

Applications of Experimental Design and Response Surface Method in Probabilistic Geothermal Resource Assessment – Preliminary Results

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ABSTRACT

Resource estimates in geothermal green-fields involve significant inherent uncertainty due to poorly constrained subsurface parameters and multiple potential development scenarios. There is also limited published information on probabilistic resource assessments of geothermal prospects. This paper explores the applications of a systematic experimental design (ED) and response surface method (RSM) approach to generate probabilistic resource results.

ED and RSM have been successfully used in uncertainty analysis and resource evaluation of petroleum fields. These techniques have also been used in a number of field management strategy assessments of geothermal brown-fields. This work presents the preliminary results of a study to extend the geothermal applications of ED and RSM to geothermal green-field resource assessments.

ED and RSM are applied to a simple geothermal process model and used to estimate the amount of electrical generating capacity from this synthetic geothermal system. A response variable (electrical generating capacity) as a function of the main uncertain parameters was derived from the simulation runs. This response function serves as the proxy model in Monte-Carlo probabilistic analysis. For this preliminary study, distributions used for the main uncertain parameters are assumed. The probabilistic results from the proxy model are compared with the probabilistic results from the mass in-place volumetric reserves method.

The results provide a preliminary understanding of the potential strengths and weaknesses of the ED and RSM methodologies as applied to geothermal resource assessment. Future work will focus on refining the appropriate workflow, understanding the distribution of uncertain parameters, and exploring the ED and RSM levels of complexity applicable to an actual green-field numerical model.

1. INTRODUCTION

Probabilistic assessment of undeveloped geothermal resources has been necessary to accommodate the uncertainties in both the subsurface parameters and the development scenario to be implemented. The geothermal industry has done this mainly through Monte Carlo simulations of the parameters in the volumetric stored heat or mass in-place estimation methodologies (Grant and Mahon, 1995; Parini et al., 1995; Parini and Riedel, 2000; Sanyal and Sarmiento, 2005; Williams et al., 2008; AGRCC, 2010; Garg and Combs, 2010; Onur et al., 2010). The Monte Carlo simulation is applied to the parameters of the volumetric stored heat equation where the parameters are allowed to vary over a range of values and within a defined probability distribution (AGRCC, 2010). The range of parameter values ideally covers the range of uncertainty for that particular variable. This is strongly influenced by the geothermal experts doing the estimate as shown by the review of geothermal resource estimation methodology by Zarrouk and Simiyu (2013).

An example of a power capacity estimate based on volumetric stored heat equation is shown below (Zarrouk and Simiyu, 2013):

$$W_e = \frac{H_{th} R_f \eta_c}{L * F} \quad (1)$$

where W_e is the power capacity in MW, H_{th} is the theoretical available heat in both the reservoir rock and fluid, R_f is the recovery factor that represents the fraction of recoverable heat from the system, η_c is the conversion efficiency, L is the project life, and F is the power plant load factor. The theoretical available heat, H_{th} , is described by the following expression (AGRCC, 2010):

$$H_{th} = Ah[(1 - \phi)\rho_r C_r (\Delta T) + \phi\{\rho_{vi} S_v (\Delta h_v) + \rho_{li} S_l (\Delta h_l)\}] \quad (2)$$

where the product of area and height, Ah , is the resource volume, ϕ is the porosity representing the fluid-filled fraction of the volume, ρ_r is the density of the rock, C_r is the heat capacity of the rock, ΔT is the difference between the initial and final rock temperature, ρ_{vi} and ρ_{li} are the initial steam and liquid densities, S_v and S_l are the steam and liquid saturations, Δh_v and Δh_l are the change in steam and liquid enthalpies.

The probabilistic resource assessment would be a Monte Carlo simulation of equation (1) where the parameters are randomly sampled within their defined probability distribution range. The result is a probability density function (PDF) or a cumulative distribution function of the power capacity (AGRCC, 2010). In this assessment, the most debated parameter is the recovery factor, R_f .

Parini and Riedel (2000) investigated the recovery factor using numerical simulation. In their approach, R_f was based on the ratio of total steam produced in 30 years to the original reservoir mass in-place. The use of numerical simulation to investigate the relationship between the physics of the reservoir and the recovery factor is an improved probabilistic assessment based on the volumetric method (equation 1).

The use of numerical simulation models for probabilistic resource assessment has never been a popular option due to the resources required to build reservoir models and the perceived weakness of a model without production history calibration. However, use of numerical simulations for the final resource assessment, the delineation stage as defined by AGRCC (2010), before a major investment decision is made—additional drilling, power plant construction, etc.—is slowly gaining ground. Grant (2000) argued for the superiority of numerical simulations in evaluating the size of a geothermal development. Similar to volumetric stored heat or mass in place estimates, the main concern with a resource assessment using numerical simulation is that it is deterministic even though the parameters that are used to build the model still have large uncertainties. In a recent geothermal development in New Zealand, Clearwater, et al. (2011) used a reservoir model as part of the resource evaluation process prior to the installation of a power station and production history calibration.

Probabilistic resource assessment using numerical simulation has been applied in geothermal reservoirs with concepts similar to ED and RSM. Parini and Riedel’s (2000) recovery factor in their probabilistic capacity equation is essentially a response surface or proxy model for the numerical simulation. Acuña et al., (2002) built and calibrated alternative full-field reservoir simulation models to evaluate field strategies. The most-likely, pessimistic, and optimistic model responses were represented by a polynomial approximation model, a similar concept to the response surface proxy models, to enable a probabilistic Monte Carlo simulation.

In both cases, varying the factors in the model is either done one factor at a time or by multiple parameter variations but without a suggestion of how these combinations are done. In the work flow by Acuña et al., (2002), the variations are done by trial and error. A systematically designed experiment through ED and RSM can improve this process by modifying parameters simultaneously and running the minimum number of reservoir simulations required to generate a response surface model. Since the design is known, it can be independently verified. The basis for the response surface or the proxy model that results from the analysis is also verifiable. This will address the concerns raised by AGRCC (2010) and Atkinson (2012) in regards to the independent verification of the results and analysis performed.

