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A FORGE Datathon Case Study to Optimize Well Spacing and Flow Rate for Power Generation

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ABSTRACT

Enhanced geothermal systems (EGS) are potential sources of low-carbon and continuous clean power. However, optimizing a profitable EGS power plant is a non-trivial task because it requires making critical design decisions (e.g., well spacing, well count) when site data uncertainty remains high (e.g., reservoir and stress characteristics). An optimal design decision maximizes the economic value of a power plant while site data and its uncertainties provide a mandate that a large number of realizations (sampling space) must be considered to search for reliably profitable scenarios. This study optimizes the range of well spacing between injection and production wells maximizing net present value in dollars (NPV). For this task, we used the GeoDT simulations from the PIVOT 2022 Datathon to simulate the whole geothermal development cycle from the initial well design to the end of production. This dataset is based on the Utah FORGE site and includes measured uncertainties. In all, the database includes 44,492 unique realizations, each with at least 30 years of production. For each realization, we computed power outputs from a combined binary and flash power plant and deducted parasitic pumping power to estimate NPV. Next, we used a binning-based optimization technique to search inputs and NPVs in bins. Bins were formed within the specified range of well spacing and flow rates. Finally, we estimated the range of well spacing and flow rates that provides the most profitable NPV with uncertainty.

1. INTRODUCTION

Enhanced geothermal systems (EGS) present a significant and long-term opportunity for widespread power production and direct heat (Olasolo et al., 2016; Tester, 2007). But high exploration costs combined with uncertainties associated with subsurface characteristics (such as permeability, reservoir temperature, fault connectivity, geochemistry, and *in situ* stress distribution) have impeded the geothermal market growth (Olasolo et al., 2016; Tester, 2007). Moreover, building a profitable EGS is a major challenge. Profitable EGS fields will depend on many design parameters (Frash, 2022, 2021). We will focus on the parameters of reservoir depth, project lifespan, injection temperature, well spacing, well length, well azimuth, well depth, well skew (i.e., non-parallel wells), well count, well toe (i.e., decreasing well spacing from heel to toe), well proportion (i.e., the ratio of injection well length to production well length), well phase (i.e., the placement of the production well above, beside, or below the injection well), well intervals (i.e., the number of isolated perforation clusters), production well pressure drawdown, stimulation flow rate, stimulation volume, and circulation flow rate. Finding optimal values for these design parameters is a computationally expensive task to say the least.

To tackle this challenge, PIVOT (a conference series supported by the U.S. Department of Energy) organized a first-ever Geo Datathon event in 2022 (PIVOT, 2022). The primary goal of this Datathon was to identify production well placement. Participants in this event used different machine-learning methods to solve a geothermal engineering problem on a simulated dataset of the Utah FORGE site (Figure 1). Data for the Datathon was generated by geothermal design tool (GeoDT) to investigate the power production potential of an EGS system. In this event, six teams (*Team Naturals*, *Benjamin Cassidy*, *Pebbles*, *GeoT360*, *S-Team*, and *GeotherML*) completed the competition. *Team Naturals* of Stanford University, *Benjamin Cassidy* of Hammer and Tongs Polymer Development, and *Pebbles* of the Colorado School of Mine were awarded champion, 1st runner up, and 2nd runner up, respectively.

Despite a short time for the competition and a challenging task, each team made a great contribution to identifying suitable locations for the production well. *Team Naturals* included metrics for risk by considering averages and standard deviations in power production. Also, they clearly demonstrated that net power production was not the best value to optimize. *Benjamin Cassidy* applied a unique set of approaches to the ML challenge to optimize well placement from more than one perspective. Crucially, these competitors also revealed several problems that needed to be solved to get the best answer to optimizing the well spacing: (1) identifying a suitable objective function (e.g., net present value), (2) finding a robust optimization method for the complex dataset, and (3) accounting for uncertainty and risk tolerance.

Here, the primary purpose of our study is to find optimal well spacing (*w_spacing*) and per-interval circulation flow rate (*Qinj*) for the same dataset. First, we define a new objective function, which yields reduced parameters for comparing realizations, e.g., average power or net present value (NPV) in dollar amount. We chose NPV because it provides the best estimate of monetary value. Second, we developed a binning-based optimization approach. Third, we identified optimized *w_spacing* and *Qinj* with an assessment of uncertainty.

