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Case study

Selection of Representative Models for Decision Analysis Under Uncertainty

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ABSTRACT

The decision-making process in oil fields includes a step of risk analysis associated with the uncertainties present in the variables of the problem. Such uncertainties lead to hundreds, even thousands, of possible scenarios that are supposed to be analyzed so an effective production strategy can be selected. Given this high number of scenarios, a technique to reduce this set to a smaller, feasible subset of representative scenarios is imperative. The selected scenarios must be representative of the original set and also free of optimistic and pessimistic bias. This paper is devoted to propose an assisted methodology to identify representative models in oil fields. To do so, first a mathematical function was developed to model the representativeness of a subset of models with respect to the full set that characterizes the problem. Then, an optimization tool was implemented to identify the representative models of any problem, considering not only the cross-plots of the main output variables, but also the risk curves and the probability distribution of the attribute-levels of the problem. The proposed technique was applied to two benchmark cases and the results, evaluated by experts in the field, indicate that the obtained solutions are richer than those identified by previously adopted manual approaches. The program bytecode is available under request.

1. Introduction

The development and management of petroleum fields introduce a series of technological challenges that range from seismic and data acquisition, geological modeling and computational simulation of the environmental and economic outcomes of the adopted strategies, among others. Particularly in the computational context, several processes of petroleum production can be modeled as optimization problems, in which a multitude of criteria (net present value, cumulative oil, water and gas production, risk etc.) can be maximized or minimized. As the resulting optimization problems are far from simple, they rarely are well-defined mathematical problems.

Given the geological model of an oil field, those companies that possess the exploration licenses must define a **production strategy** to be implemented in the next decades of field production. Such production strategy can roughly be seen as the required infrastructure of wells, pipes, platforms and manifolds combined with a schedule that establishes when each device will begin to operate and the exact location of each device in the oil field. A wrong production strategy may lead to severe financial losses.

Engineers and researchers extensively rely on simulators to analyze production strategies. Such simulators reproduce the field performance based on a reservoir simulation model and a production strategy, which is highly dependent on the geological model. However, such geological model contains uncertain variables that may severely affect the quality of the production strategy. In such context, a **scenario** s is defined as a geological model with fixed values for all uncertain variables, and a **case** x is the union of a scenario s and a production strategy P (represented by $x = (s, P)$).

When a given production strategy is simulated, different results may be obtained for each distinct scenario. A set of wells can be ideal for a specific scenario and inappropriate for others, so each scenario generally has its own optimum production strategy. Therefore, the goal of engineers and researchers is to obtain a production strategy that maximizes return and reduces risk. As the process of obtaining an optimized production strategy for a single scenario requires days of work and hundreds of computer simulations, in practice only a few different scenarios can be considered. And here lies the main contribution of this paper: the

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Nomenclature

ϕ	porosity
BHP	bottom-hole pressure
Gp	cumulative gas production
K	permeability
Np	cumulative oil production
NPV	net present value
ORF	oil recovery factor
Qg	gas rate
Qo	oil rate
Qw	water rate
RM	representative models
VoI	value of information
VoF	value of flexibility
OOIP	original oil in place
Wi	cumulative water injection
Wp	cumulative water production

proposal of a technique to select a subset of scenarios that represent the original properties of the problem and can also be used in the definition of the production strategy. Such proposal is related to the unified 12-step methodology for decision analysis in petroleum fields proposed by Schiozer et al. (2015), particularly to *Step 8* of such methodology, which consists in the **Selection of Geological Representative Models Problem** (SelRMs-Prob). In summary, the 12 steps are:

1. Characterize the reservoir under uncertainties (build models, develop scenarios and estimate probabilities);
2. Select a base case (named “Base 0”) so that the simulation model can be built and calibrated;
3. Search for inconsistencies in “Base 0” with the analysis of data collected from wells (dynamic data);
4. Probabilistically generate a set of scenarios for the problem. This step is based on the discretization of the continuous variables into **levels**, which are related to the possible values that such variables can have after discretization;
5. Explore production data (well production and pressure, among others) to verify the feasibility of each scenario, thus eliminating the unfeasible ones and reducing the total number of scenarios to be considered in the analysis. From this reduced (feasible) set of scenarios, a new base case (P_{50}) is chosen to be considered in the next step;
6. Identify a deterministic production strategy for P_{50};
7. Estimate the risk curves (Section 2) considering all the scenarios obtained in *Step 5* and the identified production strategy;
8. Reduce even more the set of scenarios obtained in *Step 5*, by identifying **representative models** (RMs);
9. Identify production strategies for each RM obtained in *Step 8*;
10. Using a risk-return analysis, identify the best production strategy under uncertainty that combines all possible strategies, reservoir and economic scenarios;
11. Refine the strategy identified in the previous step, improving robustness and flexibility;
12. Generate the final risk curves and perform the decision analysis.

