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

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ABSTRACT

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

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 (Pye, 1978; Begg et al., 2002; Bratvold and Begg, 2010). 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 (Jones and Ostroy, 1984).

Early discussions of flexibility can be traced back to the early 1920's in the economics literature when Lavington recognized the “risk arising from the immobility of invested resources” (Lavington, 1921, p. 91). Flexibility has been developed in different domains and today is a multidisciplinary concept (Sethi and Sethi, 1990; Saleh et al., 2009). Although popular, the concept of flexibility is not academically mature (Saleh et al., 2009).

In the petroleum literature, mentions of flexibility date back to the late 1980's and typically cover the general decision options for oil prospects: develop, explore, delineate, wait, or stop the project (McDonald and Siegel, 1986; Benkherouf and Bather, 1988; Bjørstad et al., 1989; Laughton, 1998; Smith and McCardle, 1998). Flexibility of the production system has been addressed mainly since the 2000's and includes capacity expansion (Lund, 2000; Begg et al., 2002; Babajide et al., 2009; Jablonowski et al., 2011; Moczydlower et al., 2012; Lin et al., 2013; Marques et al., 2013; Silva et al., 2017), modularity (Hayashi et al., 2010; Moczydlower et al., 2012), intelligent wells (Han, 2003; Moczydlower et al., 2012; Sampaio et al., 2015; Morais et al., 2017), flexible subsea layouts (Moczydlower et al., 2012; Lin et al., 2013), and the ability to redistribute injection quotas or switch the injected fluid (Moczydlower et al., 2012).

Flexibility is typically considered when (1) acquiring information is

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impossible, (2) the expected value of information is small or the acquisition cost is too high, (3) managing uncertainty that remains after information acquisition, and (4) flexibility creates additional value by exploiting potential upsides of uncertainty (Begg et al., 2002; Bratvold and Begg, 2010). 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 suited to handle uncertainty in petroleum field development. Flexibility can manage endogenous and exogenous uncertainties (Lin et al., 2013; Silva et al., 2017) including oil price (Lund, 2000; Begg et al., 2002; Lin et al., 2013; Silva et al., 2017), which cannot be managed with information. In addition, flexibility is particularly appropriate both for systems that are designed to have a long lifetime (Saleh et al., 2009) and to manage the impact of unlikely but high-consequence events (Bratvold and Begg, 2010).

However, "flexibility is not a free good" (Stigler, 1939, 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 cost of delayed production due to the time value of money (Begg et al., 2002; Bratvold and Begg, 2010). The Expected Value of Flexibility (EVoF), an approach similar to that of the Expected Value of Information (EVoI), is typically employed (Begg et al., 2002). 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) (Lund, 2000; Begg et al., 2002; Jablonowski et al., 2011; Moczydlower et al., 2012). However, the breadth of risk reduction and increased upside potential may not be recorded in the magnitude of changes in EMV. This often makes the EMV alone inadequate to base decisions on during the development phase (Santos et al., 2017a). As a result, EMV has been complemented with risk measures and other economic indicators when choosing flexible strategies (Babajide et al., 2009; Hayashi et al., 2010; Lin et al., 2013; Marques et al., 2013; Silva et al., 2017).

Determining whether and when flexibility should be implemented is a challenge. This is based on triggering conditions (referred to as decision rules or implementation rules) defined by the decision makers. Examples include achieving not only a target oil price (Lin et al., 2013; Silva et al., 2017) or a threshold estimated ultimate recovery (Lin et al., 2013), but also premature water breakthrough (Moczydlower et al., 2012), and gas-oil ratio above the expected (Moczydlower et al., 2012). 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 meeting additional investments (Babajide et al., 2009; Lin et al., 2013; Silva et al., 2017).

1.1. Motivation and objectives

To maximize project value, decision makers must consider actions to manage uncertainty both to mitigate risks and exploit upsides. While disregarding the effects of uncertainty may lead to underperformance (Begg et al., 2002, 2004), neglecting the possibility of flexibility as a response to uncertainty may result in project undervaluation (Begg et al., 2002; Jablonowski et al., 2011). Although increasingly popular, the petroleum literature still lacks systematic, objective approaches to define and evaluate flexibility.

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

2. Methodology

This work is integrated into the twelve-step decision analysis framework by Schiozer et al. (2015). Their work is based on the concept of Closed-Loop Field Development and Management and covers all stages of field development and management combining reservoir characterization under uncertainty, reservoir simulation, history matching, uncertainty reduction, representative models, and production strategy optimization.

The twelve steps by Schiozer et al. (2015) 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 attributes, (9) selection of a specialized production strategy (SPS) for each representative scenario (as in Step 6), (10) selection of the best production strategy from the set of specialized 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.

This study presents a methodology for Step 11, considering flexibility to manage reservoir uncertainty. In Fig. 1, we propose the workflow, which is an iterative procedure and compares a set of rigid specialized strategies and a robust strategy to define and select flexible strategies. The following subsections provide details for each process

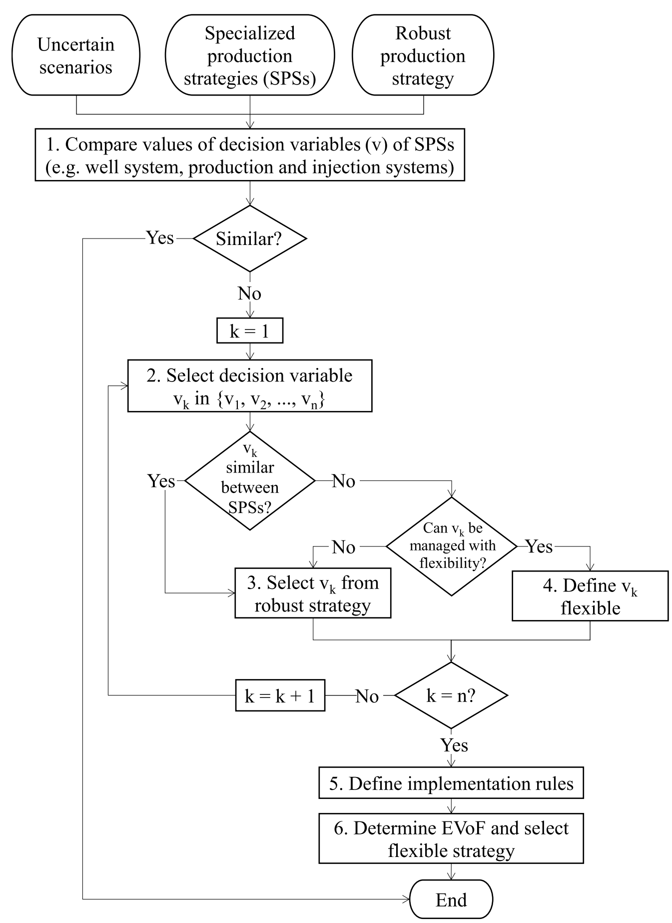

Fig. 1. Workflow to implement our proposal for EVoF analysis to manage uncertainty in petroleum field development.

