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A hybrid differential evolution algorithm approach towards assisted history matching and uncertainty quantification for reservoir models

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ABSTRACT

History matching is an important process in the reservoir model development. In the process of history matching, the most significant uncertain model parameters are identified and adjusted to get an acceptable match between the simulated production with the historical field production data. In the past decade, many population based algorithms have been applied for history matching. In this paper, a novel population based stochastic algorithm called hybrid differential evolution (HDE) is applied for the assisted history matching process. An adaptive mechanism for the control parameters is incorporated in the algorithm which automatically adjusts the control parameters according to the problem. The performance of the algorithm is tested on a 3-D reservoir model called PUNQ-S3 which is a benchmark model for the comparison of different history matching and uncertainty quantification techniques. Since history matching is an inverse problem, multiple models can give good match. So, prediction using a single history matched model involves more risk because of the parameter uncertainty. One of the methods to solve this problem is to quantify the uncertainty in the predictions. In this paper, the neighbourhood approximation Bayes (NAB) algorithm is applied to quantify the uncertainty in reservoir forecast which is a Bayesian extension of neighbourhood algorithm. The NAB algorithm quantifies the uncertainty in the predictions using multiple models generated during history matching phase and this does not require additional simulations. The main focus of this paper is to study about how HDE algorithm can be used when coupling with the NAB algorithm in predicting the true forecast with minimum uncertainty range under limited number of simulations. The influence of population size on the performance of the algorithm in history matching and forecast is analyzed. The HDE provides wide sampling of the search space and the truth case was comfortably included within the predicted confidence bounds. The results show that HDE can be used as a promising tool for assisted history matching of the reservoir models.

1. Introduction

In modern oilfield practices, reservoir simulation plays an important role because of its ability to predict the performance of the reservoir and helps to prepare optimal oilfield development plans. A good knowledge about the reservoir is required to build an effective reservoir model which can mimic the real reservoir. The petroleum reservoirs are usually geologically complex and highly heterogeneous in nature. Our knowledge about the underground reservoir is limited due to the sparse and low resolution data obtained from seismic and other well-log and well-testing methods. This leads to uncertainties in the value of parameters used in the reservoir model. In modern reservoir engineering practices, once the reservoir model is developed with the available data, it has to get validated before using it for the prediction of reservoir fluid flows and other reservoir properties. This can be done by comparing the simulation results with the oilfield production history. In history matching, the reservoir model is conditioned to the historical observations from the field such as oil production rate, water cut, bottom-hole pressure, etc.

The process of history matching in reservoir modeling started almost six decades ago. In early days, the history matching started as a manual method in which the user manually adjusts the parameters until a good match between the reservoir predictions and the actual production profiles is found (Sheldon et al., 1960; Jacquard, 1965). However, this is very time consuming and intuition-based process which may not always provide a global solution. In 1972, there came one of the first attempts of automatic history matching (Thomas et al., 1972). The authors considered the history matching problem as an optimal control problem.

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Following this, several authors have tried different optimization techniques for history matching. The main methods include gradient based methods, Monte Carlo methods, ensemble Kalman filter, etc. Gradients based methods showed less performance in history matching because of their tendency to get trapped in local minima. In stochastic methods, many authors have tried different algorithms like simulated annealing (SA) (Sultan et al., 1994), neighbourhood algorithm (NA) (Subbey et al., 2003), genetic algorithms (GA) (Castellini et al., 2005; Sangwai et al., 2007), scatter search (SS) (Sousa et al., 2006; Erbas and Christie, 2007), Markov chain Monte Carlo (McMC) (Maucec et al., 2007), particle swarm optimization (PSO) (Mohamed et al., 2009), ant colony optimization (Hajizadeh et al., 2011), differential evolution (DE) (Hajizadeh et al., 2010). It is observed that the differential evolution algorithm has shown good results for the history matching but the performance of the algorithm was very much sensitive to the value of control parameters such as crossover rate.

