ECMOR XIV

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Value of Information in Closed-loop Reservoir Management

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SUMMARY

This paper proposes a new methodology to perform value of information (VOI) analysis within a closed-loop reservoir management (CLRM) framework. The workflow combines tools such as robust optimization and history matching in an environment of uncertainty characterization. The approach is illustrated with two simple examples: an analytical reservoir toy model based on decline curves and a waterflooding problem in a two-dimensional five-spot reservoir. The results are compared with previous work on other measures of information valuation, and 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.

Introduction

Over the past decades, numerical techniques for reservoir model-based optimization and history matching 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. This paper describes a methodology to assess the VOI in a such a CLRM context.

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 and compared with other information measures. 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.

Background

Closed-loop reservoir management (CLRM)

CLRM is a combination of frequent life-cycle production optimization and data assimilation (also known as computer-assisted history matching); see Figure 1. 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. 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. Data assimilation 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).

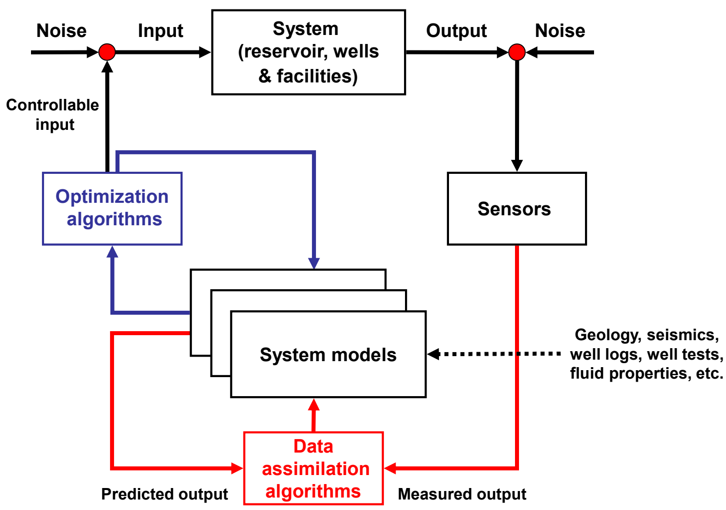

Figure 1 *Closed-loop reservoir management as a combination of life-cycle optimization and data assimilation.*

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). Figure 2 schematically represents robust optimization over an ensemble of N realizations $\{\mathbf{m}_1, \mathbf{m}_2, \ldots, \mathbf{m}_N\}$ where $\mathbf{m}$ is a vector of uncertain model parameters (e.g. grid block permeabilities or fault multipliers). The objective function J_{NPV} is defined as

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

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 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 price of water produced, r_{wi} is the price 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.

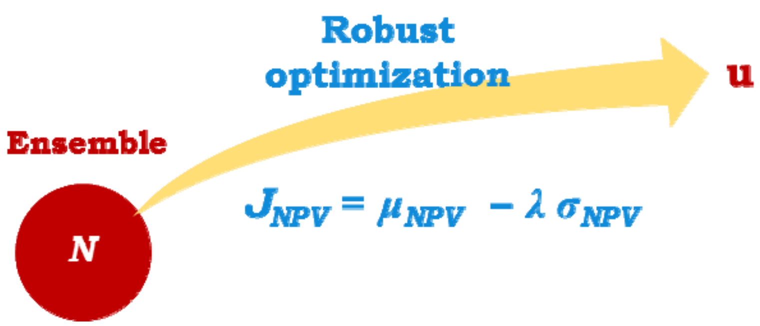

Figure 2 *Robust optimization: optimizing the objective function of an ensemble of N realizations resulting in a single control vector* **u**.

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:

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

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.

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, and Figure 3 schematically represents how measured data are used to update a prior ensemble of reservoir models, resulting in a posterior ensemble which forms the basis to compute various measures of information valuation. In Figure 3 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*.

