Application of Surrogate Models and Derivative-Free Optimization in Geothermal Reservoir Modelling*

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Abstract

Numerical models of geothermal reservoirs are valuable tools to understand the processes controlling subsurface flow and to help manage these resources. However, modelers face several uncertainties in their efforts to generate reliable predictions. This study addresses uncertainty using geostatistical simulation, using multiple-point statistics (MPS). The main feature of a MPS algorithm is that it relies on a training image, and uses multiple training images to describe spatial uncertainties in subsurface flow problems. MPS was pioneered in the petroleum industry but has received little attention in geothermal. Monte Carlo methods are a traditional approach for uncertainty assessment in many areas of science and engineering. However, Monte Carlo methods can be very computationally expensive since many forward modelling runs are required. Surrogate models are an alternative to Monte Carlo methods. The surrogate is derived from reservoir simulator output and can be generated from a small number of runs of the simulator. This approximation may then be used to produce fast estimates of the model output for different combinations of parameters gives scope for an optimization algorithm to be applied to the model. This study addresses the problem of global calibration of geological properties in a geothermal reservoir model using surrogate models and adaptive sampling. Efficient solutions were obtained for nonlinear problems, where standard, derivative-based methods may have achieved convergence to low-quality solutions. An important feature of this surrogate model calibration is that it allows the inclusion of both categorical variables and continuous variables in the analysis. This was shown to be a strategy which delivers insight on geological uncertainties from the calibration process. The paper will comment on how the methods applied relate to methods used in petroleum reservoir modelling.

Application of Surrogate Models and Derivative-free Optimization in Geothermal Reservoir Modelling

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Introduction

- Trained as a petroleum engineer
- Distinguished member of the SPE
- Director of the Geothermal Institute – University of Auckland

Introduction

- This work forms part of a recently submitted PhD thesis by Mr Ariel Vidal who has been working with me at the University of Auckland.

- Ariel wishes to acknowledge financial support from CONICYT (Chile).

Uncertainty

- Uncertainty is an ever present part of reservoir modelling.
  - Multiple conceptual models may be plausible from early geological data. Which model is correct?
  - What is the spatial distribution of flow and transport properties in the reservoir rock?

http://img.picturequotes.com/2/64/63644/the-only-certainty-is-that-nothing-is-certain-quote-1.jpg

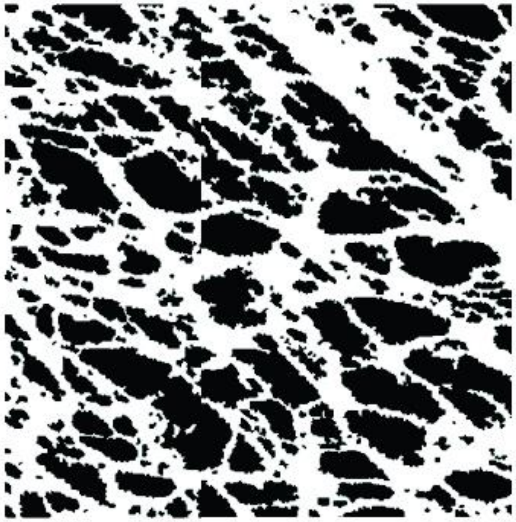
Mathematical Toolbox

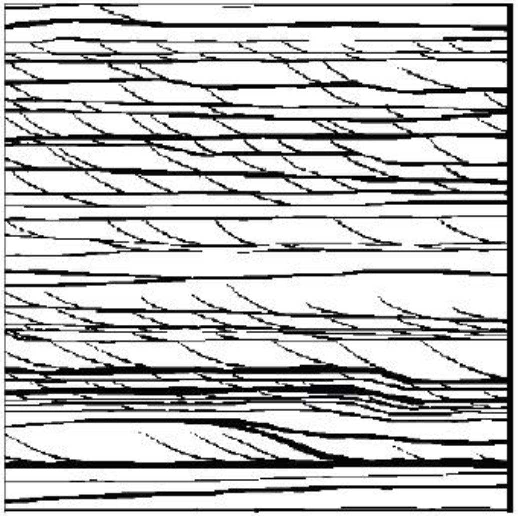
- Multiple point geostatistics
- Surrogate modelling (radial basis function)
- Derivative free optimization

