Probabilistic Resource Assessment Using Experimental Design and Second Order Proxy Model: Rotorua Geothermal System, New Zealand

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Keywords: *Rotorua, Geothermal resource assessment, probabilistic methods, natural state model, polynomial model, proxy model, response surface, Box-Behnken.*

ABSTRACT

Resource assessment plays an important role in the financing, development and operation of a geothermal power project. There are several simple (volumetric and areal) resource assessment methods used in the industry to quantify the resource potential predominantly of green field projects. On the other hand, a more complicated numerical representation of geothermal reservoirs is used to model dynamic changes in the field and make predictions of future capacity. However, there is a need to develop a more robust approach with a lower level of uncertainty in the predictions compared to the existing techniques. A hybrid approach of response surface methodology and reservoir simulation provides an alternative method for probabilistic resource assessments.

A probability distribution of production potential is generated by first determining the significant reservoir model parameters using Experimental Design (ED). A Box-Behnken response surface model design is then applied to determine the number of simulation runs required to run the experiment at three parameter levels (low, medium and high). The power potential calculated from the reservoir model runs is then used to create a polynomial (proxy) model and a Monte Carlo simulation is then applied to the proxy model to generate a probabilistic distribution of the potential power output.

The method was tested successfully to the calibrated natural state model of the Rotorua Geothermal Field. At a 95% confidence interval, the model shows that the Rotorua geothermal system has an average potential to produce: P10 between 148 and 153 MWe, P50 between 147 and 153 MWe and P90 between 146 and 151 MWe for at least 30 years. This approach offers a new perspective on geothermal resource assessment, highlights the importance of developing numerical models even for a geothermal prospect at the early due diligence stage and provides a systematic way of handling the uncertain reservoir model parameters.

1. INTRODUCTION

Geothermal resource assessment is the process of characterizing a hydrothermal system and appraising how much thermal energy can be harnessed for electricity generation or direct use applications. Decisions about whether or not a geothermal project is economically viable are often dictated by the results of this assessment. It has also become a best practice in any operating field to perform resource assessment within any strategic business planning process. Undoubtedly, the result of resource assessment is considered as one of the major business drivers. However to-date, there is still no standard process for this assessment.

Characterization of a geothermal system involves describing the mechanism of how the system was formed according to the evidences directly or indirectly measured. Geological, geochemical, geophysical and reservoir engineering data are collected and analysed to draw a collective understanding of the reservoir and is commonly called the conceptual model of a geothermal system.

For projects that are still at an early stage of development, the decision on how best to proceed is guided by the conceptual model. It also serves as an important tool in targeting the first exploratory well. Calculation of the potential power capacity of a geothermal prospect derives its assumptions from this model.

1.1. Analytical Resource Assessment Methods

Quantifying how much thermal energy or “stored heat” can be extracted from a given system is one of the main aims of a geothermal resource assessment. The most widely used methodologies for calculating stored heat are the volumetric and power density (areal) methods. In depth discussion of these two methods can be found in the works of Nathenson & Muffler (1975), Muffler & Cataldi (1978), James (1984), Grant (2000, 2015, 2018), Clotworthy *et al.* (2006), Australian Geothermal Energy Group (2010), Grant and Bixley (2011), Watson (2013), Zarrouk & Simiyu (2013), Quinao & Zarrouk (2014), and O’Sullivan & O’Sullivan (2016).

The development of most geothermal fields that are still producing today owe their success in one way or another to the use of the simple techniques for calculating resource potential such as the volumetric and areal methods. However, the industry also acknowledges that these methods are prone to overestimation largely due to the assumptions used for reservoir size and recovery factor (Grant, 2000; Sanyal, et al., 2004; Williams, 2004; Stefansson, 2005; Sanyal & Sarmiento, 2005). Consequently, some authors assume conservative assumptions while others introduce modifications to the methodology. Multiple versions of the original volumetric and areal methods are available nowadays as a result of the attempt to address the limitations that question the reliability of these methods (Williams, 2007; Williamset al., 2008; Garg, 2010; Garg & Combs, 2011, 2015; Zarrouk & Simiyu, 2013; Wilmarth & Stimac, 2014, 2015).

