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An efficient optimization process for hydrocarbon production in presence of geological uncertainty using a clustering method: A case study on Brugge field

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ABSTRACT

We present the main steps of a production optimization process in presence of geological uncertainty. The geological model is the main source of uncertainty in hydrocarbon reservoir simulation which can reduce viability of the simulation results to be utilized in a production optimization process. Optimization of the expected net present value (NPV) based on evaluations of all probable geological realizations require prohibitive computation time. In this paper, we use a clustering method named Kernel K-means Method (KKM) to select a representative subset of geological models. The suggested method has been examined on the benchmark model of Brugge field. The clustering method selected 9 out of 40 realizations tuned in a previous history matching study. The statistics derived from NPV calculations in the selected realizations demonstrate a good match with those of all 40 realizations.

A Reduced Order Modelling (ROM) coupled with a physically based optimization method named Guided Pattern Search (GPS) has been extended to take geological uncertainties into account. Four different optimization processes based on a full order or a reduced order simulation coupled with a GPS or a conventional pattern search (PS) algorithm have been carried out using the selected realizations. The best NPV results were obtained by execution of GPS on a full order simulation model. ROM led to reduction of the simulation time by a factor of eight which would make the optimization process tractable but caused some inaccuracy in the NPV evaluations. The combination of GPS and ROM resulted in an acceptable trade-off between NPV maximization and run time reduction.

1. Introduction

Production optimizing in an oil and gas field involves theoretical and computational challenges due to inherent uncertainties of this problem. The data obtained from local measurements (well log, coring, well test, seismic operation, etc.) give us little information about the geological structure of a hydrocarbon reservoir. Such lack of knowledge may be compensated by generating numerous probable geological models with different properties using geostatistical simulation. The aim of generating numerous geological realizations is to investigate the impacts of such uncertainties on some output functions of a reservoir dynamic model such as cumulative oil production or net present value (NPV).

Geological uncertainty is an important source of risk which can undermine the feasibility of production scenarios suggested by a production optimization process. There exist two main approaches in the literature for considering geological uncertainty in production optimization. The first method is to reduce the uncertainty by performing extra measurements and using them to update a reservoir model. Naevdal et al. applied a closed-loop control approach based on optimal control for water flood optimization and ensemble Kalman filter for updating their reservoir model (Naevdal et al., 2006). A similar approach was applied by Sarma et al (Sarma et al., 2005). where they used Karhunen-Loeve expansion for model parameterization and a Bayesian inversion for history matching. Wang et al. used ensemble Kalman filter for history matching and model updating (Wang and Reynolds, 2007).

Another approach to deal with geological uncertainty is to reduce the sensitivity of the objective function by performing an

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optimization process over multiple realizations. This problem in petroleum community has been considered by selecting a finite number of N_r realizations and modeling the objective function as below (Bouzarkouna et al., 2012):

$$f(x) = \frac{1}{N_r}\sum_{i=1}^{N_r} f(x, R_i)$$

In this relation $f(x,R_i)$ is the measurable fitness value depends on decision variables x and uncertain parameters R_i. Van Essen et al. (2006) expanded the work of Brouwer and Jansen (2004) and used an objective function in terms of the expected value of NPV obtained from multiple realizations. Most of the studies in the literature perform N_r simulation for every objective function evaluation. Schulze-Riegert et al. (2010), Onwunalu and Durlofsky (2010) defined objective function as the expected value of the NPV over all the realizations. Chen solved the problem using EnOpt applied to the ensemble of geological models updated by ensemble Kalman filter (Chen, 2008). Yeten et al. (2003) and Aitokhuehi et al. (2004) used multiple geostatistical realizations in the objective function formulated as below:

$$f(x) = \frac{1}{N_r}\sum_{i=1}^{N_r} f(x,\ R_i) + r\sigma$$

where r is the risk factor and σ is the standard deviation of f on R_i. Alhuthali et al. (2008) suggested an optimization method based on equalizing arrival time of the waterfront at all production wells for maximizing sweep efficiency. They deal with geologic uncertainty by employing two frameworks. The first is a stochastic framework that relies on the expected value and variance estimated from multiple realizations. The other approach consists of a min-max formulation that optimizes the worst case scenario (Alhuthali et al., 2008). Applying multiple geological realizations makes an optimization process more challenging. It leads to a large number of reservoir simulations to be performed at all geological realizations for each NPV evaluation.