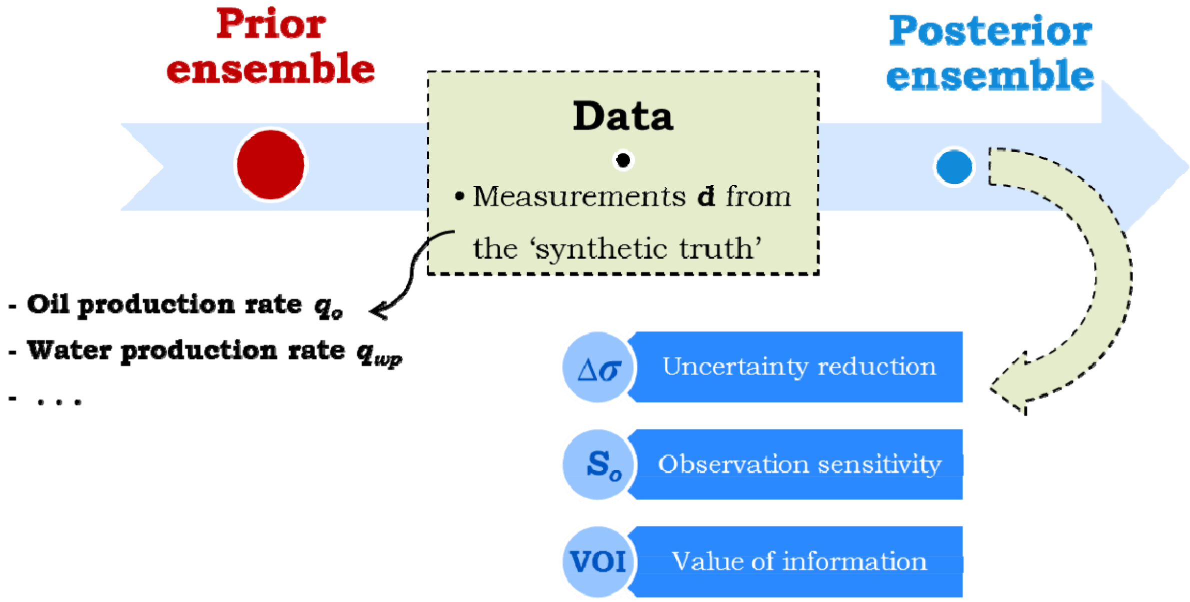

***Figure 3** Data assimilation and information valuation.*

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 'tune' his/her choice to the underlying uncertainty". Thus, their main message is that "one cannot value information outside of a particular decision context", and they continue "The fundamental question for any information-gathering process is then whether the likely improvement in decision making is worth the cost of obtaining the information." (All citations from Bratvold et al., 2009). Finding an answer to this question is the ultimate goal that drives the work described in this paper.

Methodology

In our setting, decisions in CLRM take the form of optimizing the production strategy **u** under uncertainty which involves repeated robust optimization of a large number of variables: the vector **u** typically has tens to hundreds of elements and needs to be updated when new information becomes available. As noted by Bratvold et al. (2009), in many cases the reported work on VOI in the petroleum industry is related to other types of decisions and uncertainties. Most of the examples are about whether to drill or not to drill a well in a certain location (Bhattacharjya et al., 2010), or about whether a fault is sealing or not. These problems contain limited numbers of decision alternatives and uncertainty scenarios. The tools used to solve them involve decision trees and influence diagrams, which are feasible when dealing with binary or simple discrete scenarios. The CLRM problem seems to contain too many variables to be approached in the same way. However, the question to be answered is essentially the same and so should be the conceptual approach.

Reducing uncertainty in a model prediction has no value by itself, and therefore one cannot assign a value to information without modelling the decisions that are made based on the model forecasts. VOI is decision-dependent. We therefore propose to combine data assimilation and decision making (in the form of optimization) to create a more complete workflow to value information. By doing that, we intend to not only quantify how information changes knowledge (through data assimilation), but also how it influences the results of decision making (through optimization).

The proposed workflow is depicted in Figure 4. The procedure consists of a sort of *twin experiment* on a large scale, because the analysis is performed in the design phase – when no real data are yet available. It starts with a prior ensemble of realizations which characterizes the initial uncertainty associated with the model parameters. From this ensemble, one realization is selected to be the synthetic truth and the remaining realizations form the prior ensemble for a robust optimization procedure to maximize the economic value of the ensemble. The resulting strategy is applied to the synthetic truth, and synthetic data from the analyzed measurements are generated by running a reservoir simulation over the specified control time interval (typically one or more months). With these, data assimilation is performed and a posterior ensemble obtained. As a next step robust optimization is carried out on this posterior to find a new optimal production strategy (from the time the data became available to the end of the reservoir life-cycle), and the procedure is repeated while gradually progressing over the producing life of the reservoir in time steps equal to the specified control time interval. The concept of a twin experiment in data assimilation is in this way extended to include the effects of the model updates on the reservoir management actions.

The strategies obtained for the prior and the posterior ensembles are then tested on the synthetic truth and their economic outcomes (NPV values $J_{NPV,prior}$ and $J_{NPV,post}$) are evaluated. The difference between these outcomes is a measure of the VOI incorporated through the CLRM procedure for this particular choice of the synthetic truth.

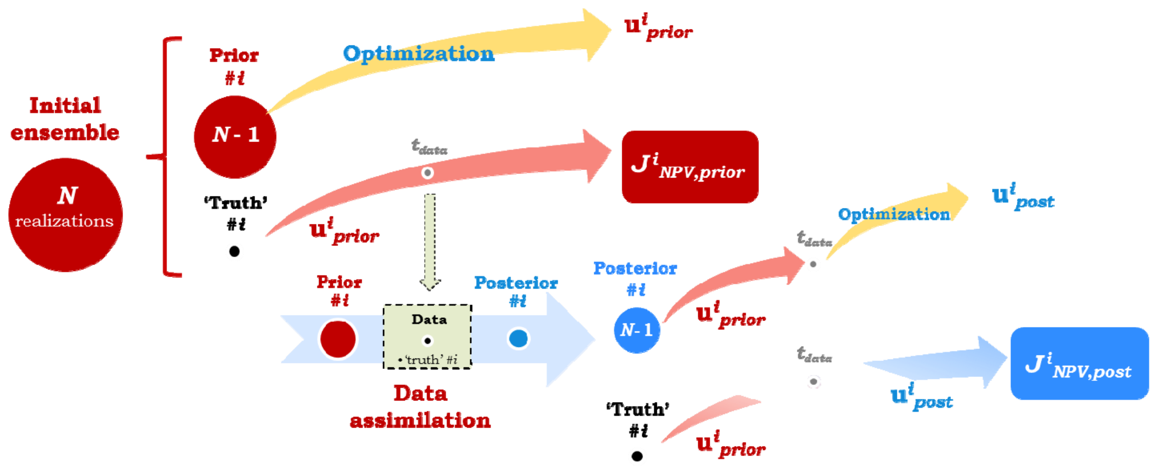

Figure 4 *Proposed workflow to compute the value of information.*

The choice of one of the realizations to be the synthetic truth in the procedure is completely random. In fact, because the analysis is conducted during the FDP phase, any of the models in the initial ensemble could be selected to be the 'truth'. One of the underlying assumptions of our proposed workflow is that the truth is captured by the initial ensemble. Hence, the methodology only allows to quantify the VOI under uncertainty in the form of *known unknowns*. Obviously, specifying uncertainty in the form of *unknown unknowns* is impossible, which therefore is a fundamental shortcoming in any VOI analysis.

