Understanding Uncertainty in Geothermal Energy Development Using a Formalized Performance Assessment Approach

Thomas S. Lowry

Sandia National Laboratories

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ABSTRACT

For over 50 years, performance assessment (PA) has been used throughout the world to inform decisions concerning the storage and management of radioactive waste. Some of the applications of PA include environmental assessments of nuclear disposal sites, development of methodologies and regulations for the long-term storage of nuclear waste, regulatory assessment for site selection and licensing at the Waste Isolation Pilot Plant and Yucca Mountain, and safety assessments for nuclear reactors. PA begins with asking the following questions: 1) *What can happen?* 2) *How likely is it to happen?* 3) *What are the consequences when it does happen?* and 4) *What is the uncertainty of the first three questions?* This work presents an approach for applying PA methodologies to geothermal resource evaluation that is adaptable and conformable to all phases of geothermal energy production. It provides a consistent and transparent framework for organizing data and information in a manner that supports decision making and accounts for uncertainties. The process provides a better understanding of the underlying risks that can jeopardize the development and/or performance of a geothermal project and identifies the best pathways for reducing or eliminating those risks. The approach is demonstrated through hypothetical examples of both hydrothermal and enhanced geothermal systems (EGS).

1. Introduction

Performance assessment (PA) is a form of probabilistic risk assessment that is used to evaluate and assess different sites, design concepts, and regulatory requirements, identify and prioritize research and development activities, estimate risk, and determine compliance. It is a framework for organizing all the relevant data and information in a manner that supports decision making, while accounting for the uncertainties in the information (Bonano and Appel, 2011; Meacham et al., 2011; Helton et al., 2014). When implemented fully, it provides transparency, traceability, and reproducibility of the analyses.

The Reactor Safety Study (NRC, 1975) is generally thought of as the beginning of formalized PA in that it was the first quantitative, probabilistic look at health risks from a large, complex facility (Meacham, et al., 2011). Over the years, PA has been applied to environmental assessments of nuclear disposal sites, development of methodologies and regulations for the long-term storage of high- and low-level nuclear waste, regulatory assessment for site selection and licensing at the Waste Isolation Pilot Plant and Yucca Mountain, and safety assessments for nuclear reactors and weapon systems (Anderson et al., 1997; Rechard, 1999; Bredehoeft, 2003; Meacham et al., 2011; Rechard et al., 2014). Since the release of the Reactor Safety Study, PA has been continuously developed and modified to include improvements in risk assessment and decision support and advances in numerical modeling and computational capacities.

PA is built on the Kaplan-Garrick ordered triple representation of risk that asks (Kaplan and Garrick, 1981):

1. What can happen?
2. How likely is it to happen?
3. What are the consequences if it does happen?

Mathematically, these questions are represented as (Helton, 1994; Helton et al., 2014):

$$R = (S_i, pS_i, \boldsymbol{cS}_i), i = 1,2,\ldots,nS \tag{1}$$

where R is risk, S_i is a set of what can happen (the answer to question 1), pS_i is the probability of S_i (the answer to question 2), $\boldsymbol{cS}_i$ is a vector of consequences associated with S_i (the answer to question 3), and nS is the number of "happenings" (i.e., scenarios).

To provide decision support and to help in understanding project risk, a fourth question must be asked: *What is the uncertainty in the answers to the initial three questions?* It is the answer to this fourth question that moves PA beyond traditional risk and decision analysis methods, and which provides credibility and confidence to decision making.

The foundation of a PA is the calculation of risk, which is a compound metric that accounts for both consequence and probability. This work relies on the approach introduced by Helton (1994) who defines the risk R as the sum of the consequence, C, multiplied by the range of the probability ΔP, over all estimations of a given exceedance probability, n, over time, t:

$$R = \sum_t \sum_n C(n,t)\Delta P(n) \tag{2}$$

The risk calculated with equation (2) represents an integrated risk meaning that it is the sum of the risk for all events that have a lower or equal probability of occurring as compared to some reference event. Typically, C is presented as a complementary cumulative distribution function (CCDF) that answers the question, *How likely is it to be this bad or worse?* For a geothermal assessment, the reference event may be a given amount of thermal drawdown over time, a mean annual power production or levelized cost of electricity (LCOE) target, or even the amount of downtime during drilling.

2. Performance Assessment Methodology

PA methodology consists of nine steps (Meacham et al., 2011): 1) define the performance goals, 2) characterize the system, 3) identify scenarios for analysis, 4) build models and abstractions, 5) construct integrated PA models and perform calculations, 6) quantify uncertainty, 7) perform uncertainty and sensitivity analysis, 8) evaluate performance, and 9) create directed science and testing programs (Figure 1). By compartmentalizing each task, the process is more transparent and repeatable while also providing a framework that ensures that the analysis is focused on the goals.