This work provides a preliminary result of the study to apply experimental design and response surface methods to reservoir simulation models and use the resulting proxy model to provide a probabilistic resource assessment.

2. EXPERIMENTAL DESIGN AND RESPONSE SURFACE METHODOLOGY

One of the earliest works on the application of experimental design methodology in oil and gas reservoir simulations (Damsleth et al., 1992) demonstrated that information can be maximized from a minimum number of simulation runs through a “recipe” of combining parameter settings. Also, the work verified the possibility of substituting a response surface for the reservoir simulation in a probabilistic Monte Carlo analysis. The response surface is a polynomial describing the relationship between the simulation output and the investigated parameters. In the geothermal industry, an ED workflow was described by Hoang et al. (2005). ED and RSM frameworks and workflows for reservoir simulations in the oil and gas industries are also described by other authors (Friedmann et al., 2003; White and Royer, 2003; Yeten et al., 2005; Amudo et al., 2008). From these works, a generalized workflow applied in this study is shown below.

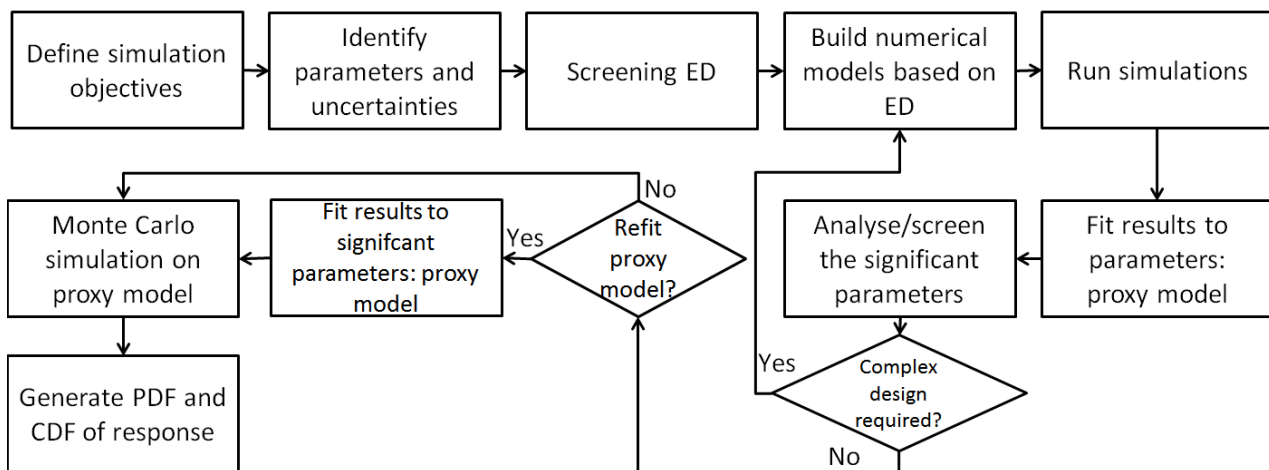


Figure 1. Experimental design workflow applicable to probabilistic resource assessment.

2.1 Experimental Design

To illustrate the ED concept, let us take for example a reservoir simulation where the response, say power capacity, to three parameters—A, B, and C—are being investigated. These parameters will have a low setting (minimum) and a high setting (maximum). These settings are known as levels and the simplest design used in this work has two levels, low and high. These designs belong to a group of designs known as 2^k factorial experiments (Walpole et al., 2012) where k is the number of parameters being investigated. In ED and RSM, the parameter levels are more conveniently dealt with using dimensionless coded variables, i.e., -1 for low, 0 for middle, and +1 for high settings (Anderson and Whitcomb, 2000; Myers and Montgomery, 2002). Their

combinations are the design points or simulation runs required by the design. A two-level, three-parameter complete factorial design requires 2^3 or 8 simulation runs. This is shown in Figure 2.

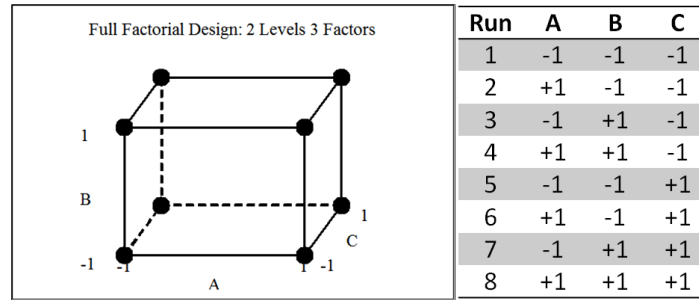


Figure 2. Design points and the parameter combinations for each run on a full factorial design.

In contrast, the one-factor-at-a-time (OFAT) sensitivity analysis for the same number of levels and parameters is illustrated in Figure 3 where a parameter is varied while the rest of the parameters are held constant. At least $k + 1$ runs are required, where k is the number of parameters.

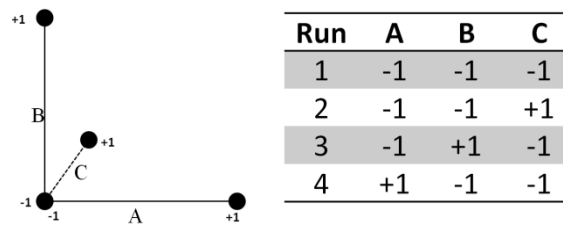


Figure 3. Design points and the parameter combinations for each run with OFAT sensitivity analysis.

If there are 10 parameters at two levels, a full factorial design will be 2^{10} or 1,024 experiments; if the design is done at three levels (low, mid, and high), the total number of experiments will be close to 60,000. A simulation run in a full-field geothermal reservoir model can range from a few minutes to a few hours dependent on the complexity of the model. With more design parameters and levels, the required number of runs becomes prohibitively time consuming.

ED maximizes the information that can be gathered from a minimal number of simulation runs by effectively choosing a number of design points (simulations) out of the complete factorial design. Some of these runs are fractions (1/2, 1/4, 1/8) of the full factorial design; these are known as fractional factorial designs (Walpole et al., 2012). Other designs are effective in screening out insignificant factors and identifying the key parameters that affect the simulation result. From the aforementioned oil and gas workflows, the most commonly used screening design is the Plackett-Burman experimental design. Doing a screening design is useful when a higher level or a more complex design may be required at a later stage. Examples of more complex designs are the Central Composite Design (CCD), and Box-Behnken design (Myers and Montgomery, 2002).