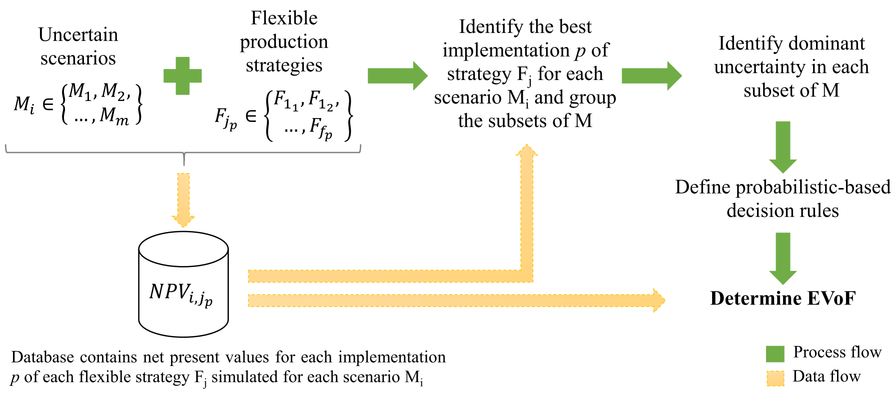

Fig. 2. Procedures for defining implementation rules (box 5 in Fig. 1) and for determining the EVoF (box 6 in Fig. 1).

(numbered boxes) of the workflow.

2.1. Inputs: uncertain scenarios, specialized production strategies, and a robust strategy

The inputs for our workflow come from previous steps of the framework by Schiozer et al. (2015): (1) a set of uncertain scenarios that match production data (obtained in Step 5), (2) a set of rigid SPSs (obtained in Step 9), and (3) a robust production strategy, the best under uncertainty, disregarding flexibility (obtained in Step 10).

Uncertain scenarios are defined here as particular combinations of all uncertain attributes and are obtained through statistical sampling techniques (e.g., Schiozer et al., 2017). Decision makers must select the uncertain scenarios that match production data before proceeding to probabilistic-based forecasts. History matching and uncertainty reduction procedures are not the focus of this work. Many tools for these analyses can be found in the literature (e.g., Maschio and Schiozer, 2016; Emerick and Reynolds, 2013).

To reduce the subjectivity of decisions and to automate analyses, we use a predefined set of candidate production strategies, including specialized strategies and a robust production strategy to define the best flexible strategy.

We obtain the specialized strategies using a small subset of scenarios, called representative models (RMs), chosen from the set of uncertain scenarios that match production data. The literature provides methods for the selection of representative models (e.g., Jiang et al., 2016; Meira et al., 2016, 2017; Shirangi and Durlovsky, 2016). In this work, we apply the proposal by 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 RMs represents both the probability distribution of the input variables (uncertain attributes) and the variability of the main output variables (production, injection, and economic forecasts).

One production strategy is optimized individually for each RM (in Step 9) to generate a set of SPSs. Multiple decision variables (v) must be defined in the optimization procedure including (1) number and placement of wells, (2) well opening schedule, (3) recovery mechanism, (4) number of platforms, and (5) fluid processing capacities. Optimization algorithms are not the focus of this work, and many tools can be found in the literature (e.g., Bittencourt and Horne et al., 1997; Yang et al., 2007; Gaspar et al., 2016; von Hohendorff Filho et al., 2016).

The robust production strategy is that which ensures the best performance across multiple scenarios without requiring system modifications after production has started. The robust production strategy can be obtained through a Robust Optimization procedure (e.g., van Essen et al., 2009; Yang et al., 2011; Yasari and Pishvaie, 2015), optimized for the set of RMs simultaneously and maximizing a probabilistic objective function (such as the EMV). Alternatively, the robustness of an SPS can be increased using probabilistic-based performance indicators over multiple scenarios (e.g., Santos et al., 2017b).

As the set of RMs represents the uncertain system, the set of SPSs provides decision makers with different possibilities to develop the field, namely number and placement of wells, number of platforms, and fluid processing capacities. Thus, we use the SPSs as indicators for the degree and type of flexibility required by the system.

2.2. Defining flexible production strategies

First, we compare the values defined for each decision variable for each SPS (box 1 in Fig. 1). If the values of decision variables (e.g., number of wells, coordinates for well placement, number of platforms, fluid processing capacities) are similar between SPSs, no further action is required. Meaning that, regardless of the true reservoir model, a similar production strategy would be selected. However, if they are different, an action is recommended to mitigate risk or exploit the upsides of uncertainty.

This iterative procedure goes through each decision variable (v_k in $\{v_1, v_2, \dots, v_n\}$) (boxes 2 to 4 in Fig. 1). If the value of the decision variable v_k is similar between SPSs, v_k is set as in the robust production strategy (box 3 in Fig. 1). Conversely, the different values of v_k are treated as candidate flexibilities (box 4 in Fig. 1), except when v_k is inflexible (e.g., placement of wells) and is set as in the robust production strategy (box 3 in Fig. 1).

Weights can be assigned for each SPS before they are compared. That is, we assess the representativeness of each SPS based on the percentage of uncertain scenarios for which each SPS is best. For details, see the results section.

2.3. Defining implementation rules

We use numerical reservoir simulation to obtain production, injection, and economic forecasts for all scenarios under all possible implementations of each candidate flexibility. This information is stored in a database and is used both to define implementation rules (box 5 in Fig. 1) and to determine the EVoF (box 6 in Fig. 1; described in §2.4) (Fig. 2).

We 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. We use these optimal values to calculate the maximum theoretical value of flexibility (i.e., EVoF is estimated without defining a decision rule), providing an upper limit for the EVoF. If the candidate is unsuitable for the theoretical case, it is rejected; otherwise, decision makers define probabilistic-based implementation rules.

