Geothermics 88 (2020) 101906

Contents lists available at ScienceDirect

Geothermics

journal homepage: www.elsevier.com/locate/geothermics

Optimizing geothermal production in fractured rock reservoirs under uncertainty

Jeremy R. Patterson*, Michael Cardiff, Kurt L. Feigl

Department of Geoscience, University of Wisconsin-Madison, 1215 W. Dayton St., Madison, WI 53706, United States

ARTICLE INFO

Keywords:
Optimization
Thermal breakthrough
Numerical modeling
Net present value
Uncertainty
EGS

ABSTRACT

Geothermal energy resources are highly available but under-utilized throughout the world. Previous studies have sought to understand reservoir response to geothermal production and optimize production rates to maximize lifetime profits of geothermal reservoirs; however, these studies largely overlook the uncertainty in subsurface structure, such as the number of preferential flow pathways (e.g., fractures) that are available for fluid and heat transport. We present a combination of simple analytical models that maximize the profits of an idealized synthetic geothermal reservoir, while considering reservoir structural uncertainty, using expected net present value. For a typical case, we find that effective reservoir transmissivity and inter-well spacing exert the largest controls on the lifetime profitability of an idealized geothermal reservoir, and for a given reservoir there exists a critical number of hydraulically active fractures beyond which additional fractures provide no increase in lifetime profits. Given initial reservoir characterization data, our model simulates reservoir performance that predicts financial outcomes, which operators can use during initial exploration stage. These predictions are also useful during normal operations to consider strategies, such as drilling make-up wells, to mitigate the effects of production-induced thermal drawdown.

1. Introduction

1.1. Purpose and scope

Geothermal energy is a ubiquitous energy resource that is largely untapped throughout the world. It is estimated that further development of Enhanced Geothermal Systems (EGS) in the United States has the potential to produce approximately 100 GW of geothermal energy, which could supply 10% of the country's energy demand (GTO, 2016). To realize this potential and bring geothermal energy production to operational status requires significant up-front capital investment to install and develop the necessary infrastructure (wells, power converters, pipes, etc...). To acquire the necessary capital investments for resource development, private companies must show that predicted long-term operational profits will exceed initial capital investments and long-term operations and maintenance (O&M) costs. Similarly, long-term forecasting models can guide operators' decisions about tuning extraction rates to ensure future reservoir sustainability. For instance, operators may have questions about whether pursuing an aggressive extraction approach – possibly at the expense of long-term sustainability – or taking a more conservative approach will be more profitable over the useful lifetime of a reservoir. Simplified models that incorporate both subsurface processes and plant operational parameters can provide a defensible platform for making such predictions and decisions.

Geothermal power plants commonly utilize re-circulating systems to pump hot water from the reservoir, extract thermal energy, and then return the cooled water to the subsurface. These re-circulating systems require site operators to determine the optimal pumping rate that allows profitable energy extraction while preventing "thermal breakthrough" of the injected cooled water into the feed zone accessed by production wells. To understand the dominant physical properties that impact thermal breakthrough due to cold water injection in geothermal fields, Patterson (2018) conducts a sensitivity analysis as a means of constraining the useful life of fully re-circulating geothermal operations. Using a simple analytical solution to simulate the movement of a thermal front away from injection wells, this analysis concludes that the surface area available for heat exchange (i.e., the number of hydraulically active flow paths) exerts the largest control on thermal breakthrough time, which is consistent with previous studies – e.g., Li et al. (2016).

Predictions of future profits – and thus the economic case for investing in and tuning geothermal site operations – can be generated using a physical model of subsurface and power-plant processes tied to

* Corresponding author.
E-mail addresses: jpatterson7@wisc.edu (J.R. Patterson), cardiff@wisc.edu (M. Cardiff), feigl@wisc.edu (K.L. Feigl).

https://doi.org/10.1016/j.geothermics.2020.101906
Received 5 December 2019; Received in revised form 30 April 2020; Accepted 23 June 2020
Available online 16 July 2020

Nomenclature

List of Variables

Q	is the volumetric flow rate in m^3/s
q	is the volumetric flow rate per fracture in m^3/s
n	is the number of fractures in the reservoir
$\Delta T(t)$	is the difference in production and injection water temperature in °C
C_w	is the specific heat capacity of water in J/(kg °C)
ρ_w	is the density of water in kg/m^3
γ_{plant}	is plant efficiency as a fraction of total energy rate
γ_{pump}	is pump efficiency as a fraction of input energy rate
g	is acceleration due to gravity in m/s^2
Δh	is the hydraulic head difference between production and injection wells in m
p	is the Laplace parameter
θ	is a dimensionless energy potential given by Eq. 3
b	is the fracture aperture in m
D	is the reservoir thickness in m
d	is the fracture half-spacing in m
ξ	is dimensionless distance given by Eq. 5
t_d	is dimensionless time given by Eq. 6
λ	is the thermal conductivity in W / (m °C)
η	is porosity [-]
$\rho_w C_w$	is the water volumetric heat capacity in J/(m^3 °C)
$\rho_f C_f$	is the fracture volumetric heat capacity in J/(m^3 °C)
$\rho_r C_r$	is the reservoir rock volumetric heat capacity in J/(m^3 °C)
$T_D(t)$	is the dimensionless temperature at the production well
$T_{prod}(t)$	is the production water temperature in °C
T_{inj}	is the injection water temperature in °C
T_0	is the initial production water temperature in °C
(x_{prod}, y_{prod})	are the spatial coordinates of the production well
(x_{inj}, y_{inj})	are the spatial coordinates of the injection well
(x, y)	are the spatial coordinates of the point of interest
Φ_0	is a specified discharge potential at a specified point in the reservoir in m^3/s
T	is transmissivity in m^2/s
f	is the friction factor [-]
τ	is the pipe tortuosity factor [-]
r_{pipe}	is the inner radius of the pipe
V	is water velocity in m/s
μ	is the dynamic viscosity in kg/(m s)
R_j	is the revenue at time step j in \$
$\dot{E}_j$	is the power produced during time step j in MW
M	is the selling price of energy in \$/MW-h
P	is installed power plant capacity in MW
i	is the annual discount rate
m	is the number of time steps

an economic model for power generation profits (Li et al., 2016). However, models of subsurface processes are subject to notoriously high uncertainty, largely due to limited available information about subsurface hydraulic properties and the associated flow pathways. In the case of deep geothermal systems, where heat is extracted from nearly impermeable rock, the characteristics of the fracture network that is transmitting fluid – such as the number of fractures and the associated fracture apertures – will exert strong controls on the rate at which heat can be extracted from the reservoir, and thus lifetime profits.

The subsurface structure of geothermal reservoirs represents a large source of uncertainty during reservoir characterizations efforts. Operators in active EGS systems may be able to estimate the number of available flow paths in their reservoir based on the number of stimulations; however, the number of hydraulically active fluid flow pathways that connect injection and extraction wells is extremely difficult to constrain in enhanced or natural reservoirs. Initial data collection efforts during reservoir prospecting typically includes estimating reservoir transmissivity via flow testing, and/or well-to-well connectivity interpreted through tracer testing. While these experiments provide effective hydraulic properties, they do not delineate the number of hydraulically active flow paths (i.e., fractures) in a reservoir.

