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Value of information in parameter identification and optimization of hydrocarbon reservoirs

E.G.D. Barros*, J.D. Jansen*, P.M.J. Van den Hof**

*Delft University of Technology, Stevinweg 1, 2628 CN Delft, The Netherlands (e-mail: e.barros@tudelft.nl).
**Eindhoven University of Technology, Den Dolech 2, 5612 AZ Eindhoven, The Netherlands.

Abstract: This paper describes a recently introduced methodology to perform value of information (VOI) analysis within a closed-loop reservoir management (CLRM) framework, and adds a first step to improve the computational efficiency of the procedure. CLRM is a combination of model-based optimization and model-parameter identification applied to large-scale models of subsurface hydrocarbon reservoirs. The approach is illustrated with a simple two-dimensional model of an oil reservoir produced with water injection. The results are compared with previous work on other measures of information valuation. We show that our method is a more complete, although also more computationally intensive, approach to VOI analysis in a CLRM framework. We recommend it to be used as the reference for the development of more practical and less computationally demanding tools for VOI assessment in real fields.

Keywords: value of information, value of clairvoyance, decision making, uncertainty, closed-loop control, model-based optimization, EnKF, parameter estimation, reservoir management, well production data.

1. INTRODUCTION

Over the past decades, numerical techniques for model-based optimization and 'history matching' (i.e. parameter identification) of subsurface hydrocarbon reservoirs have developed rapidly, while it also has become possible to obtain increasingly detailed reservoir information by deploying different types of well-based sensors and field-wide sensing methods. Many of these technologies come at significant costs, and an assessment of the associated value of information (VOI) becomes therefore increasingly important. In particular assessing the value of future measurements during the field development planning (FDP) phase of an oil field requires techniques to quantify the VOI under geological uncertainty. An additional complexity arises when it is attempted to quantify the VOI for closed-loop reservoir management (CLRM), i.e., under the assumption that frequent life-cycle optimization will be performed using frequently updated reservoir models. Recently we introduced a new methodology to assess the VOI in a such a CLRM context (Barros et al, 2014). Here we repeat the description, and, in addition, propose a modification to improve the computational efficiency of the procedure.

In the Background section we introduce the most relevant concepts and review some previous work on information measures. Next, in the Methodology section, we present the proposed workflow for VOI analysis and thereafter, in the Examples section, we illustrate it with some case studies in which the results of the VOI calculations are analyzed. Finally, in the Discussion and conclusion section, we address the computational aspects of applying this workflow to real field cases, and we suggest a direction for further research.

2. BACKGROUND

2.1 Closed-loop reservoir management

CLRM is a combination of frequent life-cycle production optimization and parameter identification (also known as 'data assimilation' or 'computer-assisted history matching'). Life-cycle optimization aims at maximizing a financial measure, typically net present value (NPV), over the producing life of the reservoir by optimizing the production strategy. This may involve well location optimization, or, in a more restricted setting, optimization of well rates and pressures for a given configuration of wells, on the basis of one or more numerical reservoir models. History matching involves modifying the parameters of one or more reservoir models, or the underlying geological models, with the aim to improve their predictive capacity, using measured data from a potentially wide variety of sources such as production data or time-lapse seismics. For further information on CLRM see, e.g., Jansen et al. (2005, 2008, 2009), Naevdal et al. (2006), Sarma et al. (2008); Chen et al. (2009) and Wang et al. (2009).

2.2 Robust optimization

An efficient model-based optimization algorithm is one of the required elements for CLRM. Because of the inherent uncertainty in the geological characterization of the subsurface, a non-deterministic approach is necessary. Robust life-cycle optimization uses one or more ensembles of geological realizations (reservoir models) to account for uncertainties and to determine the production strategy that maximizes a given objective function over the ensemble; see, e.g., Yeten et al. (2003) or Van Essen et al (2009). The objective function J_{NPV} is defined as

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$$J_{NPV} = \mu_{NPV} - \lambda \sigma_{NPV}, \tag{1}$$

where μ_{NPV} and σ_{NPV} are the ensemble mean (expected value) and the ensemble standard deviation of the objective function values J_i of the individual realizations:

$$\mu_{NPV} = \frac{1}{N}\sum_{i=1}^{N} J_i, \tag{2}$$

$$\sigma_{NPV} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(J_i - \mu_{NPV}\right)^2}. \tag{3}$$

