041 IDENTIFICATION AND REDUCTION ON UNCERTAINTIES IN AUTOMATIC HISTORY MATCHING AND FORECASTING

TONGCHUN YI and T. SEZGIN DALTABAN
Imperial College, Department of Earth Resources Engineering, Royal School of Mines
Prince Consort Road, London SW7 2BP, UK

Abstract

This paper presents novel applications of the Bayesian inversion approach and the simulated annealing method (SAM) for identifying and reducing uncertainties involved in automatic history matching and forecasting processes which are of paramount importance for optimisation of hydrocarbon recovery. The Bayesian inversion approach enables the priori knowledge about the inversion parameters to be incorporated into the objective function to form a posteriori, in conjunction with the likelihood function reflecting the mismatch between the history data and the data predicted from the numerical model. The simulated annealing method (SAM) has been applied to escape local optima which may still exist in the posteriori objective function, in order to further reduce the nonuniqueness of the inversion solutions.

Case studies have been undertaken to demonstrate the methodologies presented in this paper and the uncertainties which may be involved in the automatic history matching. The results show that SAM can effectively escape local optima to reach the global optimum, and can efficiently deal with problems with up to 100 parameters. It is also illustrated that more history information in the formulation of the objective function can have added values to the history matching and the forecasting, and that the Bayesian inversion approach makes it possible to reduce the uncertainties by incorporating the priori knowledge of the inversion parameters.

1 Introduction

Reservoir simulation is one of the essential components of best practices in reservoir management. It has been an important tool for predicting reservoir performance. The reliability of this technology depends greatly on the accuracy with which the numerical models can represent the reservoir in question. While the reservoir characterisation plays a central role in the construction of the simulation model, the history matching^{1,2} is essential for calibrating the model, therefore improving the accuracy of the simulation for the forecast of the future field performance.

Automatic history matching¹ has overcome some of the shortcomings of manual history matching which is a time consuming and sometimes a frustrating process. Automatic history matching involves a process of minimising an objective function which represents the mismatch between the observed data and the results predicted from the numerical models. Uncertainties are involved in the whole process of the history matching, from the selection of the inversion parameters, through the construction of the simulation models, to the formulation of the objective function and the minimisation process. It is important to identify and reduce these uncertainties for improving the quality of history matching and the confidence on the future forecasting.

In this paper, the Bayesian approach^{2,3} and the simulated annealing method⁴ (SAM) are presented. And examples are demonstrated for their applications in identifying and reducing uncertainties involved in the automatic history matching and performance forecasting.

2 Methodologies

Bayesian Approach

One of the uncertainties in history matching is the non-uniqueness problem which is common for a range of inversion problems. Simulation models with different sets of parameters may fit the same observed data very well. The Bayesian approach^{2,3} is effective for overcoming this kind of problems by formulating the objective function in such a way that the formulation of the problem can be very well constrained. In this approach, the prior knowledge of the inversion parameters is combined with the likelihood function which represents the mismatch between the observed data and the results predicted from the model to form the so called posteriori function. Minimising the posteriori function can very much reduce the non-uniqueness of the inversion solution. Furthermore, the shape of the posteriori function in the form of probability density function (pdf) can help to analyse the uncertainties of the forecasting. In this work, the Bayesian approach is used to formulate the posteriori objective function which will be minimised to obtain the inversion solution. The analysis of the shape of the posteriori pdf is beyond the scope of the paper, which will be discussed elsewhere.

Simulated Annealing Method (SAM)

Simulated Annealing Method (SAM)⁴ mimics the thermodynamic process of a liquid crystallising into a solid by cooling. As the liquid is cooling slowly (annealing), it reaches a low energy state. Inherent random fluctuations in energy allows the annealing system to escape from local minima to reach the global minimum of energy. SAM attempts to minimise an objective function in a way similar to annealing. When minimise the function, any downhill step is accepted and the process repeats from this new point. An uphill move may be accepted with a certain probability. Thus it can escape from local optima to find the global minimum. Because of these advantages over the conventional optimisation procedures, SAM has been successfully applied in many areas including reservoir characterisation⁵ and automatic history matching^{6,7}.

