothermal Reservoir

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Summary

The efficient development of a geothermal field can be largely affected by the inherent geological and physical uncertainties. Besides, the uncertain operational and economic parameters can also impact the profit of a project. Systematic uncertainty quantification involving these parameters helps to determine the probability of concerning outputs. In this study, a low-enthalpy geothermal reservoir with strong heterogeneity, located in the West Netherlands Basin, is selected as the research area.

Detailed geological model is constructed based on various static data including seismic and log interpretation. However, significant uncertainties still exist in definition of the model parameters, mainly reservoir permeability and porosity. Besides, the fluid properties have not been sampled in this field and can vary in the range between brackish to highly saline water. Also, the heat price and operational investment fluctuate with time and add up to uncertainty. Taking all interested parameters into consideration, the Monte Carlo method is utilized to select specific input data set. The forward simulations are powered by the GPU version of Delft Advance Research Terra Simulator (DARTS), which provides efficient simulation capabilities for geothermal applications. Through this investigation, a wide range of production temperature has been observed due to the uncertainty of the input parameters.

Uncertainty quantification of a real low-enthalpy geothermal reservoir

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Introduction

The efficient development of a geothermal field can be largely affected by the inherent geological and physical uncertainties. Besides, the uncertain operational and economic parameters can also impact the profit of a project. Systematic uncertainty quantification involving these parameters helps to determine the probability of concerning outputs (e.g., energy production, Net Present Value, system lifetime, etc.). In this study, a low-enthalpy geothermal reservoir with strong heterogeneity, located in the West Netherlands Basin, is selected as the research area [7].

Detailed geological model is constructed based on various static data including seismic and log interpretation. However, significant uncertainties still exist in definition of the model parameters, mainly reservoir permeability and porosity [4]. Besides, the fluid properties (e.g., density, viscosity, etc.) have not been sampled in this field and can vary in the range between brackish to highly saline water. Also, the heat price and operational investment fluctuate with time and add up to uncertainty [1]. Taking all interested parameters into consideration, the Monte Carlo method is utilized to select specific input data set within predefined distributions or ranges. The forward simulations are powered by the GPU version of Delft Advance Research Terra Simulator (DARTS), which provides efficient simulation capabilities for geothermal applications [3, 6]. Through this investigation, a wide range of production temperature has been observed due to the uncertainty of the input parameters.

Geological model / Input parameters

The study area is located in the West Netherlands Basin which is an inverted rift basin. Sediments in this basin range in age from Jurassic to recent and are overlying Triassic and older sediments. The Upper Jurassic and Lower Cretaceous start with the continental sediments of the Nieuwerkerk Formation and Vlieland sandstone Formation. These sediments were deposited in subsiding half-grabens, while adjacent highs were subjected to erosion [5]. In these formations two main reservoir layers have been observed, Berkel Sandstone and Delft Sandstone. Circa 3.2 million grid cells are used to characterize the model using geological scale.

Two doublets are planned to be placed in the reservoir and operated with a constant rate control. Since it is difficult to predict the lateral continuity, the reservoir boundary condition is defined as no-flow.