Because any of the N models in the initial ensemble could be the truth, the procedure has to be repeated N times, consecutively letting each one of the initial models act as the synthetic truth. This allows us to quantify the *expected VOI* over the entire ensemble:

$$\bar{J}_{NPV} = \frac{1}{N}\sum_{i=1}^{N}\left(J^{i}_{NPV,post} - J^{i}_{NPV,prior}\right). \tag{6}$$

We note that in the literature on VOI, most of the times the term VOI is used to refer to the expected VOI. An illustration of this required repetition of the procedure and the computation of the expected VOI is depicted in the Figure 5.

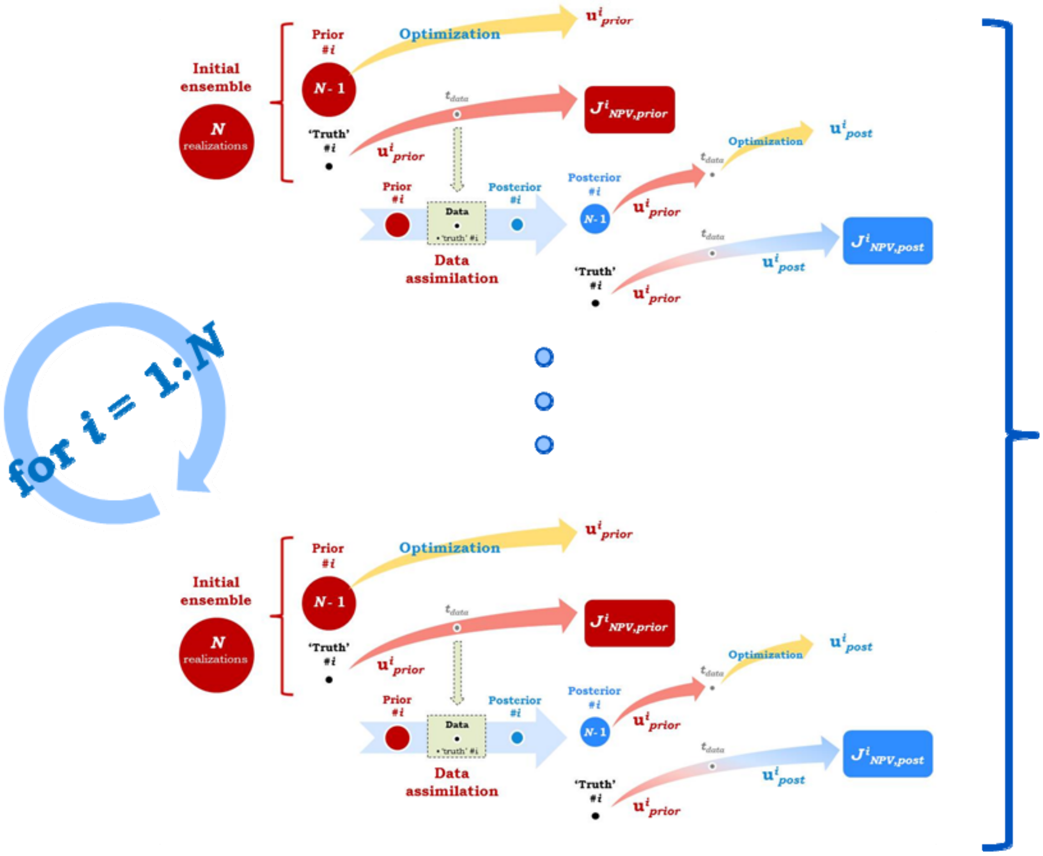

***Figure 5** Repeating the procedure from Figure 4 to compute the expected VOI.*

The workflow can be adapted to compute the expected *value of clairvoyance* (VOC), which gives a feeling for the technical limit (i.e. the maximum possible expected VOI) that could be obtained from measurements. In this case, as illustrated in Figure 6, data assimilation does not form part of the loop. Instead, perfect information is assumed to become available through a revelation of the truth at a certain moment in time. Such a clairvoyance implies the availability of completely informative data without observation errors, and the expected VOC therefore forms a theoretical upper bound to the expected VOI. Moreover, because this modified workflow does not require data assimilation, and, after the truth has been revealed, only requires optimization of a single (true) model, it is computationally significantly less demanding.