Having identified whether or not flexibility should be implemented, and the optimal level and type of implementation (for each scenario), we group the subsets of scenarios according to this preference. We

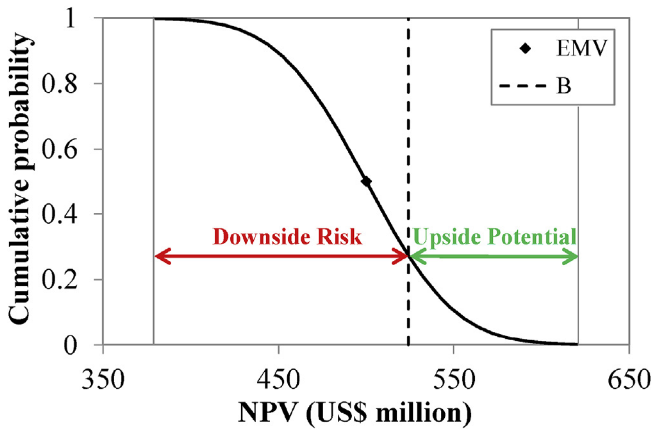

Fig. 3. Benchmark return (B) separates the domains of undesirable variability (downside risk, marked in red) and desirable variability (upside potential, marked in green) of the net present value (NPV) risk curve (continuous black) (modified from Santos et al., 2017a). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

analyze histograms for all reservoir uncertainties, comparing each subset to the full set of scenarios. This way, we identify the uncertainty dominating the implementation of flexibility and set the decision rules according to the reservoir uncertainties that control it.

2.4. Determining the expected value of flexibility

To estimate EVoF (box 6 in Fig. 1), we apply the objective-function proposed by Santos et al. (2017a) for production strategy evaluation under uncertainty, which was already applied for EVoI by Santos and Schiozer (2017). Santos et al. (2017a) follow on from the classic mean-variance model and propose a mean-semivariance framework based on the premise that variance only reflects the overall uncertainty in returns but not necessarily the risk of a project. In petroleum field development, risk is typically associated with the chance of failure to achieve a targeted or benchmark return (B). Thus, variability above this target is not commonly perceived as risk, but as potentially exploitable optimistic scenarios.

The risk curve is divided into two domains (Fig. 3): (i) the downside risk or uncertainty in losses, i.e., the undesirable domain of uncertainty, reflecting the failure to achieve the benchmark return and (ii) the upside potential or uncertainty in gains, i.e., the optimistic tail of the risk curve above B. Note that, risk curves are also referred to in the statistics literature as descending or complementary cumulative distribution functions. We construct them with the production forecasts of multiple scenarios from numerical reservoir simulation.

Santos et al. (2017a) combined the expected monetary value (EMV), downside risk, and upside potential in a new objective-function (Eq. (1)) to determine the economic value of a production strategy under uncertainty. This incorporates the decision maker's attitude while maintaining the units and dimension of the net present value (NPV).

$$\varepsilon(\mathrm{NPV}) = EMV - c_{dr}S_{B-}^2 + c_{up}S_{B+}^2 = EMV - \frac{S_{B-}^2}{\tau_{dr}} + \frac{S_{B+}^2}{\tau_{up}} \tag{1}$$

where: ε(NPV) is the economic value of the production strategy adjusted to the decision maker's attitude; NPV is the net present value; EMV is the expected monetary value (given by the sum of the NPV of each scenario weighted by its probability); 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; and τ_{dr} and τ_{up} are the tolerance (or indifference) levels to downside risk and to upside potential, respectively.

Decision makers define the benchmark depending on their definitions of loss and gain. A fair comparison uses the same benchmark for all production strategies. Santos et al. (2017a) used the SPS with maximum EMV as the reference and its EMV as the benchmark. Santos and Schiozer (2017) used the EMV of the best strategy without information acquisition as the benchmark.

Semi-deviation (short for semi−standard deviation) from the benchmark return 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.

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

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

where: S_{B-} is the lower semi-deviation from the benchmark 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, and NPV is the net present value.

In Eq. (1), the S_{B-}^2 decreases the expected value according to the level of risk of the production strategy and the decision maker's risk aversion (c_{dr}), while the S_{B+}^2 increases the expected value according to the upside potential of the strategy and the decision maker's 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 EMV.

Following the proposal by Santos et al. (2017a) and the application of EVoI by Santos and Schiozer (2017), EVoF is given by Eq. (4). This approach improves EVoF assessments because it accounts for individual changes in the risk curve, and weights the decision maker's attitude toward downsides and upsides. EVoF can be calculated as the expected increase in EMV (Eq. (5)) in a particular case of Eq. (4) ($c_{dr} = c_{up} = 0$).

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

$$EVoF = EMV_{with\ flexibility} - EMV_{without\ flexibility} \tag{5}$$

3. Case study

We applied our 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 located 80 km offshore. Based on the Namorado Field in the Campos Basin, Brazil, the field is in the development phase, with four years of initial production for four vertical production 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 81 × 58 × 20 cells measuring 100 × 100 × 8 m, with a total of 36,739 active cells. The simulation runtime for this reservoir model is approximately five minutes using a commercial black-oil numerical reservoir simulator and four processors in parallel computing.

UNISIM-I-D has a set of reservoir (Table 1), operational (Table 2), and economic uncertainties. In this application, we focused on the use of flexibility to manage reservoir uncertainties and used a deterministic economic scenario to calculate the NPV (Table 3). The reservoir has two regions separated by a fault of unknown transmissibility, the West block and the East block (Fig. 4). The absence or presence of hydrocarbons in the East block is a key uncertainty because this region has not yet been drilled. This uncertainty affects production strategy selection.

The platform investment (Inv_{plat}), in US$ million, is given by Eq. (6) (Gaspar et al., 2015) 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.

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

Table 1
Reservoir uncertainties of the UNISIM-I-D case study with updated probabilities after history-matching procedures (Gaspar et al., 2015). Data files for all uncertain attributes, namely PVT tables and water relative permeability curves are available at https://www.unisim.cepetro.unicamp.br/benchmarks/br/unisim-i/unisim-i-d.

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]	kr1 (0.08)	kr2 (0.19)	kr0 (0.41)	kr3 (0.19)	kr4 (0.13)
pv	East block pvt data	discrete [table]	–	pv1 (0.34)	pv0 (0.33)	pv2 (0.34)	–
bl	Structural model	discrete [map]	–	Without east block (0.31)	With east block (0.69)	–	–
wo	East block 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)

The initial investment of a flexible platform ($Inv_{flex\ plat}$) is given by Eq. (7) (Marques et al., 2013), 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. (8) (Marques et al., 2013), where α is the cost relationship between installing the expansion before and after the start of production.

$$Inv_{flex\ plat} = Inv_{plat} + \Delta \tag{7}$$

$$Expansion\ cost = \alpha * (Inv_{plat,\ expansion\ capacity} - Inv_{plat,\ initial\ capacity}) \tag{8}$$

In this case study, Δ = US$ 10 million and α = 1.6 as Marques et al. (2013) suggested for a similar case study.