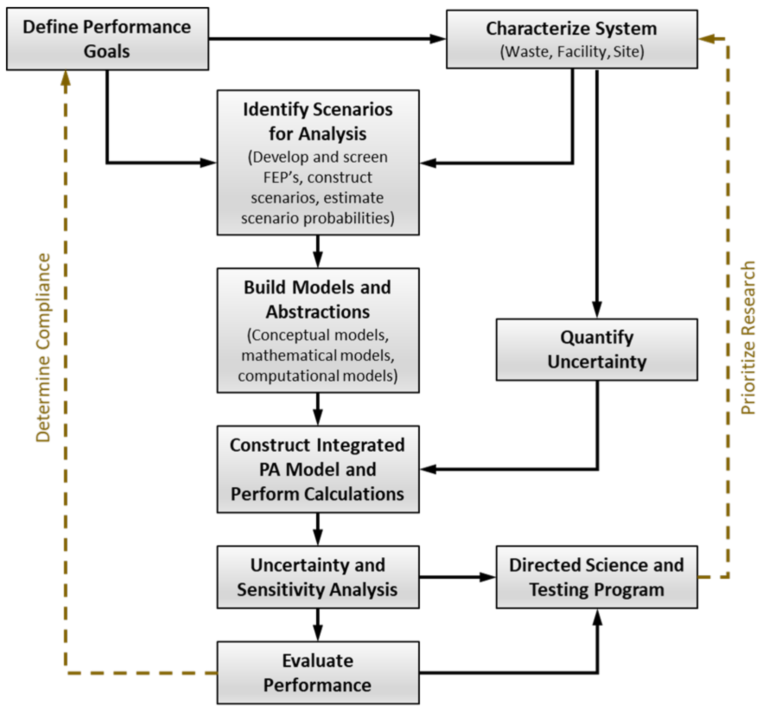

Figure 1: The steps of the PA methodology. Recreated from Meacham et al. (2011).

The flow chart shown in Figure 1 contains two key feedbacks in the process: determining compliance and prioritizing research. Determining compliance is where the decision makers must decide if the risk of not meeting the performance goal can be tolerated. Prioritizing research should occur whether or not the performance goals have been met and should focus on the work necessary to reduce uncertainty and increase decision confidence.

To apply PA to geothermal energy development, a few subtle but important changes must be made to the methods associated with PA for a nuclear repository. For the Yucca Mountain Project (YMP) PA, the US Environmental Protection Agency (40 CFR 197.12 as amended 15 October 2008) defines a PA to be an analysis that:

- **Identifies the features, events, and processes (FEP's)** and sequences of events and processes that might affect the Yucca Mountain disposal system and their probabilities of occurring.
- **Examines the effects of those FEP's** and sequences of events and processes upon the performance of the Yucca Mountain disposal system.

- **Estimates the annual committed effective dose equivalent** incurred by the reasonably maximally exposed individual, including the associated uncertainties, as a result of releases caused by all significant FEP's, and sequences of events and processes, weighted by their probability of occurrence.

It is this formalized approach to identifying and defining the set of FEP's and the probabilities associated with those FEP's that further distinguishes PA from standard probabilistic risk assessment. For geothermal energy production, we recommend the following changes to the PA definition such that a geothermal PA is an analysis that:

- **Identifies the FEP's** and sequences of events and that might affect the exploration, characterization, development, and/or operation of a geothermal system and their probabilities of occurring.
- **Examines the effects of those FEP's** and sequences of events and processes upon the risk of development and operational performance of a geothermal system.
- **Estimates the risk of development**, including the associated uncertainties, as a result of the expected operational performance given the FEP's, weighted by their probability of occurrence.

Referring to Figure 1, the first bullet refers to the activities within Step 3, the second bullet is contained within Steps 4 through 7, and the last bullet is contained in Step 8.

2.1 Features, Events, and Processes

The FEP's that may be relevant over the time frame of an analysis must be identified and included in the PA. The process begins with identifying and documenting the universe of FEP's and then down-selecting to those that are relevant. This approach maintains "completeness", which can reduce future surprises and build confidence both internally and externally (Meacham et al., 2011). FEP's are deemed relevant by excluding those that: 1) have a low probability of occurrence, 2) have a low consequence, and/or 3) are inconsistent with the objective of the analysis. Justifying why a FEP is omitted is in itself a means of reducing uncertainty. It is up to those performing the PA to determine whether the combination of probability, consequence, and consistency warrant exclusion or not (e.g., including the high consequence of a low probability event like a major earthquake will depend on the objective of the analysis).

Included in FEP's are design decisions such as the number of production and injection wells, the distance between wells, pumping rates, etc. Other decision criteria may include the type of power plant (binary, flash, etc.), working fluid (if binary), and if a combined heat and power system is developed.

2.2 Scenarios

Scenarios are created by combining FEP's such that each scenario represents a possible current or future state of the system. All retained FEP's must be included in at least one scenario. Prior to exploration, there are theoretically an infinite number of scenarios representing degrees of performance (e.g., variations in permeability). As more data are collected and the understanding of the site increases, the number of potential scenarios goes down. Conversely, when assessing operational decisions on fully developed systems, there may be relatively few scenarios that apply, beyond those that define different operational approaches.