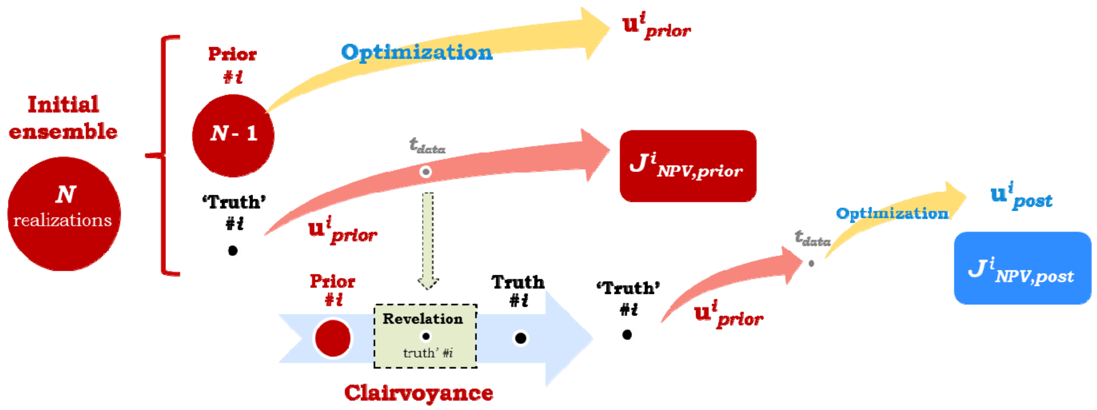

Figure 6 *Modified workflow to compute the expected VOC.*

Examples

Toy model

As a first step to test the proposed concept we used a very simple model with only a few parameters, based on reservoir decline curves. It describes oil and water flow rates q_o and q_w as a function of time t and a scalar control variable u according to the following expressions:

$$q_o(u,t) = \left(q_{o,ini} + c_1 u\right)\exp\left(-\frac{t}{a + \frac{1}{c_2}u}\right), \tag{7}$$

$$q_w(u,t) = H\left[t_{bt}\left(1 - \frac{1}{c_3}u\right)\right]\left(q_{w,\infty} + u\right)\left[1 - \exp\left(-\frac{t - t_{bt}\left(1 - \frac{1}{c_3}u\right)}{c_4 a - \frac{1}{c_5}u}\right)\right], \tag{8}$$

where $q_{o,ini}$ is the initial production rate, t_{bt} is the water breakthrough time, and $q_{w,\infty}$ is the asymptotic water production rate, all for a situation without control, i.e., for $u = 0$. The oil production follows an exponential decline and the water production builds up exponentially from a breakthrough time modelled by a Heaviside step function H. The variables have dimensions as listed in Table 1, where L, M and t indicate length, monetary value and time respectively. Some of the parameters are constants, while four uncertain parameters are Normally distributed with values indicated in Table 1. The scalar control variable u somehow mimics a water injection rate to the reservoir; higher values of u slow down the decline of oil production but accelerate water breakthrough and increase water production, as shown in Figure 7. Given the prices and costs associated with oil and water production, there is room for optimization to determine the value of u that maximizes the economics of the reservoir over a fixed producing life-time. To allow for regular updating of the control strategy over the producing life of the reservoir, the scalar u can be replaced by a vector $\mathbf{u} = [u_1 \quad u_2 \quad \cdots \quad u_M]^T$, where M is the number of control intervals.

Table 1 Parameter values for toy model.					
Variables		*Constant parameters*		*Uncertain parameters*	
q_o	[L^3 t^{-1}]	$c_1 = 0.1$	[–]	$q_{o,ini} \sim N(100, 8)$	[L^3 t^{-1}]
q_w	[L^3 t^{-1}]	$c_2 = 4$	[L^3 t^{-2}]	$a \sim N(30.5, 3.67)$	[t]
t ∫[0, 80]	[t]	$c_3 = 150$	[L^3 t^{-1}]	$q_{w,\infty} \sim N(132, 6)$	[L^3 t^{-1}]
u ∫[0, 50]	[L^3 t^{-1}]	$c_4 = 2$	[–]	$t_{bt} \sim N(32, 6)$	[t]
		$c_5 = 1.33$	[L^3 t^{-2}]		
		$r_o = 70$	M L^{-3}		
		$r_w = 10$	M L^{-3}		
		$b = 0.10$	[–]		

