PROBABILISTIC RESOURCE ASSESSMENT USING THE NGATAMARIKI NUMERICAL MODEL THROUGH EXPERIMENTAL DESIGN AND RESPONSE SURFACE METHODS (ED AND RSM)

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ABSTRACT

Reservoir simulations are becoming prevalent in geothermal resource assessments. Natural-state reservoir simulation models based on robust conceptual models are used to simulate a number of development scenarios in geothermal prospects to evaluate the long-term reservoir performance. The Experimental Design and Response Surface Methods (ED and RSM) workflow was applied to the natural-state reservoir model of the Ngatamariki geothermal field in order to assess the effects of uncertain parameters and scenarios to the simulated field generation capacity. The workflow provides a systematic way of building multiple versions of the TOUGH2 model through a designed pattern of parameter combinations. The results from multiple model runs are used to evaluate the uncertain parameters, weigh their significance, and create a response surface model. The response surface (polynomial) lends itself well to Monte Carlo methods of generating the probabilistic range of generation capacity. From the current practice of providing deterministic results from reservoir simulation scenario runs, a full probabilistic assessment was demonstrated through the ED and RSM workflow. In addition, the uncertainty analysis performed provides a basis for managing development risks and uncertainties.

1. PROBABILISTIC RESOURCE ASSESSMENT USING NUMERICAL MODELS

Probabilistic resource assessment is the practice of generating the probability distribution function of a geothermal system's resource size or resource potential based on the uncertainties of the available reservoir information. The Monte Carlo method is applied on the mathematical model of the geothermal system (e.g. volumetric stored-heat equation) through a large number of results from random sampling of the mathematical model (Thomopoulos, 2013).

The most common application of probabilistic resource assessment is carried out on the volumetric stored-heat (Garg & Combs, 2010; Muffler, 1978; Sanyal & Sarmiento, 2005) and mass in-place (Parini & Riedel, 2000) equations through the Monte Carlo method. The alternative of using complex numerical models in probabilistic resource assessment, while practiced (Acuña et a.l, 2002; Parini et al., 1995; Parini & Riedel, 2000) is still considered "*far more involved and time consuming than volumetric estimation of reserves*" (Sanyal & Sarmiento, 2005). Independent verification of the probabilistic resource assessment results from numerical models is also a concern (Australian Geothermal Reporting Code Committee [AGRCC], 2010).

A systematic approach to simulation-based probabilistic resource assessment through ED and RSM is a proven process in the oil and gas industry (Society of Petroleum Engineers [SPE], 2011) and is a promising method in geothermal applications (Hoang et al., 2005; Quinao & Zarrouk, 2014). The experimental design is a clearly defined process and can be independently verified. The basis for the reservoir model response surface (proxy model) that results from the analysis is also verifiable.

2. EXPERIMENTAL DESIGN AND RESPONSE SURFACE METHOD (ED AND RSM)

The main objectives of ED and RSM when using reservoir simulations are the following:

- To systematically design and perform simulation experiments on the reservoir model in order to understand the relationship between uncertain parameters and performance-related responses, and
- To fit a response surface (proxy polynomial) on the simulation experiment results in order to describe the performance-related responses as a polynomial function of the uncertain parameters.

Damsleth et al. (1992) are some of the pioneers in establishing experimental design methodology in oil and gas reservoir simulations. They demonstrated that information from reservoir studies can be maximized from a minimum number of reservoir simulation runs through a "recipe" of combining parameters at various settings. They also showed that this approach is a good uncertainty analysis workflow and tested the use of a derived response surface model (proxy polynomial to the reservoir simulation) to carry out probabilistic Monte Carlo analysis.

A review of the ED and RSM framework and workflow for reservoir evaluations as used in the oil and gas industry (Amudo et al., 2008; Friedmann et al., 2003; White & Royer, 2003; Yeten et al., 2005) provided the generalized workflow as summarised in Figure 1.

The resulting proxy model (response surface) from the ED and RSM workflow may be used in probabilistic resource assessment similar to the process outlined in the SPE Guidelines (Society of Petroleum Engineers, 2011) for the oil and gas industry.

In this work we will implement the ED and RSM workflow on an early model of the Ngatamariki geothermal field, New Zealand to estimate the resource potential.

