A New Methodology for Addressing Nonlinear Inverse Problems and its Application to Characterise a Real Petroleum Reservoir

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Abstract

In Petroleum Engineering, reservoir management aims to maximise the profit from a hydrocarbon reservoir. Highly nonlinear numerical models, which describe the internal structure of hydrocarbon reservoirs, are used to make reservoir management decisions. These models are aimed at providing accurate predictions of the reservoir behaviour under different scenarios. This requires that the model parameters are calibrated so that the model reproduces all the available data. Given the impossibility of directly measuring these parameters in the field, one has to infer them from indirect measurements, such as the oil production rate at a given reservoir well. This is an example of a nonlinear inverse problem.

This talk will describe a recently developed methodology for addressing nonlinear inverse problems and its application to the characterisation of a real petroleum reservoir. This methodology is based on a real-coded Genetic Algorithm which has been modified to run on a cluster of computers.

Keywords: Nonlinear Inverse Problem, Genetic Algorithm, Clustering, Parameter Estimation, History Matching, Petroleum Reservoir Characterisation

Introduction

Reservoir Characterisation can be defined as the process of identifying a numerical model, the behaviour of which must be as similar as possible to that of the hydrocarbon reservoir under study. A key stage of this process is to condition the adopted reservoir model to dynamic data from measurements in wells (the historical production data). This nonlinear parameter estimation problem, known as History Matching, usually has multiple distinct solutions (i.e. calibrated or history matched models). These solutions will manifest themselves as distinct optima for some objective function and will be separated by regions of poor objective function value.

In History Matching, the challenge is to identify all the high quality optima and sample the parameter space around them. This sampling gives rise to an ensemble of history matched models, which can thereafter be used to quantify uncertainty on production forecasts. It is useful to study each type of history matched model separately, as this will let us understand the production mechanism that may have occurred. We may also be able to identify measurements that would allow us to discriminate between the different types of history matched models. However, the task of discovering these types or clusters of models from the ensemble is very hard mainly due to the high number of model parameters involved.

Methods

In this study, a new real-coded Genetic Algorithm (GA) is applied to history match a real petroleum reservoir using its recorded production data and a numerical model of the reservoir. This GA is implemented within a non-generational, steady-state scheme. In order to shorten the computation time, the solutions (instances of the model) proposed by the GA are evaluated in parallel on a group of 24 computers. All of the solutions generated by this parallel GA are finally analysed using a clustering algorithm. This algorithm does not require the number of expected clusters to be chosen in advance, and it is able to handle a very high number of model parameters. This is done to find the number of distinct solutions within the ensemble generated by the GA.

Discussion

The application of the methodology to this nonlinear inverse problem yields a large improvement with respect to past studies in that reservoir, both in terms of the quality and diversity of the obtained history matched models.

The best history matched models are shown in Fig.1. The methodology was able to identify 19 different types (clusters) of reservoir models compatible with the measured data.

These results show that, despite the use of regularisation terms in the objective function, many distinct reservoir models may be obtained from reservoir characterisation studies. This suggests that it is more important to search for multiple solutions than is currently perceived by most of the Petroleum Engineering community.

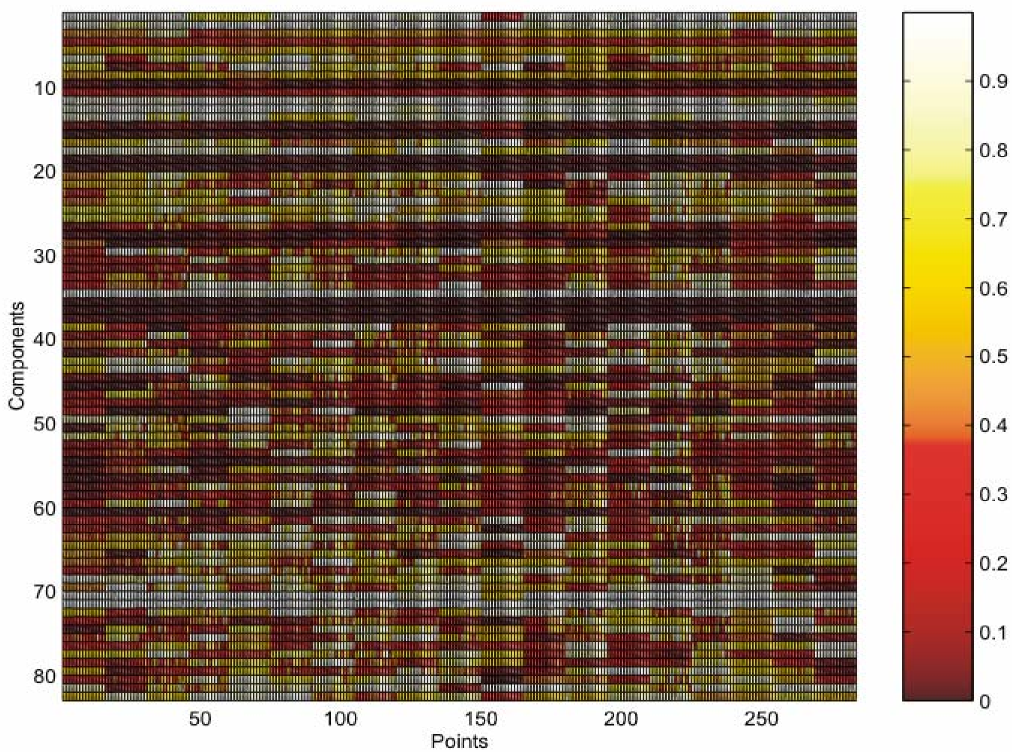

Figure 1: Results from the inversion of a real petroleum reservoir, which was described by a numerical model with 82 parameters. Each column in the plot is a calibrated reservoir model and each row is a given model parameter. The cell colour indicates the scaled value of the associated model parameter. The clustering algorithm revealed 19 different types (clusters) of history matched reservoir models (note that models within a cluster are similar, whereas models from different clusters are dissimilar). This plot constitutes a graphical representation of the uncertainty in the reservoir characterisation.

Future Work

An interesting issue for further research is to find out how well these estimated models predict future data. This validation would compare a forecast envelope of the estimated models with the two years of additional data that have now been collected. This forecast envelope could be determined in several ways, for instance, by selecting the best model for each cluster and running them forward in time.

References

P. J. Ballester. New Computational Methods to Address Nonlinear Inverse Problems. PhD thesis, Dept. of Earth Science and Engineering, Imperial College London, University of London, UK. 2005.

P. J. Ballester and J.N. Carter. An Effective Real-Parameter Genetic Algorithms with Parent Centric Normal Crossover for Multimodal Optimization. Genetic and Evolutionary Computation Conference (GECCO-04, Seattle, USA). Lecture Notes in Computer Science, Springer, 3102:901-913, 2004.

M. Sambridge and K. Mosegaard. Monte Carlo methods in geophysical inverse problems. Reviews of Geophysics, (40) 3:1–29, 2002.