2.3 Uncertainty and Risk

The focus of PA is to improve confidence in the validity of conclusions drawn from data and simulations. Risk on the other hand, is concerned with the opposite position: What are the chances that conservative estimates of system performance are actually optimistic? Thus, what becomes important in a PA are the tails of the uncertainty distributions rather than the mean estimates that are generally used most often by scientists and decision makers.

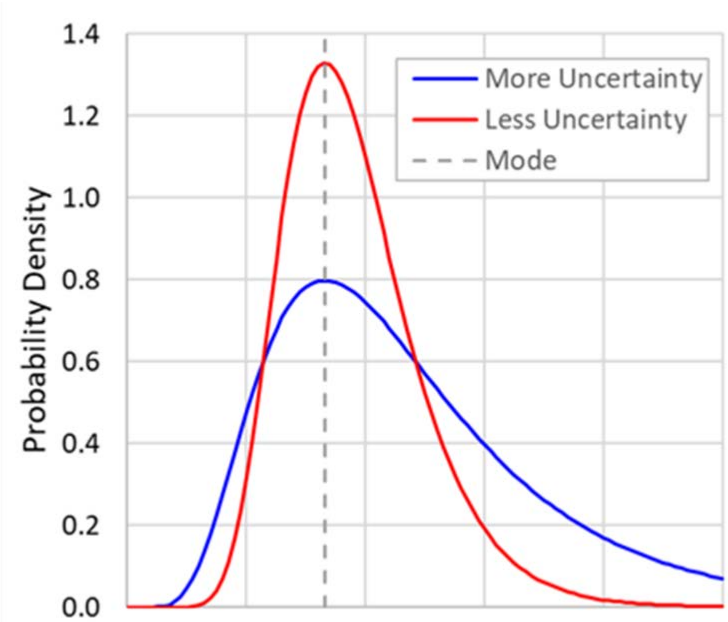

Figure 2: Two probability density functions with identical modes but having higher (blue line) and lower (red line) uncertainty.

Uncertainty is most commonly represented via a probability density function (PDF). From a statistical perspective, the density function captures the idea of how often one can expect a given value compared to other values. When the uncertainty increases, there is more of a chance that a variable will have a value different from the most common value (the mode). Figure 2 shows an illustrative PDF with the blue distribution having greater uncertainty than the red distribution while both having the same mode. The blue distribution is above the red distribution in the tails meaning there is a higher probability of an “extreme” value occurring from the blue distribution versus the red distribution. A higher probability of occurrence, along with the assumption that higher consequences occur in the tails, means a higher risk.

An important point is that when designing research efforts to reduce risk, one must look at both the uncertainty and the consequences. Unknowns with high uncertainty but low consequences may be of lower priority than unknowns with lower uncertainty but higher consequences.

3. Applying Performance Assessment to Hypothetical Cases

Two cases are presented here. The first looks at the relationship between uncertainty and risk by simulating a hypothetical hydrothermal system with eight production wells and two injection wells at three different stages of exploration. The only uncertainties considered are the productivity index (PI) of each production well, the drilling depth of the wells, and the initial temperature of the reservoir. The second case uses a hypothetical EGS to illustrate how the risk associated with different production pumping scenarios can be used to find the optimal scenario.

Economic assumptions are based on the default values used in GETEM (Entingh et al, 2006) with the exception of the surface piping, which is calculated using the coordinates of each well relative to the power plant along with a constant assumed cost of piping (also from GETEM). Drilling costs are based on the cost curves from the DOE GeoVision Reservoir Maintenance and Development Task Force report (Lowry et al., 2017) where the first case uses the curve for the Base Scenario and the second case uses the curve for the Intermediate 1 Scenario. Power production for both cases assumes the use of a binary power plant using isopentane as the working fluid.

The first case utilizes the levelized cost of electricity (LCOE) as the comparison metric while the second case uses historical power purchase prices to look at the profit margin. The simulations are conducted using the Sandia National Laboratories (SNL) in-house techno-economic model, GT-Mod. GT-Mod is a systems dynamics model that combines systems-level simulations of the subsurface, surface (i.e. power plant), and economic systems. GT-Mod accounts for the dynamics between the physical and economic performance and has the flexibility to simulate heterogeneous well fields and well configurations. The risk assessment simulations are executed using the DAKOTA analysis software (Adams et al., 2020). Uncertain variables are sampled using DAKOTA's Latin Hypercube Sampling (LHS) option.

For both cases, the model uses the Gringarten solution (Gringarten et al., 1975) to calculate the thermal drawdown of the reservoir. The Gringarten solution is an analytical solution for heat transfer through an infinite set of evenly spaced fractures of uniform aperture. For the hydrothermal system, the source of cool water is 550 m away from each well, has a temperature of 85 °C, and consists of 10 connecting fractures with an aperture of 0.25 mm. For the EGS system, the simulation assumes that the injection temperature is the same as the temperature of the power plant effluent.

Flow rates for the hydrothermal case are determined by the productivity index of each well (a random variable) by assuming a minimum drawdown of 40 m in each well. Injection well flow rates are split evenly between the injection wells and assume the power plant effluent temperature. For the EGS case, flow rates for each injection well are determined as a FEP and the distribution to each production well is then calculated as a function of the number of fractures and the fracture aperture (both random variables) between each injection and production well.