1.2 Numerical Resource Assessment Methods

A more sophisticated tool that represents the physics of fluid flow and heat transfer and the complex nature of reservoir geometry well is the reservoir simulation. The industry started to realise the compelling need for it when advancements in computer technology become readily available. Today, numerical simulation is considered as an integral component of geothermal resource management process.

Reservoir simulation is more commonly employed when a sufficient amount of production data is available to constrain a numerical model. A well-calibrated reservoir model that is deemed consistent with the understanding of the hydrothermal system and matches the measured steady-state and production data can be used to make deterministic and probabilistic resource assessments.

However, there are different views on the use of computer modelling for resource assessment at early stages of development. Factors such as limited data and longer time needed to develop and calibrate a numerical model make the volumetric and areal method more appealing and useful (Australian Geothermal Energy Group, 2010; Sanyal, 2005). Grant (2000, 2015) and O'Sullivan and O'Sullivan (2016) promote the use of reservoir modelling as their experiences have proven how a well-calibrated model can be used in making informed decisions. The Ngatamariki geothermal field is a classic example of a successful field developed based on a calibrated reservoir model (Grant & Bixley, 2011).

The ability of a numerical model to explain the steady state and historical production performance of a given reservoir makes it useful in predicting future reservoir performance. However, the non-unique solutions of a numerical model raise questions on the reliability of its predictive capability. The linear analysis offers a solution. Doherty *et al.* (2017) demonstrated the need to run 1400 models to achieve 200 acceptable models that satisfied calibration constraints. This simulation experiment can be laborious, and time-consuming particularly for projects that are still at an early stage of development.

Due to the prohibitively large number of simulation runs required for a full uncertainty analysis using numerical models, some researchers attempted to find a more practical tool for predicting reservoir performance. Using polynomial approximations as an alternative methodology, a simpler equation of power capacity or total cumulative steam as a function of key reservoir parameters was created by describing the relationship of these parameters one-factor-at-a-time (Acuna et al., 2002) or by systematically building an experimental design and fitting a polynomial (proxy) model (Hoang et al., 2005).

Pasikki et al. (2016) developed a polynomial model of field size, expressed in MWe, as a function of the average decline rate for greenfield development. However, the issues on generalizability and applicability to any greenfield remain yet to be proven.

Quinao and Zarrouk (2018) tested the response surface methodology using the Ngatamariki calibrated numerical model and were able to demonstrate the applicability of building a proxy model of the reservoir model using experimental design and linear regression analysis. The fitted linear model was then used to generate probabilistic resource capacity using Monte Carlo simulation (Quinao & Zarrouk, 2014, 2015).

1.3. The Present Research

The aim of the present research is to produce a probabilistic resource assessment of a greenfield project using a polynomial model that approximates a reservoir model. The reservoir model that will be used is calibrated against the pre-exploitation data consisting of surface mass flow of natural thermal manifestations and temperature distribution at the ground surface.

The key reservoir input parameters that will be used to build a polynomial model will be identified according to the expert knowledge of how these parameters influence the calculation of power capacity (MWe). Experimental design will be implemented to screen these parameters and to determine the significant predictors of MWe. To detect strong nonlinearities of the response variable, three levels of input parameters will be used and modelled using response surface design.

A stepwise regression will be carried out to construct an empirical model and resampling of the observations will be done by bootstrapping (Efron, 1993) to construct bootstrap standard errors and confidence intervals for the regression coefficients. Monte Carlo method will then be applied to the polynomial model with bootstrapped coefficients to generate a probabilistic distribution of MWe.

The present study adopts the same mathematical and statistical techniques for empirical (proxy) model building discussed by Quinao and Zarrouk (2018).

2. PROXY-MODELLING

Proxy modelling is the process of building an empirical model by determining a functional relationship of an output variable y to a set of input variables having a polynomial function, $f(x)$, and a random error, ε, which is assumed to be normally distributed with mean zero and variance(μ, σ^2):

$$y(x) = f(x, \beta) + \varepsilon \qquad (1)$$

The polynomial function $f(x)$ is a low order polynomial which can either be linear or quadratic. The coefficients of the parameters, β of the polynomial functions are determined through least squares regression.