A commonly-applied conceptual model describes a geothermal reservoir as a series of parallel faults or fractures that transmit fluid, which are intersected by wellbores (Fig. 1). While this model represents a drastic simplification of subsurface fracture networks, it allows efficient modeling of analytical solutions to simulate heat extraction as cooler water moves through the reservoir. Using site characterization information such as the overall reservoir transmissivity, T [m^2/s], and associated rock thermal properties, we can develop site-specific models

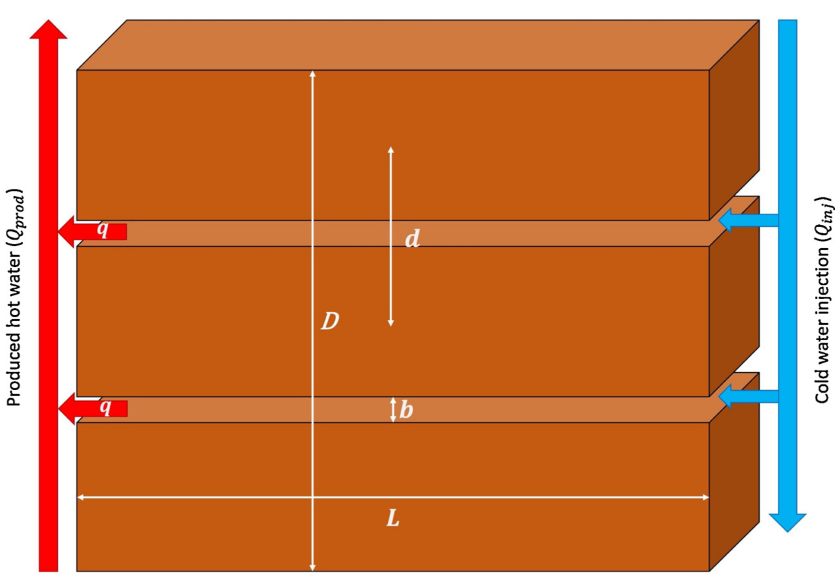

Fig. 1. Conceptual model showing reservoir geometry used to simulate production well water temperatures.

that are consistent with available observations – e.g., flow, pressure, and temperature.

In such conceptual models, a fundamental source of uncertainty is the number of hydraulically active fractures contributing to this transmissivity. For example, fluids may flow along a single fracture allowing greater flow or along several fractures allowing less flow in each fracture. To address this uncertainty, we take a probabilistic approach to predictions that recognizes this uncertainty is warranted. Here, we apply the concept of expected net present value (ENPV), which determines expected profits across multiple realizations of aquifer structure with varying numbers of hydraulically active fractures, each with an assumed probability. In this study, we present a strategy for simulating and optimizing geothermal production while accounting for the uncertainty associated with the number of hydraulically active fractures in the reservoir, using this concept of ENPV.

1.2. Optimizing geothermal systems

Understanding the production potential of geothermal reservoirs, given some initial characterization data, commonly utilizes computational modeling simulations – analytical and/or numerical – to predict future reservoir performance and inform on-site decision making (Samin et al., 2018) While computational models are more cost-efficient than testing reservoir performance in the field, they can become very complex, requiring significant costs in time, money, and computation. These modeling efforts commonly seek to improve heat extraction or efficiency or evaluate the long-term thermal and commercial reservoir potential using initial energy extraction data (Samin et al., 2018). As a first step, here we present a simple analytical model that uses available energy extraction data to evaluate the long-term value of an idealized hypothetical geothermal reservoir.

Recent studies have sought to optimize the thermal sustainability of geothermal systems using various techniques. Li et al. (2016) use the analytical solution developed by Gringarten et al. (1975) to optimize the NPV of a synthetic EGS reservoir, and find that reservoir NPV increases as the number of stages (i.e., the surface area available for heat transfer) increases; however, they use a deterministic optimization that does not consider the uncertainty in the model parameters. Specifically, their study assumes that fluid flow occurs along one fracture for each stage (i.e., five stages represent five fluid flow paths). Consequently, the optimized models do not account for the uncertainty in the number of fractures transferring fluid and heat. Furthermore, their analysis also considers neither operational costs associated with geothermal production nor installed plant capacity, both of which impose an upper limit on the total revenue expected over the lifetime of the reservoir.

Through the use of numerical simulations Juliusson and Horne (2013) use operational control modeling to present an efficient optimization method to maximize NPV by varying injection rates and timing. This study investigates two synthetic reservoirs with differing complexity to determine the distribution of injection rates through time across a given number of injection wells that maximizes NPV. Like Li et al. (2016), this study does not consider uncertainty in subsurface structure by assuming that flow occurs in all reservoir fractures. They also neglect operational costs during their simulations, which has the effect of assuming the reservoir is profitable throughout the entire simulation.

Operational control models are well studied in the oil-and-gas reservoir modeling literature; however, these studies overwhelmingly neglect uncertainty in subsurface structure. Jansen et al. (2008) and van Essen et al. (2009) consider subsurface uncertainty while using operational modeling to optimize NPV of synthetic reservoirs. However, these studies both utilize gradient-based optimization algorithms with data assimilation, requiring greater computation time compared with the analytical modeling presented in this work.

Chen and Jiang (2015) study various well placements to understand the well field arrangement that maximizes the thermal sustainability of a hypothetical geothermal reservoir. Similar to Li et al. (2016), this study neglects subsurface uncertainty and uses a deterministic approach during optimization. The authors find that well-field arrangement exerts a significant impact on thermal sustainability of the reservoir; however, they do not investigate the effects of well spacing for a given well field arrangement on thermal sustainability, which has been shown to be a significant control on thermal breakthrough at production wells (Chen et al., 2015; Li et al., 2016).

In a variation of the study by Chen and Jiang (2015); Chen et al. (2015) use a statistical model, named multivariate adaptive regression spline (MARS), to optimize well placement at the Superstition Mountain Prospect near the Salton Sea in Southern California, USA. Unlike the studies mentioned above, Chen et al. (2015) consider subsurface uncertainty, with fault length and height, fault permeability, and well injection as uncertain parameters during optimization. While this study does account for subsurface uncertainty, it assumes that the number of preferential flow paths used for fluid and heat transport is known a priori and that transport occurs only along the primary faults in the geothermal reservoir; thereby neglecting the potential of additional faults and fractures in the system, which may be critical for fluid and heat transport as well as long-term reservoir performance.

The well placement optimization problem is also well-studied in the oil-and-gas reservoir modeling literature. Forouzanfar and Reynolds (2014) present a well placement problem in a synthetic oil reservoir seeking to find injection well locations and rates that optimizes the NPV of the reservoir. The authors develop a gradient-based optimization algorithm to determine the optimal injection locations and production rates that maximizes NPV. Like Chen and Jiang (2015), this analysis neglects subsurface uncertainty and uses a numerical approach requiring longer computation times compared to the analytical models we present in this work.

Samin et al. (2018) conduct an optimization study that seeks to minimize thermal drawdown and total reservoir costs, while maximizing total thermal power extraction of a hypothetical geothermal reservoir based on the Spa Ulrach geothermal system discussed in Watanabe et al. (2010). Their approach couples a finite-element numerical model with a genetic algorithm that optimizes several parameters including, total reservoir depth, well spacing, reservoir permeability, and injection pressure. The finite-element model considers a simplified reservoir geometry, utilizing effective flow parameters, (e.g., porosity, permeability) as opposed to explicitly including fractures and faults that would act as preferential fluid flow pathways.

By utilizing deterministic approaches to maximize the long-term thermal, and thus, economic performance of geothermal reservoirs, most of the studies discussed above neglect the inherent uncertainty that exists in reservoir physical parameters and geometries. While previous studies have investigated the effect of reservoir parameter uncertainty on thermal sustainability, these studies have treated the number of preferential flow pathways in a reservoir as a known quantity. Consequently, they neglect the fact that information about the subsurface is intrinsically uncertain. For example, premature thermal breakthrough, in which cooled fluids begin flowing through previously unknown fractures, can be particularly problematic. Indeed, the study by Li et al. (2016) shows how the distribution of these flow paths in fractured or faulted reservoirs controls the lifetime profitability of the reservoir. Building on these studies, we develop a simple and computationally-efficient analytical model that considers the uncertainty in the number of preferential flow paths and optimizes the thermal and financial sustainability of geothermal reservoirs.