Due to the complexity of the reservoir history matching problems, the posteriori function from the Bayesian inversion may still have numerous local optima particularly when the number of inversion parameters is large. In this work, SAM has been used to minimise the posteriori objective function.

3 Results and Discussions

Case 1

The objective of this case study is to compare the performance of SAM with that of the Simplex Downhill (SD) approach⁸. The model used in this case is a quarter of five spot pattern with three layers. Two transmissibility multipliers between the three layers were chosen as inversion parameters. History data are generated by a black oil simulator using the two transmissibility multipliers of 100 respectively. The objective function is in a least square form with history data of the bottom hole pressure at the injector and the oil production rate at the producer. Two methods are used for the history matching. One is the Simplex Downhill method, the other is the simulated annealing method.

The two approaches start at the same point to search the global minimum. Two runs start at different points, (10, 10) and (1000, 1000). The results show that the SD method is trapped by local minima at point (7438, 83) when starting from (1000, 1000), and trapped at point (130, 107) when starting at (10, 10), while SAM can reach very near the global minimum. The matched well bottom hole pressure (WBHP) and the well oil production rate (WOPR) with the final inversion solutions from the two runs using the two methods are shown in Figures 1 and 2 respectively. It is very clear that SAM has very much reduced the uncertainties of the history matching results.

Case 2

In this case, SAM is used for solving high-dimensional inversion problems. A cross-sectional multi-layered model is used in this case. It is assumed that there is no communication between layers due to shale separating the layers. Each layer has a homogeneous permeability, but different layers have different permeabilities. One injector and one producer are involved in the model. The pressure drops between the two wells as a function of time and the water breakthrough time are recorded as history data. The inversion parameters are the permeabilities of all the layers. For such a model, the history data can be very well matched by a set of permeabilities regardless of the order of the layers (from top to bottom). This means that for given history data, mathematically there would be a large number of inversion solutions which have the same set of permeabilities but with different layer order. In the reality, however, permeabilities of different layers should be in a certain order in line with the geological environment. To reduce this kind of nonuniqueness, the prior knowledge about the permeability of each layer from geological information is incorporated into the objective function according to the Bayesian approach. In addition, SAM is used to escape numerous local optima which may still exist in the posteriori objective function. The number of parameters tested are 2, 10, 50 and 100. The performance of SAM, number of inversion parameters versus number of function evaluations needed for acceptable results, is shown in Table 1. For the case with 100 parameters the matched pressure drop as a function of time and the matched permeability distribution at three typical stages, compared with the 'truth' data are shown in Figures 3 and 4. It can be seen that SAM is fairly effective and efficient for dealing with high dimensional problems.

Case 3

In this case, the objective is to investigate the effects of different types and different time periods of history data used for the matching, on the matched results and forecasting. To this end, two runs have been undertaken using an aquifer supporting field model. The model consists of 5 layers and 10 production wells. Nine inversion parameters are selected for the two runs, that is, permeability multipliers for layer 1-5, and transmissibility multipliers between the 5 layers. In run 1, only the bottom hole pressure of 6 wells are used to match for a period of about 2000 days. In run 2, bottom hole pressure, gas oil ratio and water cut of 10 wells altogether are used to match the history data for a period of 4000 days. The truth values of all parameters are 1.0. The matched results are summarised in Table 2. It can be seen that for run 1, the permeability multipliers of layers 3-5 are near the truth values while others are far from the truth values. In run 2, the overall difference between the matched parameters and the truth values are much reduced. These parameters have been used to predict field productions of oil, water and gas for 6000 days as shown in Figures 5 to 7. It is shown that the results of run 2 are much better than those of run 1, meaning that more information of history data has added values to the results of the matching and the forecasting.

Case 4

The objective of this case is to investigate the effect of grid used in the simulator on likelihood function and the matching results. The grid used in case 3 is rotated about 25 degrees to form the grid which is used for the history matching in this case. The original grid is used to generate the history data. The matched parameters using the rotated grid are listed in Table 3. Shown in Figures 8-10 are three curves of productions of oil, water and gas versus time respectively. Curve 1 is the history data generated using the original grid with the values of the inversion parameters being 1. Curve 2 is the data generated using the rotated grid with the values of the inversion parameters being 1. Curve 3 is the data generated using the rotated grid with the matched values of the inversion parameters as listed in Table 3. It can be seen that with everything remaining the same, just rotating the grid can make significant changes for the production data. With the rotated grid a good history match can be obtained, but the values of the inversion parameters are no longer their original meanings. They actually compensate the numerical errors caused by the rotation of the grid. This should be bore in mind when undertaking a history match using different griddings. For a reservoir with high degree of permeability anisotropy, the grid axes should be aligned with the principal

permeability directions. Furthermore, it is recommended to apply the nine-point formulation if possible in order to reduce the uncertainties caused by the grid orientation effects.

