UNIVERSIDADE ESTADUAL DE CAMPINAS
FACULDADE DE ENGENHARIA MECÂNICA
E INSTITUTO DE GEOCIÊNCIAS

SUSANA MARGARIDA DA GRAÇA SANTOS

DECISION ANALYSIS APPLIED TO THE DEVELOPMENT OF PETROLEUM FIELDS CONSIDERING ROBUSTNESS, INFORMATION, AND FLEXIBILITY

ANÁLISE DE DECISÃO APLICADA AO DESENVOLVIMENTO DE CAMPOS DE PETRÓLEO CONSIDERANDO ROBUSTEZ, INFORMAÇÃO E FLEXIBILIDADE

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Thesis presented to the School of Mechanical Engineering and the Institute of Geosciences of the University of Campinas in partial fulfillment of the requirements for the degree of Doctor in Petroleum Sciences and Engineering in the area of Reservoirs and Management.

Tese apresentada à Faculdade de Engenharia Mecânica e Instituto de Geociências da Universidade Estadual de Campinas como parte dos requisitos exigidos para a obtenção do título de Doutora em Ciências e Engenharia de Petróleo na área de Reservatórios e Gestão.

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Co-supervisor: Dra. Ana Teresa Ferreira da Silva Gaspar

Este exemplar corresponde à versão final da Tese defendida pelo aluno Susana Margarida da Graça Santos e orientada pelo Prof. Dr. Denis José Schiozer.

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TESE DE DOUTORADO

DECISION ANALYSIS APPLIED TO THE DEVELOPMENT OF PETROLEUM FIELDS CONSIDERING ROBUSTNESS, INFORMATION, AND FLEXIBILITY

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A Ata da defesa com as respectivas assinaturas dos membros encontra-se no processo de vida acadêmica do aluno.

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DEDICATION

To my family.

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“Everything must be made as simple as possible,
but not simpler.”

Albert Einstein

ABSTRACT

Selecting a production strategy for oil field development is complex because multiple uncertainties affect decisions. Project value is maximized when uncertainty is managed by: (1) acquiring information to reduce reservoir uncertainty; (2) defining a flexible production strategy, allowing system modifications as uncertainty unfolds over time; or (3) defining a robust production strategy, ensuring good performance without system modifications after production has started. However, decision-making is many times subjective and based on intuition or professional experience because of the lack of objective criteria in the literature. In this study, we aimed to provide easy-to-apply decision criteria, while maintaining the complexity of the problem, reducing the subjectivity of the: (1) construction and assessment of the risk curve; (2) selection of the production strategy; and (3) selection of actions to manage uncertainty. For the construction of the risk curve, we compared two techniques: the well-established Monte Carlo with joint proxy models, with the recently proposed discretized Latin Hypercube with geostatistics, presenting their strengths and limitations. For the selection of the production strategy, we proposed a new function that combines the well-known expected value with lower and upper semi-deviations from a benchmark return, quantifying downside risk and upside potential of production strategies. We applied this function to select production strategies and to estimate the expected values of information, flexibility, and robustness. We selected actions to manage uncertainty using predefined candidate production strategies, optimized for representative models of the uncertain system. We proposed probabilistic-based decision structures to assess the potential for information, flexibility, and robustness, incorporating (1) characteristics of the field and the type of uncertainties; (2) available resources and costs; and (3) decision maker's attitude and objectives. Finally, we proposed an integrated approach looking at project sensitivity to uncertainty and at the effects of uncertainties on production strategy selection. Thus, we identify the best course of action to manage uncertainty, either reducing it with information or protecting the system with robustness and flexibility.

Keywords: oil production strategy; numerical reservoir simulation; uncertainty management; downside risk; upside potential; information; robustness; flexibility.

RESUMO

A seleção da estratégia de produção na fase de desenvolvimento de um campo de petróleo é complexa, pois múltiplas incertezas influenciam as decisões. O valor do projeto é maximizado quando a incerteza é gerenciada pela: (1) aquisição de informação para reduzir a incerteza de reservatório; (2) definição de uma estratégia de produção flexível, que possibilite modificar o sistema à medida que a incerteza se desenrola ao longo do tempo; ou (3) definição de uma estratégia de produção robusta, que garanta um bom desempenho sem requerer modificações no sistema após o início da produção. Contudo, o processo decisório é muitas vezes subjetivo e baseado na intuição e experiência profissional, pois critérios objetivos são insuficientes na literatura. O objetivo deste estudo é fornecer critérios de decisão de aplicação simples, sem comprometer a complexidade do problema, reduzindo a subjetividade da: (1) construção e avaliação da curva de risco; (2) seleção da estratégia de produção; e (3) seleção da ação de gerenciar a incerteza. Para a geração da curva de risco, foi realizada uma comparação entre o bem-estabelecido método de Monte Carlo com metamodelos, e o recém-proposto método do Hipercubo Latino discretizado com geoestatística. As vantagens e limitações de cada técnica foram apresentadas. Para a seleção da estratégia de produção, foi proposta uma nova função que combina o valor esperado com semi-desvios padrão abaixo e acima de um retorno *benchmark*, quantificando o nível de risco e o potencial de ganho de uma estratégia de produção. Esta função foi aplicada para selecionar estratégias de produção e para estimar o valor da informação, da flexibilidade e da robustez. A seleção da ação para gerenciar a incerteza usa estratégias de produção candidatas predefinidas, otimizadas para modelos representativos do sistema incerto. Foram desenvolvidas estruturas de decisão probabilísticas que avaliam o potencial para informação, flexibilidade e robustez baseadas em (1) características do campo e o tipo de incerteza; (2) custos e recursos disponíveis; e (3) atitude e objetivos do decisor. Em último lugar, foi proposta uma abordagem integrada baseada na sensibilidade do sistema às incertezas e na influência das incertezas na escolha da estratégia de produção. Essa análise permite selecionar a melhor ação de gerenciamento da incerteza, reduzindo-a com informação ou protegendo o sistema com robustez e flexibilidade.

Palavras Chave: estratégia de produção de petróleo; simulação numérica de reservatórios; gerenciamento da incerteza; risco; potencial de ganho; informação; robustez; flexibilidade.

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1. INTRODUCTION

The decisions related to the development of petroleum fields are complex. When selecting a production strategy, multiple decision variables must be defined, including: (1) number and placement of wells; (2) well-opening schedule; (3) recovery mechanism; (4) platform number; and (5) fluid processing capacities. Because of the lack of data and difficulties related to reservoir characterization, and because developing a petroleum field is a long-term project, many uncertainties coexist when the development decision must be made. The most common uncertainties are (1) reservoir uncertainties, associated with recoverable reserves and flow characteristics, (2) operational uncertainties, related to system availability, and (3) economic uncertainties, related to market variables, capital expenditures, and operational expenditures. This requires detailed analyses to identify the best production strategy under uncertainty.

A simplistic assessment of uncertainties leads, many times, to underperformance, either by (1) failure to achieve the performance levels that based the decision to invest; or (2) failure to achieve optimal performance, even though investment criteria are met. Begg et al. (2002) attribute the former to an inaccurate assessment of the impacts of uncertainties, resulting in an overestimation of returns or an underestimation of risks. Begg et al. (2004) attribute the latter to a culture of good-enough decisions that justify investments, but also to an over-focus on mitigating the risks compared to the efforts to capture the upsides.

Today, decision makers recognize the shortcomings of poor uncertainty assessments given the challenges of the new oil and gas discoveries. As a result, current research has focused on improving the decision-making process in field development and management (Nævdal et al., 2006; Chen et al., 2009; Jansen et al., 2009; Wang et al., 2009; Schiozer et al., 2015; Shirangi and Durlofsky, 2015). In particular, Schiozer et al. (2015) proposed a framework in 12 steps, summarized as follows:

(1) reservoir characterization under uncertainty;
(2) construction and calibration of the simulation base model;
(3) verification of inconsistencies in the base model using production data;
(4) generation of scenarios considering the full range of uncertainties;
(5) reduction of scenarios using dynamic data (e.g. production data, 4D seismic);

(6) selection of a deterministic production strategy using an optimization procedure;
(7) initial risk assessment;
(8) selection of representative scenarios based on multiple objective functions and the full range of uncertain attributes;
(9) selection of a production strategy for each representative scenario (as in Step 6);
(10) selection of the best production strategy from the set of candidate strategies obtained in Step 9;
(11) identification of potential for changes in the best strategy to mitigate risk or increase value (e.g. information, flexibility, and robustness) and integration with production facilities;
(12) final risk assessment.

Because optimizing a production strategy is complex, and because of limitations in reservoir characterization and history matching, finding optimal production strategies under uncertainty is difficult. Thus, Schiozer et al. (2015) proposed Steps 6 through 12 to improve production strategy selection. The methodologies we propose in this thesis integrate this framework and correspond to developments of Step 4, Step 10, and Step 11, detailed below.

In Step 4, a statistical sampling technique combines all uncertainties to generate scenarios, which we use to construct the risk curve. The literature presents several methods, but the Monte Carlo with proxy models is by far the most common. Research in this step is important because selecting a tool suitable for the case study is key to obtaining adequate uncertainty representation at minimum computational and human efforts.

In reservoir engineering, probabilistic analyses are particularly computationally expensive because flow simulation is time-consuming in itself. As a result, it is common to use proxy models, also referred to as surrogate models or meta-models, to bypass the flow simulator and accelerate analyses.

Data-fits are the most common type of proxy model in uncertainty quantification and probabilistic forecasting in petroleum fields (Peng and Gupta, 2004; Osterloh, 2008; Moeinikia and Alizadeh, 2012; Panjalizadeh et al., 2014; Schuetter and Mishra, 2015; Imrie and Macrae, 2016). However, modeling a reliable data-fit proxy model is difficult due to the high non-linearity between input (reservoir properties) and output (production, injection, and economic forecasts) variables. Furthermore, because this model is not physics-based, it is more susceptible to inaccurate predictions, in addition to non-negligible errors introduced through assumptions and approximations employed in their construction (Trehan et al., 2017).

Geostatistical realizations are particularly difficult to handle, for example, with experimental design theory, because of the multiplicity of realizations and the impossibility of prioritizing one realization over another. Because geostatistical modeling is today considered key to realistically represent the spatial variability of reservoir properties, recent literature has been developing statistical techniques able to incorporate this type of uncertainty (Zabalza-Mezghani et al., 2004; Chen and Durlofsky, 2008; Scheidt and Caers, 2008; Schiozer et al., 2017). In particular, Schiozer et al. (2017) proposed the Discretized Latin Hypercube with Geostatistics, a simplified statistical technique that allows considering a high number of geostatistical realizations without requiring the use of proxy models.

In Step 10, the decision maker selects the best production strategy under uncertainty. Selecting a production strategy is not straightforward because many factors are considered, depending on the decision maker's attitude and objectives. However, tools to quantify and incorporate different attitudes and objectives are not always well documented in the literature, leading decision makers to base decisions on intuition or on criteria that do not truly represent their interests.

Expected value is a common decision criterion in the petroleum industry (Newendorp, 1984; Newendorp and Schuyler, 2000; Koninx, 2001; Begg et al., 2002; Bickel, 2008; Nogueira and Schiozer, 2009; van Essen et al., 2009; Schiozer et al., 2015; Shirangi and Durlofsky, 2015). Although each uncertain outcome is weighted by its probability, expected value has shortcomings by assuming neutrality to the magnitude of gains and losses. Standard deviation sometimes complements decisions (Newendorp and Schuyler, 2000; Lima and Suslick, 2005; Cullick et al., 2007; Hayashi et al., 2010; Capolei et al., 2015), but inaccurately used to measure risk. This metric quantifies in a single value good and bad variability, equally penalizing uncertainty in gains and uncertainty in losses.

Step 11 is key to improving the investment decision, because it consists of analyses to manage uncertainty and further improve the optimization process. Typical actions to manage uncertainty include: (1) acquiring information to reduce reservoir uncertainty; (2) adding flexibility to the production system, allowing system modifications as uncertainty unfolds over time; and (3) defining a robust production strategy, insensitive to uncertainty to ensure good performance across scenarios without requiring system modifications after production has started.

These approaches are well documented in the engineering literature (de Neufville et al., 2004; McManus and Hastings, 2005; Chalupnik et al., 2009). Because acquiring information and defining flexible systems incur costs, the Expected Value of Information (EVoI) and the Expected Value of Flexibility (EVoF) methodologies quantify their gains (Bratvold and Begg, 2010). The Expected Value of Robustness (EVoR) was applied in a similar approach (Moczydlower et al., 2012).

In the petroleum literature, uncertainty is commonly managed with additional information (cf. Bratvold et al. 2009), but in the past decades the industry has observed a growing interest in flexibility (Lund, 2000; Begg et al., 2004; Babajide et al., 2009; Hayashi et al., 2010; Jablonowski et al., 2011; Lin et al., 2013; Marques et al., 2013; Silva et al., 2017). Robustness is still incipient (van Essen et al., 2009; Yang et al., 2011; Yasari et al., 2013; Hegstad and Saetrom, 2014; Viseras et al., 2014; Yasari and Pishvaie, 2015), and few studies integrate different approaches (Begg et al., 2002; Hayashi et al., 2007; Salomão and Figueiredo Junior, 2007; Bovolenta et al., 2012; Moczydlower et al., 2012).

According to Bratvold et al. (2009), information is typically preferred because decision makers tend to believe that more information is always better, not always analyzing whether it is economically the most viable option. Begg et al. (2002) and Bratvold et al. (2009) note that EVoI assessments are not used routinely to justify decisions, not even for the largest investments (4D seismic and appraisal wells). Many factors make information value difficult to quantify, namely its ability to reveal "unknown unknowns" (i.e. uncertainties not yet identified). However, additional information at early stages of the field lifetime may be insufficient to mitigate all uncertainties affecting production strategy selection. In such context, system protection with flexibility and robustness may be advantageous.

The decision on whether and how to manage uncertainty must be based on comprehensive analyses and quantitative criteria. This is because the best approach depends on many factors, including: (1) the characteristics of the field and the type of uncertainties; (2) the available resources and costs; and (3) the decision maker's attitude.

For clarity, we define the following terms in this thesis:

- Proxy model: data-fit function that replaces the flow simulator;
- Geostatistical realization: one of the multiple possibilities of the spatial distribution of petrophysical properties (porosity, permeability, net-to-gross);
- Attribute: uncertain parameter (reservoir, fluid, economic, operational), excluding geostatistical realizations;

- Scenario: a particular combination of all uncertainties (attributes and realizations);
- Risk curve: descendent or complementary cumulative distribution function;
- Overall uncertainty: global variability of a production strategy's performance under all possible scenarios, represented by a risk curve;
- Downside risk: variability below a benchmark return (i.e., the undesired subset of overall variability, or uncertainty in losses);
- Upside potential: variability above a benchmark return (i.e., the desired subset of overall variability, or uncertainty in gains);
- Attitude: how the decision maker perceives downsides and upsides (i.e., neutrality to downsides and upsides, aversion to downsides, or willingness to exploit upsides);
- Objective: production or economic objective functions that the decision maker aims to maximize (e.g. net present value, oil recovery factor).

1.1. Motivation

The main motivation of this research is the lack of objective and quantitative criteria to base decisions in petroleum field development. We observed that decision makers typically base decisions on intuition, professional experience, and informal procedures because criteria that meet their profiles and objectives lack in the literature. Although professional experience is invaluable, it may accompany misconceptions or bias towards particular decision options. We believe that combining the professional experience with quantitative indicators improves project performance.

The need for in-depth decision analyses also motivated this research. Despite a growing concern, decision makers many times simplify analyses to accelerate the process and do not give equal importance to mitigating the risks and to capturing the upsides of uncertainty. Decision makers many times constrain risk analysis to Steps 6 and 7, but neglecting Steps 8 through 12 may lead to underperformance because the impacts of uncertainty are not properly assessed, mitigated and exploited.

Another motivation is the need to develop methodologies that incorporate the use of a numerical reservoir simulator. Numerical simulation, unlike proxy models or decline curves, is time-consuming. However, it improves production forecasts because it can capture the physical phenomenon of fluid flow in porous media.

1.2. Objectives

We aimed to reduce the subjectivity of the decision-making process in the following stages of field development: (1) constructing and assessing the initial risk curve (Step 4); (2) selecting the best production strategy (Step 10); and (3) managing uncertainty (Step 11). Ultimately, we aimed to provide easy-to-apply decision criteria, while maintaining the complexity of the problem. To do so, we develop the following specific objectives:

- the applicability of different statistical techniques for scenario generation according to the complexity of the case study;
- metrics to improve risk curve assessment: isolate and quantify overall uncertainty, downside risk and upside potential of production strategies;
- criteria that incorporate the decision maker's attitude and objectives into the decision;
- improve EVoI, EVoR, and EVoF estimates by accounting for all changes in the risk curve and weighing the decision maker's attitude;
- indicators to identify and quantify the individual potential for information, robustness, and flexibility;
- indicators to identify the best approach to manage uncertainty in a case study, combining information, robustness, and flexibility.

1.3. Premises

In this thesis, we consider that all uncertainties have been correctly identified, mapped, characterized, and parameterized (in Step 1). Specifically for Steps 10 and 11, we also consider the following premises:

- An adequate statistical technique combined the uncertain attributes, ensuring adequate generation of the possible scenarios of the uncertain system (thus, our focus on Step 4);
- The subset of scenarios entitled here representative models (RM), selected from the set of possible scenarios that match production data (in Step 8), ensures adequate representation of the uncertain system (inputs and outputs);
- The deterministic optimization of a production strategy for each representative model (in Step 9) was a thorough process, providing different solutions for the development of the case study (entitled here candidate production strategies - CPS).

1.4. Case Study

The benchmark reservoir model UNISIM-I-D (Gaspar et al., 2015) is the case study for all articles, with exception of Article 2 where we used a different synthetic reservoir (see §1.5.2 for details). Having a known answer, we preferred synthetic models as we aimed to study different methodologies, not the answer in itself. Although synthetic, our case studies present the complexity of real reservoirs, being based on real datasets.

UNISIM-I-D is a sandstone oil reservoir, located 80 km offshore. The field, based on the Namorado Field in Campos Basin, Brazil, is in the development phase, with four years of initial production history for four vertical producing wells. The case study has a set of reservoir, operational and economic uncertainties. The reservoir has two regions separated by a fault, the High block and the East block. The absence or presence of the East block is a key uncertainty affecting production strategy selection because the presence of hydrocarbons in this region has not yet been proven (Figure 1.1).

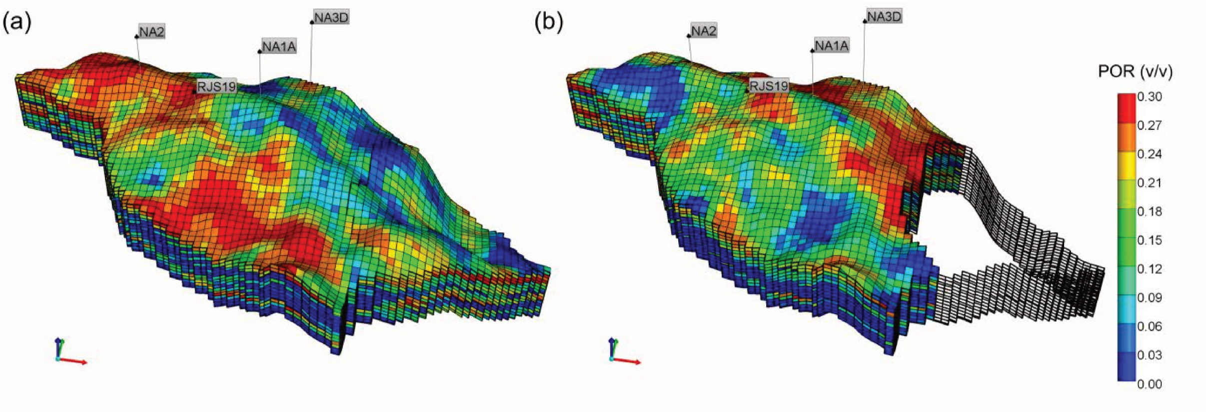

Figure 1.1: Porosity map of (a) RM1, a scenario with the East block, and (b) RM3, a scenario without the East block, including the position of the four producers already drilled.

1.5. Outline and Structure

This thesis is structured in seven scientific articles, detailed in the following subsections. Emphasis is given to the specific objectives addressed in each article, and their contributions to the construction of this thesis.

Schiozer et al. (2015) applied their twelve-step framework to UNISIM-I-D and we used results from their work in Articles 3 through 7, as follows: (1) a set of 214 equiprobable scenarios that match production data (obtained in Step 5); and (2) nine candidate production strategies optimized deterministically for nine representative models (in Step 9). Note that, in this thesis, we base all analyses on the 214 scenarios, not on the nine representative models, meaning that this set of representative models is only used to optimize the candidate production strategies.

The representative models (RM) are selected from the full set of uncertain scenarios that match production data using a procedure that ensures that system inputs and outputs are properly represented (Meira et al., 2016, 2017). That is, the set of RM represents both the uncertainty in reservoir attributes (probability distribution and range of values) and in production, injection, and economic forecasts.

As the RMs represent the uncertain system, their respective production strategies provide decision makers with the different solutions for developing the case study. Our proposals in Articles 3 through 7 use this set of candidate production strategies to conduct the EVoR, EVoI, and EVoF analyses.

1.5.1. Article 1: Comparison of Risk Analysis Methodologies in a Geostatistical Context: Monte Carlo with Joint Proxy Models and Discretized Latin Hypercube

Susana M.G. Santos, Ana Teresa F.S. Gaspar, Denis J. Schiozer

International Journal for Uncertainty Quantification, 2018, v. 8(1), p.23-41

In this article, we compare two methodologies to generate risk curves (Step 4) looking at the: (1) accuracy of the results; (2) computational cost; (3) difficulty in the application; and (4) limitations of the methods. Selecting a tool adequate to the case study is key to obtaining reliable results at minimum computational and human efforts. We considered the Monte Carlo with proxy models, the most common technique today; and the Discretized Latin Hypercube with Geostatistics (Schiozer et al., 2017), a simplified statistical technique that has shown promising results because it allows considering a high number of geostatistical realizations without requiring the use of proxy models.

This article makes a positive contribution to risk analysis studies by presenting the strengths and limitations of these techniques and the preferred conditions for their application. It also provides justification for the method we selected to generate risk curves in the subsequent articles of this thesis.

1.5.2. Article 2: Expected Value, Downside Risk and Upside Potential as Decision Criteria in Production Strategy Selection for Petroleum Field Development

Susana M.G. Santos, Vinicius E. Botechia, Denis J. Schiozer, Ana T.F.S. Gaspar

Journal of Petroleum Science and Engineering, 2017, v. 157, p.81-93

In this article, we propose a set of decision criteria to improve production strategy selection (Step 10) and to incorporate the decision maker's attitude when managing uncertainty (Step 11). Namely, we provide (1) metrics to isolate and quantify overall uncertainty, downside risk, and upside potential; (2) an objective-function to evaluate production strategies incorporating the decision maker's attitude; and (3) a framework to base production strategy selection on multiple objectives.

In our application, we compare a large set of candidate production strategies considering different attitudes and objectives. One of the candidate strategies of UNISIM-I-D (production strategy S9) outperforms the remaining strategies in all criteria (cf. Article 5). For this reason, we preferred a different synthetic case study (Botechia et al., 2016) to better illustrate the proposed criteria.

This article resulted from the evolution of knowledge acquired throughout this thesis, meaning that we did not finalize it before Articles 3 through 7, as organized in this thesis. In Article 3, we assessed production strategies using a utility function from the literature because, at that time, we had only established lower semi-deviation as the adequate risk measure. Article 4 estimates EVoI based on EMV (thus assuming neutrality to downsides and to upsides) because at that time we had not validated our objective-function for such applications. In Article 5, we showed that our function is valid for EVoI estimates, supporting its use to estimate EVoF and EVoR in Articles 6 and 7.

1.5.3. Article 3: Risk Management in Petroleum Development Projects: Technical and Economic Indicators to Define a Robust Production Strategy

Susana M.G. Santos, Ana Teresa F.S. Gaspar, Denis J. Schiozer

Journal of Petroleum Science and Engineering, 2017, v. 151, p.116-127

In this article, we address robustness to manage uncertainty (Step 11). Using probabilistic indicators, we make refinements on a deterministically optimized production strategy to further improve the optimization under uncertainty. This ensures good performance across scenarios without requiring system modifications after production has started. Additional contributions of this work include (1) identifying the need for additional actions to manage uncertainty (information and flexibility); and (2) identifying prior misconceptions or escape from local minima of the deterministic optimization.

In our case study, we successfully improved production strategy optimization under uncertainty, and strongly reduced risk, as defined in Article 2. In Article 7, we incorporate features of the robust production strategy from this study when defining a flexible production strategy.

1.5.4. Article 4: Value of Information in Reservoir Development Projects: Technical Indicators to Prioritize Uncertainties and Information Sources

Susana M.G. Santos, Ana T.F.S. Gaspar, Denis J. Schiozer

Journal of Petroleum Science and Engineering, 2017, v. 157, p.1179-1191

In this article, we address information acquisition to manage uncertainty (Step 11). We propose indicators to identify, a priori, the uncertainties that can be mitigated with information. We consider all available information sources, we calculate the value of individual, simultaneous and sequential information, and we estimated EVoI for perfect and imperfect information. This approach reduces the subjectivity of decisions and eliminates biases towards particular uncertainties or information sources.

A key contribution of this work is that we automate the EVoI analysis by using a predefined set of candidate production strategies, and a predefined set of uncertain scenarios. We use Bayes Theorem to update the probability of occurrence of each scenario given the information outcomes, eliminating the need to sample new scenarios, and thus automating the EVoI analysis.

In this study, we estimate EVoI as the expected increase in the expected monetary value, characterizing the decision maker’s attitude as that of a neutral to downsides and to upsides. This is because when we concluded this study, we had not finalized the proposals of Article 2. In Article 5, we assess EVoI according to different attitudes, by applying the concepts here developed with the proposals of Article 2. Article 7 incorporates results from this paper to find the best action to manage uncertainty in UNISIM-I-D.

1.5.5. Article 5: Assessing the Value of Information According to Attitudes Towards Downside Risk and Upside Potential

Susana M.G. Santos, Denis J. Schiozer

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In this article, we assess the EVoI according to the decision maker's attitude (Step 11). The decision to acquire information may be based on: (1) increasing the expected return of the project; (2) decreasing the risks; (3) exploiting potentially optimistic scenarios; or (4) both aversion to downsides and seeking to exploit upsides. Thus, including these attitudes is key when assessing information opportunities to create value and prevent economic loss.

We applied the function developed in Article 2 to estimate EVoI, and the approach proposed in Article 4, which uses many uncertain scenarios and a set of candidate production strategies in an automated EVoI analysis.

This study shows that decision makers with different attitudes value information differently, meaning that, an information opportunity rejected by one decision maker may be taken by another.

1.5.6. Article 6: Managing Reservoir Uncertainty in Petroleum Field Development: Defining a Flexible Production Strategy from a Set of Rigid Candidate Strategies

Susana M.G. Santos, Ana T.F.S. Gaspar, Denis J. Schiozer

Submitted to a peer-reviewed journal

In this article, we address flexibility to manage uncertainty (Step 11). We developed a decision structure that uses a predefined set of candidate rigid production strategies to define the flexible strategy, reducing the subjectivity of decisions and accelerating analysis.

A key contribution of this work is that we establish probabilistic-based implementation rules, using the reservoir simulation outputs. Because we do not apply pre-defined rules as inputs, we eliminate biases and ensure more objective decision rules.

We improve the EVoF estimate using the objective-function proposed in Article 2 to incorporate the decision maker's aim for flexibility, either to mitigate risks or exploit upside. Article 7 incorporates results from this paper to find the best action to manage uncertainty in UNISIM-I-D.

1.5.7. Article 7: Managing Uncertainty in Petroleum Field Development Considering Information, Robustness, and Flexibility

Susana M.G. Santos, Ana T.F.S. Gaspar, Denis J. Schiozer

Submitted to a peer-reviewed journal

This final article proposes a decision structure to identify the best course of action to manage uncertainty and combines the methods developed in the previous articles of this thesis (Figure 1.2).

We use indicators to assess the potential for information, robustness, and flexibility, before performing the EVoI, EVoR, and EVoF analyses themselves. We base our analyses on a set of candidate production strategies, representing the possible solutions for developing the case study. If these candidates are similar, no action is required to manage uncertainty. If different, we use multiple scenarios to assess system sensitivity to uncertainty and the effects of uncertainties on production strategy selection. These analyses identify the best course of action to manage uncertainty: acquire information to reduce uncertainty (proposals of Articles 4 and 5) or system protection with robustness and flexibility (proposals of Articles 3 and 6, respectively).

Our results showed that project value can be increased significantly if uncertainty is properly assessed and managed. This supports the need for in-depth decision analyses as proposed in Steps 6 through 12 by Schiozer et al. (2015).

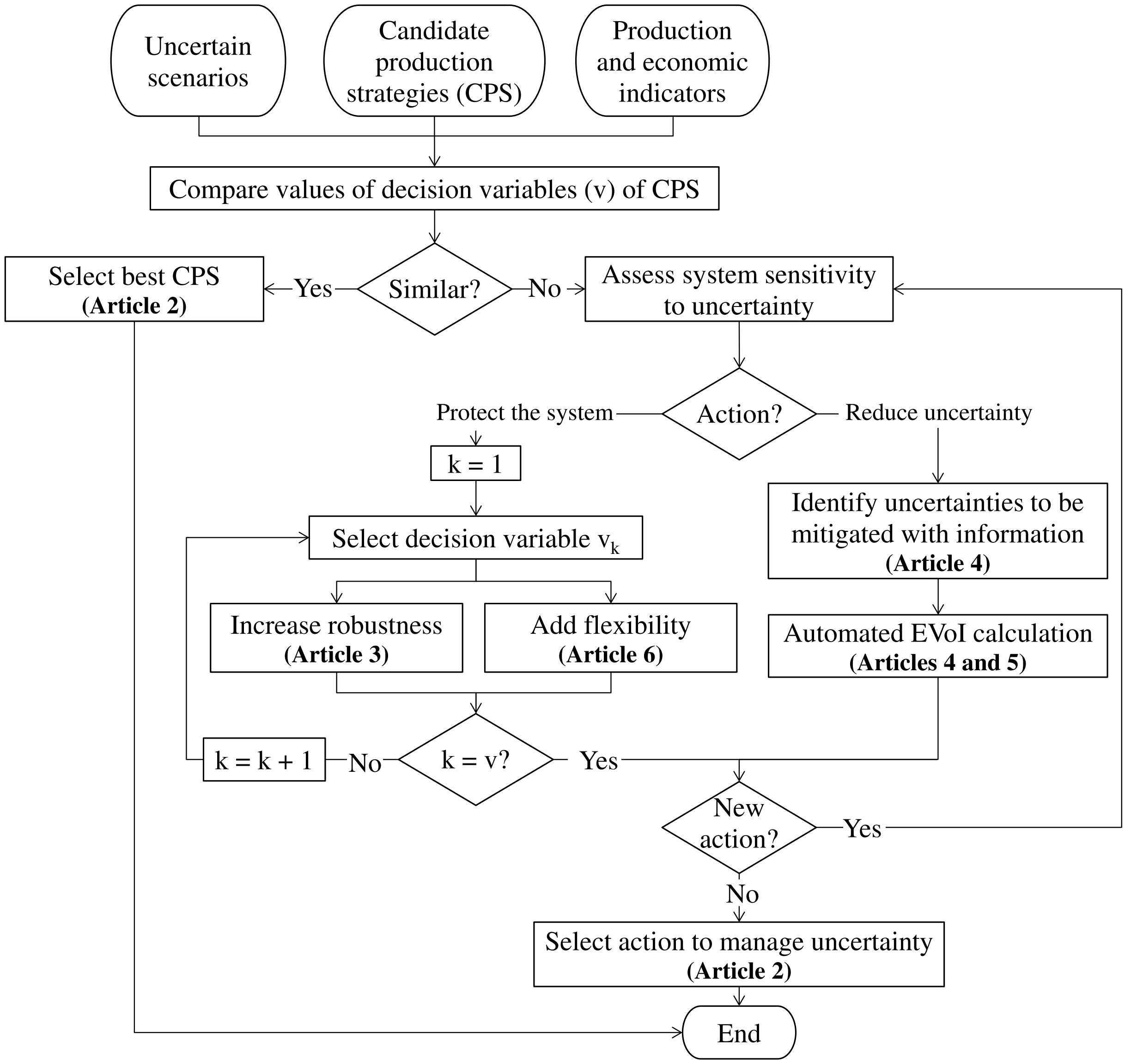

Figure 1.2: Workflow proposed in Article 7 to manage uncertainty in petroleum field development considering information, robustness, and flexibility. This workflow incorporates the methods proposed in the articles of this thesis, as identified in the flowchart.

2. ARTICLE 1: COMPARISON OF RISK ANALYSIS METHODOLOGIES IN A GEOSTATISTICAL CONTEXT: MONTE CARLO WITH JOINT PROXY MODELS AND DISCRETIZED LATIN HYPERCUBE

Susana M.G. Santos, Ana Teresa F.S. Gaspar, Denis J. Schiozer

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COMPARISON OF RISK ANALYSIS METHODOLOGIES IN A GEOSTATISTICAL CONTEXT: MONTE CARLO WITH JOINT PROXY MODELS AND DISCRETIZED LATIN HYPERCUBE

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During the development of petroleum fields, uncertainty quantification is essential to base decisions. Several methods are presented in the literature, but its choice must agree with the complexity of the case study to ensure reliable results at minimum computational costs. In this study, we compared two risk analysis methodologies applied to a complex reservoir model comprising a large set of geostatistical realizations: (1) a generation of scenarios using the discretized Latin hypercube sampling technique combined with geostatistical realizations (DLHG) and (2) a generation of scenarios using the Monte Carlo sampling technique combined with joint proxy models, entitled the joint modeling method (JMM). For a reference response, we assessed risk using the pure Monte Carlo sampling combined with flow simulation using a very high sampling number. We compared the methodologies, looking at the (1) accuracy of the results, (2) computational cost, (3) difficulty in the application, and (4) limitations of the methods. Our results showed that both methods are reliable but revealed limitations in the JMM. Due to the way the JMM captures the effect of a geostatistical uncertainty, the number of required flow simulation runs increased exponentially and became unfeasible to consider more than 10 realizations. The DLHG method showed advantages in such a context, namely, because it generated precise results from less than half of the flow simulation runs, the risk curves were computed directly from the flow simulation results (i.e., a proxy model was not needed), and incorporated hundreds of geostatistical realizations. In addition, this method is fast, straightforward, and easy to implement.

KEY WORDS: *petroleum field development, risk analysis, geostatistics, reservoir simulation, Latin Hypercube, Monte Carlo, joint proxy models*

1. INTRODUCTION

During the lifetime of a petroleum field, particularly in the development phase, assessing the impact of uncertainties is necessary to base decisions. However, this analysis is typically difficult due to the multiple sources of uncertainty, including (1) reservoir uncertainties, associated with recoverable reserves and flow characteristics; (2) operational uncertainties, related to system availability; and (3) economic uncertainties, such as oil price, capital expenditures, and operational expenditures. These uncertainties typically coexist because data are mainly acquired indirectly and sparsely, and because developing a petroleum field is a long-term project.

Zabalza-Mezghani et al. [1] classify uncertainties in petroleum fields according to their statistical behavior as (1) continuous, those that vary between a minimum and a maximum value, taking a continuous range (e.g., porosity, permeability, and the depth of the water-oil contact); (2) discrete, those that only take a finite number of discrete values (e.g., pressure-volume-temperature (PVT) tables, relative permeability curves, and the Boolean behavior of a fault that can be conductive or not); and (3) stochastic, which correspond to a variable that has a nonlinear impact on the response or an uncertainty that can take infinite equiprobable discrete values (e.g., geostatistical realizations).

Geostatistical modeling has been increasingly used to realistically represent spatially correlated reservoir properties (facies, porosity, permeability, and net-to-gross ratio). The geologic reality is respected when building the mathematical reservoir model because geosciences and reservoir engineering disciplines are integrated into reservoir characterization [2]. This method generates a set of equiprobable realizations of one or more geological scenarios. A geological scenario is a conceptual interpretation performed by geologists based on their qualitative understanding and includes geometry and spatial distribution of various rock types [3]. The degree of variability between realizations reflects the degree of uncertainty. Chambers et al. [4] give four reasons to support geostatistical modeling over conventional deterministic techniques: capturing heterogeneity, simulating facies or rock properties or both, honoring and integrating complex information, and assessing uncertainty.

Monte Carlo is a very common sampling technique in uncertainty quantification. However, because it performs random sampling, it requires a very high sampling number to ensure reliable results [5]. In the particular case of petroleum reservoir engineering, quantifying uncertainty is computationally expensive because flow simulation is time-consuming in itself. In numerical reservoir simulation, also referred to as flow simulation, a mathematical model of the physical system (reservoir) is solved numerically to predict fluid behavior over time. One flow simulation run can take minutes, hours, or even days depending on the complexity of the reservoir. For this reason, pure random sampling loses favor as computational costs increase frequently to unfeasible levels [6]. As a result, it is common to combine pure sampling techniques with proxy models, also referred to as surrogate models or meta-models, to bypass the flow simulator in the sampling step.

2. LITERATURE REVIEW ON RESERVOIR ENGINEERING APPLICATIONS

2.1 Proxy Models as a Substitute for Flow Simulation

In reservoir engineering, data-fit proxy models are common in uncertainty quantification and probabilistic forecasting [7–13], and its related applications, such as assisted history matching (known as data assimilation in other engineering disciplines) [8,14–16], and production strategy optimization [11,17]. Experimental design theory is typically applied to obtain the right set of flow simulation runs to model a deterministic function to represent the response as a function of the uncertain parameters. Other authors use stochastic processes to construct the proxy model.

The use of simplified models as a substitute for flow simulation is not straightforward. Although time-consuming and computationally expensive, flow simulation is preferred because it captures the physical phenomenon of fluid flow in porous media. In addition, proxy models often introduce non-negligible errors due to the assumptions and approximations employed in their construction [18]. Quantifying the errors introduced by the proxy is key to a rigorous application because erroneous predictions from the proxy model can lead to spurious uncertainty quantification.

In addition to errors in the modeling process itself, modeling a reliable data-fit proxy model is especially difficult due to the high nonlinearity between input variables (reservoir properties) and output variables (production and injection forecasts) of flow simulation. Furthermore, because this model is not physics-based, it is more susceptible to inaccurate predictions, especially for high-dimensional input-parameter spaces [18]. Classical statistical methods such as R^2, cross-validation, confidence intervals, and prediction intervals can be applied to validate data-fit proxy models (see, for example, [19,20]).

Lower fidelity reservoir models are also used to accelerate analyses. These models entail many simplifications to increase computational efficiency, but unlike data-fits, they still respect the physical processes governing the reservoir. In this approach, high- or medium-fidelity models are coarsened or upscaled prior to flow simulation through numerical homogenization procedures. This approach is attractive because upscaling is relatively straightforward to implement [18]. Applications of this approach include history matching [21,22] and production strategy optimization [23,24].

Although physics-based, the use of lower fidelity reservoir models as a substitute for high- or medium-fidelity models is not straightforward either. This is because upscaling errors arise from neglecting subgrid heterogeneity effects [1,25,26]. Even though procedures exist to quantify the upscaling error, it is rarely pursued [22]. This is because modeling the neglected subgrid effects is complicated and invasive, with respect to the flow simulator [18].

More details on the pros and cons of proxy modeling as a computational inexpensive alternative to flow simulation can be found in [27].

2.2 Efficient Sampling Techniques

Another approach to increasing computational efficiency consists of improving the sampling process. The major limitation of random sampling, as performed by Monte Carlo, is that there is no guarantee that the full range of the distribution is sampled evenly and consistently, meaning that low-probability but high-consequence events are likely to be missed [28]. This limitation can be overcome, for example, through stratified sampling, which forces the inclusion of specific subsets of the sample space. However, this technique has limitations because it requires defining the strata and calculating their probability, which becomes difficult in high-dimensional sample spaces [28].

The Latin hypercube sampling (LHS) is today considered more efficient because it incorporates desirable features of random sampling and stratified sampling [28]. In particular, LHS does not require determining strata and their probabilities while maintaining the property of densely stratifying the range of each parameter [28]. Initially proposed by McKay et al. [29] as an extension of quota sampling [30] and Latin square sampling [31], LHS lead to the Latin hypercube design (LHD) for computer experiments. In reservoir engineering, this space-filling design has been applied to construct proxy models [8,9,32].

In applications related to history matching, Markov chain Monte Carlo (MCMC) methods are often used [33–35]. Because it is computationally demanding, the two-stage MCMC [36–38] was developed to increase sampling efficiency. This approach evaluates candidates in a first stage using computationally inexpensive techniques, such as coarse-scale models [39,40] and polynomial chaos response surfaces [41–43].

In the statistics literature, there has been an increasing interest in Monte Carlo procedures based on Importance Sampling, a different class of techniques. Population Monte Carlo [44] and its variants [45,46], adaptive multiple importance sampling [47], and adaptive population importance sampling [48] are examples of techniques available in the statistics literature. To the best of our knowledge, these approaches are not common to quantify uncertainty in reservoir engineering.

2.3 Incorporating Geostatistics in Uncertainty Quantification

Geostatistical uncertainties are many times difficult to handle due to the multiplicity of equiprobable realizations and the impossibility of prioritizing one realization over another. Consequently, recent work has focused on methodologies capable of incorporating this uncertainty.

Zabalza-Mezghani et al. [1,49,50] proposed the joint modeling method (JMM), which computes two data-fit proxy models, one to describe the production response as a function of the nonspatial (continuous) parameters and another to describe the dispersion of the response due to the effect of the spatial (stochastic) parameter. Examples of applications of this method include uncertainty quantification and risk assessment [1,51–53] and production strategy optimization [1].

Scheidt and Caers [54,55] proposed the distance kernel method, which selects a small subset of representative realizations in terms of flow behavior. Flow simulation runs are performed only on the representative subset. An example application of this method for uncertainty quantification on a real oil field case can be found in [56].

Chen and Durlofsky [57] proposed an ensemble-level upscaling approach, which provides coarse models that capture ensemble flow statistics instead of a realization-by-realization basis. This approach was further extended by Chen et al. [58] and Li and Durlofsky [59].

Schiozer et al. [60] combined the discretized Latin hypercube sampling with geostatistical realizations (DLHG) in a new approach that: (1) preserves the geostatistical consistency of properties that vary spatially; (2) is efficient, considering the number of flow simulation runs necessary to reach good results; (3) is easy to implement and use because it avoids the complexity of proxy models; and (4) is flexible for use in different cases in terms of required precision, computational time, and type of uncertainties. Applications of this approach have shown promising results in uncertainty quantification and risk analysis [61], and history matching [62–66].

2.4 Comparative Studies

Because of the numerous methodologies available in the literature, comparative studies became necessary to allow the user to select tools adequate to the case study in order to obtain reliable and precise results at minimum computational and human efforts. Many authors compared different experimental designs (fractional factorial, Plackett-Burmann, central composite, D-Optimal, space-filling) and proxy modeling techniques (polynomial regression, multivariate kriging, thin-plate splines, artificial neural networks) in reservoir engineering applications related to uncertainty quantification, history matching, production strategy optimization, and forecasting. However, not all authors reached the same conclusions.

Yeten et al. [67] observed that experiments generated by a space-filling design and modeled as quadratic polynomial response surfaces outperformed traditional designs and the associated responses. Schuetter and Mishra [13] also recorded good results with space-filling designs but modeled with multidimensional kriging, while others [8,68,69] reported low-quality results with polynomial regression models. Cullick et al. [69] achieved good results with an artificial neural network as a proxy model, and Osterloh [8] by using kriging. Zubarev [27] observed that kriging and thin-plate splines performed best; whereas, artificial neural networks and polynomial regression models tend to reduce precision by smoothing out the response surface. Conversely, Peng and Gupta [7] found that kriging methods did not develop better proxy models when compared to a polynomial regression.

These different results can be justified by the extensive comparative study of Zubarev [27]. Zubarev observed that all models were equally good predictors provided that the methods choice agrees with the type of input date. Therefore, Zubarev [27] concluded that the choice of the type of proxy model should be problem specific. In particular, Scheidt et al. [70] observed that classical experimental designs are not suitable to represent complex, irregular responses, because they assume regular first- or second-degree polynomial-type behavior of the response. Alternatively, the authors propose using evolutive designs to gradually fit the potentially irregular shape of the response.

In terms of addressing uncertainty in both spatial and nonspatial parameters, Scheidt and Caers [71] compared the joint modeling method with the distance kernel method. They observed that the distance kernel method provides more accurate uncertainty quantification with fewer flow simulation runs.

In terms of the computational efficiency of the sampling technique itself, Madeira [72] compared the derivative tree and the Monte Carlo methods. In related work, Risso et al. [6] compared the precision of the derivative tree, the Monte Carlo sampling, and the Latin hypercube sampling, concluding that the Latin hypercube technique produced the same results as the other methods while requiring far fewer flow simulation runs.

3. SCOPE AND OBJECTIVE

Industry professionals in the petroleum industry value fast and easy-to-apply uncertainty quantification techniques. This is because the decision-making process in field development is highly complex, and the time available for such is typically limited. Thus, simplistic approaches are many times preferred to state-of-the-art uncertainty quantification techniques available in the petroleum and statistics literature.

The joint modeling method [1,49,50] is often used by industry professionals. Despite using second-order response surfaces, which can be regarded as too simplistic, the JMM is typically preferred to more sophisticated methods because it has a very close application to that of the classic experimental design.

Although not widely applied in the petroleum industry, we observed that the DLHG [60] has shown promising results in different reservoir engineering applications (see Section 2.3). This technique allows incorporating different types of uncertainties and is straightforward to apply because it does not require the use of proxy models.

Accordingly, in this study we quantify uncertainty of a petroleum field in the development phase using these two methods: (1) the discretized Latin hypercube sampling technique with geostatistical realizations [60], a technique that has shown promising results in recent studies; and (2) the Monte Carlo sampling technique combined with joint proxy models [1,49,50], a technique many times preferred by industry professional. We compare these two methods looking at the accuracy of results, computational cost, difficulties in their application, and limitations of the methods.

Ultimately, we assess the applicability of these methods to complex reservoir models. We emphasize the method's applicability in a geostatistical context because it is the most reliable way of representing reservoir spatial properties.

To validate our results, we quantify uncertainty from flow simulation with pure Monte Carlo sampling with a very high sampling number.

In this work, we define the following terms:

- *Proxy model* refers to a data-fit function that replaces the flow simulator
- *Geostatistical realizations* refers to the multiple possibilities of the spatial distribution of petrophysical properties (facies, porosity, permeability, net-to-gross ratio)
- *Attributes* refers to other uncertain parameters (reservoir, fluid, economic, operational), excluding geostatistical realizations
- *Scenarios* refers to particular combinations of all uncertainties (geostatistical realizations with other attributes)
- *Risk curve* refers to the descending or complementary cumulative distribution function

4. METHODOLOGY

This study compares two risk analysis methodologies:

- DLHG—generation of scenarios using the discretized Latin hypercube sampling technique with geostatistical realizations.
- JMM—generation of scenarios using the Monte Carlo sampling technique combined with joint proxy models.

Each technique is applied to a set of discretized attributes and geostatistical realizations to compute risk curves of production indicators.

4.1 DLHG

Figure 1 presents the workflow to apply the DLHG. Shapes and colors are used to allow comparison between flowcharts of both methods.

In step 1, reservoir characterization under uncertainty is conducted to identify all uncertainties and respective probabilities of occurrence. Then, in step 2, the simulation base model is constructed and calibrated. Note that these steps are not the focus of this study and are independent of the methodology used to assess risk. Additional details on these steps can be found in Schiozer et al. [61].

All sampled scenarios are simulated using the flow simulator, meaning that no proxy model is used for production forecasts. This is possible because DLHG [60] applies the efficient LHS and integrates all types of uncertainties in the sampling step (i.e., continuous attributes are discretized and then combined with discrete attributes and geostatistical realizations). In LHS, the range of each variable (x_j) is divided into n disjoint intervals of equal probability and one value is selected at random from each interval. The n values obtained for x_1 are paired at random without replacement with the n values obtained for x_2. This process is continued until a set of n nX-tuples is formed [28].

Each attribute is treated according to sampling number, number of discrete levels, and probability of each discrete level. The sampling number, which is equal to the number of flow simulation runs, is set at the beginning of the process based on simulation run time, importance of the study (i.e., the required precision), and available work time [60].

Schiozer et al. [60] reported that preliminary analyses showed that LHS with a few hundred flow simulation runs produces results comparable to Monte Carlo with thousands of flow simulation runs. In this study, we assessed different sampling numbers to verify its dependency on the precision of the results.

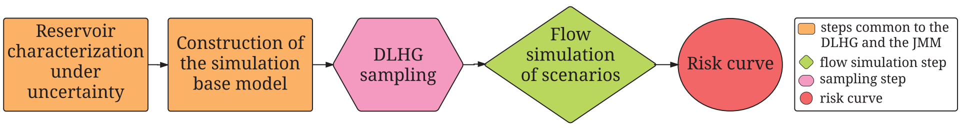

FIG. 1: Workflow to apply the DLHG. Rectangles: initial steps common to the DLHG and the JMM. Hexagon: sampling step. Diamond: flow simulation step. Circle: risk curve

4.2 JMM

Figure 2 presents the workflow to apply the JMM. Shapes and colors are used to allow comparison between flowcharts of both methods. Note that steps 1 and 2 are common to DLHG and JMM because they are independent of the methodology used to assess risk.

In this approach, a proxy is modeled as a deterministic function and replaces the flow simulator in the Monte Carlo sampling step. To define the flow simulations required to build the proxy models, we used LHD because space-filling designs are considered more accurate when compared to traditional designs [32,67,73,74].

Space-filling designs include orthogonal arrays (OAs) and Latin hypercube designs (LHDs). Wang [73] listed the following advantages of LHD over OA:

1. LHD provides more information within a design space.
2. Although OA can generate a sample with better space-filling property, generating a set of OA points is more complicated then LHD.
3. OA demands strict levels classification for each variable, which might be difficult in real designs.
4. LHD provides uniform random sampling, treating every variable as equally important and ensuring uniformly distributed sampling in a given design space.
5. The size of an LHD sample is determined by the user and can be controlled according to budget, time, and other conditions.
6. As the sample size is controllable, LHD allows generating saturated experimental design points, representing the minimum requirement to fit a second-order model.

Additionally, Scheidt and Zabalza-Mezghani [74] point out that, among space-filling designs, Latin hypercubes are the most popular for computer experiments because they are easy to construct and have good sampling properties.

To incorporate the geostatistical realizations, we used the JMM [1,49,50], which computes two proxy models: (i) a mean model, describing the production response y as a function of the continuous parameters $x_1, x_2, \ldots, x_n$ [Eq. (1)]; and (ii) a variance model, describing the dispersion of the response y due to the effect of the stochastic uncertainty [Eq. (2)]. JMM uses parametric response surfaces, a type of polynomial regression model, as a proxy model.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{12} x_1 x_2 + \beta_n x_n^2 \tag{1}$$

$$\text{Dispersion}(y) \approx \exp(\gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_{12} x_1 x_2 + \gamma_n x_n^2) \tag{2}$$

The mean model is constructed following the classic experimental design theory using all uncertain attributes (geostatistical realizations are not included in this design). The variance model is constructed by defining repetitions

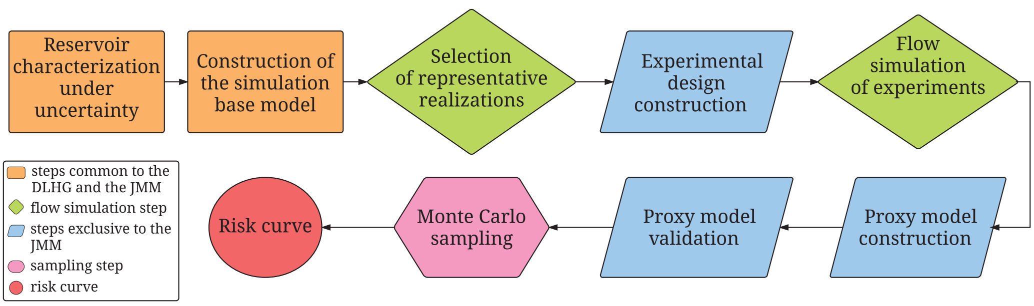

FIG. 2: Workflow to apply the JMM method. Rectangles: initial steps common to the DLHG and the JMM. Diamonds: flow simulation steps. Parallelograms: steps associated with the construction of the proxy model, therefore exclusive to the JMM. Hexagon: sampling step. Circle: risk curve

of each of these experiments (one repetition for each geostatistical realization) to calculate the variance of the response due to multiple geostatistical realizations. To exemplify this approach, consider the following case: (i) an experimental design with 20 experiments built using only the uncertain attributes and (ii) three geostatistical realizations. In this example, each of the 20 experiments is repeated three times, one repetition for each realization, totaling 60 flow simulation runs.

This example shows that JMM can become computationally prohibitive. For this reason, our workflow includes one step to select representative realizations before constructing the experimental design. This step is important for case studies that comprise many geostatistical realizations.

In this study, we selected different sets of representative geostatistical realizations. We performed a one-factor-at-a-time sensitivity analysis to rank all realizations and selected representative realizations based on the visual analysis for four objective functions: cumulative oil production (Np), cumulative water production (Wp), oil recovery factor (RFo), and original oil in place (OOIP). Our goal is to assess its effects on the precision of results and associated computational costs.

To validate the computed response surface, we conducted a variance analysis and visual diagnosis using cross-plots of simulated versus predicted values by the response surface. Finally, the Monte Carlo sampling is performed on the proxy model, and no additional flow simulation runs are needed.

4.3 Validation of Results

To validate the risk curves obtained by the DLHG and JMM methods, we analyzed risk from flow simulation with pure Monte Carlo sampling, a method that the literature puts forward as valid provided that a high sampling number is defined, on the order of thousands. This ensures that the distribution of input parameters is reproduced [5].

We refer to the method as MC: generation of scenarios using the pure Monte Carlo sampling with flow simulation, applied to a set of discretized attributes and many geostatistical retaliations, to compute risk curves of production indicators. Note that in MC, the results are obtained from flow simulation, not a proxy model.