The SelRMs–Prob basically consists in identifying the *k* most representative scenarios within a larger set. The number of Geological Representative Models (RMs) may vary but, in practice, 9 or 10 are widely used for the definition of the production strategy (Steagall and Schiozer, 2001; Schiozer et al., 2004), as these numbers often lead to feasible simulation times[1]. It is important to highlight that the goal of the SelRMs–Prob is not to identify the most profitable scenarios, but rather to select a few representative models that maintain the original characteristics of the uncertain variables without any optimistic or pessimistic bias. The goal of this paper is to select RMs in *Step 8* of Schiozer et al. (2015)'s methodology. Such RMs correspond to a subset of the scenarios previously identified in *Step 5*.

There are several different approaches in the literature intended to deal with the SelRMs-Prob, which can be divided into two main categories: *ranking* techniques, generally based on the risk curves of technical and economic production variables (Section 2), and clustering-based strategies. From the first category, in 2001 Steagall and Schiozer (2001) proposed the use of three classes of geological models: pessimistic, probable and optimistic. According to these classes, their approach selects RMs close to P_{90}, P_{50} and P_{10} (cumulative probabilities close to 90%, 50% and 10%, respectively – Section 2) with respect to the Net Present Value (NPV). Steagall and Schiozer (2001) choose two models close to P_{90}, three models close to P_{50}, and two models close to P_{10}. This final selection of RMs is made according to the “freedom” around the cumulative probability: for example, if the RMs close to P_{10} are considered, the user can choose models with low, medium and high volume of produced oil. It was observed that the resulting RMs were also representative with respect to OOIP (*Original Oil in Place*). Schiozer et al. (2004) extended the methodology presented by Steagall and Schiozer (2001). According to Schiozer et al. (2004), scenarios close to P_{10}, P_{50} and P_{90} of NPV should be selected, but such selection should be made in a way that these scenarios were also representative in Np (*Cumulative Oil Production*), Wp (*Cumulative Water Production*) and ORF (*Oil Recovery Factor*). Schiozer et al. (2004)'s methodology is illustrated in Fig. 1: RMs must be close to P_{10}, P_{50} and P_{90} of NPV(vertical axis) and well-distributed with respect to Np, Wp and ORF (horizontal axes in each figure).

The methodology proposed by Schiozer et al. (2004) was later adopted in several works, such as (Costa et al., 2005; Hayashi et al., 2010; Ligero et al., 2004). Recently, the previous contributions of the group were consolidated into the 12-step methodology already mentioned (Schiozer et al., 2015).

Ligero et al. (2005) proposed a methodology for RMs selection based on the information value of each geological model. Together with Steagall and Schiozer (2001) and Schiozer et al. (2004) works, Ligero et al. (2005)'s proposal selects scenarios according to subjective criteria that aim to maintain the original representation of geological uncertainties.

Finally, in 2013, Sarma et al. (2013) proposed a greedy algorithm, named *minimax*, which selects the closest RMs to the three predefined percentiles (P_{10}, P_{50} and P_{90}) in NPV and ORF. Such RMs are selected with maximal attribute-level coverage. The *mimimax* algorithm tries to span the multidimensional attribute-level space, choosing scenarios as widely as possible.

In general, the techniques proposed by Steagall and Schiozer (2001) and Schiozer et al. (2004) adopt a time consuming manual selection of RMs that is based on subjective criteria.

Related to the clustering-based techniques, several works in the literature discuss which is the best way to capture and evaluate the similarity (or dissimilarity) between scenarios. In this context,

[1] Although research groups and companies work with 9 or 10 scenarios to define the production strategy, the optimal number os scenarios for each problem is still an open question in the literature.