2.2 Response Surface – Proxy Models

The term “response surface” and “proxy models” are interchangeably used in this work to define the polynomial approximation of the simulation results, y , and the parameters tested, A , B , and C . Equation 3 shows an example of a first-order polynomial approximation, also known as a main effects model (Myers and Montgomery, 2002), of the simulations from the design described in Figure 2. In this equation, the β values are the coefficients of the tested parameters.

$$y = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C \quad (3)$$

Details regarding the higher-order polynomial models and the experimental designs that produce them are discussed by Myers and Montgomery (2002), and Anderson and Whitcomb (2005).

The aim of our ED and RSM study is to approximate the correct form of this function good enough to serve as a substitute for the geothermal reservoir simulation in the Monte Carlo probabilistic analysis.

2.3 Implementing the ED and RSM Workflow

In studying this technique, the preliminary approach was to find and use currently existing software packages that are accessible to industry specialists. As expected, we did not find software packages that can link the experimental design to the geothermal reservoir simulation code TOUGH2 (Pruess, et al., 1999)

Although no single integrated package performed the ED method, software packages existed for specific parts of the workflow. We used PetraSim™ for the TOUGH2 reservoir simulation interface, PyTOUGH for results extraction, (Croucher, 2011), Minitab™ for the statistics for both experimental design and response surface models, and @Risk™ for the Monte Carlo simulation. The software packages used do not affect the validity of the workflow since commercial software packages may be replaced by open-source codes like PyTOUGH to pre-process and post-process the simulation runs, and R (R Core Team, 2013) to handle the statistical analysis, i.e., design the experiments, analyze results, fit the response polynomial, and perform Monte Carlo simulation.

In this work, the scope was limited to a low-level screening design. A two-level Plackett-Burman experimental design was used to test six likely key parameters affecting the power capacity of an idealized geothermal model. The reservoir simulation model, parameters, and probability distribution of parameter uncertainties are based on the model described by Parini and Riedel (2000).

3. CASE STUDY – NUMERICAL MODEL OF A GEOTHERMAL GREEN-FIELD

The ED and RSM workflow was applied to provide a probabilistic resource assessment of a green geothermal field described by Parini and Riedel (2000).

3.1 Objective of the Assessment

The “objective of the assessment” answers the basic question: What is this model for? The significance of the parameters being investigated is based on this objective. This assessment aims to identify the key parameters that affect the estimate of the power capacity of the idealized geothermal resource normalized to 30 years of project life. It also aims to derive a proxy model to the reservoir simulation in the probabilistic Monte Carlo simulation.

3.2 Likely Key Parameters

Six parameters were investigated out of the ten parameters used in the reference model (Parini and Riedel, 2000): reservoir temperature, matrix porosity, fracture permeability, average fracture spacing, well feedzone depth, and boundary conditions. The parameters were chosen mainly based on ease and consistency of manually implementing the parameter changes to the reservoir simulation models. For example, parameters that change the physical size of the model like areal extent and reservoir thickness were not selected. Note that the range of parameter values will also limit the results to within the values identified. A reservoir management team’s experience and expert opinion should ideally guide the range of these values. For this study, the range of values was adopted from the reference model. The parameters are summarized in Table 1 showing a list of quantitative and qualitative/categorical variables.

Table 1. Reference model parameters chosen for the Experimental Design.

Parameter	Low	Mid	High
Reservoir Temperature, °C	250	265	280
Matrix porosity	0.05	0.08	0.1
Fracture permeability, mD	10	60	100
Average fracture spacing (3D)	2 (approx. single porosity)	30	100
Well feedzone depth	Shallow (1350 m)	--	Deep (1900 m)
Boundary conditions	Close	--	Open (150°C lateral recharge)

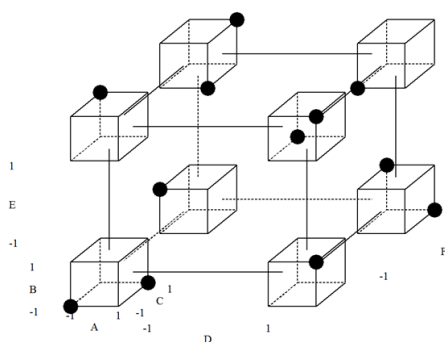
3.3 Experimental Design: Plackett-Burman

A screening design based on the chosen six parameters was implemented. A two-level (high and low) Plackett-Burman design was chosen to identify the main parameters that affect the response, 30-yr power capacity.

The experimental design generated from Minitab™ is shown in Figure 4. In the design table, the standard order column is an experimental design idea to do the experiments in a random order (run order) and avoid run-dependent effects. This is mainly useful when running physical experiments. In numerical simulation experiments, the run order may not be as important.

From the design table in Figure 4, the first row describes one reservoir simulation model where reservoir temperature is set at the high setting (+), matrix porosity is set at the high setting (+), fracture permeability is set at the high setting (+), fracture spacing is set at the low setting (-), well feed zone depths are at the high setting (deep), and boundary condition is set at the high setting (open). Each row is a reservoir simulation model for a total of 12 model runs. In contrast, a full factorial design at two levels will require 2⁶ or 64 simulation runs.

Plackett-Burman Design: 2 Levels and 6 Parameters



Std Order	Temperature	Porosity	Permeability	Frac Spacing	Well Depth	Boundary
6	+1	+1	+1	-1	deep	open
11	-1	+1	-1	-1	shallow	open
3	-1	+1	+1	-1	deep	closed
5	1	+1	-1	+1	deep	closed
9	-1	-1	-1	+1	deep	open
7	-1	+1	+1	+1	shallow	open
12	-1	-1	-1	-1	shallow	closed
2	+1	+1	-1	+1	shallow	closed
8	-1	-1	+1	+1	deep	closed
1	+1	-1	+1	-1	shallow	closed
4	+1	-1	+1	+1	shallow	open
10	+1	-1	-1	-1	deep	open

Figure 4. Plackett-Burman design for six parameters with a total number of 12 experiments.