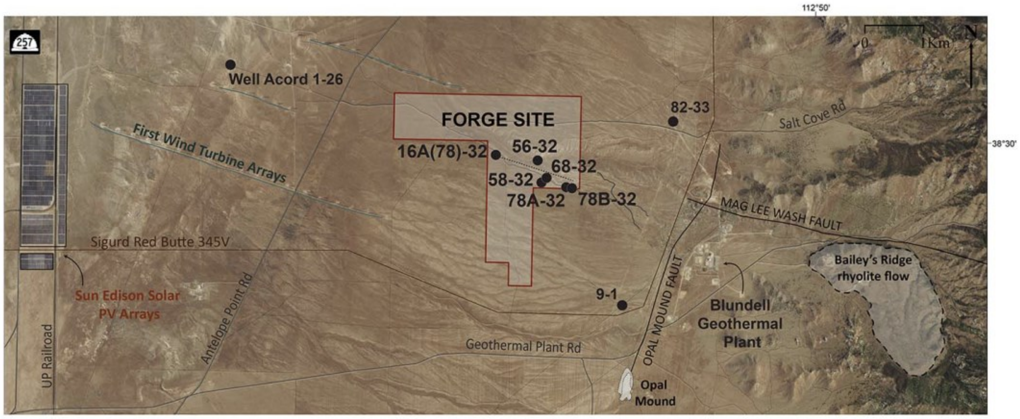

Figure 1: Utah FORGE site with the injection well 16A(78)-32 and five monitoring wells (taken from (Moore et al., 2019)).

2. GEOTHERMAL DESIGN TOOL (GEODT)

GeoDT is a fast simplified multiphysics solver to evaluate EGS designs in uncertain geologic systems (Frash, 2022, 2021; Frash et al., 2023). GeoDT is a fast numerical modeling tool to model thousands of realizations in a few hours using a desktop computer. In this example, the model included 47 site, 15 well, 5 powerplant, and 3 stimulation parameters, to which we now also add cost estimation parameters (Frash et al., 2023). The underlying assumptions of this model are empirically based on laboratory and field data to partially account for complex coupled processes obviating direct expensive numerical modeling (Frash, 2021). The intent of this model is to run it with full uncertainty, as informed by a broad spectrum of relevant prior laboratory and field measurements, and to reduce the uncertainty only when suitable information is available. When a promising EGS design is identified for a particular site, it can then be comprehensively investigated using more complex and expensive numerical modeling codes.

The primary features of GeoDT include (Figure 2):

1. **Flow module**: Predicts pressure and flow rate for 3D networks of intersecting wells and fractures that are modeled as pipes and nodes.
2. **Hydraulic stimulation module**: Predicts hydraulic stimulation with shear and tensile mechanisms where fracture apertures depend on effective stress.
3. **Heat production module**: Predicts transient heat production that depends on fluid enthalpy, rock conductivity, and stored energy change over time.
4. **Power production module**: Provides estimation of electrical power generation using the combined single-flash Rankine and isobutane binary cycle.
5. **Economic module**: Yields net present value (NPV) based on geothermal cost estimation tools, electricity sales, and a simple earthquake cost model.

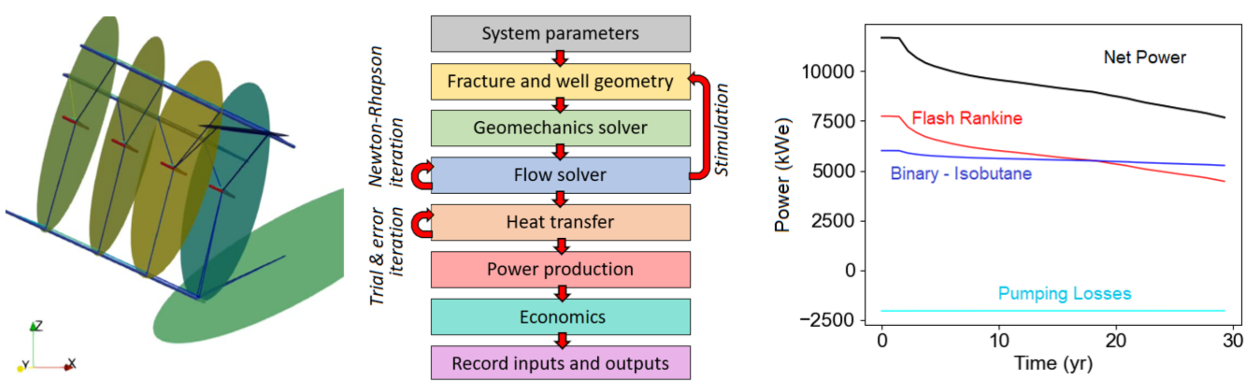

Figure 2: GeoDT stochastically predicts reservoir parameters, flow networks, hydraulic stimulation, heat production, power production, injection-induced seismicity potential, and ultimately net present value by fast and simplified methods. Most models complete in around 15 seconds using a common desktop computer with a single processor thread.