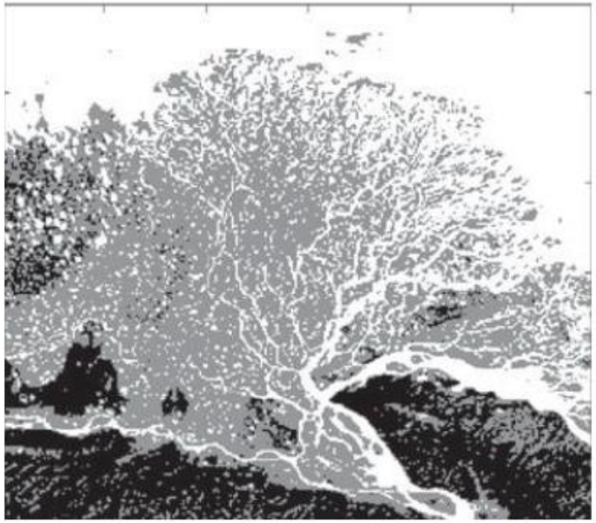
http://www.e-bas.com.au/bookkeeping-blog/employers-toolbox-free-download-2

Petroleum cross-over

Multiple Point Geostatistics







- A training image is a repository of the patterns and their respective likelihoods for the problem under study.
- Algorithms developed in petroleum allow 3D images to be created which replicate the patterns in a training image while honouring hard data (e.g. at wells).

Surrogate Modelling (Radial Basis Functions)

A radial basis function interpolates the points:

$$(x_1, f(x_1)), \ldots, (x_n, f(x_n))$$

by using a function that takes the form:

$$s_n(x) = \sum_{i=1}^{n} \lambda_i \phi(\|x - x_i\|) + p(x), \qquad x \in \mathbb{R}^d$$

where $p(x)$ is polynomial and $\phi(r) = r^3$

Derivative Free Optimization

- SO-MI algorithm used as an optimizer. Starts from an initial population of points and function evaluations on these points, the method looks for new iterates where the forward model will be evaluated and the minimum will be approximated.

- Müller et al. (2013) showed SO-MI performs well for black-box nonlinear problems.

- At each iteration of SO-MI four new groups of samples are selected to evaluate the expensive objective and constraint functions.

Derivative Free Optimization

1. Continuous variables in the solution for the current minimum are perturbed with probability 5/k (k>5).

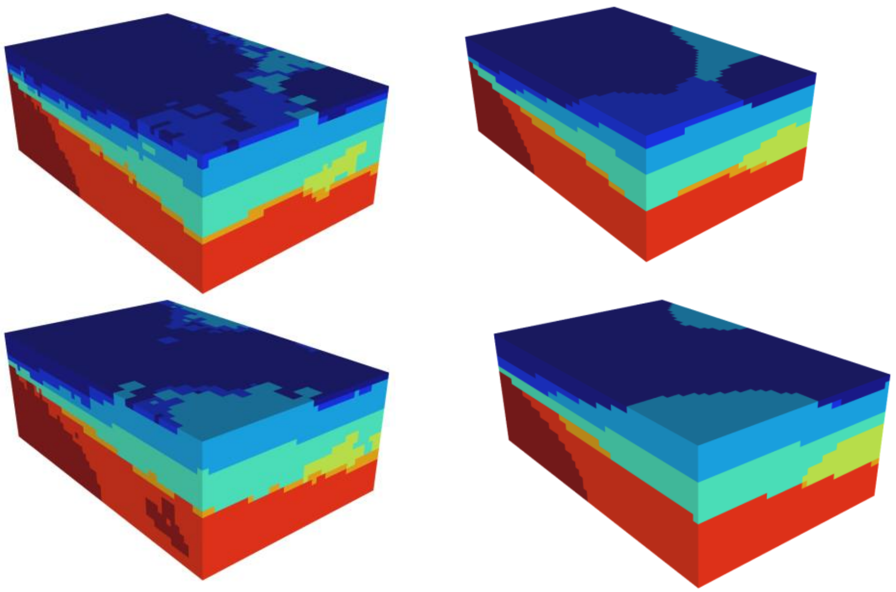
2. Discrete variables only are perturbed randomly with small, medium and large perturbations.