3.4 Numerical Simulation Models

3.4.1 Model Description

The numerical simulation models were built using the reference model (Parini and Riedel, 2000) as the basic structure and Petrasim™ as the user interface for the TOUGH2 geothermal reservoir simulator. The Equation of State (EOS) module used was

EOS1, which is the module for non-isothermal water. A three-dimensional dual-porosity formulation was used with three (3) multiple interacting continua (MINC) layers. The fracture part of the MINC layers was assigned a volume fraction of 0.05. In the material properties, fractures were assumed to have 90% porosity. Other generic model details are summarized in Table 2.

Table 2. General model parameters in all the numerical model runs.

Model parameter	Value	Unit
Reservoir volume	10.26	km ³
Number of blocks	1440	blocks
Initial reservoir pressure	$P_{\text{saturation}} + 10$	bars
Rock density	2600	kg/m ³
Rock wet heat conductivity	2.2	W/m-C
Rock heat capacity	1	kJ/kg-C
Relative Permeability	Grant's curves	
Residual liquid saturation	0.3	
Residual gas saturation	0.05	
Capillary pressure function	Linear function	
CP _{max} - CP(1)	1.0E6	
A - CP(2)	0.25	
B - CP(3)	0.4	
Production wells	15	wells
Deep injection wells	5	wells
Total mass production	555	kg/s
Total injection rate	~416	kg/s
Steam usage rate	7	kg/kW
Power capacity years	30	years

3.4.2 Model Geometry

The surface area of the model is 9 km² (3 km by 3 km) divided into 12 along the x and y model dimensions. The reservoir thickness is 1.14 km divided into 10 layers with thinner upper layers to capture the two-phase changes. The outermost lateral blocks are thin blocks used to implement fixed states. There are 1440 blocks in this simple reservoir model. The surface area was divided into four (4) main regions to represent a development strategy (Figure 5):

1. 20% - A: No drilling/no access, e.g., national park, inaccessible terrain, etc.
2. 50% - B: Production area
3. 20% - C: Production-injection buffer, and
4. 10% - D: Deep injection

Five deep injection wells were used and 15 production wells were distributed around the production area using a 500 m radius well spacing. The shallow wells tap the reservoir at -350 m above sea level (ASL) while the deep wells tap the reservoir at -900 m ASL. In the simulation runs that have "open" boundary condition settings, a fixed state at -590 m asl is implemented as thin blocks around the four lateral sides of the model, providing recharge to the reservoir at 150°C and constant initial reservoir pressure in the thin blocks.

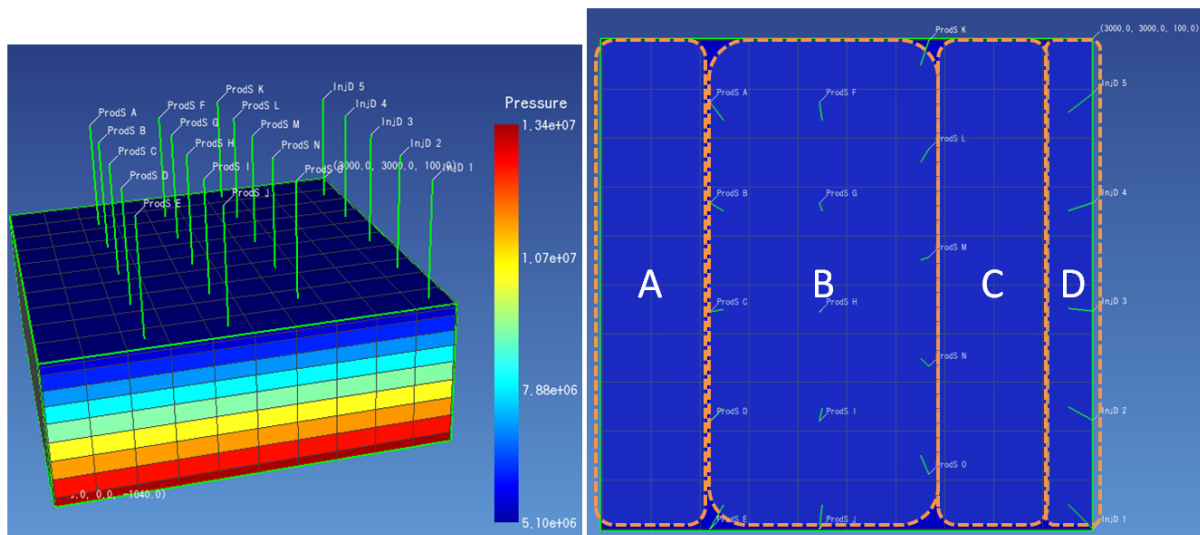


Figure 5. Model geometry showing the modeled reservoir volume, the production wells in sector B, the injection wells (D), an injection buffer area (C), and an inaccessible area (A). The surface elevation (not shown) is at 1000 m ASL and the modeled reservoir thickness is from 100 m ASL down to -1040 m ASL.

A total of 12 numerical models were created based on the ED settings in Figure 4 and the generic model parameters in Table 2. Once a reservoir simulation model is set-up, it is run to at least 10,000 simulated years to approximate a "natural state," without

production and injection. This is done to let the pressure profile settle to a natural hydrostatic gradient (see Figure 5) and is used as the initial condition for the production run.

3.4.2 Reservoir Simulation Runs: Limits and Cut-offs

The reservoir simulations were run by equally distributing the total mass production into the 15 wells and 75% of the mass produced into the 5 deep injection wells. The enthalpy of the re-injected fluid is based on an 8 barg separation pressure adopted from the reference model (Parini and Riedel, 2000). The simulations were performed until the first production well was unable to flow. The simulations are therefore a conservative run where it is terminated once the total mass production cannot be support by all 15 production wells. Once the simulation ends, a script using PyTOUGH is used to efficiently extract the results from the simulation output file. The generation is estimated using the total steam produced by all the wells at the 8 barg separation pressure and applying the steam usage rate in Table 2. The total generation is normalized to 30 years and this value is recorded as the response for that simulation run.

