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.

Keywords: field development; uncertainty management; robustness; production strategy; semi-deviation; reservoir simulation.

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, 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)).

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

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; Krokmal 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).

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

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 $c \rightarrow 0$ 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)).

$$EU \simeq u(EV) + u''(EV) \times S_B^2 \quad (3)$$

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).

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

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 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 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 (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 multi-attribute utility functions 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 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.

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. $N_p = 0$) and wells that do not inject (e.g. $W_{inj} = 0$). 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.

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 81x58x20 cells of 100x100x8 m, in a total of 36,739 active cells. The case study comprises a set of reservoir, operational, and economic uncertainties (Table 1, 2 and 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)).

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

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

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

where: Inv_{plat} – platform investment (US\$ million); Q_o – oil processing capacity (1 000 m³/day); Q_w – water processing capacity (1 000 m³/day); Q_{wi} – water injection capacity (1 000 m³/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).

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

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

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).

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

For this synthetic case study, we considered the following illustrative values: $RT(NPV) = \text{US\$ } 1.0\text{E}9$, $RT(RFo) = 30\%$; $k = 0.5$. 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).

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.

Verifying and increasing robustness of number and placement of production wells

The indicators revealed that S9 has four dry wells (null cumulative oil production, $N_p = 0$) 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 4d). 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 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 $u_{min}(S9) = 0$ 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 N_p 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.

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, $W_{inj} = 0$), 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 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.

Verifying and increasing robustness of platform size

The study of field indicators revealed that in 70% to 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, 9b and 9d, 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%.

4.3. Assessing the overall gain of increasing robustness of S9

Compared with optimized production strategy S9, defining the 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).

Nomenclature

a, b	scaling constants
AC	abandonment cost.
B	benchmark value
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

441	MAUT	multi-attribute utility theory
442	n	number of wells
443	NCF	net cash flow
444	Np	cumulative oil production
445	NPV	net present value
446	PWEI	Producer Well Economic Indicator
447	Q_l	liquid processing capacity
448	Q_o	oil processing capacity
449	Q_w	water processing capacity
450	Q_{wi}	water injection capacity
451	R	robust production strategy
452	Rev	gross revenue
453	RFo	oil recovery factor
454	Roy	royalties
455	RS	representative scenario
456	RT	corporate risk tolerance level
457	S	optimized production strategy
458	S_B^2	semi-variance below B
459	S_B^2	semi-deviation below B
460	ST	social taxes
461	T	corporate taxes
462	u	utility function
463	Wp	cumulative water production
464	x	random variable
465	σ^2	variance
466	σ	standard deviation
467	μ	mean

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Figure captions

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

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

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

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).

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).

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.

Tables and Table Captions

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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]	3074m (0.222)	3124m (0.334)	3174m (0.111)	3224m (0.222)	3274m (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	34.00
	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
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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

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%)

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%)

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%)

(a) Mean POR layer 1 (1857 days)

Std POR layer 1 (1857 days)

(b) Mean POR layer 2 (1857 days)

Std POR layer 2 (1857 days)

Global Utility