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Analysis of the performance of ensemble-based assimilation of production and seismic data

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ABSTRACT

Ensemble-based methods have gained popularity as reservoir history-matching techniques. The advantages typically attributed to these methods include the possibility of adjusting a large number of model parameters at a reasonable computational cost, the generation of several alternative models conditioned to data and the ease of implementation. In fact, it is straightforward to adapt these methods to handle different types of data and model variables. Moreover, they are easily coupled with commercial reservoir simulators. Among these methods, the ensemble Kalman filter (EnKF) is by far the most investigated. Iterative forms of the ensemble smoother (ES), on the other hand, are less widespread in the literature. However, ensemble smoothers are much better suited to practical history-matching applications, because they do not require updating dynamical (state) variables and consequently avoid the frequent simulation restarts required by EnKF. This paper presents the results of an investigation on the performance of a variant of ES, namely, ensemble smoother with multiple data assimilation (ES-MDA), to history match production and seismic data of a real field. The paper discusses the quality of the data matches, the plausibility of the history matched models, the ability of the posterior ensemble to assess the uncertainty in the forecasted water production, the effect of the number of iterations and localization. The paper also includes two appendix sections. The first one presents two alternative implementations of the ES-MDA method. The second appendix presents the matrix operations for an efficient implementation of the analysis.

1. Introduction

In the data assimilation literature, the term “ensemble-based methods” is used to refer to a class of Monte Carlo implementations of methods inspired in the Kalman filter (KF) (Kalman, 1960). Among these methods, the ensemble Kalman filter (EnKF) is the most popular. Since its introduction by Evensen (1994), the number of publications about EnKF became quite extensive. EnKF has been successfully applied in several areas including oceanography (Bertino et al., 2003), atmospheric modeling (Whitaker et al., 2008), weather prediction (Houtekamer and Mitchell, 2005) and hydrology (Reichle et al., 2002). The first application for reservoir history matching was presented by Nævdal et al. (2002). Aanonsen et al. (2009) present a review of the main developments and applications of EnKF in history-matching problems from 2002 to early 2009.

However, the sequential assimilation scheme of EnKF creates some inconveniences when applied to practical history-matching problems. The reservoir simulation restarts required by EnKF increase significantly the computational cost of the data assimilation. This fact is particularly evident when simulations are distributed in a cluster of computers. Moreover, there may be inconsistency between updated model parameters and updated states (Thulin et al., 2007), which deteriorates the performance of the data matches and introduces convergence problems in the reservoir simulations. One alternative to EnKF is the ensemble smoother (ES) (van Leeuwen and Evensen, 1996; Skjervheim et al., 2011). In ES, all data are assimilated simultaneously in a single update. Therefore, there is no need for simulation restarts, which makes ES more attractive for practical history-matching applications. Unfortunately, the single update scheme of ES seems not to be sufficient to properly condition reservoir models to dynamic data (Chen and Oliver, 2012; Emerick and Reynolds, 2013b,c). This fact motivated the development of iterative forms of ES (Chen and Oliver, 2012, 2013; Emerick and Reynolds, 2013b).

In the reservoir history-matching literature, there is a current trend of integrating different parts of the reservoir modeling process (e.g., seismic, structural, geological modeling and flow simulation) in a single workflow (Zachariassen et al., 2011). This

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kind of workflow is sometimes called "the big-loop approach." The big-loop approach requires the integration of different geomodeling softwares and it may include upscaling of the rock properties. Therefore, the use of sequential data assimilation becomes very inconvenient and time consuming, making iterative smoothers much more suitable alternatives.

Nowadays, the number of publications about ensemble-based methods applied to reservoir history matching is quite extensive. In most of these publications, EnKF is tested against synthetic reservoir problems. The number of publications with field applications is much more restricted, although it is continuously growing. Some examples of field applications of ensemble-based methods for history matching can be found in Skjervheim et al. (2007), Bianco et al. (2007), Evensen et al. (2007), Haugen et al. (2008), Cominelli et al. (2009), Zhang and Oliver (2011), Emerick and Reynolds (2011a, 2013c), and Chen and Oliver (2014)). Despite the aforementioned advantages of ES over EnKF for history matching, the number of publications with ensemble smoothers is still limited. One of the reasons is the fact that iterative smoothers are relatively new in the literature and not well-known. In this sense, one of the goals of the presented paper is to fill this gap.

