Modeling the Risk of Geothermal Energy Production Using GT-Mod

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ABSTRACT

Our ability to estimate the physical and economic performance of a potential geothermal energy project is directly proportional to our understanding of the sites geologic and hydrogeologic environments and our ability to predict its performance over time. Typically, when gaps in our understanding exist, assumptions are made to fill those gaps; an example of this would be using a constant thermal drawdown rate to predict a sites thermal performance over time. The drawback to this approach is that even if one were to perform the assessment using several different drawdown rates, consideration of the uncertainties in the 'known' inputs are usually ignored, as is the impact of using a constant drawdown rate versus a more physics-based approach. However, increasing understanding can be difficult (if not impossible) and expensive, which results in an environment where uncertainty is a constant working condition of the decision making process. This study uses an integrated systems modeling tool developed at Sandia National Laboratories called GT-Mod to test a quantitative risk assessment approach that accounts for the full range of uncertainties in the knowledge of a site to produce probabilistic outputs to support decision making. The analysis uses a hypothetical EGS site to examine the variation in the LCOE as a function of uncertainty. The variation in the LCOE is translated into a set of exceedance probabilities that describes the probability that the real LCOE will be below a certain value. An integrated risk is calculated as a function of net revenue generated over the life of the power plant.

Introduction

Geothermal energy development requires assessment of the quality and accessibility of a resource, the available materials, services and technologies, the demand for power, and the economics of the entire process. Each of these areas is a complex system that can be difficult to simulate and analyze. This difficulty is exacerbated by the fact that these systems can consist of numerous sub-systems and are dependent on the behavior and states of the other systems and sub-systems that comprise the whole.

A simple example of this concept lies in the tradeoff between depth and temperature (i.e., thermal gradient). Generally, higher geofluid temperatures results in higher rates of energy production but accessing higher temperatures requires drilling deeper. At some point, the profit gained through the increased rate of energy production is offset by the increase in drilling costs. An analysis of this example would require simulating the time-varying behavior of the thermal drawdown, energy production, drilling costs, O&M and other costs, and the revenue streams. The interdependency of these systems and their sub-systems results in a multi-tiered dependency structure with multiple feedback loops. The result of these inter-system dependencies is that the sum of the individual system uncertainties when evaluated in isolation is different from the resulting uncertainty when they are run as a system of systems.

In response to these difficulties, Sandia National Laboratories has been developing an integrated systems modeling tool called GT-Mod (Lowry et al. 2010) that dynamically links the various connected yet disparate systems of a geothermal problem to simulate the collective performance of each system over time. Built using a system dynamics framework, the various systems contained in GT-Mod are simulated as individual modules that communicate with each other through dynamic linkages that define the interdependencies between them. Each module addresses a particular process such as thermal drawdown, pressure losses in the wells, power generation, cooling facilities, etc. and contains one or more sub-models with similar characteristics. GT-Mod simulates the time varying pressure regime, thermal drawdown, plant performance, and economics as a single, system of systems. Economic analysis is accomplished through a real-time, two way connection to a modified version of the Geothermal Energy Technology Evaluation Model (GETEM) (Entingh et al. 2006) that calculates the levelized cost of electricity based on time-series performance output from GT-Mod.

GT-Mod is unique in that it allows a user to define a probability distribution function (PDF) for any and/or all inputs, including the

300+ inputs required to run GETEM. The inputs can be defined using uniform, normal, log-normal, truncated normal, exponential, or triangular distributions with each PDF defined by a set of parameters specific to that function (e.g., mean and standard deviation for the normal distribution). GT-Mod uses a Monte Carlo approach to propagate the input uncertainties to the output by varying each of the input PDF's across its range of values via a Latin Hypercube Sampling (LHS) technique.

Assessing Risk

Generally, uncertainty manifests in both the inputs and the outputs of an analysis. For the inputs, uncertainty reflects the confidence that the value of an input is the 'true' value for the analysis in question. Uncertainty in the outputs result from the propagation of input uncertainties, the assumptions used to create the simulation algorithms, and numerical inaccuracies in the solution method. The risk assessment approach used here, quantitative risk assessment, is similar to that used by the insurance industry to assess their exposure to loss and can be thought of as a method that quantifies the influence of uncertainties in the inputs on the range of outputs.

Quantitative risk assessment relies knowing the consequence(s) of an event (or set of events) as well as the probability of that event occurring. To quantify risk, we utilize the approach introduced by Helton (1994) who defines risk 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:

$$R = \sum_t \sum_n c(n,t)\Delta P(n) \tag{1}$$

The risk calculated with Equation (1) represents an integrated risk meaning that the risk is the sum of the risk for all events that have a less than or equal probability of occurring than some reference event. For our purposes, an 'event', or scenario, is a single combination of input parameters. Quantifying risk allows for evaluating the performance of different scenarios and allows one to compare the tradeoffs between lower-probability higher-reward scenarios versus higher-probability lower-reward scenarios.