3. NET PRESENT VALUE (NPV) ESTIMATION

Our new economic module in GeoDT yields estimated NPV in circa 2019 U.S. dollar amounts for a hot dry rock EGS geothermal project (Frash et al., 2023). Such a reduced value is critical for optimizing geothermal design parameters. This module considers capital costs, maintenance costs, pumping costs, and power sales. Following the theme of fast-simplified physics, this module uses simplified methods to estimate costs where the underlying goal is to give a conservative view of the economic potential of a project. The cost terms that we employ in this study are summarized in Table 1. True costs for an EGS site depend on many factors beyond what our simple model includes. Ultimately, we use this cost model as an objective function to better contrast increasing power production with increasing capital costs and other financial risks.

Table 1: Constants used to estimate NPV.

Parameter	Unit	Value	Reference
Electricity sales per kilowatt-hour	USD/kWh	0.1372	EIA, 2022
Drilling cost per length	USD/m	2763	Lowry et al., 2017
Drill pad cost	kUSD	590	Lowry et al., 2017
Power plant cost	USD	2026	GETEM
Exploration cost per depth	USD/m	2683	GETEM
Operating cost per kilowatt-hour	USD/kWh	0.0365	GETEM

Outputs from GeoDT that pair with these cost factors include the net power output (Pout) for each model timestep and timestep parameters (TimeSteps and LifeSpan). The net power production term (Pout) for the Datathon only included the flash steam cycle for power generation. In this study, we add a simplified estimate for isobutane binary-cycle power generation and an improved estimate of injection well pumping losses that accounts for open-loop fluid losses (https://github.com/GeoDesignTool/GeoDT). Each power term includes the effect of inefficiencies, with this study using a conservative 85% efficiency (GenEfficiency). Discrete fracture networks with open-flow boundaries formed the basis of all the GeoDT models.

3. DATA DESCRIPTION

The 16 most critical controllable design parameters (Table 2) can be divided into four categories: reservoir/site, power cycle, well, and stimulation. Of these, only 10 design parameters were varied to a meaningful degree because the first well at the site, well 16A(78)-32, has already been drilled at a diameter of 0.11 m to a depth of 2350 m with a highly-deviated lateral length of 1114 in the direction of 1.833 radians Azimuth at a dip of 0.483 rad below the horizon. This azimuthal direction is near-parallel to the in-situ minimum horizontal stress direction. Reservoir depth is the only controllable reservoir parameter, but it is not a variable in this study because of the preceding reasons. Injection temperature was the only power cycle parameter that was varied because this study focuses on subsurface EGS design optimization, not power systems engineering. While GeoDT is capable of modeling hydraulic stimulation separately from circulation, in this study the circulation stage is treated as a continuous stimulation stage for the lifespan of the EGS, so we did not parameterize these two stages independently. In other words, GeoDT predicts hydraulic fracturing and shearing at the same rate of injection as what is used for long-term circulation and heat mining. Our focus for design optimization will be set on well spacing (w_spacing) and per-interval circulation rate (Qinj) because these two terms were predicted to be first-order controls for power production.

Table 2: EGS project design parameters and corresponding units, minimum and maximum values, and their statistical distributions. Parameters in green color cells were optimized in this study.

Category	**Variable**	**Parameter**	**Unit**	**Min Value**	**Nominal value**	**Max Value**	**Distribution**
Site	ResDepth	Nominal reservoir depth	m	2340		2360	
Power cycle	LifeSpan	Project lifespan	yr		30		-
Power cycle	Tinj	Injection temperature	C	85		99	-
Well	w_spacing	Well spacing	m	50		1000	Uniform
Well	w_length	Well length	m		1114		Lognormal
Well	w_azimuth	Well azimuth	deg		1.833		Uniform
Well	w_dip	Well dip	deg		0.438		Uniform
Well	w_skew	Well skew	deg	-10		10	Uniform
Well	w_count	Well count	wells	1		4	Uniform
Well	w_toe	Well toe	deg	-5		5	Uniform
Well	w_proportion	Well proportion	deg	0.8		1.1	Uniform
Well	w_phase	Well phase	deg		0, 90, 180, 270		Uniform
Well	w_intervals	Well intervals	zones	1		6	Uniform
Well	dPp	Production well pressure rise	MPa	-10		2	Uniform
Well	perf	Perforation count	perfs		1		Uniform
Stimulation	Qinj	Circulation flow rate	m3/s	0.001		0.1	Exponential