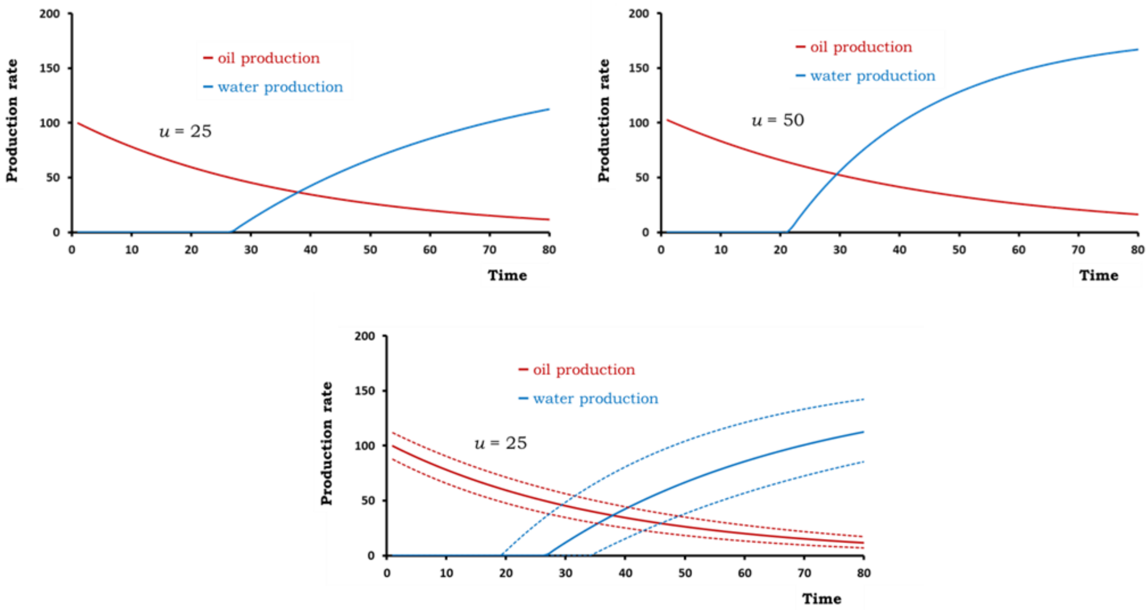

***Figure** 7 Toy model behavior: oil and water production for two fixed values of the control variable u (top); representation of uncertainty in the form of P10 and P90 percentiles (bottom).*

The question to be answered here was: given an initial ensemble of models to describe the geological uncertainties and an initial optimized control vector **u**, what is the value of a production test in the form of a measurements $\mathbf{d} = [q_o(t_{data}) \quad q_w(t_{data})]^T$ of oil and water production rates at a given time t_{data}, for different measurement errors and observation times? The VOI assessment procedure described in the previous section was applied, and repeated for different observation times, $t_{data} = \{1, 2, \ldots, 80\}$. We used a random measurement error with a standard deviation σ_{data} equal to 5% of the measured value, an ensemble of $N = 100$ model realizations and $M = 8$ control time-steps. Simple implementations of ensemble optimization (EnOpt) and ensemble Kalman filtering (EnKF) were used to perform the robust optimization and the data assimilation respectively. (For general for information on EnKF, see, e.g., Evensen (2009) or Aanonsen et al. (2009); for general information on EnOpt and ensemble-based CLRM, see, e.g., Chen et al. (2009)). The VOI, the VOC, the observation impact I_{GAI} and the uncertainty reduction $\Delta\sigma_{NPV}$ were computed for each of the 80 observation times.

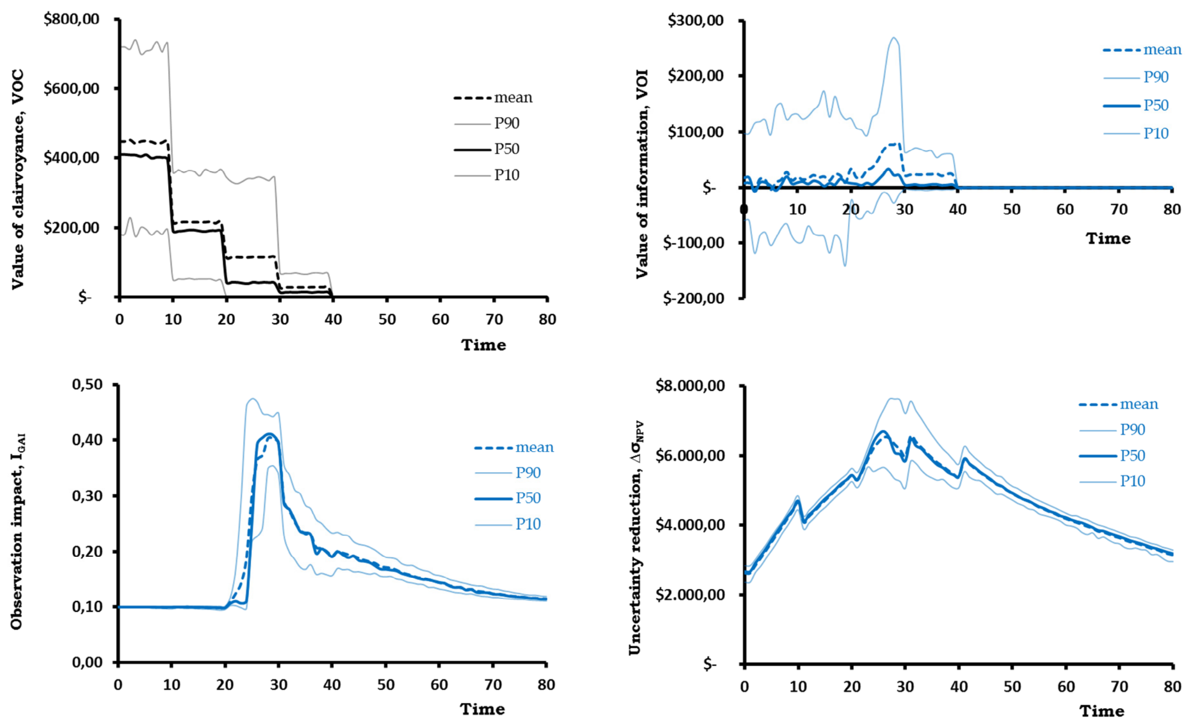

Figure 8 *Results for the VOI analysis in the toy model: VOC (top left); VOI (top right); observation impact (bottom left); uncertainty reduction (bottom right).*

The expected VOC as a function of observation time t_{data} is depicted in Figure 8 (top left), where we expressed the monetary value, arbitrarily, in $. The dashed line represents the expected VOC, i.e. the ensemble mean. The dark solid line and the two lighter solid lines represent the P50 and P10/P90 percentiles respectively. The expected VOC is the value one could obtain if the truth could be revealed and all the uncertainty could be eliminated at no costs at time t_{data}. Of course, these results depend on the operation schedule (i.e. the number of control time-steps) and on the initial ensemble of realizations that characterize the uncertainty. As can be seen, the VOC exhibits a stepwise decrease over time, with the steps coinciding with the eight control time steps. This stepwise behavior occurs because knowing the truth only affects the way one operates the reservoir from the moment of clairvoyance and because the production strategy can only be updated at the defined control time steps. The sooner clairvoyance is available, the more control time steps can be tuned to re-optimize the production strategy based on the truth, and, therefore, the more value is obtained. Thus, this plot demonstrates the importance of timing when collecting additional information to make decisions. Even clairvoyance can be completely useless (VOC = 0) when it is obtained too late (in this case after $t_{data} = 40$).