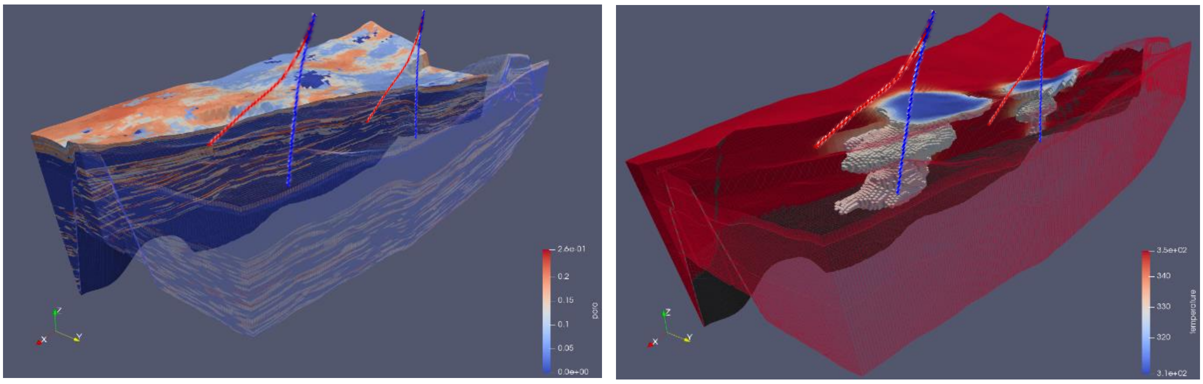


***Figure 1** One of the realizations of reservoir properties and corresponding cold plum distribution.*

100 permeability-porosity realizations have been generated based on variation of seed parameter in the base case facies model [4]. The mean and standard deviation of parameters were kept the same and only

spatial distribution (conditioned to up-scaled logs) has been varied. The sampler randomly selects realization index from 1 to 100.

The basic simulation parameters are listed in Table 1. In addition, the standard water properties are taken as the base case. A normal distribution of the multiplier to water density/viscosity are applied to represent the effect of mineral dissolution. Besides, the injection temperature and injection reduction follow the normal distribution as well (Table 2).

Table 1 *Thermal, hydraulic and operational parameters of geothermal reservoir.*

Parameters	Unit	Value
Porosity	-	10^{-5} - 0.256
Permeability	mD	0.004-1308
Shale heat capacity	kJ/(m^3.K)	2300
Sand heat capacity	kJ/(m^3.K)	2450
Shale thermal conductivity	kJ/(m.day.K)	190
Sand thermal conductivity	kJ/(m.day.K)	260
Rate (I1 & P1)	m^3/h	208
Rate (I2 & P2)	m^3/h	416

Table 2 *The distribution values of the uncertain parameters.*

Parameters	Mean	Standard deviation
Water density coefficient	1	0.1
Water viscosity coefficient	1	0.05
Injection temperature coefficient	1	0.1
Injectivity reduction coefficient	1	0.1

Mathematical model / Results

We consider the governing equations for thermal simulation with aqueous brine. This system can be described by mass and energy equations:

$$\frac{\partial}{\partial t}(\phi \rho_w) - div\,(K\frac{\rho_w}{\mu_w}(\nabla p_w - \gamma_w \nabla D)) + \rho_w \tilde{q_w} \sum_{j=1}^{n_p} \rho_j \tilde{q_j} = 0, \qquad (1)$$

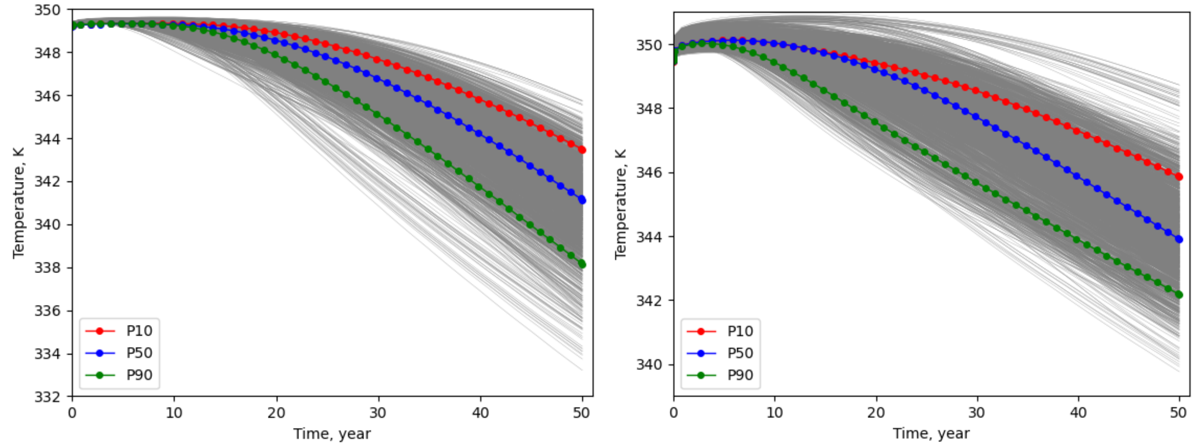
$$\frac{\partial}{\partial t}(\phi \rho_w U_w + (1-\phi)U_r) - div\,(K h_w \frac{\rho_w}{\mu_w}(\nabla p_w - \gamma_w \nabla D)) + div(\kappa \nabla T) + \rho_w \tilde{q_w} h_w = 0, \qquad (2)$$

where: ϕ is porosity, ρ_w is water molar density, U_w is water internal energy, U_r is rock internal energy, h_w is water enthalpy, κ is thermal conduction, K is permeability tensor, μ_w is water viscosity, p_w is pressure, γ_w is water gravity vector, D is depth.