3. Both continuous and discrete variables are perturbed randomly.

4. Points are generated uniformly within the search space.

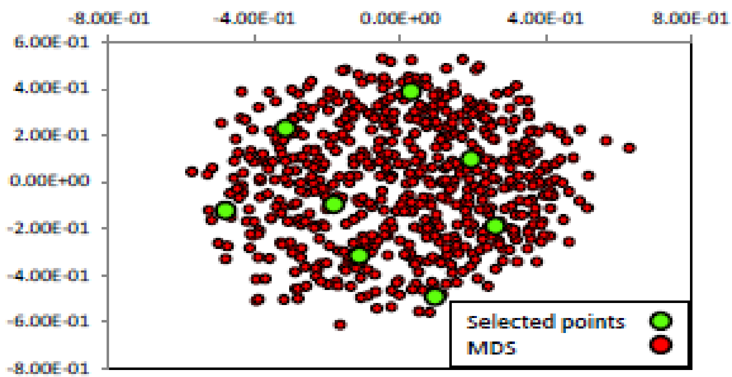
Geothermal Application

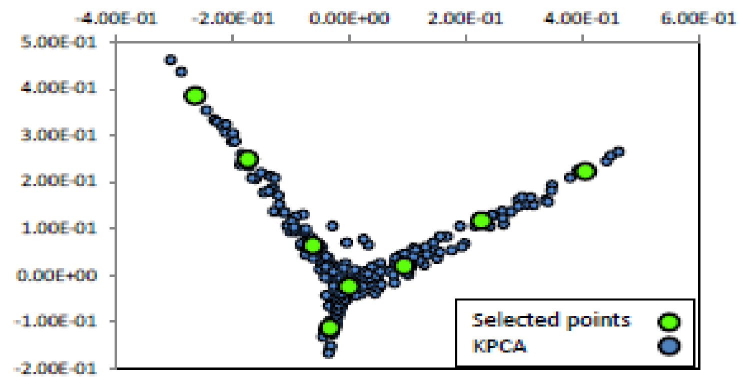
- 200 realizations generated using each of three possible trainining images using FILTERSIM algorithm in the SGeMS software.
- Images are then cleaned with the TRANSCAT routine.



Petroleum
cross-over

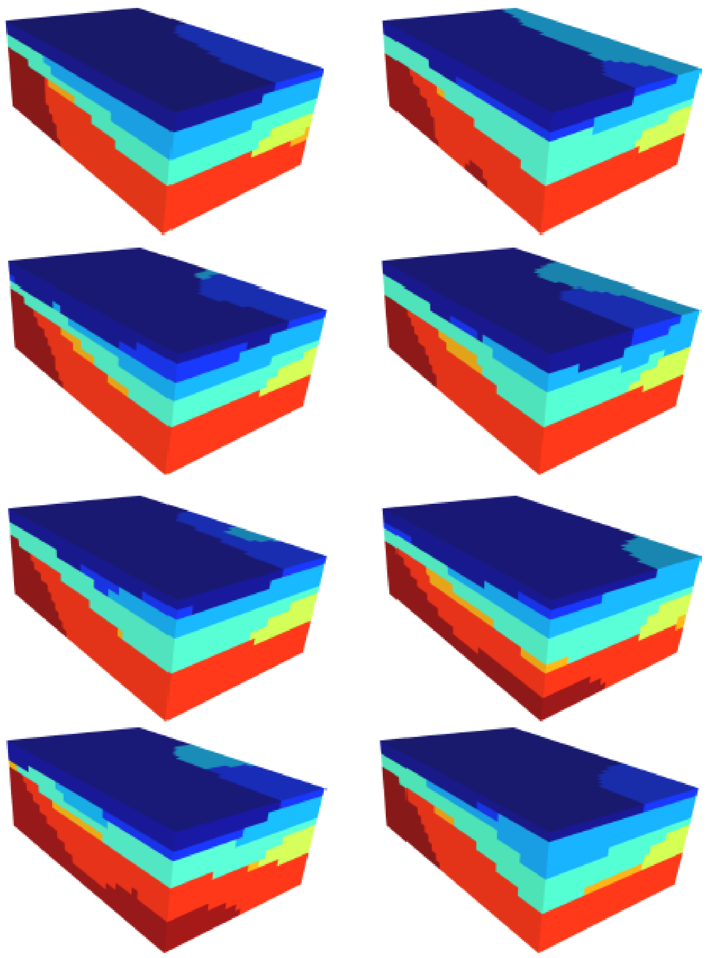
Starting Realisations





- Hausdorff distance applied to consider the dissimilarity between realisations.
- Multi-dimensional scaling used applied to initial set of realisations.
- Left plot shows the realisations plotted in the terms of the first two components of that scaling.
- Right plot shows a principal component analysis (with starting models shown as green dots).

