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Improved application of assisted history matching techniques

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ABSTRACT

In assisted history matching the calibration of a reservoir model is approached as an optimization process, i.e. defining a cost function representative of the discrepancy between measured (real) and simulated data, and in minimizing the cost function. This can be achieved by applying a suitable optimization algorithm. Over the last decade, the scientific community has taken a great leap forward in the automation of the history matching process to calibrate dynamic reservoir models. Even if the proposed algorithms have proven to be very efficient when applied to specific synthetic cases, most of them have failed — or have been only partially successful — when dealing with real, complex reservoirs. Yet, they have the potential to be reliable and efficient tools to better explore the parameter space and to speed up the convergence to one or more solutions, i.e. to calibrated models. So far no optimization methodology has truly outperformed the others. In this paper some crucial points regarding assisted history matching are discussed and some significant improvements are introduced. Advances of the optimization techniques based on multi-objective function and heuristic strategies for the efficient calibration of complex reservoir models were implemented. A social-assisted approach was developed in multi-objective optimization and the enhanced ability to efficiently steer the history matching process was demonstrated. Furthermore, the suitability of two strategies of data assimilation to reservoir history matching, the Ensemble Kalman Filter (EnKF) and Adaptive Gaussian Mixture (AGM) without particle resampling, were tested. An improved sampling algorithm was also adopted to increase the effectiveness of the EnKF solution. The results shown by the reported examples prove the validity of introducing the random generation of the initial ensemble and the benefit of using an improved sampling algorithm.

1. Introduction

History matching is a calibration process in which the uncertain parameters of a reservoir numerical model are iteratively adjusted in order to obtain an acceptable match between simulated and historically measured production data. However, the calibration of a reservoir model suffers from non-uniqueness, as history matching is an ill-posed inverse problem due to the insufficient constraints and data; thus several combinations of parameters might exist in order to satisfactorily match the past dynamic behavior of the system. In assisted history matching (AHM) the simulated dynamic data is compared to the historical data by means of a misfit function. Algorithms try to minimize the misfit function in order to obtain the model that best approximates the data recorded during the reservoir life. This procedure can be translated into an optimization problem in which the misfit function is an objective function and the optimization problem is bound by the model constraints. Even though the main objectives of AHM are clear, the different methods used to carry out the minimization task can differ considerably.[1] Some of the currently available methods have been inherited from other scientific disciplines, others have been constructed *ad-hoc* for the reservoir engineering problems; however, the lack of robustness is a common issue. Different algorithms for different kinds of reservoir models are required and the selection of the most adequate optimization algorithm among those available in the technical literature is not trivial. Furthermore, the number of independent variables involved in complex reservoir simulation does not make the solution of the optimization problem a standard procedure. As a consequence, there is no clear winner among the optimization methodologies. Nevertheless, they constitute reliable and efficient tools to better explore the parameter space and to speed up the convergence to one or more solutions, i.e. to calibrated models.

2. AHM optimization strategies

In recent years, several methodologies and techniques have been studied for the optimization problems related to AHM (Gomez et al., 2001; Schulze-Riegert et al., 2001; Schaff et al., 2008). They can be roughly divided into local and global algorithms. Local algorithms, also known as gradient based algorithms, were one of the first optimization tools adopted to tackle the history matching problem and have the advantage of converging faster to a minimum than global algorithms. They provide a single

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[1] A paper from Oliver and Chen (2010) can be consulted for a more technical description of these algorithms.

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Nomenclature

ϕ	porosity
k	effective permeability [m^2]
k_{abs}	absolute permeability [m^2]
k_r	relative permeability
Sw	water saturation
V	volume [m^3]
$y_k{}^t$	true model state vector
$WBHP$	well bottom hole pressure [Pa]
$WOPR$	well oil production rate [m^3/day]
$WGOR$	gas–oil ratio
$WWCT$	water cut
OF	objective function
h	bandwidth parameter

Subscripts

w	well
nd	nondominated
lk	liked
ar	archive
nd	nondominated

solution which is the nearest local optimum to the initial guess (Landa et al., 2005). However, multidimensional, nonlinear optimization problems often contain multiple local minima in which gradient based algorithms tend to get stuck. The use of global optimization algorithms, such as evolutionary algorithms or sequential data assimilation algorithms like the Kalman Filter, opened new horizons in assisted history matching. In fact, they provide multiple solutions in a single run and can escape from local minima efficiently.