4.4 Comparison of Methodologies

We compared both methodologies in four steps:

Step 1. We assessed the accuracy of the results by comparing the risk curves for the objective functions Np, Wp, RFo, and OOIP. Using the MC method as reference, we computed the deviation coefficient D [Eq. (3)], an extension of the formula proposed by Yeten et al. [67], corresponding to the expected value of the relative difference between risk curves

$$D = 0.1 * \sum_{i=1}^{9} \frac{\left|P_{10i} - P_{10i}^{\text{ref}}\right|}{P_{10i}^{\text{ref}}} + 0.05 * \sum_{i=0}^{1} \frac{\left|P_{5+90i} - P_{5+90i}^{\text{ref}}\right|}{P_{5+90i}^{\text{ref}}} \tag{3}$$

Step 2. We compared the number of flow simulation runs performed to assess the computational costs of the methods.

Step 3. We evaluated the overall difficulty of the methodology's application.

Step 4. We assessed the limitations of the methods.

5. APPLICATION

The methodology was applied to the synthetic reservoir model UNISIM-I-D [75], a benchmark case study for selection of production strategy. Having a known answer, we preferred a synthetic model because we aimed to compare different methodologies, not study the answer itself. Although synthetic, it presents the complexity of a real reservoir because it is based on a Brazilian field.

UNISIM-I-D is an offshore oil reservoir, 80 km from the coastline, in the development phase, with 1461 days of initial production history for four vertical producing wells (Fig. 3). The reservoir depth varies between 2900 and 3400 m, and the water depth is 166 m. The simulation model is a medium-fidelity model that comprises a corner point grid with 81 × 58 × 20 cells of 100 × 100 × 8 m, in a total of 36,739 active cells. The production strategy has 13 production wells (2 vertical and 11 horizontal) and 9 horizontal water injection wells. UNISIM-I-D comprises a set of reservoir and operational uncertainties (Tables 1 and 2), whose impact on the production response was assessed. The uncertainties of the original dataset are either discrete or have been discretized.

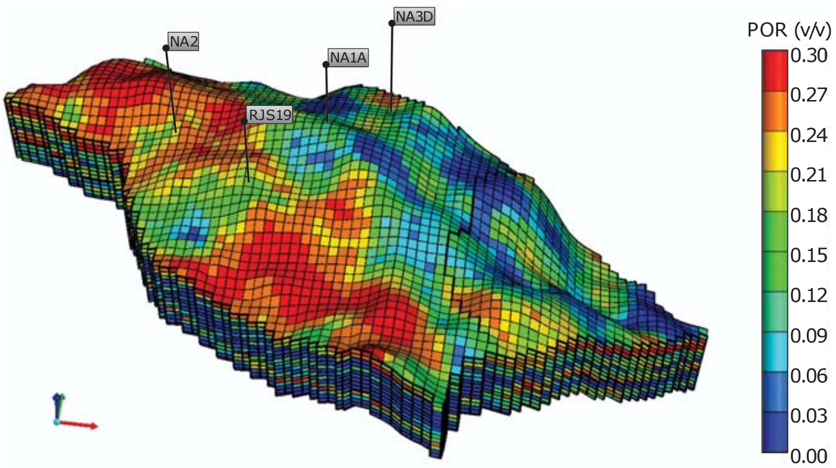

FIG. 3: Porosity map of UNISIM-I-D reservoir model, including the position of the four historic producers

TABLE 1: Set of reservoir uncertainties of UNISIM-I-D case study

Attribute	Description	Type	Value (probability)				
			–2	–1	0	+1	+2
img	Petrophysical properties	Discrete [realization]	500 geostatistical realizations of one geologic scenario for porosity, permeability, and net-to-gross ratio (0.002)				
kr	Water relative permeability	Discrete [table]	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
pv	PVT data (East block)	Discrete [table]	–	(0.33)	(0.34)	(0.33)	–
bl	Structural model	Discrete [map]	–	No east block (0.30)	With east block (0.70)	–	–
wo	Water-oil contact (East block)	Continuous discretized [scalar]	3074m (0.222)	3124m (0.334)	3174m (0.111)	3224m (0.222)	3274m (0.111)
cp	Rock com-pressibility	Continuous discretized [scalar]	–	23.6E-6 cm^2/kgf (0.20)	53.0E-6 cm^2/kgf (0.60)	82.4E-6 cm^2/kgf (0.20)	–
kz	Vertical permeability multiplier	Continuous discretized [scalar]	0.475 (0.10)	0.949 (0.20)	1.500 (0.40)	2.051 (0.20)	2.525 (0.10)

TABLE 2: Set of operational uncertainties of UNISIM-I-D case study

Attribute	Description	Type	Value (Probability)		
			−1 (0.33)	**0 (0.34)**	**+1 (0.33)**
ogr	Group availability	Continuous discretized	0.91	0.96	1.00
opl	Platform availability	Continuous discretized	0.90	0.95	1.00
opw	Producer well availability	Continuous discretized	0.91	0.96	1.00
oiw	Injection well availability	Continuous discretized	0.92	0.98	1.00
ff	Well index multiplier	Continuous discretized	0.70	1.00	1.40

6. RESULTS

6.1 DLHG with Different Sampling Numbers

Figure 4 presents risk curves obtained from the DLHG method for different sampling numbers (20, 50, 100, 300, and 500), computed for the objective functions Np, Wp, RFo, and OOIP. These curves were plotted against risk curves for the same objective functions computed using the MC method with a sampling number of 5×10^3, to ensure good representation of the full data set. Note that in the reference MC curves, the predictions were obtained directly from flow simulation, not from a proxy model.

Figure 5 presents the risk curve deviation from the reference. These results showed that the risk curves obtained by the DLHG method were similar, indicating that the results' precision is independent of the sampling number. However, because the data set included 500 geostatistical realizations, in some cases, a sampling number lower than 100 samples poorly represented some pessimistic values [e.g., Fig. 4(c)], with the highest deviations being recorded in these cases (Fig. 5).

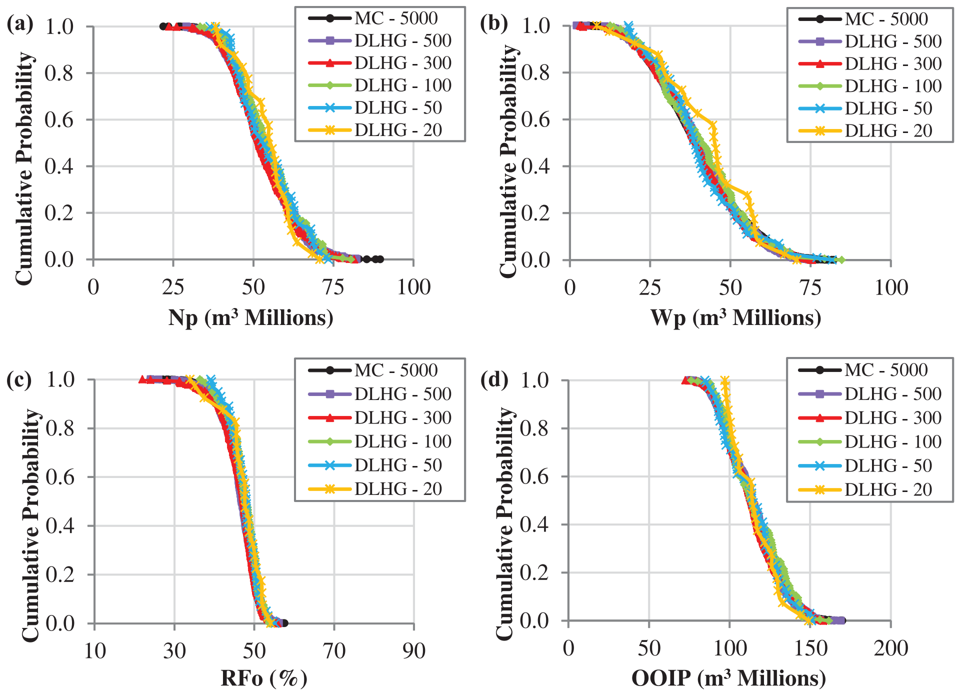

FIG. 4: Risk curves obtained by applying the DLHG method with different sampling numbers: 20 (star), 50 (cross), 100 (diamond), 300 (triangle) and 500 (square), for the objective functions: (a) Np, (b) Wp, (c) RFo, and (d) OOIP. The MC method (circle) is presented as reference.

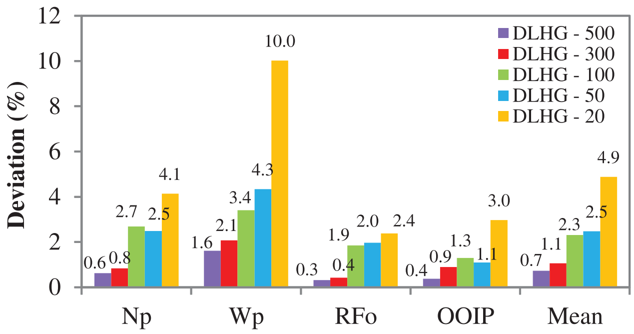

FIG. 5: Deviation D (%) for the DLHG method with different sampling numbers (from left to right: 500, 300, 100, 50, 20), for each objective function and the overall mean

For this case study, we found 300 to be a sufficient sampling number to produce smooth and reliable risk curves. These results were therefore used for the comparison with the JMM.

6.2 JMM with Different Numbers of Geostatistical Realizations

We selected 3, 5, and 11 representative geostatistical realizations through sensitivity analysis (Fig. 6) because it was unfeasible to use the full data set considering the way JMM treats this uncertainty. We built the response surface models using an LHD experimental design with 68 experiments, repeated three, five, and eleven times to capture the geostatistical uncertainty, totaling 204, 340, and 748 flow simulation runs, respectively. There were 5×10^3 scenarios sampled on the proxy model using Monte Carlo sampling. JMM risk curves were plotted against risk curves for the same objective functions computed using the MC method with a sampling number of 5×10^3 (Fig. 7). Figure 8 presents the risk curve deviation from the reference MC.

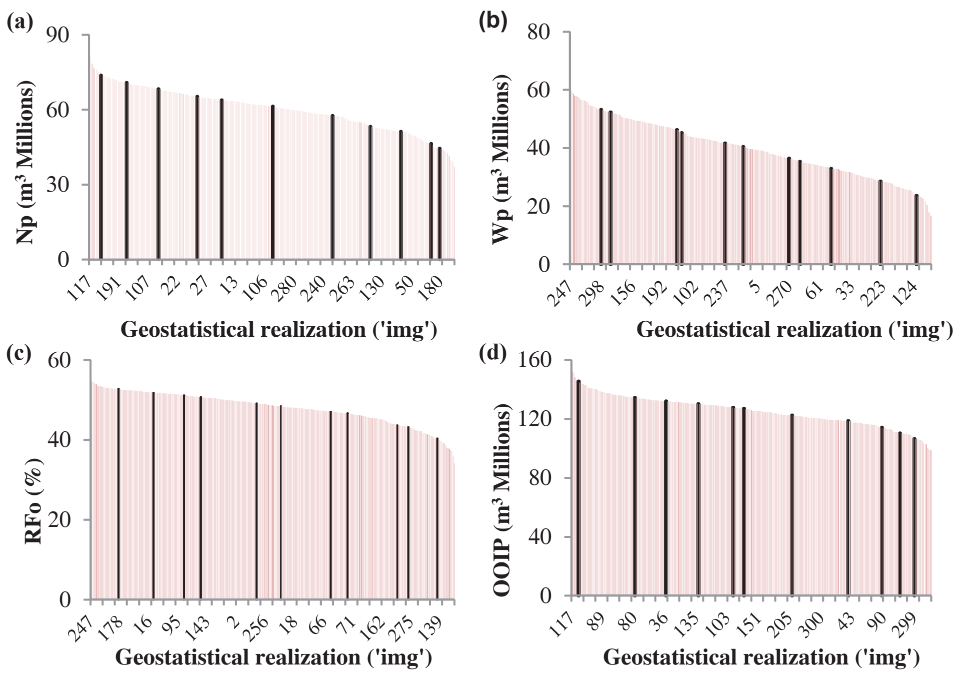

FIG. 6: Selection of 11 representative realizations based on the objective functions: (a) Np, (b) Wp, (c) RFo, and (d) OOIP

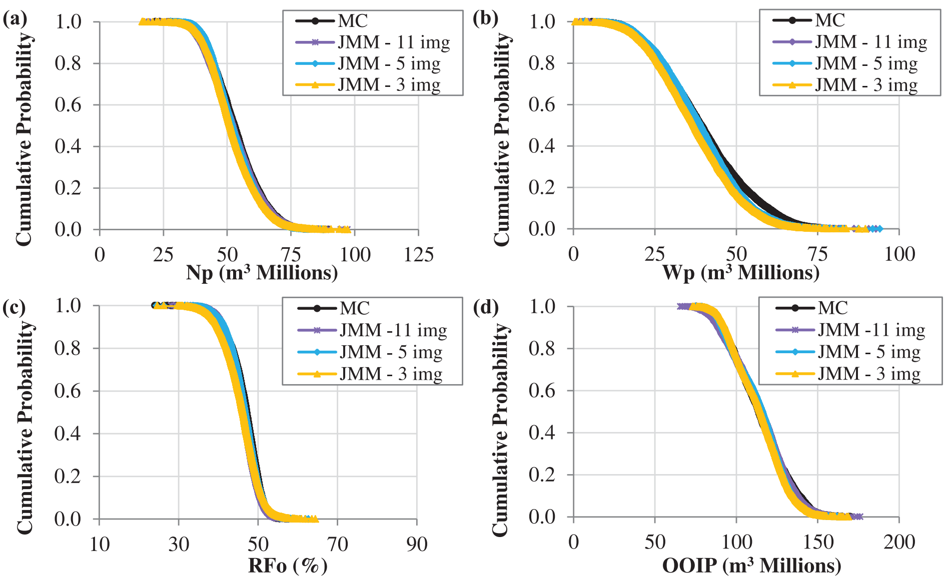

FIG. 7: Risk curves obtained by applying the JMM with 11 (star), 5 (diamond), and 3 (triangle) representative realizations (img) for the objective functions: (a) Np, (b) Wp, (c) RFo, and (d) OOIP. The MC method (circle) is presented as reference.

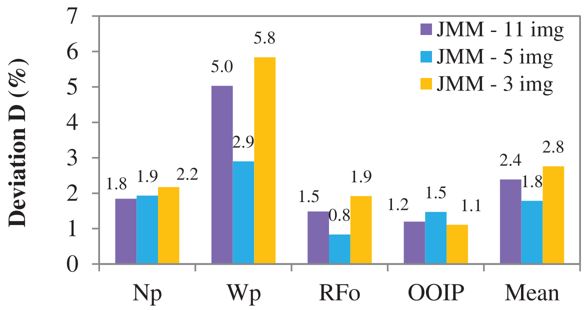

FIG. 8: Deviation *D* (%) for the JMM method with different numbers of representative realizations (from left to right: 11, 5, 3), for each objective function and the overall mean

We achieved the best results with five representative realizations, but three realizations performed well for most objective functions. Our results also showed no immediate advantage on increasing the number of representative realizations, because it did not ensure better representation of uncertainty.

6.3 Comparison between DLHG and JMM

For the DLHG method, the defined sampling number was 300 (see Section 6.1). For the JMM, we selected five representative geostatistical realizations, an LHD with 68 experiments repeated five times, and 5×10^3 Monte Carlo samples conducted on the proxy model (see Section 6.2).

Figure 9 compares risk curves generated with both methods, plotted against risk curves computed using the MC method, as reference. Figure 10 shows the risk curve deviation. JMM and DLHG produced similar risk curves, but JMM recorded higher deviations for all objective functions. Moreover, both methods recorded the highest deviation for the same objective function: Wp. Figure 11, which presents the mean to standard deviation ratio calculated from the sensitivity analysis of the geostatistical realizations, relates the increasing risk curve deviation to the increasing variability introduced by the geostatistical realizations.

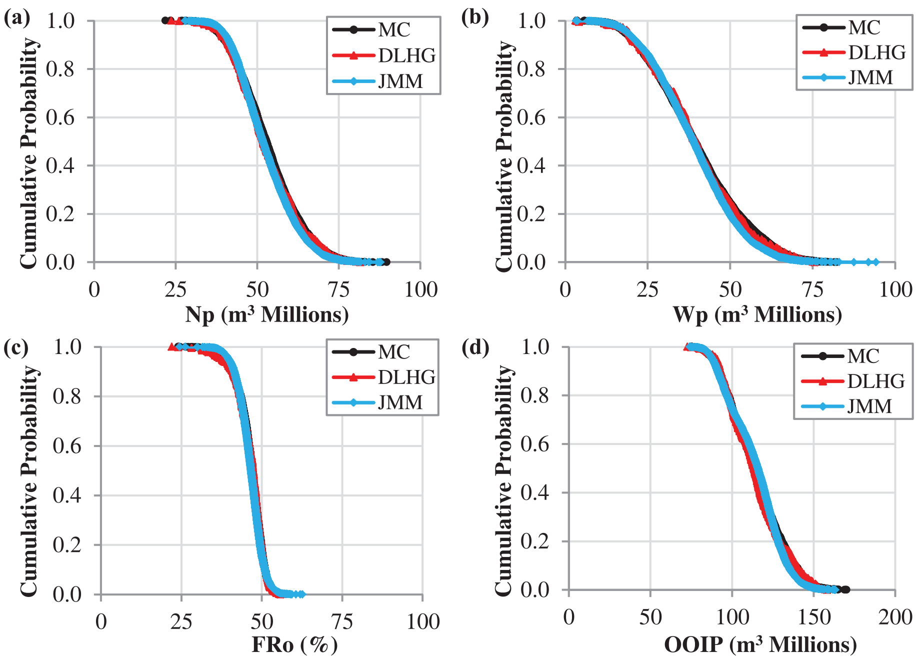

FIG. 9: Risk curves obtained by applying the DLHG (triangle) and the JMM (diamond) methods for the objective functions: (a) Np, (b) Wp, (c) RFo, and (d) OOIP. The MC method (circle) is presented as reference.

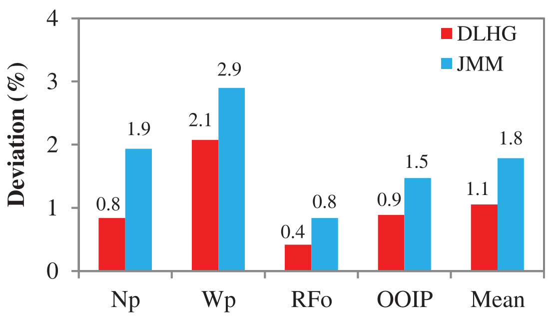

FIG. 10: Deviation D (%) for the JMM (bars on the right) and DLHG (bars on the left) methods, for each objective function and the overall mean

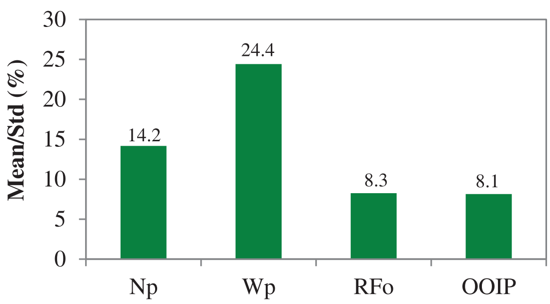

FIG. 11: Mean to standard deviation ratio, calculated for each objective function from the results of the sensitivity analysis performed on the geostatistical uncertainty

6.4 Dependency of the Computational Costs on the Accuracy of the Results

Table 3 presents the number of flow simulation runs conducted considering different sampling numbers in DLHG and different numbers of representative realizations in JMM. Note that JMM always required more flow simulation runs than DLHG.

On the basis of precision, we selected DLHG with 300 samples and JMM with five representative realizations (see Sections 6.1 and 6.2). The DLHG method used only 300 flow simulation runs, corresponding to the sampling number. Conversely, the JMM method required flow simulation runs in two steps:

Step 1. Sensitivity analysis to select the representative geostatistical realizations (300 flow simulation runs).

Step 2. Flow simulation of the experiments (68 experiments repeated five times, equaling 340 flow simulation runs), totaling 640 flow simulation runs.

Consequently, the JMM demanded 113.3% more flow simulation runs than the DLHG. Using the MC method as reference, JMM required 87.2% fewer flow simulation runs while DLHG required 94.0% fewer.

Figure 12 correlates precision of results with computational costs. Although we selected 300 samples to ensure smooth risk curves, the DLHG with 100 and even 50 samples produced good results, with a mean deviation from MC of 2.3 and 2.5%, respectively. This shows that DLHG produces very similar results to the pure Monte Carlo method while requiring considerably fewer flow simulation runs. DLHG with 100 samples required 84.4% fewer

TABLE 3: Total number of flow simulation runs performed in each application. In bold we highlight the parameters we selected for each method based on the accuracy of the results.

Method	LHD without geostatistics	Geostatistical realizations	Sampling number	Total flow simulation runs
DLHG	–	500	500	500
DLHG	–	**300**	**300**	**300**
DLHG	–	100	100	100
DLHG	–	50	50	50
DLHG	–	20	20	20
JMM	68	11	5000	1048
JMM	**68**	**5**	**5000**	**640**
JMM	68	3	5000	504
MC	–	500	5000	5000

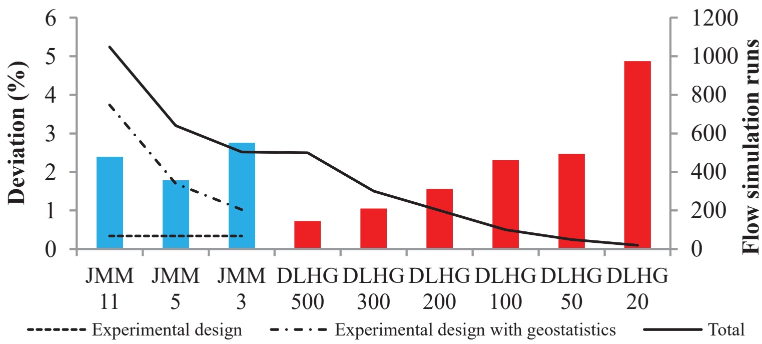

FIG. 12: Precision of results represented as the mean deviation D (bars) versus computational costs (curves), for the JMM method with different numbers of representative realizations (11, 5, 3), and the DLHG method with different sampling numbers (500, 300, 200, 100, 50, 20)

flow simulation runs than JMM and 98.0% fewer than MC, and DLHG with 50 samples required 92.2% fewer flow simulation runs than JMM and 99.0% fewer than MC.

7. DISCUSSION

In this section, we compare and discuss the methodologies in terms of the accuracy of the results, computational cost, difficulties in the application, and limitations of the methods.

7.1 Accuracy of the Results

Both methodologies proved to be reliable when applied to a complex reservoir with geostatistical context. The risk curves from both methods were visually similar to those from the reference MC. However, the JMM recorded higher deviations from the MC than the DLHG, which recorded good results from a very low sampling number (50). Increasing DLHG sampling number assures smoother risk curves and is recommended for applications that demand higher precision.

We observed that the precision of both methods decreases as uncertainty in geostatistics increases, but JMM is more sensitive to it. Unlike our expectations, an increased number of realizations in JMM did not produce better results. In our case study, five realizations produced better results than three and eleven realizations. Thus, higher precision of the JMM is not necessarily guaranteed with more representative realizations. This is further addressed in Section 7.3.

7.2 Computational Costs

Although it is typical of the experimental design theory to reduce the number of flow simulation runs, the way the JMM method treated the geostatistical uncertainty increased this number exponentially. On the one hand, we had to perform a sensitivity analysis to select representative realizations, because using the full set was computationally unfeasible. On the other hand, five repetitions were defined for each experiment to calculate the variance of the response due to this uncertainty. The latter alone increased the number of flow simulation runs by 400.0% (from 68 to 340 flow simulation runs).

The DLHG obtained the same results as JMM with substantially lower computational costs (53.1% fewer flow simulation runs) without compromising the reliability of results. Note that, in this approach, we did not use proxy models and the risk curves were computed directly from the flow simulation results.

Decreasing the DLHG sampling number can substantially reduce its costs. Sampling number 50 recorded a mean deviation of 2.5%, which shows that this method produces very similar results to the pure Monte Carlo requiring considerably fewer flow simulation runs: 99.0% fewer than MC and 92.2% fewer than JMM.

For the JMM method, computational costs can be reduced by reducing the number of representative geostatistical realizations and selecting a different experimental design. As discussed in Section 7.1, the first approach can compromise the accuracy of the results. The second approach is not recommended either because many authors reported low-quality results with traditional designs (see Section 2.4).

7.3 Difficulties in the Application

The JMM method required more steps than DLHG, demanding more user time. This included: (1) rearranging the order of the uncertainty levels to match -1, 0, and $+1$ in a scalar form, a requisite of the experimental design theory; (2) selecting representative realizations; (3) constructing the experimental design; (4) modeling two response surfaces for each objective function; and (5) validating the response surfaces.

The use of proxy models demands a good knowledge of statistics when choosing the appropriate experimental design and when modeling and validating the proxy model. In the JMM, complexity increases because the user is working with two response surfaces (mean and variance) for each objective function. However, errors can be introduced in any of the five steps previously listed.

Selecting realizations that can equally represent all objective functions is a difficult task. This can lead to implementation errors considering that: (1) the degree of variability between realizations reflects the degree of uncertainty in geostatistics, and (2) JMM incorporates the uncertainty from geostatistics through its variance. Because higher precision cannot be guaranteed with more representative realizations, the JMM accuracy strongly depends on the quality of the representative set of realizations.

Application for the DLHG method is simple and straightforward if the data set is comprised of a set of discrete attributes. Because of the simplicity of the method and considering that it needs fewer steps, there are fewer opportunities for user error.

7.4 Limitations of the Methods

Our results revealed a limitation of the JMM when applied to a complex reservoir model with a large set of geostatistical realizations. Computational costs using the full data set of geostatistical realization rose to unfeasible levels. Consequently, representative realizations had to be selected, which can incur additional computational costs and impact the representation of this uncertainty.

The DLHG method performed well with the same data set and did not show any clear limitations during this study. However, this method is suitable for random variables with a discrete distribution function and therefore requires transferring continues distributions into discrete counterparts.

LHS controls sampling from each distribution separately, which may suggest limited advantages over Monte Carlo in cases of multiple independent variables. However, results from our case study (which included a total of 11 reservoir and operational attributes plus hundreds of geostatistical realizations) showed that DLHG performed substantially better than Monte Carlo, even when combined with proxy models. LHS is suitable for application in reservoir engineering because the number of critical attributes treated in such problems is typically limited, with the exception of geostatistical realizations.

The DLHG method is independent of the geostatistical algorithm, meaning that sets of realizations generated from different geological scenarios can be incorporated into the risk analysis. In our case study, which considers only one geological scenario, a sampling number of 50 was able to assess uncertainty of 500 realizations (in addition to 11 other attributes). These results suggest that the DLHG can still be computationally feasible while handling multiple geological scenarios, each of which represented by multiple realizations.

8. CONCLUSIONS

In this study we assessed risk of a petroleum field in the development phase using the discretized Latin hypercube with geostatistical realizations (DLHG) and the Monte Carlo with joint proxy models (JMM) and compared them in terms of accuracy of results, computational cost, difficulties in the methodology's application, and limitations of the methods. Our results support the following conclusions:

- The application of the JMM method is more complex than the DLHG, requiring more time and a deeper knowledge of statistics by the user.
- Although experimental design theory typically reduces the number of flow simulation runs, when considering a geostatistical uncertainty this number increases significantly.
- When the data set comprises >10 realizations, it is unfeasible to use all realizations in the JMM and a sensitivity analysis is needed to choose representative levels.
- Increased uncertainty in geostatistics reduces the precision of DLHG and JMM, but JMM is more sensitive to it.
- The precision of the results in the JMM does not correlate to the number of representative realizations; for our case study, five realizations were ideal.

- The JMM method produced reliable results in a geostatistical context but demanded 113.3% more flow simulation runs than the DLHG.
- Independence between the precision of the DLHG and the sampling number is achieved from a low sampling number; for our case study, 50 samples were sufficient to access risk but smoother risk curves were obtained by increasing this number.
- A major advantage of the DLHG is that it produced reliable results directly from flow simulation at minimum computational costs.

Accordingly, if the data set does not comprise a geostatistical uncertainty, or comprises few realizations, the JMM method can be selected as it produces accurate results. On the other hand, if the reservoir model includes a geostatistical uncertainty, particularly in a case with dozens or hundreds of realizations, the DLHG method is recommended as it produces reliable results at minimum flow simulation runs and without requiring proxy models.

In this study, we applied a simplified approach to select representative realizations. This approach proved to be computationally expensive and difficult to apply, and may have introduced implementation errors. To improve the implementation of the JMM and potentially reduce computational costs, we recommend investigating the feasibility of more systematic workflows to select representative realizations. In particular, we refer the reader to the relevant works of Jiang et al. [76], Meira et al. [77], and Shirangi and Durlofsky [78].

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3. ARTICLE 2: EXPECTED VALUE, DOWNSIDE RISK AND UPSIDE POTENTIAL AS DECISION CRITERIA IN PRODUCTION STRATEGY SELECTION FOR PETROLEUM FIELD DEVELOPMENT

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Expected value, downside risk and upside potential as decision criteria in production strategy selection for petroleum field development

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ABSTRACT

Many factors affect production strategy selection in petroleum field development. Decision makers many times rely on informal procedures and professional experience to base decisions because tools to quantify their expectations are sometimes unclear or incoherent in the petroleum literature. In this work, we improve the decision-making process in field development by providing a set of quantitative criteria that assess production strategies under uncertainty. These criteria incorporate the decision maker's attitude and objectives in the decision. We use lower and upper semi-deviations to effectively quantify downside risk (uncertainty in losses) and upside potential (uncertainty in gains) of production strategies. These metrics assess individual subsets of project variability against reference benchmarks, in line with the decision maker's definition of loss and gain. The general formulation we propose is applicable to production and economic indicators, in a single- or multi-objective framework, and explicitly accounts for the decision maker's attitude: neutrality to downsides and upsides, minimizing exposure to downsides, and exploiting potential upsides. We created this framework using the well-known expected value concept with lower and upper semi-deviation measures. Theoretical examples illustrate problems faced by decision makers when using traditional risk measures, which are overcome by lower and upper semi-deviations. A synthetic benchmark reservoir in the development phase demonstrates the application of the proposed frameworks for production strategy selection.

1. Introduction

The decision to develop a petroleum field is complex. When selecting a production strategy, many factors are taken into account, including the expected return, the level of risk, the decision maker's attitude towards risk, and strategic objectives, such as minimizing exposure to potential downsides or exploiting potential upsides. However, tools to quantify these objectives are sometimes unclear or incoherent in the petroleum literature, leading decision makers to rely on informal procedures and professional experience to make decisions.

In the following sections we overview the most common measures of risk and decision criteria in upstream petroleum investments. We emphasize the advantages and limitations of each, and further refer to finance literature, to choose tools capable of assessing the decision maker's attitude towards production strategy selection.

1.1. Measures of risk in upstream petroleum investments: an overview

Variance (σ^2) and standard deviation (σ) are widely applied risk measures in diverse contexts in upstream oil and gas investments (e.g.: Newendorp and Schuyler, 2000; Lima and Suslick, 2005; Cullick et al., 2007; Hayashi et al., 2007; Capolei et al., 2015a). However, they are many times considered inadequate because they associate risk with volatility around the expected value (EV). Consequently: (1) when the distribution is asymmetric, variance penalizes gains and losses equally; and (2) it is unable to distinguish alternatives with the same variability but different EV (Markowitz, 1959; Harlow, 1991; Sortino and Price, 1994; Rockafellar et al., 2002; Estrada, 2007; Krokhmal et al., 2011). Accordingly, it is more precise to define these as statistical measures of uncertainty rather than measures of risk, as stated, for example, by Walls (2004), and applied by Barros et al. (2016) in petroleum reservoir management.

An alternative metric is the coefficient of variation ($CV = \sigma/EV$), a ratio to distinguish projects with the same variability but different EV. However, it is also a measure of dispersion around the EV and makes no sense if the EV is less than or equal to zero, being useful only for random variables with strictly positive distributions (Curto and Pinto, 2009). Hayashi et al. (2010), Marques et al. (2013), Morosov and Schiozer

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(2016), among others, applied this metric to select production strategies in the development phase.

The semi-variance (Eq. (1)), proposed as an alternative to variance (Markowitz, 1959), denotes the downside volatility of returns below a predefined benchmark (B), which depends on the decision maker's definition of loss and is independent of the probability distribution. Far less popular in upstream petroleum investments, it was applied by Orman and Duggan (1999) and Galeno et al. (2009) in portfolio optimization, and by Santos et al. (2017) to select production strategies in the development phase.

$$S_{B-} = \sqrt{S_{B-}^2} = \sqrt{E\{min[(X-B),0]^2\}} \tag{1}$$

where: S_{B-} – lower semi-standard deviation, or lower semi-deviation for short, from a benchmark value B; S_{B-}^2– lower semi-variance from a benchmark value B; E - expectation operator; X – random variable.

Recent advances in decision analysis have formalized two classes of risk measures: coherent measures of risk (Artzner et al., 1999; Delbaen, 2002), and averse measures of risk (Rockafellar and Uryasev, 2002; Rockafellar et al., 2006). Krokhmal et al. (2011) provide simple models to construct averse measures of risk, of which only risk measures of CVaR type and of semi-$\mathscr{L}^\beta(\Omega)$ type with $\lambda \in (0,1]$ are coherent-averse measures of risk:

(a) Risk measures of $\mathscr{L}^\beta(\Omega)$ type: $\mathscr{R}(X) = \lambda\left\|X - E[X]\right\|_\beta - E[X]$, $\beta \in [1, \infty]$, $\lambda > 0$, e.g. $\mathscr{R}(X) = \lambda\sigma(X) - E[X]$ and $\mathscr{R}(X) = \lambda S_{EV}(X) - E[X]$.
(b) Risk measures of semi-$\mathscr{L}^\beta(\Omega)$ type: $\mathscr{R}(X) = \lambda\left\|[X - E[X]]_-\right\|_\beta - E[X]$, $\beta \in [1, \infty]$, $\lambda > 0$, e.g. $\mathscr{R}(X) = \lambda S_{B-}(X) - E[X]$.
(c) Risk measures of CVaR type: (i) $\mathscr{R}(X) = CVaR_a(X)$; (ii) mixed CVaR $\mathscr{R}(X) = \int_0^1 CVaR_a(X)d\lambda(a)$, where $\int_0^1 d\lambda(a) = 1$ and $\lambda(a) \geq 0$; and (iii) worst case mixed CVaR $\mathscr{R}(X) = \sup_{\lambda \in \Lambda} \int_0^1 CVaR_a(X)d\lambda(a)$.

In light of these ideas, Capolei et al. (2015b) assessed the validity of different measures in oil production optimization under the concept of coherent-averse measures of risk. Komlosi (2001), Marques et al. (2014), and Capolei et al. (2015b) applied the financial concepts Value at Risk (VaR) and Conditional Value at Risk (CVaR) in upstream petroleum projects.

In §2.1, we explore the concepts of deviation measures, in particular lower and upper semi-deviations from benchmarks, to quantify the downside risk (uncertainty in losses) and the upside potential (uncertainty in gains) of production strategies.

1.2. Decision criteria in upstream petroleum investments: an overview

Decision makers sometimes assume that the expected value takes risk into account, as it weights each possible outcome by its probability (Walls, 1995a). However, it possesses limitations in incorporating real risk concerns by implying impartiality to the magnitude of potential profits and losses. However, for its simplicity, it is the most frequent decision criterion in upstream petroleum investments (e.g.: Newendorp, 1984; Newendorp and Schuyler, 2000; Koninx, 2001; Begg et al., 2002; Bickel et al., 2008; Nogueira and Schiozer, 2009; van Essen et al., 2009; Schiozer et al., 2015; Shirangi and Durlofsky, 2015).

In an attempt to overcome these limitations, the utility theory was formulated to recognize risk aversion as part of the decision policy. Initially proposed by von Neumann and Morgenstern (1953), utility theory is currently widely documented in the literature (Luce and Raiffa, 1957; Fishburn, 1970; Keeney and Raiffa, 1976; Howard, 1984). However, its real-world application is still controversial because: (1) managers often regard these models as theoretically complex and impractical for day-to-day decision making; and (2) managers are often uncomfortable with the notion of measuring the firm's utility function or risk preference level (Walls, 1995a). Cozzolino (1977), Walls (1995a), Nepomuceno Filho et al. (1999), Newendorp and Schuyler (2000), Suslick and Furtado (2001), among others, applied exponential utility functions to introduce a risk attitude in upstream petroleum investments.

The certainty equivalent (CE) is equal to the expected value minus a risk discount, and is derived from expected utility (EU) through its inverse transform (Keeney and Raiffa, 1976). By providing real monetary units, this formulation is common in upstream petroleum investments (e.g.: Cozzolino, 1977; Rose, 1992; Walls, 1995a; Motta et al., 2000; Newendorp and Schuyler, 2000; Lima and Suslick, 2005; Moore et al., 2005).

Mean-variance frameworks to certainty equivalent are also common. The traditional model in Eq. (2) (Pratt, 1964) was applied by Walls and Dyer (1996), Pinto et al. (2003), Walls (2004, 2005), Galeno et al. (2009), and others, in diverse contexts in upstream petroleum investments. Yeten et al. (2003), Alhuthali et al. (2010), Yasari et al. (2013), Yasari and Pishvaie (2015), Capolei et al. (2015a), and others applied mean-variance frameworks in robust optimization of production strategies.

$$CE(X) = E[X] - c\frac{\sigma^2}{2} = E[X] - \frac{\sigma^2}{2RT} \tag{2}$$

where: CE – certainty equivalent; $E[X]$ – expected value of random variable X; σ^2 – variance; c – risk aversion coefficient; RT – corporate risk tolerance.

Eq. (2) can be modeled using the risk aversion coefficient (c) or the corporate risk tolerance ($RT = 1/c$), which represents “the sum of money such that the executives are indifferent as a company investment to a 50-50 chance of winning that sum and losing half of that sum” (Howard, 1988, p. 689). This value can be estimated through questions answered by the decision maker, but rules of thumb exist in the petroleum literature. Rose (1992), Walls and Dyer (1996), Pinto et al. (2003), and Walls (1995a) provide rules for exploration investments. In petroleum development and production, Lima and Suslick (2005) considered it to be 40% of the corporation budget.

If the decision maker wishes to base decisions on two or more objectives, Multi-Attribute Utility Theory (MAUT) can be applied to handle the tradeoffs between them (Keeney and Raiffa, 1976). Many forms of multi-attribute utility functions are theoretically valid (Keeney and Raiffa, 1976). The linear additive model (Eq. (3)) is frequently preferred because it provides a close approximation for different preferences while remaining easier to apply compared to more accurate but more complex non-linear models (Huber, 1974). In upstream petroleum projects, this model was applied by Walls (1995b), Nepomuceno Filho et al. (1999), Suslick and Furtado (2001), Lopes and Almeida (2013), Santos et al. (2017) and others.

$$u(X) = \sum_{i=1}^{n} k_i u_i(X_i) \tag{3}$$

where: $u_i(x_i)$ – utility function for objective i; X – random variable; k_i – weight (i.e. relative importance) of objective i, such that. $\sum_{i=1}^n k_i = 1$.

While common in the petroleum industry, many authors assert that mean-variance models are only valid under strict assumptions, namely that returns must be normally distributed. Consequently, alternative models are common in finance literature, but we noticed that they are rare in petroleum related applications. To enhance our methodology, we referred to this body of literature to find suitable formulations (§1.3).

1.3. Decision criteria in the finance literature: recent developments

Following the original mean-semivariance concept of Markowitz (1959), Fishburn (1977) formulated a generalized mean-risk model (Eq. (4)) to capture the decision maker's attitude below the benchmark. This traditional model uses lower partial moments (LPM) of X of order β at level B (Eq. (5)), of which the semi-variance (Eq. (1)) is a particular case

($\beta = 2$). However, this model is limited by assuming neutrality above the benchmark, which holds in a limited number of cases. Consequently, performance functions defined over losses and gains relative to a benchmark have been developed in the finance literature.

$$EU(X) = E[X] - \gamma LPM_\beta(X, B) \tag{4}$$

$$LPM_\beta(X, B) = (-1)^\beta E\left\{min[(X - B), 0]^\beta\right\} \tag{5}$$

Zakamouline and Koekebakker (2009) and Zakamouline (2014) proposed a comprehensive formulation (Eq. (6)), generalizing the original models of Markowitz (1959) ($\lambda = 1$; $\gamma_+ = 0$; $\beta_1 = 2$), Pratt (1964) ($\lambda = 1$; $\gamma_- = \gamma_+$; $\beta_1 = \beta_2 = 2$), Fishburn (1977) ($\lambda = 1$; $\gamma_+ = 0$), and others.

$$E\left(\tilde{U}(W)\right) = E[W - W_0] - (\lambda - 1)LPM_1(W, W_0) - \frac{1}{\beta_1}\lambda\gamma_- LPM_{\beta_1}(W, W_0) + \frac{1}{\beta_2}\gamma_+ UPM_{\beta_2}(W, W_0) \tag{6}$$

where: $E(\tilde{U}(W))$ – equivalent expected utility of the decision marker's wealth W; W_0 – reference point where the utility function has a kink; E– expectation operator; LPM_1– lower partial moments of order 1 around W_0; LPM_{β_1} and UPM_{β_2}– lower and upper partial moments of order β_1 and β_2 around W_0, respectively; λ – aversion to expected loss; γ_- and γ_+ – attitude towards uncertainty below and above W_0, respectively. In this notation, $W = W_0 + x$, where x is a gamble.

In this generalized model, expected loss is quantified by LPM_1, uncertainty in losses is quantified by LPM_β, and uncertainty in gains is quantified by upper partial moment of order β (UPM_β) (Eq. (7)), of which upper semi-variance is a particular case ($\beta = 2$) (Eq. (8)).

$$UPM_\beta(X, B) = E\left\{max[(X - B), 0]^\beta\right\} \tag{7}$$

$$S_{B+} = \sqrt{S^2_{B+}} = \sqrt{E\{max[(X - B), 0]^2\}} \tag{8}$$

where: S_{B+} – upper semi-standard deviation, or upper semi-deviation for short, from a benchmark value B; S^2_{B+}– upper semi-variance from a benchmark value B; E - expectation operator; X – random variable; UPM_β – upper partial moment of order β.

In §2.2 we formulate a model of mean and partial moments of the distribution to incorporate the decision maker's attitude when selecting a production strategy: neutrality to downsides and upsides, minimizing exposure to downsides, or exploiting potential upsides. In §2.3 we provide a framework to base decisions on multiple objectives, by integrating the proposed formulation with concepts from MAUT.

1.4. Scope and objectives

The need to explicitly incorporate the decision maker's attitude and objectives into the decision criterion when assessing and selecting production strategies under uncertainty motivated this research. Tools to quantify these objectives are not always well documented in the petroleum literature.

In view of that, our objective is to propose such decision criteria, based on concepts from the finance literature. In particular, we provide: (1) metrics to quantify downside risk and upside potential of production strategies that agree with the decision maker's definition of loss and gain; (2) a formulation to estimate a production strategy's value adjusted to the decision maker's attitude, applicable to production and economic indicators; and (3) a framework to base a decision on multiple objectives. Above all we aim to make the application of these criteria straightforward, and reduce the subjectivity of the decision-making process.

Note that in this study attitude refers to the decision maker's perception of downsides and upsides; while objective refers to the production and economic indicators that decision makers aim to maximize.

2. Methodology

Fig. 1 presents the workflow we propose to evaluate candidate production strategies under uncertainty. This structure is applicable to production and economic indicators, in a single- or multi-objective framework. Details of each procedure can be found in the following subsections, as highlighted in the flowchart.

Note that obtaining the candidate production strategies, set of uncertain scenarios, and production forecasts under uncertainty (first set of boxes in Fig. 1) is not the focus of this work. For these steps we refer the reader to the work of Schiozer et al. (2015), who proposed a model-based decision structure for petroleum field development and management, integrating reservoir characterization under uncertainty, reservoir simulation, history matching, uncertainty reduction, representative models, and production strategy optimization.

2.1. Measuring downside risk and upside potential of production strategies

In petroleum field development, due to high investment, risk is typically associated with the chance of failure to achieve a targeted return. Decision makers are typically not averse to variability above the benchmark, but may have expectations of exploiting optimistic scenarios in this domain. In accordance, standard deviation is inadequate to measure risk and reward, expressing overall uncertainty in returns. We consider semi-deviation more useful, as it assesses individual subsets of overall standard deviation, and therefore differentiates good variability from bad (Fig. 2).

Accordingly, we recommend lower semi-deviation from a benchmark (Eq. (1)) to assess downside risk (i.e., uncertainty in losses), and upper semi-deviation (Eq. (8)) to measure upside potential (i.e., uncertainty in gains) of a production strategy. Note that semi-deviation is expressed in the same units of the objective function (semi-variance, like variance, is expressed in squared units).

The benchmark is defined by the decision maker as it solely depends on his definition of loss and gain. We do not recommend using the expected value of each distribution, but the same benchmark to allow a fair comparison of the set of production strategies.

To find this value in a case study, we propose: (1) calculating the EV of each production strategy; and (2) using the strategy with maximized EV as a reference, and its EV as benchmark (Fig. 3). This assumes that, in decisions based on expected value, the preferred production strategy maximizes EV. Note that measuring risk from the EV of one strategy is not

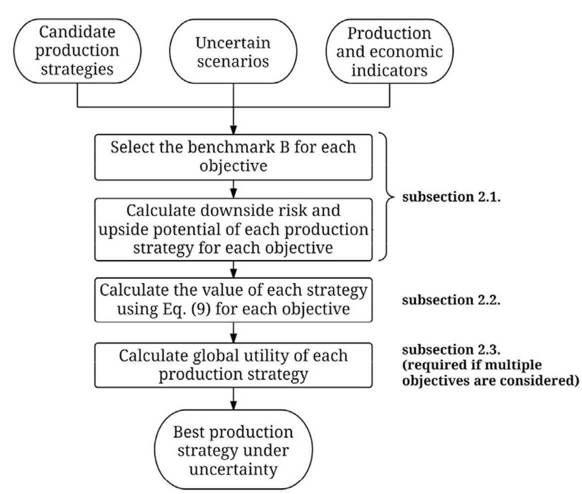


Fig. 1. Workflow to evaluate candidate production strategies under uncertainty.

the same as measuring risk from the EV of each strategy (Sortino and Price, 1994).

In a multi-objective framework, selecting B and calculating downside risk and upside potential must be conducted for each objective.

2.2. Combining expected value, downside risk, and upside potential to evaluate production strategies

To estimate the value of a production strategy adjusted to the decision maker's attitude we propose Eq. (9), which captures aversion or neutrality to uncertainty in losses (aversion to downside risk) and aversion or neutrality to uncertainty in gains (expectation of upside potential). We propose Eq. (9) as an extension of the classic mean-variance model, with the difference that we use two deviation terms (lower and upper semi-variance, weighted by independent coefficients) instead of a single deviation term (variance, weighted by one coefficient). We based this proposal on the premise that variance quantifies in a single value good and bad variability, and decision makers typically have different attitudes towards these two domains of uncertainty.

$$\varepsilon(X) = E[X] - c_{dr}S_{B-}^2 + c_{up}S_{B+}^2 = E[X] - \frac{S_{B-}^2}{\tau_{dr}} + \frac{S_{B+}^2}{\tau_{up}} \tag{9}$$

where: $\varepsilon(X)$ – production strategy's value adjusted to the decision maker's attitude; $E[X]$ – expected value of random variable X; S_{B-}^2 and S_{B+}^2 – lower and upper semi-variance from a benchmark B; c_{dr} – aversion coefficient to downside risk; c_{up} – expectation coefficient to upside potential; τ_{dr} and τ_{up} – tolerance (or indifference) level to downside risk and to upside potential.

In Eq. (9), the lower semi-variance decreases the EV, in accordance with the production strategy's level of risk and the decision maker's corresponding tolerance (τ_{dr}); while the upper semi-variance increases the EV, in accordance with the production strategy's upside potential and the decision maker's corresponding tolerance (τ_{up}). In a single-objective framework, the best production strategy maximizes Eq. (9). If more than one objective is considered, we refer the reader to subsection §2.3.

The tolerance level (τ) is expressed in the same units of the distribution and takes strictly positive values. In the downside risk term: $\tau_{dr} < \infty$ implies risk aversion, while $\tau_{dr} \to \infty$ implies risk neutrality. In the upside potential term: $\tau_{up} < \infty$ implies high expectation of high returns, while $\tau_{up} \to \infty$ implies indifference or neutrality to upside potential. These attitudes can also be modeled using the aversion or expectation coefficients, ratios given by $c = 1/\tau$.

We validate our formulation by comparing it to the existing body of finance literature. Eq. (9) can be regarded as a particular case of Eq. (6) ($\lambda = 1$; $\gamma_- > 0$; $\gamma_+ < 0$; $\beta_1 = \beta_2 = 2$). We define τ_{dr} and τ_{up} as strictly positive, thus $\gamma_- > 0$ and $\gamma_+ < 0$, meaning that decision makers are averse to uncertainty in losses and have expectations for uncertainties in gains. We do not model opposite preferences because these typically disagree with decision makers' attitudes when choosing production strategies. We use semi-variances ($\beta_1 = \beta_2 = 2$) instead of variance, many times employed in the upstream petroleum sector.

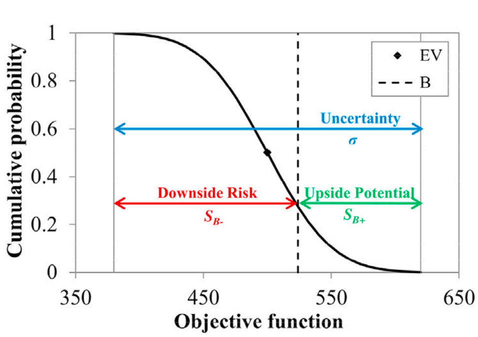


Fig. 2. Standard deviation (σ) quantifies uncertainty, lower semi-deviation (S_{B-}) quantifies downside risk, and upper semi-deviation (S_{B+}) quantifies upside potential of a risk curve (in black). EV is the expected value, and B the benchmark.

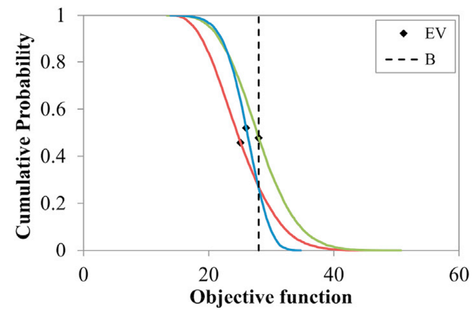


Fig. 3. Risk curves of three hypothetic production strategies (red, blue, green), highlighting their expected value (EV). In our approach, the strategy in green is the reference, and its EV the benchmark (vertical dashed line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

To reduce the subjectivity of defining the tolerance levels, we propose expressing them as functions of the benchmark B (Eq. (10) and Eq. (11)). Here, the decision maker defines the weights α_{dr} and α_{up} of B, for the terms downside risk and upside potential, respectively.

$$\tau_{dr} = \alpha_{dr}B \tag{10}$$

$$\tau_{up} = \alpha_{up}B \tag{11}$$

We recommend assessing a production strategy's value under a range of tolerance levels before establishing the tolerance itself, as conducted by Davis (2014). Doing this, the decision maker can: (1) have a sense of how the decision is affected by his attitude; (2) identify the best production strategy under different tolerance levels; and (3) identify the tolerance value that distinguishes neutrality from aversion or expectation.

2.3. Basing decisions on multiple objectives

The procedures described here are only required if more than one objective is considered. Our approach is based on the well-established Multi-Attribute Utility Theory, but we introduce the formulation proposed in §2.2 (Eq. (9)) as an alternative to the traditional von Neumann-Morgenstern utility functions.

The decision maker determines the value of each production strategy using Eq. (9) (as described in §2.2), for each objective, and constructs a multi-objective utility function to combine all objectives, in accordance with his preferences (see §1.2). To calculate global utility, the set of single-attribute values must be normalized between 0 and 1, following the convention: $\varepsilon_{min}(X) = 0$; $\varepsilon_{max}(X) = 1$. The decision maker selects the production strategy that maximizes global utility.

A main challenge in MAUT is the assessment of the relative weights of each objective. It can be done directly based on the decision maker's judgment or by means of some structured procedure (e.g.: Schoemaker and Waid, 1982; White et al., 1984; Ma et al., 1999). In the petroleum industry, the first approach is common due to its simplicity (e.g.: Nepomuceno Filho et al., 1999; Suslick and Furtado, 2001).

We recommend performing a sensitivity analysis on the weights to identify the best production strategy under different preference ranges. Several methods are found in the literature (e.g.: Butler et al., 1997; Suslick and Furtado, 2001; Chambal et al., 2011), and the choice should agree with the complexity of the case study.

3. Case study 1: theoretical examples

In this section, we provide theoretical examples to illustrate problems faced by decision makers in day-to-day situations when using traditional risk measures to assess production strategies.

3.1. Assessing asymmetric distributions with the same expected value and the same variability

In Fig. 4a, production strategy *A* is preferred to *B* because it presents higher chances of high outcomes, and lower chances of low outcomes. As these strategies have the same variability (5 units of the objective function) and the same expected value (25 units of the objective function), the standard deviation and the coefficient of variation are unable to distinguish between them (Fig. 4b). The lower semi-deviation correctly identifies the riskiest production strategy, while the upper semi-deviation identifies the one with higher chances of high outcomes. The below-mean semi-deviation is suited to this example because both production strategies have the same expected value.

3.2. Assessing asymmetric distributions with different variability

In Fig. 5a, production strategy *D* is preferred to *C* because it presents higher chances of high outcomes, and lower chances of low outcomes. As the variability of *D* is slightly higher than that of *C* ($\sigma_C = 3.2$ and $\sigma_D = 3.5$ units of the objective function) and both production strategies have similar expected value (5.0 units of the objective function), the standard deviation and the coefficient of variation indicate that *C* is riskier than *D* (Fig. 5b). The lower semi-deviation correctly identifies the riskiest production strategy, while the upper semi-deviation identifies the one with higher chances of high outcomes. The below-mean semi-deviation is suited to this example because both production strategies have the same expected value.

