# USE OF PEST FOR IMPROVING A COMPUTER MODEL OF WAIRAKEI-TAUHARA

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## ABSTRACT

This paper describes the use of PEST, Parameter ESTimation, for improving a model of Wairakei-Tauhara. The model used a simple regular rectangular grid and a water table top boundary. These two simplifications were made to try to reduce the model run-time so that each forward simulation required by PEST could be run in a reasonable time. For comparison, this model will be referred to as the 'rectangular model' in this paper. The naming convention for the other Wairakei reservoir models is by the total number of blocks, with the most recent being the 41458-block model.

In this project we have established an effective work-flow that allows automatic parameter estimation against observations, including both natural state temperatures and pressure and enthalpy data from the production history. Permeabilities, porosities and upflows at the bottom of the model are included in the parameter set to be estimated. Work has been done in formulating the objective function, measuring the fit of model results to observations, so the inversion target better matches how a modeller visually assesses the results.

The work-flow was able to produce a well-calibrated model of Wairakei for uncertainty analysis, data worth analysis and future scenario forecasting.

## 1. INTRODUCTION

Wairakei-Tauhara geothermal system is located near Lake Taupo in the centre of the North Island of New Zealand.

There is a long history of computer modelling of the Wairakei-Tauhara geothermal system. A paper by O'Sullivan et al. (2009) provides a summary of the past history of modelling of Wairakei geothermal field. The more recent modelling work by the authors was described by Yeh et al. (2014). All of the past Wairakei models were manually calibrated with only occasional aid from automatic parameter estimation tools such as iTOUGH2 and PEST. This paper describes the current effort to implement a systematic approach to calibrating Wairakei-Tauhara models using automatic parameter estimation.

The objectives of this project are twofold: (i) to establish an effective work-flow that allows automatic parameter estimation of the Wairakei-Tauhara reservoir model against observed temperature, pressure, and enthalpy data, and (ii) to produce a well-calibrated model of Wairakei that could, with some mesh refinement, become the preferred model. This will enable a well calibrated model to be used for uncertainty analysis, data worth analysis, as well as for future scenario forecasting.

## 2. MODEL DESCRIPTION

The model used here has a regular rectangular grid and the top surface of the model is set at the estimated water table. These two simplifications were made to reduce the model run-time, compared with that for the 9011-block model (used for the Tauhara II hearings), or for the more recent, finer 41458-block model (Yeh et al., 2014).

### 2.1 Model grids

The rectangular model consists of 1008 columns and 39 layers, giving a total of 31435 blocks (see Fig. 1). Each column area is 1.0E6 $m^2$ (1 km x 1 km). The area covered is slightly larger than for the 2013 model with 41458 blocks.

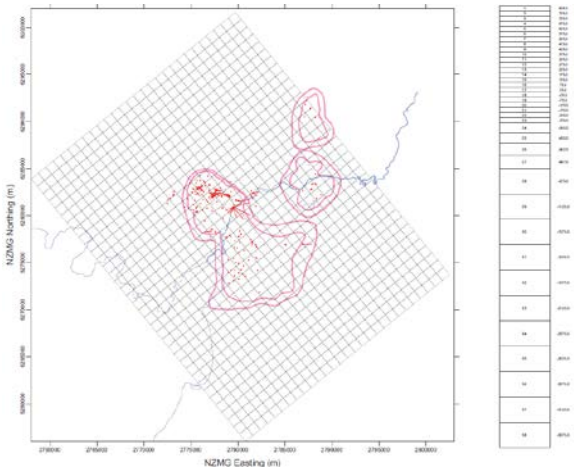


**Figure 1. Model grid (each block is 1km x 1km). Pink lines are resistivity boundaries of geothermal fields, blue lines outline LakeTaupo and Wairakto River, and wells are labelled as red dots/lines. The layer structure is shown on the right.**

The model has 50 m thick layers above -300 masl, which covers most of the historic production zones. The layer thickness ranges from 100 to 250 m below this level. The bottom of the model is at -3500 masl, the same as for the 41458-block model.

The top layers of the 31435-block model to follow the elevation of the water table. Within the inner Wairakei-Tauhara area, the water table elevation is based on the water levels observed in shallow wells. Outside of this central area the elevations of small lakes, pools and swamps are added to complement the scarce water level information.

