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Decision criteria for production strategy selection under uncertainty

Susana Margarida da Graça Santos

Introduction

This text summarizes the main contributions of a paper published in the Journal of Petroleum Science and Engineering by Santos *et al.* (2017), which proposes a set of decision criteria to improve production strategy assessment under uncertainty.

The decision maker (DM) takes many factors into account when selecting a production strategy in field development. However, the existing criteria to incorporate company objectives and risk attitudes in decisions are many times difficult to apply, leading DMs to rely on informal procedures and professional experience to make decisions.

Pitfalls of traditional decision criteria

The expected value (EV) is a widely applied decision criterion. Although easy to apply, it has limitations in incorporating real risk concerns by implying impartiality to the magnitude of gains and losses.

The utility theory was formulated to recognize risk aversion as part of the decision policy. Although widely documented in the literature, managers often regard these models as impractical for day-to-day decision making due to the difficulties in constructing the theoretically complex utility functions.

Mean-variance frameworks are many times preferred to utility functions because they are simple and easy to apply. However, the variance is inadequate to measure risk in the context of production strategy selection, where (1) risk is associated with the chance of failure to achieve a targeted return, while (2) variability above the target may be desirable.

Methodology

Figure 1 presents the proposal of Santos *et al.* (2017) for risk curve analysis, highlighting the three domains of variability: uncertainty in returns (blue); uncertainty in losses, i.e. downside risk (red); and uncertainty in gains, i.e. upside potential (green).

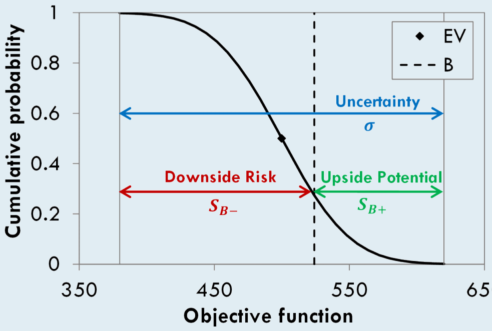

Figure 1: *Risk curve analysis, highlighting the domains of variability: uncertainty, downside risk, and upside potential.*

Standard deviation (σ) quantifies uncertainty in overall returns because it measures in a single value, good and bad variability. Semi-deviation (short for semi-standard deviation) from a target or benchmark return measures subsets of standard deviation and is used to differentiate good variability from bad. Lower semi-deviation (Eq. 1) quantifies downside risk, and upper semi-deviation (Eq. 2) quantifies upside potential. The benchmark (B) is defined by the DM as it solely depends on his definition of loss and gain. A fair comparison requires using the same benchmark for all production strategies. Santos *et al.* (2017) suggest using the strategy with maximized EV as the reference, and its EV as the benchmark.

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

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

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; X is a random variable.

The authors combined expected value, downside risk, and upside potential in a new objective function (Eq. 3) that determines the production strategy's value adjusted to the DM's attitude, $\varepsilon(X)$, while maintaining the units and dimension of X. This proposal is applicable to production and economic indicators.

$$\varepsilon(X) = E[X] - c_{dr}S_{B-}^2 + c_{up}S_{B+}^2 = E[X] - \frac{S_{B-}^2}{\tau_{dr}} + \frac{S_{B+}^2}{\tau_{up}} \quad (3)$$

In Eq. 3, the S_{B-}^2 decreases the EV, in accordance with the production strategy's level of risk and DM's risk aversion (c_{dr}); while the S_{B+}^2 increases the EV, in accordance with the production strategy's upside potential and the DM's corresponding expectations (c_{up}). Attitudes can also be modeled with tolerance levels to each domain of uncertainty, where $\tau = 1/c$. When $\tau \rightarrow \infty$, decisions are based on EV.

If more than one objective is considered, Eq. 4 is proposed to combine them, where k_i is the weight of objective X_i, such that $\sum_{i=1}^{n} k_i = 1$.

$$u(X) = \sum_{i=1}^{n} k_i \varepsilon_{normalized}(X_i) \quad (4)$$

Application and Results

The proposal for production strategy selection was applied to a benchmark offshore heterogeneous heavy oil reservoir in the development phase (Botechia *et al.*, 2017). The authors studied many candidate production strategies (Figure 2), considering an illustrative DM who bases decisions on net present value (NPV), with strong expectation for the upsides, and mild risk aversion.