The governing equations are solved with fully coupled, fully implicit approach using Operator Based Linearization (OBL) [5] in Delft Advanced Research Terra Simulation (DARTS) framework [2]. More detailed descriptions of geothermal formulation in DARTS can be found in [3, 6].

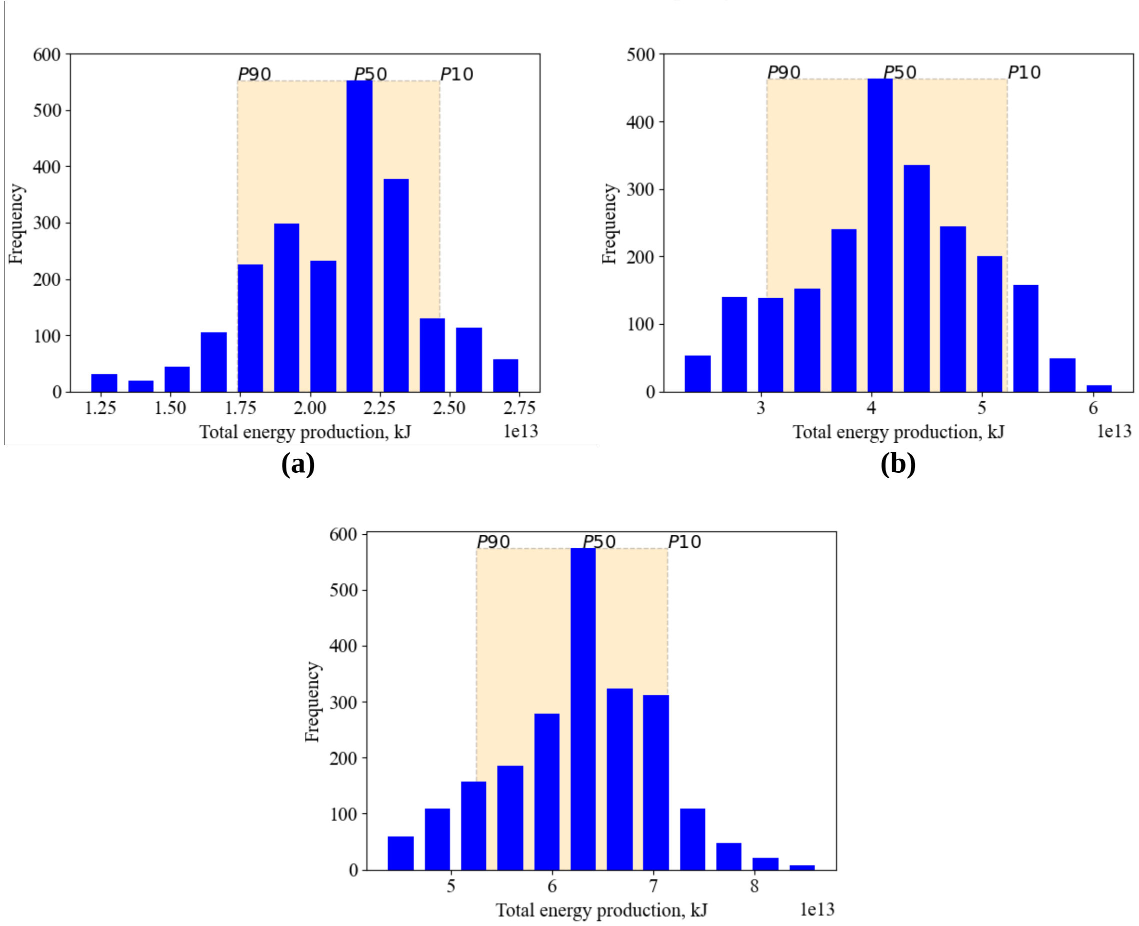
Large variation of production temperature is observed for both doublets in Figure 2. It is indicated that a 6-7 degrees temperature drop is highly probable for both doublets at the end of 50 years. In addition, the different temperature drops between P10 and P90 cases demonstrates the system lifetime can be very different. For example, if the production temperature of P10 at 50 years is selected as the breakthrough temperature, the lifetime of P10 and P90 can vary by 16 and 22 years respectively for the two doublets. Figure 3 displays the PDF of total energy production at the lifetime. The energy production follows the normal distribution.