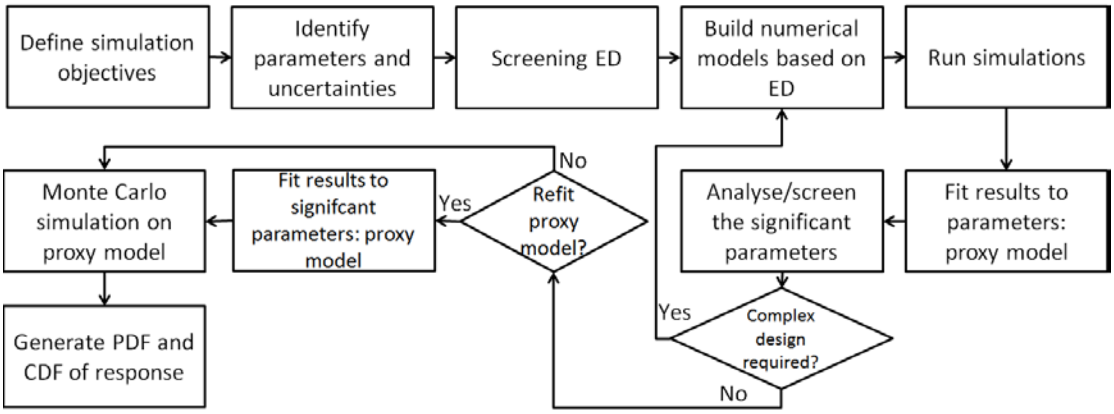

Figure 1. Oil and gas industry experimental design workflow for probabilistic resource assessment

3. NGATAMARIKI GEOTHERMAL FIELD

The Ngatamariki geothermal system is located in the prolific Taupo Volcanic Zone (TVZ) of New Zealand (Figure 2). It is about 17 km northeast of the Taupo Township and is located close to several other significant geothermal systems: Rotokawa to the southeast, Ohaaki to the east, and Orakei-Korako to the north. The geothermal system currently supports an 82 MWnet binary power plant operated by Mighty River Power Ltd. (MRP) under a 60,000 tonnes per day geothermal resource consent awarded to the Rotokawa Joint Venture Ltd. (RJVL).

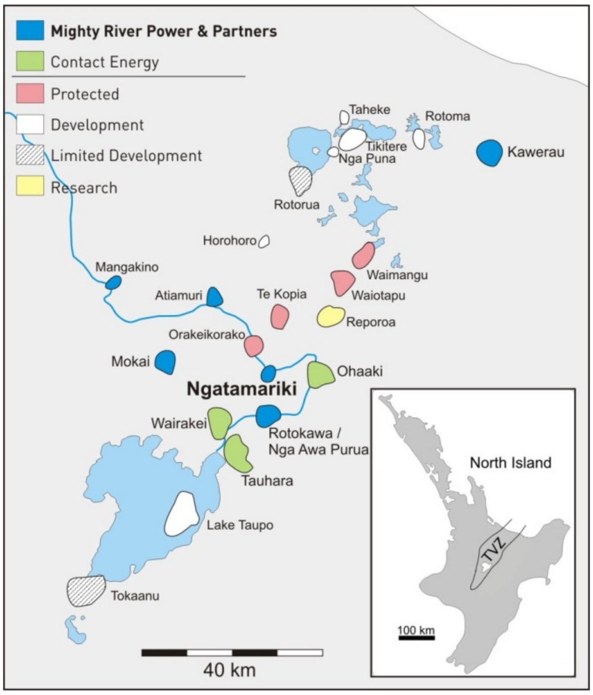

Figure 2. The Ngatamariki geothermal system surrounded by other active geothermal systems in the Taupo Volcanic Zone (from Boseley et al. 2010)

3.1 Resource conceptual model

Ngatamariki is a liquid-dominated compressed geothermal system. It is located in an area that is about 360 meters above sea level (masl). The main geothermal reservoir is delineated by the 250 °C isotherm and is located deep (Figure 3), with the altered clay cap at -500 to -1,500 (masl) (Boseley et al., 2010).

The hot up-flow is located around NM7 and outflows through a poorly altered clay cap around NM2 and NM3 into an intermediate hot carbonic aquifer and flowing to the north through the thermal features and into the Waikato River (Boseley et al., 2010).

The northern area has lower permeability likely due to the alteration caused by a diorite pluton encountered by NM4. The main reservoir is hosted in Tahorakuri formation and Andesite. The Greywacke basement was encountered at the deeper section of NM6 but was not encountered in other wells. Permeable zones were encountered both shallow (-500 and -1,500 masl) and deep (-2,500 and -3,000 masl). The interference tests suggest very good transmissivity across all the drilled exploration wells (Burnell, 2010).

3.2 Reservoir numerical model

Based on the conceptual model of Figure 3, a numerical model of the Ngatamariki geothermal system was developed by Burnell and Kissling (2009). The 2009 model is a single-porosity TOUGH2 model with 33,966 computational blocks and satisfactorily matched the natural-state reservoir pressure and the temperature profiles of the geothermal wells.

Clearwater et al. (2012) reported that the 2009 model runs showed a risk of cold down-flow from the intermediate aquifer. Imposing 100% injection to maintain pressure and mitigate this risk results in an increased injection thermal breakthrough risk. The 2009 single porosity numerical model was not suitable to assess this risk.