To determine when a well is unable to flow, wellbore simulation runs were done to create the plot of the minimum well bottom-hole pressure, P_{min} , versus discharge enthalpy (Figure 6). The wells modelled have a 13 3/8” production casing and a 10 3/4” production liner. Initially, a 10 kg/s flow was assumed as the minimum mass flow (Parini and Riedel, 2000) but as shown in Figure 6, the P_{min} showed large variations with the pressure drop correlation used. These variations are small at higher flow rates, hence the decision to increase the assigned well flow from 10 to 37 kg/s at a wellhead pressure of 10 barg.

The evolution of pressure at the well feed zone depth and the changing well discharge enthalpy of the 15 production wells were compared to the P_{min} vs discharge enthalpy line. In Figure 6, a well starts to the right of this line and gradually moves down with pressure decline and will either track farther to the right as the enthalpy increases or track to the left as it decreases. Either way, once any of the 15 producers intersects the cut-off line, the total steam produced is calculated only up to that simulation time. At the moment, this is done in a spread sheet and should ideally be coupled with the reservoir model.

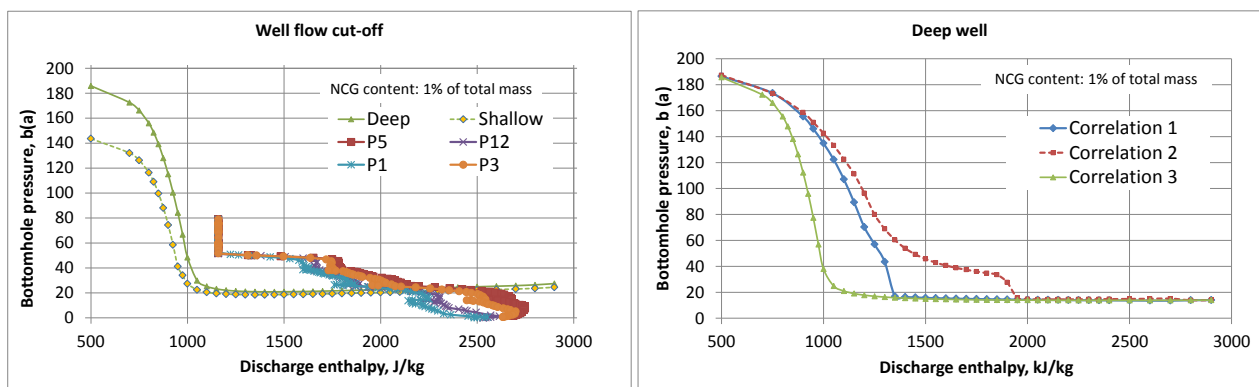


Figure 6. Cut-off based on the minimum bottom-hole pressure required for a well to flow at a certain enthalpy. On the left plot, the limit for shallow wells is shown by the green diamonds and the limit for deep wells is shown by the green triangles. On the right, the plot shows a variation in minimum bottom-hole pressure with pressure drop correlation at low mass flow rates.

3.5 Simulation Results and Fitting a Response Surface – Proxy Model

After creating 12 reservoir numerical models, performing the simulations, and calculating the responses (30-year power capacity), the results are summarized in Table 3.

Table 3. Designed simulation runs and 30-yr power capacity results.

Std Order	Temperature	Porosity	Permeability	Frac Spacing	Well Depth	Boundary	Power Capacity, MW _e
6	+1	+1	+1	-1	deep	Open	53
11	-1	+1	-1	-1	shallow	Open	65
3	-1	+1	+1	-1	deep	Closed	59
5	1	+1	-1	+1	deep	Closed	129
9	-1	-1	-1	+1	deep	Open	48
7	-1	+1	+1	+1	shallow	Open	213
12	-1	-1	-1	-1	shallow	Closed	39
2	+1	+1	-1	+1	shallow	Closed	125
8	-1	-1	+1	+1	deep	Closed	89
1	+1	-1	+1	-1	shallow	Closed	255
4	+1	-1	+1	+1	shallow	Open	361
10	+1	-1	-1	-1	deep	Open	97

The Plackett-Burman design response was analyzed in Minitab™ to approximate the response surface or the proxy model of the numerical simulations done. The regression analysis output is shown in Figure 7.

Factorial Fit: MW@30yr versus Temp, Porosity, ...

Estimated Effects and Coefficients for MW@30yr (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		127.84	16.29	7.85	0.001
Temp	84.49	42.25	16.29	2.59	0.049
Porosity	-40.92	-20.46	16.29	-1.26	0.265
Permeability	87.76	43.88	16.29	2.69	0.043
Frac Spacing	66.26	33.13	16.29	2.03	0.098
Well Depth	-97.28	-48.64	16.29	-2.99	0.031
Boundary	23.53	11.76	16.29	0.72	0.503

S = 56.4372 PRESS = 91732.6
 R-Sq = 85.35% R-Sq(pred) = 15.60% R-Sq(adj) = 67.76%

Figure 7. Summary table of the polynomial fit between the response and the parameters.

The reservoir numerical simulations are approximated by a first-order proxy model using all the coded (-1, +1) parameters to generate the response (Power Capacity). This is shown in Equation 4.

$$Power\ Capacity = 127.84 + 42.25 * A - 20.46 * B + 43.88 * C + 33.12 * D - 48.64 * E + 11.76 * F \quad (4)$$

where A is reservoir temperature, B is matrix porosity, C is fracture permeability, D is average fracture spacing, E is well feed zone depth, and F is boundary condition. This means a response may be estimated by replacing the variables with their coded value. The polynomial coefficients were taken from the ‘‘Coef’’ column in Figure 7. Note that the ED chosen at the start of the analysis, Plackett-Burman, limits the proxy model to a first-order polynomial because this design analyzes main effects only.

3.6 Analysis of the Main Effects and Response Surface

To screen out the main effects, the p-values (P) in the results table (see Figure 7) were checked to verify the parameters that are statistically significant. The significance was set at a 95% confidence level so the p-values were compared to α -level of 0.05. All p-values less than or equal to the α -level are significant while all p-values greater than the α -level are insignificant.