The percentiles of the VOC distribution in Figure 7 (top left) illustrate that the VOC is itself an uncertain parameter, because, despite knowing that the truth has been revealed, it is not possible to know which of the model realizations is this truth; all realizations are potentially true in the design phase. Hence, the VOC for a particular case may be higher or lower than the expected VOC.

In a similar fashion, Figures 8 (top right), 8 (bottom left) and 8 (bottom right) display the VOI, the observation impact and the uncertainty reduction as a function of observation time t_{data}. In Figure 8 (bottom left), the peak in the observation impact indicates that production data is most informative around $t_{data} = 30$; in Figure 8 (bottom right), the uncertainty reduction follows the same trend; and, in Figure 8 (top right), the VOI also increases at the same time. This suggests that, in this example, measurements with a higher observation impact also result in a larger uncertainty reduction, and a higher. However, whereas the observation impact and the uncertainty reduction both peak around

$t_{data} = 30$ and gently decrease afterwards, the VOI exhibits a more abrupt decrease, similar to what is observed for the VOC. This indicates that the VOI depends not only on the information content of the observations but also on their timing, just as was discussed for the VOC. Moreover, these results illustrate that the proposed workflow allows to take both information content and timing into account and, therefore, results in a more complete VOI assessment.

Figure 9 (left) shows the same results, but focusing on the expected (or mean) values of VOC (black) and VOI (blue). This plot clearly illustrates that the expected VOC is always and upper bound to the expected VOI. Indeed, production data, no matter how accurate, can never reveal all uncertainties. After water breakthrough, production data is more informative and it is more likely that the uncertainties influencing the optimization of the production strategy be revealed; thus, information more closely approaches clairvoyance. Figure 9 (right) illustrates this in a different way by displaying the chance of knowing (COK), defined as the ratio VOI/VOC (Bhattacharjya et al., 2010).

The different information measures suggest in this case that the most valuable measurements are the ones around $t_{data} = 30$. We conclude that a decision maker analyzing when to obtain a production test to optimally operate this reservoir should take a measurement around this time and should be willing to pay at most approximately \$ 80 – and not \$ 6,000 as the uncertainty reduction analysis would suggest.

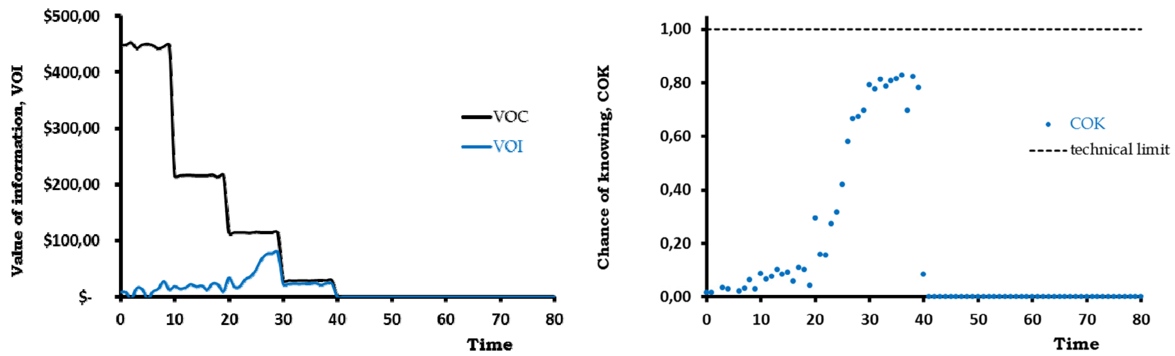

Figure 9 *Results for the toy model: the expected VOI is upper-bounded by expected VOC (left); the ratio of VOI and VOC results in the COK (right).*

2D five-spot model

As a next step, we applied the proposed VOI workflow to a simple reservoir simulation model representing a two-dimensional (2D) inverted five-spot water flooding configuration; see Figure 10. In a 21 × 21 grid (700 × 700 m), with heterogeneous permeability and porosity fields, the model simulates the displacement of oil to the producers in the corners by the water injected in the center. We used $N = 50$ realizations of the porosity and permeability fields to model the geological uncertainties. The simulations were used to determine the set of well controls (bottom hole pressures) that maximizes the NPV. The optimization was run for a 1500-day time horizon with well controls updated every 150 days, i.e. $M = 10$, and with five wells, $\mathbf{u}$ has 50 elements. The economic parameters were $r_o = 80$ \$/bbl, $r_{wi} = r_{wp} = 5$ \$/bbl and $b = 0.15$. The whole exercise was performed in the open-source reservoir simulator MRST (Lie et al., 2012), by modifying the adjoint-based optimization module to allow for robust optimization and combining it with the EnKF module to create a CLRM environment for VOI analysis. Just like for the toy model example, the workflow was repeated for different observation times, $t_{data} = \{150, 300, \dots, 1350\}$ days. For this 2D model we assessed the VOI of the production data (total flow rates and water-cuts) with absolute measurement errors (ε_{flux} = 5 m³/day and $\varepsilon_{wct} = 0.1$). The VOI, the VOC, the observation impact I_{GAI}, and the uncertainty reduction $\Delta\sigma_{NPV}$ were computed for each of the nine observation times.