Therefore a dual-porosity model was built in 2010 to improve the original model's capability to represent injection thermal breakthrough (Burnell, 2010). The dual-porosity reservoir model covers an area about 16 km^2, extending from the ground surface down to -5,000 masl (Figure 4). It has 13,156 computational blocks in total, made up of 26 identical horizontal layers and 506 grid/layer elements.

For the dual-porosity implementation, the reservoir blocks have three multiple interacting continuum (MINC) layers, with a fracture volume fraction of 0.01. The average fracture spacing used was 100 m based on an analogue study using well heat up data in another TVZ geothermal field (Clearwater et al., 2012)

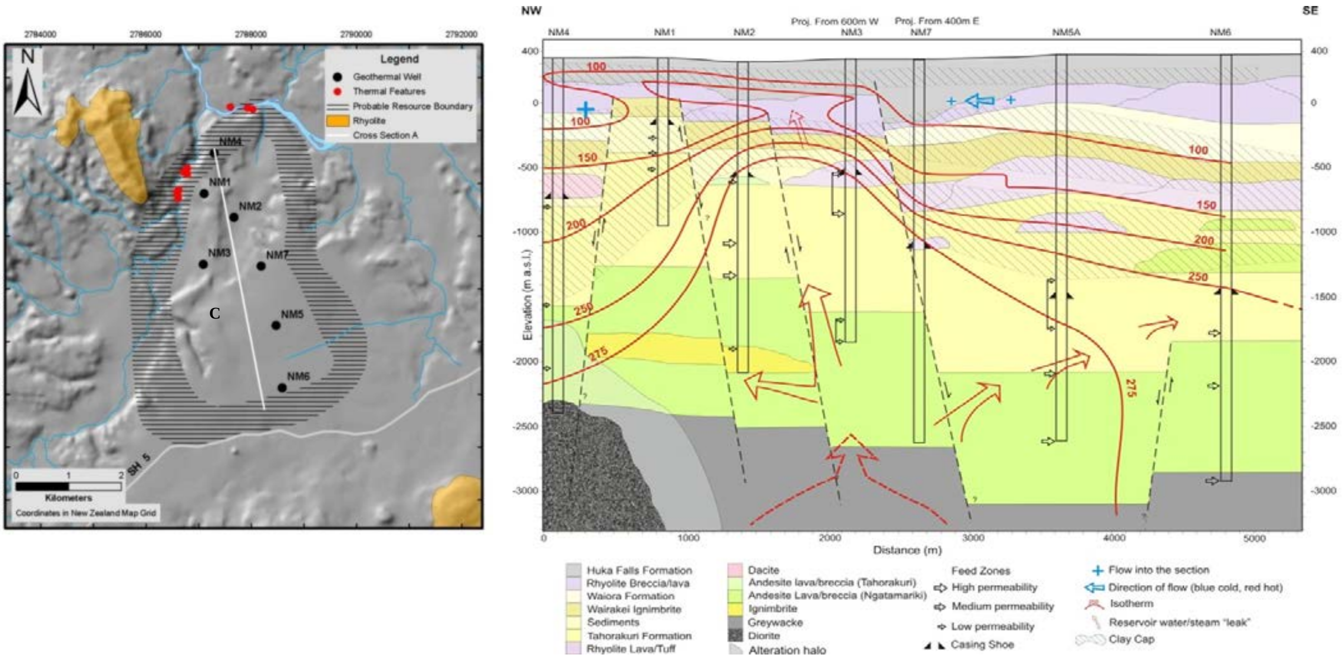

Figure 3. Ngatamariki resource conceptual model (Boseley et al., 2010)

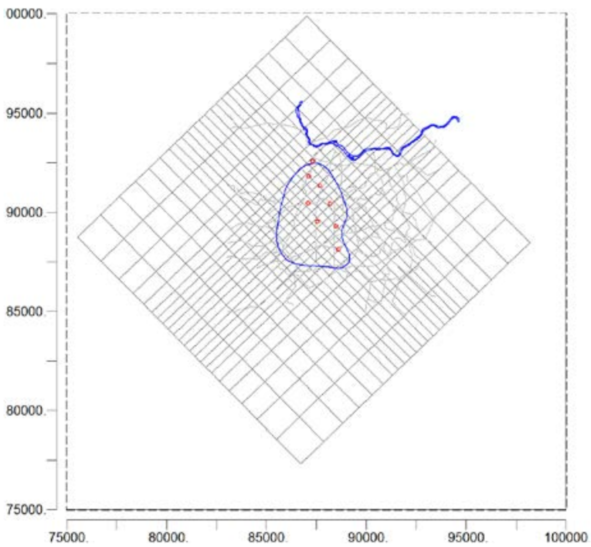

Figure 4. Ngatamariki dual porosity model plan view showing the wells (circles), the resource boundary and the Waikato river (from Clearwater et al., 2012)

4. ED AND RSM ON THE NGATAMARIKI MODEL

In applying the ED and RSM technique, the preliminary approach was to follow the oil and gas industry workflow described in Figure 1.