2. Modeling approach

Our modeling approach links two simplified models – a physical model of the geothermal reservoir and associated power plant, with an economic model of plant costs and profits – allowing for fast calculation of expected reservoir profits under uncertainty. The physical model, based on simplified reservoir geometries and geothermal plant descriptions, allows reservoir temperature and pressure predictions under a given scenario of production and recirculation rates, and also predicts the temperature of the extracted water. The economic model simulates revenues (from thermal extraction) and costs (from pumping and ongoing O&M activities) throughout the profitable lifetime of the reservoir using results from the physical model as inputs.

When reservoir parameters are uncertain, as described in Section 3, these simplified analytical models can run many plausible scenarios quickly, allowing expected profits (i.e., profits averaged across multiple scenarios) to be optimized. Such a simplified model may be highly useful, for example, during early stages of site development, after initial wells have been drilled and pump testing has provided initial hydraulic characterization information.

2.1. Reservoir conceptual model

We present a simplified conceptual model that simulates thermal front movement throughout a reservoir containing horizontal fractures. The numerical simulations presented in this study consider a geothermal system of a given thickness, D [m], with a fully penetrating well doublet, separated by a distance, L [m] (Fig. 1). The well doublet is connected by a number, n, of horizontal parallel planar fractures of infinite areal extent. Each fracture has a constant aperture, b, and may be partially filled by solids (i.e. fractures can have a porosity less than 1). Individual fractures are separated by an equivalent vertical spacing, that is the fracture half-spacing $\left(d = \frac{D}{n}\right)$, and the surrounding country rock is assumed to be impermeable (Fig. 1).

The re-injection well injects cold water at a specified temperature, T_{inj} [°C], into the reservoir at a given volumetric flow rate, Q_{inj} [m^3/s], which we assume to be constant throughout the simulation period. Under these assumptions, the total injection rate is divided equally among each fracture $\left(\text{i.e. }, q_{inj} = \frac{Q_{inj}}{n}\right)$. In reality we expect flow would likely be divided among the fractures based on the transmissivity of each fracture. To maintain mass balance in the system, we assume perfect recirculation such that the water removed from production wells at a volumetric flow rate of $Q_{prod} = -Q_{inj}$.

2.2. Reservoir mathematical model

We use analytical solutions to simulate water temperatures and reservoir pressures, which are essential for site operations. The reservoir water temperature model predicts water temperature evolution through time at the production well due to cold water injection using the radial flow solution of Bödvarsson and Tsang (1982). Described further in Section 2.3, the output of this model is used to calculate expected profits from geothermal heat extraction. The pressure model consists of two components which calculate: 1) the pressure difference between production and extraction well locations (computed as hydraulic head); and 2) the additional head losses associated with forcing fluid along a length of pipe between the extraction and injection wells. The sum of these two components produces the net head difference between the wells, which is used to calculate pumping costs within the economic model.

2.2.1. Reservoir temperature model

The analytical solution by Bödvarsson and Tsang (1982) describes thermal front movement in a radial direction away from injection wells in a geothermal reservoir with horizontal parallel planar fractures. This solution calculates water temperature at a production well ($T_{prod}(t)$) as a function of time (i.e., thermal breakthrough), which assumes that water flows in a purely radial manner through horizontal fractures of constant aperture surrounded by impermeable reservoir rock. Heat conduction within the reservoir rock occurs in the vertical direction only, and, water temperature within the fracture is in equilibrium at the rock-water interface (Bödvarsson and Tsang, 1982).

To simulate thermal movement in response to cold-water injection, the Bödvarsson and Tsang (1982) model requires reservoir rock hydraulic properties, reservoir rock thermal properties, fluid thermal properties, and reservoir geometries as inputs. Using these input parameters, we determine the dimensionless water temperature at the production well as a function of time ($T_D(t)$):

$$T_D(t) = \frac{T_{prod}(t) - T_0}{T_{inj} - T_0} \tag{1}$$

The solution derived by Bödvarsson and Tsang (1982) gives water temperature at the center of the fracture in the Laplace domain (Eq. (2)). We numerically invert Eq. (2) for the Laplace parameter (p) with respect to dimensionless time (t_d) using the algorithm developed by De Hoog et al. (1982), which yields $T_D(t)$.

$$u = \frac{1}{p}\exp\left(\frac{[\theta p + 2\sqrt{p}\tanh(\sqrt{p})]\,\xi}{2+\theta}\right) \tag{2}$$

$$\theta = \frac{\rho_f C_f b}{\rho_r C_r D} \tag{3}$$

$$p_f C_f = \eta\rho_w C_w + (1-\eta)\rho_r C_r \tag{4}$$

$$\xi = \frac{\lambda\pi r^2(2+\theta)}{QD\rho_w C_w} \tag{5}$$

$$t_d = \frac{\lambda t}{\rho_r C_r D^2} \tag{6}$$

2.2.2. Pipe friction model

To calculate head losses along the pipes between the pumping and injection wells, we use the Darcy-Weisbach equation, which quantifies energy losses due to frictional resistance (Brown, 2003). Our analysis includes a tortuosity multiplier (τ) which accounts for the increased pipe length at the land surface as water is moved from the production well, through the power plant, to the injection well (Eq. (7)).

$$h_{fric} = f\left(\frac{L\tau}{2r_{pipe}}\right)\left(\frac{V^2}{g}\right) \tag{7}$$

The unitless friction factor (f) is an empirical parameter that is dependent on pipe roughness and fluid turbulence, which is commonly determined through the use of Moody diagrams or implicit relationships such as the Colebrook equation (Round, 1980). We employ the Matlab library function *fminsearch* to solve the Colebrook equation implicitly and estimate the value of f.

2.2.3. Parasitic power losses

Our model uses the common assumption that head within a wellbore is accurately approximated by an analytical solution evaluated at the wellbore radius. We calculate hydraulic head at the borehole wall for each well using analytical solutions developed by Haitjema (1995), which simulates flow between two wells (Eq. (9)).

The total head difference, Δh [m], between production and injection wells controls the amount of energy required to pump and circulate water for thermal power production. The total head difference includes the difference in hydraulic head (i.e., water level elevations) between the injection (h_{inj}) and production (h_{prod}) wells as well as frictional head losses (h_{fric}) due to pipe flow (Eq. (10)).

$$\Phi(x, y) = \frac{Q}{4\pi}\ln\left(\frac{(x - x_{prod})^2 + (y - y_{prod})^2}{(x - x_{inj})^2 + (y - y_{inj})^2}\right) + \Phi_0 \tag{8}$$

$$h(x, y) = \frac{\Phi(x, y)}{T} \tag{9}$$

$$\Delta h = (h_{inj} - h_{prod}) + h_{fric} \tag{10}$$

This analysis provides an optimistic estimate of power production losses due to geothermal operations. A more rigorous analysis could consider other auxiliary power costs associated with geothermal power production (e.g., cooling towers and gas extractors); however, these elements are highly site-specific, and therefore, are beyond the scope of this analysis (Zarrouk and Moon, 2014).