2.1. Evolutionary algorithms and Strength Pareto Evolutionary Algorithm

Evolutionary algorithms (EA) are meta-heuristic optimization algorithms known to be highly effective search techniques (Schulze-Riegert et al., 2001). They can deal efficiently with models parameterized using discrete parameters and also with highly non-Gaussian distributions. Because they are a direct method, they can be easily adapted to different simulators. As suggested by their name, they are based on the theory of the evolution and behavior of living species. Conceptually, an individual consists of a genome or chromosome, i.e. a number of genes that altogether encode a solution to an optimization problem. The encoding, binary or real-valued, is the internal representation of the problem. The algorithm describes the evolution of a population of individuals in an iterative process in which offspring are created by mutation and/or recombination of the genetic codes of two or more parents and selected on the basis of a fitness function. The "optimal" size of a population is problem-dependent (Ferraro and Verga, 2009). The general scope of EA is to obtain several optimal solutions, which represent the fittest individuals, after a given number of iterations.

The objective or misfit function can be expressed as a single-objective function or as a multi-objective function. Traditionally, the single-objective functions have been the most used but they require the user to specify the weights associated to each matching set. However, in real hydrocarbon reservoirs, characterized by a large number of wells, strong heterogeneities, uncertainties on historical data, complex geometries, etc., the behavior of the parameters recorded at each well (such as gas and water rates, well pressure, etc.) can be strongly uncorrelated, making it difficult to obtain the right set of weighting parameters. Furthermore, in several cases different choices of the weighting parameters can lead to different matches that are equally acceptable. In multi-objective optimization the weighting problem is avoided by splitting the misfit function into several functions which are optimized simultaneously. Since different objectives are not comparable, the concept of optimality is substituted by the *Pareto optimality*. A vector of decision variables $x^* \in \Im$ is *Pareto optimal* if another $x^* \in \Im$ does not exist such that $f_i(x) \leq f_i(x^*)$ for all $I=1,\ldots,k$ and $f_j(x) \leq f_j(x^*)$ for at least one j. Usually, this concept of optimality has a set of possible solutions called the *Pareto-optimal set* or *Pareto front* (Fig. 1). The vectors x^* corresponding to the solutions included in the Pareto-optimal set are called *non-dominated* (Zitzler, 1999).

The modified Strength Pareto Evolutionary Algorithm (SPEA2) (Zitzler et al., 2001) is one of the most important multi-objective evolutionary algorithms. The objective of the algorithm is to locate and maintain a front of non-dominated solutions, ideally a set of Pareto optimal solutions. This is achieved by exploring the search space with an evolutionary process in which selection is based on a fitness criterion combining the degree to which a candidate solution is dominated (strength) and the estimation of the density of the Pareto front.

An archive of the non-dominated set is maintained separate from the population of candidate solutions used in the evolutionary process, providing a form of elitism. Eventually, in order to preserve diversity SPEA2 applies a truncation procedure that depends on the minimum distance among non-dominated individuals.

In the following an innovative socially-assisted approach of the SPEA2, in which a "social contribution" was added to the objective function, was considered. In practice the user can interact with the optimization process by expressing their preference for a candidate solution. This improves the objective function for that specific individual, thus increasing the possibilities of that individual to participate to the mating process. As a consequence, the exploration of the solution space in the vicinity of the chosen solution is favored.

2.2. Data assimilation and Ensemble Kalman Filter

The convergence rate of EA can be slow and there can be a severe loss of efficiency when dealing with a large number of parameters. In fact, heuristic methods require a large number of evaluations of the misfit function. In history matching these evaluations are represented by simulation runs; thus, for numerical models with a large number of grid cells, the computational cost of heuristic methods can be prohibitive. To overcome this limitation researchers have shown great interest for the Kalman Filter (KF) algorithm and its modifications, which are often used in other scientific fields like ocean prediction systems (Evensen, 2009). This technique is classified as a sequential data assimilation method, i.e. a process which aims at estimating and predicting (analysis step) an unknown true state of the system y_k^t by integrating the forward model (system dynamics) F in time (k) and using measurements, whenever available, to initialize the model before integration. The model equation can be written as

$$y_k^t = F(y_{k-1}^t) + q_{k-1}$$