We calculated the NPV using a simplified net cash flow formulation based on the Brazilian Royalty & Tax 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 is the operational expenditure, T is the corporate tax rate, CAPEX is the investment in equipment and facilities, and AC are abandonment costs.

$$NCF = [(R - Roy - ST - OPEX) * (1 - T)] - CAPEX - AC \tag{9}$$

In this application, we used a fictitious decision maker with the same attitude as that described by Santos and Schiozer (2017) to assess EVoI for 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 EMV of the best production strategy without flexibility.

4. Results

We used the results of the application of Schiozer et al. (2015) of UNISIM-I-D as follows: (1) a set of 214 equiprobable scenarios that match production data, combining all reservoir and operational uncertainties and (2) a set of nine rigid specialized production strategies (S1 to S9) (Table 4).

Schiozer et al. (2015) sampled 500 scenarios using the statistical technique discretized Latin Hypercube with geostatistics (Schiozer et al., 2017) combining all reservoir and operational uncertainties (Tables 1 and 2). Schiozer et al. (2015) conducted a multi-objective uncertainty reduction process (Avansi and Schiozer, 2015; Bertolini et al., 2015) using the four years of production data for four vertical production wells. Many scenarios recorded good matches because of the brief history period with almost no water production. Thus, 214 scenarios were accepted and maintained as equiprobable because of the lack of evidence to prioritize scenarios. Schiozer et al. (2015) selected a subset of nine RMs from the set of 214 scenarios using the proposal by Meira et al. (2016). The subset of RMs reflects the degree of uncertainty for input variables (reservoir and operational uncertainties) and output variables (production, injection, and economic forecasts) observed in the full set of 214 scenarios.

Schiozer et al. (2015) optimized one production strategy for each RM, providing a set of nine rigid SPSs (S1 to S9). The optimization of each SPS was divided into five phases: (1) number and type of wells, and platform capacity; (2) placement of wells and fine-tuning of platform capacity constraints; (3) well opening schedule; (4) well operating and monitoring constraints; and (5) fine-tuning. These SPSs were

Table 3
Deterministic economic scenario of UNISIM-I-D case study (Gaspar et al., 2015).

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$ Million) (% of well investment)	8.20
CAPEX	Horizontal well drilling and completion (US$ Thousand/m)	61.17
	Vertical well drilling and completion (US$ Million)	21.67
	Well – platform connection (US$ Million)	13.33

Table 2
Operational uncertainties of UNISIM-I-D case study (Gaspar et al., 2015).

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

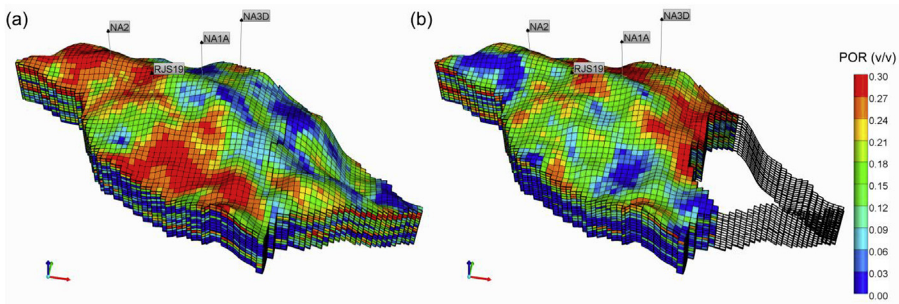

Fig. 4. Porosity map of UNISIM-I-D reservoir model, including the position of the four producers already drilled: (a) a scenario with the East block, and (b) a scenario without the East block.

optimized using CMG's commercial software CMOST, using the Designed Exploration Controlled Evolution (DECE) optimization algorithm (Yang et al., 2007).

From the set of nine SPSs, production strategy S9 was the best under uncertainty, maximizing Eq. (1). In this study, we used S9 as the robust production strategy as it ensured the best performance under uncertainty.

4.1. Comparing the specialized production strategies

We identified the best SPS for each scenario individually using a black-oil numerical reservoir simulator (Fig. 5). We used the frequency of each specialized strategy as weight when computing data statistics of decision variables.

The decision variables we considered are number of wells (Fig. 6 and Fig. 7), placement of wells, and platform size (fluid processing and injection capacities, and number of well slots) (Fig. 8). We found major differences in the number of wells in East block, placement of wells in West block, and platform size, meaning that the value of flexibility should be assessed.

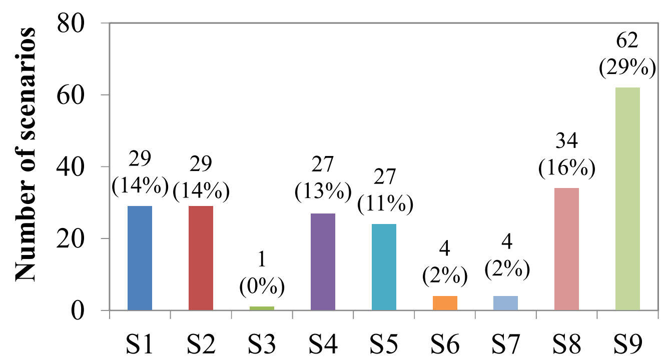

Fig. 5. Best production strategy according to the number of scenarios. Bars show the number (and frequency) of scenarios (out of 214) for which each SPS is best.

4.2. Defining candidate flexibilities

The number of wells in the West block does not vary significantly (Fig. 6) and so was set as in the robust production strategy: nine producers and five injectors, totaling fourteen wells. Regarding 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. 7). Thus, we consider the flexibility to connect additional wells in the event that hydrocarbons are found in this region: 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 West block is a key difference between production strategies, and they are placed as in the robust production strategy. In the East block, the placement of wells has similarities between the strategies with three wells (S1, S2, and S4), and those with six wells (S5, S8, and 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. 8), 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 specialized strategies (Fig. 8 and Table 4). Two degrees of expansion were considered: (1) up to S8, the largest platform of the set (Fig. 8 and Tables 4) and (2) up to S4, the medium-sized platform with capacities close to the mean values (Fig. 8 and Table 4).

Table 6 summarizes these proposed flexibilities, while investments and expansion costs are shown in Table 7.

Note that the viability of intelligent well completion as a flexibility in UNISIM-I-D was already studied by Morais et al. (2017) and we did

Table 4
Characteristics of the nine specialized production strategies. Prod: number of production wells; Inj: number of water injection wells.