3.3. Assessing symmetric distributions with the same variability but different expected values

Fig. 6a considers 5 production strategies (*E* to *I*), characterized by similar variability (3.5 units of the objective function), symmetric distributions, but different EV, including positive (E[E] = 5.0, E[F] = 2.5), zero (E[G] = 0), and negative (E[H] = −2.5, E[I] = −5.0) values. Due to identical variability, the standard deviation is unable to distinguish different levels of risk (Fig. 6b). Similarly, the below-mean semi-deviation is inadequate because risk is assessed based on different definitions of loss. The CV can only measure the risk for production strategies *E* and *F*, those with positive expected values: (1) as *G* has an EV equal to zero, the calculation of the CV is mathematically undefined; and (2) for production strategies *H* and *I*, negative values of risk are provided and have no meaning. The lower and upper semi-deviations from a fixed benchmark correctly rank the production strategies by level of risk and upside potential, respectively (Fig. 6b).

4. Case study 2: oil field development project

4.1. Reservoir description

The simulation model used in this work represents an offshore heterogeneous heavy oil reservoir, with regions of high permeability among others of very low permeability (Botechia et al., 2016) (Fig. 7). The grid has a total of 106,080 cells (104 × 102 x 10) with 100 × 100 m length and variable thickness. Table 1 presents the main parameters of the base model and Table 2, the operating values of wells (production and pressure constraints).

4.2. Candidate production strategies

Botechia (2016) conducted a detailed decision analysis on this case study (based on the methodology proposed by Schiozer et al., 2015), considering several scenarios covering the following reservoir uncertainties: (1) horizontal and vertical permeabilities; (2) porosity; (3) facies distribution; (4) rock compressibility; and (5) oil viscosity. The economic uncertainties included: (1) oil price; (2) oil and water production costs; and (3) water injection costs. The optimization variables consisted of: (1) number and location of wells; (2) platform capacity; (3) schedule of well drilling; (4) production and injection rates; and (5) economic water cut limit for well shutdown.

The uncertainties were combined using the Discretized Latin Hypercube sampling technique with geostatistical realizations (Schiozer et al., 2017), generating 100 equiprobable uncertain scenarios, each one represented by one simulation model. Since the computational effort to optimize all these models would be high and potentially unfeasible, some were selected to represent the variability of uncertainties in a small number of models (Representative Models – RM) (Schiozer et al., 2004, 2015; Marques et al., 2013; Meira et al., 2016).

RM selection was conducted by Botechia (2016) following the proposal of Meira et al. (2016), which combines a mathematical function that captures the representativeness of a set of models with a metaheuristic optimization algorithm. This approach ensures that the set of RM represents both the probability distribution of the input variables (reservoir, operational and economic uncertainties) and the variability of the main output variables (production and injection forecasts).

Botechia (2016) optimized production strategies for 9 RM for net present value (NPV), considering two recovery mechanisms: water flooding and polymer flooding. This procedure resulted in 18 candidate production strategies (nine water flooding (W) and nine polymer flooding, (P)), listed in Table 3, which details the number of wells, platform capacities and total investment. In the case of polymer flooding strategies, the total investment includes all costs of polymer injection (chemicals, logistics and possible adaptations to the platform). Note that Botechia (2016) and Botechia et al. (2016) aimed to evaluate the feasibility of polymer flooding for this benchmark field, comparing it to water flooding.

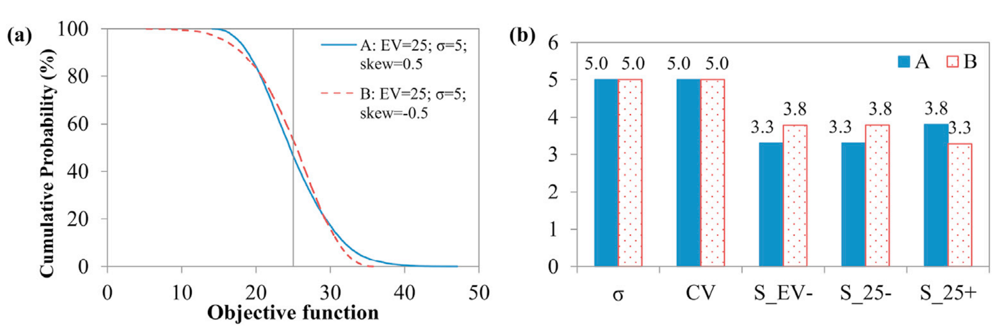


Fig. 4. Assessing production strategies *A* and *B*: (a) risk curves and data statistics, with the benchmark marked by a vertical line; and (b) alternative measures of risk: standard deviation (σ), coefficient of variation (CV), below-mean semi-deviation (S_{EV-}), and lower semi-deviation from the benchmark (S_{25-}). In (b) upper semi-deviation from the benchmark (S_{25+}) quantifies upside potential.

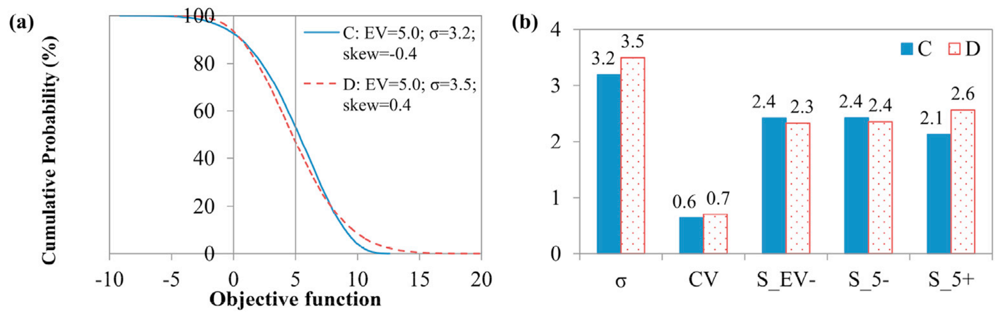


Fig. 5. Assessing production strategies *C* and *D*: (a) risk curves and data statistics, with the benchmark marked by a vertical line; and (b) alternative measures of risk: standard deviation (σ), coefficient of variation (CV), below-mean semi-deviation (S_{EV-}), and lower semi-deviation from the benchmark (S_{5-}). In (b) upper semi-deviation from the benchmark (S_{5+}) quantifies upside potential.

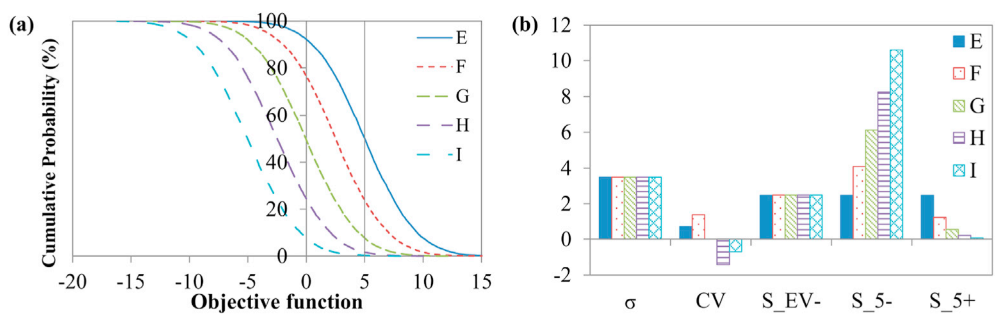


Fig. 6. Assessing production strategies *E* to *I*: (a) risk curves, with the benchmark marked by a vertical line; and (b) alternative measures of risk: standard deviation (σ), coefficient of variation (CV), below-mean semi-deviation (S_{EV-}), and lower semi-deviation from the benchmark (S_{5-}). In (b) upper semi-deviation the benchmark (S_{5+}) quantifies upside potential.

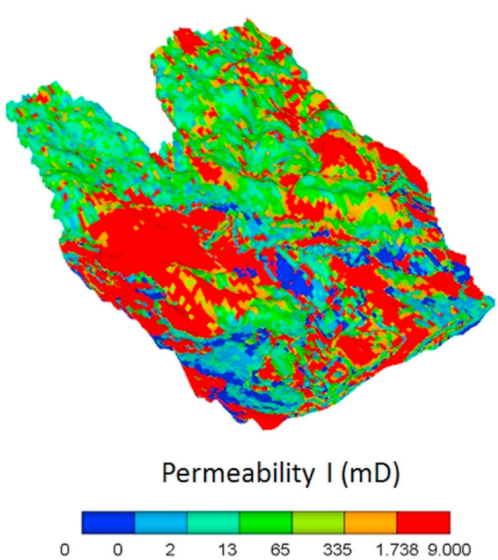


Fig. 7. 3D view of horizontal permeability in logarithmic scale (Botechia et al., 2016).

Table 1
Rock-fluid properties of the base model (Botechia et al., 2016).

Parameter	SI units	Field units
Permeability	1 to 9000 md (average ~ 1740)	1 to 9000 md (average ~ 1740)
Porosity	0.13 to 0.32 (average ~ 0.22)	0.13 to 0.32 (average ~ 0.22)
Depth	1921 to 2706 m (average ~ 2350)	6302 to 8878 ft (average ~ 7710)
Temperature	341.15 K = 78 C	632 R
Average Pressure	23668 kPa	3433 psi
Average Oil Viscosity	0.174 Pa-s	174 cP
API Gravity	15API	15API

Table 2
Well operating constraints for producers and injectors (Botechia et al., 2016).

Producers	SI units	Field units	Injectors	SI units	Field units
Max. Liquid Production	2862 m^3/d	18000 bbl/d	Max. Water Injection	7950 m^3/d	50000 bbl/d
Min. BHP	8172 kPa	1185 psi	Max. BHP	30000 kPa	4351 psi
Max. Oil Production	1908 m^3/d	12000 bbl/d			
Min. Oil Production	12 m^3/d	75 bbl/d			

Botechia (2016) obtained production and injection forecasts for the 18 candidate production strategies over the 100 equiprobable scenarios using a chemical EOR numerical reservoir simulator. We used these results in the following subsections to calculate the expected value, the downside risk and the upside potential for each objective; as well as to construct risk curves, also referred to as descending or complementary cumulative distribution functions in the statistics literature.

4.3. Decision based on economic return

In this section, the decision maker used NPV to select the best production strategy. Production strategy S8P with maximized expected monetary value (EMV) (US$ 1799 million) is the benchmark for lower and upper semi-deviations.

Risk curves for NPV are presented in Fig. 8. As this case study has many candidate production strategies (Fig. 8a), we built expected value versus semi-deviation cross-plots (Fig. 9) to focus analyses on the candidates with the highest potential. We defined acceptance regions on the cross-plots based on minimum acceptable EMV, maximum acceptable downside risk, and minimum acceptable upside potential. The definition of these values depends on the decision maker and is optional. Fig. 8b shows the risk curves of the selected strategies, corresponding to the union of the two acceptance regions.

To estimate the value of all production strategies we applied Eq. (9)

Table 3
Characteristics of the candidate production strategies (Botechia, 2016).

Production strategy	Recovery mechanism	Number of producers	Number of injectors	Total number of wells	Platform capacity (1000 m^3/d)	Platform capacity (1000 bbl/d)	Total investment (US$ millions)
S1W	Water Flooding	14	2	16	25.6	161.0	3812
S2W	Water Flooding	20	3	23	40.0	251.6	4917
S3W	Water Flooding	21	3	24	36.0	226.4	4904
S4W	Water Flooding	21	3	24	32.0	201.3	4792
S5W	Water Flooding	16	2	18	18.8	118.2	3721
S6W	Water Flooding	13	2	15	23.0	144.7	3640
S7W	Water Flooding	12	2	14	24.5	154.1	3581
S8W	Water Flooding	13	2	15	22.5	141.5	3625
S9W	Water Flooding	17	3	20	24.5	154.0	4181
S1P	Polymer Flooding	13	4	17	23.5	247.8	4120
S2P	Polymer Flooding	20	5	25	38.0	239.0	5647
S3P	Polymer Flooding	20	4	24	36.0	226.4	5374
S4P	Polymer Flooding	21	4	25	28.5	179.2	5215
S5P	Polymer Flooding	13	4	17	19.1	120.1	4033
S6P	Polymer Flooding	14	3	17	22.0	138.4	3953
S7P	Polymer Flooding	13	3	16	21.8	137.1	3881
S8P	Polymer Flooding	15	4	19	23.7	149.1	4491
S9P	Polymer Flooding	15	4	19	25.0	157.2	4372

with τ_{dr} = US$ 1500 million (0.83*xB*) and τ_{up} = US$ 1000 million (0.56*xB*), representing a decision maker concerned with downsides and upsides, but more concerned with maximizing upside potential ($\tau_{up} < \tau_{dr} < \infty$) (Table 4).

Our sensitivity analysis was conducted in two steps: (1) individual sensitivity on τ_{dr} and τ_{up}, to consider each individually (Fig. 10a and 10b); and (2) under the chosen tolerances, to incorporate both simultaneously (Fig. 10c and 10d).

Our results show that: (1) S8P is preferred in a decision exclusively based on EMV (Table 4); (2) S8P is preferred in a decision based on EMV minus downside risk (Fig. 10a); (3) S3W is preferred in a decision based on EMV plus upside potential, but as τ_{up} approaches infinity, S8P becomes preferable again (i.e., decision based on EMV) (Fig. 10b); (4) S3W is preferred by our illustrative decision maker (τ_{dr} = US$ 1500 million; τ_{up} = US$ 1000 million) (Table 4). Fig. 10 shows that the choice considering only downsides or upsides is straightforward, but may vary when handling both.

4.4. Decision based on hydrocarbon recovery

In this section, the decision maker used the oil recovery factor (RF) to select the best production strategy. Although we optimized the candidate production strategies for NPV, the results from this section are integrated in section §4.5, where we base a decision on both objectives.

Here, we follow the same approach as in §4.3. Production strategy S3W with maximized E[RF] (25.7%) is the benchmark. We constrained the large set of production strategies in Fig. 11a using acceptance regions (Fig. 12), resulting in the selected production strategies in Fig. 11b. We chose $\tau_{dr} = 20\%$ (0.78*xB*) and $\tau_{up} = 23\%$ (0.90*xB*), representing a decision maker focusing on downsides and upsides, but more concerned with minimizing downside risk ($\tau_{dr} < \tau_{up} < \infty$) (Table 5).

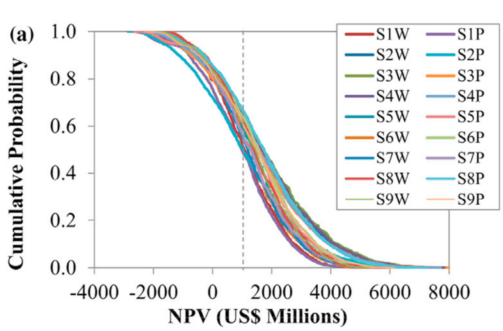
Our results show that: (1) S3W is preferred in a decision exclusively based on E[RF] (Table 5); (2) S3W is preferred in a decision based on E[RF] minus downside risk, but almost identical to S4W (Fig. 13a); (3) S2P is preferred in a decision based on E[RF] plus upside potential, but as τ_{up} approaches infinity, S3W or S4W become preferable again (i.e., decision based on E[RF]) (Fig. 13b); (4) S3W, S4W and S2P are equally attractive production strategies to our illustrative decision maker (τ_{dr} = 20%; τ_{up} = 23%) (Table 5). Fig. 13 shows that the choice considering only downsides or upsides is straightforward, but may vary when handling both.

4.5. Decision based on multiple objectives

In this section, we consider a decision maker concerned with two objectives: (1) maximizing economic return, quantified by the NPV; and (2) maximizing hydrocarbon recovery, quantified by the RF. We used the multi-attribute utility function in Eq. (12) to combine both objectives, assessed individually in sections §4.3 and §4.4. Note that each value, ε(X), must be normalized, $\varepsilon(X)_{norm}$, before calculating global utility.

$$u(NPV, RF) = k^{*}\varepsilon(NPV)_{norm} + (1-k)^{*}\varepsilon(RF)_{norm} \tag{12}$$

For a decision maker equally prioritizing both objectives (i.e., $k = 0.5$), S3W is the best production strategy (Table 6). This example is straightforward because S3W is preferred individually for both objectives, which is supported by the sensitivity analysis on the k weight (Fig. 14).



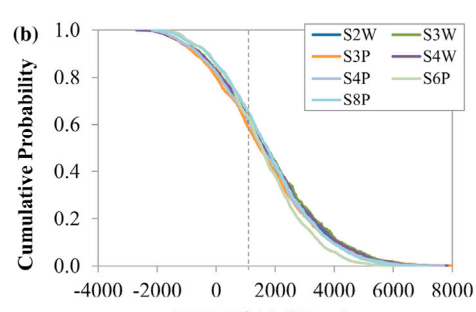


Fig. 8. Risk curves of net present value: (a) candidate production strategies; and (b) production strategies with highest potential, selected based on acceptance regions (Fig. 9). The vertical line marks the benchmark.

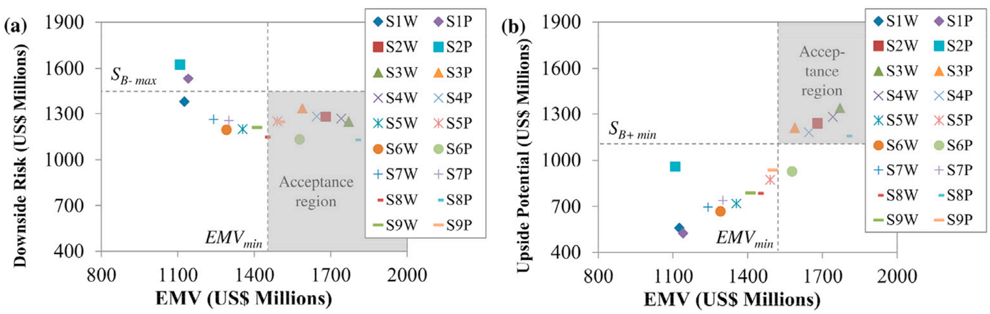


Fig. 9. Defining acceptance regions with cross-plots: (a) minimum acceptable EMV and maximum acceptable downside risk; and (b) minimum acceptable EMV and minimum acceptable upside potential.

Table 4
Candidate production strategies ranked by decreasing NPV adjusted to the decision maker's attitude. Figures in bold highlight the best production strategy under each criterion.

Production strategy	EMV (US$ millions)	Downside risk (US$ millions)	Upside potential (US$ millions)	ε(NPV) (US$ millions)
S3W	1770.8	1227.5	**1358.5**	**2611.8**
S4W	1742.0	1246.3	1299.2	2394.2
S8P	**1799.3**	**1111.0**	1177.0	2361.8
S2W	1680.6	1260.0	1257.3	2203.0
S4P	1645.8	1260.2	1199.5	2025.9
S3P	1589.3	1313.9	1228.9	1948.6
S6P	1578.5	1112.6	943.6	1643.6

5. Discussion

In this study, we proposed a set of comprehensive decision criteria to evaluate production strategies under uncertainty. We focused on: (1) isolating and quantifying uncertainty in losses (downside risk) and uncertainty in gains (upside potential) using semi-deviations from a benchmark; and on (2) integrating these criteria with the widely used expected value concept to estimate the value of a production strategy under uncertainty. Finally, we studied a framework to base decisions on multiple objectives.

The theoretical examples in §3 illustrate problems faced by decision makers in day-to-day situations when using traditional risk measures to assess production strategies. We showed that these problems can be overcome by applying the measures we propose. Lower semi-deviation effectively quantified downside risk, while traditional metrics were inadequate, because lower semi-deviation measures risk as failure to achieve a benchmark return. However, our examples revealed that the same benchmark must be used to assess all production strategies. When the expected value of each strategy is used, lower semi-deviation measures dispersion below the EV, and may label a production strategy as being low risk due to low variability, similarly to standard deviation.

Upper semi-deviation was particularly efficient in quantifying upside potential. To the best of our knowledge, this metric has never been applied in petroleum field development.

Our formulation to assess production strategies (Eq. (9)) is practical, increases confidence in the decision, is flexible in the definition of attitudes and objectives, and is easy to apply in day-to-day decision making, as exemplified in §4. This is because we use a framework of mean-partial moments, preferred to theoretically complex utility functions by allowing to specify the expected value, the level of uncertainty in losses, and level of uncertainty in gains of a production strategy. Note that decision

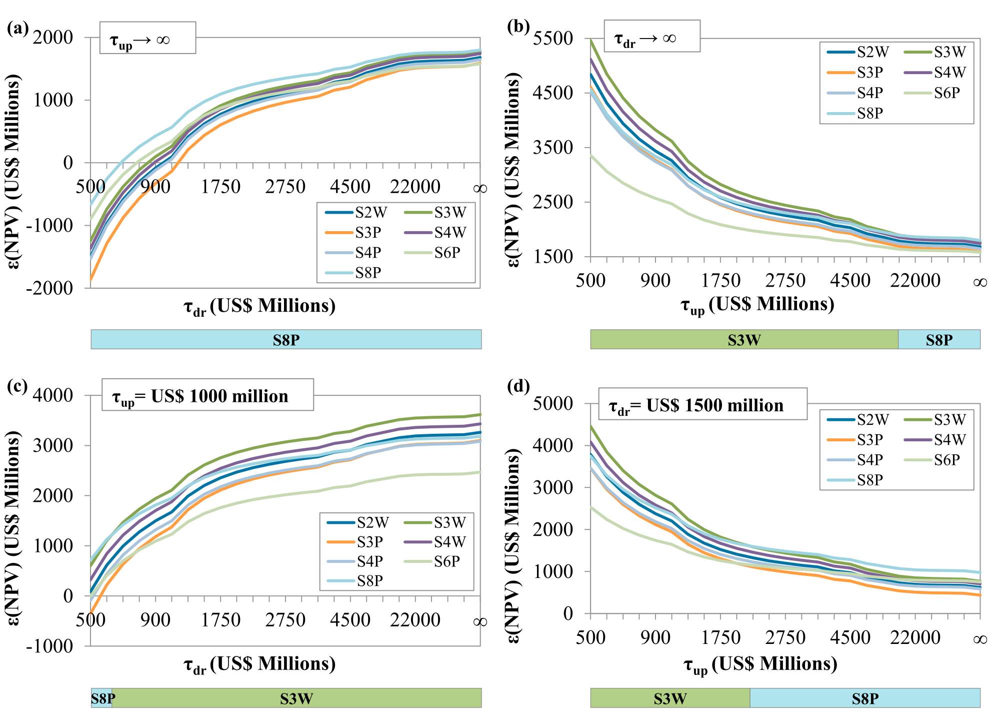


Fig. 10. Sensitivity analysis on the tolerance to downside risk (τ_{dr}) and upside potential (τ_{up}) to identify the best production strategy (highlighted in the horizontal bars) under different preferences to NPV: (a) neutrality to upside potential; (b) neutrality to downside risk; (c) τ_{up} fixed at US$ 1000 million; (d) τ_{dr} fixed at US$ 1500 million.

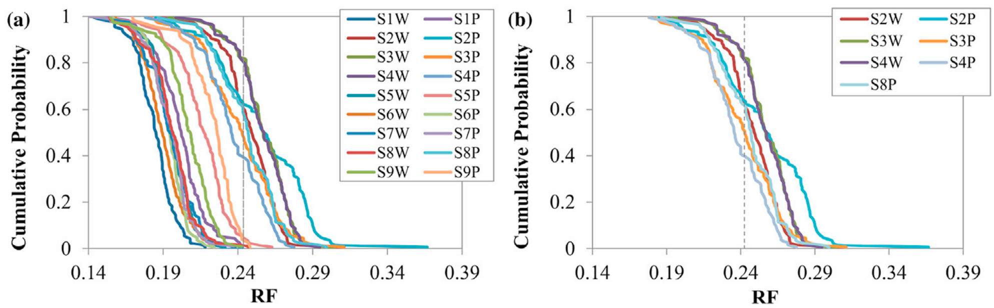


Fig. 11. Risk curves of oil recovery factor of: (a) candidate production strategies; and (b) production strategies with highest potential, selected based on acceptance regions (Fig. 12). The vertical line marks the benchmark.

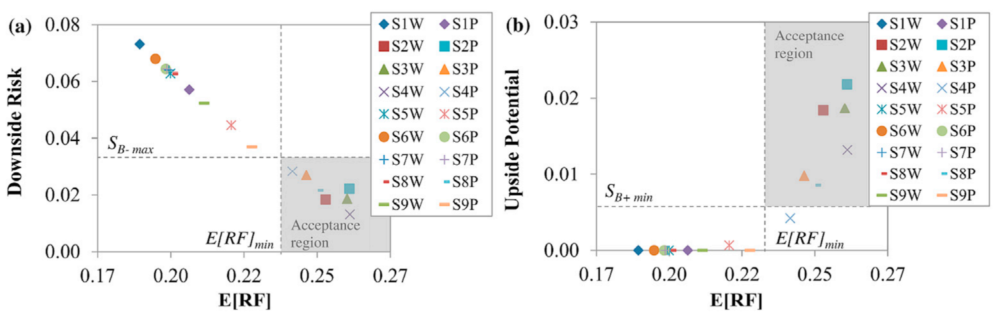


Fig. 12. Defining acceptance regions with cross-plots: (a) minimum acceptable E[RF] and maximum acceptable downside risk; and (b) minimum acceptable E[RF] and minimum acceptable upside potential.

Table 5
Candidate production strategies ranked by decreasing RF adjusted to the decision maker's attitude. Figures in bold highlight the best production strategy under each criterion.

Production strategy	E[RF] (%)	Downside risk (%)	Upside potential (%)	ε(RF) (%)
S3W	**25.7**	1.4	1.2	**25.6**
S4W	25.6	**1.3**	1.1	**25.6**
S2P	25.6	2.2	**2.2**	**25.6**
S2W	24.8	1.9	0.8	24.6
S8P	24.5	2.2	0.8	24.3
S3P	24.1	2.7	1.0	23.8
S4P	23.7	2.9	0.4	23.3

makers focused only on minimizing risk can disregard the upside potential term ($\tau_{up}\rightarrow\infty$), such that $\mathscr{R}(X) = -\,\varepsilon(X)$ is a coherent-averse measure of risk (see §1.1).

The existing body of literature supports our formulation. In particular, Zakamouline and Koekebakker (2009) and Zakamouline (2014) theoretically validated mean-partial moments frameworks as performance measures, incorporating expected value with lower and upper partial moments. By including a term quantifying uncertainty in gains, in addition to uncertainty in losses, we can improve production strategy evaluation. Disregarding bias towards uncertainty in gains can be problematic when evaluating production strategies, because the decision maker may look to exploit potential optimistic scenarios above the benchmark (e.g. adding flexibility to the production system).

In addition, accounting for uncertainty in gains and uncertainty in losses through a single value is inadequate because the decision maker typically has different perceptions towards them. This happens in the traditional mean-variance framework that uses a single coefficient to capture aversion, seeking, or neutrality. However, note that these are attitudes to overall uncertainty rather than risk, as typically referred to.

Our formulation (Eq. (9)) requires defining individual tolerance levels to downside risk and to upside potential. Several studies determine risk tolerance in petroleum upstream investments (see §1.2). However, most studies focus on exploration decisions, where risk perception can differ from that in the development phase (Rose, 1992). Additional studies are still required on methodologies to determine the tolerance levels, in particular tolerance to upside potential. In this study, we showed that a sensitivity analysis accompanying a choice increases confidence in the decision despite difficulties in finding these values.

Fishburn (1977), Zakamouline (2014) and others defend the use of partial moments of order β, defined by the decision maker. In this study, we used semi-variance ($\beta = 2$), as an alternative to variance, the traditionally employed risk measure in the upstream petroleum sector. Referring to the work of Zakamouline (2014), our suggested approach can be generalized to LPM and UPM of order β if the decision maker is characterized by different preferences. Zakamouline (2014) argues that the order of partial moments is directly linked to the shape of the decision maker's utility function. We believe that additional research is still required on techniques to find β and on its effects in production strategy evaluation.

Today, Multi-Attribute Utility Theory is a long-standing technique, and several authors have applied it in upstream petroleum investments to base a decision on multiple objectives (see §1.2). In this study, we also applied these concepts, and verified that they give transparency to the process and flexibility to the decision maker to manage tradeoffs between objectives. By integrating these concepts with the objective function we proposed to estimate the value of a production strategy, we can improve ease of use and practical application in real decision problems.

In the case study in §4, we selected very different preferences towards each objective. On the one hand, we aimed to exemplify that decision makers may prioritize downside risk minimization for one objective, and upside potential maximization for the other. On the other hand, we intended to illustrate how varied preferences affect production strategy selection, which cannot be captured by the expected value alone.

Botechia (2016) and Botechia et al. (2016) aimed to assess the feasibility of polymer flooding for this benchmark reservoir, which was

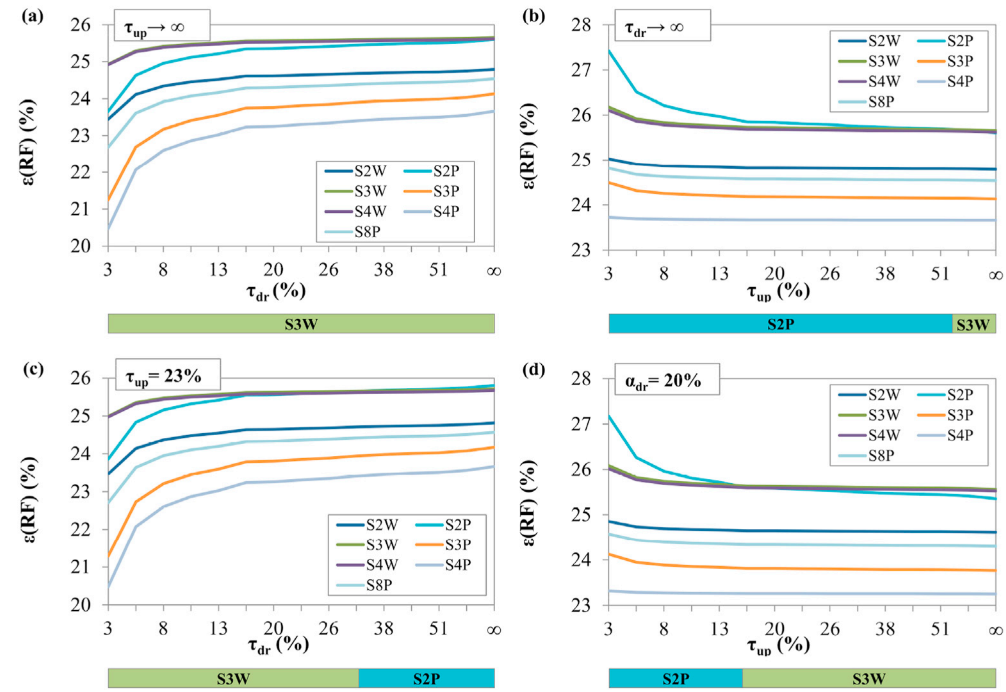


Fig. 13. Sensitivity analysis on the tolerance to downside risk (τ_{dr}) and upside potential (τ_{up}) to identify the best production strategy (highlighted in the horizontal bars) under different preferences to RF: (a) neutrality to upside potential; (b) neutrality to downside risk; (c) τ_{up} fixed at 23%; (d) τ_{dr} fixed at 20%.

Table 6
Candidate production strategies ranked by decreasing global utility.Figures in bold highlight the best production strategy under each criterion.

Production strategy	$\varepsilon(\text{NPV})_{norm}$	$\varepsilon(\text{RF})_{norm}$	$u(\text{NPV, RF})$
S3W	**1.000**	**1.000**	**1.000**
S4W	0.904	0.995	0.950
S8P	0.889	0.846	0.868
S2W	0.819	0.883	0.851
S3P	0.707	0.783	0.745
S4P	0.741	0.718	0.729
S2P	0.000	0.992	0.496
S6P	0.572	0.000	0.286

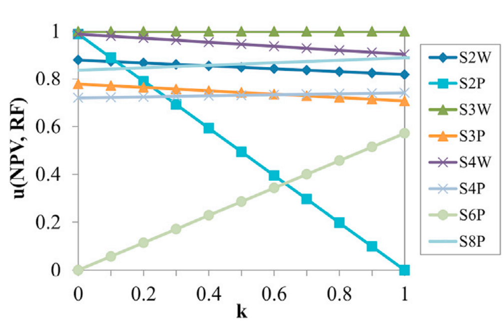


Fig. 14. Sensitivity analysis of the k weight in the multi-attribute utility function to identify the best production strategy under different preferences.

compared to water flooding. Although this benchmark case represents a heavy oil field, both recovery mechanisms recorded good recovery and economic efficiencies, provided that production strategies are properly optimized for each recovery mechanism. In this study, we showed that the choice depends on the decision maker's attitude and objectives.

These effects are noticeable in the choice between production strategies S3W and S8P based on economic return (§4.3). S3W does not maximize EMV nor does it minimize downside risk of NPV, both of which are achieved by S8P. However, the upside potential of S3W is by far the most attractive of the set, making S3W the best candidate (even over S8P) under the tolerance values we assigned to NPV.

This is also particularly noticeable in production strategy S2P, one of the best strategies considering just preferences to RF (§4.4), while the worst considering only preferences to the economic return (§4.3). This particular option is characterized by many wells, high platform capacities, and large volumes of polymer injected; all resulting in high expected recovery. However, the revenues do not balance the necessary investments and costs to recover this amount of oil. This supports using more than just a production indicator as an objective, as optimized oil returns do not imply higher economic return (§4.5).

6. Conclusions

The proposed decision criteria assess and rank alternative production strategies in petroleum field development, and include: (1) measures of downside risk (uncertainty in losses) and of upside potential (uncertainty in gains); (2) a new objective function to estimate the production strategy's value adjusted to the decision maker's attitude; and (3) a framework to base a decision on multiple objectives. Specific conclusions of this work include:

- Standard deviation assesses overall uncertainty and is inadequate to assess risk;
- Semi-deviation assesses individual subsets of overall uncertainty, distinguishing good from bad variability, making it effective to measure upside potential and downside risk;
- In particular, lower semi-deviation improves risk assessment: (1) of production strategies with asymmetric distributions, with either the same or different variability and EV; (2) of production strategies with symmetric distributions and widely different EV, including positive,

zero and negative EV; and (3) it avoids labeling a production strategy as being low risk due to low overall variability;
- The decision maker's preferences affect production strategy selection, which cannot be captured by the expected value alone;
- The proposed objective function (ε) can model neutrality to downsides and upsides, aversion to losses, and preference for upsides, in an easy-to-apply and quantitative way, and is applicable to production and economic indicators;
- The framework we provide to combine multiple objectives is straightforward to apply and gives flexibility to the decision maker to manage tradeoffs between production and/or economic indicators;
- We recommend sensitivity analyses on the tolerance levels and model weights to increase confidence in the decision;
- We recommend further research on techniques to find the tolerance levels, and on assessing the effects of the order of the partial moments in production strategy evaluation.

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Nomenclature

c_{dr}	aversion coefficient to downside risk
c_{up}	expectation coefficient to upside potential
S_{B-}	lower semi-deviation from B
S_{B+}	upper semi-deviation from B
S_{EV}	below-mean semi-deviation
S^2_{B+}	upper semi-variance from B
S^2_{B-}	lower semi-variance from B
B	benchmark
c	risk aversion coefficient
CE	certainty equivalent
CV	coefficient of variation
CVaR	conditional value at risk
E	expectation operator
EMV	expected monetary value
EU	expected utility
EV	expected value
k_i	MAUT model weight of objective i
LPM_β	lower partial moment of order β
MAUT	Multi-Attribute Utility Theory
NPV	net present value
P	polymer flooding
RF	recovery factor of oil
RM	representative model
RT	corporate risk tolerance
S	production strategy
u	utility function
UPM_β	upper partial moment of order β
VaR	value at risk
W	water flooding
X	random variable
γ_-	decision maker's attitude towards uncertainty below W_0
γ_+	decision maker's attitude towards uncertainty above W_0
ε	production strategy value adjusted to the decision maker's attitude
λ	aversion to expected loss
σ	standard deviation
σ^2	variance
τ_{dr}	tolerance level to downside risk
τ_{up}	tolerance level to upside potential

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4. ARTICLE 3: RISK MANAGEMENT IN PETROLEUM DEVELOPMENT PROJECTS: TECHNICAL AND ECONOMIC INDICATORS TO DEFINE A ROBUST PRODUCTION STRATEGY

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Risk management in petroleum development projects: Technical and economic indicators to define a robust production strategy

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ABSTRACT

In this study, we consider robustness as a risk management method in the development of complex petroleum fields, complementing the well-known techniques of acquiring new information and adding flexibility to the production system. To create a robust production strategy we aim to reduce sensitivity to uncertainty. Our methodology is based on the analyzed performance of an optimized production strategy, covering all possible scenarios. We use technical and economic indicators to objectively identify and quantify refinements in this strategy to assure good performance across possible scenarios. We focus on the robust number and placement of wells, and robust platform processing capacities. We consider the robustness of net present value and of the recovery factor, computed using Multi-Attribute Utility Theory. We quantify the risk through semi-deviation, instead of standard deviation, to focus on the downside volatility. Refining an optimized production strategy significantly improved the optimization process by increasing the expected value of each objective and, dramatically reduced the downside risk.

1. Introduction

1.1. Managing uncertainty in petroleum field development – information, flexibility and robustness

The upstream sector, particularly in offshore fields, is considered high-risk, comprising considerable investment in complex, uncertain scenarios. Various sources of uncertainties may coexist during the development phase, the focus of this study: (1) geological uncertainties, associated with recoverable reserves and flow characteristics; (2) operational uncertainties, related to system availability; and (3) economic uncertainties, such as oil price, capital expenditures (CAPEX) and operational expenditures (OPEX). Thus, uncertainty and risk analyses are fundamental to decide whether and how to develop a field.

Uncertainty management methodologies are well described in the engineering literature (de Neufville et al., 2004; McManus and Hastings, 2005; Chalupnik et al., 2009). There are two general ways to manage uncertainty: (1) reducing the uncertainty itself (usually with additional information); or (2) protecting the system by introducing attributes to reduce sensitivity to uncertainty (modifications to system via active or passive protection). In active protection, we create flexibility to adapt to uncertainty, while passive protection increases system robustness, defined as “the ability of a system to maintain its operational capabilities under different circumstances” (de Neufville et al., 2004, p.10).

Unlike information acquisition and flexibility, the concept of robustness is discussed marginally in the petroleum literature. Lappegaard and Plummer (1991) and Adlam (1995) were the first to include robustness in highly uncertain field development.

The two approaches to establish robustness in field development are: (1) Robust Optimization, an optimization problem under uncertainty; or (2) using performance indicators to assess candidate production strategies over the range of possible scenarios. This paper focuses on the second approach. Most existing studies compare two alternative strategies or present case studies, but do not propose generalized methodologies to define a robust strategy (with exceptions Viseras et al. (2014) and Hegstad and Saetrom (2014)).

Unlike previous studies, we decrease computational costs by refining a previously optimized production strategy, selected through in-depth decision analyses.

1.2. Measures of risk in petroleum field development

Variance (σ^2) and standard deviation (σ) are commonly applied measures of risk in petroleum field development. However, variance may be inadequate because it measures risk as overall variability around the expected value. Markowitz (1959) proposed semi-variance,

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Nomenclature

a, b	scaling constants
AC	abandonment cost
B	benchmark
c	risk aversion coefficient
CV	coefficient of variation
E	expectation operator
EMV	expected monetary value
EU	expected utility
EV	expected value
Inv_{plat}	platform investment
IWEI	Injector Well Economic Indicator
j	index to denote an MAUT objective
J	total number of MAUT objectives
k	MAUT model weight
MAUT	multi-attribute utility theory
n	number of wells
NCF	net cash flow
Np	cumulative oil production
NPV	net present value
PWEI	Producer Well Economic Indicator
Q_l	liquid processing capacity
Q_o	oil processing capacity
Q_w	water processing capacity
Q_{wi}	water injection capacity
R	robust production strategy
Rev	gross revenue
RFo	oil recovery factor
Roy	royalties
RS	representative scenario
RT	corporate risk tolerance
S	optimized production strategy
$S_B{}^2$	semi-variance below B
$S_B{}^2$	semi-deviation below B
ST	social taxes
T	corporate taxes
u	utility function
Wp	cumulative water production
x	random variable
σ^2	variance
σ	standard deviation
μ	mean

which denotes the *downside variance* and focuses on outcomes falling below a predefined benchmark (B). This value depends on the definition of loss and is independent of the probability distribution. The semi-standard deviation, or semi-deviation for short, is given by the square root of the semi-variance (Eq. (1)).

$$S_B = \sqrt{S_B^2} = \sqrt{E\{min[(x-B),0]^2\}} \tag{1}$$

where: S_B – semi-deviation below a benchmark B; S_B^2 – semi-variance below a benchmark B; E – expectation operator; x – random variable.

In the decision analysis literature, semi-variance is preferred to variance because: (1) it is more coherent in asymmetric distributions; (2) it avoids labeling an alternative as low-risk when presenting low variability; and (3) it allows specifying the target return, below which the decision maker considers risk (Markowitz, 1959; Sortino and Price, 1994; Krokhmal et al., 2011).

The semi-variance assumes that investors are indifferent to upside volatility adding no value for investors who focus only on the upside, neglecting the downside (Campbell et al., 2001). Note that this is uncommon in petroleum development projects due to high investment under high uncertainty.

Although seldom used to assess risk in petroleum development projects, we selected semi-deviation as we considered it to be the most representative and flexible measure of risk. Note that semi-variance, like variance, is expressed in squared units.

1.3. Decision criteria to select the best production strategy

In field development, the expected value (EV) is typically used, but by implying impartiality to the magnitude of losses, managers often use informal procedures and intuition to base decisions (Walls, 1995a). In contrast, utility theory recognizes risk aversion as part of the decision policy. Proposed by von Neumann and Morgenstern (1944) it is currently well documented in the literature (Luce and Raiffa, 1957; Fishburn, 1970; Keeney and Raiffa, 1993).

A utility curve is derived: (1) empirically, with no preconception about the utility curve; or (2) analytically, selecting a form of utility which is scaled through question to the decision maker. In the petroleum literature, the exponential utility function is typically used (Eq. (2)) (Cozzolino, 1977; Walls, 1995a; Walls and Dyer, 1996; Newendorp and Schuyler, 2000; Butler et al., 2001) because it characterizes risk by a single number, the risk aversion coefficient (c).

$$u(x) = a - be^{-cx} = a - be^{-x/RT} \tag{2}$$

where: $u(x)$ – utility function; x – random variable; a and b – constants; c – risk aversion coefficient, where $c > 0$ implies risk-averse behavior, $c < 0$ implies risk-seeking behavior, and $c \to 0$ implies risk-neutral behavior (Keeney and Raiffa, 1993); RT – corporate risk tolerance.

The corporate risk tolerance ($RT = 1/c$), representing "the sum of money such that the executives are indifferent as a company investment to a 50-50 chance of winning that sum and losing half of that sum" (Howard, 1988, p.689), can be estimated by asking the decision maker questions, but rules of thumb exist in the petroleum literature (Howard, 1988; Rose, 1992; Walls, 1995a; Walls and Dyer, 1996).

In the petroleum literature, expected utility (EU) is typically derived analytically (Walls, 1995b; Newendorp and Schuyler, 2000). The finance literature provides frameworks of mean and partial moments of the distribution which, unlike the analytical approach, are coherent with the definition of risk by considering subsets of overall variability. Estrada (2004), in particular, proposed a mean-semivariance (MS) framework (Eq. (3)).

$$EU \simeq u(EV) + u''(EV) \times S_B{}^2 \tag{3}$$

where, $u(x)$ – utility function; $u''(x)$ – second derivative of $u(x)$; x – random variable; EV – expected value, EU – expected utility; $S_B{}^2$ – semi-variance below B.

If more than one objective is considered Multi-Attribute Utility Theory (MAUT) (Keeney and Raiffa, 1993) can be applied. A common model in the petroleum literature is the additive model (Eq. (4)), valid under strict assumptions (Keeney and Raiffa, 1993), but generally a close approximation of different preferences, while remaining easier to use (cf. Huber, 1974).

$$u(x) = \sum_{j=1}^{J} k_j u_j(x_j) \tag{4}$$

where, $u_j(x_j)$ – utility function for objective j; x – random variable; k – weight (i.e. relative importance) of objective j, totalizing J objectives such that $\sum_{j=1}^{J} k_j = 1$.

Despite extensive literature on weight assessing procedures, decision makers in the petroleum industry typically assign them directly (Nepomuceno Filho et al., 1999; Suslick and Furtado, 2001).

In this study, we use the MAUT, which supports decision making with multiple objectives and incorporates the decision maker's risk attitude. Furthermore, we derive EU using the mean-semivariance framework proposed by Estrada (2004), which agrees with our definition of risk.

1.4. Scope and objectives

Today, information and flexibility are widely used to manage uncertainty in the field development phase but the literature also shows advantages in adding robustness to the system. Accordingly, our objective is to assess and increase the robustness of an optimized production strategy, selected through detailed decision analyses. We propose a methodology which: (1) integrates the characteristics of the decision maker and the petroleum field; (2) is quantitative and objective, reducing the subjectivity of the decision making process; and (3) is general and applicable to different case studies. We achieve these objectives by: (1) incorporating comprehensive decision criteria from the decision analysis literature; and (2) providing well and field indicators, computed using the probabilistic predictions of the production strategy. This approach lowers computational costs when compared to automated optimization problems under uncertainty.

2. Methodology

Schiozer et al. (2015) proposed a comprehensive decision analysis framework in twelve steps covering all stages of field development and management, summarized as follows: (1) reservoir characterization under uncertainty; (2) construction and calibration of the simulation base model; (3) verification of inconsistencies in the base model using dynamic data; (4) generation of scenarios considering the full range of uncertainties; (5) reduction of scenarios using dynamic data; (6) selection of a deterministic production strategy using an optimization procedure; (7) initial risk assessment; (8) selection of representative scenarios based on multiple objective functions and the full range of uncertain parameters; (9) selection of a production strategy for each representative scenario (as in Step 6); (10) selection of the best production strategy from the set of candidates strategies obtained in Step 9; (11) identification of potential for changes in the best strategy to mitigate risk or increase value (e.g. information, flexibility, and robustness); and (12) final risk assessment.

Our proposed methodology integrates this framework, and corresponds to the developments of Step 10 and Step 11, detailed below. Further details of Steps 1 through 9 can be found in Schiozer et al. (2015). Note that in this study a scenario is a particular combination of all uncertain parameters.

2.1. Step 10: Selecting the best production strategy from a set of candidate strategies

In this step, the decision maker selects the best production strategy from the set of candidate strategies obtained in Step 9. The decision criteria presented here are based on Expected Utility and Multi-Attribute Utility Theory, to consider risk and multiple objectives in the decision (see §1.3).

In this study we use the semi-deviation below a benchmark as a measure of risk (Eq. (1)), due to advantages over traditional measures (see §1.2). To objectively find the benchmark, we calculate the expected value (EV) of each production strategy, and use the strategy with maximized EV as reference, and consequently as the benchmark. This assumes that, in decisions based on expected value, the preferred production strategy maximizes EV (without further analyses). Note that the same benchmark is used for all strategies to fairly assess risk.

The decision maker constructs an appropriate utility function for each objective (see §1.3). If only one objective is considered, the best production strategy is the one that maximizes expected utility.

If multiple objectives are considered, the decision maker constructs a multi-attribute utility function according to its preferences (see §1.3). To calculate global utility, the set of single-attribute values must be normalized between 0 and 1, following the convention: $u_{min}(x) = 0$; $u_{max}(x) = 1$. The decision maker ranks the production strategies to select the one that maximizes global utility. However, before making the final decision, a sensitivity analysis on the model weights is recommended to identify the best production strategy under different weight ranges. Several sensitivity analysis methods are found in the literature (Butler et al., 1997; Suslick and Furtado, 2001; Chambal et al., 2011), and its choice must be in accordance with the complexity of the case study.

2.2. Step 11: Increasing robustness of the best production strategy to manage uncertainty

Although Step 10 identifies probabilistically the best production strategy from the set of candidate strategies, this production strategy was optimized deterministically, implying that improvements may arise when all scenarios are considered. We provide technical and economic indicators, computed with the predicted performance of this production strategy over all scenarios, for the decision maker to objectively identify refinements and introduce robust attributes to ensure good performance across scenarios. First, the decision maker analyzes well indicators to increase robustness of the number and placement of wells. Then, field indicators are analyzed to define a robust platform size, in terms of fluid processing and injecting capacities.

The decision maker can use the strategies obtained in Step 9 to

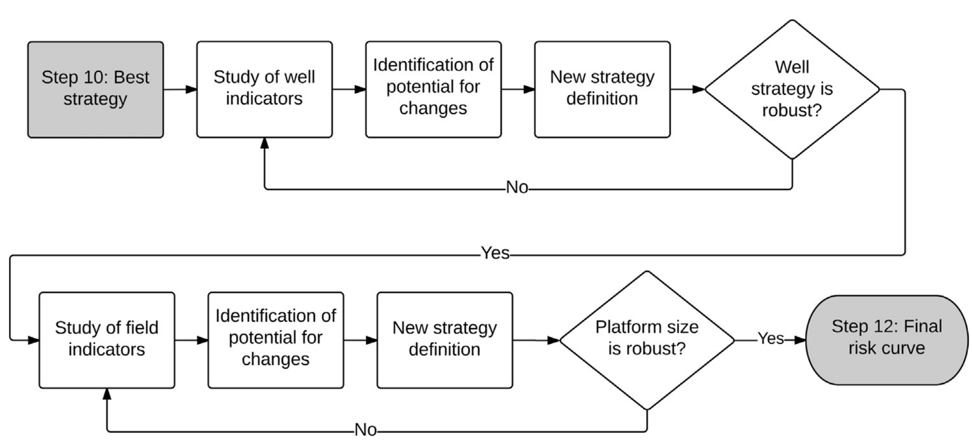

Fig. 1. Flowchart to increase robustness of a production strategy.

define variation boundaries of strategy parameters (such as in well number and platform size). This can be done because the set of representative scenarios was selected to represent the full range of uncertain scenarios and therefore, the set of optimized strategies should have an adequate range of characteristics. Fig. 1 summarizes the proposed workflow, which is detailed below.

2.2.1. Step 11.1: Verifying and increasing robustness of number and placement of wells

The proposed well indicators to assess and increase robustness of well strategy are as follows:

1. Probability of n wells placed in an unfavorable position and not producing or injecting;
2. Probability of each individual well placed in an unfavorable position and therefore not producing or injecting;
3. Variability in well technical performance: cumulative hydrocarbon production and cumulative fluid injection;
4. Variability in well economic performance: producer and injector well economic indicator (PWEI and IWEI, respectively; indicators proposed by Ravagnani et al. (2011));
5. Probability of each producer presenting a negative PWEI;
6. Probabilistic maps of mean and standard deviation of the reservoir static and dynamic properties (porosity, permeability, net-to-gross, and oil saturation).

To assess the probability of wells being placed in unfavorable positions (indicators 1 and 2), we analyze the cumulative hydrocarbon production and cumulative fluid injection of each well in each scenario to identify wells that do not produce (e.g. Np=0) and wells that do not inject (e.g. Winj=0). In indicators 3 and 4, we look at minimizing variability in well performance to prevent wells from presenting good performance in some scenarios, but bad performance in others.

The well economic indicators PWEI and IWEI quantify individual contribution of each well to the field's net present value (NPV). It is desired to maximize PWEI (reflecting maximum hydrocarbon production) and to minimize IWEI (reflecting maximum fluid injection).

Using these combined indicators, we can identify wells with high probability of being placed in unfavorable positions, wells with overall bad performance, and wells with a highly variable performance. Having identified these, probabilistic maps allow identifying robust regions for well placement, characterized by high mean values and low standard deviation values of the reservoir static and dynamic properties.

Before proceeding, the decision maker assess the value of the new production strategy using the criteria described in Step 10.

2.2.2. Step 11.2: Verifying and increasing robustness of platform size

The fluid processing and injecting capacities optimized for a single scenario may not be ideal when considering all scenarios. Therefore, we study the probabilistic percentage of the prediction period that the platform capacities are utilized. Based on this indicator, we can verify if the platform is over or under dimensioned, and so adjust capacity to a more robust level across scenarios.

We then apply the criteria described in Step 10 to assess the value of the new production strategy.

3. Case study

3.1. Reservoir description

We applied the methodology to the synthetic reservoir model UNISIM-I-D (Gaspar et al., 2015), a case study for selection of production strategy that has the complexity of a real reservoir, being based on a Brazilian field.

UNISIM-I-D is an offshore oil reservoir, 80 km from the coastline, in the development phase, with 1461 days of initial production history of four vertical producing wells (Fig. 2). The reservoir depth varies between 2900 to 3400 m and the water depth is 166 m. The simulation model comprises a corner point grid with 81×58×20 cells of 100×100×8 m, in a total of 36,739 active cells. The case study comprises a set of reservoir, operational, and economic uncertainties (Tables 1–3, respectively). The uncertainties of the original dataset are discrete or have been discretized. The absence or presence of the east region in the reservoir is a key geological uncertainty affecting production strategy selection, including well placement and number, and platform capacity because of lower levels of oil in place.