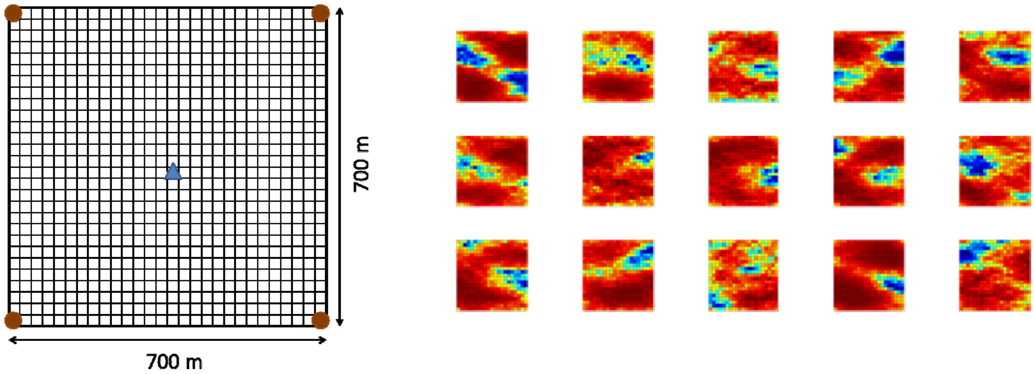

Figure 10 *2D five-spot model (left); 15 randomly chosen realizations of the uncertain permeability field (right).*

Figure 11 depicts the results of the analysis for production data. Again, dashed lines correspond to expected values and solid lines to percentiles quantifying the uncertainty of the information measures. The markers correspond to the observation times at which the analysis was carried out. In Figure 11 (top left) we note that, like for the toy model example, clairvoyance loses value with observation time, following the previously described stepwise behavior. In addition, by observing the percentiles, we realize that, in this case, the VOC has a non-symmetric probability distribution. The high values of P90 indicate that, for some realizations of the truth, knowing the truth can be considerably more valuable than indicated by the expected VOC; however, the P50 values, which are always below those of the expected VOC, indicate what is more likely to occur. The same holds for the VOI, as can be observed in Figure 11 (top right). The observation that provides the best VOI is the one at t_{data} = 150 days, followed by a second modest peak at t_{data} = 450 days.

Figure 11 (bottom left) shows that the information content of the production data increases when water breaks through in the producers but gently decreases thereafter. The observation impact achieves its maximum at t_{data} = 450 days; this is the time when, on average, most of the realizations observe first water breakthrough. In Figure 11 (bottom right) we observe that the uncertainty reduction peaks and then goes down again, stabilizing at a constant value. The measurements at t_{data} = 300 days are those that maximally reduce the uncertainty for the variable of interest (NPV).

Figure 12 (left) depicts the expected values of VOI (blue dots) and VOC (black line). The plot confirms that clairvoyance can be considered the technical limit for any information gathering strategy and that the expected VOC forms an upper-bound to the expected VOI. We also note that the expected VOI comes closer to the expected VOC with time. Indeed, as water breakthrough is observed in more producers, the production data of this five-spot pattern become more effective in revealing the main features of the true permeability and porosity fields. Figure 12 (right) displays the COK with time. Although the VOI clearly approaches the VOC (Figure 12a), their ratio does not change substantially with time, unlike what was observed for the toy model example.

In contrast to the toy model case, for this example the different information measures indicate different times for the most valuable measurements. This shows that taking into account the update of the optimal production strategy can influence the conclusions drawn by this kind of analysis. Using the proposed workflow as the reference for VOI assessment, for this case, we recommend the production data to be collected at t_{data} = 150 days and we estimate the value of this additional information to be worth $ 1.4 million.