2.3. Simplified economic model

2.3.1. Energy production modeling

We model the net power production rate, $\dot{E}_{net}$ [W], as the difference in thermal power production rate ($\dot{E}_{prod}$) and parasitic power consumption rate ($\dot{E}_{loss}$) as described by Eq. (11). We impose an upper limit on the net power production rate by not allowing it to exceed the installed plant capacity (Fig. 2). Plant operators must balance production rates accordingly to minimize the amount of lost revenue due to excessive thermal power extraction, while maximizing plant revenues and reservoir longevity.

$$\dot{E}_{net} = \dot{E}_{prod} - \dot{E}_{loss} \tag{11}$$

$$\dot{E}_{prod} = Q\rho_w Cp_w \Delta T(t)\gamma_{plant} \tag{12}$$

$$\dot{E}_{loss} = \frac{Q\rho_w g\Delta h}{\gamma_{pump}} \tag{13}$$

Power losses due to turbines, generators, and heat loss in water during pipe flow have been shown to be a function of reservoir temperature, reservoir enthalpy, and chosen plant type (Bodvarsson, 1974; Nathenson, 1975; Zarrouk and Moon, 2014). While water does lose thermal energy during pipe flow, Zarrouk and Moon (2014) show that the losses are commonly less than 1% and can be considered negligible for most analyses. Our simplified energy production model assumes that power plant operators have a working understanding of total plant efficiency, which incorporates all of the above factors; therefore, we do not determine them individually. In situations where power production has yet to begin, a more thorough analysis could estimate the individual components and total plant efficiency based on initial characterization data using established analytical expressions – e.g., Zarrouk and Moon (2014).

2.3.2. Operational costs

Numerous studies report that geothermal reservoir development benefits from economies of scale with respect to capital and labor as initial capital investments can be recouped more easily with larger plant capacities and labor costs become more efficient per MW with increasing plant capacities (Lovekin, 2000). Consistent with the economies of scale, operational costs have been shown to decrease in an exponential manner as a function of installed plant capacity (Chamorro et al., 2012; Sanyal, 2004). To simulate monthly operational costs, we use the exponential expression described by Chamorro et al. (2012) that describes unit operational costs ($c_{O\,\&\,M}$) in \$/MWh as a function of installed power plant capacity, P [MW] (Eq. (14)).

$$c_{O\,\&\,M} = 20\exp(-0.0025(P-5)) \tag{14}$$

2.3.3. Generated profits

We use standard net present value (NPV) analysis to determine the generated income at monthly time steps (Eq. (15)) using an assumed energy price (M) in \$/MWh. While NPV analysis commonly occurs on an annual basis, we utilize monthly time steps in our analysis because we assert that it is unreasonable to assume a constant water temperature in geothermal production wells over a one-year period; therefore, we choose smaller monthly time steps, which we argue is a more reasonable time period over which we can assume an approximately constant temperature for the production water.

$$R_j = \frac{\dot{E}_{net\,j}\Delta t_j M}{(i+1)^j} \tag{15}$$

Our model calculates the profits (Eq. (16)) at a given time step by considering the difference in monthly generated revenue (R_j) and monthly operational costs ($c_{O\,\&\,M}$). The profits are then integrated across the total time series to determine NPV (Fig. 3). Our model assumes that any negative profit represents the end of thermal power production. At this point in time, integration stops when calculating NPV for an individual realization (Fig. 3). Physically, negative monthly profits represent a situation requiring plant operators to modify their current production strategy, commonly drilling new production wells while the previous wells are allowed to recover or decreasing the production rate to a point where the well can recharge while still producing. More complex numerical models can account for these dynamic changes in production strategy; however, our simple analytical model does not account for this and assumes that production ceases when the plant is no longer profitable.

$$NPV = \sum_{j=1}^{m} R_j - (\dot{E}_{net\,j}\, c_{O\,\&\,M_j}\,\Delta t_j) \tag{16}$$

2.4. Optimization under uncertainty

Our optimization strategy seeks to find the production rate that maximizes *ENPV* of an idealized synthetic reservoir by calculating the *NPV* across a range of realizations with varying numbers of hydraulically active fractures. Due to the large uncertainty in the number of hydraulically active fractures in a given reservoir, we assume that the number of fractures being accessed for fluid flow, and thus heat transport, are equally likely, which equates to *ENPV* being the arithmetic mean of *NPV* across all realizations (Eq. (17)).

$$ENPV = \sum_{k=1}^{\#\ realizations} Pr_k NPV_k \tag{17}$$

We assume the geothermal field is operating under normal production conditions (i.e., beyond the exploration and initial characterization stages) and that site operators have an understanding of reservoir physical properties, including, primarily, reservoir effective transmissivity, rock thermal conductivity, and rock volumetric heat

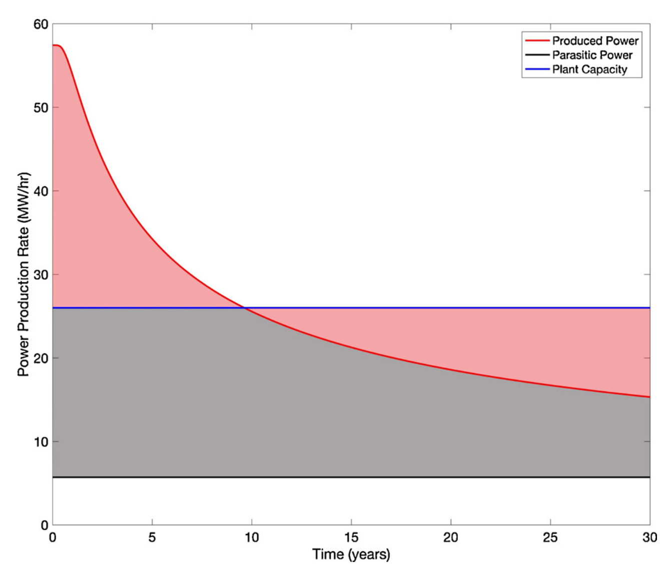

Fig. 2. Power production rate, parasitic power consumption, and power plant capacity throughout the 30-year simulation period showing the extracted thermal power available for energy conversion and revenue generation. Red regions indicate revenue loss due to over / under production.

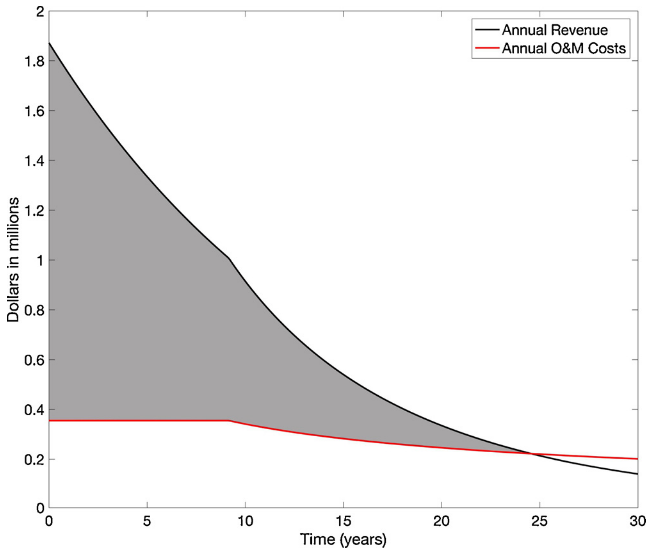

Fig. 3. Annual revenues and annual O&M costs throughout the 30-year time period. The shaded region represents the integrable area used to determine NPV for individual realizations.

capacity. Given these known reservoir parameters (Table 1), we utilize a two-level optimization scheme (Fig. 4) which seeks to maximize *ENPV* given these reservoir parameters, $\boldsymbol{m}$, by varying the volumetric flow rate (Eq. (18)). To conduct the optimization, we employ the MATLAB function *fminsearch* (MATLAB, 2016). This algorithm uses the simplex method, which is a non-gradient based direct search algorithm as described by Lagarias et al. (1998). We maintain the non-negativity constraint on Q by perturbing $\ln(Q)$ during the optimization.

$$\max_{Q} E\left[NPV\,(Q|\boldsymbol{m})\right] \tag{18}$$

subject to:

$$Q > 0$$

3. Example application scenario

In this section we present an example application of the above described models in an idealized synthetic geothermal reservoir with assumed known physical parameters (Table 1), many of which are based on the analysis presented by Li et al. (2016). Our analysis simulates plant profits over a 30-year time period, which is a common time frame for studies seeking to understand the thermal sustainability, and thus profitability, of geothermal reservoirs. While longer simulations may be informative, their usefulness is limited because they potentially extend beyond the useful lifetime of production equipment (e.g., pumps, generators, turbines, etc…). Similarly, longer simulations do not account for the rapid progression and incorporation of technological advances by site operators. Due to these factors, changes to geothermal production and infrastructure are typical beyond the 30-year timeframe (Patterson, 2018).