3.2. Criteria to calculate the value of production strategies

In this study, the net cash flow formulation is based on the Brazilian concession fiscal regime (Gaspar et al., 2015) (Eq. (5)).

$$NCF = [(Rev - Roy - ST - OPEX) \times (1-T)] - CAPEX - AC \tag{5}$$

where: NCF – net cash flow; Rev – gross revenue; Roy – royalties; ST – social taxes; OPEX – operational expenditure; T – corporate taxes; CAPEX – capital expenditure; AC – abandonment cost. OPEX includes operating costs associated with fluid production and injection. CAPEX includes all investments in equipment and facilities, such as platform,

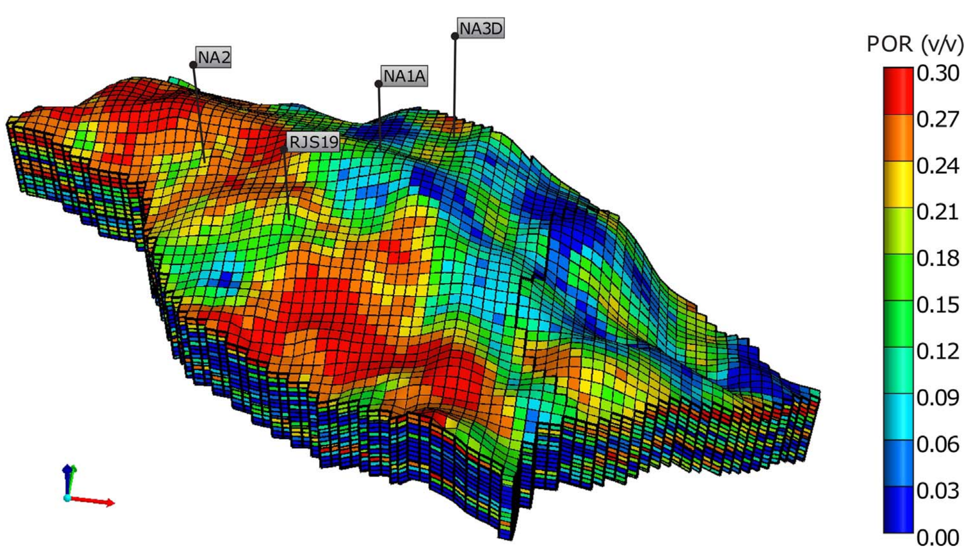

Fig. 2. Porosity map of UNISIM-I-D, including the position of the four historic producers.

Table 1
Set of reservoir uncertainties of UNISIM-I-D case study.

Attribute	Description	Type	Value (probability)				
			-2	-1	0	+1	+2
img	Petrophysical characteristics	discrete [realization]	500 equiprobable geostatistical realizations of porosity, permeability and, net-to-gross ratio (0.002)				
kr	Water relative permeability	discrete [table]	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
pv	Region 2 pvt data	discrete [table]	–	(0.33)	(0.34)	(0.33)	–
bl	Structural model	discrete [map]	–	No east block (0.30)	With east block (0.70)	–	–
wo	Region 2 water-oil contact	continuous discretized [scalar]	3074 m (0.222)	3124 m (0.334)	3174 m (0.111)	3224 m (0.222)	3274 m (0.111)
cp	Rock compressibility	continuous discretized [scalar]	–	23.6E-6 cm^2/kgf (0.2)	53.0E-6 cm^2/kgf (0.6)	82.4E-6 cm^2/kgf (0.2)	–
kz	Vertical permeability multiplier	continuous discretized [scalar]	0.475 (0.1)	0.949 (0.2)	1.500 (0.4)	2.051 (0.2)	2.525 (0.1)

Table 2
Set of operational uncertainties of UNISIM-I-D case study.

Attribute	Description	Type	Value (probability)		
			−1 (0.33)	0 (0.34)	+1 (0.33)
ogr	Group availability	continuous discretized	0.91	0.96	1.00
opl	Platform availability	continuous discretized	0.90	0.95	1.00
opw	Producer well availability	continuous discretized	0.91	0.96	1.00
oiw	Injection well availability	continuous discretized	0.92	0.98	1.00
ff	Well index multiplier	continuous discretized	0.7	1.00	1.4

Table 3
Set of economic uncertainties of UNISIM-I-D case study.

Type	Attribute (unit)	Value (probability)		
		−1 (0.25)	0 (0.5)	+1 (0.25)
Market variables	Oil price (US$/$m^3$)	251.60	314.50	440.30
	Discount rate (%)	9.00	9.00	9.00
Taxes	Royalties (%)	10.00	10.00	10.00
	Social taxes (%)	34.00	34.00	34.0)
	Corporate taxes (%)	9.25	9.25	9.25
OPEX	Oil production (US$/$m^3$)	52.40	62.90	81.80
	Water production (US $/$m^3$)	5.24	6.29	8.18
	Water injection (US$/$m^3$)	5.24	6.29	8.18
	Abandonment (US$ million) (% of well investment)	8.20	8.20	8.20
CAPEX	Horizontal well drilling and completion (US$ million)	54.00	61.17	76.46
	Vertical well drilling and completion (US$ million)	18.96	21.67	27.34
	Well – platform connection (US$ million)	11.66	13.33	16.66
	Platform Investment (US$ million)	0.8xEq. (6)	Eq. (6)	1.25xEq. (6)

wells drilling and completion, network systems, and pipelines. Platform investment is given by Eq. (6) (Gaspar et al., 2015).

$$Inv_{plat}=417+(16.\ 4\times Q_o+3.\ 15\times Q_w+3.\ 15\times Q_{wi}+0.\ 1\times n) \tag{6}$$

where: Inv_{plat} – platform investment (US$ million); Q_o – oil processing capacity (1000 m^3/day); Q_w – water processing capacity (1000 m^3/day); Q_{wi} – water injection capacity (1000 m^3/day); n – number of wells.

We considered two objectives to evaluate alternative production strategies: (1) maximize economic return, measured by the net present value (NPV); and (2) maximize hydrocarbon recovery, measured by the oil recovery factor (RFo). We applied exponential utility functions for both objectives, for its advantages over other formulations (see §1.3). We selected the exponential utility function that Newendorp and Schuyler (2000) recommend for NPV (Eq. (7)). For RFo, we considered the typical form of exponential utility function (Eq. (2)), assuming a=b=1, resulting in Eq. (8).

$$u(NPV) = RT(1-e^{-NPV/RT}) \tag{7}$$

$$u(RFo) = 1-e^{-RFo/RT} \tag{8}$$

We applied the mean-semivariance approximate to the expected utility as defined by Estrada (2004) (Eq. (3)), coherent with our definition of risk. We used the additive model in Eq. (4), resulting in Eq. (9).

$$u(NPV,\ RFo) = kEU(NPV)+(1-k)EU(RFo) \tag{9}$$

For this synthetic case study, we considered the following illustrative values: RT(NPV)=US$ 1.0E9, RT(RFo) =30%; k=0.5. In this study, as we considered only two objectives, a one-factor-at-a-time sensitivity analysis was conducted.

4. Results

Schiozer et al. (2015) applied the 12 step framework to UNISIM-I-D case study from Steps 1 to 9. Of the 500 equiprobable scenarios combined with the Discretized Latin Hypercube sampling technique (Schiozer et al., 2016), 214 were accepted through a matching indicator using production data. Many scenarios recorded a good match due to the brief history period with almost no water production, and they were kept equiprobable due to lack of evidence to prioritize scenarios. An intermediate scenario (P50) was chosen as the base model and a deterministic production strategy (S1) was selected. Schiozer et al. (2015) conducted a risk analysis for the 214 equiprobable scenarios and production strategy S1, and selected 9 representative scenarios (RS1 to RS9). Finally, they optimized a production strategy for each representative scenario, resulting in 9 candidate production strategies (S1 to S9), summarized in Table 4.

We determined US$ 1822 million as the benchmark to assess the level of risk for NPV, corresponding to the expected monetary value (EMV) of production strategy S9 (maximizing EMV). We determined 51.8% as the benchmark to assess the level of risk for RFo, corresponding to the expected RFo of production strategies S8 and S9 (maximizing expected RFo).

Table 4
Characteristics of the 9 candidate production strategies. V: vertical well; W: horizontal well; Q_l: liquid processing capacity; Q_o: oil processing capacity; Q_w: water processing capacity; Q_{wi}: water injecting capacity.

Production strategy	Production wells			Injection wells			Platform capacities (1000 m^3/day)			
	V	H	Total	V	H	Total	Q_l	Q_o	Q_w	Q_{wi}
S1	2	10	12	0	6	6	16.3	16.3	9.1	23.3
S2	2	8	10	0	6	6	16.3	16.3	11.2	22.8
S3	2	7	9	0	5	5	14.0	14.0	9.8	19.5
S4	1	10	11	0	6	6	18.2	18.2	11.5	25.5
S5	3	10	13	0	7	7	17.8	17.8	10.5	23.8
S6	1	8	9	0	6	6	14.3	14.3	7.3	20.6
S7	2	7	9	0	6	6	13.2	13.2	5.2	19.5
S8	3	11	14	0	7	7	21.7	21.7	14.6	29.8
S9	3	10	13	0	7	7	20.2	20.2	9.8	28.2

Table 5
Value of the 9 candidate production strategies.

Production strategy	EMV (US$ million)	Risk of NPV (US$ million)	E{RFo} (%)	Risk of RFo (%)	EU(NPV) norm.	EU(RFo) norm.	u(NPV, RFo)
S9	1822	500	51.8	2.5	1.000	1.000	1.000
S8	1694	609	51.8	3.1	0.885	0.997	0.941
S2	1736	516	49.1	5.0	0.951	0.855	0.903
S1	1718	510	49.1	5.2	0.945	0.854	0.900
S4	1694	559	49.6	4.8	0.909	0.885	0.897
S5	1657	613	50.2	4.3	0.860	0.915	0.888
S7	1383	660	40.5	13.2	0.635	0.105	0.370
S6	1267	773	40.9	12.9	0.427	0.149	0.288
S3	1078	930	39.8	14.2	0.000	0.000	0.000

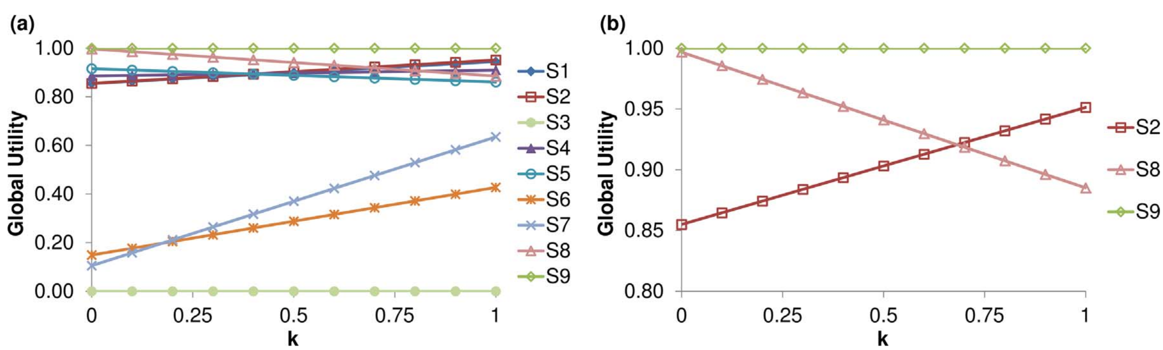

Fig. 3. (a) Sensitivity analysis of the MAUT weights for the 9 candidate production strategies. (b) Zoom in the best strategies.

4.1. Step 10: Selecting the best production strategy from 9 candidates (S1 to S9)

We assessed the 9 candidate production strategies (S1 to S9) and ranked them by order of global utility (Table 5), revealing S9 as the best production strategy. Choosing the best candidate here is simple as S9 maximizes both objectives. Therefore, regardless the weights of the MAUT model, S9 is always preferred (Fig. 3).

4.2. Step 11: Increasing robustness of production strategy S9

To obtain the well and field probabilistic indicators we predicted the performance of S9 over the 214 possible scenarios, using a black-oil reservoir simulator.

4.2.1. Verifying and increasing robustness of number and placement of production wells

The indicators revealed that S9 has four dry wells (null cumulative oil production, Np=0) in roughly 30% of the possible scenarios (Fig. 4a). This is because of the uncertainty in the structural model, as these wells are in a reservoir region whose existence is uncertain (Fig. 4b). Thus, the probability of wells not producing is strongly related to the structural uncertainty. However, without this structural uncertainty there is still a chance of dry wells (Fig. 4c and d). We verified that this is linked to near null values of permeability and porosity in some scenarios.

In S9, all horizontal producers are placed in the first layer of the reservoir model. However, the mean and standard deviation maps for the static and dynamic properties revealed that layer 2 has better properties, on average, when considering all scenarios. Fig. 5 presents the mean and standard deviation porosity maps for layers 1 and 2, computed for the beginning of the prediction period (1857 days).

Based on these indicators, we defined a new strategy (R1). All horizontal producers (initially placed in layer 1) were relocated to layer 2. Well number was found to be robust. In addition, the indicators suggest conducting a Value of Information analysis, as the high probability of wells not producing is strongly related to the structural uncertainty, which could be clarified with an appraisal well.

R1 is preferred to S9, with an overall gain on global utility of +5.2%, increasing EMV by +6.2% (+US$ 110 million), reducing economic risk

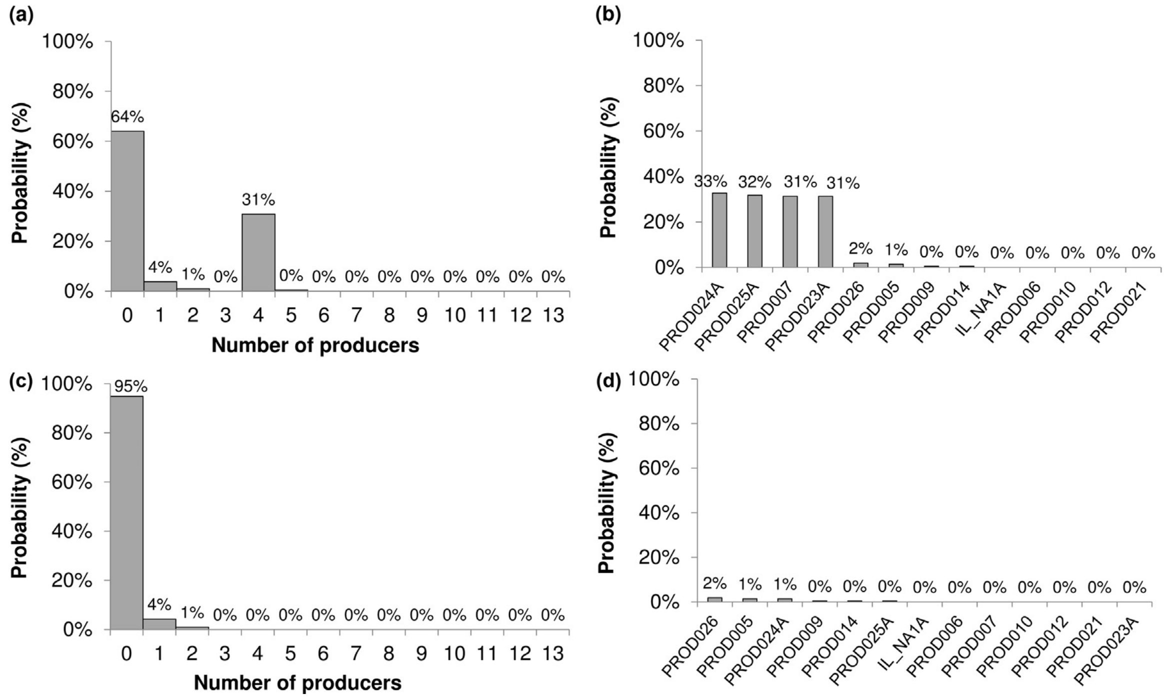

Fig. 4. Probability of (a) n wells, and (b) each well not producing for strategy S9. In (c) and (d) the effect of dry wells due to the structural uncertainty was removed from the probabilistic calculation.

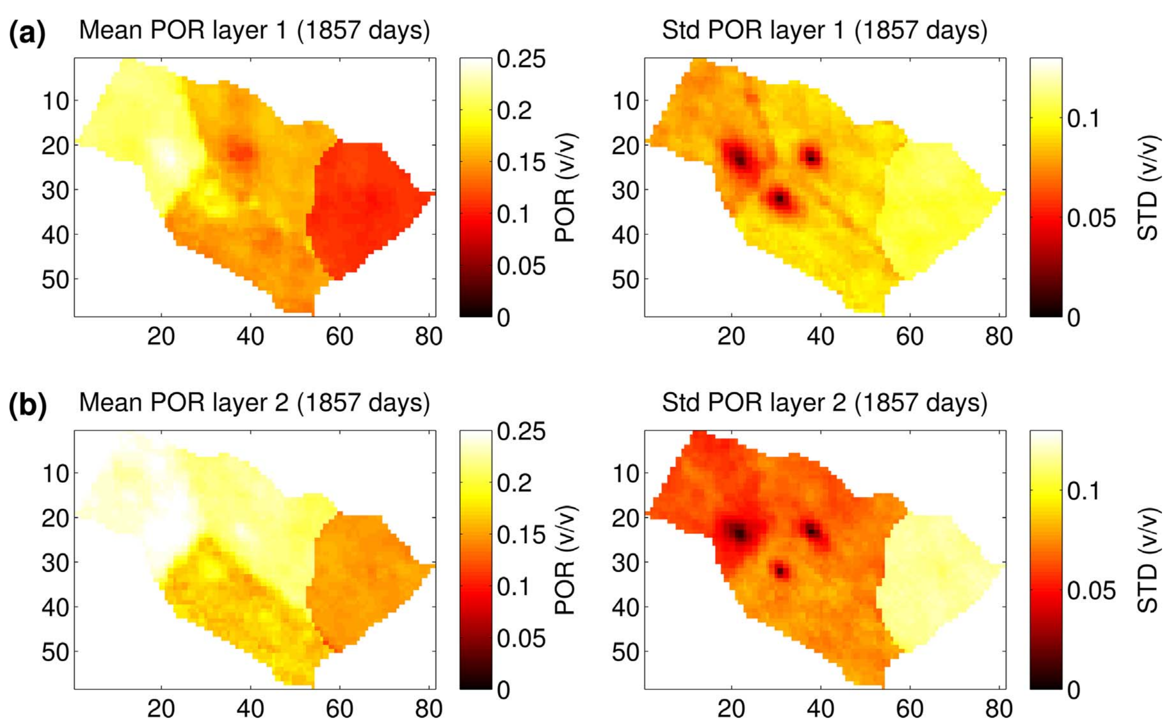

Fig. 5. Mean (left) and standard deviation (right) porosity maps for (a) layers 1, and (b) layer 2. These maps were computed for the beginning of the prediction period (1857 days).

Table 6
Value of the robust strategy R1, compared with S9.

Production strategy	EMV (US$ million)	Risk of NPV (US$ million)	E{RFo} (%)	Risk of RFo (%)	u (NPV, RFo)
S9	1822	500	51.8	2.5	1.000
R1	1935 (+6.2%)	433 (−13.3%)	52.5 (+1.4%)	1.9 (−26.9%)	1.052 (+5.2%)

by −13.3%, increasing expected RFo by +1.4%, and reducing recovery risk by −26.9% (Table 6, Fig. 6). Note that, the single-attribute utility values were not normalized again, maintained at $u_{min}(S3) = 0$ and $u_{max}(S9) = 1$. The probability of dry well is now exclusively related to the structural uncertainty, i.e., the chance of dry wells due to low petrophysical properties was eliminated (Fig. 7). Additionally, the variability of well performance in Np was reduced, marked by reduced chances of scenarios with low performance (Fig. 8). The sensitivity analysis performed on the model weights showed that R1 is always preferred to S9.

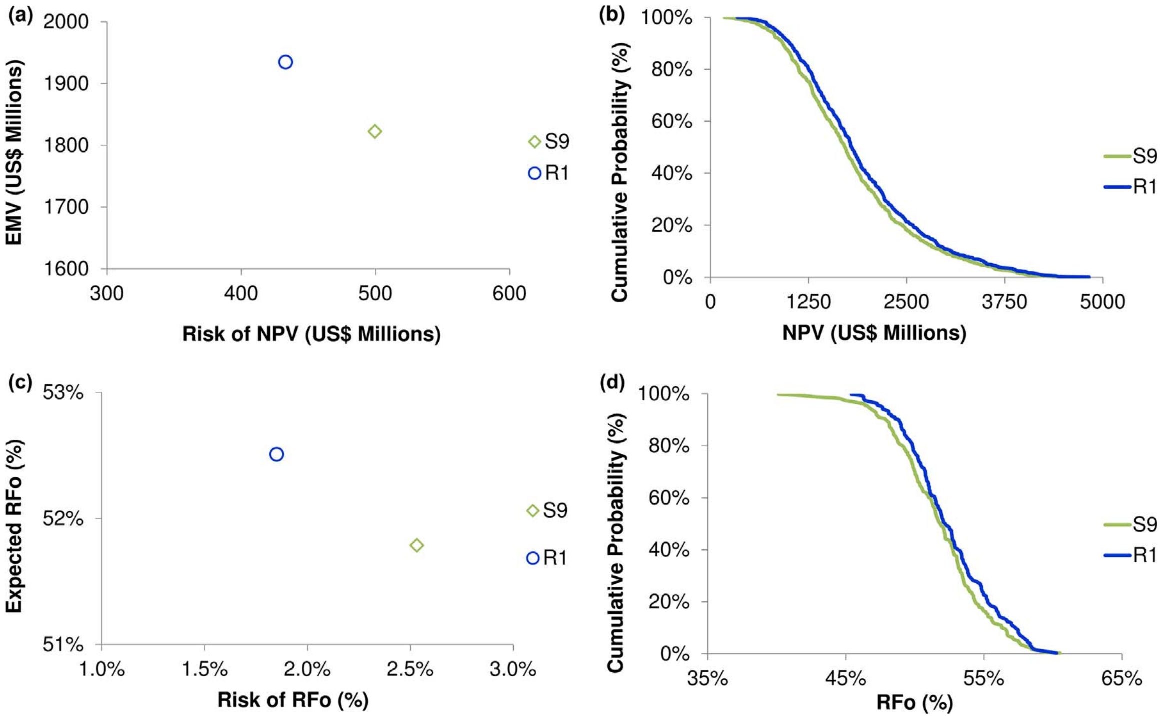

Fig. 6. Analyzing the optimized production strategy S9 and the robust production strategy R1: (a) risk-return analysis of NPV, (b) risk curves of NPV, (c) risk-return analysis of RFo, and (d) risk curves of RFo.

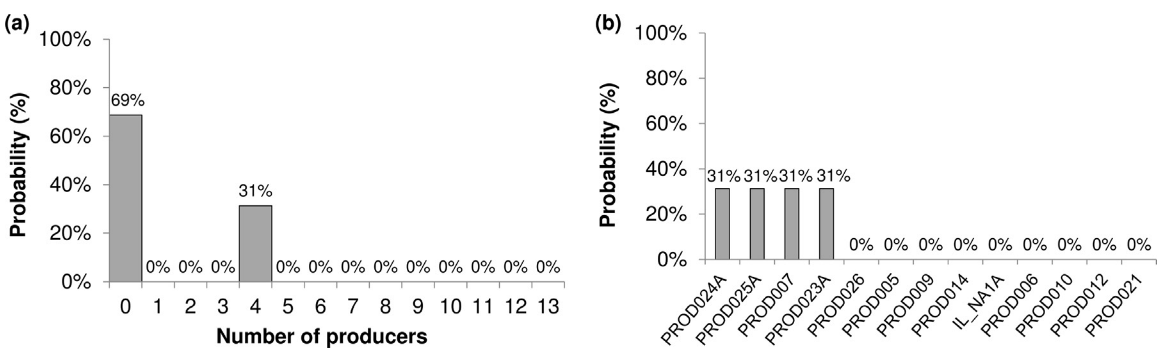

Fig. 7. Probability of (a) *n* wells, and (b) each well not producing for strategy R1.

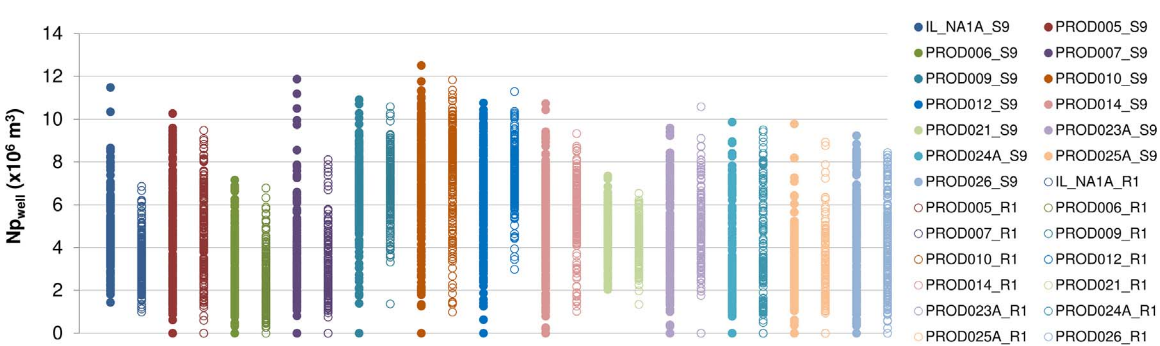

Fig. 8. Comparison of variability of well performance: optimized production strategy S9 (markers with filling) versus robust production strategy R1 (markers without filling).

4.2.2. Verifying and increasing robustness of number and placement of injection wells

As we observed for the producers, we verified a high probability (roughly 30%) of wells not injecting (null cumulative water injection, Winj=0), strongly related to the structural uncertainty. However, when we removed these scenarios from the probability calculation, we identified some wells with a chance of not injecting, associated with extremely low values of permeability and porosity in some geological scenarios.

We defined a new production strategy (R2), differing from R1 in the placement of 3 injectors (of a total of 7), which were relocated to regions with, on average, better reservoir properties using the probabilistic maps. We found the well number to be robust. Again, the high probability of wells not injecting is strongly related to the structural

Table 7
Value of the robust production strategy R2 (robust injectors number and placement), compared with R1 (robust producers number and placement).

Production strategy	EMV (US$ million)	Risk of NPV (US$ million)	E{RFo} (%)	Risk of RFo (%)	u (NPV, RFo)
R1	1935	433	52.5	1.9	1.052
R2	1946 (+0.6%)	424 (−2.1%)	52.4 (−0.3%)	2.0 (+8.3%)	1.052 (+0.02%)

uncertainty, suggestion that a Value of Information analysis should be conducted.

R2 is preferred to R1, with an overall gain on global utility of +0.02% over R1, increasing EMV by +0.6% (+US$ 20 million), reducing economic risk by −2.1%, decreasing expected RFo by −0.3% and, increasing recovery risk by +8.3% (Table 7). The sensitivity analysis of the MAUT model weights showed that R2 is not always preferred to R1. When prioritizing RFo (i.e. $k < 0.5$), R1 is preferred.

4.2.3. Verifying and increasing robustness of platform size

The study of field indicators revealed that in 70–80% of the scenarios, the maximum liquid and oil processing capacities (Q_l and Q_o, respectively) and the water injection capacities (Q_{wi}) are never utilized during the field lifetime (Fig. 9a, b and d, respectively). For the water processing capacities (Q_w), in 35% of the possible scenarios the full capacity is not utilized but capacity is reached in the remaining scenarios (Fig. 9c). These suggest that this platform is over dimensioned in terms of Q_l, Q_o and Q_{wi}.

We selected two alternative platform sizes (production strategies R3 and R4, Table 8), characterized by different risk-return profiles for NPV and RFo (Table 9, Fig. 10) and always preferred to R2. Their preference changes with the MAUT model weights, with R3 preferred to R4 only when $k < 0.3$, i.e., strong preference for RFo (Fig. 11). R4 encompasses an overall gain on global utility of +0.9% when compared to R2, increasing EMV by +0.7% (+US$ 137 million), reducing economic risk by −5.1%, increasing expected RFo by +0.3%, and decreasing recovery risk by −9.2%.

Table 8
Platform processing capacities for the optimized production strategy (S9) and for two alternative robust production strategies (R3 and R4).

Production strategy	Platform capacities (m^3/day)			
	Q_l	Q_o	Q_w	Q_{wi}
S9, R1 and R2	20150	20150	9765	28210
R3	15795	15795	9765	22525
R4	17825	17825	9765	23870

Table 9
Value of the robust production strategies R1 (robust number and placement of production wells), R2 (robust number and placement of production and injection wells), R3 and R4 (alternative robust platforms), compared with the optimized strategy S9.

Production strategy	EMV (US$ Millions)	Risk of NPV (US$ Millions)	E{RFo} (%)	Risk of RFo (%)	u (NPV, RFo)
S9	1822	500	51.8	2.5	1.000
R1	1935 (+6.2%)	433 (−13.3%)	52.5 (+1.4%)	1.9 (−26.9%)	1.052 (+5.2%)
R2	1946 (+68%)	424 (−15.2%)	52.4 (+1.1%)	2.0 (−20.8%)	1.052 (+4.2%)
R3	19.41 (+65%)	392 (−21.4%)	52.6 (+1.5%)	1.8 (−30.6%)	1.060 (+6.0%)
R4	19.60 (+75%)	402 (−19.5%)	52.6 (+1.5%)	1.9 (−28.1%)	1.061 (+6.2%)

4.3. Assessing the overall gain of increasing robustness of S9

Compared with optimized production strategy S9, defining the

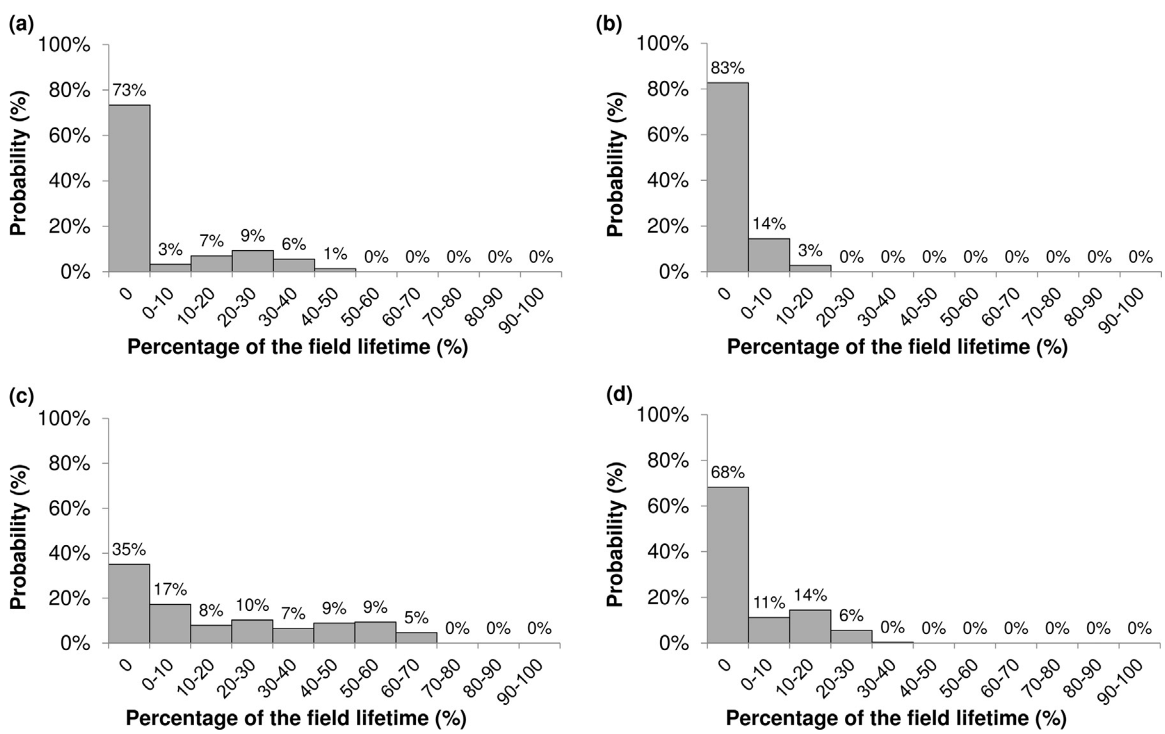

Fig. 9. Percentage of time that the platform processing capacities are utilized: (a) liquid processing capacity, (b) oil processing capacity, (c) water processing capacity and, (d) water injection capacity.

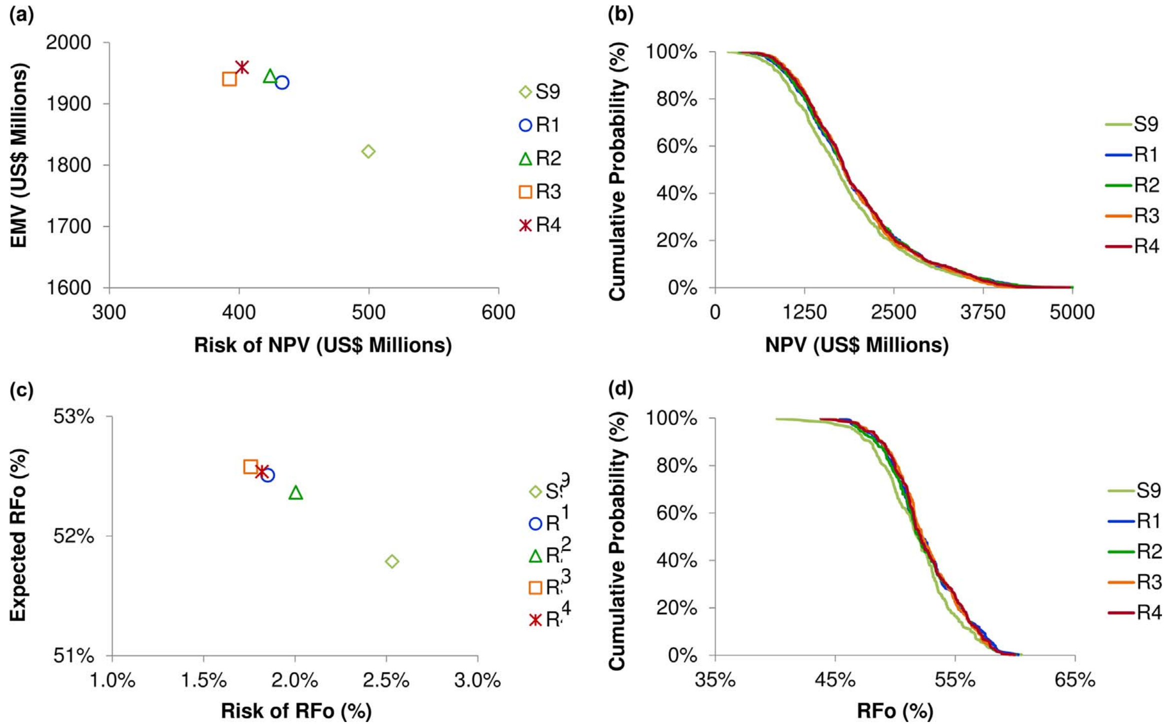

Fig. 10. Analyzing the optimized production strategy S9 and the robust production strategies R1 to R4: (a) risk-return analysis of NPV, (b) risk curves of NPV, (c) risk-return analysis of RFo, and (d) risk curves of RFo.

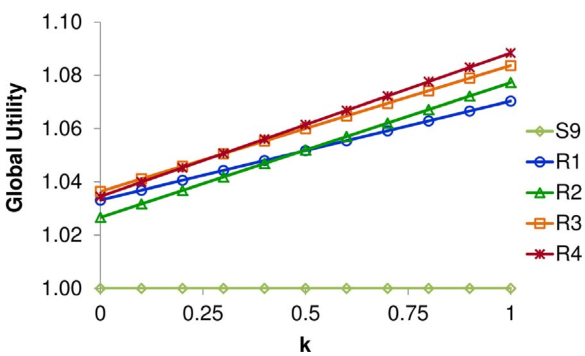

Fig. 11. Sensitivity analysis of the MAUT weights for the optimized production strategy S9 and the 4 robust production strategies, R1 to R4.

robust strategy R4 resulted in an increased overall utility of +6.2%, characterized by: (1) an increased EMV of US$ 137 million (+7.5%); (2) a reduced economic risk (−19.5%) without reducing the chance of high return; (3) an increased expected RFo of +1.5%; and (4) a reduced recovery risk (−28.1%).

5. Discussion

The decision criteria used in this study to evaluate production strategies were based on concepts from the Multi-Attribute Utility Theory. These models are sometimes regarded as theoretically complex and impractical for day-to-day use, and managers are often uncomfortable measuring the firm's utility function or risk tolerance level. However, the MAUT is based on solid, fundamental mathematical concepts allied to practical assessment techniques and extensive literature exists on the method (see §1.3). We defend its use as it assists the decision maker to quantitatively assess candidate production strategies under multiple objectives and considering the decision maker's risk attitude.

Here we considered two objectives: maximizing the economic return (NPV) and maximizing the hydrocarbon recovery (RFo). Each objective had different weights to assess the best production strategy under different concepts of robustness: robustness of economic return and robustness of production. This proved to impact the choice of the production strategy.

In this study, we applied an alternative measure of risk. We considered risk as the variability below a certain benchmark not as overall variability, commonly found in the literature. Accordingly, we applied the semi-deviation, allowing us to compare the level of risk of different production strategies on the basis of the same reference, defined by the decision maker. This avoided labelling a production strategy as low risk for having low variability and allowed focus on downside scenarios, without penalizing upside volatility. Consequently, we choose a formulation of expected utility that allows considering semi-deviation as the measure of risk.

We demonstrated that increasing production strategy robustness can achieve high gains, and ensure better performance across scenarios without requiring system modifications after production has started. Due to limitations in reservoir characterization and history matching, it is important to consider the set of possible scenarios when making a decision. Still, there are difficulties in finding optimal production strategies under uncertainty. Thus, the quality of the robust production strategy from our methodology depends on a proper characterization of uncertainty. Note that this study does not focus on characterizing uncertainty and history matching (Steps 1 through 5) (cf. Schiozer et al., 2015).

In our methodology, we modify a deterministically optimized production strategy, based on analyzed performance using probabilistic indicators. Other works also focus on defining robust development plans through well and field indicators (Hegstad and Saetrom, 2014; Viseras et al., 2014). Our work differs as we reduce computational costs by analyzing a previously optimized production strategy that has passed through detailed decision analyses. This strategy provides a starting point for the probabilistic optimization in Step 11, intended as a refinement, sub-optimal for the base model, but better across scenarios. In addition, possessing a set of candidate strategies optimized for extremely different representative scenarios increases confidence in the decision by providing optimal solutions for different scenarios.

The indicators we provide quantify the quality of a production strategy under uncertainty, namely the chances of locating wells in unfavorable positions, and the chances of over or under sizing the platform. This ensures objectivity when identifying attributes that lack robustness and must be changed. In the case studied, due to many geostatistical realizations, increasing robustness of well placement was the biggest gain. Adjusting platform size contributed little to EV but was key to reducing downside risk, due to pessimistic scenarios where maximum platform capacities were never reached.

Although our main goal is to increase robustness (i.e., increase insensitivity to uncertainty) of the best candidate strategy, our approach can and did identify and correct possible misconceptions from previous steps, or escape from possible local minima of the deterministic optimization. For complex problems with a large search space, automatic procedures yield local minima many times and Step 11 can improve that as our case study shows. The indicators identified that the producers had been placed in a sub-optimal layer in a previous step of the methodology, resulting in major changes (not a refinement) of the best strategy in Step 10.

We complemented traditional approaches of managing uncertainty, using information and flexibility, with robustness to enhance rather than replace techniques already found in the literature. Our results show that our case study could have also benefitted from further information, and demonstrated that our proposed indicators effectively assessed the performance of the production strategy, regardless of how uncertainty is to be mitigated. This also supports our suggestion to consider all three approaches and quantitatively identify the best for a case study.

6. Conclusions

We proposed a methodology to assess and increase robustness of production strategies, which is suitable for use in other cases and is flexible in the definition of risk and robustness. Robustness is considered as an uncertainty management method complementing well-known techniques of acquiring new information and adding flexibility to the production system. A robust strategy possesses attributes that create insensitivity to uncertainty.

The proposed method is based on performance analysis of a deterministically optimized production strategy over all possible scenarios, refining it to further improve the optimization process and reduce risk. Technical and economic indicators allow the decision maker to objectively identify potential for changes in the optimized production strategy. We focused on the robust number and placement of wells, and robust platform processing capacities.

We used concepts from the Multi-Attribute Utility Theory, which supports decision making with multiple objectives and incorporates the decision maker's risk attitude. We considered robustness of economic return and robustness of production. Different weights were given to each objective, showing that the best production strategy depends on the definition of robustness.

We defined risk as the downside variability of returns and quantified it by the semi-deviation. We successfully used this measure of risk to approximate expected utility according to how we defined risk.

Our case study showed that refining an optimized production strategy allowed significant improvements: we improved the optimization process by increasing the expected value of each objective (+7.5% on NPV, and +1.5% on RFo), and achieved a strong reduction of the downside risk (−19.5% on NPV, and −28.1% on RFo).

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5. ARTICLE 4: VALUE OF INFORMATION IN RESERVOIR DEVELOPMENT PROJECTS: TECHNICAL INDICATORS TO PRIORITIZE UNCERTAINTIES AND INFORMATION SOURCES

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Value of information in reservoir development projects: Technical indicators to prioritize uncertainties and information sources

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ABSTRACT

In this study, we consider information acquisition to manage uncertainty in reservoir development projects. Expected Value of Information (EVoI), a long-standing and widely applied technique, is traditionally used to base the decision to acquire additional data. In the field development phase, this calculation can be very complex, a consequence of high uncertainty and multiple decision variables. We propose a methodology to facilitate and reduce the subjectivity of the EVoI analysis, eliminating misconceptions and bias towards particular uncertainties and information sources. We provide indicators to identify, a priori, the uncertainties that can be mitigated with information, on which the EVoI calculation is based. Our workflow considers all available information sources, and integrates the concepts of individual, simultaneous and sequential acquisition of information, and estimates EVoI for perfect and imperfect information. We use a predefined set of candidate production strategies, previously optimized for representative models, which reflect system inputs and outputs. These combined approaches enable automating the EVoI calculation. We applied the methodology to the synthetic reservoir model UNISIM-I-D, a complex case in the development phase. Although there seemed to be great gains with an additional appraisal well, the economic gains from the improved decision did not compensate for delayed production. This supports the importance of performing the EVoI calculation, and not relying on the assumption that more information is always preferable.

1. Introduction

The upstream sector, particularly in offshore fields, is considered high-risk, comprising considerable investment in complex uncertain scenarios. During the field development phase, the focus of this study, various sources of uncertainties may coexist: (1) geological uncertainties, associated with recoverable reserves and flow characteristics; (2) operational uncertainties, related to production system availability; and (3) economic uncertainties, such as oil price, capital expenditures and operational expenditures.

The three main approaches to manage uncertainty in this phase are: (1) acquiring information to reduce geological uncertainty; (2) adding flexibility to the production system, allowing, at a cost, to put contingencies in place to profit from potential upsides or, mitigate downsides; and (3) defining a robust strategy able to cope with the range of possible scenarios without requiring system modifications after production has started. This study focuses on the first approach.

The benefits of collecting additional information can be quantified by the Value of Information methodology. The term "information" is typically used in a broad sense and may refer to acquiring data, performing technical studies, hiring consultants, and performing diagnostic tests (Bratvold et al., 2009). In this study, we use the term Expected Value of Information (EVoI) to emphasize that we are estimating information value before the information is acquired.

Today, the EVoI is a long-standing and widely applied concept. Initially proposed by Schlaifer (1959) in the context of business decisions, it was introduced in the oil and gas industry by Grayson (1960). Early work in information value in the context of decision analysis may be attributed to Howard (1966, 1967) and Matheson (1968), particularly because of their considerations on the value of clairvoyance, which led to the concept of perfect information. The pioneer works of Raiffa (1968), Winkler (1972), Gould (1974), Hilton (1981) and Howard (1988) also greatly contributed to the discussion of information value, especially the concept of expected value of information.

Bratvold et al. (2009) present an extensive overview of EVoI studies applied to the petroleum industry, published by the *Society of Petroleum Engineers* between 1962 and 2006. The main conclusions of this survey include: (1) few papers address theory with innovation (e.g. Moras et al.,

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1987; Aggrey et al., 2006), which is not considered surprising because the EVoI is a mature method; (2) few published real applications (e.g. Portella et al., 2003; Branco et al., 2005); (3) the literature is dominated by illustrations, many repeating published ideas; (4) several common misconceptions exist; (5) most papers are focused on evaluating seismic information (e.g. Head, 1999; Waggoner, 2002; Bickel et al., 2008); and (6) most papers consider only one source of information (exceptions include Dougherty, 1971; and Wills and Graves, 2004).

Some decision makers are averse to postponing field development to acquire information; while others tend to believe that more data are always better, expecting that information reduces uncertainty. However, reducing uncertainty or increasing confidence in a decision has no value in itself. Any information must meet four criteria to add value: (1) *observable*, the test result must be observable; (2) *relevant*, the test result must change our understanding of the reservoir parameter; (3) *material*, the test result must hold the possibility to change a decision that would be made otherwise; and (4) *economic*, the cost of the test must be less than its value (Howard, 2005 apud Bratvold et al., 2009).

As stated by Abbas et al. (2013), various measures have been proposed to determine information value in decision analysis: expected utility increase, utility indifference selling price, probability price, certainty equivalent, and utility indifference buying price. For its simplicity, the expected increase in expected monetary value (EMV) is usually employed in petroleum development projects (e.g. Warren, 1983; Demirmen, 1996; Koninx, 2001; Begg et al., 2002; Wills and Graves, 2004; Cunningham and Begg, 2008; Bickel, 2012) (Eq. (1)). However, note that this measure assumes risk-neutrality, and decision makers with different risk attitudes may value information differently (Abbas et al., 2013; Davis, 2014).

$$EVoI = EMV_{with\ \ information} - EMV_{without\ \ information} \tag{1}$$

The uncertainties the decision maker wants to define cannot be observed directly. Instead, a test result is obtained, which is used to alter the prior perception of the state of nature. Bayes' Theorem (Eq. (2)) is employed to update the probabilities of occurrence given the new information. For an introduction to Bayesian calculation see, for example, Clemen (1996).

$$P(E_i|B) = \frac{P(B|E_i)^*P(E_i)}{\sum_{i=1}^{N}[P(B|E_i)^*P(E_i)]} \tag{2}$$

where, $P(B|E_i)$ is the conditional probability of information B interpreting state of nature E_i (*likelihood function*); $P(E_i)$ is the initial probability of occurrence of state of nature E_i (*prior distribution*); $P(E_i|B)$ is the updated probability, i.e. the modified perception about the state of nature E_i, given information B (*posterior distribution*); and i is an index to denote the possible states of nature of parameter E. The denominator is the *marginal* probability of B occurring (i.e., all the ways that B can occur with the various E_i).

When information completely defines an uncertain parameter it is referred to as perfect information and its reliability equals 1. When uncertainty still remains, it is called imperfect information and its reliability is less than 1. This is usually the case in petroleum development projects. Note that information with reliability of 0.5 has no value because it fails to meet the relevancy criterion (Bratvold et al., 2009).

Estimating information reliability is a difficult task. It can be assessed by historical data from previously acquired information when available. Recent research provides models to increase the objectivity of this assessment (e.g. Wills and Graves, 2004; Bickel et al., 2008; Trainor-Guitton et al., 2011). As the EVoI strongly depends on information reliability, a sensitivity analysis of this input is an important step and should not be neglected, as demonstrated, for example, by Wills and Graves (2004).

Different acquisition scenarios can be considered: (1) *individual acquisition,* the decision maker obtains information from one information source, after which the decision is made; (2) *simultaneous acquisition*, information is obtained from two or more sources, after which the decision is made; and (3) *sequential acquisition*, after obtaining information from one source, the decision maker decides whether to collect further information or to proceed to the final decision (Miller, 1975).

When different information sources are available, the information index (II) (Warren, 1983; Wills and Graves, 2004) is proposed to rank and compare them (Eq. (3)). Note that the EVoI is generally non-additive across different information sources (Samson et al., 1989).

$$II = \frac{EVoI}{Cost} \tag{3}$$

where, *II* is the information index; *EVoI* is the expected value of information; and *Cost* is the cost of acquiring that information.

1.1. Motivation and objectives

The decision to acquire information is a simple problem to model in situations with few uncertain outcomes and few decision options, as in the exploration phase. However, in development projects, where high uncertainty is coupled with the choice of a production strategy, this decision problem becomes highly complex (e.g. Gerhardt and Haldorsen, 1989; Demirmen, 1996; Ligero et al., 2005). Adding this to usually imperfect information has strongly increased the complexity of recently proposed EVoI methodologies. To our knowledge, there is a lack of methodologies in the literature that facilitate this process by focusing on the key uncertainties that can be mitigated with information, by means of a quick assessment, before conducting the EVoI calculation itself.

Additionally, further improvements can be obtained by (1) quantifying all available sources of information to objectively identify those that bring the highest value to the project; and (2) combining different information sources, either simultaneous or sequentially. These situations have been discussed marginally in the petroleum literature.

This study proposes a value of information methodology that integrates: (1) indicators to identify the uncertainties that can be mitigated with information; (2) procedures for individual, simultaneous and sequential acquisition of information, and for perfect and imperfect information; (3) the concept of representative models; and (4) the application of a predefined set of candidate production strategies. By applying this structure we can facilitate and automate the EVoI analysis, reduce the subjectivity of the decision-making process, and eliminate prior misconceptions or bias toward particular uncertainties and information sources.

2. Methodology

Schiozer et al. (2015) proposed a comprehensive decision analysis framework in twelve steps covering all stages of field development and management, which incorporates reservoir characterization under uncertainty, reservoir simulation, history matching, uncertainty reduction, production strategy optimization and risk analysis. The twelve steps are summarized as follows: (1) reservoir characterization under uncertainty; (2) construction and calibration of the simulation base model; (3) verification of inconsistencies on the base model using dynamic well data; (4) generation of scenarios considering the full range of uncertainties; (5) reduction of scenarios using dynamic data; (6) selection of a deterministic production strategy using an optimization procedure; (7) initial risk assessment; (8) selection of representative scenarios based on multiple objective functions and the full range of uncertain parameters; (9) selection of a production strategy for each representative scenario (as in Step 6); (10) selection of the best production strategy from a set of candidates (strategies obtained in Step 9); (11) identification of potential for changes in the best strategy to mitigate risk or increase value (e.g. information, flexibility, and robustness); and (12) final risk assessment.

The methodology we propose here is integrated into such framework and corresponds to developments of Step 11 using information to manage uncertainty. Fig. 1 summarizes the proposed workflow, detailed below.

2.1. Identifying uncertainties that can be mitigated with information

Complex reservoir models typically include a high number of uncertain parameters. The technical indicators here proposed are intended to identify, a priori, the best candidates for information acquisition, on which the EVoI calculation is based.

We propose four indicators: (1) impact on the performance of the field; (2) potential to reduce uncertainty; (3) potential to modify the decision; and (4) likelihood of the information sources to define the parameter. This step corresponds to the first gray box of the flowchart in Fig. 1, and the indicators are detailed in the following subsections.

2.1.1. Impact on the performance of the field

We conduct a sensitivity analysis to identify the critical parameters in the response. We consider the net present value (NPV) a good field indicator. A typical representation is through a tornado plot, as exemplified in Fig. 2, where *A* and *B* are the most influential parameters.

Sensitivity analysis methods are common in decision analysis and can be classified as local or global. The local methods consist of varying one parameter at a time while fixing the remaining. Some authors assert that ignoring potential interactions between parameters can be misleading and suggest using global methods with the simultaneous manipulation of multiple parameters (e.g. Butler et al., 1997; Suslick and Furtado, 2001; Chambal et al., 2011; Chen et al., 2013). As the focus of this paper is not the study of sensitivity analysis methods, we refer the reader to the relevant literature to select a tool appropriate to the case study.

2.1.2. Potential to reduce uncertainty

When acquiring information, the expectation is to reduce uncertainty to make better decisions. The decision maker aims at reducing uncertainty and not at reducing risk. A test result may reveal a pessimistic scenario, which increases the project's level of risk. However, this can be valuable if it helps improve the decision.

In this step, the analysis is based on the NPV risk curve, also referred to as descending or complementary cumulative distribution function in the statistics literature. Risk curves are constructed using the production forecasts of multiple scenarios, where one scenario is a particular combination of all uncertain parameters.

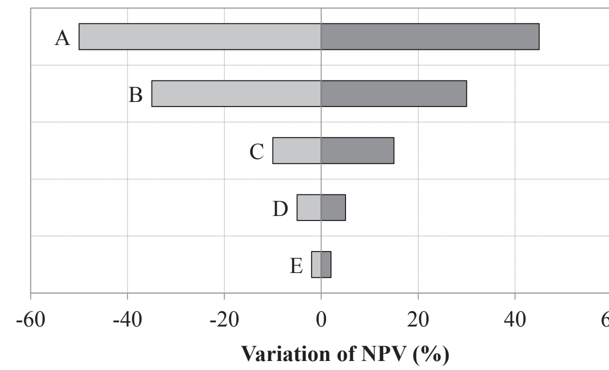

Fig. 2. Sensitivity analysis of the uncertain attributes *A* to *E* on NPV, represented by a tornado plot.

First, we propose a qualitative analysis by visualizing the position on the risk curve of each value of the uncertain parameter. An example is provided in Fig. 3 and Fig. 4: (1) if the values are clustered on the risk curve, this parameter has high potential to be mitigated with information (Fig. 3); whereas (2) if the values are scattered over the risk curve, the potential to reduce economic uncertainty is low (Fig. 4). Note that in Figs. 3 and 4 colored dots highlight the scenarios that have the different values the uncertain parameter can take.

Then, a quantitative analysis complements the visual analysis. Standard deviation (σ) is a typical statistical measure of uncertainty, as it quantifies the dispersion of a set of values around its expected value. We propose comparing the standard deviation of the original risk curve with the standard deviation of the curve plotted using individually the possible values of the parameter, to quantify the reduction of uncertainty (Figs. 3 and 4).