Using statistical distributions for all the known and unknown site, fracture network, and design parameters, 44,492 realizations were generated for the Datathon (PIVOT, 2022). All the well parameters were generated using uniform distributions. The minimum and maximum values of the distribution are listed in Table 2, and histograms of six example parameters are shown in Figure 3. The lifespan of the field was considered only 30 years, and injection temperatures varied from 85-99°C (Figure 4). The injection rates per-interval (*Qinj*), which also serve as the stimulation rates, were generated using exponential distribution because this offers improved resolution for realizations with low flow rates, relative to the maximum simulated flow rate. When the optimal flow rate is not known, the exponential distribution helps explore a larger probability space in order to more clearly identify the optimal flow rates.

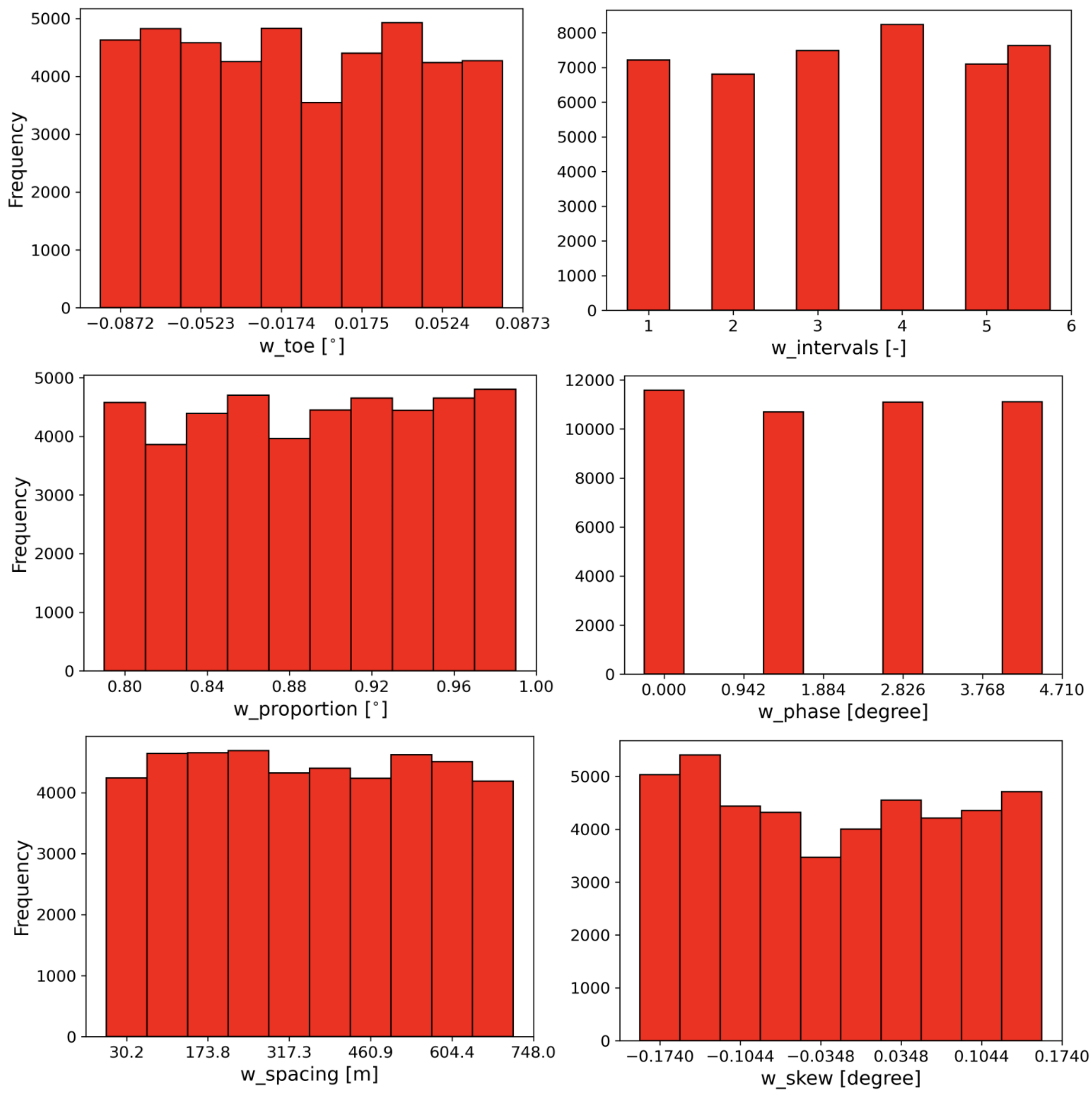

Figure 3: Distribution of design parameters for well.

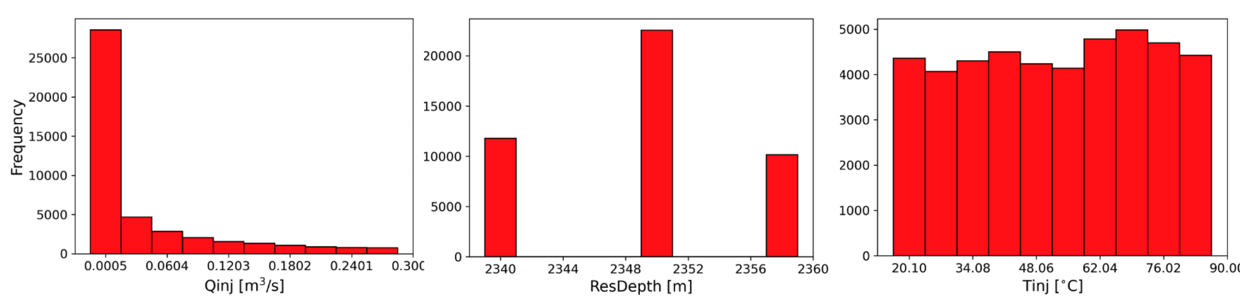

Figure 4: Distribution of injected flow rate (Qinj), reservoir depth (ResDepth), and temperature of injected fluid (Tinj).

4. METHODS

In any optimization technique, identifying a suitable objection function is a crucial first step. Here, our goal is to maximize the NPV value of a geothermal project because NPV provides a common framework to measure the relative benefit and cost of each design decision. This contrasts with optimizing power production where the most productive scenarios can be unreasonably expensive with