Separate commercial software packages were found to be feasible for use in specific parts of the workflow and were used in the preliminary test: Minitab® (Minitab Inc., 2010) for the experimental design table, PetraSim™ (Thunderhead Engineering, 2012) as the interface for building multiple TOUGH2 reservoir simulations based on the ED, PyTOUGH (Croucher, 2011) for extracting the results from the output files, Minitab® for the ED results analysis, statistics, and multivariate regression to yield a response surface model, then @Risk™ (Palisade Corporation, 2012) in Microsoft Excel for the Monte Carlo simulation on the response surface.

After the workflow was tested on an idealized geothermal system, it became clear that to be able to handle higher number of designed simulations, the next step is to expedite the process of building numerical models and extracting results (Quinao & Zarrouk, 2014). To improve the workflow, Python scripts were written for both pre and post-processing routines, including translating the ED design table into scripts or using pyDOE (Lee, 2014) that link with PyTOUGH. This enabled the building of multiple reservoir numerical models from a base reservoir model. A schematic diagram of this workflow showing where the abovementioned software applications were used is shown in Figure 5.

Applying the ED and RSM workflow, the Ngatamariki dual-porosity model (Burnell, 2010) was used to assess the feasibility of supporting a 50,000 tonnes per day geothermal fluid production for 50 years.

4.1 Uncertain parameters

Eight parameters were chosen based on the parameters that Clearwater et al. (2012) tested for uncertainty assessment. These parameters are summarized in Table 1 and Figure 6.

4.1.1 Matrix porosity (A)

Reservoir porosity is known to affect the reservoir pressure behaviour during the production. The investigation included porosity to verify its significance to the reservoir pressure response and the power capacity MWe (through the enthalpy response) estimate of the dual-porosity model. The porosity of the main reservoir rocks in the dual-porosity model is the same over the reservoir depth.

The probability distribution chosen for porosity is a skewed triangular distribution with values assigned based on the Ngatamariki reservoir rock porosity measurements carried out by Wyering et al. (2014).

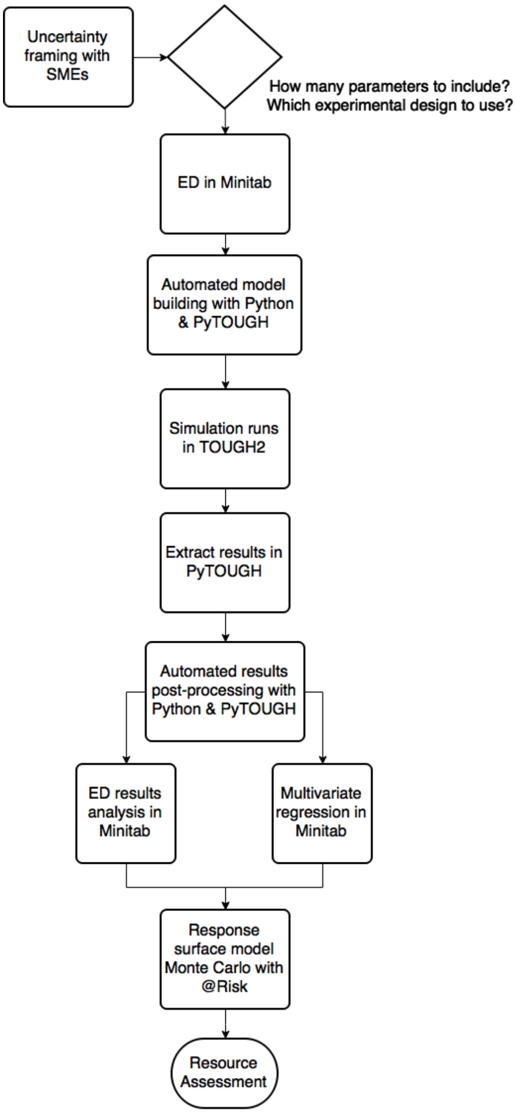

Figure 5. Updated geothermal ED and RSM workflow with pre- and post-processing Python script automations

4.1.2 Fracture spacing (B)

Fracture spacing is a modeling parameter that affects the heat exchange in a fractured reservoir. This parameter was investigated to verify the significance of the dual-porosity implementation and the effect of this parameter on the model's temperature and enthalpy response.

The probability distribution chosen for the parameter is skewed triangular, skewed to lower fracture spacing levels (Figure 6).

4.1.3 South marginal recharge (C)

The resource conceptual model suggests that NM6 to the south of the reservoir is drilled close the edge of the system. A risk of marginal recharge originating from this area was identified and tested to verify whether this recharge (100°C fluid supplied by a constant-pressure block) will significantly affect the modeled reservoir performance.