The regression model contained three significant parameters that affect the 30-yr power capacity estimate of the numerical simulation: (1) well feed zone depth, (2) fracture permeability, and (3) reservoir temperature. The absolute values in the ‘‘Effects’’ column show the relative strength of a parameter’s effect on the response. Well feed zone depth has the greatest effect (-97.28), followed by fracture permeability (87.76), and reservoir temperature (84.49). From the sign of the effects, we can additionally infer that using just deep production wells in the strategy results in lower power capacity, while finding high permeability (100 mD) and high reservoir temperature (280°C) results in higher power capacity.

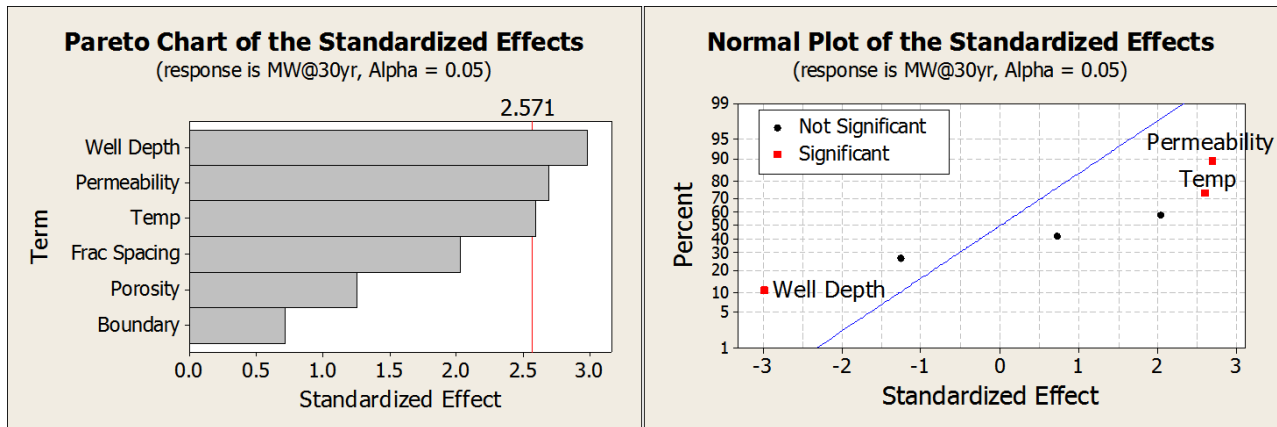


Figure 8. Pareto Chart and the Normal Plot of the effects showing the three significant parameters based on a 95% confidence level ($\alpha = 0.05$).

Fracture spacing does not meet the 95% interval but, as shown in Figure 7, has a p-value almost close to the required α level of <0.05. Also, based on their p-values, porosity and boundary conditions are not significant. While $\alpha = 0.05$ is typical of this type of analysis, this shows that selecting a lower confidence level, for example $\alpha = 0.1$, would have included fracture spacing as a significant parameter and could be employed in such circumstances.

The validity of the regression and of the proxy model is verified by the plots of the residuals shown in Figure 9. The plots show that the errors are normally distributed and are independent of each other. It should be noted here that numerical simulation experiments do not have a random error or measurement error (Sacks, et. al., 1989; Myers and Montgomery, 2002) and the error is mainly from fitting the wrong proxy polynomial or the choice of parameters to include in polynomial fitting.

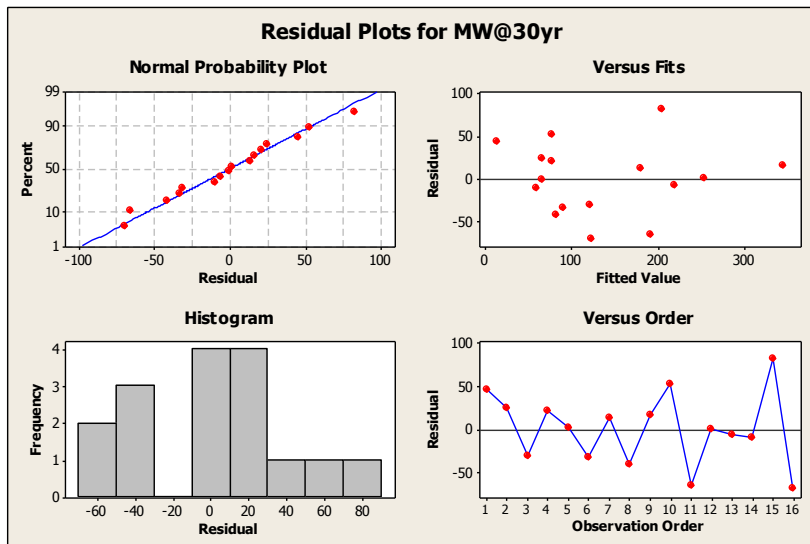


Figure 9. Residual plots showing residuals on a normal plot, residuals and fits, histogram of the residuals, and residuals versus the order simulations were performed.

3.7 Refitting the Response Surface with Only the Significant Parameters

Keeping the full response equation might be a good idea for the particular purpose of approximating the reservoir simulation response to the tested parameters (Myers and Montgomery, 2002). Refitting the proxy model to the significant parameters simplifies the model to the main effects terms. Also, if a more detailed design like CCD or Box-Behnken is required in the analysis, the workflow suggests applying the design to the significant parameters. A similar issue about keeping the full model or refitting was discussed by Anderson and Whitcomb (2005). To compare, we refitted the model using only the significant terms, the response polynomial of coded parameters becomes:

$$Power\ Capacity = 127.84 + 42.25 * A + 43.8871 * C - 48.64 * E \tag{5}$$

3.8 Monte Carlo Simulation on the Reservoir Simulation Proxy Model

To provide a probabilistic resource assessment of the 30-yr power capacity of the system being investigated, we ran a Monte Carlo simulation using @Risk™ on the proxy model shown in equations 4 and 5. The probability distributions of the polynomial variables were applied to the coded low, mid, and high values. Around 100,000 iterations were done, randomly sampling the probability distribution functions of the parameters. The result is a probability distribution function of the power capacity covering the full range of possible outcomes.