respect to drilling and pumping costs. The traditional parameter estimation study fits a physical model to data, finding optimal parameters. Such a study finds a single optimal value for each parameter and then the Markov chain Monte Carlo (MCMC) method or its variant is performed to generate distributions of parameters to provide uncertainty of the value in its distribution. However, MCMC cannot provide uncertainty based on the most likely scenarios for peak NPVs, an important attribute to investors.

Investors would like to see what is the most likely chance of a profitable geothermal project based on NPVs; for instance, what are the 10^{th}, 50^{th}, and 90^{th} percentile of NPVs for a given set of design parameters? Therefore, we chose binning-based optimization in this study (Figure 5). In this technique, we define a bin volume based on discrete splitting of the design parameter values of injection rate and well spacing. Then, we compute NPVs of each realization in the corresponding volume. Finally, we compute the 10^{th}, 50^{th}, and 90^{th} percentile of NPVs and their corresponding design parameters. Here, percentile values of NPV demonstrate the profitability of geothermal fields while the design parameter ranges provide the range within which the NPV would be profitable. For this study, *w_spacing* and *Qinj* were evenly split into 9 and 4 intervals, giving a total of 36 bins for our realizations. Nine intervals provided the finest discretization that yielded suitably large populations of data within each bin for achieving statistical significance.