3.1 Case 1

Case 1 is a hypothetical hydrothermal system consisting of eight 8.5" production wells and two 12.5" injection wells. The production wells are aligned along a NNE-SSW line and are grouped with 4 wells north of the power plant and 4 wells south of the power plant (Figure 3). The spacing between the wells in each group and the power plant is ~250 m. The system assumes a dipping fault system with a mean temperature of 207.5 °C centered at a depth of 1500 m. The injection wells are located east and west of the power plant, each 250 m away from the fault. Injection water is assumed to flow away from the fault and not mix with the production water.

The objective of the simulation is to understand the potential of the sub-surface to meet a performance goal of an LCOE that is 8.0 ¢/kWh or less. The relevant FEP's include the productivity index, the terminal depth, and the initial temperature of each production well.

Two examples are simulated: Ex1, which is an early exploration analysis with high uncertainty on the relevant FEP's and Ex2, which is a late exploration analysis with low uncertainty on the relevant FEP's. The sampling parameters are listed in Table 1. 2500 simulations are conducted for each example.

The sampled parameters include the mean productivity index (PI), the PI standard deviation, the standard deviations of the production and injection well depths, the mean of the bottom hole temperature, and the standard deviation of the bottom hole temperature. An assumption is made that the injection wells can handle all the fluid sent to them, meaning that the injectivity index (II) of the injection wells is not included in the simulation. Each of the parameters are sampled from a uniform distribution for each simulation. Within each simulation, values are assigned to each well by randomly sampling from a normal distribution based on the means and variances for that simulation. In that way, each simulation has a consistent variability around its own mean for each parameter. For depth, the mean is kept constant across all simulations at 1500 m.

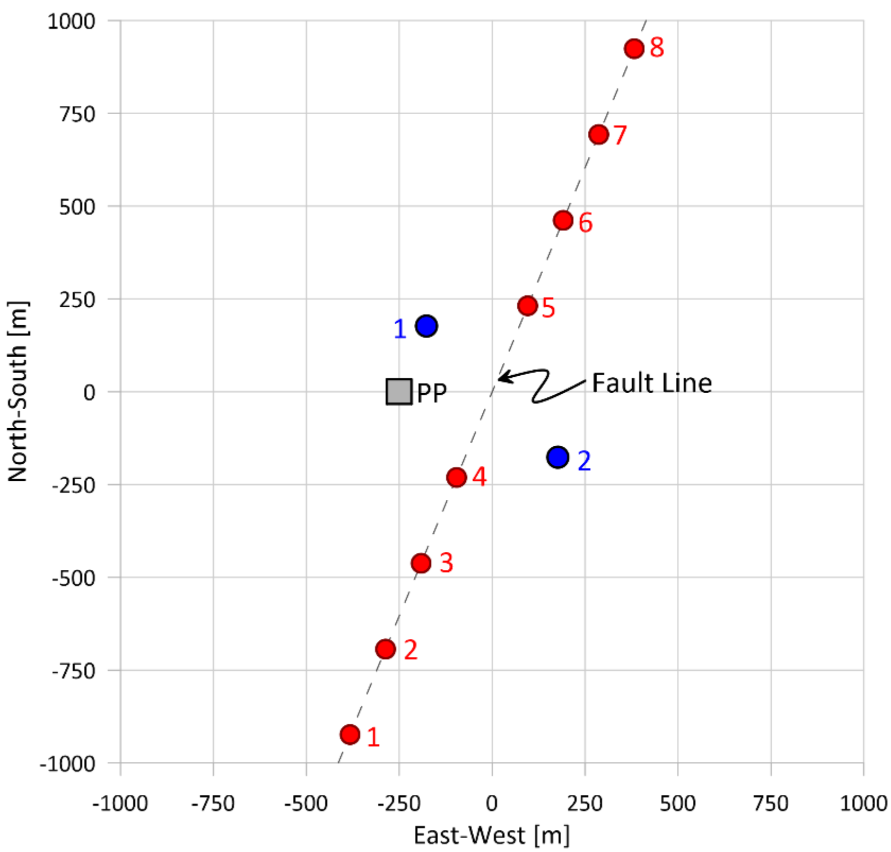

Figure 3: Map view of the hypothetical hydrothermal system simulated in Case 1.

Table 1 - List of parameter ranges for Case 1. The simulated values show the maximum and minimum value across all wells and all simulations and are the calculated values based on the sampled mean and standard deviation for each simulation.

Parameter	Ex1		Ex2		Simulated Values*			
					Ex1		Ex2	
	Low	High	Low	High	Min	Max	Min	Max
PI mean [kg/s/MPa]	75	100	81.25	93.75	8.50	182.23	53.31	126.93
PI std dev [kg/s/MPa]	1	30	1	10	Na	Na	Na	Na
PD std dev [m]	100	250	137.5	212.5	Na	Na	Na	Na
ID std dev [m]	100	250	137.5	212.5	Na	Na	Na	Na
PT mean [C]	200	215	205	210	182.50	225.00	205.0	210.0
PT std dev [C]	5	10	5	6	Na	Na	Na	Na

* These are the high and low values across all 2500 simulations.