We prescribe water density and viscosity values consistent with what would be expected at the injection wells after heat extraction, in line with the analysis by Li et al. (2016). This decision is consistent with our temperature model which describes radial flow away from injection wells and determines cold water breakthrough at production wells at a given radial distance. A brief analysis shows that using the lower fluid density and viscosity values expected at production wells – again using values from Li et al. (2016)– results in a negligible difference in *ENPV*, implying that our model is insensitive to these parameters, and provided that reasonable density and viscosity values are chosen, their impact on predicted outputs are negligible.

Li et al. (2016) establish a water temperature threshold of 150 °C at which geothermal operations cease; however, our study takes a different approach, in that we do not use a water temperature threshold for production cessation. In contrast, we use simulated monthly profits as our termination threshold. That is, our model assumes the power plant remains operational as long as monthly revenues (Eq. (14)) exceed monthly O&M costs (Eq. (13)), shown by the shaded area in Fig. 3. More simply, the plant is assumed to remain operational as long it is generating profits.

As discussed above in 2.3.1, total plant efficiency is based on many factors. Our analysis assumes that total plant efficiency is well known by site operators; therefore, we do not determine component contributions to efficiency on an individual basis. Our analysis uses a total plant efficiency of 10 % to simulate the profit time series curves, which is based on an approximate average value of the temperature – efficiency relationships as presented by Zarrouk and Moon (2014).

We set the electricity selling price at 0.10 $/kW-hr, which is based on the average selling price of electricity across all sectors within the U.S. in 2017, (United States Energy Information Administration, 2018). Present value analysis commonly assumes an annual discount rate of 2–3 percent consistent with expected inflation rates; however, because geothermal energy represents a high-risk capital investment, discount rates trend significantly higher. Mines and Nathwani (2013) present a variable discount rate approach based on operational stage, starting at 30 % during exploration, 15 % during well development and completion, and 7% under normal production conditions. Our analysis assumes the reservoir is beyond the well completion stage and energy production has started; therefore, we use a 7 % discount rate. The analysis of Li et al. (2016) applies a discount rate of 16 %; however, the higher discount rates associated with geothermal exploration and production are front-loaded in the first ~5 years, making 7 % a more reasonable rate for longer-term present value analysis occurring on decadal time scales (Mines and Nathwani, 2013). It is worth noting that the discount rate is applied only to plant revenues. We chose not to apply the discount rate to O&M costs so that our analysis represents more conservative profit predictions.

4. Results and discussion

4.1. Production optimization – base case

Fig. 5 shows simulated thermal breakthrough curves at the production well for a 30-year time period using the optimization scheme shown in Fig. 4 and the parameters in Table 1. As expected, we see slower declines in water temperature (i.e., delayed thermal breakthrough) as the number of fractures in the reservoir increases. Fig. 6a shows simulated profit time series for the entire 30-year period, with the black dot – at a time of 24 years – indicating the point when production would cease due to the geothermal field no longer being profitable. Under this scenario, we find an *ENPV* of $170 million with an optimal production rate of 0.65 m^3/s (Fig. 6a). It should be noted that not all realizations are shown in Figs. 5 and 6a due to the fact that the thermal breakthrough and profit curves would overlie each other when considering realizations with more than three fractures in the

Table 1
Base case reservoir input parameters used to simulate power plant profits over a period of 30 years.

λ	3.0 [W/(m °C)]	T	0.013 [m^2/s]
ρ_r	2500 [kg/m^3]	ρ_w	983 [kg/m^3]
C_r	1000 [J/(kg °C)]	μ_w	0.00047 [kg/(m s)]
T_{inj}	80 [°C]	C_w	4000 [J/(kg °C)]
T_{prod}	190 [°C]	D	1000 [m]
τ	1.5[−]	L	1500 [m]

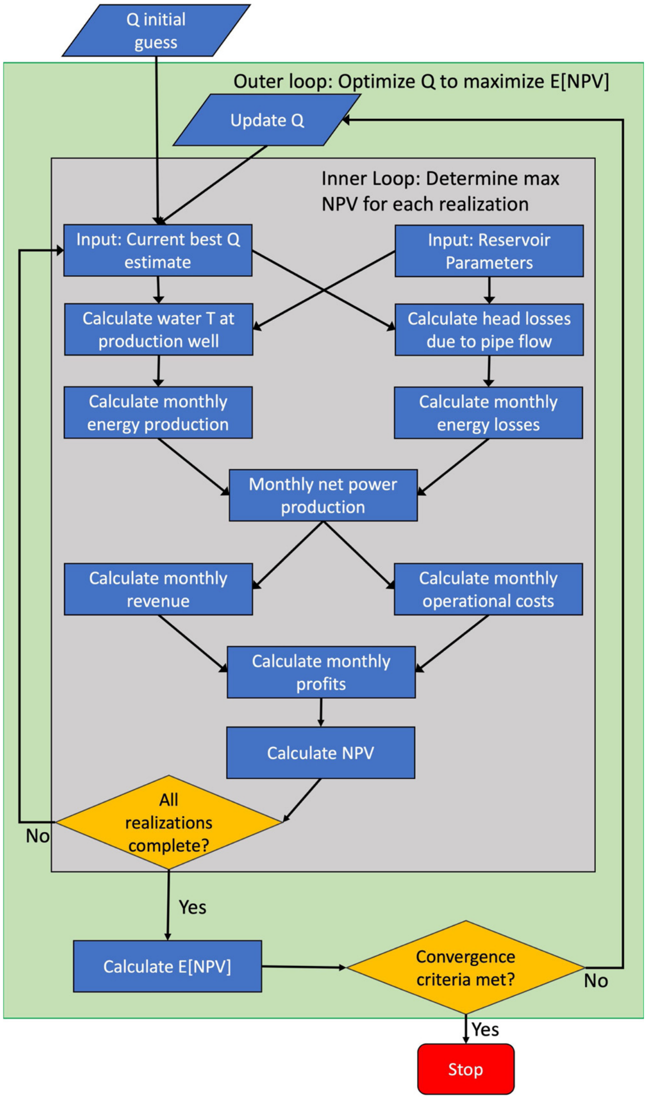

Fig. 4. Flow chart describing optimization scheme. Inner loop determines NPV across multiple realizations. E[NPV] calculation and flow-optimization occur in the outer loop.

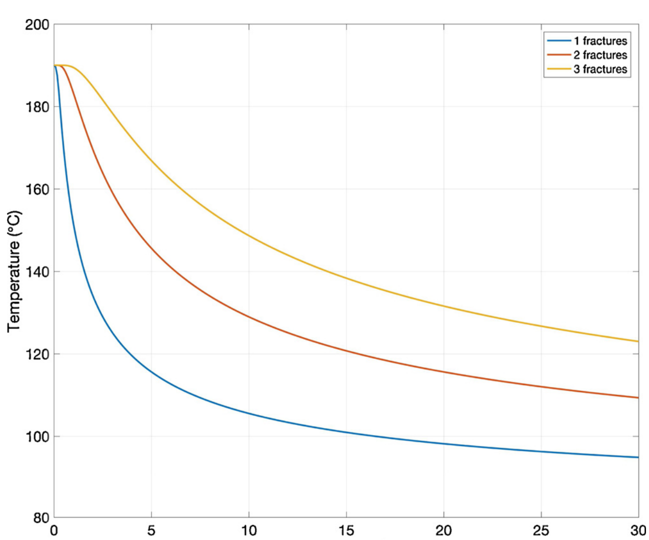

Fig. 5. Production well water temperature profiles through the 30-year simulation period for realizations up to 3 hydraulically active fractures.

reservoir under this scenario.