A desirable sequence of building approximations of computer simulations involves choosing and applying experimental design or design of experiments (ED or DoE), selecting the appropriate response surface model (RSM) and carrying out model fitting such as regression analysis.

2.1 Design of Experiment (DoE)

The approach on designing any physical or computer experiment depends on the nature of the problem that needs to be investigated. A strategic framework for planning and conducting research to improve product and process performance and reliability is more popularly known as Design of Experiment (DoE). It was first introduced in the 1920s and is explained in details in the works of Box *et al*. (1978), Box (1999), and Myers and Montgomery (2002).

A computer experiment differs from physical experiments in the sense that a given set of input parameters will yield the same output response, even if repeatedly performed. The prevailing concern with a computer simulation experiment is that it is very exhaustive to conduct. The number of runs and the amount of time required for each experiment varies depending on the number of parameters that will be investigated, the range of possible values of these parameters and the complexity of the numerical model that represents reality. In geothermal reservoir engineering application, solving the non-linear mass and energy balance equations for fluid and heat flow with the occurrence of phase transitions from one thermodynamic region to another makes the run times longer

Another problem with computer simulation is that the functional relationship between the input and response variable is concealed within the process of solving linear and nonlinear equations of a numerical model. This adds uncertainty as the true nature of the distribution of parameters and the response variable is unknown and unverifiable.

For problems involving a large number of input parameters, DoE offers several factorial designs that can be used for screening the most influential parameters. The aim of experimental design is to get the most information from the least data using a minimal number of simulations.

Response surface higher-order designs are useful for estimating interaction and quadratic effects. The two classical quadratic designs are Box-Wilson Central Composite and Box-Behnken design. The Box-Behnken design is an independent quadratic design that requires three levels for each factor and can be implemented with a fewer number of runs.

2.2 Model Fitting

Once the experiment has been designed and the required simulation runs have been carried out, the next step is to fit the responses using regression analysis. There are different ways to fit the responses into a model of choice. A useful reference is tabulated in the paper of (Simpson, 1998).

Modelling requires finding the equation form $f(x,\beta)$ of a given problem, finding the values of the coefficients and characterizing the nature of the distribution of error. The error term in the regression equation is assumed to be random and normally distributed. Plotting the residuals, the difference between the observed value and the predicted value of the response variable, against the predicted value is a common practice for describing the nature of error and detecting if properties assumed for the true errors are violated. Bootstrapping regression models can provide more accurate inferences when data are not well behaved or when the sample size is small. This is done by directly resampling the observations, selecting bootstrap samples of the residuals, calculating the bootstrapped response values and then fitting a regression model to obtain bootstrap regression coefficients. The resampled observations can be used in constructing bootstrap standard errors and confidence intervals for the regression coefficients.

2.3 Proxy Model Sampling using Monte Carlo Method for Uncertainty Analysis

One of the most common techniques for handling uncertainty in any estimation, prediction or estimation is through the use of Monte Carlo methods. This technique produces a probability distribution of possible outcomes of response variable which is a much more realistic way of describing uncertainty in predicted values.

To apply the Monte Carlo method, random sampling of input variables of the proxy model is carried out. Each input parameter has a pre-assigned distribution. Random values are generated for each input variable and computations are run through the proxy model. This will then yield random outcomes of the output variable.

The process of building polynomial approximations of a numerical model discussed herein is applied to the recently calibrated numerical model of Rotorua Geothermal Field. To date, there is still no attempt done to investigate the potential of producing from the deeper/intermediate geothermal reservoir for a full commercial power generation purposes. This study will attempt to estimate the potential of developing the Rotorua Geothermal Field using the calibrated natural state model. The authors are well aware of the Regional Policy Statement where the Rotorua Geothermal system is classified as Group 2: Surface feature values override extractive values (Doorman & Barber, 2017). The intent of this paper is solely to demonstrate the applicability of using response surface methodology to develop a proxy model of a numerical model and generate probabilistic estimates of megawatt (MWe) potential.