3.1.1 Case 1 Results

Figure 4 shows the cumulative distribution function (CDF) for the examples of Case 1. The blue line represents Ex1 and the red lines represent Ex2. The impact of the greater uncertainty of Ex1 is clear based on the range of LCOE values (~7.1 to 10.0 ¢/kWh for Ex1 and ~7.25 to 8.5 ¢/kWh for Ex2). The dotted lines show the risk of each simulation where there is a positive consequence, which is calculated as the difference between the simulated LCOE and the target LCOE of 8.0 ¢/kWh. Negative consequences (i.e. the LCOE is less than the target) are considered as zero. Integrating under the dotted line curves using equation 2 returns a total risk of 34.04 ¢/kWh for Ex1 (blue line) and 2.14 ¢/kWh for Ex2 (red line). The values of the total risk by themselves are meaningless and should only be used to compare one scenario against another.

The total risk values are useful in decision making as they give an indication of the potential *downside* of a particular decision. The CDF lines (the solid lines in Figure 4) show that there is a 62% and 83% chance that the LCOE will be less than or equal to the target LCOE for Ex1 and Ex2, respectively. While this information is useful, understanding that the risk associated with the uncertainty in Ex1 is ~16 times that of Ex2 gives perspective on the downside. In this case, a decision maker would likely look to explore the sources of uncertainty and work to reduce the uncertainty of the most consequential unknowns. This is where the feedback loop of creating a targeted science and testing program (Step 9 in Figure 1) comes into play.

Figure 5 shows the correlation between the total mass flow (i.e., the sum of the production wells) and the temperature drawdown. In the Gringarten solution, temperature drawdown is a function of the mass flow rate and thus there is a direct correlation between the two variables. Because there is variability amongst the eight production wells within each simulation, the correlation between the total mass flow rate and the production temperature drawdown is reduced as the variability amongst the wells increases. If there is no variability between the wells in each simulation, the dots would all collapse onto the smooth boundary on the lower part of the dot cloud.

The colors of the dots in Figure 5 indicate the value of the LCOE for each simulation. As expected, there is a positive correlation between the total mass flow rate and the LCOE where lower values of LCOE occur at higher total flow rates. There is no real correlation between LCOE and temperature drawdown.

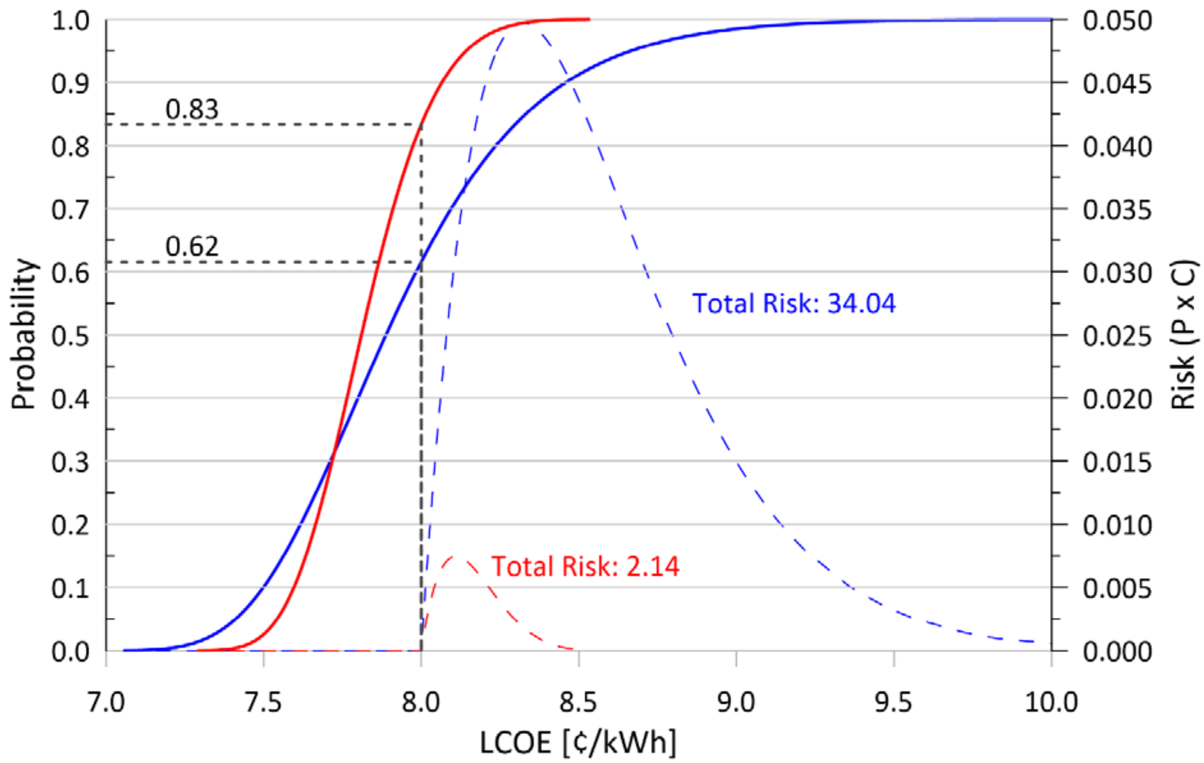

Figure 4: CDF output of the LCOE estimates for Ex1 (blue line) and Ex 2 (red line) for Case 1. The probability of meeting the LCOE target is 62% for Ex1 and 83% for Ex2.