As with previous studies (Li et al., 2016; Patterson, 2018), we see that as the number of fractures accessed for fluid transport increases and the surface area available for heat exchange increases, temperature declines in the production well are delayed (Fig. 5) thereby increasing plant profits and maximum *NPV* (Fig. 6b). However, as the number of hydraulically active fractures increase, we also observe a non-linear decrease in the amount by which the maximum *NPV*, and thus *ENPV*, increases before becoming constant beyond three fractures. We attribute this behavior to the installed plant capacity imposing a ceiling on the maximum amount of thermal energy that can be converted to electrical energy (Fig. 2), thereby placing a ceiling on the lifetime profits that a reservoir can produce.

While it has been shown that increasing heat exchange surface area prolongs the thermal lifetime and profitability of a reservoir, our analysis implies there is a maximum number of hydraulically active fractures above which profits are not improved. These findings are in contrast to those of Li et al. (2016), who found that *NPV* consistently increased with an increasing number of EGS stages (i.e., hydraulically active fractures). We attribute this difference in findings to a combination of two things. First, their analysis and conclusions are based on the assumption that all the extracted thermal energy is converted to electrical energy, minus some conversion efficiency, with no upper limit. Our study enforces a maximum lifetime profit by assuming that energy production is limited by the installed capacity of a power plant, thereby limiting the amount of electrical energy that can be produced and sold any given year (Fig. 3). This cap implies that for a system with a known transmissivity, there exists a point at which there is no additional increase in revenue with an increasing number of available fluid flow pathways (Fig. 6b).

Second, we assume the overall reservoir transmissivity is a known value and remains constant, regardless of the number of fractures considered; therefore, the transmissivity of individual fractures decreases as the total number of fractures in the reservoir increases. In contrast, Li et al. (2016) assumes that reservoir transmissivity increases as the number of stages increases, that is the total reservoir transmissivity is the sum of individual fracture transmissivities. The increasing transmissivity has the effect of increasing the maximum production rate, thus improving *ENPV*. However, the increase in ENPV seen with increasing transmissivity is negligible when compared to the effect of placing an upper limit on annual revenue by considering the installed capacity of a power plant. (We discuss this point in more detail in Section 4.2)

As discussed above in Section 3, Li et al. (2016) established a temperature floor of 150 °C below which geothermal production ceased, and their analysis found it took more than a decade for thermal drawdown at the production well to reach this temperature. Our simulations show that water temperature at the production well declines to this temperature floor in as short as two years and as long as ten years as the number of fractures in the reservoir increases (Fig. 5). Nonetheless, our analysis demonstrates that the plant remains profitable for a period of 24 years with water temperatures at the production well below 150 °C (Fig. 5). Had our analysis enforced the floor temperature as in previous studies, the *ENPV* under this scenario would have decreased by approximately $34 million, compared to our baseline scenario. Accordingly, we argue that the profit analysis produced by our model provides a useful metric that can be adapted for a specific reservoir to support decision-making about ceasing production.

4.2. Sensitivity analysis

Following the base case, we conduct a brief sensitivity analysis to determine the physical parameters that exert the largest influence on the financial sustainability of our idealized reservoir. Although it is well known that a chosen discount rate has a large effect on net present value calculations, we do not consider the discount rate in our

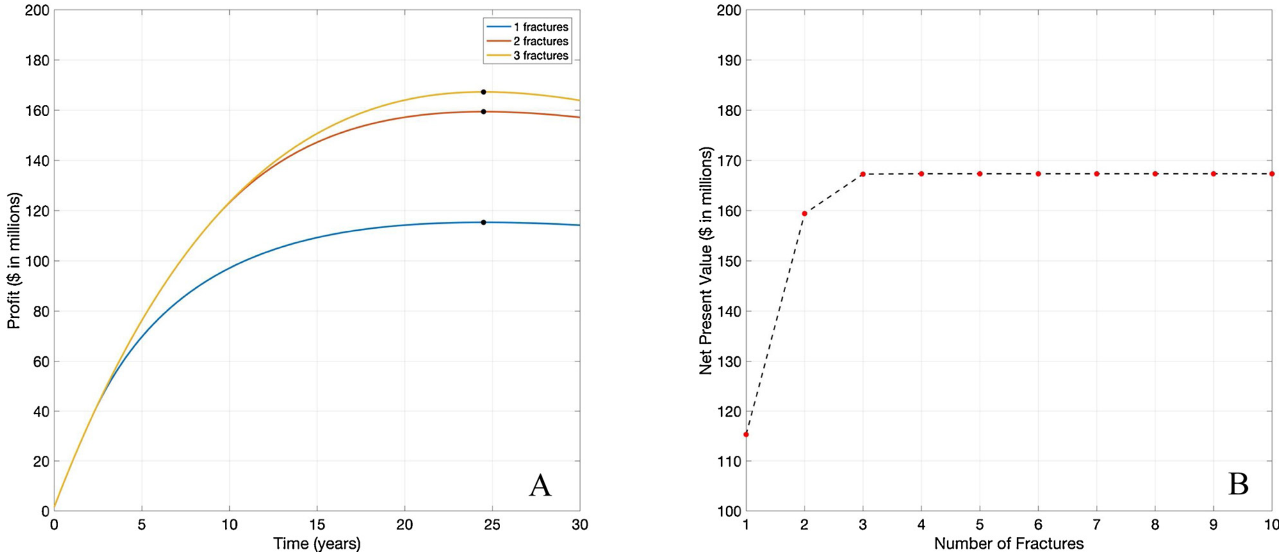

Fig. 6. Annual profits through the 30-year simulation period for realizations up to 3 hydraulically active fractures. Black asterisk indicates last year plant is profitable (A), and maximum NPV for each realization, showing that NPV becomes constant after more than 3 hydraulically active fractures are considered under this scenario (B).

sensitivity analysis, as these rates are controlled by multiple non-physical factors. Since our analysis focuses on reservoir physical properties that control *ENPV* by changing the thermal regime within the reservoir, the effects of discount rates are beyond the scope of this work.

Our sensitivity analysis finds that changes to well spacing (L) and reservoir effective transmissivity (T) exert the largest effect on $ENPV$. We varied well spacing over a range of two km, from 500 m to 2500 m. Despite the fact that transmissivity values can vary over a range of ~ 15 orders of magnitude, we restricted our analysis of effective transmissivity values to two orders of magnitude, since this range clearly illustrates the sensitivity of *ENPV* to this parameter.

Changes to *ENPV* occur by changing thermal breakthrough time at the production well – directly impacting plant revenues – or by controlling the production rate – affecting the power production rate and parasitic power requirements to pump water from production to injection wells. Increasing well spacing increases the radial distance the cold-water front must travel to reach the production well, thereby increasing the amount of time the plant can produce at maximum capacity and generate maximum profits. In contrast transmissivity controls the head gradient between the two wells, and thus, the maximum production rate the plant can sustain, which directly affects the power production rate and power inputs necessary to pump water from production wells.

Fig. 7 shows surfaces of optimal production rate and *ENPV* for the range of transmissivity and well spacing pairs analyzed during the sensitivity analysis. We see that for any given reservoir effective transmissivity, changing the well spacing has little impact on the optimal production rate (Fig. 7a); however, a small change to well spacing yields a large impact on *ENPV* (Fig. 7b). In contrast, we see that for any given well spacing, changing transmissivity yields large changes to the optimal production rate (Fig. 7a), while changes to *ENPV* are small across the range of transmissivity values (Fig. 7b).