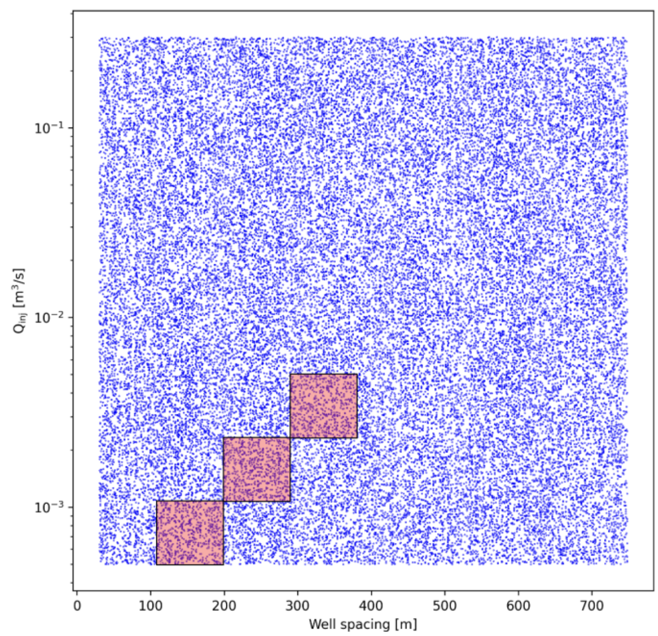

Figure 5: Binning based optimization technique where blue dots represent each realization and red color rectangle shows example binned areas.

5. RESULTS

The model's NPV values are widely distributed, ranging from negative to hundreds of millions USD (Figure 6). We plotted the frequency distribution plot of NPVs using 30 bins. The most common outcome was negative NPV due to the relatively cold 200°C temperature at the current depth of FORGE, when treated as an EGS. Out of 44,492, 42,960 (96.55%) realizations fall into this non-profitable category. Only 3.45% or 1,532 realizations fall into the profitable category. The profitable NPVs range from 0 to ~1500 million USD. The most likely profitable range was 25 to 676 million USD.

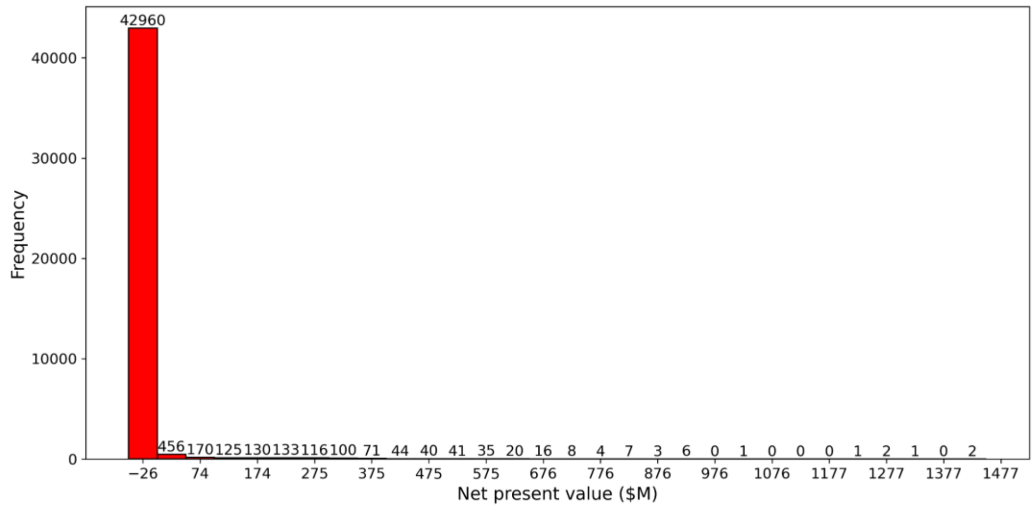

Figure 6: Histogram of NPVs where negative and positive values represent non-profitable and profitable geothermal fields, respectively. The number on top of each bar represents the total count of NPV for the corresponding bar. All drilling costs and pumping losses are included in this model.

All NPVs are plotted against *Qinj* and *w_spacing* in Figure 7. Here, only positive or profitable NPVs are present, while negative values are absent. It is clearly shown that geothermal fields are non-profitable or marginally profitable for *Qinj* < 0.01 m^3/s. High and extreme *Qinj* at rates above 0.2 m^3/s do not make a geothermal project profitable either. Therefore optimization of *Qinj* is critical for achieving economic EGS, which confirms our apriori expectation but now better quantifies this trend. A similar optimization trend is less visible for *w_spacing* because profitable to non-profitable geothermal fields are present across the full *w_spacing* range. Therefore, we applied a binning-based optimization technique to find optimal *w_spacing* and *Qinj*.