A uniform distribution was chosen to describe the probability distribution between the absence and presence of a southern recharge.

4.1.4 Pressure-induced up-flow/hot recharge (D)

The model has a constant input of 100 kg/s hot fluid in the up-flow that is fixed as the simulation is run on production (Burnell, 2010). There have been cases when reservoir pressure drawdown appears to have stimulated the up-flow input (Yeh et al., 2010). A pressure-induced hot recharge (100 kg/s + Pressure-dependent hot recharge) was tested in the experiments to quantify its effect on the reservoir model.

The pressure-induced hot recharge is implemented as a constant pressure boundary providing fluids at the same enthalpy as the up-flow during the production run only. Similar to the southern recharge, a uniform probability distribution between the two parameter end points was chosen for this parameter.

4.1.5 Percentage reinjection (E)

The amount of reinjected fluid was central to the Ngatamariki development assessment due to the risk of downflow from the intermediate aquifer if excessive pressure drawdown occur (Clearwater et al., 2012).

This parameter was included in the investigation to verify if reinjection below 100% would significantly affect the development for the 50 years development lifetime. A triangular probability distribution was chosen with the parameter range between 75% and 100% reinjection.

4.1.6 Reinjection temperature (F)

The reinjection temperature is a function of the two-phase separator pressure (flash steam power plants) or the lowest geothermal fluid temperature exiting a binary power plant. Lower exit temperatures usually mean better conversion efficiency. The range of temperatures considered for the reinjection fluid was investigated to see if this has significant effect on the modelled reservoir performance.

A triangular distribution was chosen for the probability distribution of this parameter, ranging from 80 °C to 120 °C.

4.1.7 Injection location [North and South distribution] (G)

The location of reinjection wells was of primary consideration to ensure that reservoir pressure support is available and at the right location. This parameter was chosen to verify whether injection location would affect long-term modelled reservoir performance.

A triangular probability distribution was chosen for this parameter with range from a low level of 50/50 North-South to a high level of 100% North-only injection distribution reflecting the capability of the surface injection system.

4.1.8 Production location [concentrated or spread out] (H)

From the seven exploration wells (Figure 3) drilled at Ngatamariki, three production areas (Pad A [NM7], Pad B [NM5], and Pad C) were identified and simulated for production. The locations of production wells were investigated to verify if additional production in the Pad A (near NM7) or in the Pad C area would significantly affect the modelled reservoir performance.

A uniform probability distribution was chosen between the concentrated (Pad A and Pad B only) and the distributed production option (Pad A, Pad B and Pad C).

Table 1. Uncertain parameters to be tested on the Ngatamariki dual-porosity model using the ED and RSM workflow

Parameter	Low (-1)	Mid (0)	High (+1)	Distribution
Matrix porosity	0.05	0.07	0.2	Triangular
Fracture spacing, (m)	50	100	300	Triangular
South marginal recharge	No	(No)	Yes	Uniform
P-induced up-flow	No	(No)	Yes	Uniform
Percentage reinjection	75%	85%	100%	Triangular
Reinjection temperature, (°C)	80	90	120	Triangular
Injection location (North/South)	50/50%	75/25%	100%	Triangular
Production location	NM5, NM7	(NM5, NM7)	NM5, NM7, Pad C	Uniform

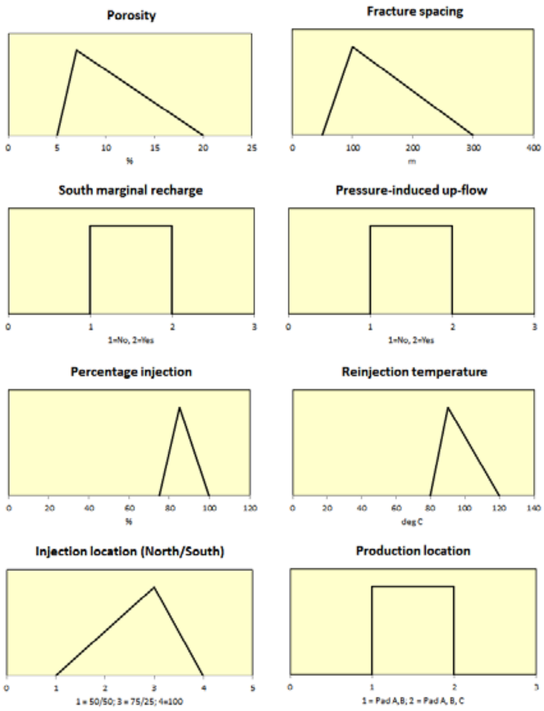

Figure 6. Probability distribution for eight tested parameters

4.2 Experimental Design: Plackett-Burman (PB)

A Plackett-Burman (PB) design (Plackett & Burman, 1946) for the eight parameters (n = 8) was chosen to identify the significant parameters affecting production-dependent reservoir responses and to generate response surfaces. Based on the PB design, 12 (Table 2) numerical models were built according to the design pattern for combining the parameters at two levels (high [+] and low [-]). The alternative design was a fractional factorial design at half-fraction (2^{n-1}, n = 8) for a total of 127 numerical model runs. To illustrate the concept of minimised runs with maximum information, the PB design requiring fewer simulations was chosen for testing.