The symbol λ in equation (1) is a risk attitude parameter to represent risk-averse or risk-prone decision strategies with positive or negative values respectively. The objective function J_i, for a single realization i is defined as

$$J_i = \int_{t=0}^{T} \frac{q_o(t,\mathbf{m}_i)\, r_o - q_{wp}(t,\mathbf{m}_i)\, r_{wp} - q_{wi}(t,\mathbf{m}_i)\, r_{wi}}{(1+b)^{t/\tau}}\, dt, \tag{4}$$

where $\mathbf{m}_i$ is a realization of the vector of uncertain model parameters (e.g. grid block permeabilities or fault multipliers), t is time, T is the producing life of the reservoir, q_o is the oil production rate, q_{wp} is the water production rate, q_{wi} is the water injection rate, r_o is the price of oil produced, r_{wp} is the cost of water produced, r_{wi} is the cost of water injected, b is the discount factor expressed as a fraction per year, and τ is the reference time for discounting (typically one year). The outcome of the optimization procedure is a vector $\mathbf{u}$ containing the settings of the control variables over the producing life of the reservoir. Note that, although the optimization is based on N models, only a single strategy $\mathbf{u}$ is obtained. Typical elements of $\mathbf{u}$ are monthly or quarterly settings of well head pressures, water injection rates, valve openings etc.

2.3 Data assimilation

Efficient data assimilation algorithms are also an essential element of CLRM. Many methods for reservoir-focused data assimilation have been developed over the past years, and we refer to Oliver et al. (2008), Evensen (2009), Aanonsen et al. (2009) and Oliver and Chen (2011) for overviews. An essential component of data assimilation is accounting for uncertainties, and it is generally accepted that this is best done in a Bayesian framework:

$$p(\mathbf{m}\,|\,\mathbf{d}) = \frac{p(\mathbf{d}\,|\,\mathbf{m})\, p(\mathbf{m})}{p(\mathbf{d})}, \tag{5}$$

where p indicates the probability density, and $\mathbf{d}$ is a vector of measured data (e.g. oil and water flow rates or saturation estimates from time-lapse seismic). In equation (5) the terms $p(\mathbf{m})$ and $p(\mathbf{m}|\mathbf{d})$ represent the prior and posterior probabilities of the model parameters $\mathbf{m}$, which are, in our setting, represented by initial and updated ensembles respectively. The underlying assumption in data assimilation is that a reduced uncertainty in the model parameters leads to and improved predictive capacity of the models, which, in turn, leads to improved decisions. In our CLRM setting, decisions take the form of control vectors $\mathbf{u}$, aimed at maximizing the objective function J.

2.4 Information valuation

Previous work on information valuation in reservoir engineering focused on analyzing how additional information impacts the model predictions. One way of valuing information is proposed by Krymskaya et al. (2010). They use the concept of observation impact, which was first introduced in atmospheric modelling. Starting from a Bayesian framework, they derive an observation sensitivity matrix, which contains self and cross-sensitivities (diagonal and off-diagonal elements of the matrix, respectively). The self-sensitivities, which quantify how much the observation of measured data impacts the prediction of these same data by a history-matched model, provide a measure of the information content in the data.

Another approach is taken by Le et al. (2014) who address the usefulness of information in terms of the reduction in uncertainty of a variable of interest (e.g. NPV). They introduce a method to estimate, in a computationally feasible way, how much the assimilation of an observation contributes to reducing the spread in the predictions of the variable of interest, expressed as the difference between P10 and P90 percentiles, i.e. between the 10% and 90% cumulative probability density levels.

Both approaches are based on data assimilation to obtain a posterior ensemble which forms the basis to compute various measures of information valuation. In this case, the measurements are obtained in the form of synthetic data generated by a synthetic truth. This preempts our proposed method of information valuation in which we will use an ensemble of models in the FDP stage, of which each realization will be selected as a synthetic truth in a consecutive set of twin experiments.

2.5 VOI and decision making

The two studies that we referred to above (Krymskaya et al., 2010 and Le et al., 2014) only measure the effect of additional information on model predictions and do not explicitly take into account how the additional information is used to make better decisions. In these studies it is simply assumed that history-matched models automatically lead to better decisions. However, there seems to be a need for a more complete framework to assess the VOI, including decision making, in the context of reservoir management. VOI analysis originates from the field of decision theory. It is an abstract concept, which makes it into a powerful tool with many potential applications, although implementation can be complicated.

An early reference to VOI originates from Howard (1966) who considered a bidding problem and was one of the first to formalize the idea that information could be economically valued within a context of decision under uncertainties. Since then, several applications have appeared in many different fields, including the petroleum industry. Bratvold et al. (2009) produce an extensive literature review on VOI in the oil industry and also identify several potential misconceptions and misunderstandings in the use of VOI analysis. Through examples with a petroleum-oriented perspective they show how a VOI analysis should be carried out rigorously. They affirm that "VOI attributes no value to 'uncertainty reduction' or 'increased confidence'" and that "value is added by enabling the decision maker to better