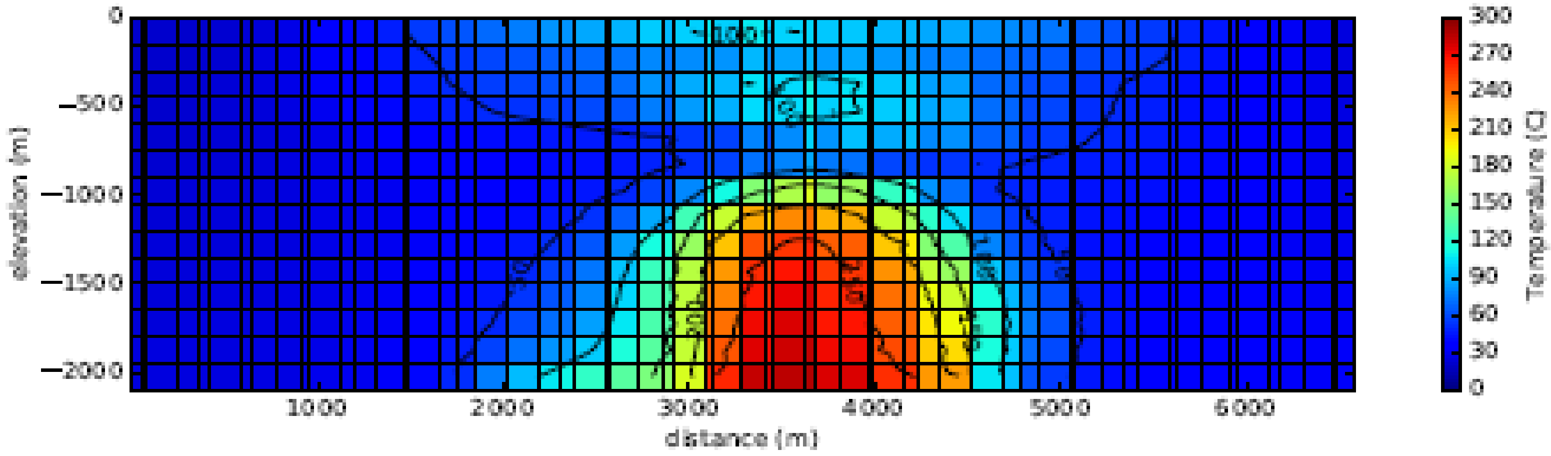
Starting Realisations



Model Details

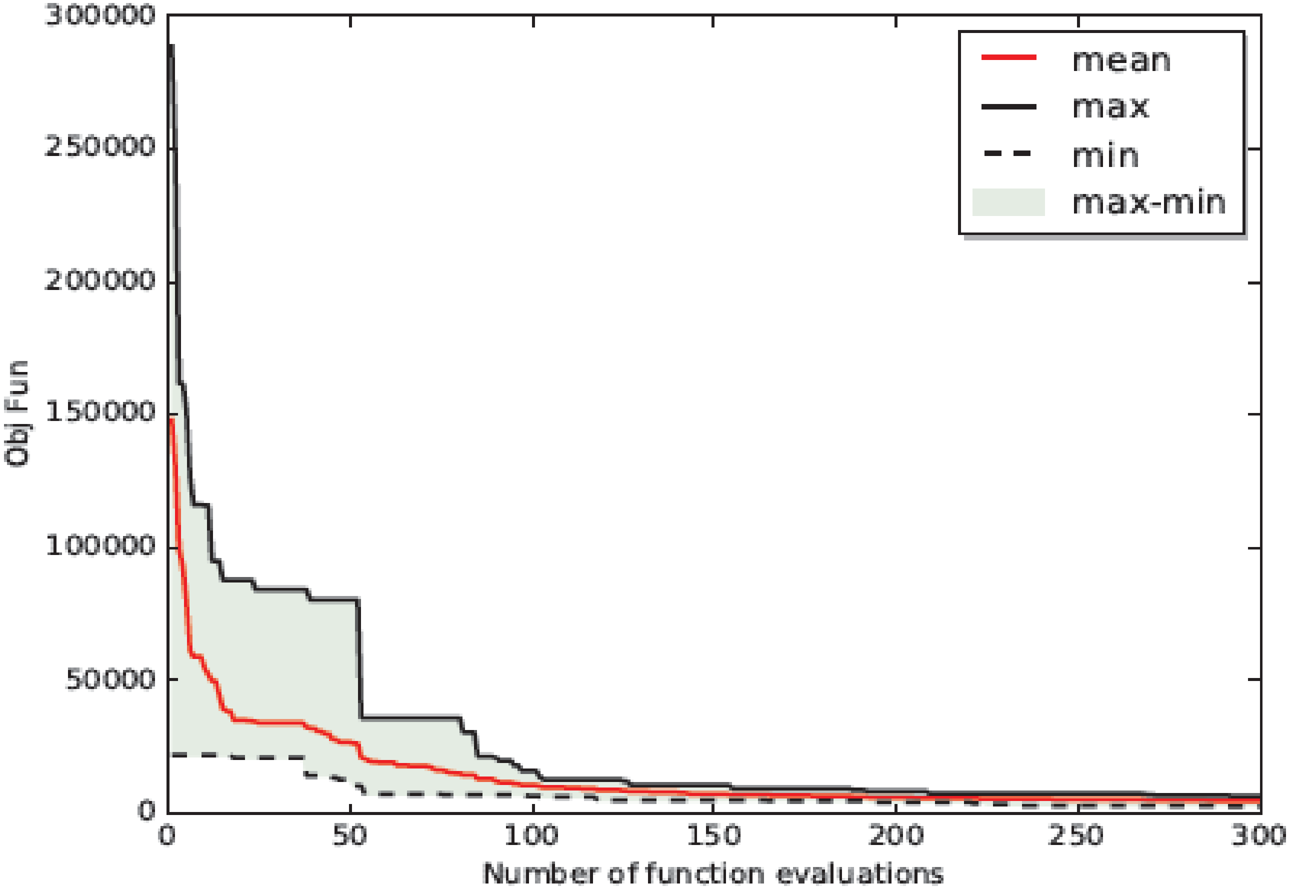
- The modelled system size is 3750 x 5700 x 2100 m
- 25 x 38 x 14 blocks
- Block size of 150 x 150 x150 m, comprising a total of 13,300 blocks.
- Boundary conditions at the bottom layer of the model correspond to a rectangle of 9 x 10 blocks with a fluid mass input of 0.3 kg/sec and a bigger rectangle of 13 x 20 blocks with a heat flux of 500 mW/m^2.
- Horizontal and vertical permeability in 8 rock types treated as unknown (continuous) variables (with lower and upper bounds).

Reference Model

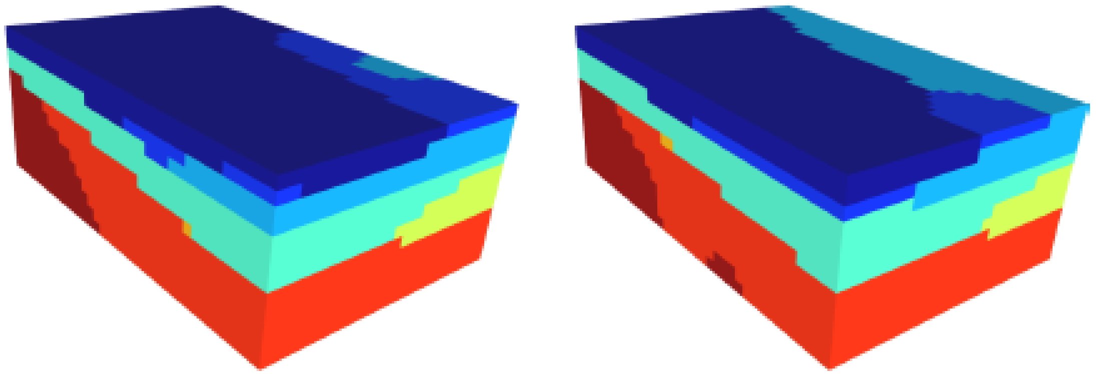


- Temperature in a reference case model.
- Data extracted from some vertical wells in this models to be treated as "data" to be matched in SO-MI optimization.

SO-MI Performance



Multiple Calibrated Models



- Two reservoir models which minimise the temperate misfit objective function – from two different training images.
- The third alternative geological interpretation was dismissed by the method, suggesting that the basement rocks are confined to the northern part of the system, and they do not extend towards the south, in agreement with the reference geological model.

Conclusion

- This work successfully combines the SO-MI optimization algorithm with training image geostatistics.
- SO-MI balances local and global search and rapidly finds “good solutions”.
- SO-MI can handle optimization problems which include both continuous and discrete variables.
- Alternative conceptual models (captured in training images) can be retained or ruled out.
- The set of rock properties that give an optimal objective function value can be found.

Questions?
Comments?

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