Production Strategy	Wells in West block			Wells in East block			Total Wells	Platform (1000 m^3/day)			
	Prod	Inj	Total	Prod	Inj	Total		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

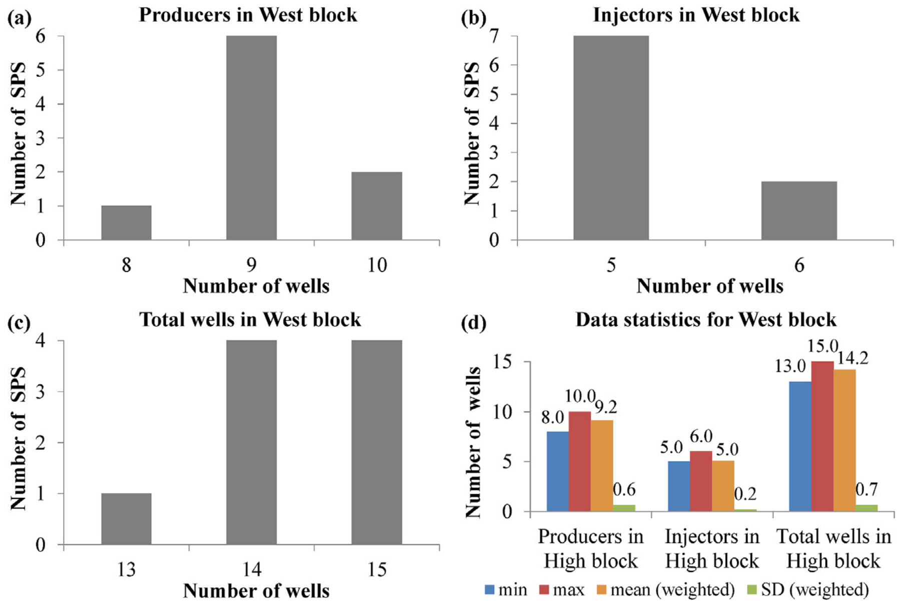

Fig. 6. Comparison of specialized production strategies considering number of wells in the West block: (a) number of producers; (b) number of injectors; (c) total number of wells; and (d) data statistics, including minimum (min), maximum (max), mean, and standard deviation (SD) of number of wells.

not consider this type of flexibility here. Also note that we applied the same rules for well control as in the SPS and we did not further optimize these variables.

4.3. Assessing candidate flexibilities and defining implementation rules

The first assessment of viability is estimated using 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. 9) 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 ε(NPV) by −5.7%.

4.3.2. Candidate flexibility F2

Candidate flexibility F2 is accepted because of the potential to increase ε(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 (50.5%), but platform expansion to the highest capacities (S5, S8, S9) is rarely used (Fig. 10) (9.8% of scenarios use capacities S5, S8, or S9, i.e., 21 out of 214 scenarios). 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 because it mostly coincides with that for F2 (expansion up to S8) (Fig. 11).

We defined probabilistic-based implementation rules (Table 8) by

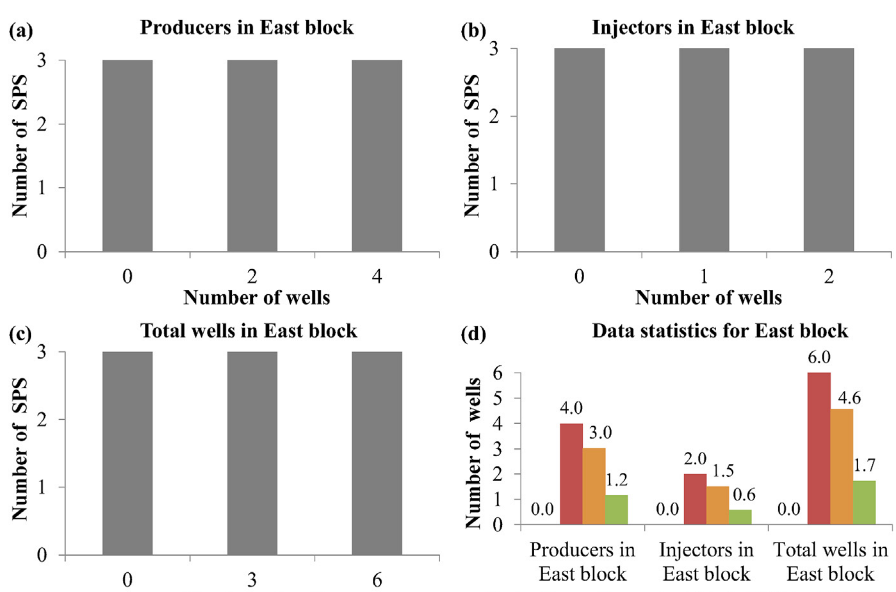

Fig. 7. Comparison of specialized production strategies considering number of wells in the East block: (a) number of producers; (b) number of injectors; (c) total number of wells; and (d) data statistics, including minimum (min), maximum (max), mean, and standard deviation (SD) of number of wells.

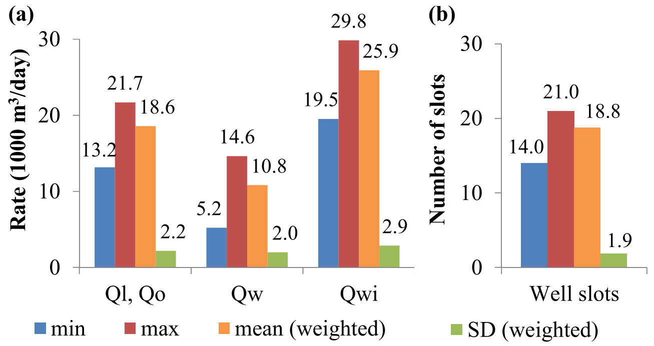

Fig. 8. Comparison of specialized production strategies considering platform size: (a) fluid processing capacities for liquid (Q_l), oil (Q_o), water (Q_w) production, and for water injection (Q_{wi}); and (b) number of well slots. Data statistics include minimum (min), maximum (max), mean, and standard deviation (SD).

Table 5
Best production strategy, based on ε(NPV), for the subset of scenarios (out of 214) grouped by uncertainty level (−2 to +2) of the uncertain attributes *bl* and *wo*.

	bl		wo				
	−1	0	−2	−1	0	+1	+2
Best strategy based on ε(NPV)	S1	S9	S1	S9	S9	S9	S9

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. Although this case study has multiple uncertain attributes (Tables 1 and 2), we found that only *bl*, *wo*, and *kr* significantly impact the response and correlate with the choice of flexibility. Fig. 12 exemplifies analyses of the number of wells according to the presence (*bl*[0]) or absence (*bl*[−1]) of hydrocarbons in the East block and the five depths of water-oil contact (*wo*[−2] to *wo*[+2]).