This paper presents an evaluation of the performance of a variant of ES, namely, ensemble smoother with multiple data assimilation (ES-MDA) (Emerick and Reynolds, 2013b), to history match production and seismic data in a real reservoir problem. The paper is organized as follows: the next section presents the general formulation of ensemble-based methods with particular attention to ES-MDA, where it presents a derivation based directly on Bayes' rule. The section after that describes the field case followed by a section presenting the results of assimilation of production data. In this section, some aspects of the data assimilation are analyzed, including the quality of the data match, model plausibility, ability to evaluate the uncertainty in water production forecasts, the effect of the number of iterations and localization. The section after that presents the results of assimilation of seismic data (3D and 4D) in conjunction with production data. In this section, the ability of ES-MDA to assimilate a large amount of data is investigated. The last section of the paper presents the conclusions. The paper also includes two appendix sections. The first one presents two alternative algorithms for ES-MDA. The first algorithm corresponds to the standard ES-MDA, in which the number of data assimilations and inflation coefficients are selected in advance. In the second algorithm, the number of data assimilations and inflation coefficients are automatically selected in accordance with the evolution of the data-mismatch objective function. The second appendix describes the matrix operations for an efficient implementation of the ES analysis in case of assimilation of large number of measurements.

2. Ensemble-based methods

In the ensemble-based methods, an ensemble of states is used to approximate the first two moments of the distribution. Here, the term "states" refers to the unknown model properties of interest in the data assimilation. However, in the history-matching literature it is usual to make a distinction between model parameters and states. The term "model parameter" is used to refer to a reservoir rock property such as porosity or permeability. "State," on the other hand, is used to refer to a dynamic variable, such as pressure or fluid saturation. This distinction is particularly important to emphasize the difference between filter and smoother. In the filter, data are assimilated sequentially in time. Therefore, it is necessary to update both parameters and states, so reservoir simulations can be restarted from the current time step. In the smoother, however, because all data are assimilated simultaneously, there is no need to update state variables. This fact makes the smoothers very similar to the traditional "assisted history-matching methods" present in the reservoir literature (Oliver et al., 2008).

Table 1
Prior distributions of water relative permeability parameters and the natural logarithm of fault transmissibilities, $\ln(x)$.

Parameter	Distribution	Mean	Standard deviation
$k_{rw,max}$	Normal	0.25	0.03
e_w	Normal	2.30	0.50
$\ln(x)$	Normal	−2.30	1.0

Table 2
Measurement errors adopted for observed production data.

Data	Measurement error
Oil production rate	10% of the data value (minimum of 1 m^3/d)
Water production rate	15% of the data value (minimum of 1 m^3/d)
Gas–oil ratio	20% of data the value (minimum of 10 m^3/m^3)
Bottom-hole pressure	500 kPa

There is a clear connection between ensemble-based methods and Bayesian statistics. In fact, the KF can be derived from Bayes' rule with the assumptions that the prior model follows a Gaussian distribution, measurement and model errors are additive also following Gaussian distributions and the relationship between model and predicted data is linear (Evensen, 2007). In this sense, the initial ensemble corresponds to samples of the prior distribution. Then, these samples are updated to incorporate the measurements. Ideally the updated samples will be closely distributed according to the posterior distribution. It is possible to prove that the updated ensemble samples asymptotically correct the posterior distribution for the linear-Gaussian case as the size of the ensemble goes to infinity. For nonlinear problems, such as history matching, there is no guarantee that ensemble-based methods sample the posterior PDF adequately. Actually, it is relatively easy to find synthetic test problems in which these methods provide very poor sampling. This is particularly evident in heavily skewed and multimodal distributions. Nevertheless, there are also computational evidence that ensemble-based methods can obtain "acceptable" sampling in reservoir problems. For example, in Emerick and Reynolds (2013a), the ES-MDA method was able to approximate the results of a rigorous MCMC sampling for a very simple, but highly nonlinear reservoir problem. Unfortunately, rigourous methods such as MCMC and rejection sampling are computationally too demanding for large-scale field applications, except if one uses a proxy to approximate the reservoir response (Emerick and Reynolds, 2012b) or parameterize the problem in terms of very few uncertainty variables (Ma et al., 2008). In both cases, however, it is no longer possible to guarantee the correct sampling. On the other hand, reservoir engineers face everyday the problem of forecasting production in their fields and providing uncertainty ranges for these forecasts, so they can manage risk. Therefore, less computationally demanding approximate solutions, such as ensemble-based data assimilation, are very important in practice.

In the data assimilation literature, the process of updating model parameters and state variables is typically referred to as analysis. The analysis for EnKF and ES is almost identical. In the following, the analysis equation is presented in terms only of a vector of models parameters, $\mathbf{m}$, which is the case for ES. In ES, the jth forecasted vector $\mathbf{m}_j^f$ is updated using