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UNISIM ON-LINE

YEAR 13, NUMBER 3
121ST EDITION
APRIL, 2018

Assessing the Expected Value of Information using Candidate Production Strategies

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> *"Using a predefined set of candidate production strategies and uncertain scenarios, the EVoI analysis becomes an automated procedure."*

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Introduction

Developing a petroleum field is a complex and risky process. Projects are long-term and capital intensive, and decisions are made under high uncertainty. Typical actions to manage uncertainty include: (1) acquiring additional information to reduce reservoir uncertainty (the focus of this work); (2) defining a flexible production system, allowing system modifications as uncertainty unfolds over time; and (3) defining a robust production strategy, ensuring good performance across multiple scenarios without requiring system modifications over time.

This text presents a key contribution of a paper published in the Journal of Petroleum Science and Engineering by Santos et al. (2017), which is an automated method to assess the value of information using a predefined set of production strategies.

Acquiring Information to Manage Uncertainty

Decision makers defer the development decision until new information is acquired. They aim to change the current knowledge of uncertain reservoir attributes so that decisions can be improved. However, information acquisition incurs costs and potentially delays production. In addition, reducing uncertainty has no value in itself, i.e., new information must have the potential to change a decision that would be made otherwise. The Expected Value of Information (EVoI) analysis quantifies the advantages of acquiring additional information. Therefore, information should be acquired only if the EVoI surpasses the cost of acquisition.

Some authors observed that while information acquisition is typically the preferred action to manage uncertainty, EVoI assessments are not used routinely to justify this decision. This is because assessing the EVoI in the development phase is complex, where multiple uncertain attributes are coupled with the definition of multiple decision variables (i.e., the production strategy). Santos et al. (2017) aimed to facilitate this analysis and eliminate biases toward particular uncertainties and information sources.

Note that the term "information" is typically used in a broad sense and commonly refers to acquiring data, namely seismic surveys, well testing, and drilling appraisal wells, but may also cover performing technical studies and hiring consultants.

Methodology

The proposal by Santos et al. (2017) integrates the twelve-step model-based decision-analysis framework by Schiozer et al. (2015) and corresponds to developments of Step 11. Integrated into such framework, the proposal uses as input: (1) a predefined set of uncertain scenarios that match production data (obtained in Step 5), and (2) a predefined set of production strategies, optimized deterministically for representative scenarios (obtained in Step 9). Please refer to Schiozer et al. (2015) for details on the twelve-step framework.

Because we use a predefined set of uncertain scenarios with updated probabilities given the information outcomes, we remove the need to sample new scenarios and, thus, automate the EVoI analysis. We use Bayes' Theorem (Eq. (1)) to update the probabilities of occurrence of each scenario given the information outcomes, $P(A_i|I)$, using: (1) the prior probability of the uncertain attribute, $P(A_i)$, and (2) the information reliability, $P(I|A_i)$.

$$P(A_i|I) = \frac{P(I|A_i) * P(A_i)}{\sum_{i=1}^{N}[P(I|A_i) * P(A_i)]} \qquad (1)$$

A subset of representative models (RMs) is chosen from the set of scenarios that match production data, using the proposal by Meira et al. (2016), which ensures that the set of RMs represents the variability of the input variables (uncertain attributes) and the variability of the output variables (production, injection and economic forecasts).

One production strategy is optimized deterministically for each RM. These strategies are possible solutions for field development because the RMs reflect the uncertain system. Thus, deterministic optimization is advantageous because it is part of a probabilistic process.

Using a predefined set of scenarios and production strategies, we obtain project values for each production strategy under each scenario before analyzing the EVoI itself. Thus, the expected value of each strategy becomes a function of the posterior probability of the scenarios given the information outcomes. This way, EVoI analyses are automated (Figure 1).

We determine the EVoI using Eq. (2), where EMV_{wi} is the expected monetary value of the project with information, and EMV_{woi} is the EMV without information.

$$EVoI = EMV_{wi} - EMV_{woi} \qquad (2)$$

Santos et al. (2017) also developed indicators to identify the uncertainties with highest potential to be mitigated with information, before analyzing the EVoI itself. Because of space constraints, we do not present them in this text and refer interested readers to Santos et al. (2017).

Application and Results

Our case study is the UNISIM-I-D, a benchmark oil reservoir with multiple uncertainties. The reservoir has two regions separated by a fault of unknown transmissibility. The presence of hydrocarbons in the East block is a key uncertainty (*bl*) because this region has not yet been drilled, making this a textbook case for EVoI analysis. The scenarios where oil is present in the East block also consider uncertainty in the water-oil contact (*wo*). For further details on the case study, refer to Santos et al. (2017).

We considered drilling an appraisal well to gather information on both *bl* and *wo*, simultaneously. We used 214 scenarios that match production data, equiprobable a priori. We used nine candidate production strategies (S1 to S9), optimized deterministically for nine representative models. Candidate strategy S9 is the best without further information acquisition, having the highest EMV of the set of candidates (EMV_{woi} = US$ 1690 million). We considered imperfect information (95% reliable for *bl*, and 80% for *wo*) and a 3-month delay in the decision to develop due to information acquisition. We obtained an EMV_{wi} of US$ 1651 million, which is lower than the EMV_{woi}. Thus, this information has no value and acquiring it would incur an expected loss of US$ 39 million.