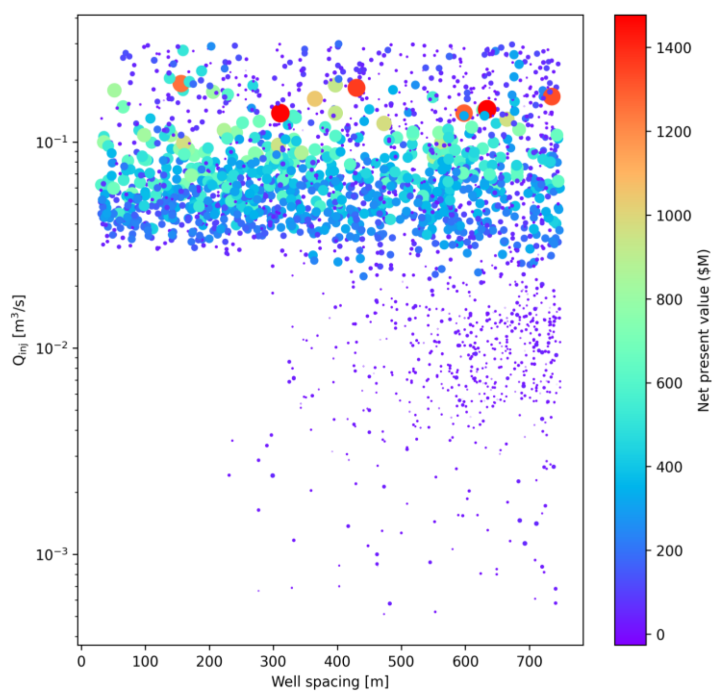

Figure 7: Positive (profitable) NPVs against *Qinj* and *w_spacing* where color and size represent NPVs. Warm and larger size circles represent higher NPVs or vice versa. Most of the realizations are not in this plot because of their negative USD values.

The 10^{th} percentile values show that profitable geothermal fields most likely occur between 110 to 348 m *w_spacing* and 0.0005 to 0.001 m^3/s *Qinj* (Figure 8(a)). Here, the closer space provides more profit because of the presence of fluid. The highest profit within the 10^{th} percentile reached up to 0.5 million USD. The 50^{th} percentile values demonstrate that profitable geothermal fields are feasible between

190 to 747 m *w_spacing* and 0.001 - 0.01 m^3/s *Qinj* (Figure 8(b)). The highest profit within the 50th percentile reached up to 5.5 million USD.