Figure 6 is a scatter plot of total mass flow rate and the initial temperature, colored by the LCOE. For both the Ex1 and Ex2 examples, there is a visible relationship between the three variables where low values of total mass flow rate coupled with low values of initial temperature result in higher LCOE values. One can also see the shapes of the CDF's in Figure 4 reflected in the color of the dots with Ex1 having a higher number of dark reds and blues than Ex2, which are indicative of the larger number of LCOE values in the tails of the Ex1 distribution.

3.2 Case 2

The second case assumes an EGS system with eight producers and four injectors that are arranged into four, 3-well systems (Figure 7). The performance goal is to look at how the profit margin and risk change as a function of the mass flow rate injected into the system. Profit margin is calculated using the approach defined in Hernandez et al. (2016) that equates the LCOE as the product of the profit margin and the relative revenue. To calculate the relative revenue, we assume an initial purchase price agreement (PPA) price of 81.53 $/MWh and an escalation rate of 2.0%. The initial PPA price is the median value from Hernandez et al. (2016) while the escalation rate is the average escalation rate rounded up to the nearest percent to capture the increase in prices since 2016. The risk calculation uses the profit or loss from the breakeven point as the consequence.

The relevant FEP's include the number of fractures and the fracture aperture between the injectors and the producers, which are unique for each injection/production well pair. Similar to Case 1, there is variability both within a single simulation as well as across all simulations. Within each simulation, the number of fractures is assumed to be log-normally distributed and the fracture apertures are assumed to be normally distributed as prescribed by a randomly sampled mean and standard deviation for each parameter. Across the simulations, the means and the standard deviations are uniformly distributed based on the parameters in Table 2. 1500 simulations are conducted for each flow rate.

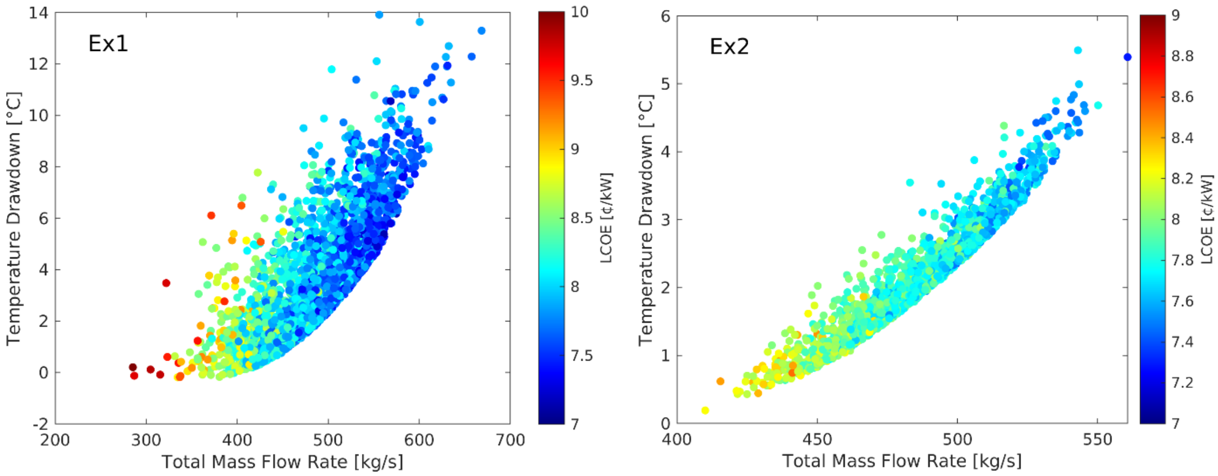

Figure 5: Correlation between total mass flow rate and temperature drawdown. The color of the dots reflects the LCOE value for each simulation.