> *"Our procedure discarded an apparently attractive information source, ensuring more quantitative and objective decision-making."*

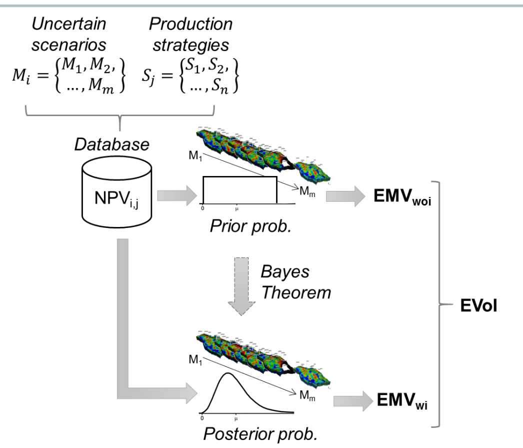

Figure 1: Automated EVoI analysis proposed in this study (decision tree analysis is not required).

Traditionally, decision trees are required to estimate the EVoI. Our proposal eliminates this need by performing automated evaluations. For illustrative purposes only, we show the decision tree for this problem in Figure 2, where circles are chance nodes and squares are decisions. The first chance node (on the left) models the information result on the presence or absence of hydrocarbons, while the second chance node corresponds to the depth of the water-oil contact indicated by well logs. A decision node follows, representing the selection of one of the nine candidate production strategies. At last, a chance node represents the true reservoir. However, note that as we used a set of 214 scenarios, combining not only *bl* and *wo*, but all mapped rock and fluid uncertainties, the branches in the final chance node do not correspond to a single scenario, but to a group of scenarios. Thus, the decision tree in Figure 2 is not fully represented due to space constraints. Because of multiple information outcomes, uncertain attributes, and candidate decisions, this is a difficult problem to analyze manually. This way, the use of an automated procedure that does not require a decision tree enabled a complex analysis with an accurate EVoI estimate.

Concluding Remarks

This work proposes an automated procedure for EVoI analysis using predefined sets of candidate production strategies and uncertain scenarios. We use Bayes Theorem to update the probability of each scenario given the information outcomes, eliminating the need to sample new scenarios.

Today, the EVoI is still not assessed routinely by companies because it is a complex problem to model. Our proposal makes EVoI assessments straightforward and feasible for day-to-day decisions, while ensuring a reliable estimate.

Our case study showed the importance of estimating the EVoI, which is better than assuming that new information will always bring benefits. Although significant gains appeared to exist with an additional appraisal well, the improved decision was insufficient to compensate economically the delayed production. Thereby, our procedure discarded an apparently attractive information source, ensuring quantitative and objective decision-making.

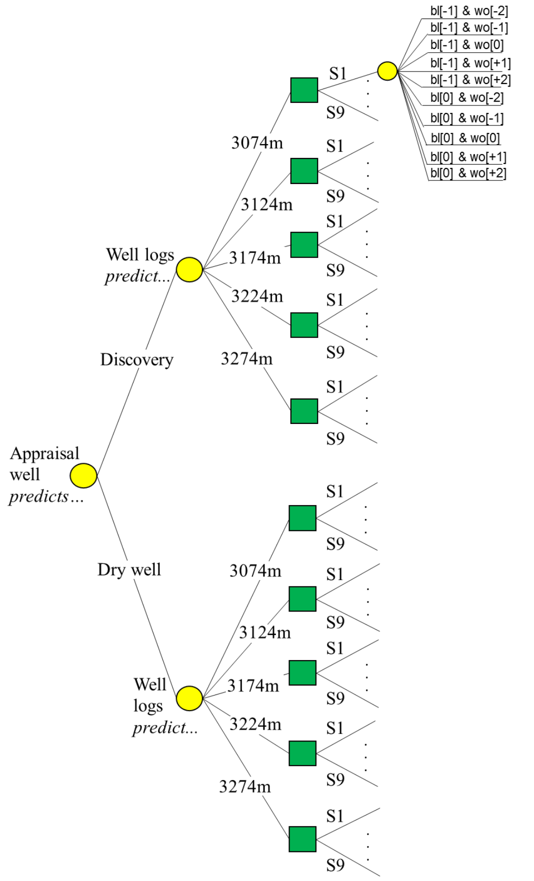

Figure 2: Traditional EVoI analysis with a decision tree (shown here for comparison but not required in our method).

Finally, a successful application of our proposal depends on a: (1) systematic characterization of uncertainty; (2) set of reliable history-matched models; (3) subset of representative models that reflect uncertainty in system inputs and outputs; and (4) thorough optimization of each RM. UNISIM currently develops research in these topics.

References

Meira, L. A., Coelho, G. P., Santos, A. A. S. and Schiozer, D.J. 2016. Selection of Representative Models for Decision Analysis Under Uncertainty. Comput. Geosci. 88: 67-82.

Santos, S. M. G., Gaspar, A. T. F. S. and Schiozer, D. J. 2017. Value of Information in Reservoir Development Projects: Technical Indicators to Prioritize Uncertainties and Information Sources. J. Pet. Sci. Eng. 157: 1179-1197.

Schiozer, D. J., Santos, A. A. S., and Drumond, P. S. 2015. Integrated Model Based Decision Analysis in Twelve Steps Applied to Petroleum Fields Development and Management. In: SPE EUROPEC, Madrid, 1-4 June. SPE-174370-MS.

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