Example Problem

The example is a fictitious EGS site where the default parameter values are set to produce an LCOE of 8.5 ¢/kW-hr. The specifics of the example are listed in Table 1. Within GT-Mod, the Gringarten (Gringarten et al. 1975) analytical solution option was chosen to calculate the thermal drawdown and the Snow estimation (Snow 1968) was chosen to calculate the pressure drop through the reservoir.

The model input parameters can be lumped into three categories: 1) parameters used to define the geology, 2) parameters used to define the costs, and 3) model specific parameters. Model specific parameters include the thermal drawdown solution method mentioned above, the simulation timestep, the numerical integration type, etc., and are fixed for this analysis.

Eleven variables are defined using a PDF and represent input parameters that we may be uncertain about (Table 2). The power plant is designed based on an initial reservoir temperature of 225°C. Since the thermal gradient is allowed to fluctuate, the depth of the wells is determined by the depth that achieves the 225 °C requirement. The depth at the default gradient of 43.87 °C/km is 4900 m (a ground surface temperature of 10 °C is assumed). Seven of the eleven variable input parameters are multipliers against a default value that is hard-wired into GETEM. The default values listed for those variables in Table 2 are the hardwired values in GETEM. 350 simulations were run for this analysis.

With regards to a geothermal site assessment, the default case can be thought of as the 'best guess' scenario or the scenario that

Table 1. List of key fixed input parameters for the example problem.

Description	Value / Input
Power Plant Size	50 MW
Initial reservoir temperature	225 °C
Solution method of thermal drawdown	Gringarten Analytical (Gringarten et al. 1975)
# of Wells	3 Injections, 5 Producers
Mass flow rate per producer	144 kg/s
Distance between injection and producer	1000 m
Reservoir height and width	400 m x 1000m
Reinjection temperature	80 °C
# of Fractures	10

Table 2. List of variable input parameters, their default values, and their distribution functions.

Name	Description	Default Value	Distribution Type	Distribution Parameters
Utilization Factor	% time plant is operating	95%	Triangular	Min: 85.0% Peak: 95.0% Max: 98.0%
Power Plant Cost Multiplier	Adjusts turbine generator, condenser, heat exchanger, and working fluid pump costs	\$398.65 / kW, \$204.32 / kW, \$50.21 / kW, \$36.32 / kW	Uniform	0.80 – 1.20
Percent Indirect Costs	% of plant cost to calculate indirect costs	8%	Triangular	Min: 5.0% Peak: 8.0% Max: 12.5%
Casing Cost Multiplier	Material costs of casing	\$2.01 / lb	Uniform	0.80 – 1.20
Cement Cost Multiplier	Material costs of cement	\$175.00 / ft^3	Uniform	0.80 – 1.20
Fracture Aperture	Effective fracture aperture	2 mm	Uniform	0.50 – 4.00 mm
Subsurface Water Loss	% water loss that must be replaced	5%	Triangular	Min: 2.0% Peak: 5.0% Max: 10.0%
Trouble Index Multiplier	Adjusts estimated drilling and casing time	1.0	Uniform	0.80 – 1.20
Penetration Rate Multiplier	Adjusts drilling penetration rate	30 ft/hr < 10k ft 15 ft/hr > 10k ft	Uniform	0.80 – 1.20
Bit Life Multiplier	Adjusts life of drilling bit	100 hrs	Uniform	0.80 – 1.20
Thermal Gradient	Adjusts thermal gradient	43.87 °C/km	Normal	μ = 43.87 °C/km σ = 9.9 °C/km

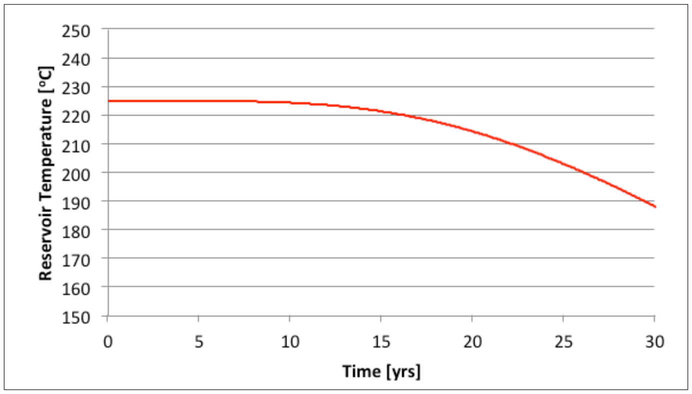

Figure 1. The thermal drawdown for the default scenario.

is most agreed upon to be the most likely. For this example, it also serves as the scenario by which all other scenarios are compared. For each scenario, GT-Mod calculates the thermal drawdown in the reservoir, temperature changes in the injection and production wells, and pressure changes through the whole system. A plot of the thermal drawdown from the default scenario is shown in Figure 1.