2.4 Case Study: The Rotorua Geothermal Field (RGF)

The Rotorua Geothermal Field (Fig. 1) is located near the southern margin of the Rotorua caldera within the Taupo Volcanic Zone (TVZ) (Alcaraz & Barber, 2015). Known to host one of New Zealand's two largest remaining geysers (Pohutu geysers at Whakarewarewa). It has a unique history of geothermal utilization. Surface features preservation is of prime importance. A total of more than 1300 wells have been drilled to date. Less than 300 wells are currently operating. These wells tap the hot shallow geothermal fluid for domestic, recreational and commercial use.

2.4.1 The RGF Numerical Reservoir Model

A new model of RGF was developed and calibrated by Ratouis *et al.* (2017) to better represent the behaviour of surface thermal features (Fig. 2). This full-field model consists of 48,034 blocks and covers an area of 12.4 km x 18.3 km centred on Rotorua City with a block size ranging from 125 m x 125 m to 1000 m x 1000 m. There are 30 layers extending to a depth of 2000 m below sea level. The overall match of surface temperatures and all surface activity are represented in the model (Fig. 2 & 3).

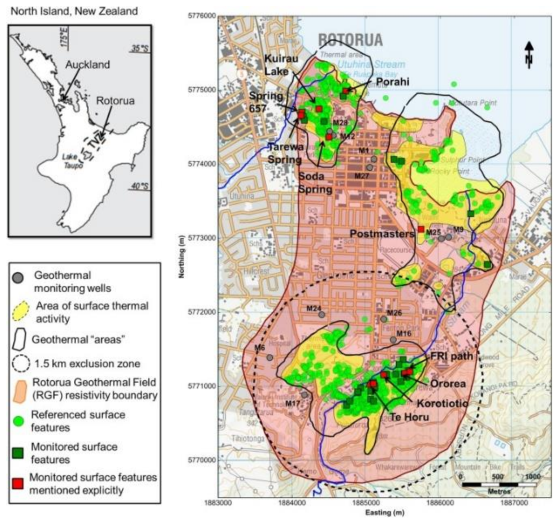

Fig. 1: The Rotorua Geothermal Field (after Ratouis, 2017).

3. IMPLEMENTATION

There are three different prominent up flow areas in RGF: Kuirau, Ngapuna and Whakarewarewa. The proposed development of RGF in this experiment is to produce from the deeper reservoir and develop each of these areas separately.

To investigate the power potential of the deeper part of RGF, the high-level process maps of the empirical model building using Experimental Design (ED) and Response Surface Methods (RSM) discussed by Quinao and Zarrouk (2018) were used. The regression analysis was carried out using a statistical software R.

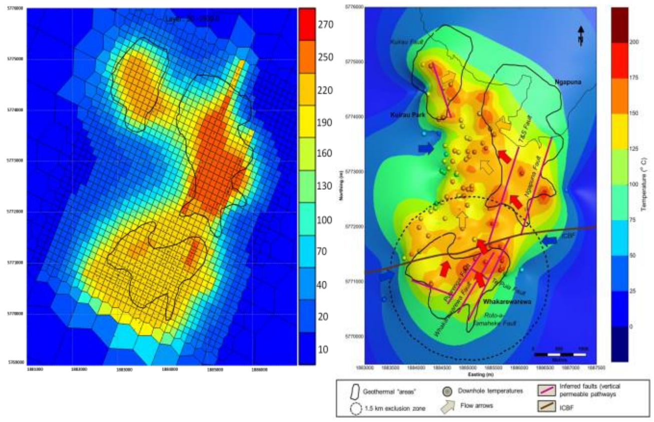

Fig. 2: Temperature distribution at the bottom of the model (left) and the natural state temperature distribution (after Ratouis, 2017).

3.1. Parameter selection and values

The simulation experiment requires choosing the parameters that will be included in the investigation. The following parameters are deemed sufficient for the current study:

1. Rock properties
2. Enthalpy of separated water (reinjection)
3. Ratio of reinjection to production
4. Number of wells and feedzones and their location in the model
5. Allocation of production for each feedzone

The model of Rotorua Geothermal Field is a single porosity model. The rock parameters that were chosen to include in the empirical model building are horizontal permeability and porosity. The rock properties that are adjusted to match the pre-exploitation conditions are the horizontal and vertical permeability. Together with porosity, these three rock properties are the main calibration parameters of production history modelling. Porosity is the one usually adjusted to match pressure and enthalpy response to production. The range of rock properties of the main production area in the calibrated natural state model of RGF will be used for the simulation experiment.