Using both the refitted (Equation 5) and the full proxy model (Equation 4), the cumulative distribution function for the 30-year power capacity of the resource is shown in Figure 10. Note that the P50 values are almost the same while the power capacity range, standard deviation, is larger when more factors are included in the proxy model and smaller when refitted to the significant few.

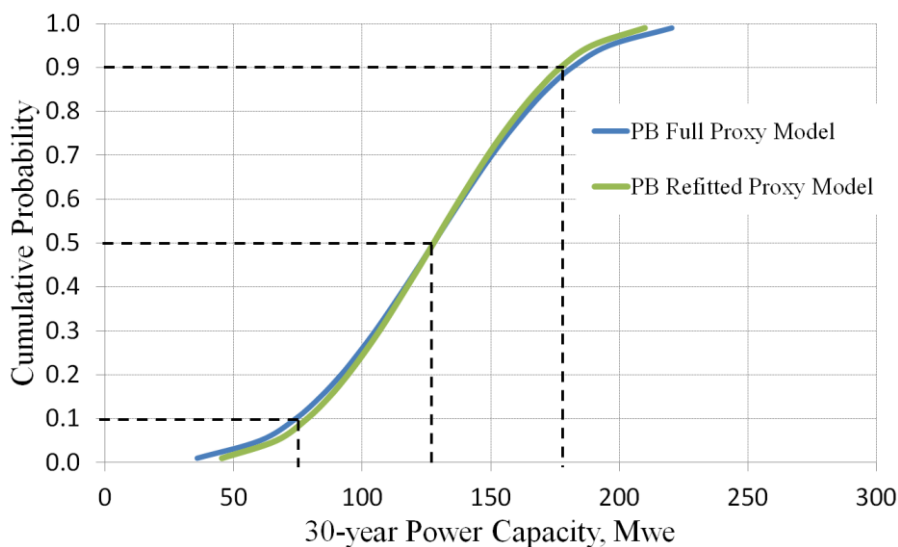


Figure 10. Cumulative distribution functions with P10, P50, and P90 indicated.

4. DISCUSSION

The concept of approximating the reservoir simulation runs with response surface models and the proxy models' ability to provide a probabilistic resource assessment has been demonstrated. The main strengths of the methodology are as follows:

- Recorded simultaneous parameter variations to generate the different reservoir simulation models;
- Use of proxy polynomial that approximates the reservoir simulation runs in probabilistic Monte Carlo analysis;

4.1 Choice of Experimental Design

The choice and the implementation of an experimental design type is an important decision. In this work, Plackett-Burman, a screening design, was chosen to approximate the response surface because it was commonly used in literature as a simple design to implement and was viewed as a good starting point in exploring this technique. Due to the characteristics of this design, it is useful for identifying significant main effects but not significant interactions between parameters as shown by the lack of interaction variables in the full proxy model in equation 4. In future assessments, experimental designs appropriate to geothermal numerical simulations will be explored. For example, a screening design that analyzes interactions, e.g., fractional factorial designs, may be tested (Amudo, et al., 2008).

A center point was added into the set of 12 Plackett-Burman simulation runs to test the effect of adding mid-value runs to this design. Due to the two categorical parameters, well feed zone depth and boundary conditions, the center point run ended up being four additional simulation runs. The full proxy model coefficients were different but the statistically significant parameters were the same. In addition, a curvature parameter and a lack-of-fit parameter were found to be insignificant. The probabilistic responses plotted with the original results are shown in Figure 11.

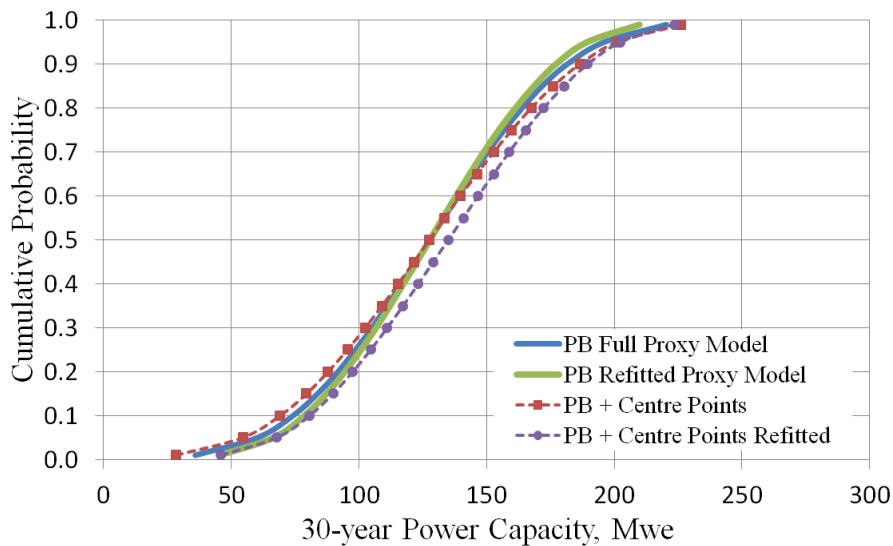


Figure 11. Cumulative distribution functions of the response with the PB design + center points.

4.2 The Tested Parameters and the Significant Few

The design table provides a list of the required parameter settings for all the simulation runs done, making it independently verifiable. With a pre-determined pattern by which the parameter settings will be combined, the resource assessment team's focus shifts to the list of likely parameters and the uncertainty in each parameter. The choice to do six parameters out of 10 in the Parini and Riedel (2000) reference model was based on ease in building the simulation models and not through a rigorous uncertainty framing exercise. While there may be hundreds of uncertain parameters in a geothermal green-field, the final list of parameters that are built into the ED and RSM workflow should be determined by an integrated team of experts that will narrow down the list based on the objective of the assessment, e.g., power capacity, total years of production for a X-MW development, etc.

