Year 11, Number 2
98th edition
February, 2016

UNISIM ON-LINE

Bayesian History Matching Using Artificial Neural Network and MCMC

Célio Maschio

Introduction

Bayesian inference is a well-established statistical technique used to solve a wide range of inverse problems. For the great majority of practical problems, it is not possible to formulate the posterior distribution analytically and the most practical manner to solve the problem is by using sampling techniques.

Metropolis-Hastings algorithm that belongs to the class of Markov Chain Monte Carlo (MCMC) is very suitable to sample the posterior distribution because it is not necessary to know the normalization constant that arise from the Bayes theorem. However, its application in the probabilistic history matching problem can be prohibitive due to the very high computational cost involved because the algorithm requires a high number of samples to reach convergence.

The purpose of this work is to replace the flow simulator by proxy models generated by artificial neural network (ANN) to make feasible the application of the sampling algorithm in the history matching. An iterative procedure combining MCMC sampling and ANN training is proposed. The proposed procedure was successfully applied to a reservoir model with 16 uncertain attributes and promising results were obtained.

Methodology

The key idea of this work is to propose an iterative procedure for Bayesian history matching using Markov chain Monte Carlo and artificial neural network. The proposed procedure is divided into two main stages: MCMC sampling and ANN training. The two stages (that consists of one iteration) are carried out sequentially, i.e, a sampling stage is followed by an ANN training and vice-versa (Fig. 1).

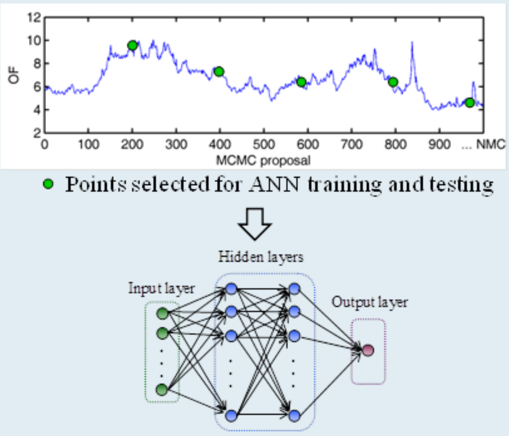

Figure 1: MCMC sampling and ANN training.

The general steps of the methodology are:

1) To sample an initial set of points from the prior distribution in order to train the first neural network. These initial samples are generated using Latin Hypercube sampling method. This generates the data set (for training and testing) for the first ANN set.

2) Using the Metropolis-Hastings MCMC algorithm, generate a chain of length n using the proxy output to compute the likelihood.

3) Select m models from the chain generated previously. The procedure consists of selecting a given number of equally spaced points from the Markov chain. The distance between two consecutive points depends on the size of the chain and depends on the number of desired points. In the sequence, the selected models are run using the reservoir simulator to compute the target output data used to retrain the ANN.

4) Retrain the ANN with the new points generated in Step 3. The topology defined in the first training is kept in the following iterations. In order to define the best ANN topology, an automatic procedure was developed for the first ANN training (details can be found in Maschio and Schiozer, 2014).

5) Repeat Steps 2, 3 and 4, which comprise one iteration of the method, until the stop criterion (the maximum number of iteration Niter) is reached.

6) Assessment of the results. The last Markov chain generated in the process is used to evaluate the results. The models after the burn-in period are utilized to build a cumulative probability curve of the corresponding OF values.

This curve is used to select n equally spaced percentiles between two chosen extreme values, for example, between P10 and P90. The models corresponding to the selected percentiles are submitted to the reservoir simulator and the simulation outputs are considered as the final result, assessed in terms of uncertainty reduction.

Application

The proposed procedure was applied to a realistic reservoir model, shown in Fig. 2. The reservoir model was discretized in a corner-point grid with 90×110×5 blocks, 60 m in size in the x and y directions (5400 x 6600 m^2) and 15 m (on the average) in the z direction and has 123 x 10^6 m^3 of oil in place. There are 16 uncertain attributes. Nine of them are porosity and permeability (Kx and Kz) multipliers in three facies. The other are four fault transmissibility multipliers and three exponent of relative permeability of water considering the Corey model. A combination of these

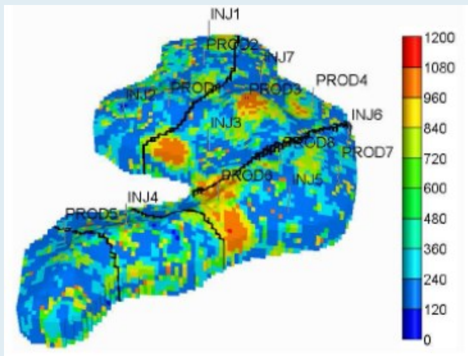

Figure 2: Permeability (mD) of the reservoir model studied (Maschio and Schiozer, 2014).

"The key idea of this work is to propose an iterative procedure for Bayesian history matching using Markov chain Monte Carlo and artificial neural network."

Specials interests:

- *UNISIM*
- *UNISIM Publications*
- *Reservoir Simulation and Management Portal*
- *Previous Issues*

Links:

- *UNICAMP*
- *Cepetro*
- *Petroleum Engineering Division*
- *School of Mechanical Engineering*
- *Petroleum Sciences and Engineering*

Graduate:

Petroleum Sciences and Engineering: interested in Masters and PhD in the Simulation and Oil Reservoir Management area click here.