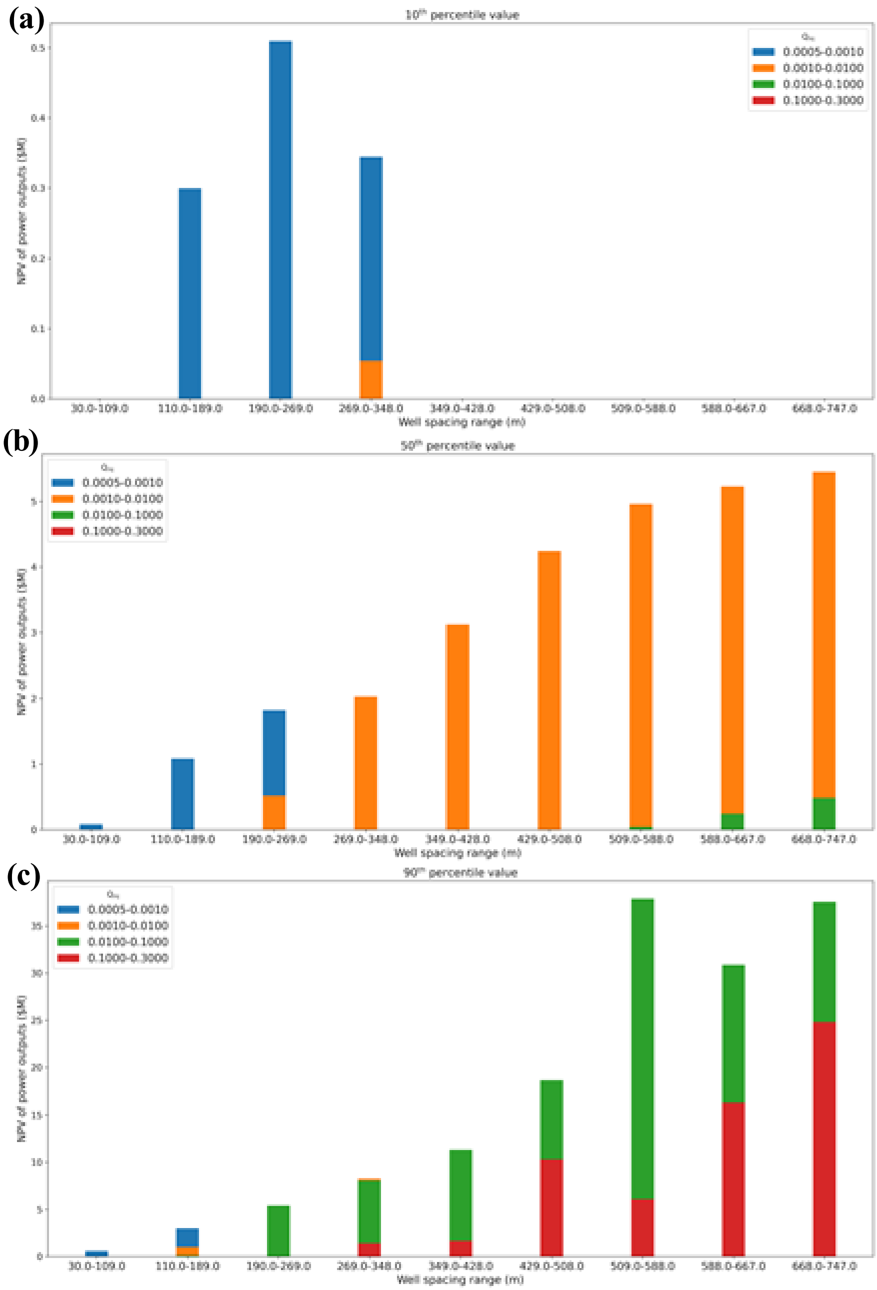

Figure 8: 10th (a), 50th (b), and 90th (c) percentile values of NPV in USD for different *Qinj* and *w_spacing* ranges.

The 90th percentile values show more interesting characteristics across the ranges for both *Qinj* and *w_spacing* (Figure 8(c)). Although all *Qinj* seem profitable, the prominent *Qinj* is 0.01 to 0.1 m^3/s. The next most profitable *Qinj* range is 0.1 to 0.3 m^3/s. The *w_spacing* range between 190 to 747 m is profitable. Among these ranges, the most profitable range is between 509 to 588 m. The next most profitable w_spacing range is between 668 to 747 m. The highest profit within the 90th percentile can reach up to ~36 million USD. For both 50th and 90th percentile cases, low *w_spacing* provides less profit, and high *w_spacing* provides higher profits. This phenomenon contradicts the idea that close spacing will benefit from having a better flow rate. Here, the total fluid volume generated more heat, thereby, more profits. So, it is clear that a total hot fluid volume is preferred to the flow rate in estimating NPV. In other words, more *w_spacing* provides more volume facilitating more fluid extraction.

6. CONCLUSIONS

We analyzed GeoDatathon data based on the Utah FORGE site parameters. The dataset has a total of 16 design parameters that control geothermal energy production, hence, its NPVs in USD. The primary goal of this study is to find the optimal design values for well spacing (*w_spacing)* and per-interval injection rate (*Qinj*) for developing profitable geothermal fields with specified uncertainties. We used a binning-based optimization technique to compute NPVs. We subdivided the whole realizations into 36 bins based on nine ranges for both *w_spacing* and *Qinj*. Following, NPV was calculated for all realizations in each bin. Next, we computed 10^{th}, 50^{th}, and 90^{th} percentile scores of NPV in all bins. Based on the analysis, we came to the following conclusions:

1. The 10^{th} percentile values demonstrate that profitable geothermal fields are feasible between 110 to 348 m w_spacing and 0.0005 to 0.001 m^3/s *Qinj*. The maximum profit can reach up to 0.5 million USD.

2. The 50^{th} percentile values demonstrate that profitable geothermal fields are possible between 190 to 747 m *w_spacing* and 0.001 - 0.01 m^3/s *Qinj*. Low *w_spacing* provides less profit, and high *w_spacing* provides high profits. The maximum profit can reach up to 5.5 million USD.

3. The 90^{th} percentile values are better to consider than the 10^{th} and 50^{th} percentile values because of (1) higher certainty and wide ranges of *w_spacing* and *Qinj*. The most profitable *Qinj* is between 0.01 to 0.3 m^3/s. The *w_spacing* range between 190 to 747 m is profitable. Among these ranges, the most profitable range is between 509 to 588 m. The next most profitable w_spacing range is between 668 to 747 m. The maximum profit can reach up to 35 million USD.

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