### 2.2 Boundary conditions

Large volume boundary blocks with atmospheric pressure and temperature (1 bar and 15°C) are connected to the top of most columns to represent conditions at the water table.

Columns underneath Lake Taupo have similar "atmosphere" blocks but with different pressures and temperatures. The pressure is calculated as the hydrostatic pressure of the water column above the block while temperature corresponds to the mean lake/river temperature of 10 $^{0}$C.

The boundaries on the sides of the model are closed, i.e., they do not allow flow of mass or heat in or out of the model, in the natural state. This reflects the assumption that the model is large enough to contain the whole of the pre-production undisturbed convective system, and therefore flows of heat and mass at the sides of the model are very small.

However, when modelling the production history or future scenarios, recharge boundary conditions are imposed, allowing flows into and out of the side boundaries. This type of boundary condition allows recharge into model for the case of pressure draw-down (production) and allows flow out of the model, avoiding spurious pressure build-up, in the case of injection near the edge of the model.

Note that the no-flow assumption may not be satisfied at the parts of the boundary near Ngatamariki and Orakei-Korako geothermal fields. Further experimentation with modified boundary conditions in these areas is planned for the future.

Heat and mass are injected at constant rates into the bottom of the model. The locations and amount of these heat and mass flows are included as parameters to be estimated.

The locations of deep inflows are set to be where faults intercept the base of the model. The locations of these faults are based on the 3D geological model developed by Alcaraz et al. (2010). Note at the moment, only the areas within resistivity boundaries of geothermal fields are assigned deep inflows.

In the production model, additional pressure-controlled, recharge sources are placed at the same locations as the up-flows in the natural state model. The magnitudes of the flows are controlled by productivity indices. This hot recharge is only induced if the pressure at the bottom boundary drops below the natural state pressure.

### 2.3 Summary of forward model

For parameter estimation, a single forward simulation includes a natural state (or steady state) model run, followed by a production history run. The converged reservoir conditions from the natural state model are passed to the production run as initial conditions.

The boundary conditions for the natural state and production runs are summarised in Table 1.

**Table 1: Boundary conditions for the model**

| | **Natural state** | **Production history** |
|---|---|---|
| **Top** | Constant (wet) atmosphere and surface water | Constant (wet) atmosphere and surface water |
| **Side** | Closed | Recharge allowed |
| **Bottom heat** | Constant | Constant |
| **Bottom mass** | Constant | Constant and pressure controlled recharge |

## 3. PARAMETER ESTIMATION WITH PEST

Parameter estimation with PEST (Doherty, 2011), and other similar software such as iTOUGH2 (Finsterle, 1999), requires preparation of the observation data to be matched and a list of model parameters to be varied. The observations are the measured field data to be matched with outputs from the model. The parameters are inputs for the model that are allowed to change in order to improve the match between the observed data and the model results.

The goodness-of-fit of the model to the observations is quantified as a single value, called the objective function, which is calculated from the weighted sum of squares of the difference between model-generated results and the observations (real-world data). PEST minimises the objective function by altering parameters using the Gauss-Levenberg-Marquardt nonlinear optimisation algorithm .

### 3.1 Observations

#### 3.1.1 Objective function and expectation

In parameter estimation, it is not uncommon to achieve an improved objective function while visual inspection of the results reveals little obvious improvement. One of the reasons for this is that the way objective function is formed does not match how a modeller visually assesses the results.

To improve the objective function, it is important to understand the process experts go through when they visually evaluate the goodness of fit. For example in matching a time series, modellers do not focus on and judge the fit for each single observation point, which can have variable frequency in various parts of the history. Instead, modellers perceive an average trend from the available data, and see how well the model meets the trend. Hence the field data should be processed into an evenly spaced time series. Currently we process field data into one point per year, which PEST compares against model outputs at yearly intervals.

Another difficulty with calibration data is when more than one set of field data is observed in the same model block. Instead of working out the sum of misfits between a single model result and multiple data sets, it is better to work out the average or pick what is considered to be the most reliable data set and then match the model result to a single value. Again, this process was done before passing field data to PEST as observations.