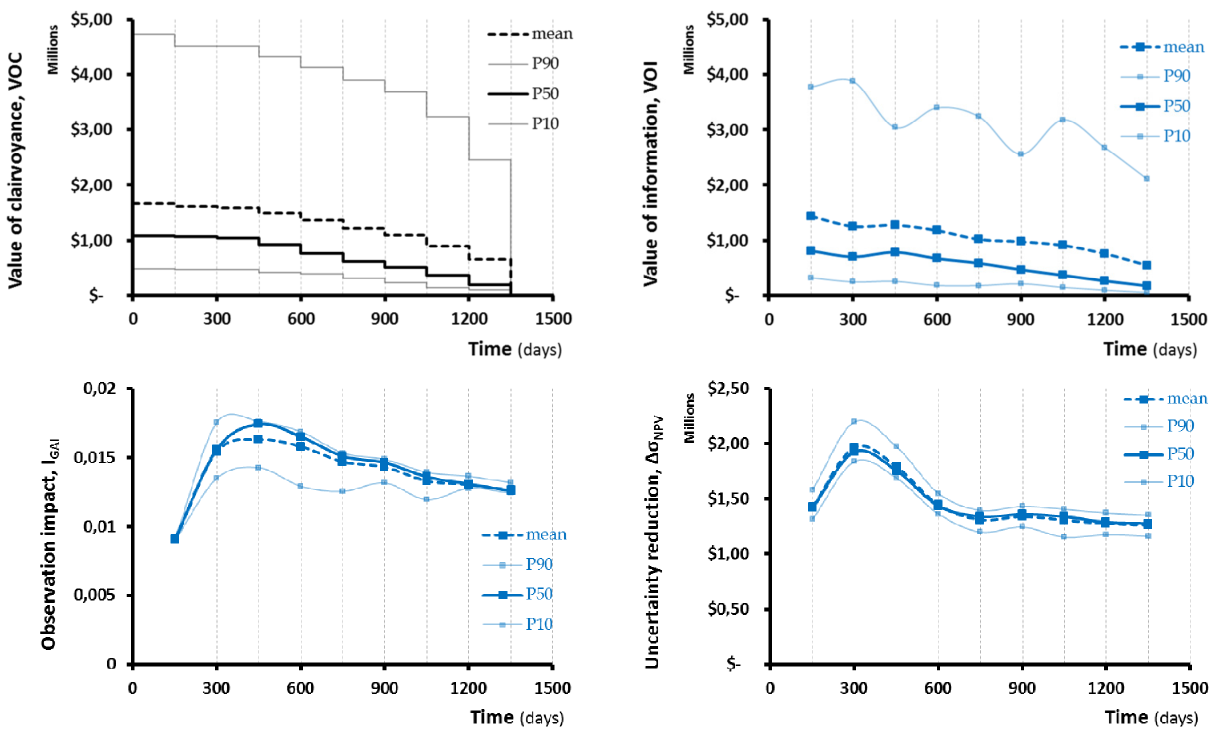

Figure 11 *Results for the VOI analysis of production data in the 2D model: VOC (top left); VOI (top right); observation impact (bottom left); uncertainty reduction (bottom right).*

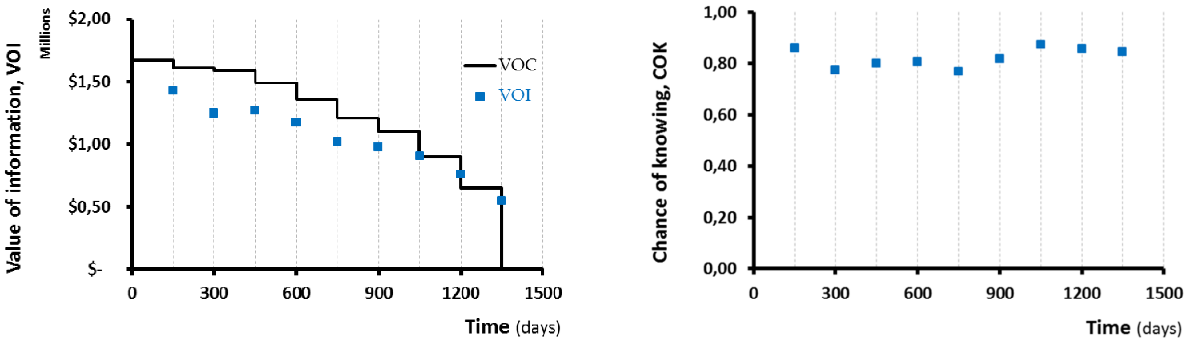

Figure 12 *Results for the 2D model: the expected VOI is upper-bounded by expected VOC (left); the COK (right) is less informative than for the toy model (c.f. Figure 9).*

Discussion and conclusion

We proposed a new workflow for VOI assessment in CLRM. The method uses elements available in the CLRM framework, such as history matching and robust optimization. First, we identified the opportunity to combine these elements with concepts of information value theory to create a VOI analysis instrument. We then designed a generic procedure that can, in theory, be simply implemented in a variety of applications, including our optimal reservoir management problem. Next, the workflow was illustrated with two examples and the results were compared with previous measures for information valuation. Because we take into account that the production strategy is updated periodically after new information has been assimilated in the models, we believe that our proposed method is more complete than previous work to estimate the VOI in a reservoir engineering context.

The main drawback of our proposed VOI workflow is its computational costs; it involves the repeated application of robust optimization and data assimilation, which requires a very large number of reservoir simulations. Depending on the types of optimization and assimilation methods used (e.g.

adjoint-based, ensemble-based, or gradient-free) there may be large differences in the computational requirements, but even in case of using the most efficient (i.e. adjoint-based) algorithms, the computational load of the workflow will be huge. For instance, for the toy model example with 100 realizations, we ran more than 6.7 million forward simulations (200 robust optimizations with EnOpt) in order to obtain one of the 80 values of VOI displayed in Figure 8 (top right). Hence, if the method is to be applied to real-field cases, some serious improvements regarding the number of simulations required are necessary. One potential method could be to use clustering techniques to select a few representative realizations rather than a full ensemble. Furthermore, reduced-order modelling or response surface techniques to generate surrogate models could facilitate the application of our workflow to larger reservoir models by reducing the number of full reservoir simulations. Despite its computational cost, we conclude that our approach constitutes a rigorous VOI assessment for CLRM. For this reason, we recommend that it be used as the reference for the development of more practical and less computationally demanding tools to be applied in real-field cases.

Acknowledgements

This research was carried out within the context of the ISAPP Knowledge Centre. ISAPP (Integrated Systems Approach to Petroleum Production) is a joint project of TNO, Delft University of Technology, ENI, Statoil and Petrobras.

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