We present the main steps of a production optimization process in presence of geological uncertainty. The main steps of this process are:

1) Selection of representative geological realizations
2) Using a Reduced Order Model (ROM) to substitute a full order reservoir simulation model
3) Devising a physically-based optimization algorithm, named herein as Guided Pattern Search (GPS)

Our focus in this research is to apply a clustering method in order to select a small representative subset of all geological realizations to be used for production optimization. This step requires fewer numerical reservoir simulations while still covering the impact of geological uncertainties on the desired objective function (e.g., NPV). As we mentioned earlier the effect of geological uncertainties will be considered in optimization process by using the expected value of objective function computed in various geological realizations. Here, the selected representative geological realizations have been used to calculate expected value of NPV in optimization problem. It leads to fewer simulation runs in comparison to the case that all realizations are going to be utilized to obtain the average NPV.

The problem investigated here is the optimization of well controls in a producing oil field under water flooding. The well controls include both injection and production flow rates and the objective function is to maximize discounted NPV.

Besides the earth model selection, we also consider the use of previously developed ROM and a GPS algorithm for production optimization in presence of uncertainty (Foroud et al., 2016). Applying a ROM technique based on Discrete Empirical Interpolation Method (DEIM) coupled with an Artificial Neural Network (ANN) will provide significant reduction in optimization run time by decreasing computational efforts involved in reservoir simulation. On the other hand, GPS is intended to decrease the number of function evaluations in the optimization process using physical properties of the reservoir.

In the next section, the application of Kernel K-mean method in geological model selection will be introduced. Then, after a brief explanation about ROM and GPS methods, we explain how these techniques are extended to make them applicable in presence of uncertainty in Sections 3 and 4. Numerical results of applying the suggested optimization process to a case study on Brugge filed will be presented and discussed in Section 5. Finally, Section 6 provides some conclusions of this research.

2. Clustering and earth model selection

Due to the large computation time, it is not possible to run numerical flow simulators to evaluate all generated geological realizations in oil production optimization. To overcome this difficulty, a technique to identify the subset of realizations will be employed here which depends on flow simulation outputs. This method was proposed by Scheidt and Caers (2007). It is based on the definition of a dissimilarity distance between the realizations, which indicates how similar two realizations are in terms of their dynamic outputs. Using the distance to select a few representative realizations, the objective function can be evaluated by only performing a small number of simulations.

The general process of this method is summarized in Fig. 1. A dissimilarity distance matrix is constructed based on dynamic simulation outputs of multiple geological realizations. This matrix describes similarity between any two reservoir models in terms of flow behavior.

The next step is mapping all realizations into a Euclidean space using multidimensional scaling (MDS) technique. MDS takes the dissimilarity matrix and return a configuration matrix of points in n-dimensional Euclidean space (Borg and Groenen, 1997). MDS maps each point in a way that their Euclidean distances correspond as much as possible to the dissimilarity distance of the realizations.

Clustering tools allow the selection of a few representative reservoir models that have different flow behavior, among a potentially very large set. These algorithms assume that the structure of the points in Euclidian space is linear. Since it is not the case in most situations, we use kernel methods to transform the Euclidean space into a new feature space. The goal of the kernel transform is to make the relationship between the points in this new space more linearly (Schöelkopf and Smola, 2002). In this way the standard linear pattern detection techniques can be used more successfully.

After applying the kernel transform, the k-means clustering algorithm can be employed in the feature space, which is also called kernel k-means (KKM) method. Each cluster contains similar realizations in terms of flow response and the cluster centroids will constitute the desired subset of realizations.

3. Reduced order modeling considering model uncertainty

An ROM is intended to represent the dynamic behavior of a numerical simulator with a smaller and cheaper computation. ROM can reduce Computational cost of optimization in the presence of uncertainty. Proper Orthogonal Decomposition (POD) is a