Increasing well spacing prolongs the time to thermal breakthrough at the production well, accounting for the observed high sensitivity of ENPV to well spacing. Delaying thermal breakthrough increases the amount of time the power plant can operate at its installed capacity, thereby increasing profits and ultimately $ENPV$. As discussed above, increased well spacing yields increased production rates, which has the effect of increasing ENPV – to a much lesser extent than delaying breakthrough – by increasing the power production rate (Eq. (12)).

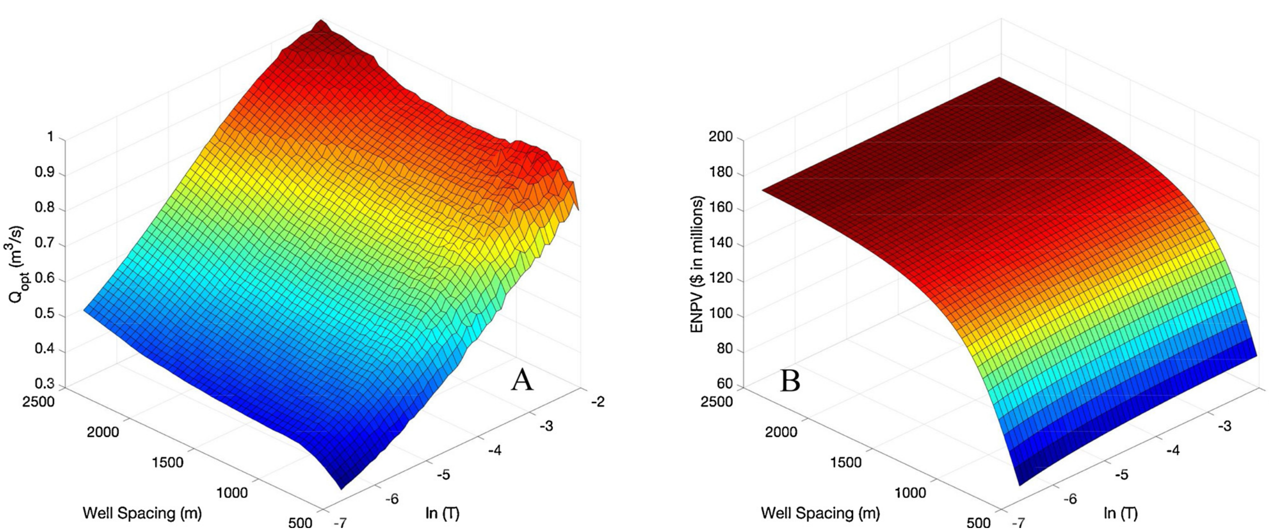

Fig. 7. A.) Optimal production rate as a function of well spacing and effective transmissivity, and B.) ENPV as a function of well spacing and effective transmissivity.

The observed sensitivity of Q_{opt} to transmissivity occurs as the two factors work together to create the pressure gradient between injection and production wells. More specifically, low-transmissivity reservoirs yield lower production rates (Fig. 7a) so that the pressure gradient – and thus parasitic power consumption – is minimized, and high-transmissivity reservoirs, experience lower resistance to flow; therefore, they accommodate a higher production rate while maintaining the necessary head gradient to minimize parasitic power consumption (Fig. 7a).

When varying transmissivity over two orders of magnitude, temperature breakthrough curves at the production well remain unchanged (Fig. 8a), implying that heat sweep efficiency is not sensitive to changes in reservoir transmissivity for a reservoir with a given number of hydraulically active fractures. In contrast to the lack of change seen in the thermal breakthrough curves, a change in transmissivity produces noticeable changes to the net power production rate over the 30-year simulation period (Fig. 8b), directly impacting NPV. As described above, reservoir transmissivity changes reservoir $ENPV$ by changing the amount of energy required by the plant to pump water from production to injection wells. The pressure gradient between wells dictates the necessary power required for pumping operations, and as this power consumption increases the plant's net power production rate – and thus profits – will decrease (Eq. (11)). We see that the decreased $ENPV$ from lower transmissivity reservoirs can be overcome with a slight increase in well spacing (e.g., as little as 100 m), which lowers the pressure gradient between the two wells, and thus the parasitic power costs necessary to pump water from production wells (Fig. 8).

5. Conclusions

In this study, we present a combination of simple analytical models that determine expected profits of an idealized geothermal reservoir given uncertainty about the subsurface reservoir structure. With very basic reservoir characterization data, such as effective thermal and hydraulic reservoir properties, this modeling approach provides plant operators with a time efficient tool that produces lifetime power plant profit estimates, which can help guide decision-making processes throughout all stages of reservoir development. Since the models are analytic, the calculations are quite fast, taking typically less than one minute per run. This approach is most useful as an initial assessment tool prior to more time- and computationally-intensive numerical modeling approaches, to decide if a reservoir has the potential to yield the desired return on investment.

One limitation in our analytical model is the assumption of a known reservoir transmissivity. While this may be a valid assumption in the case where initial reservoir testing and production has commenced, in the case where reservoir testing or production are not yet underway, this assumption is not valid, and transmissivity represents a large source of uncertainty. Given that transmissivity exerts significant controls on heat transport, it follows that transmissivity should influence decision-making about installing additional infrastructure. A natural extension of our analysis would be to consider the case with an unknown reservoir transmissivity and incorporate this uncertainty into the optimization by varying production rates and installed plant capacity to maximize $ENPV$. While such an analysis is beyond the scope of this work, future research in this area would improve the utility of this modeling approach.

Our model simulations indicate that the lowest $ENPV$ estimates are slightly more than \$60 million for a given well spacing and transmissivity (Fig. 7), which is an order of magnitude larger than the approximate \$6 million cost of drilling one make-up well (Lowry et al., 2014). In light of this result, we argue that such a reservoir could yield enough profits over 30 years to overcome the cost of drilling make-up wells. This example demonstrates how quantitative modeling can help reservoir operators manage production wells undergoing production-induced thermal drawdown or premature thermal breakthrough.

While our analysis clearly shows that lifetime profits of a reservoir will provide a return on investment that exceeds well drilling costs by an order of magnitude, it is less clear that a reservoir will provide reasonable returns on investment during the initial exploration stages. To fully understand this issue, a more thorough analysis could be conducted using numerical software packages that allow for more complex subsurface fracture geometries, variable well field geometries, and dynamic production operations that respond to reservoir performance. A more robust analysis would also include initial capital costs related to plant installation and local governmental tax policies, all of which are beyond the scope of this work.