4.3 Performance-related response and ED results

The performance-related responses are the simulation results we want to observe and record at the end of each simulation run. For the Ngatamariki model assessment, we focussed on the 50-year power capacity. The results are recorded per output time (at least one every five years) where each production well's flow rate and enthalpy are multiplied by the time step to estimate the total MW_{th} produced during that time step. The sum of the MW_{th} produced is converted to MWe at a conversion efficiency of 12% and divided over 50 years to estimate the power capacity.

Table 2. Plackett-Burman design results for 12 parameters at two levels

Simulations	A	B	C	D	E	F	G	H	MWe
1	+	-	+	-	-	-	+	+	82.8
2	+	+	-	+	-	-	-	+	76.6
3	-	+	+	-	+	-	-	-	77.2
4	+	-	+	+	-	+	-	-	83.3
5	+	+	-	+	+	-	+	-	78.3
6	+	+	+	-	+	+	-	+	76.6
7	-	+	+	+	-	+	+	-	78.3
8	-	-	+	+	+	-	+	+	84.9
9	-	-	-	+	+	+	-	+	84.8
10	+	-	-	-	+	+	+	-	87.2
11	-	+	-	-	-	+	+	+	84.9
12	-	-	-	-	-	-	-	-	86.6

4.4 Uncertainty analysis

Based on the statistical analysis carried out on the PB-designed results, only fracture spacing (parameter B) and southern marginal recharge (parameter C) among the parameters tested have a significant effect (90% confidence level) on the 50-year power capacity of the Ngatamariki development. These results are shown in Figure 7 and Figure 8.

The normal plot (Figure 8) shows that parameters B and C both have a negative effect on 50-year power capacity, as expected of high fracture spacing and the presence of cold marginal recharge.

Figure 7 shows that matrix porosity (parameter A), while insignificant (below the red reference line), has the third largest effect on the power capacity response, showing that lower matrix porosity impacts the capacity more positively. This is likely due to the increase in production enthalpy as pressure declines and fluid boils/flashes in a lower porosity reservoir.

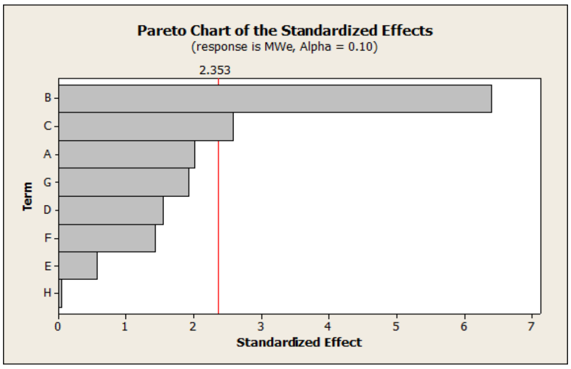

Figure 7. Pareto chart of effects show significant parameters A (fracture spacing) and B (south marginal recharge) at 90% confidence level. The red reference line on the chart indicates which parameters/effects are significant.

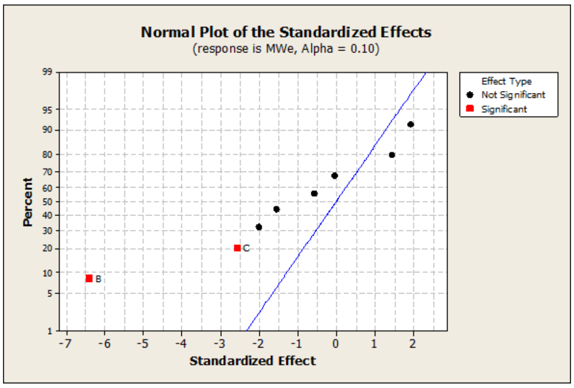

Figure 8. Normal plot of the effects showing the significant parameters in red. The blue line indicates where the points would be if all effects were zero.

4.5 Response surface model for 50-year power capacity

After a multivariate regression of the results in Table 2, the response surface/proxy model for the 50-year power capacity, (coded units, i.e., -1 to +1 input range) containing all eight variables tested is shown in the equation below:

$$\boldsymbol{MWe} = 81.796 - 0.985\boldsymbol{A} - 3.136\boldsymbol{B} - 1.266\boldsymbol{C} - 0.759\boldsymbol{D} - 0.281\boldsymbol{E} + 0.704\boldsymbol{F} + 0.946\boldsymbol{G} - 0.024\boldsymbol{H}$$

This proxy model explains 95.25% of the variability in the power capacity response (R^2 = 95.25%). Note that the coefficient of the parameter represents the magnitude of its effect on the power capacity, consistent with the Pareto chart of Figure 7 above.