We compared risk curves for the case with the maximum value of flexibility and with decision rules (Fig. 13 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.

4.3.3. Candidate flexibility F3

Candidate flexibility F3 is accepted because of the potential to increase ε(NPV) by +7.6%. We defined probabilistic-based implementation rules (Table 10) by characterizing the scenarios that use each level of flexibility using the same procedure as described for F2.

We compared risk curves for the case with the maximum value of flexibility and with decision rules (Fig. 14 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 7
Platform investment and capacity expansion costs for the flexible candidate production strategies (excluding drilling and completion costs of additional wells). Values in US$ million.

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

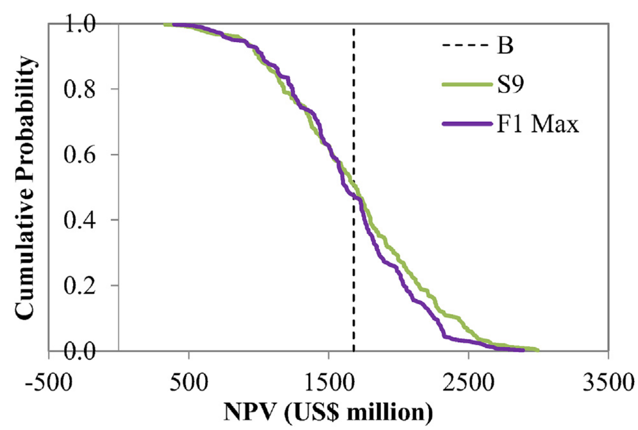

Fig. 9. NPV risk curve for the robust production strategy S9 and the candidate flexibility F1 without an established decision rule. The vertical dashed line marks the benchmark separating downside risk from upside potential.

4.4. Selecting the best flexible candidate production strategy

Candidates F2 and F3 with decision rules are both suitable, but F2 is the best (Fig. 15 and Table 12). Platform capacity expansion is installed in 51% of the scenarios (Fig. 16a), with 69% usage of the additional well slots (Fig. 16b), and F2 recording an EVoF of US$ 123 million.

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 West block), i.e., 1.5 years after the beginning of production. However, many factors can delay implementation, such as logistics, time for uncertainty

Table 6
Flexible candidate 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 West 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 West 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 West block: S9 - Placement of wells in East block, if present: S1 (if 3 wells) or S9 (if 6 wells) - Number of well slots: 20

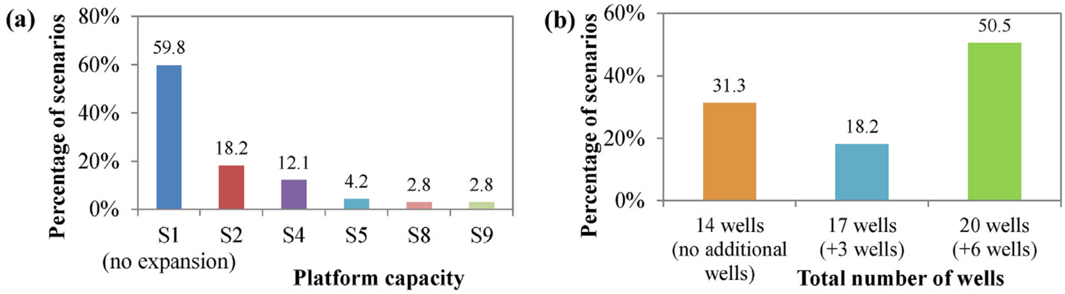

Fig. 10. Assessing the percentage of scenarios that implement the flexibility F2 (expansion up to S8): (a) platform capacity expansion and (b) additional well slot usage.

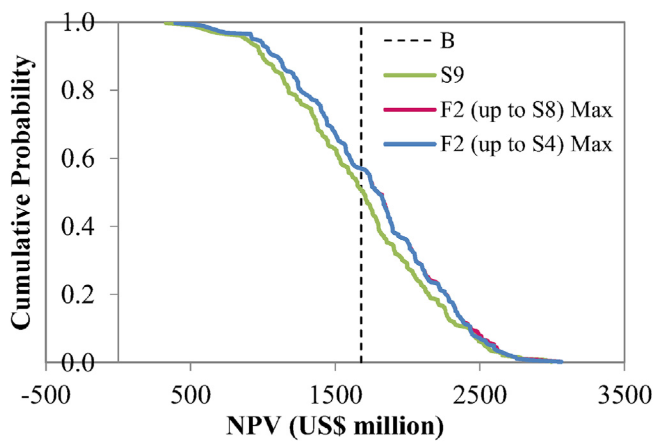

Fig. 11. NPV risk curve for the robust production strategy S9 and the candidate flexibility F2 with platform expansion up to S4 and S8, without an established decision rule. The vertical dashed line marks the benchmark separating downside risk from upside potential.

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	

to unfold, and time to incorporate this information into model updating and decision-making. Here, we did not investigate these causes, only assessed how implementation delays affected the EVoF.

We considered a one-year delay (t_2) and a two-year delay (t_3), which revealed that delays in implementation decrease the value of flexibility and may completely negate its value (Fig. 17 and Table 13).

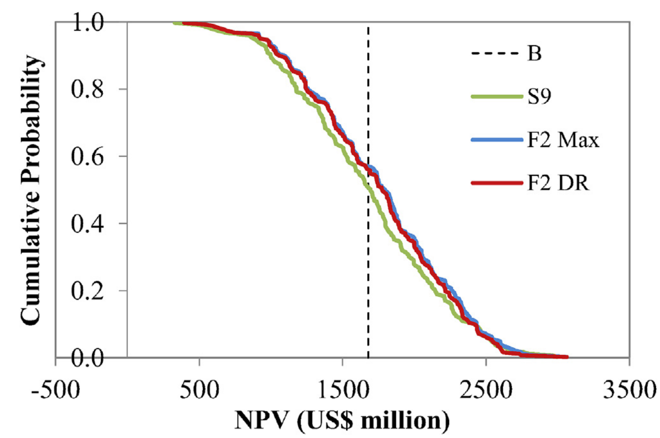

Fig. 13. NPV risk curve for the robust production strategy S9 and the candidate flexibility F2 without an established decision rule (Max), and with the probabilistic-based decision rule (DR). The vertical dashed line marks the benchmark separating downside risk from upside potential.