2.1.3. Potential to modify the decision

We analyze the best production strategy for each value of the uncertain parameter and the economic gain obtained from choosing this alternative. We follow the rationale that information only has value if it

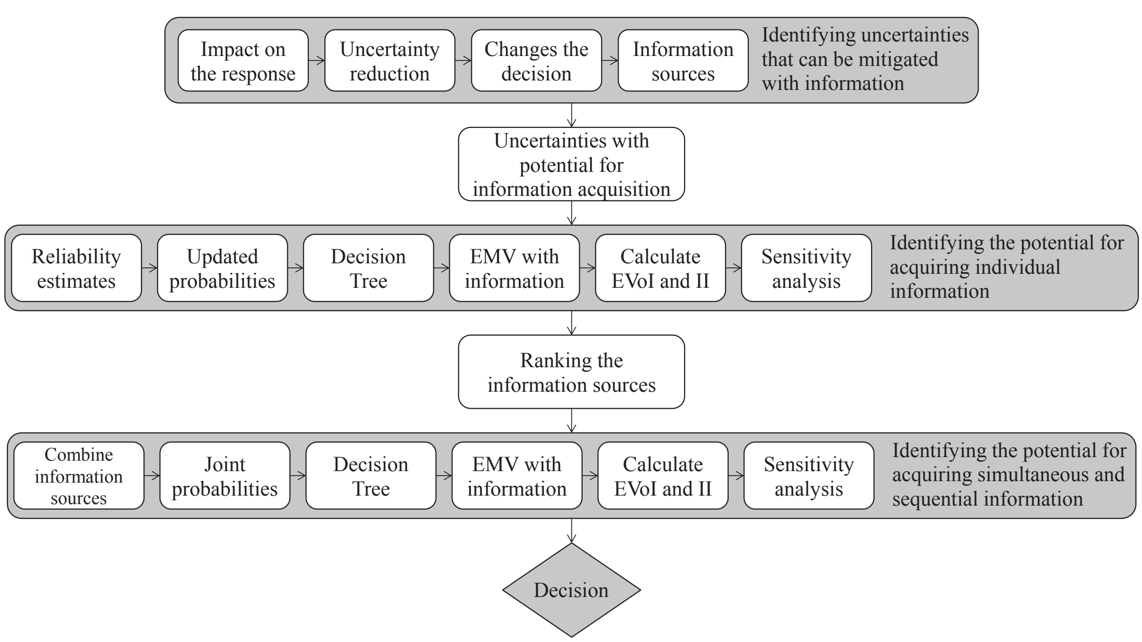

Fig. 1. Flowchart for value of information analysis in three steps: (1) study of technical indicators to identify the uncertainties that can be mitigated with information; (2) identifying the potential for acquiring individual information; and (3) identifying the potential for acquiring simultaneous and sequential information.

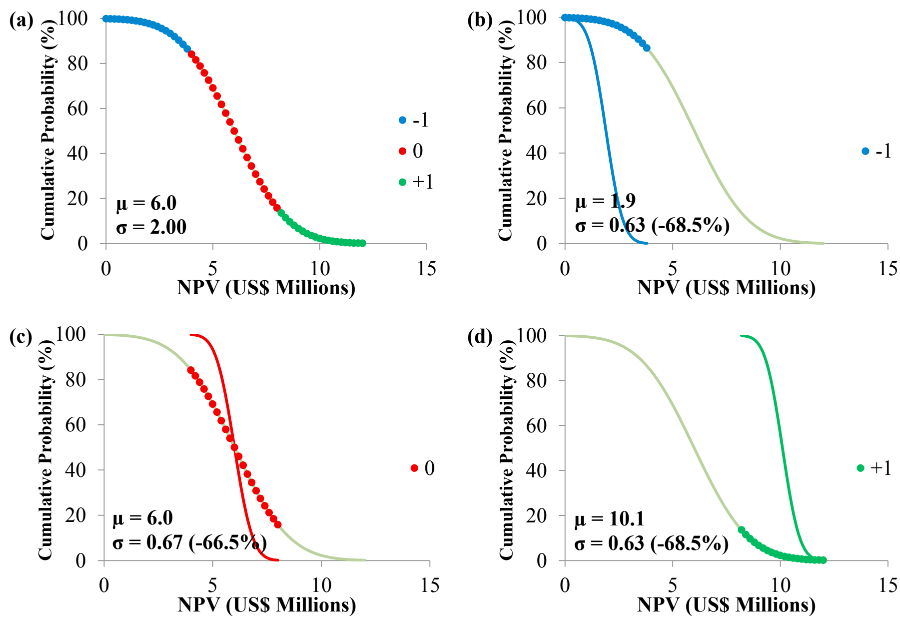

Fig. 3. Qualitative and quantitative analysis of risk curves of a parameter with high potential to reduce economic uncertainty: (a) NPV risk curve, with mean (μ) and standard deviation (σ) without information, highlighting the three possible values as clusters; (b), (c) and (d) NPV risk curves, with mean (μ) and standard deviation (σ) for each uncertain level individually.

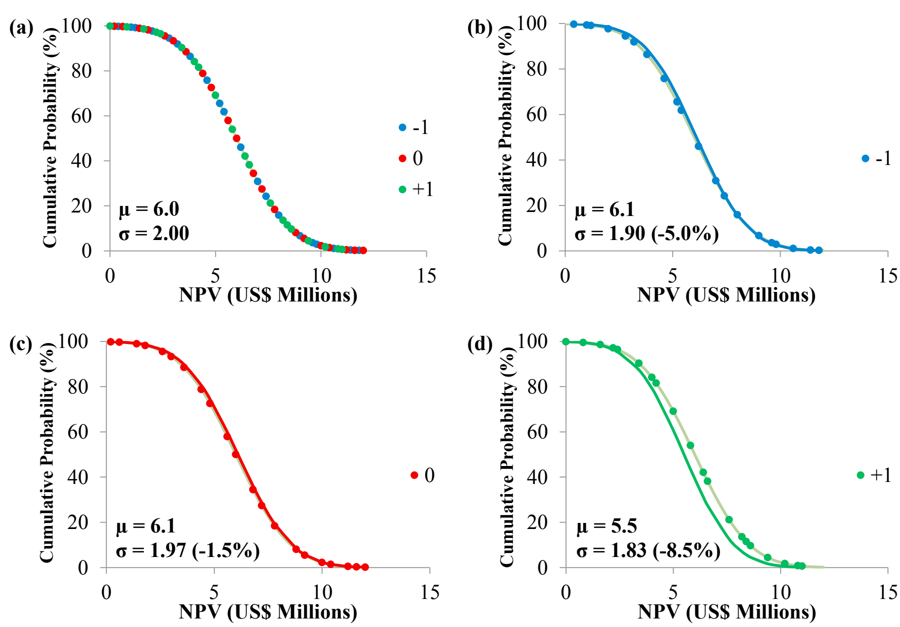

Fig. 4. Qualitative and quantitative analysis of the risk curves of a parameter with low potential to reduce economic uncertainty: (a) NPV risk curve, with mean (μ) and standard deviation (σ) without information, highlighting the three possible values scattered over the curve; (b), (c) and (d) NPV risk curves, with mean (μ) and standard deviation (σ) for each uncertain level individually.

brings the possibility to change the decision.

Table 1 exemplifies this analysis. Considering two uncertain parameters (A and B), each discretized in three levels (-1, 0 and $+1$); and three production strategies (PS1 to PS3); and that without further information PS1 is the best option. For parameter A, depending on the true state of nature, we choose a different strategy, which is accompanied by an economic gain if this is chosen over PS1 (a gain of +2% in the pessimistic level -1; and a gain of +5% in the optimistic level $+1$). On the other hand, for parameter B, regardless of its true state of nature, we would not change our decision. Parameter B may strongly affect the EMV, but the information is worthless because it does not change the decision.

Table 1
Potential to change the decision: best production strategy (PS1 to PS3) for each level (-1, 0, $+1$) of uncertain parameters A and B, detailing the increase in EMV (between parenthesis) obtained by preferring a better production strategy to PS1 (the best strategy without further information).

	Parameter A			Parameter B		
	−1	0	+1	−1	0	+1
Best production strategy	PS2 (+2%)	PS1	PS3 (+5%)	PS1	PS1	PS1

2.1.4. Available information sources

The decision maker lists all available information sources and assesses the likelihood of each source to define the uncertain parameters. For example, if there is high uncertainty in the spatial distribution of the petrophysical properties, one additional well will increase their understanding but is certainly insufficient to fully define the spatial distribution of this properties.

Different factors should be accounted for when assessing the reliability of an information source. Typically this analysis is made by combining the decision maker's professional experience and historical data on previous acquisitions. Some studies provide models to estimate this parameter in petroleum projects (see §1). As our focus is not on methodologies to estimate the reliability of information, we refer the reader to the relevant literature to select a tool appropriate to the case study.

2.1.5. Combining all indicators to select uncertainties that can be mitigated with information

In this final step, we construct a summary table to combine the analysis of the four indicators. With this, we can rank the parameters from high to low potential for information acquisition. The uncertainties with most potential and respective available information sources are subject to a full EVoI analysis.

2.2. Identifying the potential for acquiring individual information

This step corresponds to the second gray box of the flowchart in Fig. 1. Here, we evaluate the benefits of obtaining information on one uncertainty at a time, from one information source at a time.

Using the reliability estimates previously obtained (see §2.1.4), we update the initial probabilities to find the new probabilities of occurrence given each test result (Eq. (2)).

EVoI analyses are traditionally modeled using decision trees, as they give transparency to the process (e.g. Clemen, 1996; Newendorp and Schuyler, 2000; Begg et al., 2002). With this structure, we can: (1) identify the best production strategy for each information outcome; and (2) calculate the monetary value of the strategy with information. In the traditional notation, square nodes represent decisions; while circles represent uncertain outcomes in a chance node, and are associated with a probability of occurrence.

The example in Fig. 5 considers one uncertainty with two possible outcomes, *A* and *B*. Imperfect information implies that when the test predicts *A*, *B* may still occur, and vice versa. If information predicts *A*, the best production strategy is PS2; while if information predicts *B*, the best production strategy is PS1.

Many methodologies calculate the EVoI. In this study, we selected the expected increase in EMV (Eq. (1)). As our objective is not to assess the

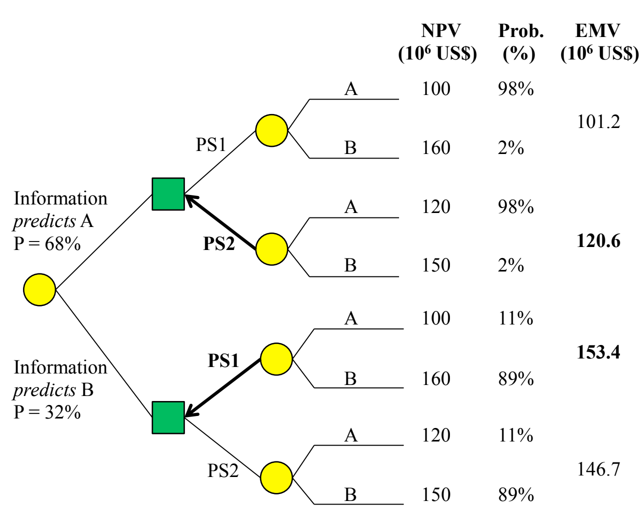

Fig. 5. Decision tree representing the EVoI analysis, considering imperfect information. If information predicts *A* the best production strategy is PS2; while if information predicts *B* the best production strategy is PS1.

effect of risk aversion on information value, a simple EMV analysis is sufficient and allows focus on the indicators we propose here. As we intend to compare different information sources, which may have different acquisition costs, we use the information index (Eq. (3)) to rank them.

Before making a decision, it is fundamental to perform a sensitivity analysis on the reliability of information to determine the limit of positive EVoI.

If at this point, two or more information sources reveal high value, the value of combining them should be assessed.

2.3. Identifying the potential for acquiring simultaneous and sequential information

This step corresponds to the third gray box of the flowchart in Fig. 1. The first step consists of calculating the probability of two events occurring together: (1) the multiple test results; and (2) the different values of each uncertainty. The joint probabilities of two discrete random variables *X* and *Y* can be obtained using the multiplication rule (Eq. (4)). Eq. (5) gives the particular case of two independent variables.

$$p(X = x, Y = y) = P(X = x|Y = y)P(Y = y) = P(Y = y|X = x)P(X = x) \tag{4}$$

$$p(X = x, Y = y) = P(X = x).P(Y = y) \tag{5}$$

When information is acquired simultaneously, the development decision is made based on the knowledge obtained from both tests. When information is acquired sequentially, the decision maker waits for the first test results to decide whether to acquire further information or to proceed with field development. These two situations are modeled with distinct decision trees (Fig. 6).

After obtaining the project value with information, the decision maker should rank the different alternatives using the information index (Eq. (3)), and assess its sensitivity to the reliability of information, as conducted for the individual acquisition case.

2.4. Calculating EVoI using multiple scenarios and candidate production strategies

To improve EVoI assessment, we use a large set of scenarios (obtained in Step 5) with updated probabilities to consider the effects of all uncertainties. To facilitate and accelerate analyses, and also to allow its automation, we determine EVoI using a predefined set of candidate production strategies (obtained in Step 9). These strategies were optimized for extremely different scenarios, entitled representative models (RM).

Meira et al. (2016, 2017) present an efficient RM selection (conducted in Step 8) by combining a mathematical function that captures the representativeness of a set of models with a metaheuristic optimization algorithm. This approach ensures that the set of RM represents both the probability distribution of the input variables (uncertain attributes), ensuring that not only all the attributes but also all the uncertain levels are represented; and the variability of the main output variables (production and injection forecasts).

One production strategy is optimized for each RM, providing a set of candidates for field development. Because the set of RM reflects the set of uncertainties, the set of candidate production strategies provide decision makers with the different possibilities for developing the field, including well number and placement, and platform processing capacities.

3. Case study

We applied the methodology to the benchmark reservoir model UNISIM-I-D (Gaspar et al., 2015), a case study for selection of production strategy, based on the reference model UNISIM-I-R (Avansi and Schiozer,

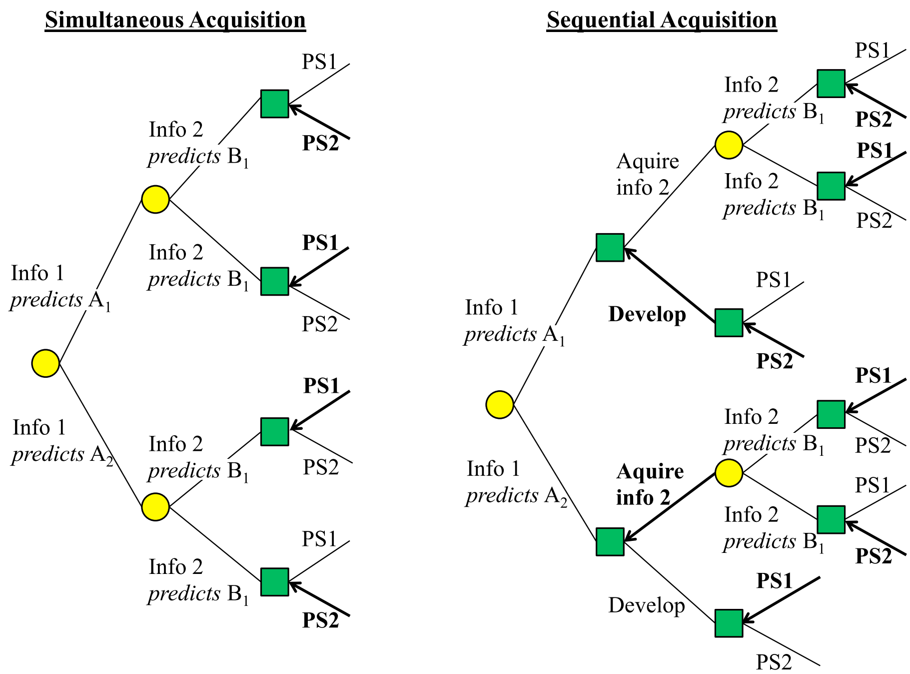

Fig. 6. Decisions trees for simultaneous acquisition (left) and sequential acquisition (right) of information.

2015a). UNISIM-I-D is a sandstone oil reservoir, 80 km offshore from the coast, in the field development phase, with 1461 days of initial production for four vertical producing wells. The reservoir depth varies between 2900 and 3400 m and the water depth is 166 m. The simulation model comprises a corner point grid with 81 × 58 × 20 cells of 100 × 100 × 8 m, in a total of 36,739 active cells (Fig. 7).

UNISIM-I-D comprises a set of reservoir, operational, and economic uncertainties. In this application, we focused on the reservoir uncertainties (Table 2), and we considered a deterministic economic scenario (Table 3). The absence or presence of the East region is a key uncertainty affecting production strategy selection because the presence of hydrocarbons in this location has not been proved yet. This influences well placement, well number, and platform capacity due to lower levels of oil in place.

Platform investment is given by Eq. (6) where, $\mathrm{Inv}_{\mathrm{plat}}$ is the platform investment (US$ millions); Q_o is the oil processing capacity (1000 m^3/day); Q_w is the water processing capacity (1000 m^3/day); Q_{wi} is the water injection capacity (1000 m^3/day); and n is the number of wells.

$$Inv_{plat} = 417 + (16.4 \times Q_o + 3.15 \times Q_w + 3.15 \times Q_{wi} + 0.1 \times n) \tag{6}$$

To calculate the NPV, we used a simplified net cash flow formulation

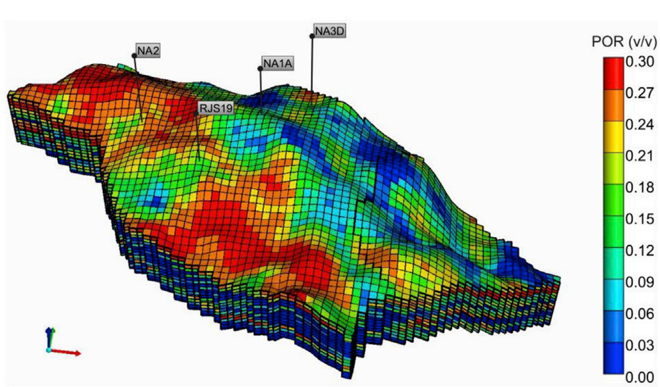

Fig. 7. Porosity map of UNISIM-I-D reservoir model, including the position of the four producers already drilled.

(Eq. (7)) based on the Brazilian R&T fiscal regime where, NCF is the net cash flow; R is the gross revenue; Roy is the amount paid in royalties; ST is the amount paid in social taxes; OPEX are operational expenditures; T is the corporate tax rate; CAPEX are investments on equipment and facilities; and AC are abandonment costs.

$$NCF = [(R - Roy - ST - OPEX)*(1 - T)] - CAPEX - AC \tag{7}$$

The expected monetary value (EMV) is the economic indicator of this study and is given by the sum of the NPV of each scenario weighted by its probability.

4. Results

In this study, we followed on from step 10 of Schiozer et al. (2015)'s application of UNISIM-I-D. Schiozer et al. (2015) generated 500 equiprobable scenarios using the Discretized Latin Hypercube with Geostatistics (Schiozer et al., 2017). The authors applied a probabilistic history-matching procedure (Avansi and Schiozer, 2015b) to reduce the number of scenarios from the initial set of 500 models, where the misfit between the models and the production data from 4 producers was evaluated using quantification and diagnostic procedures, and considering acceptance levels and several objective functions simultaneously, including fluid rates and bottom-hole pressures. This resulted in a set of 214 models, which honors production data and considers all uncertainties.

Each scenario corresponds to a particular combination of all reservoir and operational uncertainties, and we used the 214 scenarios to calculate the EVoI. That is, after updating the probability of occurrence of the uncertain parameter considering information (posterior probability), we updated the probabilities of occurrence of the 214 scenarios (equiprobable a priori), maintaining this set throughout the study. Note that the prior probabilities in Table 2 (for the 500 scenarios) were adjusted to the frequency of occurrence in the 214 filtered scenarios (Table 4).

Following the proposal of Meira et al. (2016), Schiozer et al. (2015) selected nine representative models (RM) from the set of 214 scenarios. They then optimized one production strategy for each RM, resulting in nine alternative production strategies (S1 to S9), whose characteristics are summarized in Table 5. In the set of 214 scenarios, 147 scenarios consider the presence of East block (69%), while 67 consider no oil in

Table 2
Set of reservoir uncertainties with probabilities from UNISIM-I-D case study.

Attribute	Description	Type	Value (probability)				
			−2	−1	0	+1	+2
img	Petrophysical characteristics	Discrete [realization]	500 equiprobable geostatistical realizations of porosity, permeability, and net to gross ratio (0.002)				
kr	Water relative permeability	Discrete [table]	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
pv	Region 2 pvt data	Discrete [table]	–	(0.33)	(0.34)	(0.33)	–
bl	Structural model	Discrete [map]	–	Without east block (0.30)	With east block (0.70)	–	–
wo	Region 2 water-oil contact	continuous discretized [scalar]	3074 m (0.222)	3124 m (0.334)	3174 m (0.111)	3224 m (0.222)	3274 m (0.111)
cp	Rock compressibility	continuous discretized [scalar]	–	23.6E-6 cm^2/kgf (0.2)	53.0E-6 cm^2/kgf (0.6)	82.4E-6 cm^2/kgf (0.2)	–
kz	Vertical permeability multiplier	continuous discretized [scalar]	0.475 (0.1)	0.949 (0.2)	1.500 (0.4)	2.051 (0.2)	2.525 (0.1)

that region (31%). Because the RMs represent the probability distribution of the input variables, six RM comprise the East block while three RM do not, meaning that six candidate production strategies (S1, S2, S4, S5, S8, and S9) have wells located in this region, while three do not (S3, S6, and S7). When applying the six strategies in the 67 models where the block is absent, the drilling sequence would include gaps corresponding to wells planned for that location. Thus, for the case with no information, and when the East block is absent (which is verified once the first well is drilled there), we adjusted the well sequence of the six strategies by eliminating these wells. Note that we maintained the first well (the one confirming the absence of the block), and did not alter the drilling sequence.

From this set of candidates, S9 maximizes EMV, making it the best production strategy without additional information (i.e., under the current uncertain knowledge of 214 equiprobable scenarios), yielding an expected return of US$ 1690 million (Table 5). We considered the nine candidate production strategies the alternative choices for the case with information.

We obtained production and injection forecasts by simulating the 214 scenarios using a black-oil numerical reservoir simulator.

4.1. *Identifying the reservoir uncertainties that can be mitigated with information*

Of the set of reservoir uncertainties, we did not analyze the geostatistical realizations that represent the spatial distribution of the petrophysical properties. This type of parameter is difficult to treat because it requires wide reservoir coverage to significantly reduce uncertainty.

Appropriate methodologies to handle this uncertainty exist in the literature. A possibility is the Closed-Loop Field Development Optimization under Uncertainty (Shirangi and Durlofsky, 2015), a continuous update of the geological model and of the production strategy, as new information arrives from the drilling sequence of development wells. Morosov and Schiozer (2017) present an application of this methodology on the UNISIM-I-D reservoir.

4.1.1. *Impact on the performance of the field*

We identify the structural uncertainty (*bl*), the water/oil contact (*wo*), and the water relative permeability (*kr*) as the critical parameters on NPV (Fig. 8).

4.1.2. *Potential to reduce uncertainty*

We analyze the risk curves to assess how likely a defined parameter is to reduce economic uncertainty. The results for parameters *bl* and *wo* are shown in Fig. 9 and Fig. 10, respectively. The structural uncertainty *bl* has a high potential to reduce economic uncertainty: (1) the scenarios are clustered on the risk curve (Fig. 9a); and (2) we observe a strong reduction in the standard deviation (Fig. 9b and c). On the other hand, the risk curves for the water/oil contact indicate moderate potential: (1) there is no clear clustering of the five possible levels (Fig. 10a); (2) a strong potential to reduce uncertainty in the pessimistic and most-likely levels (Fig. 10b to d); while (3) in the optimistic levels we observe an increased standard deviation due to increased dispersion around the mean (Fig. 10e and f). The uncertainties not presented here (*kr*, *cp*, *pv*, and *kz*) revealed low potential for uncertainty reduction.

4.1.3. *Potential to modify the decision*

We identified the best production strategy (S1 to S9) for each level (−2 to +2) of each uncertain parameter, and then we assessed the economic gain (increase in EMV) obtained by preferring this strategy over S9, the best strategy without further information.

Only three parameters show potential to change the decision if they are defined: *kr*, *bl* and *wo* (shown in Table 6). These are critical parameters identified in the sensitivity analysis step.

However, note the following: (1) *bl* is the most influential parameter on the economic response, and the production strategy clearly changes depending on the true structural model, with significant economic gain; (2) *wo* is the second most influential parameter on the economic response, however solely in the most pessimist scenario we would prefer a different production strategy, i.e. information reduces uncertainty but may not change the decision; and (3) *kr* does not strongly influence NPV but has high potential to change the decision when we learn its true state of nature.

4.1.4. *Available information sources*

In this synthetic case study we considered a limited number of sources, as we aim to exemplify the proposed methodology. An important uncertainty in this case study is the structural model (*bl*), with a reservoir region whose existence is uncertain. Consequently, some uncertainties are exclusive to this region (*wo* and *pv*), which implies that defining these uncertainties requires defining *bl* first. Common to the entire reservoir are *kr*, *cp* and, *kz*.

The first information source we considered is an appraisal well in the uncertain block. This could define the structural model as well as reduce

Table 3
Deterministic economic scenario of UNISIM-I-D case study.

Type	Attribute (unit)	Value
Market variables	Oil price (US$/$m^3$)	314.50
	Discount rate (%)	9.00
Taxes	Royalties (%)	10.00
	Social taxes (%)	34.00
	Corporate taxes (%)	9.25
OPEX	Oil production (US$/$m^3$)	62.90
	Water production (US$/$m^3$)	6.29
	Water injection (US$/$m^3$)	6.29
	Abandonment (US$ Millions) (% of well investment)	8.20
CAPEX	Horizontal well drilling and completion (US$ Millions)	61.17
	Vertical well drilling and completion (US$ Millions)	21.67
	Well – platform connection (US$ Millions)	13.33

Table 4
Set of reservoir uncertainties from UNISIM-I-D case study, with the prior probabilities after filtering the 214 scenarios.

Attribute	Description	Type	value (probability)				
			−2	−1	0	+1	+2
img	Petrophysical characteristics	discrete [realization]	214 equiprobable geostatistical realizations of porosity, permeability, and net-to-gross ratio (0.0047)				
kr	Water relative permeability	discrete [table]	(0.08)	(0.19)	(0.41)	(0.19)	(0.13)
pv	Region 2 pvt data	discrete [table]	–	(0.34)	(0.33)	(0.34)	–
bl	Structural model	discrete [map]	–	Without east block (0.31)	With east block (0.69)	–	–
wo	Region 2 water-oil contact	continuous discretized [scalar]	3074 m (0.248)	3124 m (0.341)	3174 m (0.121)	3224 m (0.173)	3274 m (0.117)
cp	Rock compressibility	continuous discretized [scalar]	–	23.6E-6 cm^2/kgf (0.12)	53.0E-6 cm^2/kgf (0.66)	82.4E-6 cm^2/kgf (0.22)	–
kz	Vertical permeability multiplier	continuous discretized [scalar]	0.475 (0.12)	0.949 (0.19)	1.500 (0.25)	2.051 (0.23)	2.525 (0.21)

Table 5
Characteristics of the 9 candidate production strategies (S1 to S9). EMV: expected monetary value; V: vertical well; H: horizontal well; Q_l: liquid processing capacity; Q_o: oil processing capacity; Q_w: water processing capacity; Q_{wi}: water injecting capacity.

Production strategy	EMV (US$ millions)	Production wells			Water injection wells			Platform capacities (1000 m^3/day)			
		V	H	Total	V	H	Total	Q_l	Q_o	Q_w	Q_{wi}
S1	1581	2	10	12	0	6	6	16.3	16.3	9.1	23.3
S2	1597	2	8	10	0	6	6	16.3	16.3	11.2	22.8
S3	974	2	7	9	0	5	5	14.0	14.0	9.8	19.5
S4	1563	1	10	11	0	6	6	18.2	18.2	11.5	25.5
S5	1530	3	10	13	0	7	7	17.8	17.8	10.5	23.8
S6	1143	1	8	9	0	6	6	14.3	14.3	7.3	20.6
S7	1265	2	7	9	0	6	6	13.2	13.2	5.2	19.5
S8	1556	3	11	14	0	7	7	21.7	21.7	14.6	29.8
S9	1690	3	10	13	0	7	7	20.2	20.2	9.8	28.2

uncertainty on the water/oil contact, as open-hole well logs are obtained for all drilled wells. Determining *kr* and *cp* would require coring the appraisal well to perform laboratory procedures; while defining *pv* would require additional PVT analysis. Well testing could provide information on the vertical permeability multiplier *kz*.

Table 7 summarizes the information sources previously discussed and includes the respective reliability estimates. For this synthetic case study, we did not conduct an extensive reliability analysis; instead, we assigned example values to validate the proposed methodology.

4.1.5. Combining all indicators to select uncertainties that can be mitigated with information

We combined the findings of the four indicators in a summary table to identify the uncertainties with potential for information acquisition (Table 8). We used a qualitative scale to classify the potential of each indicator: +++ very high; ++ high; + moderate; - low potential.

Combining the four indicators we decided to precede the EVoI analysis with the following parameters: *bl*, *wo*, and *kr*. Analyzing the value of

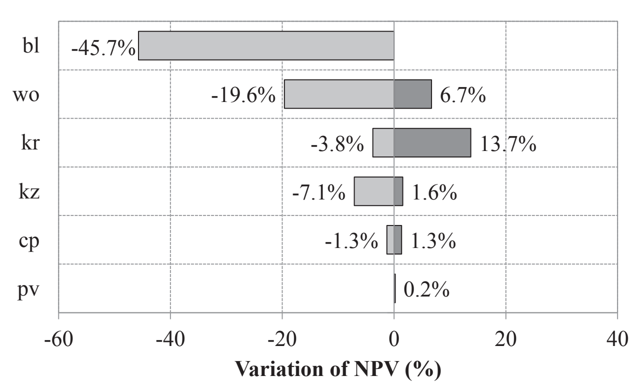

Fig. 8. Sensitivity analysis of the reservoir uncertainties on the economic response NPV: structural uncertainty (*bl*), water/oil contact (*wo*), water relative permeability (*kr*), vertical permeability multiplier (*kz*), rock compressibility (*cp*), and PVT data (*pv*).

defining *bl* and *wo* separately is unrealistic because the same source provides information on both uncertainties: an appraisal well. However, defining *kr* would require additional tests.

We consider two acquisition cases, whose value is assessed in the subsequent subsections: (1) appraisal well with well logs to simultaneously define *bl* and *wo*; and (2) appraisal well with well logs and core analysis to simultaneously define *bl*, *wo*, and *kr*.

4.2. Calculating the value of information

4.2.1. Appraisal well with well logs to simultaneously define bl and wo

The decision tree for this EVoI problem is presented in Fig. 11, with two initial branches corresponding to the result of the appraisal well: (1) information indicates "discovery", suggesting the presence of oil in the uncertain block; or (2) information indicates "dry well", suggesting no oil in the uncertain block. The next chance node corresponds to the depth of water-oil contact indicated by well logs, and is followed by a decision node. As we maintained the set of 214 scenarios, the branches in the final chance node with the updated probabilities of occurrence (labeled *bl&wo*), do not correspond to a single model, but to a group of scenarios that include the specified levels of *bl* and of *wo*.

If the information were to be perfect, and if it predicted a dry region, it would make no sense to discuss *wo* in that area. As information is imperfect, there is a chance that the "dry well" prediction is incorrect and therefore *wo* exists. Note that this tree is not fully represented due to space constraints.

Table 9 summarizes: (1) the best production strategy under each test result; (2) its EMV, in parentheses (); and (3) the joint probabilities of occurrence of the two test result, in brackets [].

When calculating the value with information we considered a 3-month delay in the decision to develop due to information acquisition. This resulted in an EMV with information of US$ 1651 million, which is lower than the EMV without information (U$ 1690 million). Therefore, this information has no value and its acquisition would incur an expected loss of US$ 39 million.

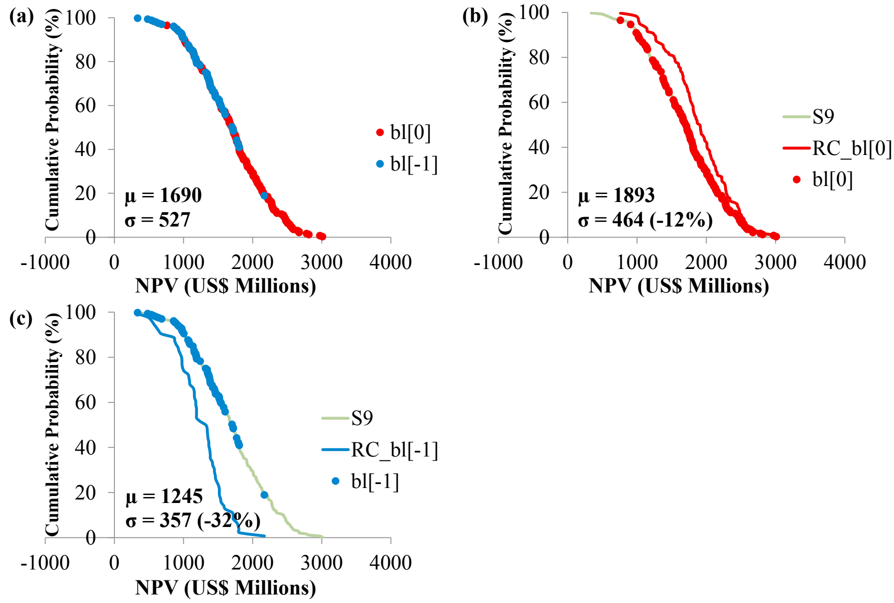

Fig. 9. Qualitative and quantitative analysis of risk curves to assess potential to reduce economic uncertainty of parameter *bl*: (a) NPV risk curve, with mean (μ) and standard deviation (σ) of production strategy S9, without information, highlighting the position of the two possible levels; (b) and (c) NPV risk curves, with mean (μ) and standard deviation (σ) for each uncertain level individually.

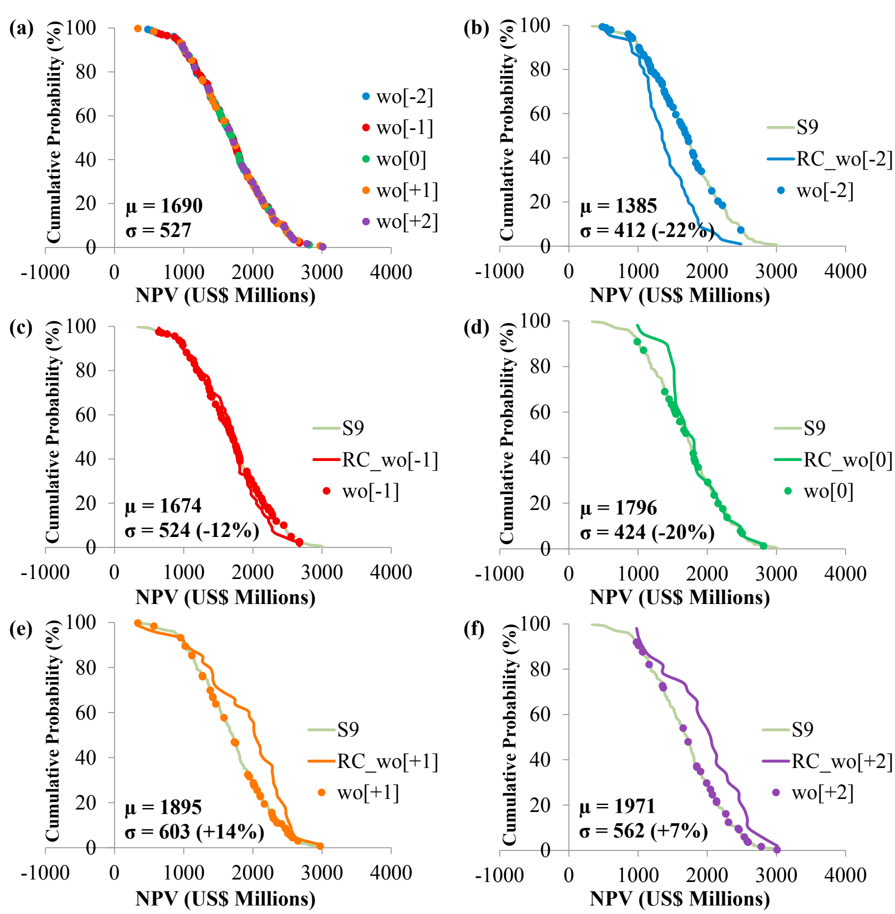

Fig. 10. Qualitative and quantitative analysis of risk curves to assess potential to reduce economic uncertainty of parameter *wo*: (a) NPV risk curve, with mean (μ) and standard deviation (σ) of production strategy S9, without information, highlighting the position of the five possible levels; from (b) to (f) NPV risk curves, with mean (μ) and standard deviation (σ) for each uncertain level individually.

Table 6
Potential to change the decision: best production strategy (S1 to S9) for each level (−2 to +2) of uncertain parameters *kr*, *bl*, and *wo*, detailing the increase in EMV (between parenthesis) obtained by preferring a better production strategy to S9 (the best strategy without further information).

	kr					bl		wo				
	−2	−1	0	+1	+2	−1	0	−2	−1	0	+1	+2
Best production strategy	S9	S9	S9	S2 (+1.4%)	S8 (+4.4%)	S1 (+4.1%)	S9	S1 (+2.9%)	S9	S9	S9	S9

4.2.2. Appraisal well with well logs and core analysis to simultaneously define bl, wo and, kr

The complexity of this analysis increased greatly because it required calculating joint probabilities of occurrence of three information results: (1) appraisal well, to define *bl*; (2) well logs, to define *wo*; and (3) core analysis, to define *kr*. Additionally, due to imperfect information, each test result does not solely indicate one true state of nature, increasing the complexity of the analysis.

The decision tree for this EVoI problem is presented in Fig. 12 (incomplete due to space constraints). When calculating the value with information we considered a 4-month delay in the decision to develop. This resulted in an EMV with information of US$ 1596 million, which is lower than the EMV without information (U$ 1690 million). Therefore, this information has no value and its acquisition would incur an expected loss of US$ 94 million.

5. Discussion

In this study, we provided a set of tools to facilitate EVoI analysis in the field development phase: (1) indicators to identify the uncertainties that can be mitigated with information; and (2) a decision structure to model the value of individual, simultaneous and sequential information.

Our proposal integrated two procedures. First, we used the full set of 214 reservoir scenarios, each corresponding to a particular combination of all uncertain parameters. This implies that in the cases with information, we did not generate new scenarios; instead, we maintained the set of 214 models and updated their probabilities of occurrence, in accordance with the defined parameters. Second, as the nine representative models represent the range of possible scenarios and their outputs, the nine production strategies constitute the possible candidates for this case study. That is, instead of optimizing a new production strategy according to the test result, we selected the candidate strategy that is best for the 214 scenarios with updated probabilities. Because of these combined approaches: (1) we could maintain the interactions between parameters in a probabilistic context by maintaining all scenarios, instead of isolating the uncertain parameter under analysis, in a deterministic context; and (2) we accelerated the EVoI analysis and reduced computational costs as it did not require extended optimization procedures.

Note that this proposal is only possible due to an efficient representative model selection, which ensures that both system inputs and outputs are properly represented. Because the set of RM reflects the set of uncertainties, the set of production strategies provide decision makers with the different possibilities for developing the field, including well number and placement, and platform processing capacities. On the one hand, decision makers can have a sense of how different (or similar) these alternatives are and their characteristics, reducing the subjectivity of the decision-making process. On the other hand, analyses are accelerated and facilitated because extensive optimization procedures are not necessary at this stage. Additional research is suggested on the optimal number of representative models and candidate production strategies, and on the potential economics gains of further optimizing the best candidate strategy for each information outcome.

The results showed how complex the EVoI analysis can be in the development phase, as a result of the many scenarios and information outcomes, and aggravated by imperfect information. The proposed indicators allowed focus on the key uncertainties that can be mitigated with information, and therefore avoided either: (1) performing the EVoI analysis on all uncertain parameters and available information sources; or (2) prioritizing parameters and information sources based on intuition or bias. We intended to reduce the subjectivity of the decision-making process, which we believe can be achieved with these indicators.

The decision to acquire information is rarely simple or obvious because the economic gain of improving the production strategy must surpass: (1) the cost of obtaining information; and (2) the delayed revenue from delaying production. Our case study appeared to be a classic example of information acquisition. Due to a key structural uncertainty, great improvements appeared to exist with an additional appraisal well. However, the results showed that it is better to develop the field with the current uncertain knowledge than to defer field development to acquire information. By analyzing the best production strategy without information, we understand why delaying the decision is unprofitable. The first development well is to be drilled in this uncertain region, and if its inexistence is proved, no additional wells will be drilled in this area. Consequently, the additional information would allow optimizing the platform size but would delay production. This result also supports the importance given to incorporate the delay in production when evaluating the production strategies with information. Not accounting for this delay means overestimating the information value and potential monetary losses.

In the methodology section (§2) we discussed approaches to assess the value of individual, simultaneous and sequential information. In our case study, the decision to drill an appraisal well would provide information simultaneously about more than one attribute (structural model, fluid contacts, rock-fluid properties), affecting the probability estimates. Accounting for these effects by updating the probabilities of these attributes ensures a more accurate EVoI assessment. Other applications of our proposal, in particular, the case of sequential acquisition, are planned for other case studies.

Estimating the probability distribution of attributes is the main challenge in uncertainty quantification and management. In the particular case of information acquisition, there is additional uncertainty about information reliability. Although methods can be found in the recent literature (see §1), these are still difficult to estimate. As they strongly affect EVoI, we recommended accompanying decisions with sensitivity analyses of these inputs.

Due to the several uncertainties and candidate production strategies

Table 7
Information sources under analysis and respective reliability estimates.

Information Source	Uncertainty	Reliability
Appraisal well (including well logs)	bl	0.95
	wo	0.80
Core Analysis	kr	0.80
	cp	0.80
PVT Analysis	pv	0.85
Well testing	kz	0.75

Table 8
Summary of the analysis conducted on all uncertain parameters using the four proposed indicators to identify those that can be mitigated with information. Qualitative scale: +++ very high; ++ high; + moderate; - low potential for information acquisition.

	kr	pv	bl	wo	cp	kz
Impact on the economic response	+	–	+++	++	–	–
Potential to reduce economic uncertainty	–	–	+++	+	–	–
Potential to modify the decision	+++	–	+++	+	–	–
Information sources	+	++	+++	++	+	+

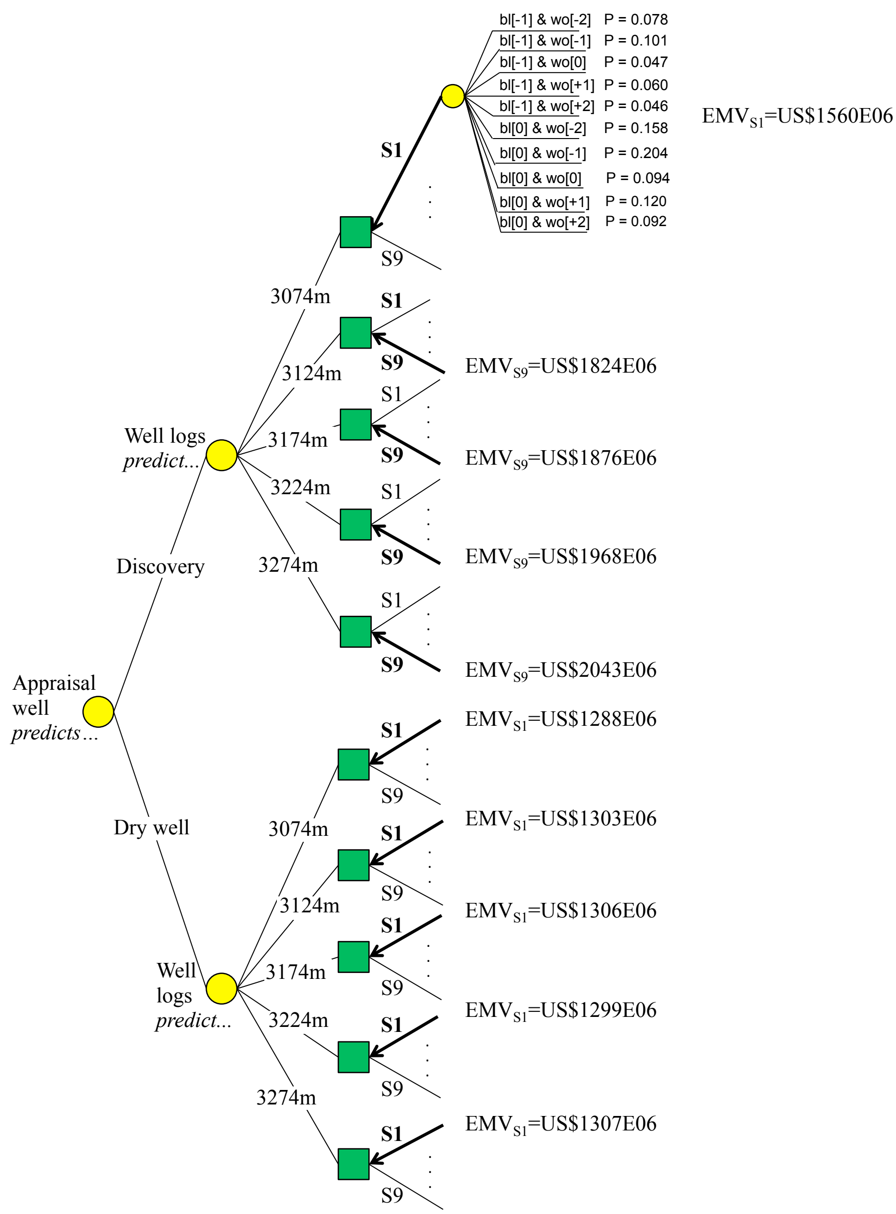

Fig. 11. Decision tree for an appraisal well with well logs, to simultaneously define the structural model (*bl*) and the water/oil contact (*wo*).

Table 9
Best production strategy under each information result, the respective EMV (in parentheses; units in US$ millions), and the joint probabilities of occurrence of the two-test result (in brackets).

		and the well logs *predict…*				
		3074	3124	3174	3224	3274
If the appraisal well *predicts…*	Discovery	S1 (US$1560) [0.158]	S9 (US$1824) [0.204]	S9 (US$1876) [0.094]	S9 (US$1968) [0.120]	S9 (US$2043) [0.092]
	Dry well	S1 (US$1288) [0.078]	S1 (US$1303) [0.101]	S1 (US$1306) [0.047]	S1 (US$1299) [0.060]	S1 (US$1307) [0.046]

considered in the case study, difficulties arose when modeling the decision tree. Visualizing the problem became spatially unfeasible using this traditional structure. To our knowledge, no alternative representations are currently being used for petroleum development, and we believe that additional research is required on this topic.

6. Conclusions

To face the difficulties and complexity of valuing additional information to manage uncertainty in oil field development, we proposed a set of indicators to identify, a priori, the uncertainties that can be mitigated with information. In the approach we propose, the decision maker begins by assessing the set of reservoir uncertainties using four indicators: (1) impact on the performance of the field; (2) potential to reduce uncertainty; (3) potential to modify the decision; and (4) likelihood of the available information source to define the uncertain parameter. These combined indicators determine the potential for an uncertain parameter to be mitigated with information, and the EVoI analysis should be based on the parameters with high potential.

In addition, our methodology quantifies the value of all available

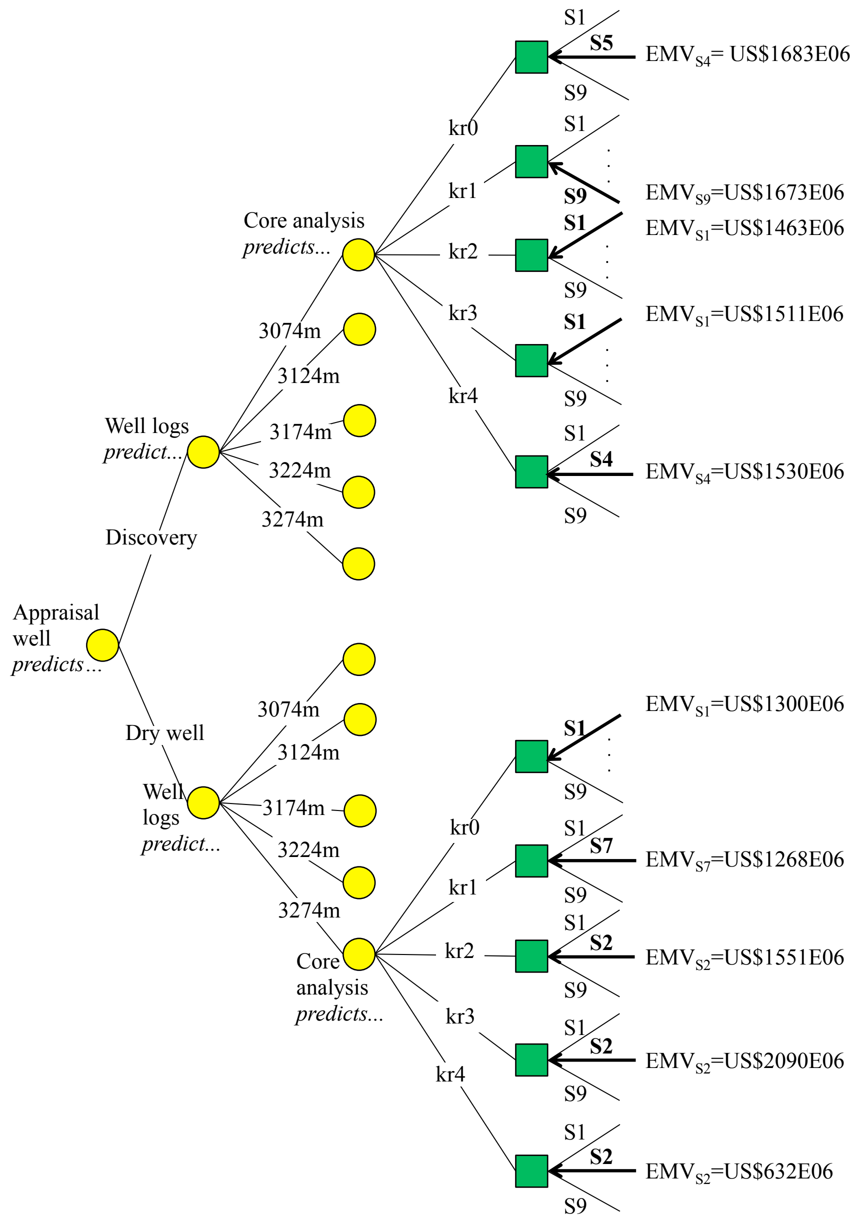

Fig. 12. Decision tree for an appraisal well with well logs and core analysis, simultaneously defining the structural model (*bl*), the water/oil contact (*wo*), and the water relative permeability (*kr*).

information sources, to identify the best for the project. By doing this, we reduce the subjectivity of the decision-making process, eliminating misconceptions and biases toward particular uncertainties and information sources. We determine EVoI using a large set of scenarios, with updated probabilities for perfect and imperfect information and using a predefined set of candidate production strategies, previously optimized for representative models. This process accelerates and automates the EVoI analysis. Finally, our workflow assesses the value of individual, simultaneous and sequential acquisition of information.

We applied the proposed methodology to the reservoir model UNISIM-I-D, a benchmark case in the development phase. Using the proposed indicators we identified the uncertainties with the highest potential for information acquisition. As we considered multiple scenarios and imperfect information, the statistical analysis was complex, which sustains our proposal of constraining the EVoI analysis to the uncertainties with high potential for information acquisition. The case study also demonstrated the importance of performing the EVoI calculation. Although great 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, ensuring a more quantitative and objective decision-making process.

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6. ARTICLE 5: ASSESSING THE VALUE OF INFORMATION ACCORDING TO ATTITUDES TOWARDS DOWNSIDE RISK AND UPSIDE POTENTIAL

Susana M.G. Santos, Denis J. Schiozer

Presented at the SPE Europec featured at 79th EAGE Annual Conference and Exhibition held in Paris, France, 12-15 June 2017

SPE-185841-MS

Assessing the Value of Information According to Attitudes towards Downside Risk and Upside Potential

Susana M. G. Santos and Denis J. Schiozer, University of Campinas

This paper was prepared for presentation at the SPE Europec featured at 79th EAGE Conference and Exhibition held in Paris, France, 12–15 June 2017.

Abstract

The Value of Information (VoI) analysis typically assesses information opportunities to manage uncertainty. The VoI is traditionally estimated using the expected monetary value (EMV), which overlooks the decision maker's (DM) attitude towards upsides and downsides. In this study, we assess the VoI for DMs with different attitudes, under different levels of information reliability. We define attitude to be as: neutrality to upsides and downsides, aversion to downside risk, and willingness to exploit upside potential. We applied a simple and flexible formula, which incorporates EMV with lower and upper semi-deviations from a benchmark, to quantify downside risk and upside potential. We determined VoI using many uncertain scenarios to maintain interactions between parameters instead of deterministically isolating the uncertainty under analysis. To accelerate analysis and reduce computational costs, we used a set of candidate production strategies optimized for extremely different scenarios. Our case study was the UNISIM-I-D, a benchmark reservoir model with a key structural uncertainty affecting production strategy selection. We used an appraisal well as an information source, and four hypothetical DMs with different attitudes. Our results showed that these DMs value information differently, that one DM may decide to acquire information while another may not, for the same situation. In our case study, information reduced downside risk but did not increase upside potential, meaning that information was more valuable to risk-averse DMs (which was up to 20 times higher), and less valuable to DMs exclusively focused on maximizing upsides.

Introduction

Acquiring additional information before deciding on field development is common in uncertainty management. However, the cost and potential delays in production should not outweigh the benefits of acquiring additional information. The Value of Information (VoI) methodology quantifies the advantages of acquiring additional information. This calculation is essential because reducing uncertainty or increasing confidence in a decision has no value in itself. To add value, the information must: change our understanding of the uncertain parameter, have the potential to influence a decision that would be made otherwise, and cost less than its value (e.g. Delquié, 2008; Bratvold et al., 2009).

Various measures determine information value, including: expected utility, selling price of information, buying price of information, probability price, and certainty equivalent (cf. Delquié, 2008; Abbas et al., 2013). For its simplicity, the increase in expected monetary value (EMV) is usually employed in petroleum development projects (e.g. Warren, 1983; Demirmen, 1996; Koninx, 2000; Begg et al., 2002; Wills and Graves, 2004; Cunningham and Begg, 2008; Bickel, 2012; Santos et al., 2016) (Equation (1)).

$$VoI_{EMV} = EMV_{with\ information} - EMV_{withou\ information} \tag{1}$$

However, EMV assumes neutrality to upsides and downsides, and decision makers (DM) with different attitudes may value information differently. The relationship between attitudes and VoI has been extensively examined in the decision analysis literature. Although it is commonly accepted that risk-averse DMs tend to value information more highly than risk-neutral DMs (5 to 30 times higher), it is also commonly accepted that there may not be monotonicity or a positive correlation between risk aversion and VoI, and that increased aversion to risk may actually decrease VoI (Gould, 1974; Hilton, 1981; Byerlee and Anderson, 1982; Willinger, 1989; Eeckhoudt e Godfrod, 2000; Davis, 2014). This is due to the inherent risks of information acquisition.