There is some concern that genuine detailed behaviour in the field may be lost by using these field data processing techniques. However, it is acceptable if the level of smoothing and averaging is appropriate for the resolution of model. Details that are not expected to be captured by the model should not be included in the observations used to calculate the objective function.

In the current study, observations of natural state temperatures, and production history pressures and enthalpies are included in the objective function. In the case of wells drilled after production commenced in 1958, the downhole temperatures are compared to model results from the appropriate time in the production history simulation.

#### 3.1.2 Temperature

Most of the temperature data available from Wairakei are downhole temperature profiles. To assess the goodness-of-fit, the temperatures from the downhole measurement are

interpolated on to model blocks first. Then each of the interpolated temperature values has a corresponding model block. The interpolated temperatures are fed into PEST as observations. PEST will calculate the contribution to the objective function for each well as the weighted sum of squares of residuals between the two profiles.

In the past, the weighting of these points was set according to the assumed measurement error (usually the inverse of the standard deviation). This weighting method was found to be undesirable because the thickness of layers in the model is not uniform throughout the depth of model and generally models have thinner layers in the shallow zone. Thus too much weight was assigned to the temperatures in the thin shallow layers.

To overcome this problem, the weighting of each temperature observation (at a block) is assigned to be the thickness (length in the z direction) of that block. The same interpolation and weighting procedure is applied to each well.

If we had simply included all available well temperature profiles with the same weight, the observation set would have had: (1) more observations at the shallow zone than at the deeper part of the model, because there are many more shallow wells than deep wells and (2) a lot of observations would have been clustered over a few columns with few observations available across the rest of the model, because drilling tends to concentrate on the productive parts of a system.

The first characteristic contradicts our modelling experience, namely, that matching the deep temperatures of a convection dominated system is more important than matching the detailed shallow/near-surface temperatures.

The second characteristic is also undesirable. The wells on the edge or outside of the resistivity boundaries sometimes provide valuable information regarding the extent of the reservoir and the long term sustainability of geothermal fields.

To overcome these two issues, the choice of temperature observations was restricted and only temperatures from a selected set of wells were included as observations:

1. First temperature profiles with deep data were selected. These wells were plotted on a map, with a model grid overlaid, to show the coverage.
2. After the coverage map was considered, some shallower wells were included so that the areal coverage was increased.
3. If there were measurements from multiple wells occupying the same model block and inconsistent with each other, a decision was made, case-by-case, to exclude some of the contradictory data.

3.1.3 Pressure

As briefly described as an example in Section 3.1.1, historical data series should be processed into an evenly spaced time series. We processed the pressure data in several steps:

1. Pressure data from liquid feeds were adjusted to block midpoint elevations by adding on a hydrostatic pressure increment using the local water density. Values of density used by Contact Energy's reservoir engineers to process pressure data were used.
2. The pressure history for each well is interpolated in time to the end of each year
3. These interpolated pressures from all the wells were then assigned to model blocks and when multiple observations occurred in one block they were averaged at each time. .

3.1.4 Enthalpy

The processing of production enthalpy history data was very similar to that applied to the pressure data. Observations were interpolated to fixed yearly intervals for comparison with model outputs.

Because of the coarse grid size in the production zone of the current model, it is not realistic to expect the model to be able to match all the individual wells. Therefore the wells are grouped together into separate groups. Within each group, the average enthalpy is matched against field data.

At present, the traditional grouping by borefields in Wairakei is followed: Eastern, Western, Te Mihi and Poihipi. Wells within each zone have similar behaviour over the Wairakei production history, and hence an average enthalpy represents a reasonable overall behaviour within each borefield. In the near future, wells will be further split into sub-groups of shallow steam wells and the deeper liquid wells, especially for the Te Mihi borefield.

3.1.5 Boiling

Matching enthalpy is a challenge because in some wells there is a large change in enthalpy between liquid production (<~1100 kJ/kg) and boiling/dry steam production (~ 2800 kJ/kg). In this case boiling causes a jump in enthalpy in a highly non-linear fashion, which is very difficult to cope with by a parameter estimation method, like PEST, that assumes a smooth dependence of the objective function on model parameters.