The enthalpy of reinjection and ratio of reinjection to production are dictated by the chosen separator pressure, which is a function of the wellhead pressure. An indicative value can be estimated after performing preliminary simulation runs. Enthalpy at 9 bara and a ratio of 80-90%, respectively is usually assumed as an initial estimate

The assignment of wells and feedzone will be based on the following criteria:

- Block temperature of at least 220 °C
- Block permeability of at least 1 millidarcy
- A distance of at least 200 m between feed zone
- Provision for make-up wells

This approach for selecting the number of wells and feedzones is a bit subjective. There are available techniques such as space-filling designs for randomly assigning wells. The optimum location of wells can be determined using response surface methods, kriging or other stochastic methods such as Particle Swarm Optimization, Well Pattern Optimization, Genetic Algorithms or Simulated Annealing. Recent works of Adiga et al. (2017) uses Mixed Integer Programming (MIP) to determine the optimum production well placement.

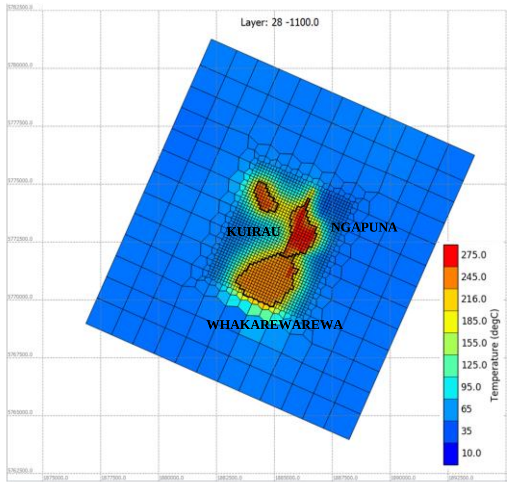

Fig. 3: Simulated natural state temperature distribution at layer 28 of Rotorua Geothermal Field (after Ratouis, 2017).

3.2 Empirical Modelling Approach

This simulation experiment employs a targeted methodology to analyse and select the variables for the model building (Fig. 4). A two-stage model building will be implemented. An initial modelling will be done to screen the variables and identify the significant predictors of MWe and determine the number of wells and feedzones at a fixed mass flow per area. This stage is also necessary to be able to detect strong nonlinearities by doing an initial fitting of the simulation results and parameters.

A full factorial design was implemented for the first stage of experiment. The process involved is summarized in Figure 4.

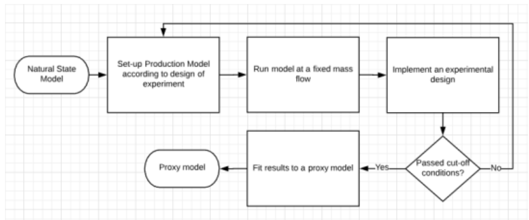

Fig. 4: Screening process to determine significant variables and production and injection parameters

The second stage is the final modelling part of the experiment. It involves running the simulation using the significant parameters identified from the initial modelling process. The required number of runs will be determined based on the Box-Behnken design.

A stepwise regression analysis will be carried out to fit the model parameters and produce the regression equation. The final regression model will be then subjected to Monte Carlo simulation. Simple triangular distributions, based upon the most likely, minimum and maximum values, will be assigned to each of the significant variables. A simple triangular distribution is usually adequate to describe the uncertainty level of the key reservoir parameters (Parini & Riedel, 2010).

3.3 Acceptance Criteria

For each phase of the modelling, the model will be subjected to evaluation according to the following criteria:

- Reservoir model:
    - The reservoir simulation must reach a simulation run time of at least 30 years.
    - Production wells should have a wellhead pressure of at least 9 bara. This can be assessed by doing a wellbore simulation.
- Proxy model:
    - R-square
    - Adjusted R-square
    - Unbiased, normally distributed residuals

4. RESULTS

The experiment resulted in a trial and error process. The most difficult part of the iterative process is finding the appropriate number of wells and feedzones and their mas flow distribution that will allow them to produce up to 30 years

Figure 5 is a plot of pressure at the feedzone block for one of the scenarios. The cut-off pressure is 80 bar as indicated by the red line. Feedzones that are way below this pressure were removed from the reservoir model. There were some wells with a block pressure a little lower than 80 bars but have higher enthalpy and still have at least 9 bar pressure at the wellhead. Wells that did not meet the 30 years criteria can be considered as make-up wells. Results of the first stage of the experiment suggest that RGF can sustain production if produced at -1100 mRSL.