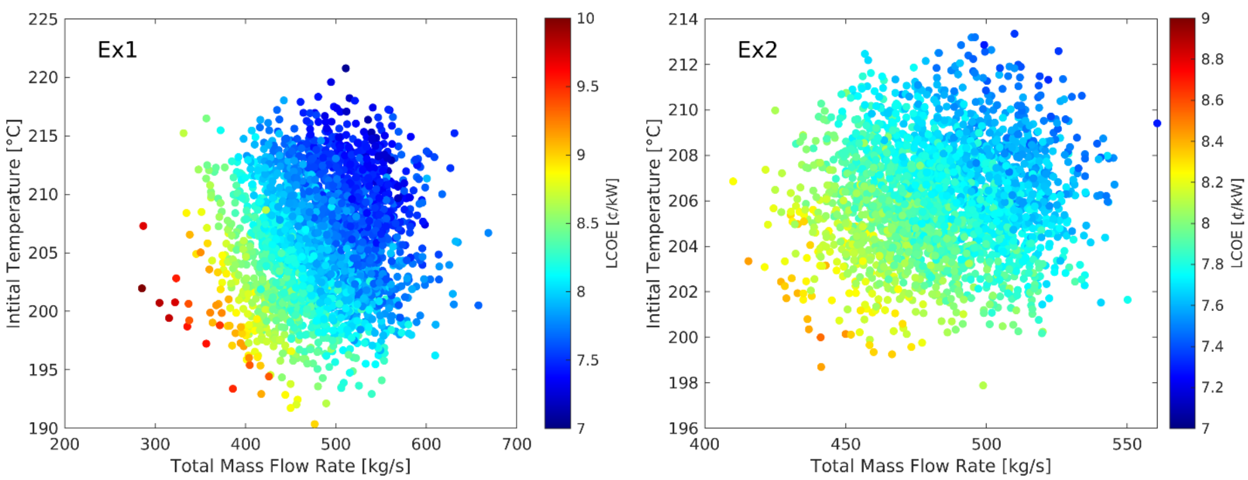

Figure 6: Correlation between total mass flow rate and the initial production temperature. The color of the dots reflects the LCOE value for each simulation.

Three different scenarios are examined: 80, 100, and 120 kg/s per injection well. Flow to each of the production wells is distributed based on the effective hydraulic conductivity (calculated as a function of the number of fractures and the fracture aperture) between each injection and production well pair such that the pressure losses between each pair for each injection well are equal.

3.2.1 Case 2 Results

Figure 8 shows the complementary CDF's (CCDF) for each scenario (the complementary CDF is 1 minus the CDF). Looking at the solid lines in Figure 8, the probability of breaking even is 22.9%, 49.1%, and 46.9% for the 80, 100, and 120 kg/s scenarios respectively while the maximum profit margins are 2.23%, 15.8%, and 24.0%, respectively. The lowest risk ($2.43 mil) is for the 100 kg/s scenario while the highest risk ($3.62 mil) is for the 120 kg/s scenario. The risk is $3.21 mil for the 80 kg/s scenario (note that risk is expressed as millions of dollars in Figure 8). The impact of the tails of the distributions on risk are evident with the 120 kg/s showing an 89.5% probability of having a profit margin (i.e., loss) of -50% or better. As a comparison, the probabilities of achieving that same performance are 93.4% and 95.2% for the 100 kg/s and the 80 kg/s scenarios, respectively.

Table 2 - List of parameter ranges for Case 2. The simulated values show the maximum and minimum value across all wells and all simulations and are the calculated values based on the sampled mean and standard deviation for each simulation.

Parameter	Sampled Range		Simulated Values*	
	Low	High	Low	High
fNum mean**	1.60	2.71	5.0	30.0
fNum std dev**	0.10	0.70	Na	Na
fAp mean [mm]	0.075	0.30	0.01	0.60
fAp std dev [mm]	0.01	0.10	Na	Na

* These are the high and low values across all 4500 simulations from the three scenarios.
** Lognormal parameters

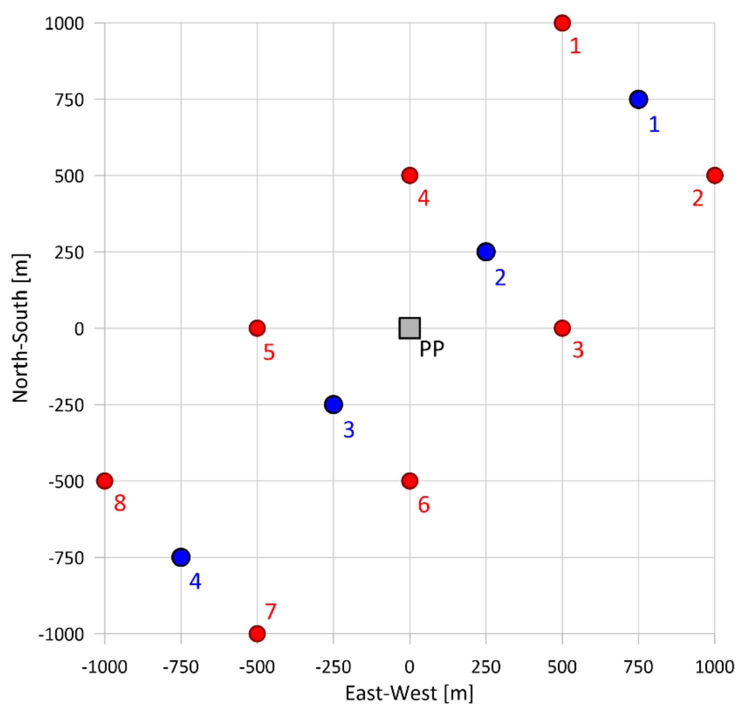

Figure 7: Map view of the hypothetical EGS system simulated in Case 2. Red dots are production wells, blue dots are injection wells.