The onset of boiling within a geothermal reservoir is generally caused by pressure drawdown resulting from mass withdrawal (instead of an increase in temperature). Unlike the abrupt jump in enthalpy, the pressure change from liquid conditions to boiling is smooth. This makes pressure a better observation than enthalpy, on its own, in order to match the onset of boiling in a reservoir.

If a model block is known to be boiling at a certain time, the pressure of the block will coincide with the saturation pressure for the temperature of the block (superheated steam conditions are not considered in the current case). Fig. 2 shows the enthalpy in well WK52 and Fig. 3 show the match to the “boiling observation”.

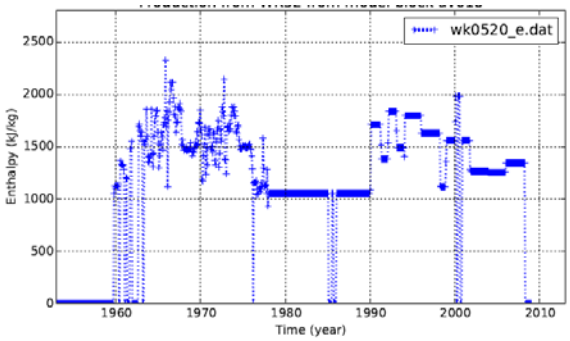


**Figure 2. Measured enthalpy for well WK52**

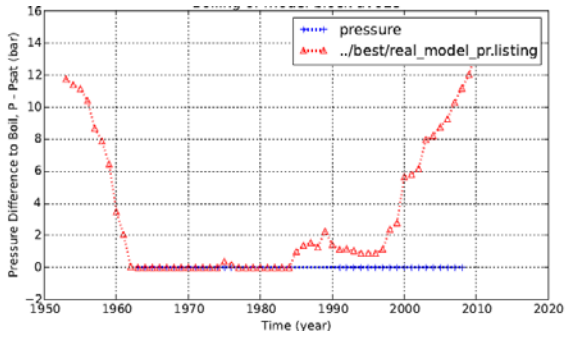


**Figure 3. Difference between reservoir pressure and boiling pressure. Data points are only added when the flowing enthalpy indicates boiling. Red line are pressure difference to boil of the model block.**

The method used involved the following steps:

1. The enthalpy history of a well is checked against a criteria (1200 kJ/kg for Wairakei) to determine if boiling is expected, at fixed yearly intervals (as used for other history matching observations).
2. At each point in the time series, a zero is inserted if the block is boiling at the time. The time interval is skipped if no boiling is observed at that time. A zero means the actual block pressure and its saturation pressure should coincide. Note that these values can be thought as measuring "closeness to boiling" or how "far" a block is from boiling.
3. After each forward run, a saturation pressure of the block is calculated from the block temperature (using steam tables). Then the difference between the saturation pressure and actual block pressure is calculated. These values are then treated as normal observations and compared against the zeros inserted previously.

If an observation is greater than zero when the block should boil, the estimation process will determine that the pressure difference needs to be driven towards zero. As mentioned earlier, this pressure observation will change smoothly as the model approaches boiling. This helps in guiding the estimation process to match the abrupt changes in enthalpy.

Overall this process worked well. In most of the parameter estimation runs, the model average enthalpies (for the four borefields) matched the data well and certainly with accuracy comparable to that achieved with our manually calibrated models. Most of the boiling observations are reduced to zero as the model boils when and where it should.

3.1.6 Weighting between observation groups

The objective function is calculated by a weighted sum of observations from all groups and types. If care is not taken with the relative weighting, the optimised results can be biased towards one of the observation group or type, and leave others having too little influence.

Several factors were considered in choosing the weightings:

1. Magnitude of units. Generally this effect can be simply eliminated by normalisation, using the estimated measurement error variance as the inverse of the weighting for each observation.
2. Expected model performance. If we have a perfect model describing the real world, we can expect a calibrated model to match field observations within the measurement errors. However, the calibrated model here is not expected to match within the measurement noise as the total error includes the system error (caused by an imperfect model) that is often much larger than the measurement error. Hence our weighting should reflect the magnitude of overall error, generally larger than the field measurement errors.
3. Relative weighting among groups. Another factor that affects the weighting greatly is the number of observations available in each group. For example, several tens of pressure histories are used but only four average enthalpy histories are included. Even after being normalised by units and expectation of the modeller, each point in the enthalpy history still requires a much larger weighting so that the contribution from all enthalpy observations to the objective function can be roughly the same level as from all pressure observations.