Fitting the results of the three-level full factorial design of a simulation experiment to a first-order polynomial does not satisfy randomness and normal distribution of residuals even after transforming the response and input variables. Moreover, the residual plots (Figure 6) suggest a higher order polynomial model is required for the regression analysis. Previous studies by Simpson (1998) suggest that fitting of modelling results obtained from computer experiment require building a second order polynomial model.

The parameters that turned out to be significant predictors of MWe and were used for the second stage of the experiment are summarized in Table 1. A total of 25 runs was required to build the proxy model: 24 runs for all possible combinations of the four parameters at three different levels and one run for the centre points. The final second order polynomial model is given in equation (2):

$$\begin{aligned}\boldsymbol{MWe} = 153.3 &- 17.9A + 1.428B + 1.56e12C \\ &+ 2.366e13D - 21.19Asq - 3.62Bsq \\ &+ 1.103e25Csq - 2.422e26Dsq \\ &- 4.986A*B + 6.041e12A*C \\ &- 5.976e12A*D + 5.517e11B*C \\ &- 5.526e12 + 1.852e25C*D \qquad (2)\end{aligned}$$

The results of the regression analysis are summarized in Table 2. The regression model has an R-squared and adjusted R-squared of 1 and 0.9999. These high values may signify overfitting but are expected as there are only small data to fit. The result of Shapiro-Wilk test gave a p-value of 0.4716 suggesting that the residuals are normally distributed. This is also evident in the Normal Q-Q and Residuals plots shown in Figure 7.

Porosity, based on its coefficient in the model, has the highest impact on MWe. The model suggests that porosity is inversely proportional to output. The lower the porosity, the higher the estimated MWe. This insight is consistent with the accepted knowledge that a lower rock porosity is needed to match two-phase enthalpy values. High enthalpy wells produce higher MWe.

Table 1. Input parameters (variables) and values used to build the proxy model of the Rotorua Geothermal Field reservoir model.

PARAMETER	LOW	MID	HIGH
Porosity (A)	0.05	0.125	0.2
% RI (B)	70	80	90
kx (C)	2e-15	2.6e-14	5e-14
ky (D)	2e-15	2.6e-14	5e-14

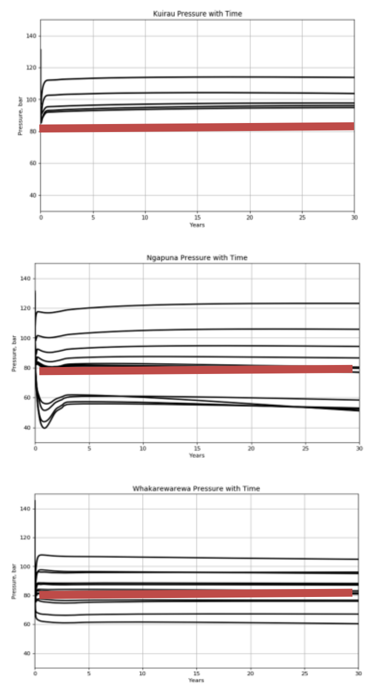

Fig. 5: Plot of feedzone block pressure for one of the simulation scenarios for Kuirau (top), Ngapuna (mid) and Whakarewarewa (bottom) areas.

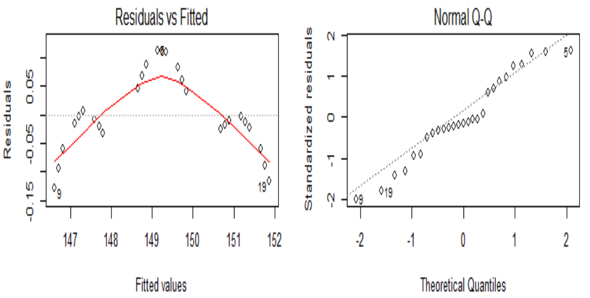

Fig. 6: Residual and Normal Q-Q plot for a first order polynomial model.