Table 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$ million.

	S9	F2 Max		F2 DR	
EMV	1677.9	1761.2	+5.0% ✓	1742.0	+3.8% ✓
S_{B-}	369.3	324.8	−12.1% ✓	330.2	−10.6% ✓
S_{B+}	373.6	410.7	+9.9% ✓	391.2	+4.7% ✓
ε(NPV)	1682.4	1851.5	+10.1% ✓	1804.9	+7.3% ✓
EVoF(EMV)		83.3		64.1	
EVoF(ε)		169.6		122.5	

As the fault separating the West and the East blocks is sealing, implementation delays resulted in delayed oil recovery. Thus, we attributed the decreases of EVoF to the time value of money.

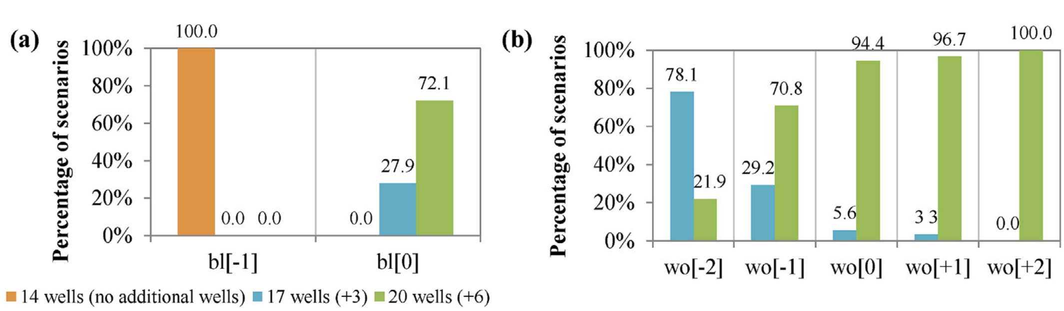

Fig. 12. Optimal number of wells according to the attributes: (a) structural uncertainty (*bl*) and (b) water-oil contact (*wo*) in the East block (exclusive to the scenarios with East block, *bl*[0]).

Table 10
Decision rules for candidate flexibility F3.

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

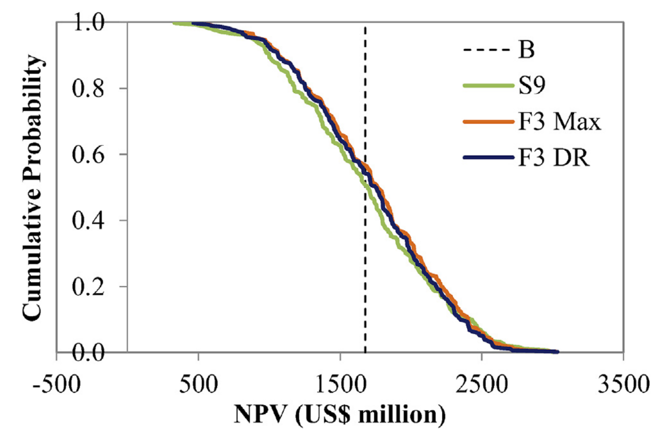

Fig. 14. NPV risk curve for the robust production strategy S9 and the candidate flexibility F3 without an established decision rule (Max), and with the probabilistic-based decision rule (DR). The vertical dashed line marks the benchmark separating downside risk from upside potential.

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$ million.

	S9	F3 Max		F3 DR	
EMV	1677.9	1742.8	+3.9% ✓	1718.3	+2.4% ✓
S_{B-}	369.3	321.8	−12.9% ✓	329.5	−10.8% ✓
S_{B+}	373.6	389.0	+4.1% ✓	366.7	−1.8% ✗
ε(NPV)	1682.4	1811.0	+7.6% ✓	1755.4	+4.3% ✓
EVoF(EMV)		64.9		40.4	
EVoF(ε)		128.6		72.9	

5. Discussion

Our proposal is based on the concept of representative models and uses a predefined set of specialized production strategies optimized individually for these models. This is only possible if RMs are adequately selected, ensuring that both system inputs (probability distribution of uncertain attributes) and outputs (variability of production, injection, and economic forecasts) are represented. If the set of RMs represents the system, the set of production strategies provides decision makers with the different possibilities to develop the field, including number and placement of wells, and platform processing capacities. Decision makers objectively assess how different (and similar) these alternatives are and their characteristics, reducing the subjectivity in defining a flexible system. Previous studies suggest that around nine RMs are sufficient for production strategy selection (Schiozer et al., 2004, 2015), but we recommend additional research on the optimal number of RMs and specialized production strategies applied to EVoF analyses.

Furthermore, note that the effectiveness of the flexible strategy in managing uncertainty depends on a thorough optimization process to generate adequate SPSs. In addition, similarly to any risk management procedure, our method also relies on the adequate representation of uncertainty. As reservoir characterization under uncertainty, uncertainty reduction, or history matching are not the focus of this work, we refer interested readers to Steps 1 through 5 of Schiozer et al. (2015).

We used the specialized strategy that performed best under uncertainty as the robust production strategy. The Robust Optimization, an optimization problem formulated under uncertainty to maximize a probabilistic objective function, has shown good results in the literature. For future research, we plan to consider a robust production strategy obtained through a Robust Optimization procedure as an input for our method. Note that both economic gains and additional computational costs should be carefully assessed.

The comparison of candidate production strategies was a manual process. To enable automation of this step, we recommend research on quantitative indicators to compare the SPSs, especially for well placement. Automating this step, the workflow we proposed to define 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. We used histograms to compare different subsets of scenarios according to the optimal implementation of flexibility. This way, we aimed to correlate the reservoir uncertainties that will unfold over time with the optimal production strategy. Thus, limitations of decision rules may be attributed to difficulties in identifying the dominant reservoir uncertainties affecting production strategy selection, namely the effects of geostatistical realizations. Further research is recommended on indicators to improve this analysis.

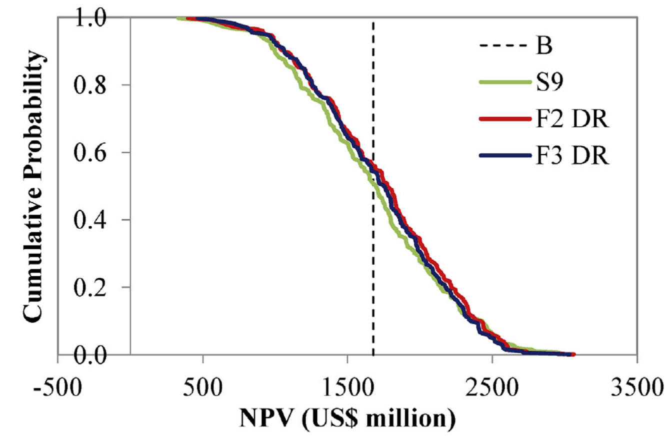

Fig. 15. NPV risk curve for the robust production strategy S9 and the candidate flexibilities F2 and F3 with the probabilistic-based decision rule (DR). The vertical dashed line marks the benchmark separating downside risk from upside potential.