Often if the weightings are not balanced well, the calibrated model may match some of the observations satisfactorily but not the others. A number of trial and error experiments were used to establish a set of weightings that work well.

Currently, we use the following set of (approximate) relative weighting for the contributions of observations to the initial objective function:

- 20% from temperature profiles
- 20% from liquid pressure history
- 10% from vapour pressure history
- 40% from average enthalpy history
- 10% from difference between block pressure and boiling pressure

Note that the relative contribution among the groups changes during the process of optimisation. The changes in approximate contribution to the overall objective function from each observation group is summarised in Table 2.

**Table 2: Contribution to the objective function**

| Approx. contribution (%) | Initial model (% of obj. fn. ~59.0e+10) | Calibrated model (% of obj. fn. ~4.1e+10) |
|---|---|---|
| **Temperature profiles** | 20% | 32% |
| **Liquid pressure history** | 20% | 35% |
| **Vapour pressure history** | 10% | 19% |
| **Average enthalpy history** | 40% | 13% |
| **Diff. pressure to boiling** | 10% | 1% |

Note that increase in contribution does not mean the match is worse. It simply reflects the larger contribution to the greatly reduced objective function. It can also be observed from this table that the calibrated model showed the largest improvements in enthalpy and boiling.

### 3.2 Parameters

Permeability and porosity of the reservoir rock, the deep heat and mass upflow and recharge parameters are considered to be the most important parameters influencing the behaviour of a geothermal system and they were selected as the parameters to be adjusted in the estimations process.

#### 3.2.1 Rock-types

The numerical method used to solve heat and mass flow requires the discretisation of rock mass hydraulic and thermal properties (usually referred to as rock properties) into model blocks. Because it is usually not feasible to include properties of every single block as separate parameters, the strategy for grouping rock properties is important.

In TOUGH2 models these properties are implemented using rock-types. Each grid block in the model is assigned one of many rock-types. The permeabilities and porosities of the rock-types are then used as some of the parameters to be estimated.

Rock-types in the basic model were determined from the LEAPFROG-based 3D Wairakei-Tauhara geological model.

The area outside of the available Wairakei-Tauhara geological model was manually filled in based on published geological slices from Rotokawa (Bowyer and Holt, 2010) and Ngatamariki geothermal fields (Boseley et al., 2010).

The fault planes from the geological model were used to divide each rock formation into two variants: faulted and un-faulted.

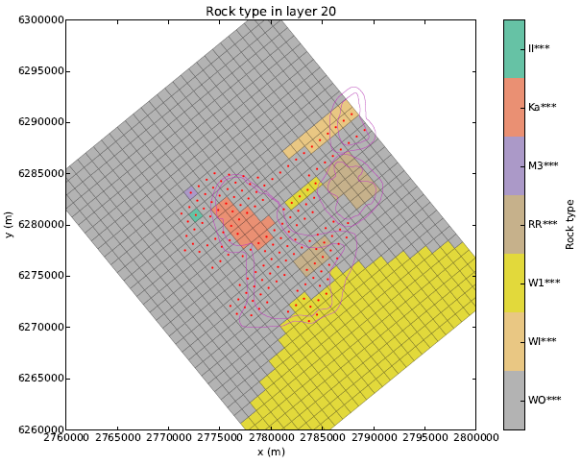


**Figure 4. Rock-types in layer 20. Red dots indicate faults**

Fig. 4 shows the original rock-types based on geological units. Blocks crossed by faults are labelled by red dots. The first level of sub-division splits each geological unit into faulted and un-faulted sub-rock-types.

#### 3.2.2 Base boundary conditions

The locations of mass upflows are restricted to blocks where faults intercept the base of the model (based on the 3D Wairakei geological model). The mass upflow in each column is included as a parameter that is allowed to vary as part of the estimation process.