Bootstrapping was then applied to the final proxy model to calculate the range of possible values for P10, P50 and P90 of MWe at 95% confidence interval. Both the final proxy model and bootstrapped proxy model were subjected to Monte Carlo simulation. The probabilistic results after sampling the two polynomial models using Monte Carlo techniques are summarized in Table 3.

Table 2. The final Rotorua Geothermal Field prediction model from regression analysis ($MWe = 153.3 - 17.9A + 1.428B + 1.56e12C + 2.366e13D - 21.19Asq - 3.62Bsq + 1.103e25Csq - 2.422e26Dsq - 4.986A * B + 6.041e12A * C - 5.976e12A * D + 5.517e11B * C - 5.526e12 + 1.852e25C * D$)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	153.3	2.512e-01	610.455	< 2e-16
A	-17.9	5.688e-01	-31.463	< 2e-16
B	1.428	5.938e-01	2.404	0.0272
C	1.560e+12	1.756e+12	0.889	0.3859
D	2.366e+13	1.756e+12	13.480	7.60e-11
Asq	-21.19	6.469e-01	-32.754	< 2e-16
Bsq	-3.62	3.639e-01	-9.948	9.68e-09
Csq	1.103e+25	6.317e+24	1.746	0.0978
Dsq	-2.422e+26	6.317e+24	-38.339	< 2e-16
A:B	-4.986	6.678e-01	-7.466	6.46e-07
A:C	6.041e+12	2.783e+12	2.171	0.0435
A:D	-5.976e+12	2.783e+12	-2.148	0.0456
B:C	5.517e+11	2.087e+12	0.264	0.7945
B:D	-5.526e+12	2.087e+12	-2.648	0.0164
C:D	1.852e+25	8.696e+24	2.130	0.0472
R-squared = 1		**Adjusted R-squared: 0.9999**		

Table 3. Summary of power potential (MWe) of Rotorua geothermal field.

	MWe (Without Bootstrap, Fig 8)	MWe (With Bootstrap, 95% CI)
P90	149	146 to 151
P50	150	147 to 153
P10	151	148 to 153

The calculated P90, P50 and P10 without doing bootstrapping is within the range of P50 MWe with bootstrapping. The results of the bootstrapping reveal there is a 95% chance that the P10, P50 and P90 estimates could be 146 MWe. 147 MWe and 148 MWe, respectively.

Moreover, the results can also be used to infer the average output per sector or the optimum location to drill the first well. In the Whakarewarewa area, the output of the wells is fairly the same. However, in Kuirau and Ngapuna, the well output varies with location as shown in Fig. 9.

An iterative approach is often the best and most economical way before a sound conclusion can be achieved from any simulation experiment. The approach taken in this study proved that it is logical to move through stages of experimentation as each stage provides insight as to how the next experiment should be carried out.

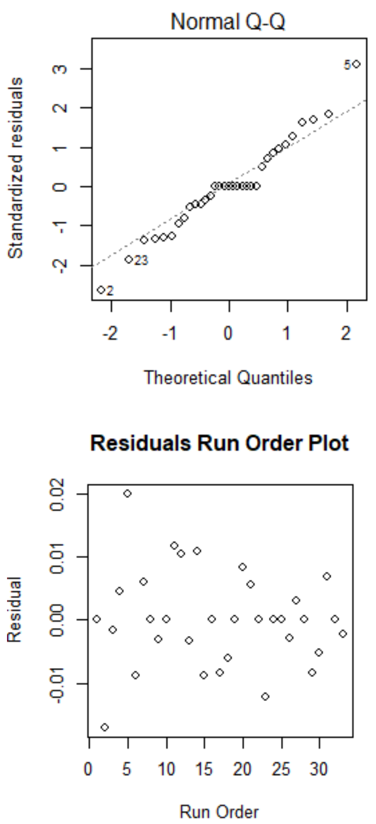

Fig. 7: Normal Q-Q and residual plot of the final regression model.