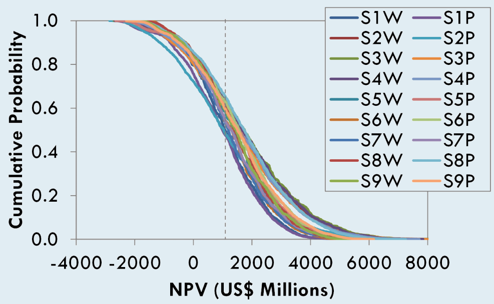

Figure 2: *NPV risk curves for the candidate production strategies.*

Table 1: *Best candidate production strategies ranked by decreasing NPV adjusted to the DM's atitude. Figures in bold highlight the best production strategies under each criterion. Units: US$ millions.*

Prod. Strategy	EMV	Downside Risk	Upside Potential	ε(NPV)
S3W	1770.8	1227.5	**1358.5**	**2611.8**
S4W	1742.0	1246.3	1299.2	2394.2
S8P	**1799.3**	**1111.0**	1177.0	2361.8
S2W	1680.6	1260.0	1257.3	2203.0
S4P	1645.8	1260.2	1199.5	2025.9
S3P	1589.3	1313.9	1228.9	1948.6
S6P	1578.5	1112.6	943.6	1643.6

"The existing criteria to incorporate company objectives and risk attitudes in decisions are many times difficult to apply."

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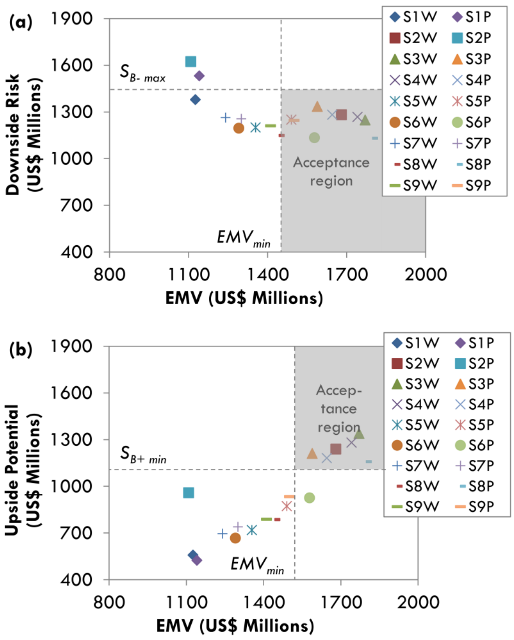

***Figure 3:** Cross-plots to constrain analyses on the candidate production strategies with the highest potential to be chosen: (a) expected value versus downside risk; and (b) expected value versus upside potential.*

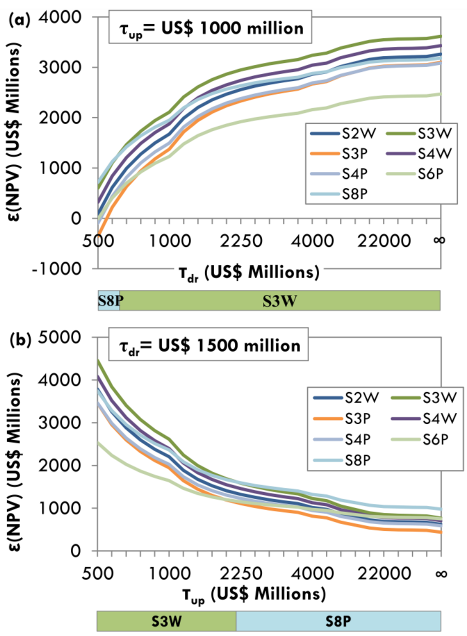

***Figure 4:** Sensitivity analysis on tolerance to downside risk and to upside potential. Horizontal bars identify the best production strategy.*

As the case study has many candidate strategies, the authors built expected value versus semi-deviation cross-plots (Figure 3) to focus analyses on the candidates with the highest potential to be chosen (Table 1).

The effects of the DM's attitude on production strategy selection are noticeable. S3W does not maximize the expected monetary value (EMV) nor does it minimize downside risk, both of which are achieved by S8P. However, the upside potential of S3W is by far the most attractive of the set, while that of S8P is one of the least attractive, making S3W the preferred choice. Sensitivity analyses on the tolerances to downside risk and to upside potential (Figure 4) show how production strategy selection varies according to the DM's perception of these domains of uncertainty.

Despite the difficulties in finding the tolerance levels, the use of mean-partial moment frameworks is preferred to utility functions, because their interpretation is straightforward. This is because DMs can weigh the expected value with the magnitude of uncertainty in losses and in gains, separately.

Further discussions and other applications can be found in Santos *et al.* (2017), including production strategy selection based on NPV and oil recovery factor combined. Theoretical examples illustrate problems faced by DMs when using traditional risk measures, which are overcome by semi-deviations.

Concluding remarks

1) Combining expected value with semi-deviations as decision criteria improves production strategy selection while remaining easy to use in real decision problems.
2) Standard deviation measures overall uncertainty in returns and is inadequate to measure risk.
3) Semi-deviation from a benchmark assesses individual subsets of overall uncertainty, measuring downside risk and upside potential.
4) The decision maker's attitude affects decisions, which cannot be captured by the expected value alone.

References

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About author:

Susana M. G. Santos holds a BSc in Geology (University of Lisbon, Portugal), an MSc in Petroleum Economics and Management (IFP School, France), and is a PhD Candidate in Petroleum Sciences and Engineering at UNICAMP. Her research at UNISIM focuses on decision risk analysis.

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