The value of information does not depend only on the DM's attitude. More reliable information is more valuable than less reliable information (Blackwell, 1953). When information completely clarifies an uncertainty it is referred to as perfect information (reliability of 1); but if uncertainty still remains it is referred to as imperfect information (reliability less than 1). Note that information with reliability of 0.5 or less has no value because it is unable to change our prior perceptions (Bratvold et al., 2009). Because estimating the reliability of information is difficult, sensitivity analyses are essential to identify at what point information loses value. While acknowledged as important in the decision analysis literature, this procedure is uncommon in the petroleum literature (exceptions include Wills and Graves (2004)).

VoI is also determined by indecision; whether or not there is strong preference for one course of action over another. The VoI increases with the DM's indecision (Delquié, 2008).

Although an extensive body of literature on decision analysis shows that many factors affect the VoI, these are typically not included in the petroleum literature. This is important because how information is valued implies that when an opportunity to gather information is rejected by one DM it may be taken by another.

Objective

We aim to show that, in the development of petroleum reservoirs, DMs with different attitudes value information differently; in particular, they value imperfect information differently. In this study we define attitude to be as: neutrality to upsides and downsides, aversion to downside risk, and willingness to exploit upside potential. The proper quantification of information value is key when assessing information opportunities to create value and prevent economic loss. The decision to acquire information in the development phase may be based on: (1) increasing the expected return of the project; (2) decreasing the risk of the project; (3) exploiting potentially optimistic scenarios; or (4) both aversion to downsides and seeking to exploit upsides.

To do so, we apply a straightforward formula previously proposed by Santos et al. (2017), which assesses the value of production strategies incorporating the DM's attitude. We use this formula to calculate VoI for different hypothetical DMs, and considering different levels of information reliability.

We use the term "information" in a broad sense which can refer to acquiring data, performing technical studies, hiring consultants, and performing diagnostic tests (Bratvold et al., 2009).

Methodology

We apply the methodology proposed by Santos et al. (2016), which is an extension of the twelve-step decision analysis framework by Schiozer et al. (2015), summarized below. Santos' methodology continues on from Step 11, which determines VoI using many uncertain scenarios (obtained in Step 5), and using a set of candidate production strategies optimized for extremely different representative scenarios (obtained in Step 9).

The comprehensive decision analysis framework by Schiozer et al. (2015) covers all stages of field development and management: (1) reservoir characterization under uncertainty; (2) construction and calibration of the simulation model; (3) verification of inconsistencies in the base model using dynamic well data; (4) generation of scenarios considering the full range of uncertainties; (5) reduction of scenarios using dynamic data; (6) selection of a deterministic production strategy using an optimization procedure; (7) initial risk assessment; (8) selection of representative scenarios based on multiple objective functions and the full range of uncertain parameters; (9) selection of a production strategy for each representative scenario (as in Step 6); (10) selection of the best production strategy from a set of candidates (strategies obtained in Step 9); (11) identification of potential for changes in the best strategy to mitigate risk or increase value (information, flexibility, robustness); and (12) final risk assessment.

A scenario is a particular combination of all uncertainties. By using all scenarios, we can maintain the interactions between parameters in a probabilistic context, instead of deterministically isolating the uncertain parameter under analysis. Using a set of candidate production strategies accelerates the VoI analysis and reduces computational costs, as extended optimization procedures are unnecessary.

New information changes our previous understanding of an uncertainty, which cannot be observed directly. Bayes' Theorem (Equation (2)) updates the probabilities of occurrence given the new information, using two inputs: (1) the *prior* distribution of the uncertain parameter; and (2) information reliability. Using the updated probabilities, we update the probability of each uncertain scenario to match the *posterior* distribution.

$$P(E_i|I) = \frac{P(I|E_i) * P(E_i)}{\sum_{i=1}^{N}[P(I|E_i) * P(E_i)]} \tag{2}$$

where: $P(I|E_i)$ – conditional probability of I interpreting state of nature E (likelihood function); $P(E_i)$ – initial probability of occurrence of state of nature E (*prior* distribution); $P(E_i|I)$ – updated probability, i.e., the modified perception about the state of nature E, given information I (*posterior* distribution).

To determine the value of production strategies with and without information, considering different attitudes towards upsides and downsides, we apply Equation (3) (Santos et al., 2017).

$$\varepsilon = EMV - c_{dr}S_{B-}^2 + c_{up}S_{B+}^2 = EMV - \frac{S_{B-}^2}{\tau_{dr}} + \frac{S_{B+}^2}{\tau_{up}} \tag{3}$$

where: ε – production strategy value adjusted to the decision maker's attitude; EMV – expected monetary value; S_{B-}^2 and S_{B+}^2 – lower and upper semi-variance (squared semi-deviation) from the benchmark B; C_{dr} – aversion coefficient to downside risk; C_{up} – expectation coefficient to upside potential; τ_{dr} and τ_{up} – tolerance level to downside risk and to upside potential, expressed in the same units of the distribution and taking strictly positive values. In the downside risk term: $\tau_{dr} < \infty$ implies risk aversion, while $\tau_{dr} \to \infty$ implies risk neutrality. In the upside potential term: $\tau_{up} < \infty$ implies high expectation of high returns, while $\tau_{up} \to \infty$ implies indifference or neutrality to upside potential. These attitudes can also be modeled using the aversion or expectation coefficients, ratios given by $c = 1/\tau$.

In this formula, the lower semi-variance (Equation (4)) measures downside risk and decreases the EMV, in accordance with the production strategy's level of risk and the DM's corresponding tolerance; while the upper semi-variance (Equation (5)) measures upside potential and increases the EMV, in accordance with the production strategy's upside potential and the DM's corresponding tolerance (Figure 1). Note that a fair assessment requires estimating lower and upper semi-variance considering the same B for all candidate production strategies. Following the suggestion of Santos et al. (2017), we used the strategy with maximized EMV as reference, and its EMV as benchmark.

$$S_{B-} = \sqrt{S_{B-}^2} = \sqrt{E\{min[(X-B),0]^2\}} \tag{4}$$

$$S_{B+} = \sqrt{S_{B+}^2} = \sqrt{E\{max[(X-B),0]^2\}} \tag{5}$$

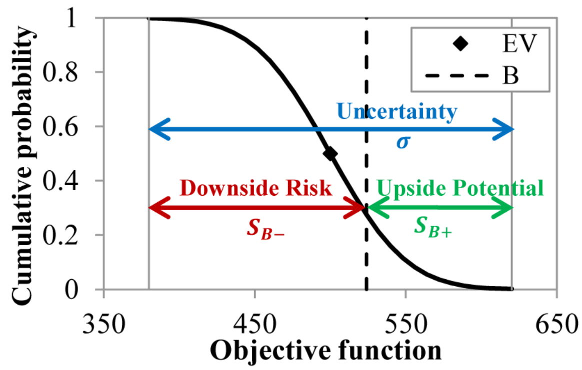

Figure 1—Hypothetical risk curve with three statistical measures: standard deviation (σ) quantifies uncertainty; lower semi-deviation (S_{B-}) quantifies downside risk; and upper semi-deviation (S_{B+}) quantifies upside potential. EV is the expected value, and B is the benchmark return (in Santos et al., 2017).

where: S_{B-} and S_{B+} – lower and upper semi-deviation from the benchmark B; S_{B-}^2 and S_{B+}^2 – lower and upper semi-variance from the benchmark B; E – expectation operator; X – random variable.

Santos' methodology requires that the value of the project with information be calculated using Equation (3), i.e., not an expected value calculation. This is achieved in two steps: (1) using the updated probabilities, we calculate the value of all production strategies to identify the best for each information outcome; and (2) we generate the risk curve of the project with information and calculate its value using Equation (3) with the same benchmark of the case without information. The Value of Information is given by Equation (6).

$$VoI_{\varepsilon} = \varepsilon_{with\ information} - \varepsilon_{without\ information} \tag{6}$$

Application

We applied the methodology to the benchmark reservoir model UNISIM-I-D (Gaspar et al., 2015), a case study for production strategy selection. UNISIM-I-D is a sandstone oil reservoir, 80 km offshore the coast, in the field development phase, with 1461 days of initial production history for four vertical producing wells. The reservoir depth varies between 2900 and 3400 m and the water depth is 166 m. The simulation model comprises a corner point grid with 81x58x20 cells of 100x100x8 m, with a total of 36,739 active cells (Figure 2).

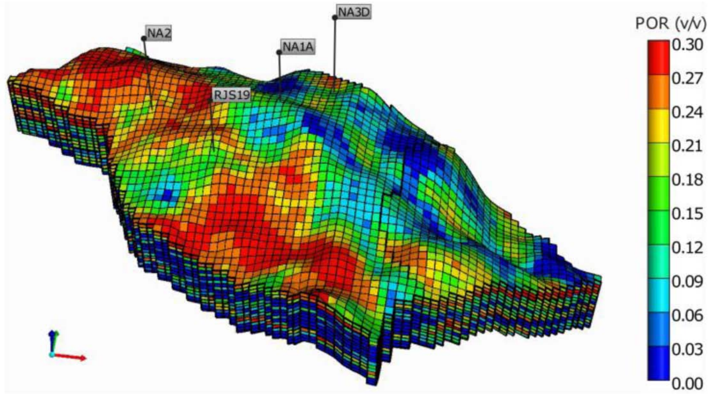

Figure 2—Porosity map of UNISIM-I-D reservoir model. The absence or presence of the East region is a key uncertainty.

The absence or presence of the East region (*bl*) is a key uncertainty affecting production strategy selection (well placement, well number, and platform capacity) due to lower levels of oil in place. We used an appraisal well as an information source to clarify this uncertainty, with two possible outcomes: (1) "discovery," indicating the existence of the East block (level *bl0*); or (2) "dry well," indicating the absence of the East block (level *bl1*). In this application, we assumed that information is acquired without delaying production, and we considered the deterministic economic scenario of this case study (Gaspar et al., 2015).

We considered four hypothetical decision makers with different attitudes:

1. DM-A, neutral to downside risk ($\tau_{dr} \to \infty$) and to upside potential ($\tau_{up} \to \infty$), basing decisions on EMV.
2. DM-B, averse to downside risk (τ_{dr} = US\$ 700 million) and neutral to upside potential ($\tau_{up} \to \infty$).
3. DM-C, neutral to downside risk ($\tau_{dr} \to \infty$) and willing to exploit upside potential (τ_{up} = US\$ 700 million).
4. DM-D, averse to downside risk (τ_{dr} = US\$ 700 million) and willing to exploit upside potential (τ_{up} = US\$ 700 million).

Note that because DM-A is neutral to downside risk and to upside potential, ε = EMV and Equation (6) becomes Equation (1).

Results and Discussion

Schiozer et al. (2015) applied his twelve-step methodology to UNISIM-I-D and we use the results from his work, as follows: (1) 214 equiprobable scenarios that match production data; and (2) 9 candidate production strategies (S1 to S9) (Table 1). Note that each scenario is a particular combination of all reservoir and operational uncertainties of this case study, detailed in Gaspar et al. (2015). Reservoir uncertainties include: geostatistical realizations of petrophysical properties; structural model; PVT data (uncertain region); depth of water-oil contact (uncertain region); water relative permeability; vertical permeability multiplier; and rock compressibility. Operational uncertainties include: systems availability (platform, groups of wells, producers, injectors); and well index multiplier. The *prior* probabilities of *bl* (Table 2) match the frequency of occurrence in the 214 filtered scenarios.

Table 1—Characteristics of the 9 candidate production strategies. V: vertical well; W: horizontal well; Q_l: liquid processing capacity; Q_o: oil processing capacity; Q_w: water processing capacity; Q_{wi}: water injecting capacity.

Production Strategy	Producers			Injectors			Platform (1000 m³/day)			
	V	H	T	V	H	T	Q_l	Q_o	Q_w	Q_{wi}
S1	2	10	12	0	6	6	16.3	16.3	9.1	23.3
S2	2	8	10	0	6	6	16.3	16.3	11.2	22.8
S3	2	7	9	0	5	5	14.0	14.0	9.8	19.5
S4	1	10	11	0	6	6	18.2	18.2	11.5	25.5
S5	3	10	13	0	7	7	17.8	17.8	10.5	23.8
S6	1	8	9	0	6	6	14.3	14.3	7.3	20.6
S7	2	7	9	0	6	6	13.2	13.2	5.2	19.5
S8	3	11	14	0	7	7	21.7	21.7	14.6	29.8
S9	3	10	13	0	7	7	20.2	20.2	9.8	28.2

Table 2—Structural uncertainly (*bl*) with the *prior* probabilities after filtering the 214 scenarios.

Attribute	Description	Type	level (probability)	
			bl0	bl1
bl	Structural model	discrete [map]	With east block (0.69)	No east block (0.31)

Figure 3 shows the decision tree for this problem considering perfect information. Note that each branch labeled *bl0* and *bl1* corresponds to a set of scenarios (147 and 67, respectively). Chance nodes are circles (uncertain outcomes with probabilities of occurrence), and decision nodes are squares (choices).

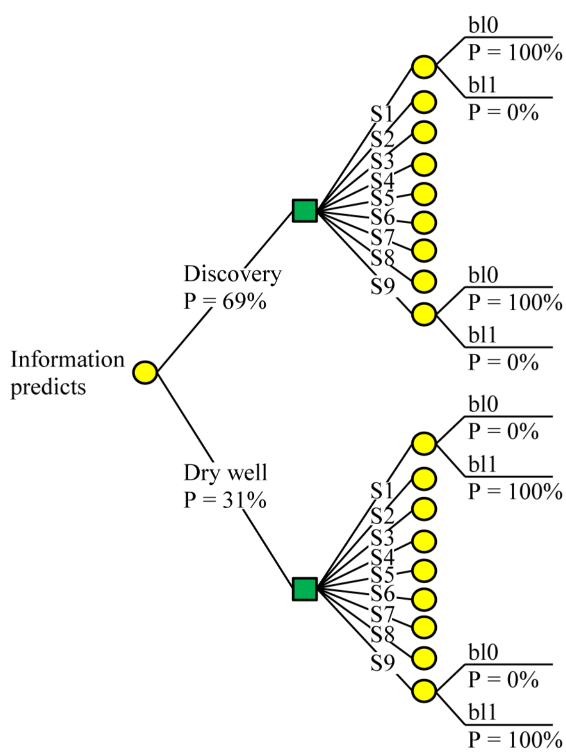

Figure 3—Decision tree for an appraisal well to define the structural uncertainty (*bl*) considering perfect information.

We calculated the value of all strategies without information using Equation (3) and confirmed that without further information all DMs would select S9 (Table 3). We used production strategy S9 with maximized EMV (US$ 1673.4 million) as the benchmark for lower and upper semi-deviations.

Table 3—Evaluation of the 9 candidate production strategies without information. Values in US$ millions.

Production Strategy	EMV	S_{B-}	S_{B+}	Value of the Production Strategy			
				DM-A	DM-B	DM-C	DM-D
S1	1579.5	381.6	255.6	1579.5	1371.5	1672.8	1464.8
S2	1596.8	396.1	294.2	1596.8	1372.6	1720.4	1496.2
S3	973.7	818.8	15.7	973.7	15.9	974.0	16.3
S4	1554.8	440.0	310.5	1554.8	1278.3	1692.5	1416.0
S5	1525.5	494.0	313.9	1525.5	1176.9	1666.3	1317.6
S6	1142.7	655.6	45.3	1142.7	528.7	1145.6	531.7
S7	1264.7	518.9	40.5	1264.7	880.0	1267.1	882.4
S8	1547.8	497.7	344.0	1547.8	1193.9	1716.9	1363.0
S9	1673.4	380.0	383.8	1673.4	1467.1	1883.9	1677.5

When calculating the value of the project with information: (1) using the updated probabilities, we calculated the value of all production strategies to identify the best for "discovery" and for "dry well" outcomes (i.e., each branch of the decision tree); and (2) we generated the risk curve of the project with information, calculating the value using Equation (3) with B = US$ 1673.4 million. Figure 4 and Tables 4 to 7 show the results for information with varying degrees of reliability for each DM.

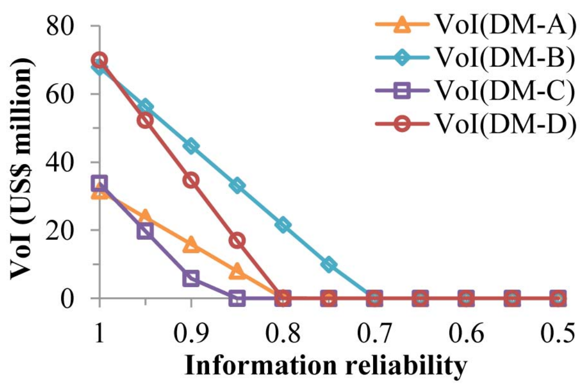

Figure 4—VoI with information reliability for DM-A (orange), DM-B (blue), DM-C (purple) and DM-D (red).

Table 4—VoI analysis for DM-A under different levels of information reliability. Values in US$ millions.

Information Reliability	Best strategy if information predicts:		EMV with information	EMV without information	VoI
	Discovery	Dry well			
0.50	S9	S9	1673.4	1673.4	0.0
0.55	S9	S9	1673.4	1673.4	0.0
0.60	S9	S9	1673.4	1673.4	0.0
0.65	S9	S9	1673.4	1673.4	0.0
0.70	S9	S9	1673.4	1673.4	0.0
0.75	S9	S9	1673.4	1673.4	0.0
0.80	S9	S1	1673.6	1673.4	0.2
0.85	S9	S1	1681.4	1673.4	8.0
0.90	S9	S1	1689.3	1673.4	15.9
0.95	S9	S1	1697.1	1673.4	23.7
1.00	S9	S1	1705.0	1673.4	31.6

Table 5—VoI analysis for DM-B under different levels of information reliability. Values in US$ millions.

Information Reliability	Best strategy if information predicts:		EMV with information	S_{B-} with information	ε with information	ε without information	VoI
	Discovery	Dry well					
0.50	S9	S9	1673.4	380.0	1467.1	1467.1	0.0
0.55	S9	S9	1673.4	380.0	1467.1	1467.1	0.0
0.60	S9	S9	1673.4	380.0	1467.1	1467.1	0.0
0.65	S9	S9	1673.4	380.0	1467.1	1467.1	0.0
0.70	S9	S9	1673.4	380.0	1467.1	1467.1	0.0
0.75	S9	S1	1665.7	363.4	1467.1	1477.1	10.0
0.80	S9	S1	1673.6	359.8	1467.1	1488.6	21.5
0.85	S9	S1	1681.4	356.2	1467.1	1500.2	33.1
0.90	S9	S1	1689.3	352.5	1467.1	1511.7	44.7
0.95	S9	S1	1697.1	348.8	1467.1	1523.3	56.2
1.00	S9	S1	1705.0	345.1	1467.1	1534.8	67.8

Table 6—VoI analysis for DM-C under different levels of information reliability. Values in US$ millions.

Information Reliability	Best strategy if information predicts: Discovery	Best strategy if information predicts: Dry well	EMV with information	S_{B+} with information	ε with information	ε without information	VoI
0.50	E9	S9	1673.4	383.8	1883.9	1883.9	0.0
0.55	E9	S9	1673.4	383.8	1883.9	1883.9	0.0
0.60	E9	S9	1673.4	383.8	1883.9	1883.9	0.0
0.65	E9	S9	1673.4	383.8	1883.9	1883.9	0.0
0.70	E9	S9	1673.4	383.8	1883.9	1883.9	0.0
0.75	E9	S9	1673.4	383.8	1883.9	1883.9	0.0
0.80	E9	S9	1673.4	383.8	1883.9	1883.9	0.0
0.85	E9	S9	1673.4	383.8	1883.9	1883.9	0.0
0.90	E9	S1	1689.3	374.6	1883.9	1889.7	5.8
0.95	E9	S1	1697.1	380.2	1883.9	1903.6	19.7
1.00	E9	S1	1705.0	385.7	1883.9	1917.5	33.7

Table 7—VoI analysis for DM-D under different levels of information reliability. Values in US$ millions.

Information Reliability	Best strategy if information predicts: Discovery	Best strategy if information predicts: Dry well	EMV with information	S_{B-} with information	S_{B+} with information	ε with information	ε without information	VoI
0.50	S9	S9	1673.4	380.0	383.8	1677.5	1677.5	0.0
0.55	S9	S9	1673.4	380.0	383.8	1677.5	1677.5	0.0
0.60	S9	S9	1673.4	380.0	383.8	1677.5	1677.5	0.0
0.65	S9	S9	1673.4	380.0	383.8	1677.5	1677.5	0.0
0.70	S9	S9	1673.4	380.0	383.8	1677.5	1677.5	0.0
0.75	S9	S9	1673.4	380.0	383.8	1677.5	1677.5	0.0
0.80	S9	S9	1673.4	380.0	383.8	1677.5	1677.5	0.0
0.85	S9	S1	1681.4	356.2	368.8	1677.5	1694.5	17.0
0.90	S9	S1	1689.3	352.5	374.6	1677.5	1712.1	34.6
0.95	S9	S1	1697.1	348.8	380.2	1677.5	1729.8	52.2
1.00	S9	S1	1705.0	345.1	385.7	1677.5	1747.4	69.9

Figure 5 shows the evolution of the risk curves with information reliability for DM-B. The risk curves without information were generated for the 214 equiprobable scenarios using production strategy S9 (best strategy without information). Conversely, the risk curves with information have 428 points, corresponding to the 214 scenarios with updated probabilities for the two information outcomes ("discovery" and "dry well"): (1) when reliability is higher than 0.7, we have 214 scenarios for S9 (for "discovery"), and 214 scenarios for S1 (for "dry well"); but (2) when reliability is equal to or lower than 0.7, we have 428 for S9 (best production strategy for both information outcomes).

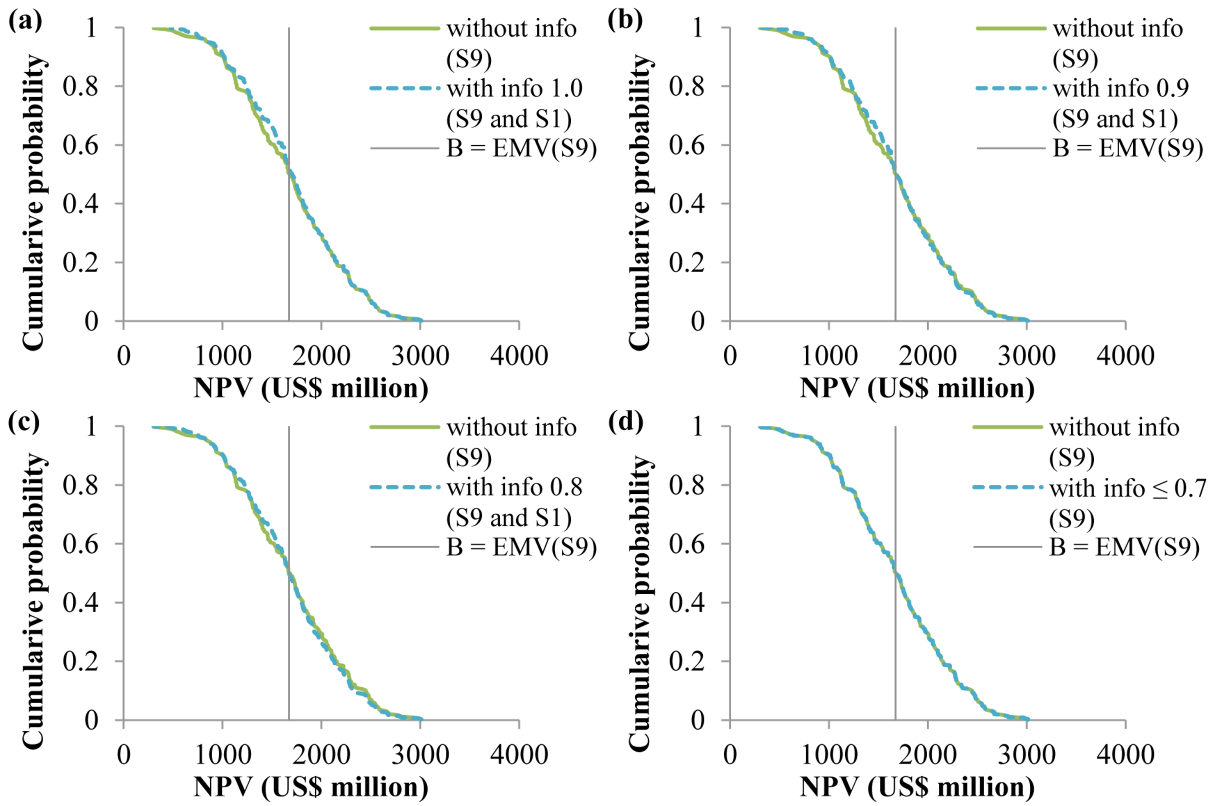

Figure 5—Evolution of risk curves with information for DM-B (dashed blue), compared with the risk curve without information (continuous green), for information reliability: (a) 1.0, (b) 0.9, (c) 0.8, and (d) less or equal to 0.7.

All decision makers choose S1 or S9, but value the information differently:

1. The point at which information loses its value differs according to reliability (at 75% for DM-A, 70% for DM-B, 85% for DM-C and 80% for DM-D);
2. Information is more valuable to the risk-averse DM-B and DM-D;
3. Information is least valuable to DM-C who focuses on upsides.

Information is more valuable to the risk-averse DMs because the information source we considered is mainly important to reduce risk (Figure 5). Note that while DM-A bases decisions only on EMV (Figure 6a), the others make compromises between the increase in EMV, decreased downside risk and/or increased upside potential (Figure 6b to 6d), according to their attitudes.

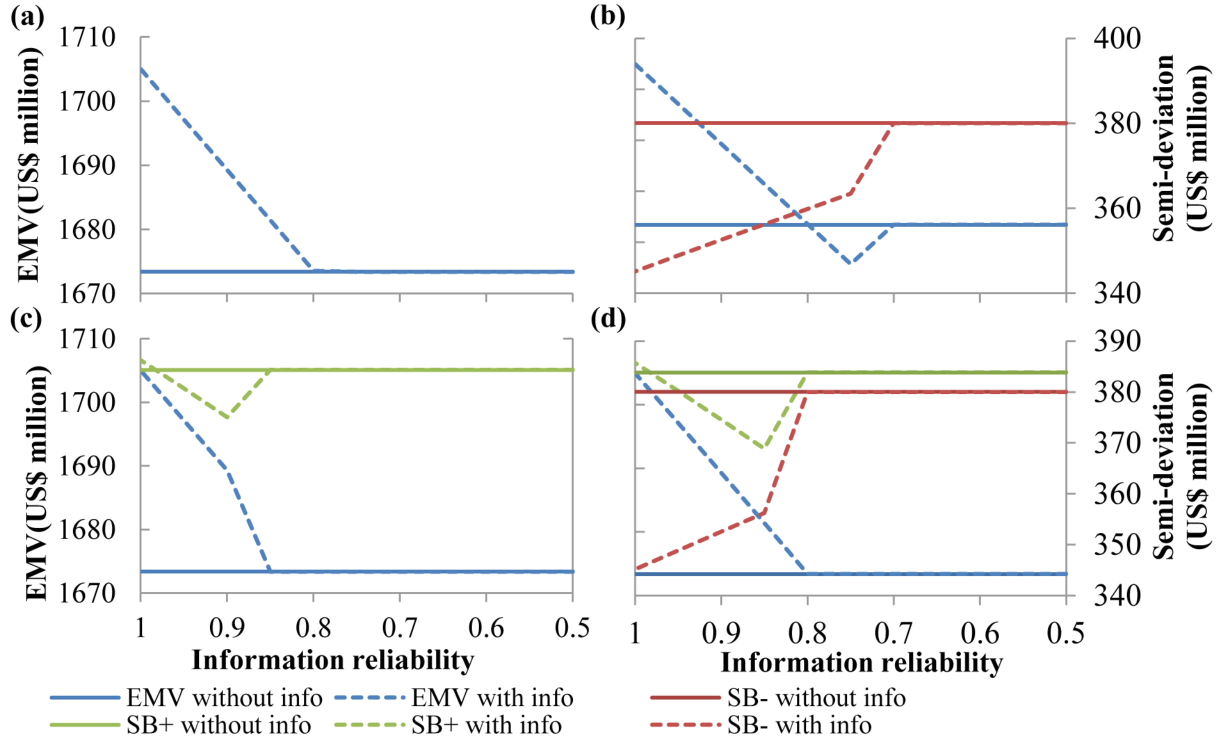

Figure 6—Evolution of EMV (dashed blue; left axis), downside risk (dashed red; right axis) and upside potential (dashed green; right axis) with information reliability: (a) DM-A, (b) DM-B, (c) DM-C, and (d) DM-D. Continuous lines are the same metrics without information, as reference.

We also assessed the impact of tolerance to risk and to upside potential on VoI_{ε} (DM-B, DM-C and DM-D), comparing it to VoI_{EMV} (DM-A) (Figure 7). As both tolerances approach infinity, and VoI_{EMV} nears VoI_{EMV}, this suggests that decisions can be based only on EMV and are not affected by downsides or upsides.

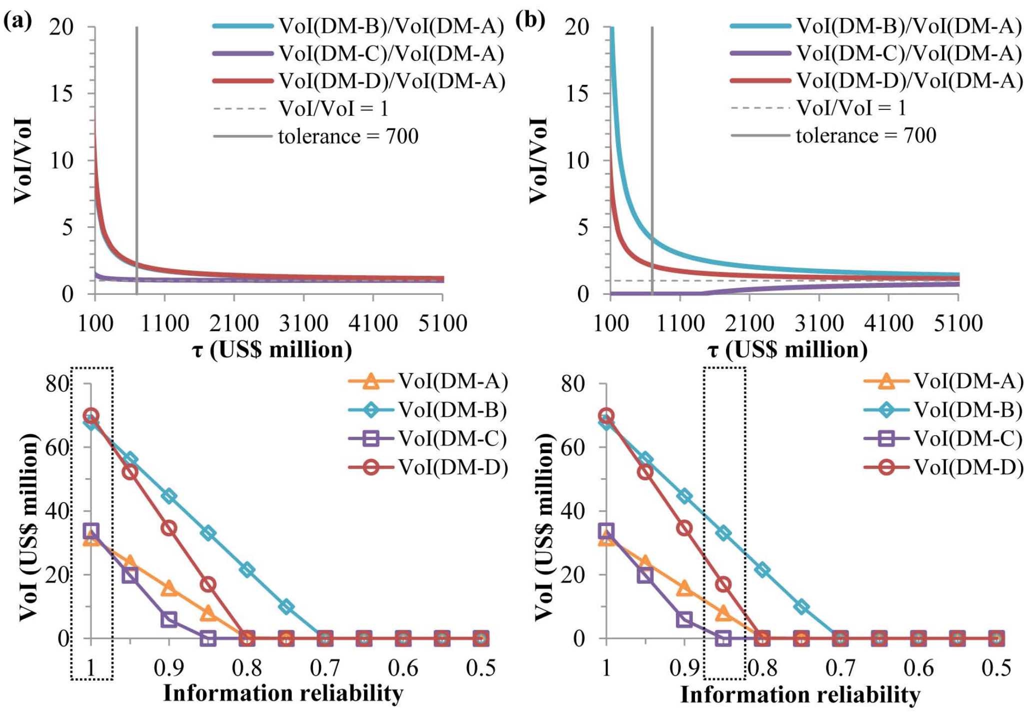

Figure 7—Effects of tolerance to downside risk and to upside potential on VoI quantified by the ratio between VoIε and VoI_{EMV} (DM-A) for: (a) perfect information; and (b) imperfect information with reliability 0.85. DM-B in blue, DM-C in purple, and DM-D in red. The vertical line marks the tolerance level considered in this study, and taken in the sensitivity analysis below.

For DM-B, averse to risk: (1) as the tolerance τ to risk decreases (i.e., increased risk aversion), VoI_ε increases; (2) perfect information is valued up to 10 times higher than for DM-A (Figure 7a); and (3) imperfect information is valued up to 20 times higher than for DM-A (Figure 7b).

For DM-C, seeking upsides: (1) perfect information is valued up to 2 times higher than for DM-A (Figure 7a); (2) imperfect information is valued less than the VoI_{EMV} (Figure 7b); and (3) for imperfect information, when expectations of upside potential are high (τ_{up} < US$ 1500 million) information is not valued, but with decreased willingness to exploit upsides (τ_{up} > US$ 1500 million), information is valued because priority is given to increasing EMV (Figure 7b).

Because DM-D makes compromises between decreased downside risk (the focus of DM-B) and increased upside potential (the focus of DM-C), the value profile is between the DM-B and DM-C.

These results support that EMV does not capture different attitudes, and that a suitable VoI methodology can add value, largely for risk averse decision makers in our case study.

We also observed that the VoI of this case study (ranging from US$ 30 million to US$ 70 million) was low considering the magnitude of this project (corresponding to 1.8% to 4.2% of the EMV without information). This could be because S9 is clearly the best strategy, so there is a strong preference for S9 before information acquisition for all DMs' attitudes, and in most cases S9 remains the best production strategy with information.

Conclusions

In this study, we quantified the value of information for decision makers with different attitudes towards upside potential and downside risk, and different levels of information reliability. We used a straightforward and flexible formula (Santos et al., 2017), which incorporates the EMV with lower and upper semi-deviations from a benchmark to quantify downside risk and upside potential. We drew the following conclusions from our results:

1. Decision makers with different attitudes value information differently.
2. The decision to acquire information may be rejected by one decision maker but accepted by another.
3. A strong preference for one production strategy decreases information value.
4. In our case study, information reduced downside risk, resulting in maximum information value for risk-averse decision makers; and minimum information value for decision makers exclusively focused on maximizing upsides.
5. In particular, VoI was up to 20 times higher for decision makers averse to risk.
6. EMV disregards the decision maker's attitude, and a suitable VoI methodology can add value, largely for risk-averse decision makers, in our case study.

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7. ARTICLE 6: MANAGING RESERVOIR UNCERTAINTY IN PETROLEUM FIELD DEVELOPMENT: DEFINING A FLEXIBLE PRODUCTION STRATEGY FROM A SET OF RIGID CANDIDATE STRATEGIES

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Submitted to a peer-reviewed journal

Managing reservoir uncertainty in petroleum field development: Defining a flexible production strategy from a set of rigid candidate strategies

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Abstract

The decisions in petroleum field development are typically complex because of high investments under high uncertainty. To improve project performance, decision makers must study the effects of uncertainty, and consider actions to both mitigate the risks and exploit the upsides of uncertainty. Flexibility has high potential to manage uncertainty in petroleum field development, where systems have a long lifetime and uncertainty unfolds over time. Although increasingly popular in the petroleum industry, the literature still lacks systematic and objective approaches to quantitatively estimate the value of flexibility. This work sets out a decision structure to analyze the expected value of flexibility (EVoF) applied to petroleum field development that (1) uses a predefined set of rigid candidate production strategies to define the flexible strategy, (2) establishes probabilistic-based implementation rules, and (3) improves the EVoF estimate by accounting for the purpose of flexibility (to mitigate the risks or to exploit the upsides of uncertainty) and weighing the decision maker's attitude. We show that our proposed method is applicable to complex reservoirs in the development phase, with multiple uncertainties affecting production strategy selection. We also assessed the effects of delayed implementation on EVoF.

Keywords: decision analysis, uncertainty management, value of flexibility, field development, production strategy, reservoir simulation

1. Introduction

Petroleum field development is a high-risk venture because of considerable investment in complex uncertain scenarios. These typically include (1) reservoir uncertainties, associated with recoverable reserves and flow characteristics, (2) operational uncertainties, related to production system availability; and (3) economic uncertainties, related to market variables, capital expenditures, and operational expenditures. Three approaches are typically considered to manage the uncertainties: (1) acquiring additional information to reduce reservoir uncertainty, (2) defining a flexible production system that allows system modifications as uncertainty unfolds over time, and (3) defining a robust production strategy able to cope with uncertainty without requiring system modifications after production has started. This study focuses on the second approach.

Flexibility can be considered a way of creative stochastic thinking [1, 2, 3]. When defining a flexible system, decision makers split the development decision into a sequential problem of multiple decisions over time. This allows an active-reaction based on the knowledge gained between decisions. Thus, the appeal of flexibility stems from options to mitigate risk and exploit the upsides of uncertainty [4].

Early discussions of flexibility can be traced back to the early 1920's in the economics literature when Lavington termed the "risk arising from the immobility of invested resources" ([5], p.91). The concept of

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flexibility has been developed in different domains and is today a multidisciplinary concept [6, 7]. Although popular, the concept of flexibility is not academically mature [7].

In the petroleum literature, mentions of flexibility date back to the late 1980's and typically refer to the option to develop, explore, delineate, wait, or stop [8, 9, 10, 11, 12]. Flexibility of the production system has been addressed mainly since the 2000's, and include capacity expansion [2, 13, 14, 15, 16, 17, 18, 19], modularity [16, 20], intelligent wells [16, 21, 22, 23], flexible subsea layouts [16, 17], and the ability to redistribute injection quotas or switch the injected fluid [16].

Flexibility is typically considered when (1) acquiring information is impossible, (2) the expected value of information is small or the acquisition cost is too high, (3) managing residual uncertainty after information is acquired, and (4) flexibility creates additional value by exploiting potential upsides of uncertainty [2, 3]. Flexibility may also be attractive in cases of multiple uncertainties affecting production strategy selection, where robust solutions may be insufficient to cope with the possible scenarios.

Although less discussed than information, flexibility is particularly suitable to handle uncertainty in petroleum field development. Flexibility can manage endogenous and exogenous uncertainties [17, 19], including oil price [2, 13, 17, 19], which cannot be managed with information. In addition, flexibility is particularly appropriate for systems that are designed to have a long lifetime [7], and for managing the impact of unlikely but high-consequence events [3].

However, "flexibility is not a free good" ([24], p. 310-311), meaning that the benefits of defining a flexible production system must be quantified prior to the decision, because (1) flexible systems incur additional upfront investment, and (2) implementing flexibility has a cost, in addition to the time value cost of delayed production [2, 3]. The Expected Value of Flexibility (EVoF), an approach similar to that of the Expected Value of Information (EVoI), is typically employed [2]. In this study, we use the term "expected" to emphasize that we are determining the expected gain of investing in a flexible system.

EVoF is often calculated as the expected increase in expected monetary value (EMV) [2, 13, 15, 16]. However, the breadth of risk reduction and increased upside potential may not be recorded in the magnitude of changes in EMV. This often makes this indicator inadequate to base decisions in the development phase [25]. As a result, some authors complemented the conventional EMV with risk measures and other economic indicators when choosing flexible strategies [14, 17, 18, 19, 20].

Determining whether and when flexibility should be implemented is a challenge. This is based on triggering conditions, also referred to as decision rules or implementation rules, defined by decision makers. Examples include achieving a target oil price [17, 19] or a threshold estimated ultimate recovery [17], but also premature water breakthrough [16], and gas-oil ratio above the expected [16]. It is common for decision makers to define minimum and maximum dates to implement the flexibility, based on various reasons including logistics, estimated time for uncertainty to unfold, remaining hydrocarbon reserves, and difficulties in paying off additional investments [14, 17, 19].

1.1. Scope and objectives

To maximize project value, decision makers must consider actions to manage uncertainty, both to mitigate risks and exploit upsides. While neglecting the effects of uncertainty may lead to underperformance [2, 26], neglecting the possibility of flexibility as a response to uncertainty may result in project undervaluation [2, 15]. Although increasingly popular, the petroleum literature still lacks systematic and objective approaches to define and value flexibility.

This study presents a method to facilitate the assessment of the potential for flexibility in the development phase of a petroleum field. The focus is on indicators that assess the potential for flexibility and on probabilistic-based implementation rules to reduce the subjectivity of decisions. To further improve the EVoF estimate we include decision maker's objective when buying a flexible system, whether mitigating risks or exploiting the upsides of uncertainty.

2. Methodology

This work is integrated into the twelve-step decision analysis framework by Schiozer et al. [27], which covers all stages of field development and management, and integrates reservoir characterization under uncertainty, reservoir simulation, history matching, uncertainty reduction, representative models, and production strategy optimization. The twelve steps are summarized as follows: (1) reservoir characterization under uncertainty, (2) construction and calibration of the simulation base model, (3) verification of inconsistencies in the base model using dynamic well data, (4) generation of scenarios considering the full range of uncertainties, (5) reduction of scenarios using dynamic data, (6) selection of a deterministic production strategy using an optimization procedure, (7) initial risk assessment, (8) selection of representative scenarios based on multiple objective functions and the full range of uncertain parameters, (9) selection of a production strategy for each representative scenario (as in Step 6), (10) selection of the best production strategy from the set of candidate strategies (obtained in Step 9), (11) identification of potential for changes in the best strategy to mitigate risk or increase value (e.g. information, flexibility, and robustness) and integration with production facilities, and (12) final risk assessment. Note that a scenario is treated here as a particular combination of all uncertain attributes.

This study presents a methodology for Step 11, considering flexibility to manage reservoir uncertainty (Fig. 1). The inputs for our workflow come from previous steps in the framework by Schiozer et al. [27]: (1) uncertain scenarios that match production data; (2) candidate rigid production strategies; and (3) a robust production strategy, the best under uncertainty and excluding flexibility.

2.1. Candidate production strategies

To reduce the subjectivity of decisions and to automate analyses, we use a predefined set of candidate production strategies (CPS) to define the flexible production strategy. These rigid strategies were optimized deterministically (in Step 9) for representative models (RM), chosen from the set of scenarios that match production data (in Step 8). Meira et al. [28, 29] proposed an efficient RM selection by combining a mathematical function that captures the representativeness of a set of models with a metaheuristic optimization algorithm. This approach ensures that the set of RM represents both the probability distribution of the input variables (uncertain attributes), ensuring that not only all the attributes but also all the uncertain levels are represented; and the variability of the main output variables (production, injection, and economic forecasts).

2.2. Defining flexible production strategies

As the set of RM represents the uncertain system, the set of CPS provide decision makers with different possibilities to develop the field, namely well number and placement, platform size, and fluid processing capacities. Thus, we use the CPS as indicators for the degree and type of flexibility required by the system.

In the initial diagnosis, we assess the representativeness of each CPS based on the percentage of uncertain scenarios that choose each CPS. This procedure provides weights for each CPS when comparing them.

If the values of decision variables are similar between CPS, no further action is required. However, if different, actions may be taken to mitigate the risks or to exploit the upsides of uncertainty.

This iterative procedure goes through each decision variable. If the value of the decision variable is similar between CPS, the variable is set as in the robust production strategy. Conversely, the different possibilities are treated as candidate flexibilities, except for when a decision variable is inflexible (e.g. well placement), and it is thus set as in the robust production strategy.

2.3. Assessing the candidate flexibilities

We use the hypothetical maximum value of flexibility for the initial assessment of the candidate flexibilities. That is, we obtain production, injection and economic forecasts for all scenarios, and identify and select the best action for each scenario individually (i.e., whether or not flexibility should be implemented, and the level and type of implementation). So, at this stage, EVoF is estimated without defining a decision rule. If the candidate is unfeasible for the hypothetical case, it is rejected; otherwise, decision makers define probabilistic-based implementation rules (see §2.4).

The feasibility assessment is based on the risk curve analysis (see §2.5). Risk curves are also referred to in the statistics literature as descending or complementary cumulative distributions functions, and we construct them with the production forecasts of multiple scenarios from numerical reservoir simulation.

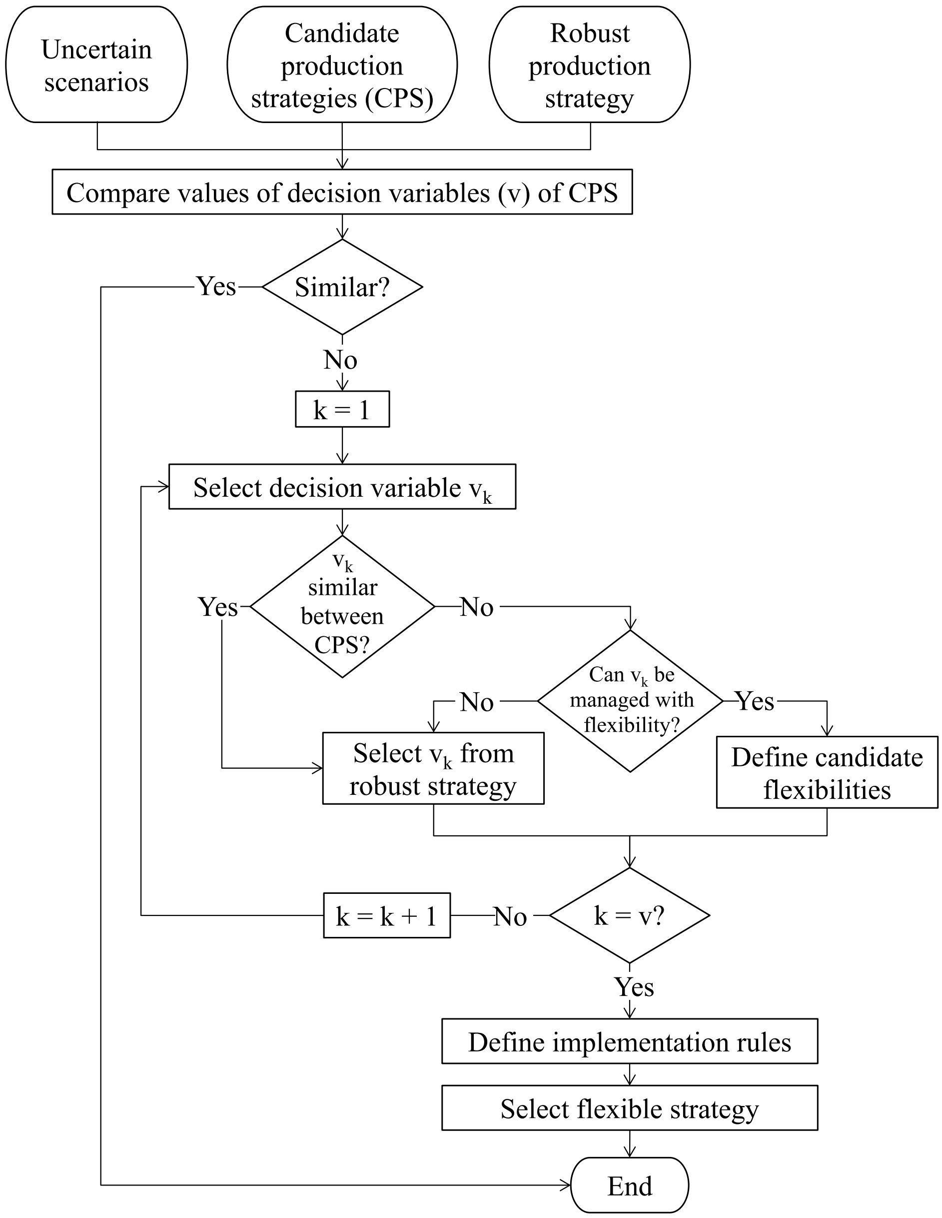

Figure 1: Workflow for expected value of flexibility analysis applied to petroleum field development.

2.4. Defining the implementation rule

We define probabilistic-based implementation rules using the simulation outputs obtained from the case of the hypothetical maximum value of flexibility (see §2.3). That is, we identify, for individual scenarios, whether or not flexibility should be implemented, and the level and type of implementation preferred. Then, we group subsets of scenarios according to the preference and analyze their histograms for all reservoir uncertainties. The comparison of the histograms between the subsets and the full set of scenarios allows the identification of the dominant uncertainty in each level of implementation. Specifically, we set the decision rules according to the reservoir uncertainties that control the preference for each type of implementation.

2.5. Determining the Expected Value of Flexibility

To estimate EVoF, we apply the objective-function proposed by Santos et al. [25] for production strategy evaluation, which has already been applied by Santos and Schiozer [30] for EVoI. This approach improves EVoF assessment because it accounts for all changes in the risk curve, and weights the decision maker's attitude toward downsides and upsides.

Santos et al. [25] combined the expected value (EV), downside risk, and upside potential in a new objective-function (Eq. (1)) that determines the value of the production strategy adjusted to the decision maker's attitude, $\varepsilon(X)$, while maintaining the units and dimension of X. This equation is applicable to production and economic indicators, and we apply it to the net present value (NPV).

$$\varepsilon(X) = E[X] - c_{dr} S_{B-}^2 + c_{up} S_{B+}^2 = E[X] - \frac{S_{B-}^2}{\tau_{dr}} + \frac{S_{B+}^2}{\tau_{up}} \tag{1}$$

where: $\varepsilon(X)$ is the value of the production strategy adjusted to the decision maker's attitude; $E[X]$ is the expected value of random variable X; S_{B-}^2 and S_{B+}^2 are the lower and upper semi-variance from the benchmark B, respectively; c_{dr} is the aversion coefficient to downside risk; c_{up} is the expectation coefficient to upside potential; τ_{dr} and τ_{up} are the tolerance (or indifference) levels to downside risk and to upside potential, respectively.

Semi-deviation (short for semi-standard deviation) from a benchmark or target return (B) measures subsets of standard deviation and differentiates good variability from bad. Lower semi-deviation (Eq. (2)) quantifies downside risk, while upper semi-deviation (Eq. (3)) quantifies upside potential.

$$S_{B-} = \sqrt{S_{B-}^2} = \sqrt{E\{min[(X-B),0]^2\}} \tag{2}$$

$$S_{B+} = \sqrt{S_{B+}^2} = \sqrt{E\{max[(X-B),0]^2\}} \tag{3}$$

where: S_{B-} is the lower semi-deviation from the benchmark value B; S_{B-}^2 is the lower semi-variance from B; S_{B+} is the upper semi-deviation from B; S_{B+}^2 is the upper semi-variance from B; E is the expectation operator; X is a random variable.

In Eq. (1), the S_{B-}^2 decreases the expected value, according to the level of risk of the strategy and the decision maker's risk aversion (c_{dr}); while the S_{B+}^2 increases the expected value, in accordance with the upside potential of the strategy and the decision maker's corresponding expectations (c_{up}). Attitudes can also be modeled with tolerance levels to each domain of uncertainty, where $\tau = 1/c$. When $\tau \to \infty$, decisions are based on expected value.

The benchmark (B) is defined by the decision maker, depending solely on his/her definition of loss and gain. A fair comparison uses the same benchmark for all production strategies. Santos et al. [25] used the CPS with maximized EV as the reference and its EV as the benchmark. Santos and Schiozer [30] used the EMV of the production strategy without further information acquisition as benchmark.

Following the proposal by Santos et al. [25] and the application to EVoI by Santos and Schiozer [30], EVoF is given by Eq. (4). EVoF as the expected increase in EMV ($EVoF = EMV_{with\,flexibility} - EMV_{without\,flexibility}$) is a particular case of Eq. (4) (c_{dr}=c_{up}=0).

$$EVoF = \varepsilon(NPV)_{with\,flexibility} - \varepsilon(NPV)_{without\,flexibility} \tag{4}$$

3. Case Study

We applied our methodology to the benchmark reservoir model UNISIM-I-D [31], a case study for selection of production strategy. UNISIM-I-D is a sandstone oil reservoir located 80 km offshore. The field, based on the Namorado Field in Campos Basin, Brazil, is in the development phase, with four years of initial production for four vertical producing wells. The reservoir depth varies between 2900 m and 3400 m and the water depth is 166 m. The recovery mechanism for this reservoir is waterflooding. The simulation model has a corner point grid with 81x58x20 cells measuring 100x100x8 m, in a total of 36,739 active cells (Fig. 2).

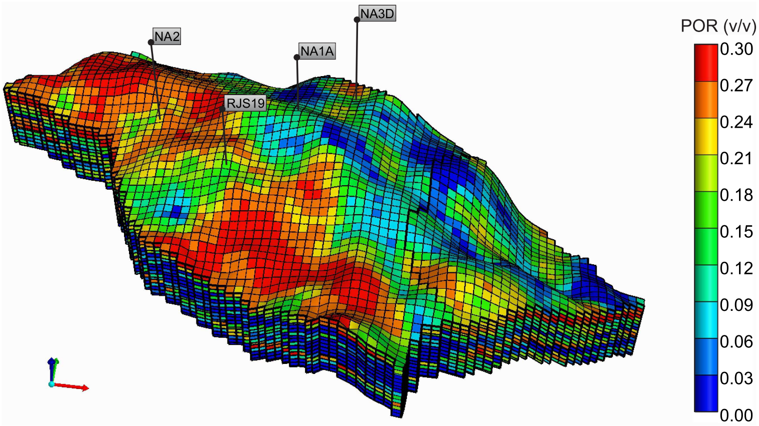

Figure 2: Porosity map of UNISIM-I-D reservoir model, including the position of the four producers already drilled.

UNISIM-I-D has a set of reservoir (Table 1), operational (Table 2), and economic uncertainties. As we focused on flexibility to manage reservoir uncertainties, we considered a deterministic economic scenario (Table 3). The reservoir has two regions separated by a fault, the High block and the East block. The absence or presence of the East block is a key uncertainty affecting production strategy selection because the presence of hydrocarbons in this region has not yet been proven.