Consistent with previous studies, Fig. 6 shows that increasing the surface area available for heat transfer increases the thermal sustainability, and thus the $ENPV$, of geothermal reservoirs (Li et al., 2016; Patterson, 2018). Unlike these previous studies we observe a threshold above which increasing the number of hydraulically active fractures in a reservoir does not increase NPV of the reservoir, a result imposed by the plant's installed production capacity. While it is not reasonable to generalize a specific number of fractures at which this threshold exists across a range of geothermal reservoirs, it is a useful concept for plant operators in an EGS setting to incorporate into the decision-making process as they consider the potential cost benefits of stimulating a reservoir. This understanding can help operators decide how many stages may be necessary to maximize profits, and if there is a point at which the cost of additional stages will no longer provide a return on

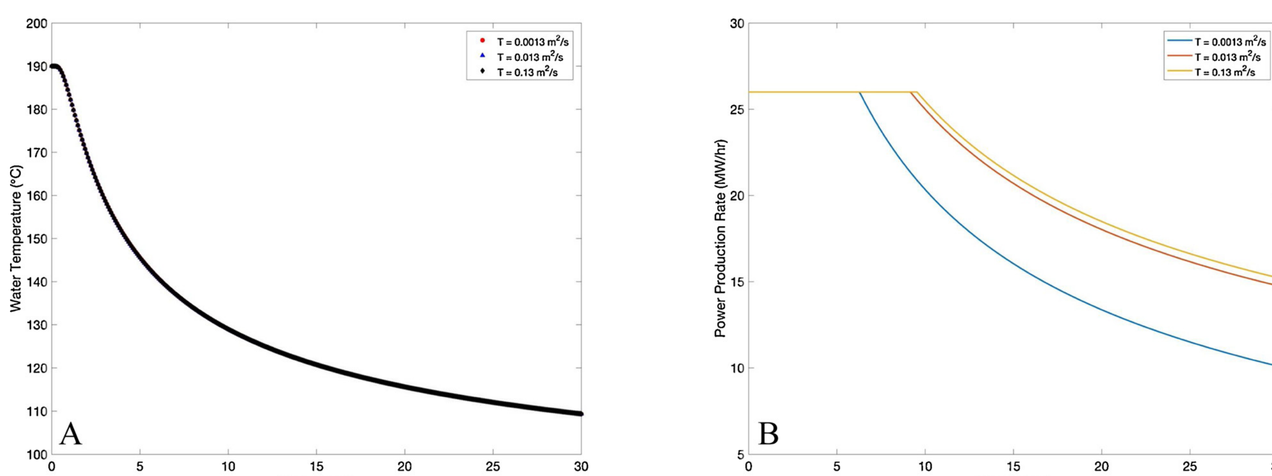

Fig. 8. Production well water temperature profiles in a reservoir with two hydraulically active fractures (left), and net power production rate throughout the 30-year simulation period in a reservoir with two hydraulically active fractures (right) with varying effective transmissivity.

investment.

CRediT authorship contribution statement

Jeremy R. Patterson: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Visualization. **Michael Cardiff:** Funding acquisition, Conceptualization, Methodology, Writing - review & editing, Resources, Supervision, Project administration. **Kurt L. Feigl:** Funding acquisition, Project administration, Supervision, Writing - review & editing.

Declaration of Competing Interest

There are no known conflict of interest.

Acknowledgements

This research was supported by grants DE-EE0005510 and DE-EE0006760 from the U.S. Department of Energy Geothermal Technologies Office, and NSF grant 1654649 "CAREER: Understanding transport processes in fractured sedimentary rock through multi-frequency and multi-method investigations." The authors wish to thank two anonymous reviewers for their comments and feedback, which greatly improved the quality of this work.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.geothermics.2020.101906.

References

Bodvarsson, G., 1974. Geothermal resource energetics. Geothermics 3 (3), 83–92.
Bödvarsson, G.S., Tsang, C.F., 1982. Injection and thermal breakthrough in fractured geothermal reservoirs. J. Geophys. Res. Solid Earth 87 (B2), 1031–1048.
Brown, G.O., 2003. The history of the Darcy-Weisbach equation for pipe flow resistance. Environ. Water Resour. Hist. 34–43.
Chamorro, C.R., Mondéjar, M.E., Ramos, R., Segovia, J.J., Martín, M.C., Villamañán, M.A., 2012. World geothermal power production status: energy, environmental and economic study of high enthalpy technologies. Energy 42 (1), 10–18.
Chen, J., Jiang, F., 2015. Designing multi-well layout for enhanced geothermal system to better exploit hot dry rock geothermal energy. Renew. Energy 74, 37–48.
Chen, M., Tompson, A.F., Mellors, R.J., Abdalla, O., 2015. An efficient optimization of well placement and control for a geothermal prospect under geological uncertainty. Appl. Energy 137, 352–363.
De Hoog, F.R., Knight, J., Stokes, A., 1982. An improved method for numerical inversion of Laplace transforms. SIAM J. Sci. Stat. Comput. 3 (3), 357–366.
Forouzanfar, F., Reynolds, A., 2014. Joint optimization of number of wells, well locations and controls using a gradient-based algorithm. Chem. Eng. Res. Des. 92 (7), 1315–1328.
Gringarten, A., Witherspoon, P., Ohnishi, Y., 1975. Theory of heat extraction from fractured hot dry rock. J. Geophys. Res. 80 (8), 1120–1124.
GTO, D, 2016. 2015 Annual Report Geothermal Technologies Office. U.S. Department of Energy, pp. 30.
Haitjema, H.M., 1995. Analytic Element Modeling of Groundwater Flow. Academic Press, San Diego [1995] ©1995.
Jansen, J.-D., Bosgra, O.H., Van den Hof, P.M., 2008. Model-based control of multiphase flow in subsurface oil reservoirs. J. Process Control 18 (9), 846–855.
Juliusson, E., Horne, R.N., 2013. Optimization of injection scheduling in fractured geothermal reservoirs. Geothermics 48, 80–92.
Lagarias, J.C., Reeds, J.A., Wright, M.H., Wright, P.E., 1998. Convergence properties of the Nelder–Mead simplex method in low dimensions. SIAM J. Optim. 9 (1), 112–147.
Li, T., Shiozawa, S., McClure, M.W., 2016. Thermal breakthrough calculations to optimize design of a multiple-stage enhanced geothermal system. Geothermics 64, 455–465.
Lovekin, J., 2000. The Economics of Sustainable Geothermal Development. Transactions-Geothermal Resources Council, pp. 113–118.
Lowry, T.S., Kalinina, E.A., Hadgu, T., Klise, K.A., Malczynski, L.A., 2014. Economic valuation of directional wells for EGS heat extraction. In: Thirty-Ninth Workshop on Geothermal Reservoir Engineering. Stanford University.
MATLAB, 2016. Version 9.1.0.441655 (R2016b). The Mathworks Inc., Natick, Massachusetts.
Mines, G., Nathwani, J., 2013. Estimated power generation costs for EGS. In: Proc. 38th Workshop on Geothermal Reservoir Engineering. Stanford University.
Nathenson, M., 1975. Physical Factors Determining the Fraction of Stored Energy Recoverable from Hydrothermal Convection Systems and Conduction-Dominated Areas. Geological Survey, Menlo Park, Calif. (USA).
Patterson, J.R., 2018. Understanding Constraints on Geothermal Sustainability through Reservoir Characterization at Brady Geothermal Field. Department of Geoscience University of Wisconsin - Madison, Nevada.
Round, G., 1980. An explicit approximation for the friction factor-Reynolds number relation for rough and smooth pipes. Can. J. Chem. Eng. 58 (1), 122–123.
Samin, M.Y., Faramarzi, A., Jefferson, I., Harireche, O., 2018. A hybrid optimisation approach to improve long-term performance of enhanced geothermal system (EGS) reservoirs. Renew. Energy 134, 379–389.
Sanyal, S.K., 2004. Cost of geothermal power and factors that affect it. In: Proceedings of the Twenty-Ninth Workshop on Geothermal Reservoir Engineering. Stanford, California. Stanford, California.
United States Energy Information Administration, 2018. Electricity Data Browser. https://www.eia.gov/electricity/data/browser/. (Accessed December 13 2018). .
van Essen, G., Zandvliet, M., Van den Hof, P., Bosgra, O., Jansen, J.-D., 2009. Robust waterflooding optimization of multiple geological scenarios. SPE J. 14 (01), 202–210.
Watanabe, N., Wang, W., McDermott, C.I., Taniguchi, T., Kolditz, O., 2010. Uncertainty analysis of thermo-hydro-mechanical coupled processes in heterogeneous porous media. Comput. Mech. 45 (4), 263.
Zarrouk, S.J., Moon, H., 2014. Efficiency of geothermal power plants: a worldwide review. Geothermics 51, 142–153.