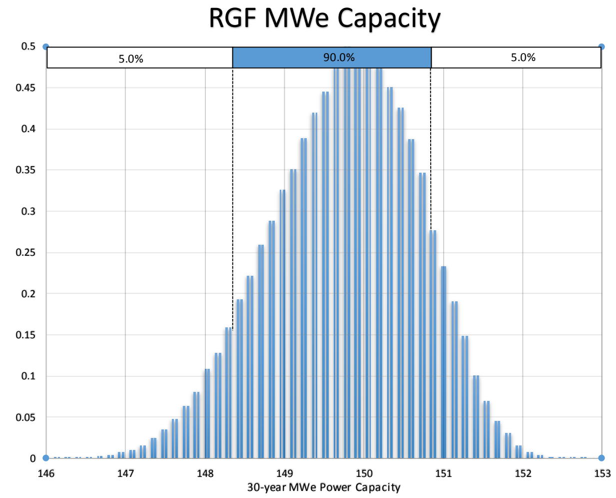

Figure 8: Distribution of MWe capacity after subjecting the final regression model to Monte Carlo simulation using @Risk.

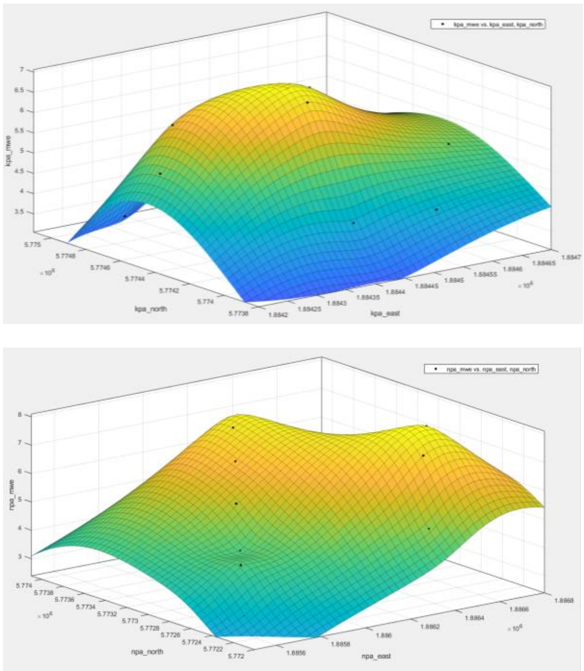

Fig. 9: Spline generated surface showing simulated MWe of wells of Kuirau (top) and Ngapuna (bottom) areas.

Other important observations and insights from this study are as follows:

- A separate proxy model for each up- flow area (Kuirau, Ngapuna and Whakarewarea) can be and was developed but was not presented in this paper as the objective is to produce the whole Rotorua Geothermal Field.

- The production scenario that can be investigated is limited by the vertical extent of the model.

- The output response, MWe, may be affected by factors other than the chosen input variables.

- The importance of expert knowledge in selecting the predictors of the response variable, MWe, and in supporting the insights uncovered by the polynomial model.

- A calibrated natural state reservoir model enables a systematic way of investigating the effect of different possible perturbations to the model. The results from this investigation may aid in guiding future project or investment decisions, solving other business problems and other future business initiatives.

- Proxy modelling and reservoir modelling are excellent tools for carrying out a cost-effective and efficient probabilistic resource assessment.

5. CONCLUSION

A second order proxy model of the natural state reservoir model of the Rotorua geothermal field was built to carry out a probabilistic resource assessment. The results suggest that:

- There is a 95% chance that the P90, P50 and P10 of output MWe will be 146 to 151 MWe, 147 to 153 MWe and 148 to 153 MWE, respectively if RGF will be produced at -1100 mRSL and a single flash power plant will be built.

- A calibrated natural state model can be very useful in carrying out different production simulation experiments.

- A proxy model in lieu of the reservoir model can be built and used to predict the likelihood potential capacity of a green field project.

- A hybrid approach of using reservoir simulation and response surface methodology provides a promising way of developing models that quickly add values to projects and project evaluation process.

6. ACKNOWLEDGEMENTS

The authors would like to express their appreciation to the New Zealand Ministry of Business, Innovation and Employment (MBIE) for their financial support through the Empowering Geothermal Energy funds.

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