It was also observed that a parameter's range size may influence its significance in the model approximation process. This work did not have the freedom to set the parameter uncertainty ranges because these values were adopted from the reference model. Fracture spacing, the fourth parameter with the strongest effect on the response, will possibly be significant if the high setting of the uncertainty range was investigated up to 300 m. However, parameters with very strong effects on the response were still found significant even within a narrow range of parameter values (reservoir temperature at 250-280°C) while parameters with very weak effects on the response were still insignificant even with a wide range of investigated values (boundary conditions at fully closed and fully open).

The three parameters that were found to be significantly affecting the 30-yr power capacity of the reservoir model being assessed make good sense. When evaluating the size of a geothermal development, the usual questions to answer are: (1) How hot is the resource? (2) Is there enough permeability for the geothermal fluid to flow? (3) How can we bring the fluid to the surface?

4.3 The Proxy Models and the Volumetric Stored-heat/Mass in Place

The probabilistic resource assessment based on ED and RSM proxy models were compared with the probabilistic resource assessments based on volumetric stored heat and combined volumetric/numerical simulation methods. The parameters that were varied were limited to the parameters chosen in the ED and RSM workflow, i.e., reservoir area and thickness were kept constant.

Table 4. Parameters used in the volumetric stored heat and the volumetric/numerical simulation probabilistic analyses.

	Parameters	Low	Mid	High	Distribution
Common to both	Area, km ²	--	9	--	N.A.
	Thickness, km	--	1.14	--	N.A.
	Average porosity	0.05	0.08	0.1	Triangular
	Reservoir Temperature, °C	250	265	280	Triangular
	Reject Temperature, °C	--	175.36	--	N.A.
	Rock heat capacity, J/kg	--	1000	--	N.A.
	Rock density, kg/m ³	--	2600	--	N.A.
	Plant load factor	--	0.85	--	N.A.
	Project life, years	--	30	--	N.A.
Stored heat	Recovery factor, stored-heat ¹	0.1	0.15	0.5	Triangular
	Conv. efficiency (stored heat) ²	--	0.12	--	N.A.
Vol/numerical	Recovery factor, (volumetric/numerical) ³	0.205	0.468	0.75	Triangular
	Steam usage rate, kg steam/kW	--	7.5	--	N.A.

¹The stored heat recovery factor parameter range was based on the review done by Zarrouk and Simiyu (2013). ²Conversion efficiency is based on review by Zarrouk and Moon (2013). ³Mass in place recovery factor was parameterized by Parini and Riedel (2000) but no proxy polynomial was published so this range was estimated from the main effects plot between parameters and % recovery.

The results of the different probabilistic resource assessments are shown in Figure 12.

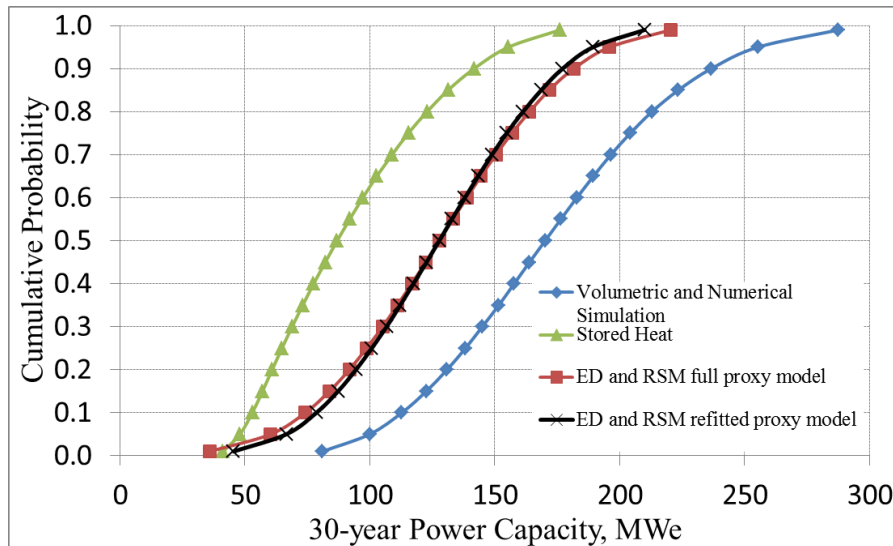


Figure 12. ED and RSM, stored heat, and volumetric/numerical cumulative distribution functions.

The comparison showed in Figure 12 should be limited to a simple illustration of the different probabilistic assessment results and how similar methods—(1) volumetric stored heat with volumetric/numerical simulation and (2) ED/RSM proxy model and volumetric/numerical simulation—result in different estimates due to different assumptions in the methodologies. The volumetric stored heat had the lowest power capacity range due to the lower range of thermal recovery factors and is probably due to the lower conversion efficiency used. The other two methods have recharge components providing them access to a larger fluid volume. Although the ED and RSM proxy model was based on the volumetric and numerical simulation model, the implementations of the numerical simulations were different. The simplification done by estimating the mass in place recovery factors from the published main effects plots (Parini and Riedel, 2000) and assigning a triangular probability distribution to the parameter was a large assumption.

5. CONCLUSION

A probabilistic resource assessment methodology based on numerical simulations was demonstrated using an experimental design and response surface method (ED and RSM) workflow. The strength of the workflow lies in the experimental design's ability to be independently verified because the parameter settings and combinations are recorded in the design table. The response surface or proxy model is a good approximation of the relationship between the response and the tested parameters generated from reservoir numerical simulations. There are existing commercial software packages that can be used to implement the ED workflow in geothermal reservoir simulation though the process is still manual and inefficient. In this scenario, resource assessment specialists can focus more on refining the list of parameters and the range and distribution of parameter uncertainties because the design pattern is available.

6. NEXT PHASE

In the next stage of the study the ED and RSM workflow will be improved and tested on a large numerical model of a geothermal green-field and will transition out of the commercial software packages into available open-source codes. Appropriate experimental designs will be explored. A response surface method (RSM) experimental design, with quadratic proxy models, will be tested to evaluate the possible optimization of controllable parameters e.g. the impact of well depths and the impact of well spacing. Also, a more efficient way of implementing the workflow, e.g., building the numerical simulation runs through PyTOUGH (O'Sullivan et al., 2013), will be explored.

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