In this work, a hybrid differential evolution (HDE) (Reynoso-Meza et al., 2011) algorithm is being introduced for the history matching problem in which the algorithm itself adapts the best value for the control parameter according to the type of the problem. Since the history matching is an inverse problem, multiple models may show good match with the oilfield data. So, planning reservoir development decisions based on a single reservoir model carries more risk. This can be solved by taking information from multiple history matched models. The uncertainty in the predictions can be quantified from the posterior probability distribution of the models. In this paper, hybrid differential evolution algorithm is applied to the history matching of a 3-D petroleum reservoir called PUNQ-S3 which is a benchmark model for the comparison of different history matching and uncertainty quantification techniques. The uncertainty in the oil production forecast is quantified using neighbourhood approximation Bayes (NAB) algorithm (Sambridge, 1999a, 1999b) which is Bayesian extension of neighbourhood algorithm. The approach taken in this work for assisted history matching and uncertainty quantification using HDE algorithm and NAB routine is shown in Fig. 1. The data collected through several field tests and measurements gives us some idea about the reservoir. It helps us to get information about the initial ranges of uncertain parameters. With this, the history matching loop is initiated in which the misfit between the simulated production data and field production data is minimized using the hybrid differential evolution (HDE). The history matching loop will continue until the termination criteria are met which is either an acceptable misfit or maximum number of simulations. This step will generate an ensemble of history matched models. This ensemble of models is submitted to the inference step. The uncertainty in reservoir predictions is quantified from the posterior probability distributions of the models calculated using NAB algorithm.

2. Theory and methodology

2.1. Differential evolution

Recently, differential evolution has gained much importance because of its efficacy in solving real parameter optimization problems (Das and Suganthan, 2010). It is a powerful population based stochastic optimization algorithm with three operators which are:

2.1.1. Mutation

In differential mutation, the difference between two vectors is multiplied by a constant which is called scaling factor and this is added to a third vector in the population. This will produce a new mutant vector which makes some perturbation in the models in each generation. Based on the selection of vectors for mutation makes different variants for DE.

$$m_i^G = p_1^G + \mathrm{F} \times \left(p_2^G - p_3^G\right) \tag{1}$$

where, m_i^G is the mutant vector generated, p is the parent vector in the generation G. F is called the scaling factor and is always positive and ranges between 0 and 2. The magnitude of the

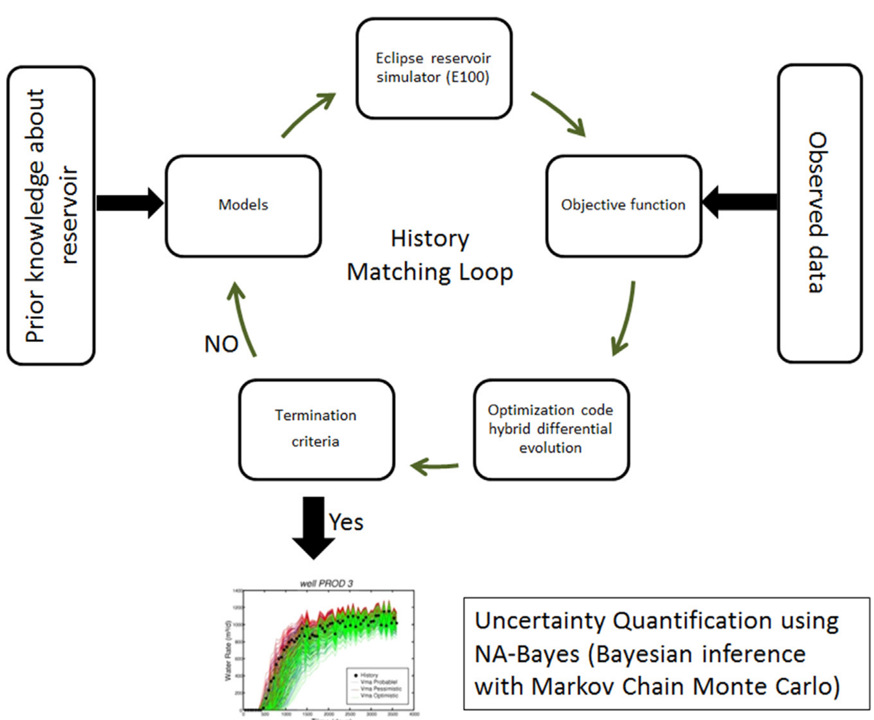

Fig. 1. Approach taken for history matching and uncertainty quantification.