Coefficients that control the amount of pressure-controlled recharge (Sec. 2.2) are also included as parameters

For columns without any mass upflow, heat is injected. The amount of heat injected in each column is determined separately for several high heat flow areas. Each area is represented by a circle within which there is a Gaussian heat flow distribution. If a column is not in any of the circles, a default low background heat flow is used.

#### 3.2.3 Increasing number of parameters

Two opposite approaches are commonly used in parameter estimation:

1. Start from a simple model with as few parameters as possible, and then gradually add parameters until an acceptable objective function is achieved.
2. The other way is to use a large number of parameters in the beginning (as many as computing resources allow). The estimation process can then explore the lowest objective function a model can achieve. In the likely case of estimated parameters being unrealistically variable in space (over-fitting), the estimation can be restarted with regularisation to keep the parameters within a reasonable range. The amount of regularisation can then be adjusted to compromise between obtaining a low objective function and reasonable parameters.

In the early stage of the project, the first approach was followed. Unfortunately it was difficult to determine what the model could ultimately achieve at the time. During each re-run of inverse modelling with additional parameters, it was difficult to know whether the objective function was limited by the number of parameters or the settings used in PEST.

As the project progressed, we were able to observe benefits in using the second approach. Results from experimentation showed that sub-dividing rock-types improved the final objective function. With heavily sub-divided rock-types, a significantly lower objective function was achieved.

In the current configuration, 79 rock-types are used instead of the 29 geological units from the original geological model.

Initial values of these parameters were assigned based on experiences from past manual calibrations. They act as preferred values when Tikhonov regularisation is used to constrain the optimisation process.

There are total of 403 parameters being used currently. These include:

- 4 independent parameters for each of the 79 rock-types (permeabilities in all three directions and porosity), a total of 316 parameters.

- 82 mass flow rates, one for each upflow column at the base.
- 5 upflow recharge coefficients, one for each area.

### 3.3 Minimisation algorithm and PEST settings

The non-linear optimisation algorithm used by PEST is based on the well-known Gauss-Levenberg-Marquardt method. This iterative method requires computation of the derivatives of all observations with respect to all parameters. The derivatives are then used to compute updated parameters that give (hopefully) improved matches to observations. This process is repeated iteratively until one of the termination criteria are met (Doherty, 1994).

We have tried many PEST settings and adjusted them throughout the project in attempts to improve the overall goodness of fit. This report only outlines the most effective options found so far.

#### 3.3.1 SVD

With the current model, we include a large number of parameters in the whole model as parameters, but the observations are only located in a relatively small number of model blocks. Many of the parameters are inevitably insensitive or strongly correlated. This insensitivity and correlation causes the matrix evaluated during the calculation of the parameter upgrade vector to be singular or near-singular and it cannot be inverted.

To overcome this problem, the truncated singular value decomposition method (SVD) in PEST is used. Using singular value decomposition, PEST effectively splits the parameter space into 'solution space' and 'null space'. By discarding the combinations of parameters that form the null space, only the sensitive combinations of parameters are being estimated as a result. Hence SVD overcomes the non-unique issues of over-parameterisation. This has been found to work well for Wairakei and was used for all parameter estimation runs.

#### 3.3.2 Regularisation

The regularisation method in PEST adds the deviation of parameters from preferred values into the objective function. The contribution of regularisation to the objective function against that from the observations is balanced adaptively in PEST. This adaptive weighting enables a low objective function to be achieved while keeping some of the less sensitive parameters close to the assigned initial or preferred values.

Currently Tikhonov regularisation is employed, where the initial values of parameters are used as the preferred values (Doherty and Skahill, 2006). Thus PEST tends to keep parameters at or near their specified initial values, unless matching the observations strongly drives change in the parameters. These initial values are directly assigned based on our previous experiences in calibrating the model manually. They served as the so-called expert knowledge.

#### 3.3.3 Upgrade tests with Marquardt lambdas

In the Gauss-Levenberg-Marquardt method used by PEST, the value of lambda controls the direction of parameter upgrade. When lambda is very small or zero, the upgrade direction follows the Gauss-Newton strategy. When lambda is large, the upgrade vector moves towards steepest descent. The Levenberg-Marquardt method combines the two to improve the convergence speed of the nonlinear optimisation process by initially using a large lambda, and then progressively reducing lambda as the minimum is approached.