Table 12
Assessing the candidate flexibilities F2 and F3 with decision rules versus robust production strategy S9. Values in US$ million.

	S9	F2 DR		F3 DR	
EMV	1677.9	1742.0	+3.8% ✓	1718.3	+2.4% ✓
S_{B-}	369.3	330.2	−10.6% ✓	329.5	−10.8% ✓
S_{B+}	373.6	391.2	+4.7% ✓	366.7	−1.8% ✗
ε(NPV)	1682.4	1804.9	+7.3% ✓	1755.4	+4.3% ✓
EVoF(EMV)		64.1		40.4	
EVoF(ε)		122.5		72.9	

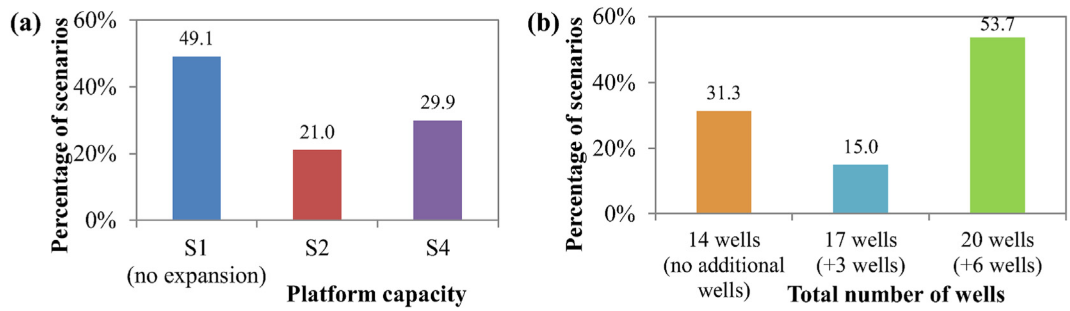

Fig. 16. Assessing the percentage of scenarios that implement the flexibility F2: (a) platform capacity expansion and (b) additional well slot usage.

Because we used hundreds of scenarios, we ensured a more accurate estimate of the EVoF. This is key because, as the difference between two expected values, EVoF is highly sensitive to approximations and susceptible to errors. However, this approach made defining the decision rules computationally demanding, requiring hundreds of flow simulation runs. Future research is planned on assessing the feasibility of defining the probabilistic analyses based on the small subset of representative models, each characterized by a probability of occurrence. Having validated all steps of the workflow using the small subset of RMs alone, we achieve a fully automated and computationally feasible procedure to define flexible strategies.

In our case study, risk curve analyses showed that flexibility is important to reduce risk (−10.6%) and improve the upside potential (+4.7%). However, the flexible production strategy recorded a mild increase in the EMV (+3.8%), meaning that using the EMV alone tended to underestimate the potential of flexibility. Conversely, when considering delays in implementation, we recorded strong compromises on the upside potential (decreases of up to −10.0%), while the EMV still increased (+0.6%). In this case, the EMV overestimated the EVoF. Thus, our proposal ensured a more quantitative EVoF estimate when considering the decision makers attitude toward upsides and downsides.

We proposed flexibility to manage reservoir uncertainty. In our case study, the use of flexibility was limited to the development of the East block, which has lower oil in place than the already proven West block. Still, we recorded an EVoF of US$ 123 million, an increase in project value of over +7%. Higher increases are expected for case studies with a higher degree of uncertainty and more uncertain attributes affecting production strategy selection. Specifically, we recommend future research on the use of flexibility to mitigate or exploit exogenous uncertainties, such as uncertainty in oil price.

Simplifications may affect the EVoF. We defined decision rules according to the different values of the uncertain reservoir attributes, 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. Conversely, the EVoF may have been underestimated because we used a simplified approach for well control. We also demonstrated implementation delays may strongly compromise the estimated EVoF. That is, 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 had no value. Accordingly, including all factors that may affect EVoF improves 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 (robust and specialized 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 allow analyses to be based on a predefined set of candidate production strategies;
- Defining the flexible strategy based on a set of rigid candidate 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;
- Implementation delays decrease EVoF to a point where flexibility may lose its value.

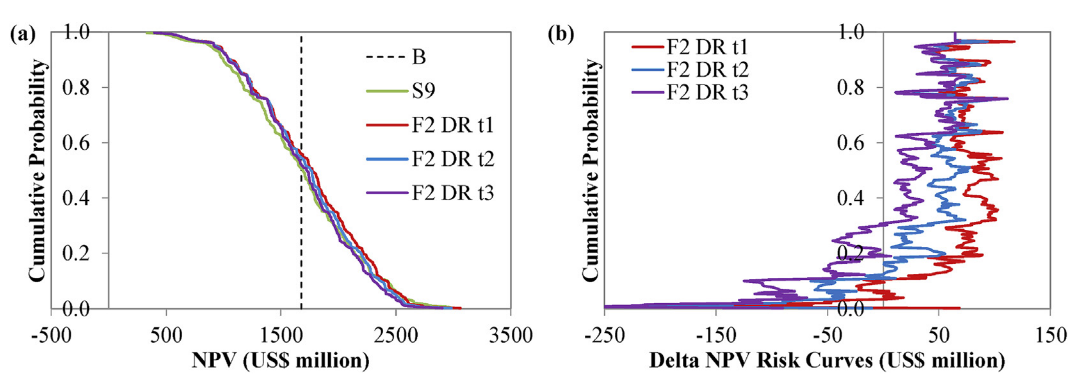

Fig. 17. (a) NPV risk curves for the robust production strategy S9 and the candidate flexibility F2 implemented at different times; the vertical dashed line marks the benchmark separating downside risk from upside potential. (b) Difference between the NPV risk curves for F2 implemented at different dates and the NPV risk curve for S9.

Table 13
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% ✓
S_{B-}	369.3	330.2	−10.6% ✓	333.9	−9.6% ✓	338.3	−8.4% ✓
S_{B+}	373.6	391.2	+4.7% ✓	364.7	−2.4% ✗	336.3	−10.0% ✗
ε(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	

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