The comparisons between the scenarios are done on the net revenue generated over the 30 year lifetime of the plant using the following equation:

$$R_{tot} - C = R_{net} \tag{2}$$

where R_{tot} [\$] is the total revenue and C [\$] is the total cost. The total revenue is calculated using:

$$S_e P_c T U = R_{tot} \tag{3}$$

where S_e is the effective sale price of electricity [¢/kW-hr], P_c is the production capacity of the power plant, T is the lifetime of the power plant, and U is the utilization factor. The costs, C, for each scenario are also calculated using equation (3) by substituting the calculated LCOE for the effective sale price, S_e. The effective sales price is 9.829 ¢/kW-hr and is based on data from the US Energy Information Administration (US Energy Information Administration 2011). It was derived as a weighted average of the monthly sales price of electricity from all sources for the residential, commercial, industrial, and transportation sectors for 2009 and 2010. The net revenue for the default case, D_{net}, is \$166.0 million dollars over 30 years (D_{net} assumes an LCOE of 8.5 ¢/kW-hr and a utilization factor of 95%).

Figure 2 shows the results for the LCOE as a cumulative distribution function (CDF) that describes the probability that the LCOE will be below a given value. It is interesting to note that there is only a 32.1% chance that the LCOE will be less than or equal to the default LCOE value of 8.5 ¢/kW-hr, despite the fact that the default values for the variable inputs lie either at the center or the peak of their respective PDF's. While the default case is deemed the most probable from a parameter estimation point of view, the distribution of the LCOE is not necessarily symmetrical about that value. In this case, the results are skewed towards a higher LCOE than the default would indicate.

Figure 3 shows a plot complimentary cumulative distribution (CCDF) plot of the net revenue, R_{net}, as well as the difference between R_{net} and D_{net}. A CCDF plot describes the probability that

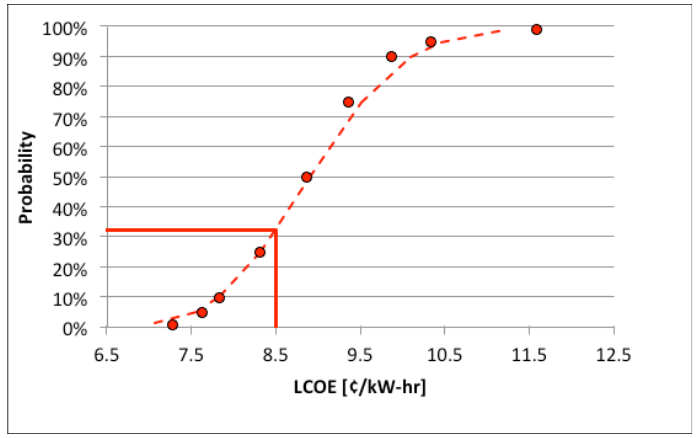

Figure 2. Cumulative distribution function of the LCOE. The CDF shows the probability that the LCOE will be less than a given value. The solid red line indicates the LCOE (8.5 ¢/kW-hr) and probability (32.1%) of the default case.

the 'real' scenario will be greater than the value at that probability. The plot shows that the probability of producing positive revenue is about 89% (solid blue line). Conversely, the probability of exceeding the default performance is only 31.2%, which means that if projections are based solely on the default input values, there is a 2 out of 3 chance that the actual performance will fall below that number.

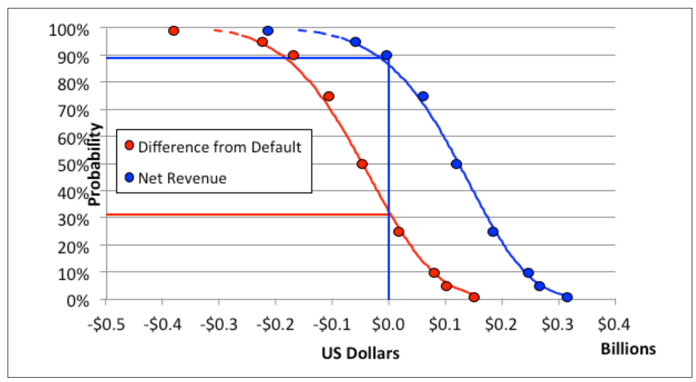

Figure 3. Complimentary CDF for net revenue and the difference between net revenue and the default case. The solid red and blue lines indicate the probabilities associated with the 'break even' point of each distribution (31.2% for net revenue, 89.0% for the difference.