The results show and interesting dilemma for a decision maker. First, is that none of the scenarios are particularly compelling for investment. There is only about a 50% chance that the project will break even and at best, the maximum profit margin is 24.0%, which in reality, would likely be the minimum one would look for before making the investment. Secondly, assuming that our hypothetical field *is* going to be developed, one could use these results to aid in the operations of the system by operating the system at 100 kg/s per injector and then monitoring the systems performance and adjusting accordingly over time. Starting at 100 kg/s provides the most upside in comparison to the downside (i.e., lowest risk) amongst the three scenarios that were simulated. Ideally, one would use these results as the foundation to optimize the mass flow rate to find the flow with the lowest risk, which will presumably be between 80 and 120 kg/s. As the system is developed and the true subsurface conditions become known, the uncertainty around the performance will drop, adding more certainty to the operating decisions.

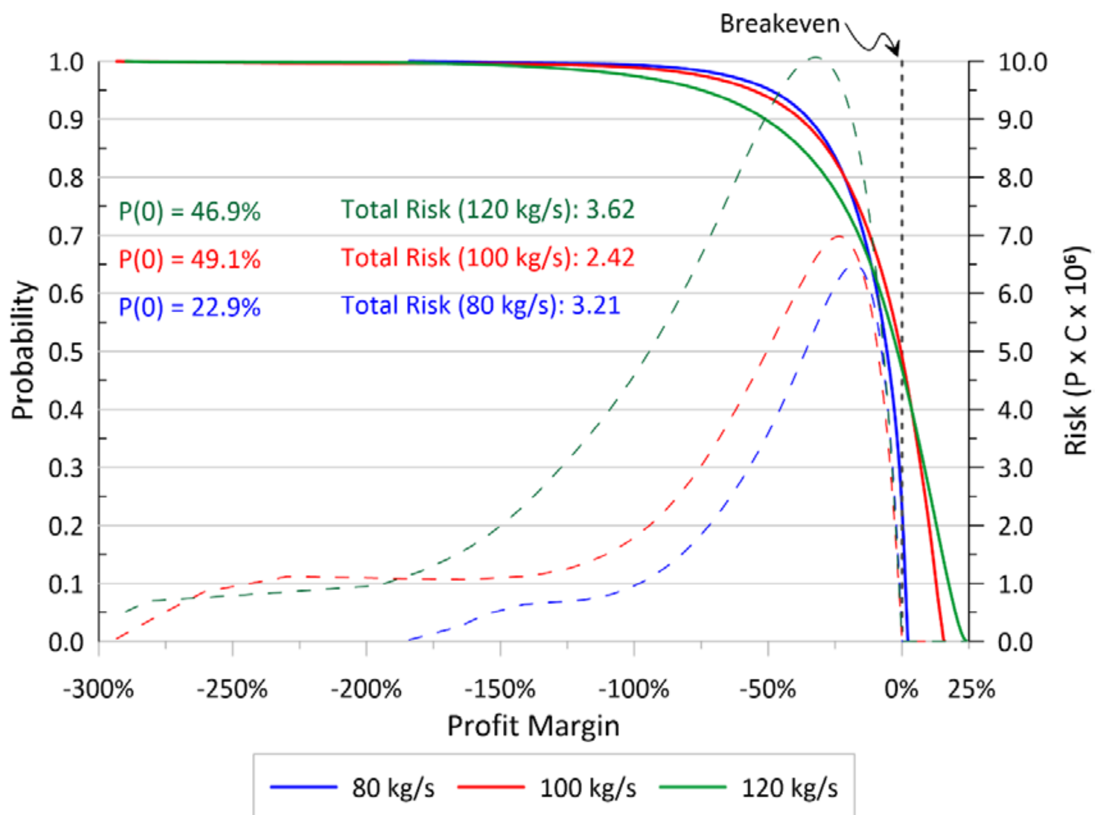

Figure 8: The CCDF output of LCOE for Case 2.

4. Summary

This paper presents a formalized performance assessment (PA) approach for assessing and developing geothermal energy. Adapted from the PA methodology developed for the nuclear repository program at Yucca Mountain, the goal is to improve confidence in the validity of conclusions drawn from data and simulations and to provide a more accurate method of identifying and reducing key uncertainties. The foundation of a PA is the calculation of risk, which is a compound metric that accounts for both consequence and probability. PA provides a consistent and transparent framework for organizing data and information in a manner that supports decision making while accounting for the uncertainties. The process provides a better understanding of the underlying risks that can jeopardize the development and/or performance of a geothermal project and identifies the best pathways for reducing or eliminating those risks.

The examples are meant to illustrate how PA might be applied to different analyses and to show the types of information and output that are possible. PA can be applied at any scale, from a full project-scale analysis like the examples here, to more focused analyses that might look at drilling costs as a function of down time and/or equipment failure. PA should be applied during all phases of development, from the earliest exploration of a site to assessing ongoing operations and even closure. As more data and information become available, PA should be repeated to update the estimates and to identify when uncertainty for each variable has been reduced enough. When used correctly, PA creates a fully documented and transparent approach for adding insight and confidence to the decision-making process.

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