Owing to the high computing performance of the GPU version of DARTS, the mean simulation time for a 50 years simulation (with a maximum timestep of one year) stabilizes at 5.5 minutes on Titan RTX GPU card. Figure 4(b) displays the convergence of the production energy probability density function (PDF) with the increasing of simulation runs. The infinite norm of distribution difference (e.g., with an interval of 100 runs) is evaluated as an indicator of convergence. As can be seen, the energy PDF converges after 1000 runs and the distribution difference is lower than 0.01 afterwards.



(a) **(b)**

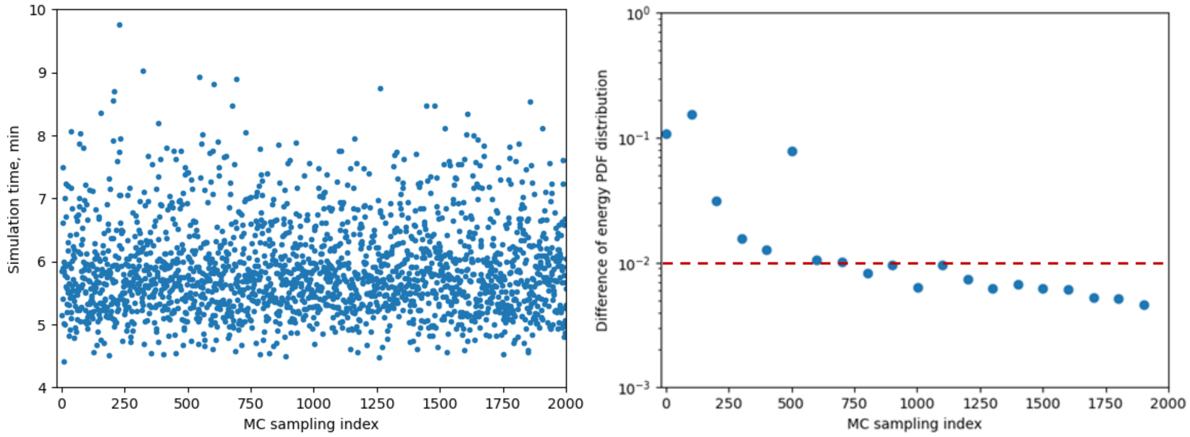
Figure 2 *The production temperature of the two doublets for different realizations (in solid gray), (a) doublet 1, (b) doublet 2. The P10, P50 and P90 are also specified.*



(a) **(b)**

(c)

Figure 3 *The PDF of total energy production for both doublets at the lifetime (defined by 4 degrees temperature drop in the production well). (a) doublet 1, (b) doublet 2, (c) the summation of doublet 1 and 2.*



(a) **(b)**

Figure 4 *(a) Simulation time of each sample (b) The infinite norm of the difference of energy PDF with the number of realizations.*

Conclusions

In this study, the uncertainty quantification using a high-resolution geological model of a real reservoir has been performed. The high computing performance of DARTS on GPU speeds-up the simulations by more than an order of magnitude in comparison to the CPU version and allowed us to use a high-fidelity model without compromising the accuracy. An accurate model treatment ensures an accurate uncertainty quantification for a realistic representation of reservoir features. A wide interval of production temperature responses indicates the high impact of concerning uncertain parameters. Based on this methodology, more efficient development strategies with an accurate representation of uncertainties can be designed and utilized in real geothermal projects.

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