The calculated risk for the difference between R_{net} and D_{net} is about \$72.0 million (Figure 4). The risk is calculated using Equation (1) and assumes that the risk is zero for scenarios where R_{net} is greater than D_{net} and in this case, represents a loss as compared to the default scenario. The figure shows the cumulative risk plotted over the R_{net} - D_{net} CCDF, with the axes rotated so that probability is now on the x-axis, and dollars are on the y-axis. The risk is not a probability function meaning that the final value of \$72.0 million is integrated across all revenues and all probabilities. The difference between D_{net} and the risk is about \$94.0 million, which now becomes the probabilistically weighted estimate of R_{net} and which represents a LCOE of 9.1 ¢/kW-hr. From a risk-based decision making point of view, the decision maker must now decide if the potential gains are worth the risk.

Correlation analysis is used to determine which inputs contribute the most to the variability in the LCOE estimates (Figure 4) and is useful for deciding on where to place future efforts to reduce uncertainty (i.e., risk) the most. In this case, changes in the trouble index, the penetration rate multiplier, and the thermal gradient influence the value of the LCOE the most. The trouble index as used in this version of GETEM is a multiplier on the components to the total drilling time other than the time for the actual drilling, which is controlled by the penetration rate and the penetration rate multiplier. Since the thermal gradient sets the depth of the resource, it is clear that factors concerning the drilling time are important to the LCOE and if one desires to reduce the LCOE, effort should be placed on reducing the drilling time. Conversely, if reducing the drilling time is not feasible, reducing the uncertainty in the estimations of the drilling time will provide more certainty to the LCOE predictions and reduce the risk of incorrectly assessing the site. The next most influential inputs are the indirect costs followed by the casing material costs. It should be noted that the correlations can be highly influenced by the PDF and more importantly, the spread of potential values for each input and that when risk analysis of this type is used in the real world, care should be given when forming the PDF's.

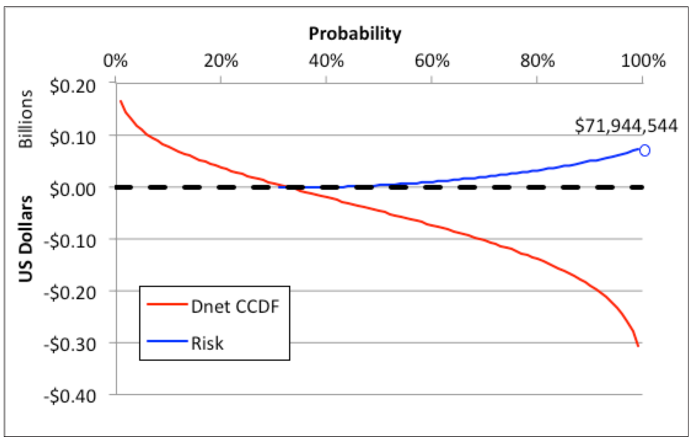

Figure 4. The CCDF for the difference in net revenue, Dnet, and the integrated risk. The total risk for this example is $71,944,544.

Table 3. Correlation coefficients for each of the variable inputs against the LCOE.

Variable Name	Correlation with LCOE
Utilization Factor	0.011
Fracture Aperture	-0.010
Subsurface Water Loss Percentage	0.001
PP Cost Adjustments	-0.044
Indirect Cost Percentage	-0.061
Trouble Index	-0.192
Penetration Rate Multiplier	0.156
Bit Life Multiplier	0.007
Casing Cost Multiplier	-0.052
Cement Cost Multiplier	0.039
Thermal Gradient	-0.123

Summary

Most of our understanding of a geothermal resource is obtained from indirect measurement and or inference and even for cases where the knowledge is high, uncertainty remains. Models used to assess the resource rely on this understanding to populate their inputs such that they reflect the effective characteristics at the site. Due to model sensitivity, some inputs require high precision while others are less stringent. Historically, when simulating thermal or economic performance, uncertainty has typically been addressed by assuming a mean value for each of the inputs, and then perturbing the values about that mean to try and bound the range of possible answers. That range is then reported as a mean prediction plus or minus the variability about that mean.

Here we demonstrate a new and unique approach to addressing uncertainty for geothermal assessments. The approach is based on the concept of quantitative risk assessment that accounts for the consequences and the probability of a particular scenario. Uncertainties in the inputs are propagated through the model using a Monte Carlo approach to produce probabilistic output that is used to calculate risk. As implemented here, risk describes the integrated consequences of wrongly assessing a site and is a direct function of our level of understanding of the site. Quantitative risk assessment provides a decision maker with a higher degree of insight regarding the consequence of his or her decision while simultaneously identifying the areas where better understanding would most help the decision making process.

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