Normally lambda is controlled by a user specified initial value and then adjusted by the Levenberg-Marquardt method as the optimisation iteration moves on. PEST has an additional feature that searches for a near optimal lambda at each step of the optimisation procedure. This search is achieved by running a series of upgrade tests, varying lambda, and calculating the optimal lambda by inspecting the dependence of the objective function on lambda. BeoPEST (a parallel version of PEST) can partially parallelise this search.

If there is enough computing resources, BeoPEST can be set up to perform a large number of upgrade tests in parallel, covering a good range of lambdas at each optimisation iteration. From our recent experience, this approach significantly improves the reduction of the objective function at each iteration.

#### 3.3.4 Using BeoPEST on NeSI

Due to the large number of parameters (403) and the slow forward TOUGH2 run (taking anywhere between 20 minutes to 5 hours), a personal computer with only 4 to 12 CPUs is not ideal for performing parameter estimation. In this project, we set up BeoPEST (a parallel version of the PEST software) running on the University of Auckland's Pan Cluster, managed under NeSI (New Zealand eScience Infrastructure).

A suite of scripts have been developed to automate the complex procedure of an optimisation run with BeoPEST on NeSI. They carry out the following steps:

1. Create/modify a list of parameters and a list of observations. All files required to interface PEST and the TOUGH2 simulator are then generated automatically by goPEST, a Python script that makes heavy use of the PyTOUGH library.
2. Generate and run scripts required for submitting the job into the cluster's job queue. The submission scripts requests enough CPUs for the optimisation run, usually about 400 CPUs for a duration of 24 hours.
3. Once a job goes through the queue, a master and multiple slave BeoPEST runs are launched on the allocated resources. File management and communication among master and slaves are dealt with automatically.
4. Each slave computer controlled by BeoPEST is able to start a forward run as dictated by the master BeoPEST.
5. Each forward run consists of a steady state run followed by a production history run with the AUTOUGH2 simulator, including all the associated pre- and post-processing.
6. After an optimisation run, scripts are also available to extract the best model results and produce all the plots of observations for visual inspection.

## 4. RESULTS AND DISCUSSION

This project established an effective framework of parameter estimation for the Wairakei model. The model

development work flow can be briefly summarised as follows:

1. Build a flow model with enough different rock-types by sub-dividing those from the basic geological models. Create locations of possible upflows, mainly where faults intercept the base of the model within the resistivity boundaries.
2. Assign initial values of parameters for these rock-types and bottom boundary conditions based on past modelling experiences. Then the model is run to ensure the convergence of the natural state simulation and that the production history simulation will finish.
3. Add all permeabilities, porosity of rock types, all bottom boundary conditions as parameters for PEST.
4. Add temperature, pressure, enthalpy and boiling observations for PEST.
5. Adjust weighting between these groups so their contribution to the objective function matches the desired relative goodness of fit among groups.
6. Add regularisation to the PEST optimisation.
7. Run PEST/BeoPEST.
8. Visually inspect the results for the model with best objective function against the results from the original model:
    - If the overall match is poor, go back to step 1 and change the model setup, such as sub-divide rock-types further.
    - If some observations groups match well but not others, go back to step 5.
    - If the overall matching is good but parameters are unrealistic, go back to step 6 and increase regularisation weighting.

These steps have been largely automated by a suite of codes and scripts and can be repeated easily with the required adjustments, such as addition or removal of parameters and observations or using a different model. Currently it works well with approximately 400 parameters. Each PEST run takes about two days if an allocation of 400 CPUs is successfully acquired from NeSI.

The results can be summarised as follows:

- Most of medium to deep downhole temperatures of the 37 key wells from Wairakei, Tauhara, Rotokawa, and Ngatamariki fields are matched reasonably well, including a few edge- and out-field wells. (e.g., Fig. 5)
- Infield liquid pressure drawdown at Te Mihi, Wairakei and Tauhara are matched reasonably well. Pressures from a couple of edge- and out-field wells are not matched as well, but this aspect of the model is limited by the current division of some rock-types. A few steam pressures are still low compared to the field data. (e.g., Fig. 6)
- Average production enthalpies of Eastern, Western, Te Mihi and Poihipi production fields are matched well (e.g., Fig. 7). Most of the boiling trends in the production wells are matched well (e.g., Fig. 8).