4.6 Monte Carlo simulation for power capacity

Monte Carlo simulation was carried out on the proxy model, using the probability distributions of the individual parameters as described in Table 1.

The probability density function (PDF) and the cumulative distribution functions (CDF) in Figure 9 show that in the design space (the parameter ranges investigated), the 50-year power capacity of the Ngatamariki system at 50,000 tonnes per day total take has P10 of 80 MWe, mean of 83 MWe and P90 of 85 MWe.

The standard deviation is small (1.745 MWe) indicating that the tested parameters do not drastically affect the power capacity (from the production enthalpy) of the resource at the 50,000 tonnes per day level of extraction. At worst, the power capacity is at 76 MWe (P1) and at best, 88 MWe (P99).

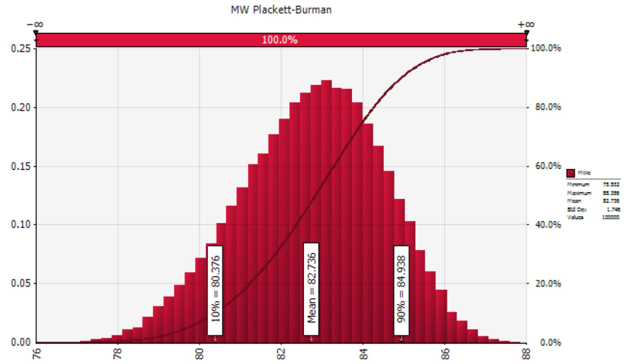

Figure 9. Monte Carlo simulation on the PB-designed response surface for power capacity (MWe)

5. EXPERIMENTAL DESIGN: TWO-LEVEL FULL FACTORIAL (FF)

A two-level full factorial experimental design was carried out to illustrate the complete range of parameter combinations and generate the response surface that fits the array of results. The motivation here is to compare the results derived from a large design with a simpler design like Plackett-Burman.

To do a full factorial design for eight parameters (n = 8) at two levels (high [+] and low [-]), a total of 2^n = 256 numerical models were required. The 256 TOUGH2 input files were built using PyTOUGH (Croucher, 2011) and pyDOE (Lee, 2014) according to the design table shown in Table 3.

The simulation run time requirement was 64 hours for one set of experiments increasing exponentially if errors meant that repeat experiments were required. The risk of increasing run time requirement was greatly mitigated through parallelized computation.

Table 3. Full factorial design results for 12 parameters at two levels (abridged)

Simulations	A	B	C	D	E	F	G	H	MWe
1	-	-	-	-	-	-	-	-	86.6
2	+	-	-	-	-	-	-	-	86.4
3	-	+	-	-	-	-	-	-	83.6
4	+	+	-	-	-	-	-	-	83.2
5	-	-	+	-	-	-	-	-	82.7
6	+	-	+	-	-	-	-	-	82.1
7	-	+	+	-	-	-	-	-	75.5
8	+	+	+	-	-	-	-	-	74.7
*	*	*	*	*	*	*	*	*	*
249	-	-	-	+	+	+	+	+	84.9
250	+	-	-	+	+	+	+	+	84.6
251	-	+	-	+	+	+	+	+	80.1
252	+	+	-	+	+	+	+	+	79.6
253	-	-	+	+	+	+	+	+	84.8
254	+	-	+	+	+	+	+	+	84.5
255	-	+	+	+	+	+	+	+	80.0
256	+	+	+	+	+	+	+	+	79.5

The 50-year power capacity responses were collated and the proxy model, including interaction terms, is shown below:

$$\begin{aligned} \boldsymbol{MWe} = {} & 82.1967 + 0.21\boldsymbol{A} + 2.47\boldsymbol{B} + 1.2\boldsymbol{C} + 0.87\boldsymbol{D} - 0.47\boldsymbol{E} \\ & - 0.09\boldsymbol{F} - 0.32\boldsymbol{G} - 0.21\boldsymbol{H} - 0.105\boldsymbol{EH} \\ & + 0.106\boldsymbol{DH} + 0.085\boldsymbol{CH} + 0.156\boldsymbol{BH} \\ & + 0.084\boldsymbol{EG} - 0.107\boldsymbol{DG} + 0.087\boldsymbol{CG} \\ & + 0.154\boldsymbol{BG} + 0.0197\boldsymbol{AG} + 0.0186\boldsymbol{EF} \\ & + 0.0157\boldsymbol{DF} + 0.02\boldsymbol{CF} + 0.051\boldsymbol{BF} \\ & - 0.148\boldsymbol{DE} + 0.147\boldsymbol{CE} + 1.215\boldsymbol{CD} \\ & - 0.286\boldsymbol{BD} - 0.015\boldsymbol{AD} - 0.476\boldsymbol{BC} \\ & - 0.0387\boldsymbol{AC} - 0.0425\boldsymbol{AB} + 0.0153\boldsymbol{EHC} \\ & + 0.0925\boldsymbol{DHC} + 0.022\boldsymbol{EHB} \\ & - 0.0386\boldsymbol{DHB} - 0.019\boldsymbol{CHB} \\ & - 0.018\mathbf{EGC} + 0.0815\mathbf{DGC} - 0.053\mathbf{EGB} \\ & + 0.046\mathbf{DGB} - 0.0552\mathbf{CGB} + 0.17\mathbf{DEC} \\ & + 0.0844\mathbf{DEB} + 0.021\mathbf{CEB} - 0.486\mathbf{CDB} \\ & - 0.0489\mathbf{CDA} \end{aligned}$$

The full factorial proxy model from the 256 responses fit the capacity response 99.93% of the time (R^2=99.93%). This proxy model is more complex when compared to the PB proxy model of section (4.5). As expected, a larger number of simulations results in a better proxy model fit (i.e. higher R^2).

5.1 Monte Carlo simulation for power capacity

The full factorial proxy model result showed that at 50,000 tonnes per day, the Ngatamariki geothermal system has a probabilistic 50-year power capacity of P10 = 79.7 MWe and P90 = 83.7 MWe with a mean of 81.6 MWe. This result is similar to that generated by the PB proxy model but with a smaller standard deviation (1.53 MWe). The comparison between the probabilistic power capacities from the two proxy models are shown below.

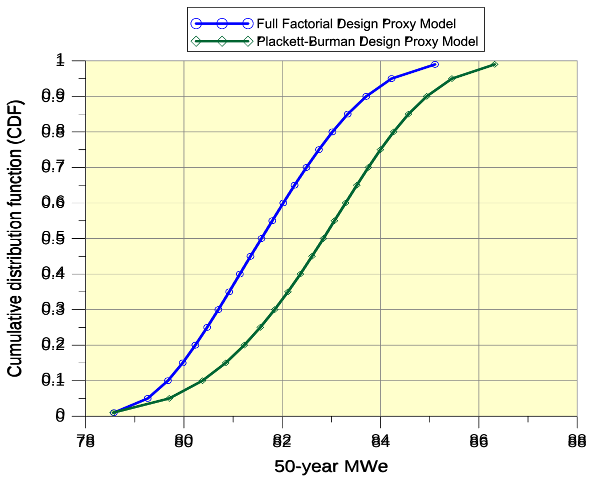

Figure 10. Comparison between PB and FF cumulative distribution functions for power capacity

6. LIMITATIONS OF THE ED AND RSM METHOD

Uncertainty framing is a very important exercise. The chosen uncertain parameters limit the response surface parameters of the tested reservoir model. It does not mean that there are no other parameters affecting the reservoir response. Eight out of twelve parameters were chosen from Clearwater et al. (2012) for demonstration purposes only. They were not deemed more important than the rest. The probability density functions (PDF) of the uncertain parameters are also a source of error. Care should be taken to ensure that the uncertainty range is sufficient and the PDF is appropriate for the parameter.

Also, no matter how complex the resulting response surface model is, the proxy model is still a simplified version of the dual-porosity numerical model and only describes the response we are interested in e.g., MWe. The information contained in the proxy model is dependent on the experimental design, the experimental design space and the number of experiments performed. The main challenge is to balance the need for information with the efficiency and costs of simulations especially for very complex geothermal reservoir models.

There are other experimental designs that may be applied (including: Central Composite Design, Box-Behnken, three-level factorial design, D-Optimal, Latin hypercube sampling [LHS], and others). The two-level factorial designs were chosen because the main objective was to show the ability of designed experiments to simplify the complex numerical simulation model into simpler proxy polynomials, enabling the use of geothermal reservoir simulation models in probabilistic resource assessment and uncertainty analysis.

7. CONCLUSIONS

The results of the experimental design and response surface method (ED and RSM) workflow show that 50,000 tonnes per day is a feasible development for the Ngatamariki geothermal resource using the existing dual-porosity model (Burnell, 2010).

The augmented number of simulation runs from 12 to 256 resulted in only a small reduction in standard deviation, showing that the additional number of runs to perform a full factorial experiment did not meaningfully improve the results. For this test, the Plackett-Burman proxy model is sufficient and is the better option to use for probabilistic assessment.

The results also showed that ED and RSM can generate proxy models from designed reservoir simulation experiments. Probabilistic resource assessment is possible through Monte Carlo methods carried out on the proxy models.

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