4 Summaries

- 1) Different sources of uncertainties in automatic history matching have been identified. These include uncertainties from the construction of the model, the formulation of the objective function and the minimisation of the objective function.
- 2) Bayesian approach can reduce the nonuniqueness of the inversion solutions by incorporating the prior knowledge of the inversion parameters in the formulation of the objective function.
- 3) The simulated annealing method can effectively escape local minima to reach the global minimum so as to reduce the uncertainties of the solution.
- 4) More history data can have added values to the history matching results and the future forecasting.
- 5) Grid orientation has significant effects on the history matching results and the forecasting.

Acknowledgements

This work is part of the project 'Production forecasting with uncertainty quantification' which is sponsored by the European Commission. The authors wish to thank EC for the financial support for this work, and to acknowledge all our colleagues who work on the project for their fruitful corporation.

References

1. Mattax, C. C. and Dalton, R. L.: Reservoir Simulation, SPE Monograph Vol. 13, 1990.
2. Tan, T. B. and Kalogerakis, N.: 'Improved Reservoir Characterization Using Automatic History Matching Procedures', J. of Canadian Petroleum Technology, Vol. 32, No. 6, 26-33, June 1993.
3. Gavalas, G. R., Shah, P. C., and Seinfeld, J. H.: 'Reservoir History Matching by Bayesian Estimation', SPEJ, 337-350, December 1976.
4. Goffe, W., Ferrier, G. and Rogers, J.: 'Global Optimization of Statistical Functions with Simulated Annealing', J. of Econometrics, No. 60, 65-99, 1994.
5. Ouenes, A., Meunier, G., Pelce, V., and Lhote, I.: 'Enhancing Gas Reservoir Characterisation by Simulated Annealing Method (SAM)', Paper SPE 25023 presented at the European Petroleum Conference, Cannes, France, November 16-18, 1992.
6. Ouenes, A., Brenfort, B., Meuenier, G., and Dupere, S.: 'A New Algorithm for Automatic History Matching', unsolicited paper SPE 26297, 1993.
7. Yi, and Daltaban, T.S.: 'Application of a Hybrid Algorithm of the Simulated Annealing Method and the Genetic Algorithm in Petroleum Reservoir History Matching', to be presented at ANNIE'97, St. Louis, Missouri, November 9-12, 1997.
8. Press, W.H., Teukolsky, S.A., Vetterling, W.T., and Flannery, B.P.: Numerical Recipes in FORTRAN, the art of Scientific Computing, second edition, Cambridge University Press, 1992.

Table 1 - SAM performance for case 1

Table 2 - Results of case 3

	No. of Function evaluation	Value of objective function	Matched values of parameters								
			1	2	3	4	5	6	7	8	9
Run1	715	6.6e-4	11.66	3.14	0.84	0.97	0.87	98.54	1.38	70.62	3.6
Run2	826	1.09	1.63	0.72	1.83	1.44	1.61	5.52	1.04	1.58	0.4

Table 3 - Values of inversion parameters (case 4)

Initial values	1	1	1	1	1	1	1	1	1
Matched values	1.95	4.5	2.97	0.43	0.68	1.31	1.54	2.07	1.39

Figure 1 - Injection well bottom hole pressure versus time

Figure 2 - Oil production rate versus time

Figure 3 - Matched pressure drops (case 2)

Figure 4 - Matched permeabilities (case 2)

Figure 5 - Field oil production rate versus time (case 3)

Figure 6 - Field water production rate versus time (case 3)

Figure 7 - Field gas production rate versus time (case 3)

Figure 8 - Field oil production rate versus time (case 4)

Figure 9 - Field water production rate versus time (case 4)

Figure 10 - Field gas production rate versus time (case 4)