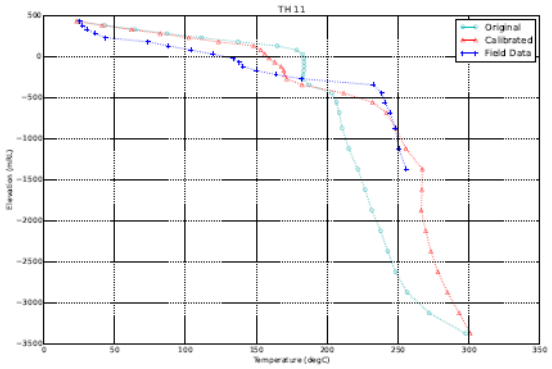


**Figure 5. Results of calibration: temperatures in TH11**

Overall results from the calibrated model are about as good as it can be achieved with the current set of parameters. More optimisation iterations do not meaningfully improve the objective function (and hence the match) further. Adjustments to the model such as mesh refinement or rock-type subdivision are needed to further improve the match.

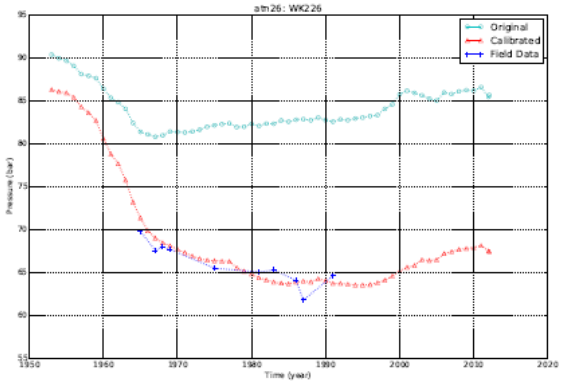


**Figure 6. Results of calibration: pressures in WK226**

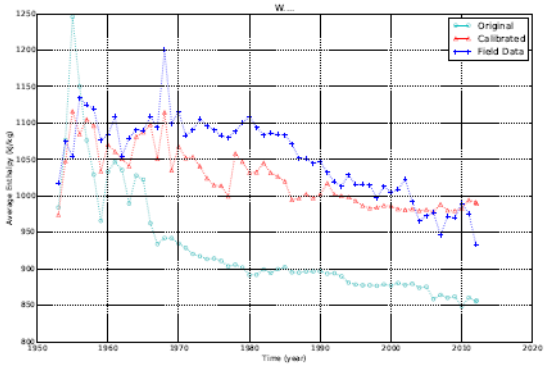


**Figure 7. Results of calibration: enthalpy from Western Borefield.**

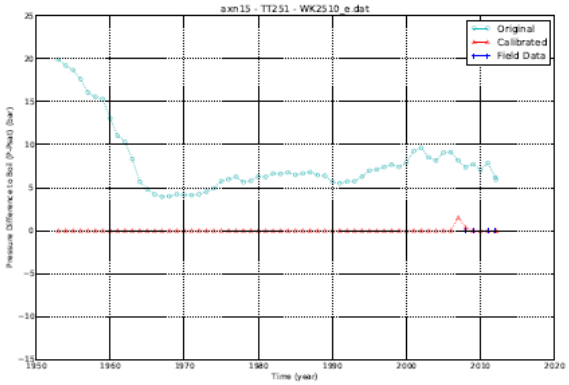


**Figure 8. Results of calibration: boiling state of WK251.**

## 5. FUTURE WORK

Here is a short list of tasks for the near future:

(i) Increase the number of parameters to include more subdivision of rock-types. This involves checking the identifiability of rock-types and determining which should be subdivided.

(ii) Add more details of enthalpy observations by breaking averaged enthalpy matching into smaller groups such as deep and shallow zones.

(iii) Add shallow Tauhara pressure data as observations.

(iv) Add hot springs into model along with observations such as massflow and heatflow from surface features.

(v) Upgrade the rectangular Wairakei model from a water-only model to an air-water model.

(vi) Refine model mesh to capture more details within the production areas at Wairakei and Tauhara.

(vii) Experiment with pilot points instead of rock-types.

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