"The proposed method allows a significant decrease in the computational effort, making feasible the treatment of the history matching as a probabilistic approach."

UNISIM opportunities:

If you are interested in working or developing research in the UNISIM Group, please contact us.
Immediate interest in:

- Researcher in the simulation area, management and reservoir characterization.

For further information, click here.

Research in Reservoir Simulation and Management Group

Petroleum Engineering Division - Energy Department
School Of Mechanical Engineering
Center for Petroleum Studies
University of Campinas
Campinas - SP

Phone: 55-19-3521-1220
Fax: 55-19-3289-4916

unisim@dep.fem.unicamp.br

attributes was used as reference model to generate synthetic history data for a period of 10 years.

Results

An example of the retraining result is shown in Fig. 3, which gives a cross plot for two consecutive iterations (1 and 2). The points represented by stars were used as test point in the first iteration. In the second iteration, these points were used to retrain the ANN and the circles shows the results improvement, in terms of correlation coefficient and MSE reduction. Fig. 3 shows that ANN is learning as new points are extracted from the current chain and presented in next training stage.

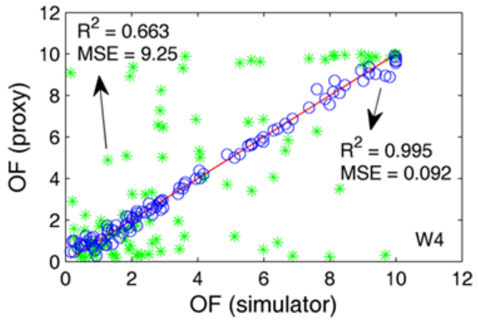

***Figure 3**: Cross plot for two consecutive iterations (green stars: Iteration 1; blue circles: Iteration 2)*

In order to test the accuracy of the ANN, a shorter chain (1000 samples) was generated using the flow simulator output to compute the OF values. The starting point, the proposal distribution and its corresponding scaling factor were the same used to generate the chains with ANN proxy model. The comparison of the results is shown in Fig. 4. The histogram shows that the frequency of the OF values corresponding to the chain generated in iteration 5 using the ANN proxy model is very similar to the frequency of the OF values computed using the reservoir simulator output. It can also be seen that the frequency corresponding to the first chain (iteration 1) is quite different from those generated using the reservoir simulator. This highlights the improvement from iteration 1 through 5.

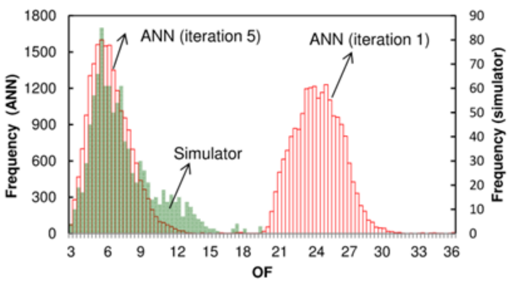

***Figure 4**: Comparative OF histograms from the iterations 1 and 5 (ANN) and from the reservoir simulator*

To assess the results in terms of uncertainty reduction in the production forecast, the set of models obtained from Step 6 were extrapolated 10 years after the end of history period. Figure 5 shows, for five wells, a box plot for cumulative water after 20 years of production.

More details about this work can be found in Maschio and Schiozer (2014).

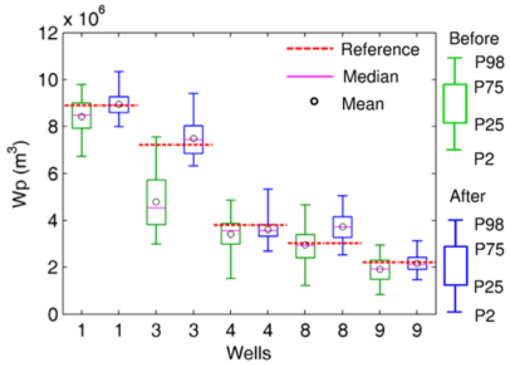

***Figure 5**: Box plot for cumulative water after 20 years of production comprising history (10 years) and forecasting (10 years) periods*

Final remarks

In this work, a new iterative procedure was developed for Bayesian history matching using artificial neural network in conjunction with MCMC method. The proposed method allows a significant decrease in the computational effort, making feasible the treatment of the history matching as a probabilistic approach. The incremental training process proposed allowed an increase on the ANN accuracy in the search space sampled by the Metropolis-Hastings algorithm, generating reliable results. The application of the method to a realistic synthetic case showed that the use of ANN adequately trained can make feasible the application of MCMC-based methods to the Bayesian history matching problem, allowing uncertainty reduction in prediction forecast under a probabilistic and consistent framework.

References

Maschio, C.; Schiozer, D.J. 2014. "Bayesian History Matching using Artificial Neural Network and Markov Chain Monte Carlo", Journal of Petroleum Science and Engineering, v. 123, p. 62-71.
http://dx.doi.org/10.1016/j.petrol.2014.05.016

About author:

Célio Maschio graduated in mechanical engineering from Unesp, obtained a MSc and a DSc degree in mechanical engineering from Unicamp and is a researcher at UNISIM.

For further information, please visit
http://www.unisim.cepetro.unicamp.br

The UNISIM Research Group is part of UNICAMP (Petroleum Engineering Division, Energy Department, School of Mechanical Engineering, Center for Petroleum Studies) that aims to develop Works and projects in the simulation and reservoir management area.