The platform investment (Inv_{plat}), in US$ millions, is given by Eq. (5) [31] where, Q_o is the oil processing capacity (1000 m^3/day), Q_w is the water processing capacity (1000 m^3/day), Q_{wi} is the water injection capacity (1000 m^3/day), and n is the number of well slots.

$$Inv_{plat} = 417 + (16.4 * Q_o + 3.15 * Q_w + 3.15 * Q_{wi} + 0.1 * n) \tag{5}$$

The initial investment of a flexible platform ($Inv_{flex\,plat}$) is given by Eq. (6) [18], which considers a premium (Δ) paid to prepare the system for expansion. The cost of expansion from the initial capacity ($Inv_{plat,\,initial\,capacity}$) to the expansion capacity ($Inv_{plat,\,expansion\,capacity}$) is given by Eq. (7) [18], were α is the cost relationship between installing the expansion before and after production has started. In this case study, we use Δ=US$ 10 million and α=1.6 as suggested by Marques et al. [18] for a similar case study.

$$Inv_{flex\,plat} = Inv_{plat} + \Delta \tag{6}$$

$$Expansion\,cost = \alpha * (Inv_{plat,\,expansion\,capacity} - Inv_{plat,\,initial\,capacity}) \tag{7}$$

We calculated the NPV using a simplified net cash flow formulation based on the Brazilian R&T fiscal regime (Eq. (8)) where, NCF is the net cash flow; R is the gross revenue; Roy is the amount paid in royalties; ST is the amount paid in social taxes; OPEX are operational expenditures; T is the corporate tax rate; CAPEX are investments on equipment and facilities; and AC are abandonment costs.

$$NCF = [(R - Roy - ST - OPEX) * (1 - T)] - CAPEX - AC \tag{8}$$

In this application, we used a fictitious decision maker with the same attitudes as that described by Santos and Schiozer [30] for EVoI assessment applied to the development of UNISIM-I-D. The decision maker is averse to downside risk (τ_{dr} = US$ 700 million) and willing to exploit upside potential (τ_{up} =

US$ 700 million). For the semi-deviation calculation, we set the benchmark as the expected monetary value (EMV) of the best candidate production strategy without flexibility. The EMV is given by the sum of the NPV of each scenario weighted by its respective probability.

Table 1: Reservoir uncertainties from UNISIM-I-D case study, with updated probabilities after history-matching procedures.

Attribute	Description	Type	Value (probability)				
			-2	-1	0	+1	+2
img	Petrophysical properties	discrete [realization]	214 geostatistical realizations of one geological scenario for porosity, permeability, and net-to-gross ratio (0.0047)				
kr	Water relative permeability	discrete [table]	(0.08)	(0.19)	(0.42)	(0.19)	(0.13)
pv	PVT data[a]	discrete [table]	-	(0.34)	(0.33)	(0.34)	-
bl	Structural model	discrete [map]	-	No east block (0.31)	With east block (0.69)	-	-
wo	Water-oil contact[a]	continuous[b] [scalar]	3074 m (0.248)	3124 m (0.341)	3174 m (0.121)	3224 m (0.173)	3274 m (0.117)
cp	Rock compressibility	continuous[b] [scalar]	-	23.6x10^{-6} cm^2/kgf (0.12)	53.0x10^{-6} cm^2/kgf (0.66)	82.4x10^{-6} cm^2/kgf (0.22)	-
kz	Vertical permeability	continuous[b] [scalar]	0.475 (0.12)	0.949 (0.19)	1.500 (0.25)	2.051 (0.23)	2.525 (0.21)

[a] East block. [b] Discretized.

Table 2: Operational uncertainties of UNISIM-I-D case study.

Attribute	Description	Type	Value (probability)		
			-1 (0.33)	0 (0.34)	+1 (0.33)
ogr	Group availability	continuous discretized	0.91	0.96	1.00
opl	Platform availability	continuous discretized	0.90	0.95	1.00
opw	Producer well availability	continuous discretized	0.91	0.96	1.00
oiw	Injection well availability	continuous discretized	0.92	0.98	1.00
ff	Well index multiplier	continuous discretized	0.70	1.00	1.40

Table 3: Deterministic economic scenario of UNISIM-I-D case study.

Type	Attribute (unit)	Value
Market variables	Oil price (US\$/m^3)	314.50
	Discount rate (%)	9.00
Taxes	Royalties (%)	10.00
	Social taxes (%)	9.25
	Corporate taxes (%)	34.00
OPEX	Oil production (US\$/m^3)	62.90
	Water production (US\$/m^3)	6.29
	Water injection (US\$/m^3)	6.29
	Abandonment (US\$ millions) (% of well investment)	8.20
CAPEX	Horizontal well drilling and completion (10^3 US\$/m)	61.17
	Vertical well drilling and completion (US\$ millions)	21.67
	Well - platform connection (US\$ millions)	13.33

4. Results

We followed on from the application of Schiozer et al. [27] of UNISIM-I-D, and used results from their work as follows: (1) a set of 214 equiprobable scenarios that matches production data, combining reservoir and operational uncertainties; (2) a set of nine rigid candidate production strategies (S1 to S9) (Table 4), optimized deterministically for nine representative models; and (3) the production strategy S9, previously chosen as the best under uncertainty.

Table 4: Characteristics of the 9 candidate rigid production strategies. Prod.: number of producing wells; Inj.: number of water injection wells.

Production	Wells in High block			Wells in East block			Total	Platform (1000 m^3/day)			
Strategy	Prod	Inj	Total	Prod	Inj	Total	Wells	Q_l	Q_o	Q_w	Q_{wi}
S1	10	5	15	2	1	3	18	16.3	16.3	9.1	23.3
S2	8	5	13	2	1	3	16	16.3	16.3	11.2	22.8
S3	9	5	14	0	0	0	14	14.0	14.0	9.8	19.5
S4	9	5	14	2	1	3	17	18.2	18.2	11.5	25.5
S5	9	5	14	4	2	6	20	17.8	17.8	10.5	23.8
S6	9	6	15	0	0	0	15	14.3	14.3	7.3	20.6
S7	9	6	15	0	0	0	15	13.2	13.2	5.2	19.5
S8	10	5	15	4	2	6	21	21.7	21.7	14.6	29.8
S9	9	5	14	4	2	6	20	20.2	20.2	9.8	28.2

4.1. Comparing the candidate production strategies

We identified the best candidate production strategy for each scenario individually using a black-oil numerical reservoir simulator (Fig. 3). We used the frequency of each candidate strategy as weight when computing data statistics of decision variables.

The decision variables we considered are number of wells (Figs. 4 and 5), well placement, and platform size (fluid processing and injection capacities, and number of well slots) (Fig. 6). We found major differences in the number of wells in East block, well placement in High block, and platform size, meaning that the value of flexibility must be assessed.

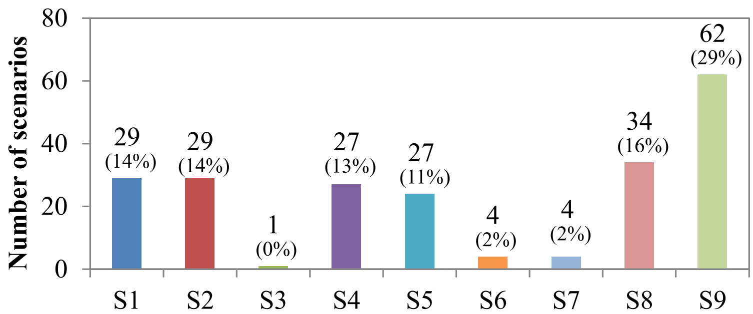

Figure 3: Best production strategy according to the number of scenarios. Bars show the number (and frequency) of scenarios (out of 214) that prefer each candidate production strategy individually.

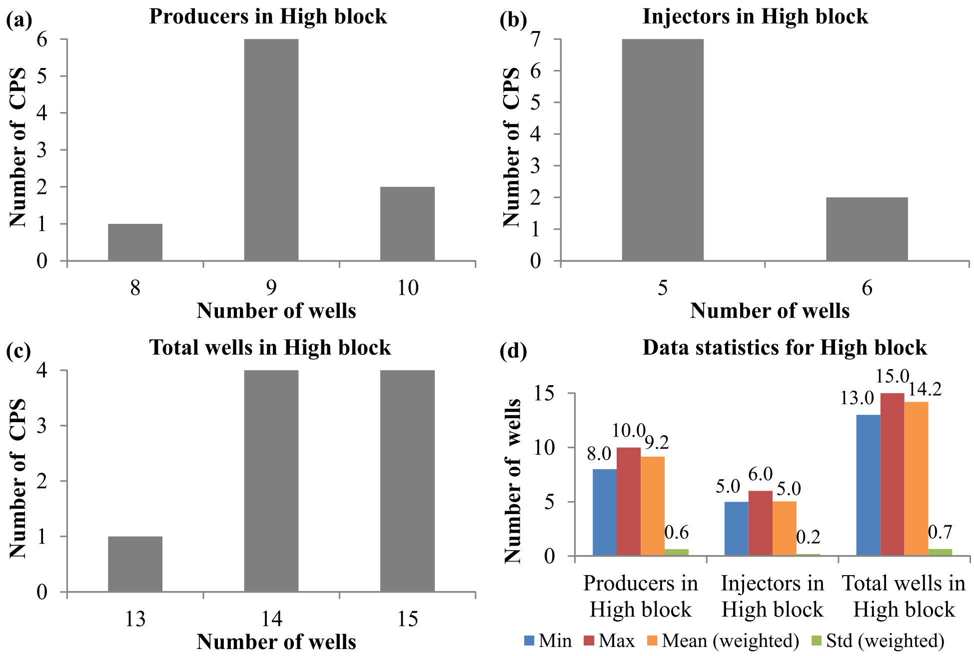

Figure 4: Comparison of candidate production strategies considering number of wells in the High block: (a) number of producers; (2) number of injectors; (c) total number of wells; and (d) data statistics, including minimum (min), maximum (max), mean, and standard deviation (std) of number of wells.

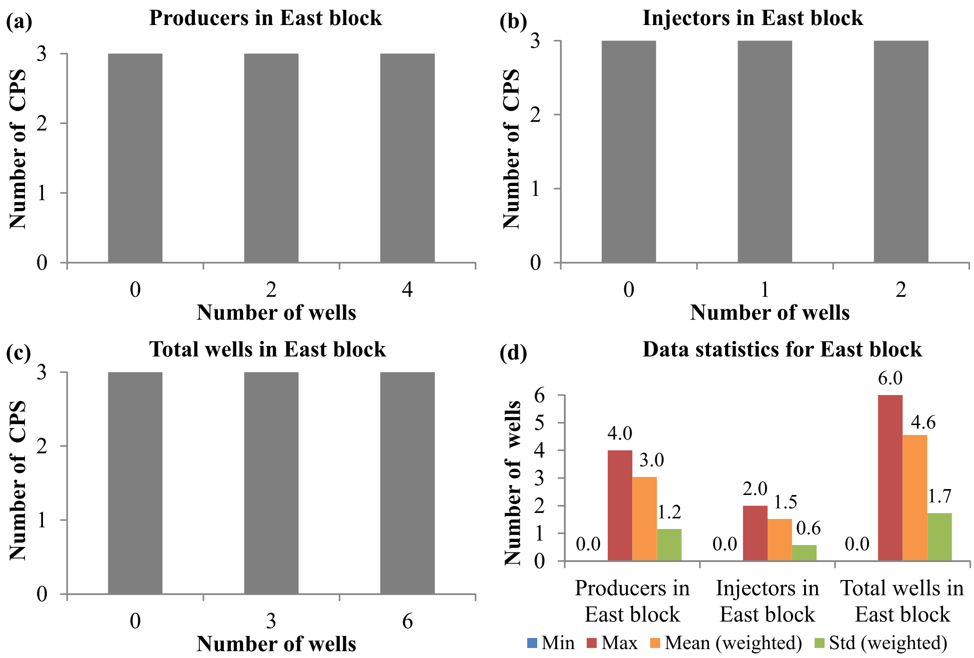

Figure 5: Comparison of candidate production strategies considering number of wells in the East block: (a) number of producers; (2) number of injectors; (c) total number of wells; and (d) data statistics, including minimum (min), maximum (max), mean, and standard deviation (std) of number of wells.

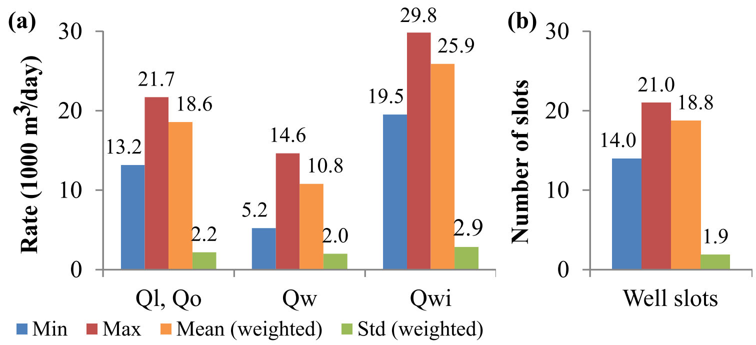

Figure 6: Comparison of candidate production strategies considering platform size: (a) fluid processing capacities for liquid (Q_l), oil (Q_o), water (Q_w) production, and for water injection (Q_{wi}); and (b) number of well slots. Data statistics include minimum (min), maximum (max), mean, and standard deviation (std).

4.2. Defining candidate flexibilities

The number of wells in the High block is not significantly variable (Fig. 4), so it was set as in the robust production strategy: nine producers and five injectors, totaling fourteen wells. As for the number of wells in the East block, one-third of the strategies has no wells in this block, one-third has three wells (two producers and one injector), and the remaining third has six wells (four producers and two injectors) (Fig. 5). Thus, we consider the flexibility to connect additional wells in case the presence of hydrocarbons in this region is proven: three well slots available (allowing the connection of three additional wells), and six well slots available (allowing the connection of up to six additional wells).

The placement of wells in the High block is a key difference between production strategies, and they are placed as in the robust production strategy. The placement of wells in the East block has similarities between the strategies with three wells (S1, S2, S4), and those with six wells (S5, S8, S9). To choose the robust placement of wells for each case, we identified the best strategy for each value the uncertain attributes can take (Table 5).

Platform sizes also differed significantly (Fig. 6), so we added flexibility by starting with smaller capacities to expand as needed. The two possibilities for the initial capacity correspond to the following strategies: (1) S1, the best on average for the subset of models without hydrocarbons in the East block (Table 5); and (2) S7, the smallest platform of the set of strategies (Fig. 6 and Table 4). Two degrees of expansion were considered: (1) up to S8, the largest platform of the set (Fig. 6 and Table 4); and (2) up to S4, the medium-sized platform with capacities close to the mean values (Fig. 6 and Table 4).

Table 5: Best production strategy, based on $\varepsilon(NPV)$, for the subset of scenarios (out of 214) for each level (-2 to +2) of the uncertain attributes *bl* and *wo*.

	bl		**wo**				
	-1	0	-2	-1	0	+1	+2
Best strategy based on $\varepsilon(NPV)$	S1	S9	S1	S9	S9	S9	S9

Table 6 summarizes the proposed candidate flexibilities, while investments and expansion costs are shown in Table 7. Note that the viability of intelligent wells as a flexibility in UNISIM-I-D was already studied by Morais et al. [23], and we did not consider this type of flexibility here. Also note that we applied the same rules for well control as in the CPS, and we did not further optimize these variables.

Table 6: Candidate flexible production strategies.

Candidate flexibility	Flexible attributes	Rigid or pre-established attributes
F1	- Initial platform capacity S1, expandable up to S8 - 3 well slots available for the East block	- Number and placement of wells in High block: S9 - Placement of wells in East block, if present: S1 - Number of well slots: 17
F2	- Initial platform capacity S1, expandable up to S8 - 6 well slots available for the East block	- Number and placement of wells in High block: S9 - Placement of wells in East block, if present: S1 (if 3 wells) or S9 (if 6 wells) - Number of well slots: 20
F3	- Initial platform capacity S7, expandable up to S4 - 6 well slots available for the East block	- Number and placement of wells in High block: S9 - Placement of wells in East block, if present: S1 (if 3 wells) or S9 (if 6 wells) - Number of well slots: 20

Table 7: Platform investment and capacity expansion costs for the candidate flexible production strategies. Values in US$ millions.

Candidate flexibility	Platform investment	Expansion costs
F1	$\text{Inv}_{plat\,S1,\,17\,well\,slots}+\Delta = 797.7$	Capacity S2 = 10.5 Capacity S4 = 74.1 Capacity S5 = 50.4 Capacity S8 = 203.3 Capacity S9 = 129.8
F2	$\text{Inv}_{plat\,S1,\,20\,well\,slots}+\Delta = 798.0$	Capacity S2 = 10.5 Capacity S4 = 74.1 Capacity S5 = 50.4 Capacity S8 = 203.3 Capacity S9 = 129.8
F3	$\text{Inv}_{plat\,S7,\,20\,well\,slots}+\Delta = 723.1$	Capacity S1 = 119.8 Capacity S2 = 127.6 Capacity S4 = 194.7

4.3. Assessing the candidate flexibilities and defining the implementation rules

The first assessment of viability is estimated by means of the maximum value of flexibility, which is calculated by selecting the best action for each scenario, without pre-defining a decision rule. The probabilistic-based decision rule is defined only for the viable candidates.

4.3.1. Candidate flexibility F1

Candidate flexibility F1 is rejected (Fig. 7) because it is less attractive than S9. Despite some risk reduction (-3.9%), F1 recorded lower EMV (-2.5%) and lower upside potential (-19.2%), thus reflecting an expected loss of $\varepsilon(NPV)$ by -5.7%.

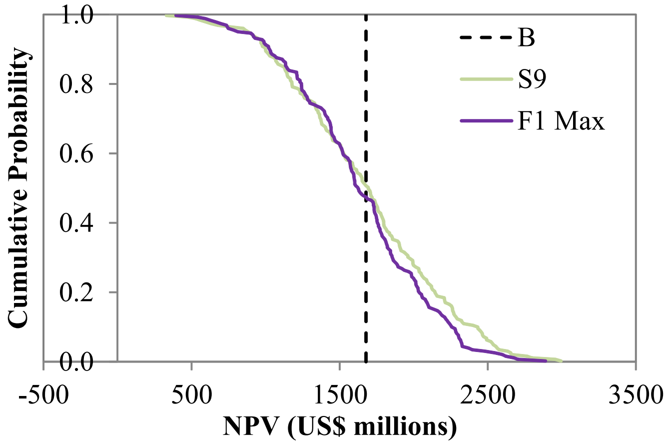

Figure 7: NPV risk curve for the robust production strategy S9 and the candidate flexibility F1 without an established decision rule. The vertical dashed line marks the benchmark separating downside risk from upside potential.

4.3.2. Candidate flexibility F2

Candidate flexibility F2 is accepted because of the potential to increase $\varepsilon(NPV)$ by +10.5%. Before defining the implementation rule, we assessed the percentage of scenarios that implement the candidate flexibility. Many scenarios use all six available well slots, but platform expansion to the highest capacities (S5, S8, S9) is rarely used (Fig. 8). Thus, we modify F2 to consider capacity expansion only up to the medium-sized S4, maintaining six available well slots. The new risk curve for the maximum value of flexibility supports this modification (Fig. 9).

We defined probabilistic-based implementation rules (Table 8) by characterizing the subsets of scenarios that implement each level of flexibility. That is, we analyzed histograms of uncertain attributes, comparing the different subsets of scenarios. Fig. 10 exemplifies analyses of the number of wells.

Risk curves for the case with the maximum value of flexibility and with decision rules are compared (Fig. 11 and Table 9), revealing that the probabilistic rule we defined closely captures the full potential of flexibility F2, with mild limitations in capturing the upsides.

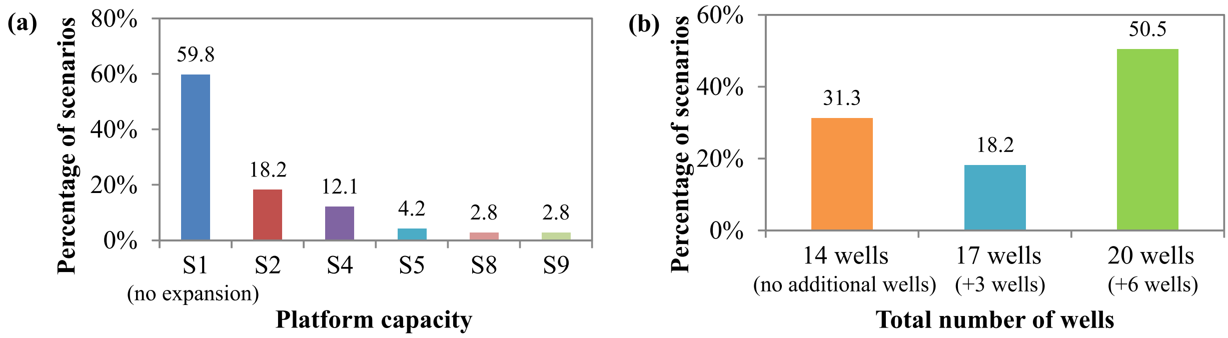

Figure 8: Assessing the percentage of scenarios that implement the flexibility: (a) platform capacity expansion; and (b) additional well slot usage.

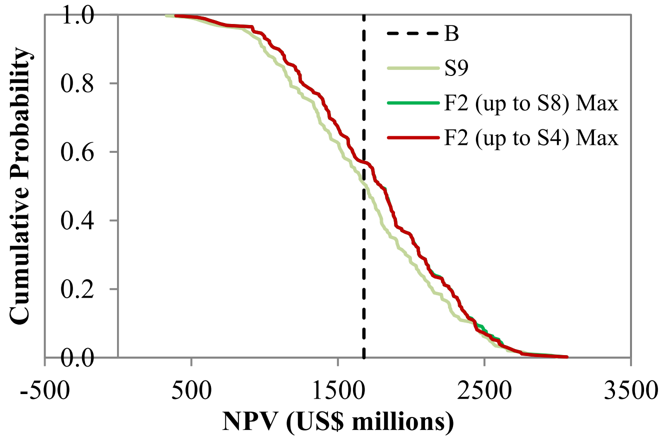

Figure 9: NPV risk curve for the robust production strategy S9 and the candidate flexibility F2 with platform expansion up to S4 and S8, without an established decision rule. The vertical dashed line marks the benchmark separating downside risk from upside potential.

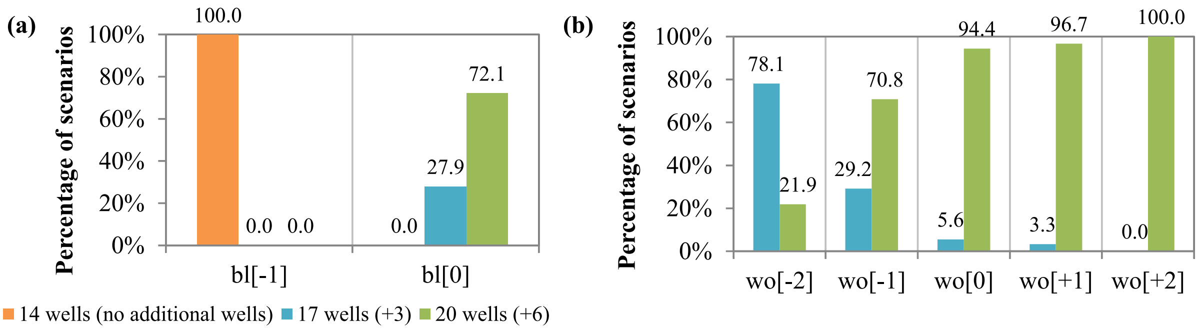

Figure 10: Optimal number of wells according to the attributes: (a) structural uncertainty (*bl*), and (b) water-oil contact (*wo*) in the East block (exclusive to the scenarios with East block, *bl*[0]).

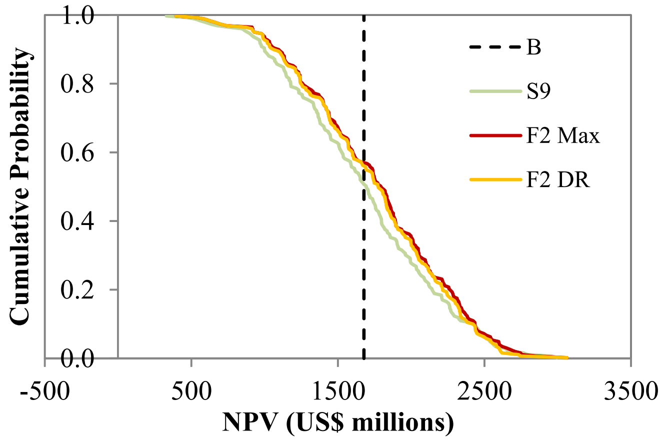

Figure 11: NPV risk curve for the robust production strategy S9 and the candidate flexibility F2 without an established decision rule (Max), and with the probabilistic-based decision rule (DR). The vertical dashed line marks the benchmark separating downside risk from upside potential.

Table 8: Decision rules for candidate flexibility F2.

bl	wo	kr	Platform expansion?	Additional wells?
-1	–	all	No	No
0	-2	-2, -1	No	+3
		0,+1,+2	S2	
	-1,0,+1,+2	-2	No	+6
		-1	S2	
		0,+1,+2	S4	

Table 9: Assessing the candidate flexibility F2 versus robust production strategy S9, considering the maximum value of flexibility (Max) and the probabilistic-based decision rule (DR). Values in US$ millions.

	S9	**F2 Max**		**F2 DR**	
EMV	1677.9	1753.7	+4.5%	1740.0	+3.8%
$\mathbf{S}_{B-}$	369.3	324.7	-12.1%	330.2	-10.6%
$\mathbf{S}_{B+}$	373.6	410.7	+9.9%	391.2	+4.7%
$\varepsilon(NPV)$	1682.4	1844.0	+9.6%	1804.9	+7.3%
EVoF(EMV)		75.8		64.1	
EVoF(ε)		161.6		122.5	

4.3.3. Candidate flexibility F3

Candidate flexibility F3 is accepted because of the potential to increase $\varepsilon(NPV)$ by +8.4%. Similarly to F2, we defined probabilistic-based implementation rules (Table 10) by characterizing the scenarios that used each level of flexibility.

Risk curves for the case with the maximum value of flexibility and with decision rules are compared (Fig. 12 and Table 11), revealing that the probabilistic rules we defined captured the downsides but limited the upsides of flexibility. Positive EVoF is still ensured.

Table 10: Decision rules for candidate flexibility F3.

bl	wo	kr	Platform expansion?	Additional wells?
-1	–	-2,-1,0,+1	No	No
		-2	+2	
0	-2	-2	No	+3
		-1	S1	
		0,+1,+2	S2	+6
	-1,0,+1,+2	-2	S1	
		-1	S2	
		0,+1,+2	S4	

Table 11: Assessing the candidate flexibility F3 versus robust production strategy S9, considering the maximum value of flexibility (Max) and the probabilistic-based decision rule (DR). Values in US$ millions.

	S9	**F3 Max**		**F3 DR**	
EMV	1677.9	1748.0	+4.2%	1718.3	+2.4%
$\mathbf{S}_{B-}$	369.3	318.0	-13.9%	329.4	-10.8%
$\mathbf{S}_{B+}$	373.6	392.2	+5.0%	366.7	-1.8%
$\varepsilon(NPV)$	1682.4	1823.4	+8.4%	1755.4	+4.3%
EVoF(EMV)		70.2		40.4	
EVoF(ε)		140.9		72.9	

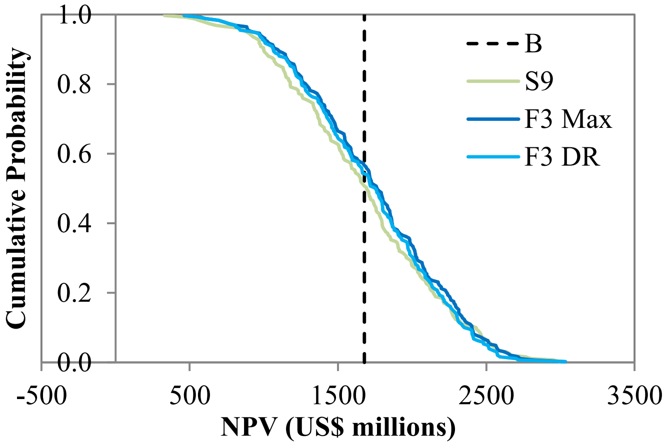

Figure 12: NPV risk curve for the robust production strategy S9 and the candidate flexibility F3 without an established decision rule (Max), and with the probabilistic-based decision rule (DR). The vertical dashed line marks the benchmark separating downside risk from upside potential.

4.4. Selecting the best candidate flexible production strategy

Candidates F2 and F3 with decision rules are feasible, but F2 is the best (Tables 9 and 11). Platform capacity expansion is installed in 51% of the scenarios (Fig. 13a), with 69% usage of the additional well slots (Fig. 13b), and F2 recording an EVoF of US$ 123 million.

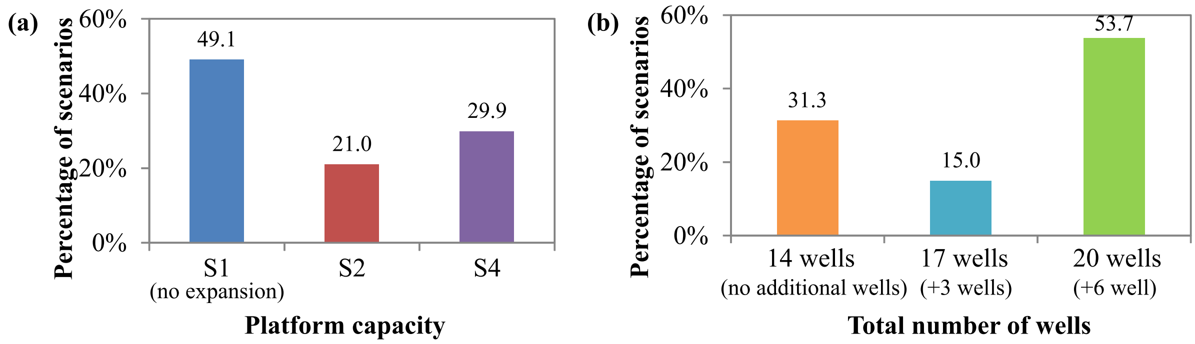

Figure 13: Assessing the percentage of scenarios that implement the flexibility F2: (a) platform capacity expansion; and (b) additional well slot usage.

4.5. Assessing the effects of delays in the implementation time

The results presented so far assumed that flexibility could be implemented immediately following the installation of the initial production strategy (t_1) (initial platform capacities and wells in the High block), i.e., 1.5 years after the beginning of production. We then considered a one-year delay (t_2) and a two-year delay (t_3), revealing that delays in implementation decrease the value of flexibility, and may completely negate this value (Fig. 14 and Table 12).

Table 12: Assessing the effects of delays in implementation time for flexibility F2 versus robust production strategy S9.

	S9	**F2 DR t1**		**F2 DR t2**		**F2 DR t3**	
EMV	1677.9	1742.0	+3.8%	1716.5	+2.3%	1688.2	+0.6%
$\mathbf{S}_{B-}$	369.3	330.2	-10.6%	333.9	-9.6%	338.3	-8.4%
$\mathbf{S}_{B+}$	373.6	391.2	+4.7%	364.7	-2.4%	336.3	-10.0%
$\varepsilon(NPV)$	1682.4	1804.9	+7.3%	1747.2	+3.9%	1686.3	+0.2%
EVoF(EMV)		64.1		38.6		10.3	
EVoF(ε)		122.5		64.8		3.9	

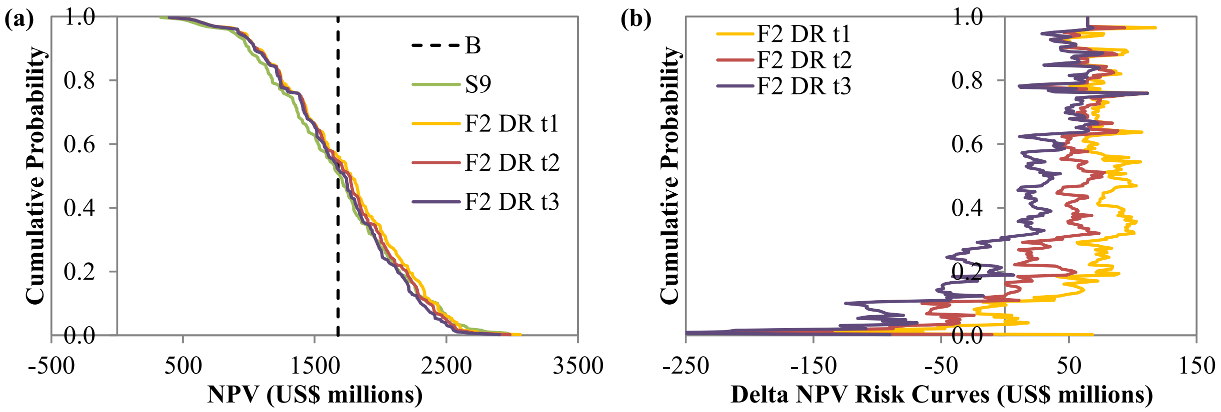

Figure 14: (a) NPV risk curve for the robust production strategy S9 and the candidate flexibility F2 implemented at different times; the vertical dashed line marks the benchmark separating downside risk from upside potential. (b) Difference between the NPV risk curves for F2 implemented at different dates and the NPV risk curve for S9.

5. Discussion

Our proposal is based on the concept of representative models and uses a predefined set of candidate production strategies optimized deterministically for these models. This is only possible if an adequate RM selection is guaranteed, ensuring that both system inputs (uncertain attributes) and outputs (production, injection, and economic forecasts) are represented. If the set of RM represents the system, the set of production strategies provide decision makers with the different possibilities to develop the field, including well number and placement, and platform processing capacities. Decision makers have an objective assessment of how different (and similar) these alternatives are and their characteristics, reducing the subjectivity in defining a flexible system. Previous studies suggest that around nine RM are sufficient for production strategy selection [27, 32], but we recommend additional research on the optimal number of RM and candidate production strategies applied to EVoF analyses.

Our comparison of candidate production strategies was a manual process. To enable automation of this step, we recommend research on quantitative indicators to compare the CPS, namely for well placement. In this way, defining candidate flexible production strategies can become a fully automated procedure.

A key challenge when choosing a flexible strategy is defining the implementation rules. A prime advantage of our methodology is that it does not apply pre-defined rules as inputs, thus eliminating biases and ensuring more objective decision rules. However, the decision rules we established did not capture the full potential of all flexibilities. This may be attributed to difficulties in identifying the dominant reservoir uncertainties affecting production strategy, namely the effects of geostatistical realizations, and further research is recommended on indicators to improve this analysis.

Because we used hundreds of scenarios, we ensured more accurate estimates of flexibility values. This is key because, as the difference between two expected values, EVoF is highly sensitive and susceptible to errors. However, this approach made defining the decision rules computationally demanding, requiring hundreds of flow simulation runs. Future research is recommended on assessing the feasibility of defining the probabilistic analyses based on the small subset of representative models, each characterized by a probability of occurrence.

In our case study, risk curve analyses showed that flexibility is important to reduce risk (-10.6% in our case study), but also improves the upside potential (+4.7% in our case study). However, the flexible production strategy records a mild expected increase in EMV (+3.8%), meaning that using the EMV alone tended to underestimate the potential of flexibility. Conversely, when we considered delays in implementation, we recorded strong compromises of the upside potential (up to -10.0%), while positive EMV was still recorded (+0.6%). In this case, EMV overestimated the EVoF. Thus, our proposal ensured a more quantitative EVoF estimate.

Our results showed that many factors affect EVoF. We defined decision rules according to the different values the uncertain reservoir attributes took, in other words, the decision to implement is based on knowledge gained over time. We may have overestimated the EVoF because we did not consider imperfect information; the EVoF may have also be underestimated because we used a simplified approach for well control. We also demonstrated that if it takes too long to learn about the reservoir, or if logistics prevent an early implementation, the EVoF decreased to the point that it was of no value. Accordingly, accounting for all factors that may affect EVoF ensures improved estimates of the value of flexibility, and so improves decisions.

6. Conclusions

We proposed a decision structure to objectively define a flexible production strategy to manage reservoir uncertainty in petroleum field development. Our methodology (1) used a predefined set of rigid candidate production strategies to define the flexible strategy, (2) established probabilistic-based implementation rules, and (3) applied an objective-function that improved the EVoF calculation by accounting for the purpose of flexibility, to mitigate risks or to exploit the upsides of uncertainty. Specific conclusions of this work include:

- Efficient representative model selection and optimization allows basing analyses on a predefined set of candidate production strategies;
- Defining the flexible strategy based on a set of candidate rigid strategies reduces the subjectivity of decisions and eliminates prior misconceptions and bias toward particular flexibilities;
- Implementation rules can be defined objectively using the reservoir simulation outputs for multiple uncertain scenarios;
- Accounting for all changes in risk curves (increased EMV, reduced downside risk, and increased upside potential) improves the EVoF estimate, which cannot be ensured by the EMV alone;
- Delayed implementation decreases EVoF to a point where flexibility may lose its value.

Acknowledgments

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8. ARTICLE 7: MANAGING UNCERTAINTY IN PETROLEUM FIELD DEVELOPMENT CONSIDERING INFORMATION, ROBUSTNESS, AND FLEXIBILITY

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Managing uncertainty in petroleum field development considering information, robustness, and flexibility

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Abstract

Costly development decisions for petroleum fields, based on multiple variables with high levels of uncertainty, are complex. Actions to manage uncertainty include acquiring information to reduce uncertainty and protecting the system with flexibility or robustness. Although often preferred, acquiring additional information may be inadequate to mitigate all uncertainties. Thus, system protection with flexibility or robustness may be advantageous. This study proposes a decision structure to quantitatively estimate the best approach to manage uncertainty considering information, robustness, and flexibility combined. Our methodology uses a predefined set of candidate production strategies optimized for representative models, eliminating the need for extensive optimization procedures and automating analyses. We assess system sensitivity to uncertainty and the uncertainties controlling production strategy selection using the candidate strategies to identify potential improvements with information, robustness, or flexibility. Finally, we apply a function to improve estimation of the expected value of information (EVoI), robustness (EVoR), and flexibility (EVoF) accounting for all changes in the risk curve and weighing the decision maker's attitude. Our proposal is a good starting point for more quantitative and objective decision-making at early stages of field development and ultimately prevents discarding attractive solutions based on biases or inadequate metrics. Some improvements may be necessary in the EVoI, EVoR, and EVoF estimates depending on the stage of the lifetime of the field.

Keywords: uncertainty management, information, robustness, flexibility, field development, reservoir simulation

1. Introduction

The decisions related to the development of petroleum fields are complex. When selecting a production strategy, multiple decision variables are defined, including (1) number and placement of wells, (2) well-opening schedule, (3) recovery mechanism, (4) platform number, and (5) fluid processing capacities. Because of challenges in reservoir characterization, and since developing petroleum fields are long-term projects, endogenous and exogenous uncertainties typically coexist when development decisions are made. The most common uncertainties include (1) reservoir uncertainties, associated with recoverable reserves and flow characteristics, (2) operational uncertainties, related to system availability, and (3) economic uncertainties, related to market variables, capital expenditure, and operational expenditures.

To maximize project value, decision makers should quantify and manage the effects of uncertainty, either to mitigate risks or exploit upsides. Actions to manage uncertainty include (1) acquiring additional information to reduce reservoir uncertainty, (2) defining a flexible production system that allows system modifications as uncertainties unfold over time, and (3) defining a robust production strategy able to cope with uncertainty without requiring system modifications after production has started. That is, uncertainty

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can be managed by reducing the uncertainty itself or by protecting the system, with reduced sensitivity to uncertainty. These approaches are well documented in the engineering literature [1, 2, 3], but methods used in the petroleum industry are still immature.

The decision to collect additional information should be based on the quantitative Expected Value of Information (EVoI) analyses, because reducing uncertainty or increasing confidence in a decision has no value in itself. To add value, the information must: change our understanding of the uncertain attribute, have the potential to influence a decision that would be made otherwise, and cost less than its value [4, 5]. Estimating information reliability is a challenge, and strongly affects EVoI. The term "information" is typically used in a broad sense and commonly refers to acquiring data, namely seismic surveys [6], well testing [7], and drilling appraisal wells [8]. The term also covers performing technical studies, hiring consultants, and performing diagnostic tests [5].

The attractiveness of flexibility arises from the options available over time [9, 10], allowing active reactions based on the knowledge gained over time. The Expected Value of Flexibility (EVoF), an approach similar to that of EVoI, was proposed to base the decision to invest in a flexible system [11]. The EVoF analysis takes into account the additional upfront investments of a flexible system and the cost of implementing the flexibility. Examples of flexible production systems include platform capacity expansion [12], modularity [13], intelligent wells [14], flexible subsea layouts [15], and the ability to redistribute injection quotas or switch the injected fluid [16].

A robust production strategy is insensitive to uncertainties, meaning that system modifications are unnecessary to ensure good performance over time. Robust Optimization has become increasingly preferred over deterministic optimization [17, 18, 19]. However, the robustness of a deterministically-optimized production strategy can also be increased using probabilistic-based indicators [20]. Moczydlower et al. [16] calculated the Expected Value of Robustness (EVoR) in an approach similar to that of the EVoI and EVoF. A textbook example of robustness is the placement of producers and injectors in relation to a fault to cope with uncertainty in fault transmissibility [21].

1.1. Scope and objectives

Despite the growing interest in flexibility and robustness, uncertainty in petroleum field development is commonly managed with additional information [5]. According to Bratvold et al. [5], the bias toward information acquisition is because decision makers tend to believe that more data is better, without always analyzing economic viability. Many factors make information value difficult to quantify, namely its ability to reveal "unknown unknowns" (i.e. uncertainties not yet identified). However, additional information at early stages of the field lifetime may be inadequate to mitigate all uncertainties affecting production strategy selection. In such contexts, system protection with flexibility and robustness may be advantageous.

The choice between information and flexibility is debated in the literature [10, 11, 22]. Flexibility is said to be considered when (1) acquiring information is impossible, (2) the EVoI is small or the acquisition cost is too high, (3) managing residual uncertainty after information acquisition, and (4) flexibility creates additional value by exploiting potential upsides of uncertainty. Flexibility may also be attractive in cases of multiple uncertainties affecting production strategy selection, where robust solutions may be insufficient to cope with the possible scenarios.

Few studies consider information, robustness, and flexibility combined [16], and typically present decisions made in the development of real fields, without introducing general methodologies.

The decision on whether and how uncertainty is best managed should be based on comprehensive analyses and quantitative criteria to maximize project value. The decision structure we present here considers information, robustness, and flexibility as complementary actions to manage uncertainty, incorporating (1) the characteristics of the field, namely the type of uncertainties, (2) the available resources and costs, and (3) the decision maker's attitude and objectives.

2. Methodology

This work is integrated into the twelve-step decision analysis framework by Schiozer et al. [23], which covers all stages of field development and management, and integrates reservoir characterization under uncertainty, reservoir simulation, history matching, uncertainty reduction, representative models, and production strategy optimization.

The twelve steps are summarized as follows: (1) reservoir characterization under uncertainty, (2) construction and calibration of the simulation base model, (3) verification of inconsistencies in the base model using dynamic well data, (4) generation of scenarios considering the full range of uncertainties, (5) reduction of scenarios using dynamic data, (6) selection of a deterministic production strategy using an optimization procedure, (7) initial risk assessment, (8) selection of representative scenarios based on multiple objective functions and the full range of uncertain parameters, (9) selection of a production strategy for each representative scenario (as in Step 6), (10) selection of the best production strategy from the set of candidate strategies (obtained in Step 9), (11) identification of potential for changes in the best strategy to mitigate risk or increase value (e.g. information, flexibility, and robustness) and integration with production facilities, and (12) final risk assessment. Note that a scenario is treated here as a particular combination of all uncertain attributes.

The decision structure we propose (Fig. 1) sets the course of action for Step 11, assessing the potential for information, robustness, and flexibility to manage uncertainty. Once identified, we apply the methods developed individually in previous studies for information [24], robustness [20], and flexibility [25].

The inputs for our workflow come from previous steps in the framework by Schiozer et al. [23]: (1) uncertain scenarios that match production data, (2) candidate production strategies (CPS), and (3) production and economic indicators from probabilistic forecasts obtained from numerical reservoir simulation. We use the forecasts of the multiple scenarios that match production data to construct risk curves. Note that risk curves are also referred to in the statistics literature as descending or complementary cumulative distribution functions.

2.1. Candidate production strategies

To reduce the subjectivity of decision making, we use a predefined set of candidate production strategies (CPS), each one optimized deterministically (in Step 9) for one representative model (RM).

A set of RMs is chosen from all scenarios that match production data, using the proposal by Meira et al. [26, 27], which combines a mathematical function to capture the representativeness of a set of models with a metaheuristic optimization algorithm. This approach ensures that the set of RMs represents both the probability distribution of the input variables (uncertain attributes), so that all attributes and all the uncertain levels are represented; and the variability of the main output variables (production, injection, and economic forecasts).

As the RMs represent the uncertain system, their respective production strategies provide decision makers with the different solutions for field development. In this context, deterministically optimizing each RM is advantageous because it is not limited to the most-likely scenario, meaning that it is part of a probabilistic process.

Decision makers compare the CPS, looking at the values for each decision variable (e.g. number of wells, well placement, platform capacities). If the CPS are similar (i.e., no significant differences are recorded), the best candidate is chosen using the criteria described in subsection §2.5 and no further action is needed. However, if significantly different, actions may be taken to mitigate risks or exploit upsides.

2.2. Assessing system sensitivity to uncertainty

Additional information or system protection against uncertainty is required only when production strategy selection is sensitive to uncertainty. The preferred course of action depends on the type of uncertainty controlling production strategy selection, which we identify using the production forecasts of the CPS under uncertainty.

A one-factor-at-a-time (OFAT) sensitivity analysis isolates the effects of each attribute, indicating the best strategy for each value the uncertain attributes can take. Analyzing the multiple scenarios that match

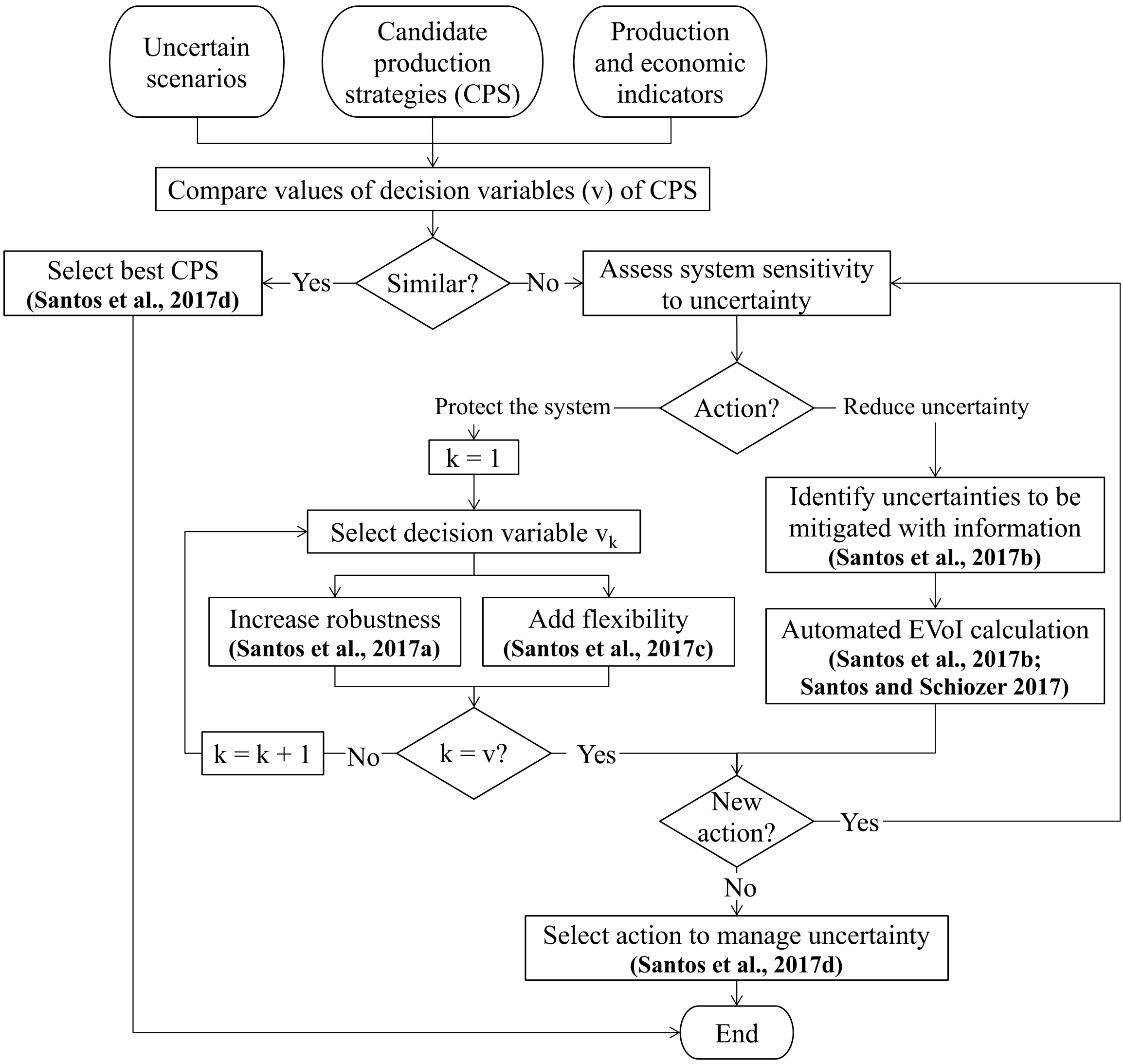

Figure 1: Workflow to manage uncertainty in petroleum field development considering information, robustness, and flexibility.

production data illustrates the effects of interactions between parameters, indicating the best strategy, on average, for each subset of scenarios that have each value the uncertain attributes can take.

Information has useful potential when one or more reservoir attributes strongly affect CPS selection, and information sources exist that can clarify such uncertainties. However, note that uncertainty in the spatial distribution of porosity, permeability and net-to-gross ratio, preferably represented by multiple geostatistical realizations, may be difficult to manage with information. If this uncertainty dominates CPS selection, robust well placement should be considered.

System protection with flexibility has reactive potential in cases of significant economic uncertainty or the combined effects of multiple reservoir attributes, situations where waiting and reacting as uncertainties unfold over time is economically better. This is because additional information at early stages of the field lifetime may be insufficient to improve decisions, and robust solutions inadequate to cope with the multiple possible scenarios.

2.3. Reducing uncertainty

We apply the methodology proposed by Santos et al. [24]. First, we identify reservoir uncertainties that can be mitigated with information using four indicators: (1) impact on the performance of the field, (2) potential to reduce uncertainty, (3) potential to modify the decision, and (4) likelihood of the available information to define the uncertain attribute. The EVoI analysis, which focuses on parameters with high potential, is automatic because it is based on the predefined set of candidate production strategies. That is, we select the best candidate strategy for the set of uncertain scenarios with updated probabilities, without requiring further optimization or reservoir simulation. In this proposal, EVoI is determined using many uncertain scenarios to maintain interactions between parameters, instead of deterministically isolating the uncertain attribute for analysis.

2.4. Protecting the system

Increased robustness and added flexibility protect systems against uncertainty. We followed Santos et al. [20] to define a robust production strategy (§2.4.1) and Santos et al. [25] to define a flexible production strategy (§2.4.2).

2.4.1. Protecting the system with robustness

Robustness is assessed and increased based on performance analyses of the best candidate production strategy over all possible scenarios, refined to reduce sensitivity to uncertainty. Probabilistic indicators are computed using the simulation results for the set of uncertain scenarios, assessing well and platform performance under uncertainty. Indicators include (1) probability of wells placed in unfavorable positions and not producing or injecting, (2) variability in well performance, and (3) probabilistic percentage of the prediction period that the platform capacities are utilized. Robustness of well placement is improved using probabilistic maps of mean and standard deviation of the reservoir static and dynamic properties (porosity, permeability, net-to-gross ratio, and oil saturation).

2.4.2. Protecting the system with flexibility

Flexibility is added in an iterative procedure that processes each decision variable, as proposed by Santos et al. [25]. If the decision variable was defined similarly in all CPS, it is defined as in the robust production strategy. Conversely, we take the different possibilities as candidate flexibilities, except if the decision variable is inflexible (e.g. well placement), and we thus set it as in the robust production strategy.

We use the hypothetical maximum value of flexibility to define probabilistic-based implementation rules of flexibility, as proposed by Santos et al. [25]. That is, we obtain production, injection, and economic forecasts for all scenarios, and select the best action for each scenario individually (i.e., whether or not flexibility should be implemented, and the level and type of implementation). So at this stage, EVoF is estimated without defining a decision rule.

Then, we use these simulation outputs to set the decision rules. We group subsets of scenarios of each preferred action and analyze their histograms for all reservoir uncertainties. Comparing the histograms between the subsets and the full set of scenarios, we identify the dominant uncertainty controlling each level of implementation. So we set the decision rules according to the reservoir uncertainties that control the preference for each implementation.

2.5. Evaluating production strategies and determining the expected value of information, robustness, and flexibility

Information, robustness, and flexibility typically incur additional investment and may delay production, which should be included in the EVoI, EVoR, and EVoF calculations to check the incurred costs do not outweigh any benefits. These are often calculated as the expected increase in expected monetary value (EMV) [11, 16, 28, 29], which has the drawbacks of strong risk reductions or increased upside potential not reflecting a significant increase in EMV. Thus, estimating EVoI, EVoR, and EVoF based only on EMV may underestimate the value of these investments.

Santos et al. [30] overcomes this underestimation by combining expected value (EV), downside risk, and upside potential (Eq. (1)) to determine the value of the production strategy adjusted to the decision maker's attitude, $\varepsilon(X)$, while maintaining the units and dimension of X. This function is applicable to production and economic indicators, and we apply it to the net present value (NPV).

$$\varepsilon(X) = E[X] - c_{dr}S^2_{B-} + c_{up}S^2_{B+} = E[X] - \frac{S^2_{B-}}{\tau_{dr}} + \frac{S^2_{B+}}{\tau_{up}} \tag{1}$$

where: $\varepsilon(X)$ is the value of the production strategy adjusted to the decision maker's attitude; $E[X]$ is the expected value of random variable X; S^2_{B-} and S^2_{B+} are the lower and upper semi-variance from benchmark B, respectively; c_{dr} is the aversion coefficient to downside risk; c_{up} is the expectation coefficient to upside potential; τ_{dr} and τ_{up} are the tolerance (or indifference) levels to downside risk and upside potential, respectively.

Semi-deviation (short for semi-standard deviation) from a benchmark or target return (B) measures subsets of standard deviation and differentiates good variability from bad. Lower semi-deviation (Eq. (2)) quantifies downside risk, while upper semi-deviation (Eq. (3)) quantifies upside potential.

$$S_{B-} = \sqrt{S^2_{B-}} = \sqrt{E\{min[(X-B),0]^2\}} \tag{2}$$

$$S_{B+} = \sqrt{S^2_{B+}} = \sqrt{E\{max[(X-B),0]^2\}} \tag{3}$$

where: S_{B-} is the lower semi-deviation from the benchmark value B; S^2_{B-} is the lower semi-variance from B; S_{B+} is the upper semi-deviation from B; S^2_{B+} is the upper semi-variance from B; E is the expectation operator; X is a random variable.

In Eq. (1), the S^2_{B-} decreases the expected value, in accordance with the level of risk of the production strategy and decision maker's risk aversion (c_{dr}); while the S^2_{B+} increases the expected value, in accordance with the upside potential of the production strategy and the decision maker's corresponding expectations (c_{up}). Attitudes can also be modeled with tolerance levels to each domain of uncertainty, where $\tau = 1/c$. When $\tau \to \infty$, decisions are based on expected value.

The benchmark (B) is defined by the decision maker as it depends solely on his/her definition of loss and gain. All production strategies use the same benchmark for impartiality. Santos et al. [30] used the CPS with maximized EV as the reference and its EV as the benchmark, while Santos and Schiozer [31] used the EMV of the production strategy without information, and Santos et al. [25], the EMV of the production strategy without flexibility. In this work, we use the EMV of the best CPS before considering information, robustness, and flexibility to manage uncertainty.

Using Eq. (1) to evaluate production strategies, EVoI, EVoR, and EVoF become Eq. (4), (5), and (6), respectively.

$$EVoI = \varepsilon(NPV)_{with\,information} - \varepsilon(NPV)_{without\,information} \tag{4}$$

$$EVoR = \varepsilon(NPV)_{with\,robustness} - \varepsilon(NPV)_{without\,robustness} \tag{5}$$

$$EVoF = \varepsilon(NPV)_{with\,flexibility} - \varepsilon(NPV)_{without\,flexibility} \tag{6}$$

3. Case Study

We applied our proposed method to the benchmark reservoir model UNISIM-I-D [32], a case study for production strategy selection. UNISIM-I-D is a sandstone oil reservoir located 80 km offshore. The field, based on the Namorado Field in Campos Basin, Brazil, is in the development phase, with four four years of initial production for four vertical producing wells. The reservoir depth varies between 2900 m and 3400 m and the water depth is 166 m. The recovery mechanism for this reservoir is waterflooding. The simulation model has a corner point grid with 81x58x20 cells measuring 100x100x8 m, in a total of 36,739 active cells (Fig. 2). UNISIM-I-D has a set of reservoir (Table 1), operational (Table 2), and economic uncertainties (Table 3). The reservoir has two regions separated by a fault, the High block and the East block. The absence or presence of the East block is a key uncertainty affecting production strategy selection because the presence of hydrocarbons in this region has not yet been proven.

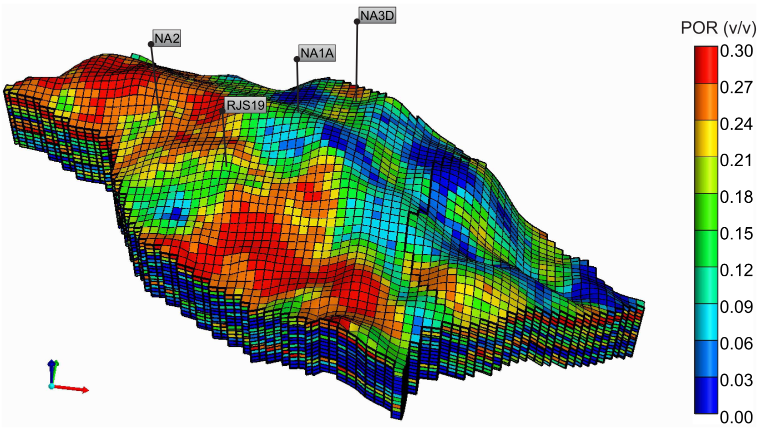

Figure 2: Porosity map of UNISIM-I-D reservoir model, including the position of the four producers, already drilled.

The platform investment (Inv_{plat}), in US$ millions, is given by Eq. (7) [32] where, Q_o is the oil processing capacity (1000 m^3/day); Q_w is the water processing capacity (1000 m^3/day); Q_{wi} is the water injection capacity (1000 m^3/day); and n is the number of well slots.

$$Inv_{plat} = 417 + (16.4 * Q_o + 3.15 * Q_w + 3.15 * Q_{wi} + 0.1 * n) \tag{7}$$

The initial investment of a flexible platform ($Inv_{flex\,plat}$) is given by Eq. (8) [33], which considers a premium (Δ) paid to prepare the system for expansion. The cost of expansion from the initial capacity ($Inv_{plat,\,initial\,capacity}$) to the expansion capacity ($Inv_{plat,\,expansion\,capacity}$) is given by Eq. (9) [33], where α is the cost relationship between installing the expansion before and after production has started. Here, we use Δ=US$ 10 million and α=1.6 as suggested by Marques et al. [33] for a similar case study.

$$Inv_{flex\,plat} = Inv_{plat} + \Delta \tag{8}$$

$$Expansion\,cost = \alpha * (Inv_{plat,\,expansion\,capacity} - Inv_{plat,\,initial\,capacity}) \tag{9}$$

We calculated the NPV using a simplified net cash flow formulation based on the Brazilian R&T fiscal regime (Eq. (10)) where, NCF is the net cash flow; Rev is the gross revenue; Roy is the amount paid in royalties; ST is the amount paid in social taxes; OPEX are operational expenditures; T is the corporate tax rate; CAPEX are investments on equipment and facilities, and AC is abandonment costs.

$$NCF = [(Rev - Roy - ST - OPEX) * (1 - T)] - CAPEX - AC \tag{10}$$

In this application, we used a fictitious decision maker with the same attitude as described by Santos and Schiozer [31] for EVoI, and by Santos et al. [25] for EVoF in UNISIM-I-D. The decision maker is averse to downside risk (τ_{dr} = US$ 700 million) and willing to exploit the upside potential (τ_{up} = US$ 700 million). For the semi-deviation calculation, we used the expected monetary value (EMV) of the best candidate production strategy before considering information, robustness, and flexibility to manage uncertainty as the benchmark. The EMV is given by the sum of the NPV of each scenario weighted by its respective probability.

Table 1: Reservoir uncertainties from UNISIM-I-D case study, with updated probabilities after history-matching procedures.

Attribute	Description	Type	Value (probability)				
			-2	-1	0	+1	+2
img	Petrophysical properties	discrete [realization]	214 geostatistical realizations of one geological scenario for porosity, permeability, and net-to-gross ratio (0.0047)				
kr	Water relative permeability	discrete [table]	(0.08)	(0.19)	(0.42)	(0.19)	(0.13)
pv	PVT data[a]	discrete [table]	-	(0.34)	(0.33)	(0.34)	-
bl	Structural model	discrete [map]	-	No east block (0.31)	With east block (0.69)	-	-
wo	Water-oil contact[a]	continuous[b] [scalar]	3074 m (0.248)	3124 m (0.341)	3174 m (0.121)	3224 m (0.173)	3274 m (0.117)
cp	Rock compressibility	continuous[b] [scalar]	-	$23.6 \mathrm{x} 10^{-6}$ $\mathrm{cm}^2/\mathrm{kgf}$ (0.12)	$53.0 \mathrm{x} 10^{-6}$ $\mathrm{cm}^2/\mathrm{kgf}$ (0.66)	$82.4 \mathrm{x} 10^{-6}$ $\mathrm{cm}^2/\mathrm{kgf}$ (0.22)	-
kz	Vertical permeability	continuous[b] [scalar]	0.475 (0.12)	0.949 (0.19)	1.500 (0.25)	2.051 (0.23)	2.525 (0.21)

[a] East block. [b] Discretized.

Table 2: Operational uncertainties of UNISIM-I-D case study.

Attribute	Description	Type	Value (probability)		
			-1 (0.33)	0 (0.34)	+1 (0.33)
ogr	Group availability	continuous discretized	0.91	0.96	1.00
opl	Platform availability	continuous discretized	0.90	0.95	1.00
opw	Producer well availability	continuous discretized	0.91	0.96	1.00
oiw	Injection well availability	continuous discretized	0.92	0.98	1.00
ff	Well index multiplier	continuous discretized	0.70	1.00	1.40

Table 3: Deterministic economic scenario of UNISIM-I-D case study.

Type	Attribute (unit)	Value (probability)		
		-1 (0.25)	0 (0.50)	+1 (0.25)
Market	Oil price (US$/$m^3$)	251.60	314.50	440.30
variables	Discount rate (%)	9.00	9.00	9.00
Taxes	Royalties (%)	10.00	10.00	10.00
	Social taxes (%)	9.25	9.25	9.25
	Corporate taxes (%)	34.00	34.00	34.00
OPEX	Oil production (US$/$m^3$)	52.40	62.90	81.80
	Water production (US$/$m^3$)	5.24	6.29	8.18
	Water injection (US$/$m^3$)	5.24	6.29	8.18
	Abandonment (US$ Millions) (% of well investment)	8.20	8.20	8.20
CAPEX	Horizontal well drilling and completion (10^3 US$/m)	54.00	61.17	76.49
	Vertical well drilling and completion (US$ millions)	18.96	21.67	27.34
	Well - platform connection (US$ millions)	11.66	13.33	16.66
	Platform (US$ millions)	0.80xEq.(7)	Eq.(7)	1.25xEq.(7)

4. Results

We followed on from the application of UNISIM-I-D by Schiozer et al. [23], and used results from their work, as follows: (1) a set of 214 equiprobable scenarios that match production data, combining reservoir and operational uncertainties; and (2) nine rigid candidate production strategies (S1 to S9) (Table 4), deterministically optimized for the respective nine RMs. We obtained production forecasts using black-oil numerical reservoir simulation. Without further action to manage uncertainty, S9 is chosen as the best candidate. Thus, we used the EMV of S9 as the benchmark for semi-deviations.

Table 4: Characteristics of the 9 CPS (S1 to S9). Prod: number of producing wells; Inj: number of water injection wells
.

Production	Wells in High block			Wells in East block			Total	Platform (1000 m^3/day)			
Strategy	**Prod**	**Inj**	**Total**	**Prod**	**Inj**	**Total**	**Wells**	$\mathbf{Q}_l$	$\mathbf{Q}_o$	$\mathbf{Q}_w$	$\mathbf{Q}_{wi}$
S1	10	5	15	2	1	3	18	16.3	16.3	9.1	23.3
S2	8	5	13	2	1	3	16	16.3	16.3	11.2	22.8
S3	9	5	14	0	0	0	14	14.0	14.0	9.8	19.5
S4	9	5	14	2	1	3	17	18.2	18.2	11.5	25.5
S5	9	5	14	4	2	6	20	17.8	17.8	10.5	23.8
S6	9	6	15	0	0	0	15	14.3	14.3	7.3	20.6
S7	9	6	15	0	0	0	15	13.2	13.2	5.2	19.5
S8	10	5	15	4	2	6	21	21.7	21.7	14.6	29.8
S9	9	5	14	4	2	6	20	20.2	20.2	9.8	28.2

4.1. Comparing the candidate production strategies

The decision variables we considered are number of wells (Figs. 3 and 4), well placement, and platform size (fluid processing and injection capacities, and number of well slots) (Fig. 5). Major differences exist in number of wells in the East block, well placement in the High block, and platform size, suggesting that uncertainty management should be evaluated.

4.2. Assessing system sensitivity to uncertainty

We performed a one-factor-at-a-time (OFAT) sensitivity analysis of the reservoir and economic uncertainties and identified the best candidate strategy (S1 to S9) for each value these attributes can take (the first line in Table 5 shows results for critical attributes). Note that the CPS S1 was optimized for the base case, for which we performed the OFAT sensitivity analysis. Also note that we obtained results for OFAT using numerical reservoir simulation and that we assessed the reservoir uncertainties under the most-likely economic scenario (eco[0]).

To assess the effects of interactions between reservoir attributes on CPS selection, we grouped the 214 scenarios according to uncertainty levels and identified the best CPS for each subset based on its expected value $\varepsilon(NPV)$ (Table 5).

Because we have hundreds of geostatistical realizations, results from the OFAT for this uncertainty are presented in Fig. 6 , which shows how often each CPS is chosen as best. As a reference, we identified the best CPS for each of the 214 uncertain scenarios individually and determined how often each CPS is chosen as best.

Finally, we identified the best CPS for each of the 214 uncertain scenarios individually, combined with the three economic scenarios (Fig. 7).

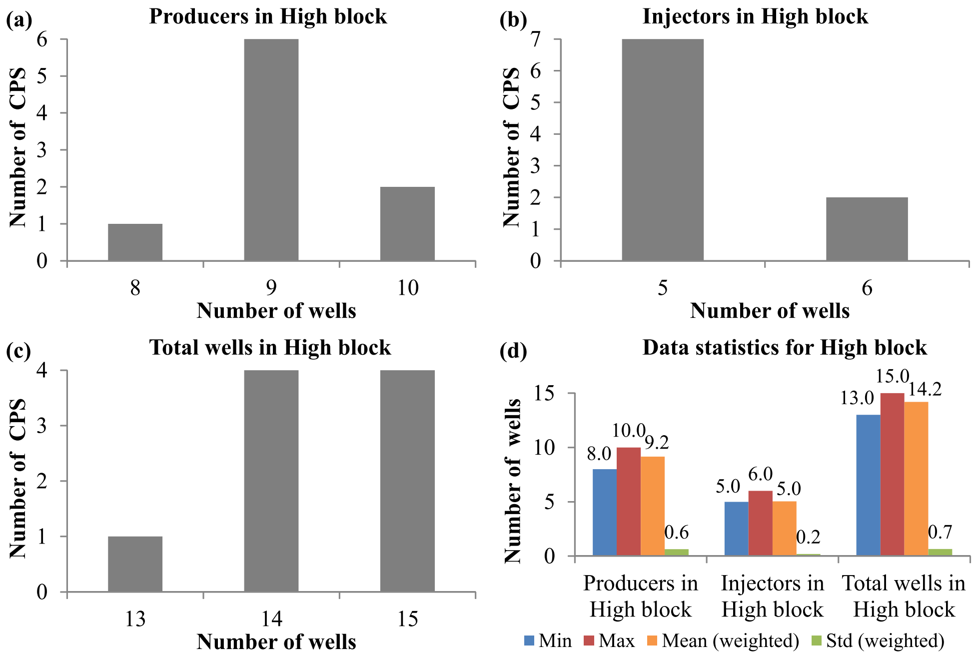

Figure 3: Comparison of CPS considering number of wells in the High block: (a) number of producers; (2) number of injectors; (c) total number of wells; and (d) data statistics, including minimum (min), maximum (max), mean, and standard deviation (std) of number of wells.

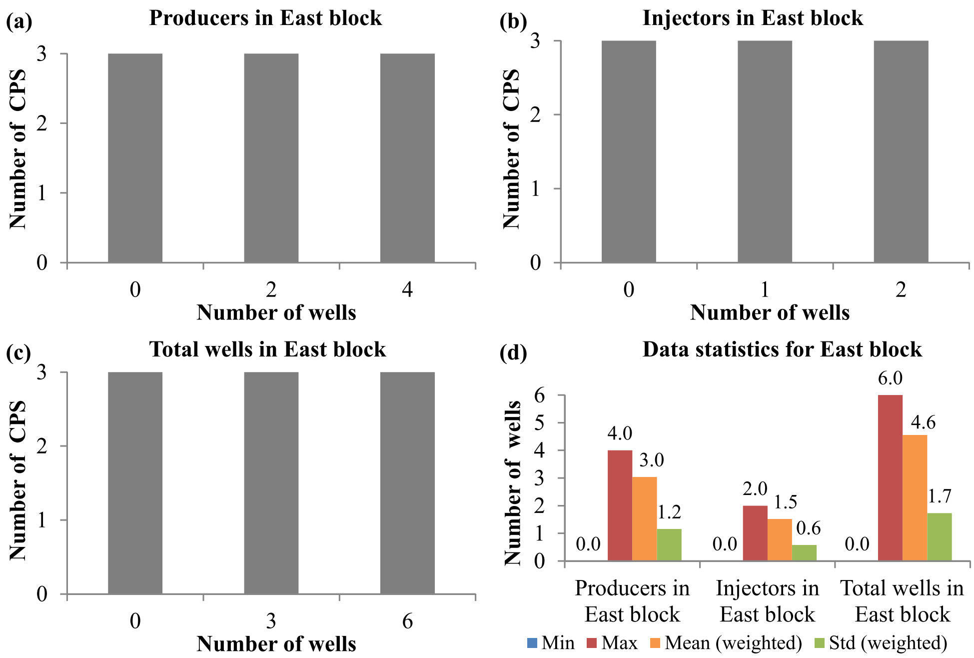

Figure 4: Comparison of CPS considering number of wells in the East block: (a) number of producers; (2) number of injectors; (c) total number of wells; and (d) data statistics, including minimum (min), maximum (max), mean, and standard deviation (std) of number of wells.

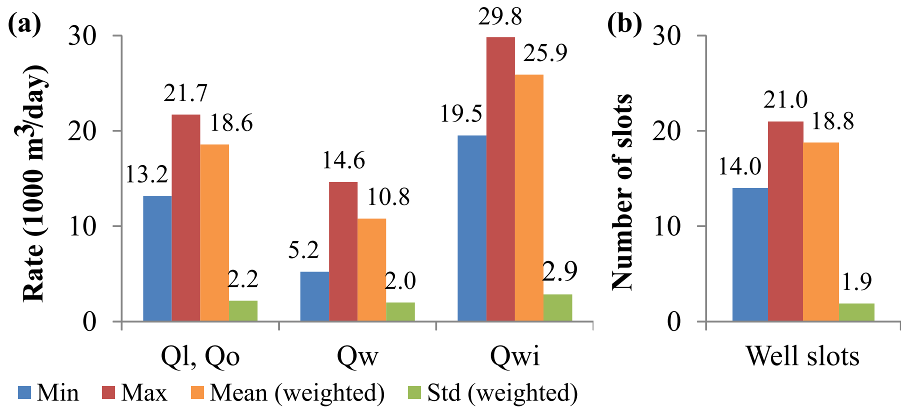

Figure 5: Comparison of CPS considering platform size: (a) fluid processing capacities for liquid (Q_l), oil (Q_o), water (Q_w) production, and for water injection (Q_{wi}); and (b) number of well slots. Data statistics include minimum (min), maximum (max), mean, and standard deviation (std).

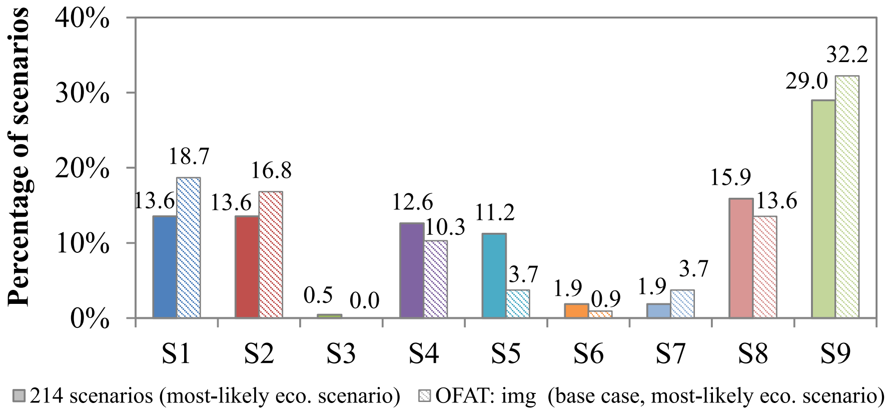

Figure 6: Percentage of scenarios according to the preferred CPS (S1 to S9). Bars on the left: 214 uncertain scenarios, considering the most-likely economic scenario. Bars on the right: OFAT sensitivity analysis of the multiple geostatistical realizations (img), considering deterministic reservoir attributes (base case) and the most-likely economic scenario.

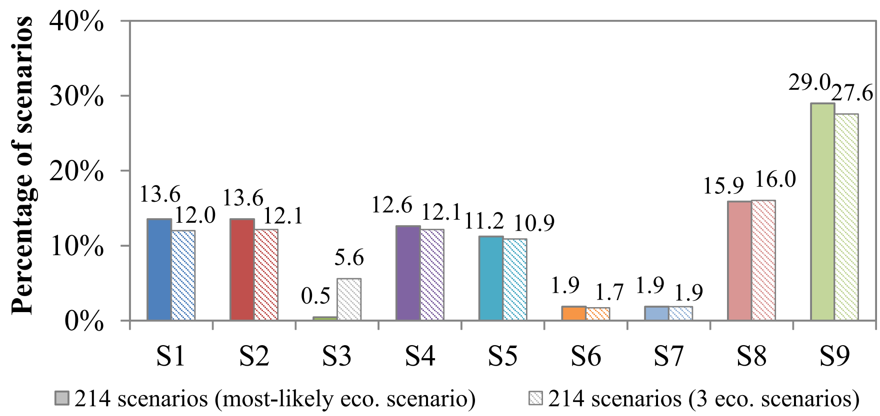

Figure 7: Percentage of scenarios according to the preferred CPS (S1 to S9). Bars on the left: 214 uncertain scenarios, considering the most-likely economic scenario. Bars on the right: 214 uncertain scenarios, considering the three economic scenarios.

Results from Table 5 and Fig. 6 suggest that production strategy selection is highly dependent on the geostatistical realization and on interactions between reservoir attributes, while isolated effects of attributes are minor. Thus, there is potential when defining robust well placement, and possibly a flexible system adaptable as uncertainty unfolds, mitigating the remaining differences between CPS (platform capacities and well number in East block). Because of a strong preference for S9 in most cases, additional information at this stage may add little value due to little indecision.

Results from Table 5 and Fig. 7 suggest that production strategy selection is minimally sensitive to economic uncertainty. In this case, because the preferred CPS does not change, the project does not benefit from flexibility to mitigate or exploit uncertainty in oil prices. Note that while an uncertain attribute may not alter CPS selection, it may still strongly affect the performance outputs (such as NPV). Thus, although we focused our analyses on managing reservoir uncertainty, we determined EVoI, EVoR, and EVoF under economic uncertainty.

4.3. Protecting the system with robustness

In a related work [20], we assessed the performance of S9 (the best candidate without further action) under the 214 scenarios and proposed production strategy R4 with robust well placement and robust platform capacities ($Q_l = Q_o = 17.8$; $Q_w = 9.8$; $Q_{wi} = 23.9$ thousand m^3/day). Robust well placement was defined based on probabilistic maps looking at locations with maximum mean values and minimum variance values of the reservoir spatial properties (porosity, permeability, net-to-gross ratio, and oil saturation). R4 improved project performance under uncertainty, resulting in an EVoR of US$ 385 million (Fig. 8).

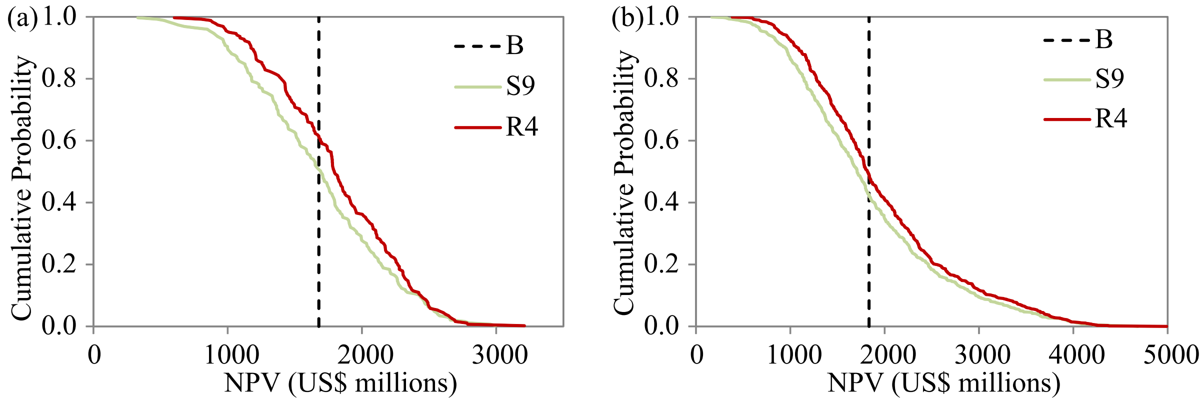

Figure 8: Net present value (NPV) risk curve for the best CPS S9 and the robust strategy R4: (a) NPV for the most-likely economic scenario; and (2) NPV considering the economic uncertainty. The vertical dashed line is the benchmark, separating downside risk and upside potential.

4.4. Protecting the system with flexibility

In a related work [25], we proposed a flexible production strategy (F2), which can expand fluid processing capacities and connect additional wells as reservoir uncertainty unfolds (*bl*, *wo*, and *kr*). F2 was proposed based on candidates S1 to S9, resulting in an EVoF of US$ 134 million.

In this study, we used the robust strategy R4 in addition to the candidates S1 to S9 when defining the flexible strategy (F4). Because of the importance of the geostatistical realizations in production strategy selection in UNISIM-I-D, considering robust well placement (inflexible feature) is key to maximizing the project value.

As suggested in Santos et al. [25], before setting decision rules for F4, we assessed its full potential considering the maximum hypothetical value of flexibility (i.e., we selected the best implementation for each scenario individually, without establishing a decision rule). This case recorded an EVoF of US$ 429 million when compared to S9, an added value of US$ 44 million to R4 (Fig. 9).

We defined probabilistic-based implementation rules using the simulation outputs of this hypothetical case, where we identified the best implementation according to uncertainty levels. F4 with decision rules recorded an EVoF of US$ 350 million when compared to S9 (Fig. 10), with no added value to R4.

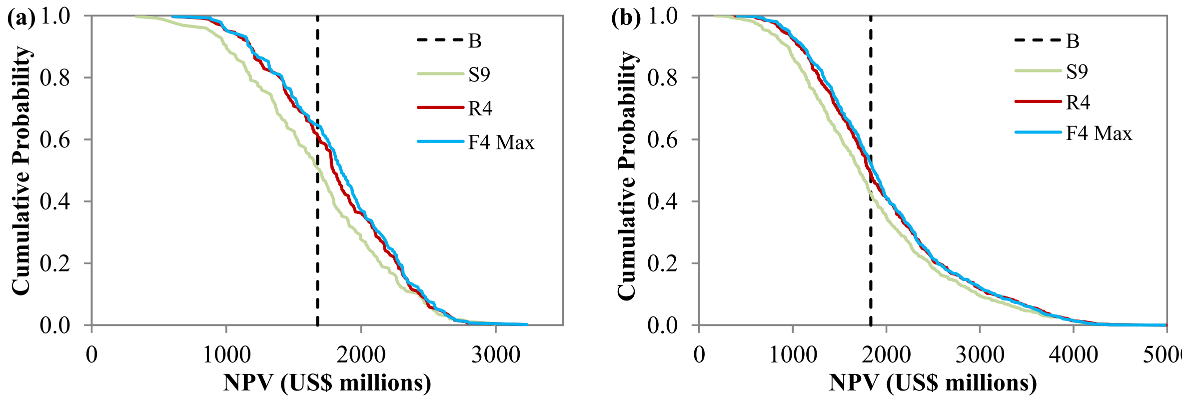

Figure 9: Net present value (NPV) risk curve for the best CPS S9, robust strategy R4, and flexible strategy F4 without decision rules (Max): (a) NPV for the most-likely economic scenario; and (2) NPV considering the economic uncertainty. The vertical dashed line is the benchmark, separating downside risk and upside potential.

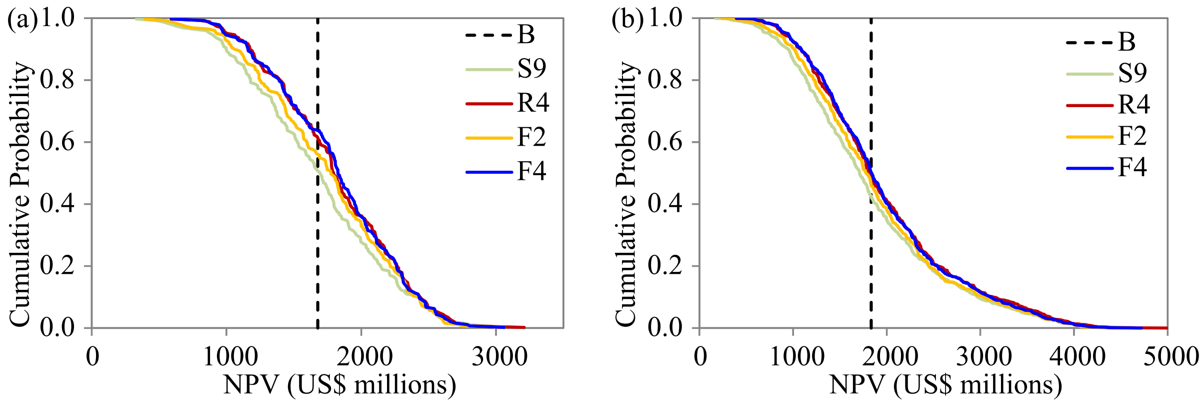

Figure 10: Net present value (NPV) risk curve for the best CPS S9, robust strategy R4, and flexible strategies F2 and F4 with decision rules: (a) NPV for the most-likely economic scenario; and (2) NPV considering the economic uncertainty. The vertical dashed line is the benchmark, separating downside risk and upside potential.

4.5. Acquiring information to reduce uncertainty

In a related work [24], we showed that the reservoir uncertainties bl and wo have the highest potential to be mitigated by an appraisal well. However, we also showed that information has no value if it delays production [24], but it may add value if acquired within the period designated for field development [31].

Santos and Schiozer [31] considered a simplified case where an appraisal well only updates the probabilities of bl, because they focused on assessing the effects of risk attitudes on EVoI. However, this information source also provides information on wo, meaning that both probabilities should be updated, as in Santos et al. [24]. We did so in this study and considered no delay in production.

Using the candidates S1 to S9, we obtained an EVoI of US$ 56 million for perfect information, and an EVoI of US$ 33 million for imperfect information (considering the reliability estimates made by Santos et al. [24] for this case study: 95% reliability interpreting bl, and 80% reliability interpreting wo) when compared to S9. Using the candidates S1 to S9 plus the robust strategy R4, information has no value because R4 is always chosen, regardless of the information outcome (i.e. test result). Note that, in the case where R4 is also a candidate, there is no reason to assess EVoI against S9, because without information R4 is the preferred choice.

4.6. Best action to manage uncertainty

Table 6 and Fig. 11 summarize the possible actions to manage reservoir uncertainty and their valuation, comparing them to selecting CPS S9, as though no further action would be taken to manage uncertainty (i.e., no analyses performed in Step 11).

Results show that the project value increased when information, robustness, and flexibility are considered (aims of Step 11). For this case study, the robust production strategy was best to manage uncertainty. Note that EVoI, EVoR, and EVoF consistently recorded lower values when calculated using the EMV than when calculated using $\varepsilon(NPV)$. Table 6 shows that all actions improved EMV, downside risk, and upside potential individually, meaning that EMV did underestimate EVoI, EVoR, and EVoF.

Cross-plots of EMV versus downside risk (Fig. 11a) and of EMV versus upside potential (Fig. 11b) reveal that (1) production strategies R4 and F4 have similar EMV, (2) F4 is mildly less risky than R4, and (3) the upside potential of R4 is significantly more attractive than that of F4. So R4 is preferred by our illustrative decision maker who equality prioritizes risk minimization and upside maximization. Sensitivity analyses on the tolerance level to downside risk and to upside potential show that this preference may change (Fig. 12).

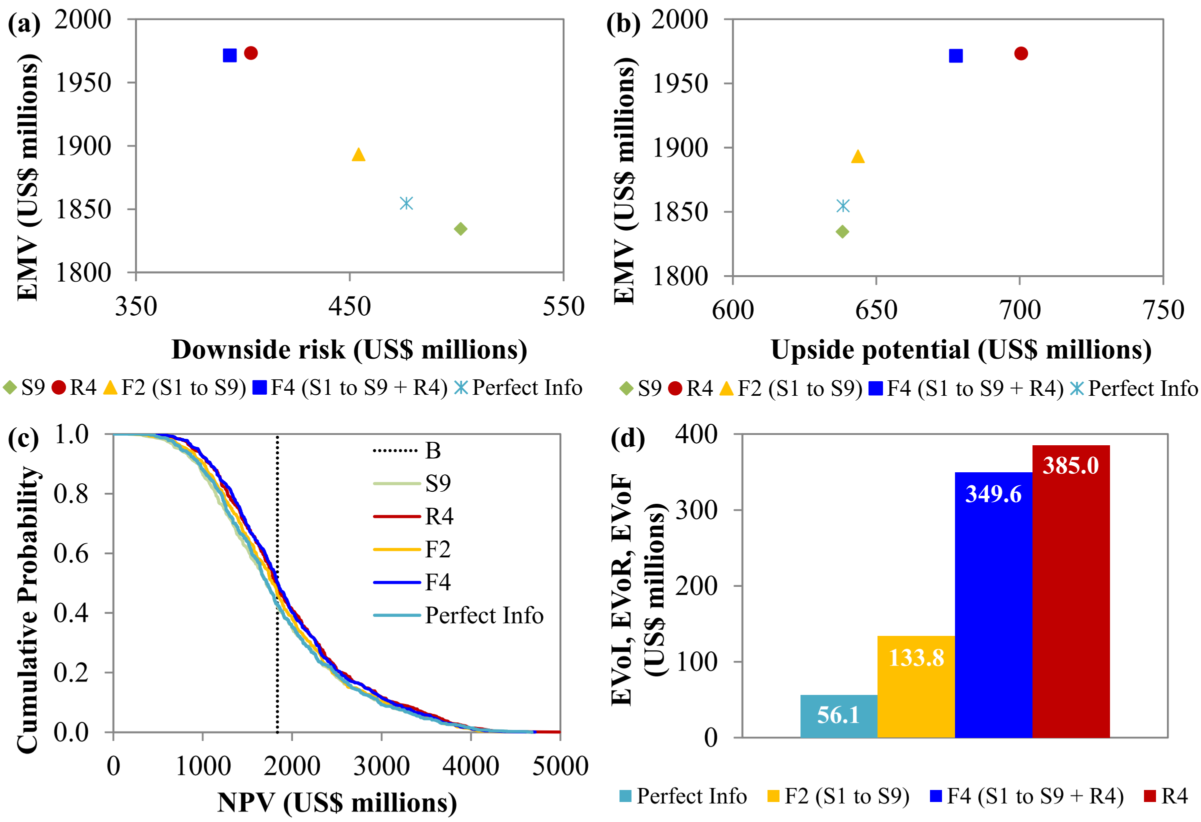

Figure 11: Assessing the actions to manage reservoir uncertainty in UNISIM-I-D, considering three economic scenarios: (a) cross-plot of EMV versus downside risk; (b) cross-plot of EMV versus upside potential; (c) NPV risk curves; and (d) EVoI, EVoR, and EVoF.

Table 5: Best CPS according to critical attributes. First line: OFAT sensitivity analysis using the base case; second line: on average for the multiple scenarios (214), determined based on $\varepsilon(NPV)$ for each subset of scenarios, grouped by uncertainty level.

	bl		**kr**					**kz**					**wo**					**eco**		
	-1	0	-2	-1	0	+1	+2	-2	-1	0	+1	+2	-2	-1	0	+1	+2	-1	0	+1
Best strategy for OFAT	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1	S1
Best strategy for multiple scenarios	S1	S9	S9	S9	S9	S8	S8	S9	S9	S9	S9	S9	S1	S9	S9	S9	S9	S9	S9	S9

Table 6: Assessing the possible actions to manage uncertainty, comparing them to S9 (the best strategy if no further action is taken), under three economic scenarios. Units in US$ millions.

Action	**EMV**	**Δ S9**	**S**$_{B-}$	**Δ S9**	**S**$_{B+}$	**Δ S9**	$\varepsilon(NPV)$	**Δ S9**	**EVoR, EVoF, EVoI (EMV)**	**EVoR, EVoF, EVoI** $[\varepsilon(NPV)]$
Select the best candidate (S9)	1834.4		501.9		638.2		2056.4			
Select robust strategy (R4)	1973.3	+7.6%	403.8	-19.5%	700.5	+9.8%	2441.4	+18.7%	138.9	385.0
Select flexible strategy without robustness (F2)	1893.2	+3.2%	454.2	-9.5%	643.6	+0.8%	2190.3	+6.5%	58.8	133.9
Select flexible strategy with robustness (F4)	1971.4	+7.5%	393.9	-21.5%	677.8	+6.2%	2406.0	+17.0%	137.0	349.6
Acquire perfect information, choose between CPS	1854.7	+1.1%	476.6	-5.1%	638.5	0.0%	2112.6	+2.7%	20.3	56.2
Acquire imperfect information, choosing between CPS	1846.1	+0.6%	483.0	-3.8%	635.2	-0.5%	2089.3	+1.6%	11.7	32.9
Acquire perfect information, choose between CPS and R4	1973.3		403.8		700.5		2441.4		0.0	0.0

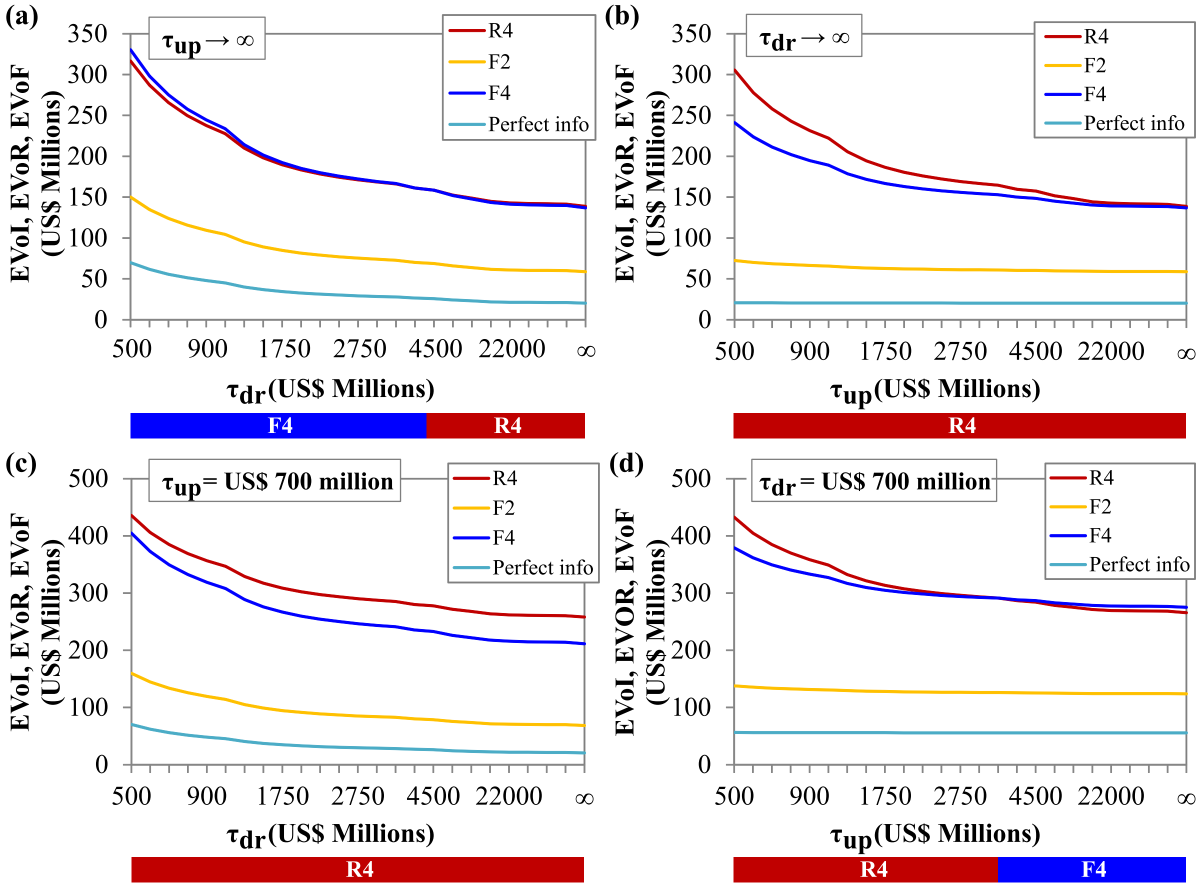

Figure 12: Sensitivity analysis on the tolerance to downside risk (τ_{dr}) and upside potential (τ_{up}) to identify the best production strategy (highlighted in the horizontal bars) under different preferences: (a) neutrality to upside potential; (b) neutrality to downside risk; (c) τ_{up} fixed at US$ 700 million; (d) τ_{dr} fixed at US$ 700 million.

5. Discussion

Our proposal assesses the potential of information, robustness, and flexibility to manage uncertainty before performing the EVoI, EVoR, and EVoF analyses themselves. We use multiple uncertain scenarios that match production data and a predefined set of candidate production strategies, optimized deterministically for representative scenarios.

The Robust Optimization, an optimization problem formulated under uncertainty to maximize a probabilistic objective function, has shown good results under uncertainty when compared to deterministically optimizing the most-likely scenario. Although strong in robustness, this single production strategy gives little information on the different possibilities to develop the field, such as number and placement of wells, and platform processing capacities. Conversely, if an adequate representative model selection is guaranteed, representing system inputs (uncertain attributes) and outputs (production, injection, and economic forecasts), their respective deterministic production strategies provide decision makers with an objective assessment of how different (and similar) these alternatives are, bringing valuable insights for EVoI and EVoF studies. In addition, analyses are accelerated and automated because extensive optimization procedures are unnecessary at this stage. Thus, deterministic optimization can be advantageous in decision and risk analyses, provided that it is part of a probabilistic process (i.e., it is not limited to the most-likely scenario). Previous studies suggest that around nine RM is sufficient for production strategy selection [23, 34]. We recommend future research on the optimal number of RM and candidate production strategies applied to EVoI, EVoR, and EVoF analyses, and on the possible loss of precision that this simplification may cause. Furthermore, research is recommended to account for the value of well-control optimization and of the possibility of future investments such as infill drilling and well workover, on the EVoI, EVoR, and EVoF estimates.

The assisted procedure proposed by Santos et al. [20] to define a robust production strategy based on a set of candidate strategies was effective. As the set of candidates was available, computational time was reduced and improvements were defined objectively. However, we recommend considering a robust production strategy obtained through a Robust Optimization procedure, in addition to the set of candidates optimized deterministically, as input for EVoI and EVoF analyses. Note that both the economic gains and the additional computational costs should be carefully assessed.

A major difficulty when choosing a flexible strategy is defining the implementation rules. Although the proposal by Santos et al. [25] eliminated biases and ensured more objective decision rules, these rules showed drawbacks in fully capturing the theoretical potential of flexibility. This may be attributed to the strong effects of the geostatistical realizations on production strategy selection and to difficulties in capturing these effects on decision rules. So despite flexibility being theoretically able to add value to robustness, the decision rules did not capture it.

Our results indicated that, when compared to the best candidate strategy S9, the robust strategy (R4) had an EVoR of US$ 385 million and the flexible strategy (F2) and EVoF of US$ 134 million. However, when combined, we verified that the flexible strategy with robustness had a maximum EVoF of US$ 429 million (but US$ 350 million after setting decision rules), meaning that EVoF and EVoR are not additive. We also recorded a maximum EVoI of US$ 56 million before considering robustness, and a zero EVoI with robustness, meaning that EVoI and EVoR are not additive either.

When we assessed system sensitivity to uncertainty and the effects of uncertainties on production strategy selection, indicators suggested a low potential for information acquisition and strong potential for protecting the system. EVoI, EVoR, and EVoF calculations support these analyses. Namely, we found no value in information if production is delayed, and a maximum EVoI of US$ 56 million for perfect information with no production delays, a very small value when compared to EVoR and EVoF.

The petroleum literature shows a strong preference for acquiring more information to reduce uncertainty and consequently improve decisions. Our case study showed that this is not necessarily true, and that system protection with flexibility or robustness can add more value, depending on the uncertainties controlling production strategy selection. Thus, EVoI analysis cannot be discarded and must base the decision to acquire information. We understand that quantifying the value of information is difficult because of its ability to reveal unknown unknowns. We recommend future research on this remark.

We used hundreds of scenarios to obtain EVoI, EVoR, and EVoF estimates because these are highly sensitive and susceptible to errors, being the difference between expected values. However, this approach was computationally demanding and so unlikely to be feasible for simulation models with a very high runtime. We recommend assessing the feasibility of conducting the probabilistic-based analyses we proposed on the small subset of representative models, each characterized by a probability of occurrence.

Our case study showed that estimating the value of information, robustness, and flexibility as the expected increase in EMV underestimated the value of these actions. This is because the magnitude of risk reduction and increased upside potential is not recorded in the scale of increased EMV. Thus, accounting for all changes in the risk curve when evaluating alternative decisions ensures a more quantitative and objective decision-making and prevents the discard of attractive solutions.

6. Conclusions

We proposed a decision structure to objectively find the best approach to manage uncertainty in petroleum field development considering information, robustness, and flexibility. Our methodology (1) used a predefined set of candidate production strategies, (2) assessed system sensitivity to uncertainty and the uncertainties controlling production strategy selection, and (3) applied a function that improved EVoI, EVoR, and EVoF estimates by accounting for all changes in the risk curve and weighing the decision maker's attitude. We used indicators to assess the potential for information, robustness, and flexibility, before performing the EVoI, EVoR, and EVoF analyses themselves.

Our results showed that when candidate production strategies are different, the project value can be increased if information, robustness, and flexibility are considered. Specific conclusions of this work include:

- Efficient representative model selection and optimization allows analyses to be based on a predefined set of candidate production strategies;
- Performance analysis of candidate production strategies under uncertainty ensures a more quantitative and objective decision-making;
- The values of information, robustness, and flexibility are not additive;
- EVoI, EVoR, and EVoF estimated as the expected increase in EMV tends to underestimate the value of these actions;
- Accounting for all changes in the risk curve (increased EMV, reduced downside risk, and increased upside potential) improves the EVoI, EVoR, and EVoF estimates.

Our proposal ensures a more quantitative and objective decision-making at early stages of field development and ultimately prevents discarding attractive solutions based on biases or inadequate metrics. Some improvements may be necessary in the EVoI, EVoR, and EVoR estimates to account for (1) well-control optimization, (2) future investments such as infill drilling and well workover, (3) the discovery of unknown unknowns with new information, and (4) the possible precision losses that arise from considering a predefined set of candidate production strategies.

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9. CONCLUSIONS

In this research, we aimed to reduce the subjectivity of the decision-making process in the following stages of field development: (1) constructing and assessing the risk curve; (2) selecting the best production strategy; and (3) managing uncertainty. Ultimately, we aimed to provide easy-to-apply criteria, while maintaining the complexity of the problem.

We demonstrated that project value can be increased substantially if in-depth decision analyses are performed to assess and manage the effects of uncertainties. Our proposals ensure a quantitative and objective decision-making and prevent decision makers from discarding attractive solutions based on biases or inadequate metrics. We presented seven scientific articles to support the specific conclusions detailed below.

9.1. Constructing and assessing the risk curve

- Selecting a risk analysis method adequate to the case study is key to ensure reliable results at minimum computational and human efforts.
- If the case study does not comprise a geostatistical parameter or comprises no more than 10 realizations, the Monte Carlo simulation with Joint Proxy Models (JMM) method can be selected to generate risk curves as it produces accurate results with minimum flow simulation runs because of the experimental design.
- If the case study has a geostatistical uncertainty, particularly with dozens or hundreds of realizations, the Discretized Latin Hypercube with Geostatistics (DLHG) method is better suited as it produces reliable results with minimum flow simulation runs and without requiring proxy models.
- Independence between the precision of the DLHG method and the number of trials is achieved from a low sampling number (above 50).
- The application of the JMM method is more complex, requires more time and a deeper knowledge of statistics by the user.
- Although JMM and DLHG produced visually similar risk curves, JMM recorded higher deviation from the reference in all situations.
- Standard deviation assesses overall uncertainty in the performance of a production strategy and is inadequate to assess risk.

- Semi-deviation from a benchmark successfully measures downside risk and upside potential because it assesses subsets of overall uncertainty based on the decision maker's definition of loss and gain (defined by the benchmark return).
- Lower semi-deviation improves risk assessment: (1) of production strategies with asymmetric distributions; (2) of production strategies with symmetric distributions and widely different expected values, including positive, zero and negative values; and (3) it avoids labeling a production strategy as being low risky because of low overall variability.

9.2. Incorporating the decision maker's attitude and objectives into the decision

- We successfully integrated the expected value with semi-deviations from a fixed benchmark in a new objective-function to incorporate the decision maker's attitude into the decision.
- Our objective function is applicable to production and economic indicators and maintains their units and dimensions. It is also applicable in single and multi-objective frameworks.
- Our formulation is applicable to select production strategies and to base the decision to manage uncertainty, including EVoI, EVoR, and EVoF estimates.
- The decision maker's attitudes and objectives affect production strategy selection and the decision to manage uncertainty.
- The EMV tends to underestimate EVoI, EVoR, and EVoF because it does not account for all improvements in the risk curve.
- Accounting for all changes in the risk curve as we proposed (increased EMV, reduced downside risk, and increased upside potential) improves the EVoI, EVoR, and EVoF estimates.
- Decision makers with different attitudes value information differently, meaning that the decision to acquire information may be rejected by one decision maker but accepted by another. This is not captured by the EMV alone.
- A strong preference for one production strategy decreases information value.
- Quantifying the decision maker's tolerance to downsides and upsides is difficult, but sensitivity analyses assist and increase confidence in decisions.

9.3. Managing uncertainty with robustness, information, and flexibility

- Efficient representative model selection and optimization allows analyses to be based on a predefined set of candidate production strategies. This reduces the subjectivity of decisions and automates analyses.
- Performance analyses of candidate production strategies under uncertainty ensure a more quantitative and objective decision-making.
- When differences exist between candidate production strategies, project value can be increased if information, robustness, and flexibility are considered.
- Assessing system sensitivity to uncertainty and the effects of uncertainties on production strategy selection allows identifying the potential for information, robustness, and flexibility, before performing the EVoI, EVoR, and EVoF analyses themselves.
- Robustness complements well-known techniques of acquiring information and defining flexible production systems, by ensuring good performance across scenarios without requiring system modifications after production has started.
- A robust well placement process is key to improving project value when uncertainty in spatial distribution of petrophysical properties (represented by geostatistical realizations) dominates production strategy selection.
- Our indicators assess and increase the robustness of number and placement of wells, and of platform processing capacities, further improving the optimization under uncertainty and reducing risk.
- Performing the EVoI calculation is key to ensuring a more quantitative and objective decision-making and to prevent economic loss.
- The EVoI statistical analysis is complex, which sustains the need for a prior study of uncertainties using indicators, eliminating bias toward particular uncertainties and information sources.
- The reservoir uncertainties that can be mitigated with information can be identified, a priori, by combining four indicators: (1) impact on the performance of the field; (2) potential to reduce uncertainty; (3) potential to modify the decision; and (4) likelihood of the available information to define the uncertain parameter.

- A flexible production strategy can be defined objectively using a predefined set of candidate rigid production strategies, reducing the subjectivity of decisions and eliminating prior misconceptions and bias toward particular flexibilities.
- Probabilistic-based implementation rules for flexibility can be defined objectively using the reservoir simulation outputs for multiple uncertain scenarios.
- The values of information, robustness, and flexibility are not additive.

10. RECOMMENDATIONS FOR FUTURE WORK

Previous studies suggest that around nine representative models are sufficient for production strategy selection. We recommend future research on the optimal number of RM and candidate production strategies applied to EVoI, EVoR, and EVoF analyses. In addition, the possible precision losses that may arise from considering a predefined set of candidate production sections should also be assessed.

Using a large set of scenarios improves probabilistic-based decision analyses, but becomes computationally demanding. We recommend future research on techniques to allow the applicability of the proposed methods on computationally demanding reservoir models. Namely, we recommend assessing the feasibility of our proposals using the small subset of representative models, each characterized by a probability of occurrence.

We proposed semi-deviations (second-order partial moments) as alternatives to standard deviation, the typical risk metric in the petroleum industry. We recommend research on assessing the effects of the order of the partial moments in production strategy selection.

The existing petroleum literature provides techniques to find the corporate risk tolerance, but they are only valid for mean-variance models. In addition, it does not discuss the concept of tolerance to upside potential. We recommend further research on techniques to find quantitatively the tolerance to downside risk and to upside potential applied to production strategy selection and to EVoI, EVoR, and EVoF analyses.

We showed that a set of candidate production strategies optimized for representative models reduces subjectivity of decisions and accelerates analyses. We recommend future work on quantitative criteria to automate the comparison of the candidate strategies (e.g., well number, well placement, platform capacities). In this way, defining candidate flexible production strategies can become a fully automated procedure.

We showed that the expected value of information is affected by the information reliability, the decision maker's attitude, and the simultaneous choice of system protection with flexibility or robustness. We recommend future research to account for other factors that may affect EVoI, such as delays in information acquisition with existent competing sources of data, and the discovery of "unknown unknowns" (i.e., uncertainties not yet identified).

We assessed the value of imperfect information but we did not elaborate on how to conduct the reliability estimate in itself. We recommend future research on this procedure.

We proposed flexibility to manage reservoir uncertainty. We recommend future research on the value of flexibility to mitigate or exploit exogenous uncertainties, namely on defining probabilistic-based implementation rules applied to uncertainty in oil price.

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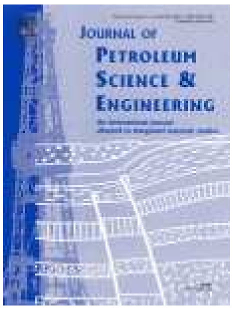

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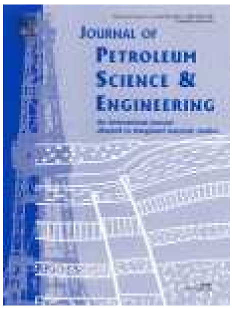

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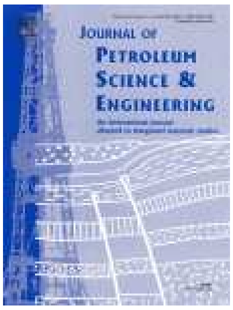

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Author: Susana M.G. Santos,Ana T.F.S. Gaspar,Denis J. Schiozer

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