Abstract
A risk analysis process can be applied to several phases of a petroleum field. The methodologies required in the decision-making process depend on the level of uncertainties, which vary according to the field phase. This work is focused on the development phase and the decision process is based on probabilistic procedure to represent all possible scenarios of the reservoir.

The uncertain attributes can be combined through derivative tree or Monte Carlo technique. The risk can be evaluated by the Net Present Value, which depends on the reservoir performance. The reservoir production prediction can be obtained through numerical simulation or response surface. Most of works consider only the application of these procedures and comparisons of these techniques are not well evaluated. The goal of this work is to apply the alternative combinations of these techniques to petroleum fields and compare them to determine the result reliabilities.

The combination of Monte Carlo and numerical simulation is not viable, in some cases, due to the great number of simulations. The attribute combination by derivative tree can be an alternative, but can also yield a high number of simulation runs. Alternatives to speedup the process are to reduce the number of attributes and their discretization levels or substitute the conventional reservoir modeling by faster ones, such as the response surface, which is suited to evaluate the impact of uncertainty on production forecasts.

The contributions of this work are to: (1) to determine if the response surface can substitute the reservoir simulator, (2) to evaluate the capability of the response surface to substitute the reservoir simulator in order to obtain the risk curves, (3) to provide a guide to select an adequate combination of techniques according to the desired precision and (4) to determine if it is possible to reduce the number of simulation runs, maintaining the precision.

Introduction
Risk is always associated to a petroleum field, with minor or major intensity, depending on its life phase. In development phase, the number of uncertainties is high, affecting strongly the financial results and requiring high investment. Demirmen (2001) states the risk associate in development decision-making process involves suboptimal development and opportunity loss. For this reason, the decision-making process in such phase must be probabilistic. Probabilistic approaches are common in exploration phase (Newendorp and Schuyler, 2000 and Rose, 2001). In development phase, the importance of uncertainties increases significantly, mainly on the recovery factor, however probabilistic methodologies are not used frequently to assess the risk (Schiozer et al, 2004).

Most of works present methodologies to assess risk in development phase and they present only illustrative examples of their application. Comparison of the performance of different risk analysis methodologies is not common in the literature. For this reason, the main goal of this work is to compare risk assessment methodologies in development phase.

The first step of a risk methodology is to combine the geological uncertainties. Two possible manners are: Monte Carlo and Derivative Tree techniques, resulting in many reservoir geological models. The second step is to calculate the value of some specific objective functions, such as Net Present Value and Cumulative Oil Production. These values can be obtained through numerical simulation flow or faster simulation models. In the last step, the risk curves are built through a statistical treatment (Figure 1).

![Figure 1. Risk assessment in development phase.](image-url)
Monte Carlo Technique: according to Schuyler (2001), this technique is used for modeling the behavior of a stochastic system. It generates trial values for key uncertain model input variables. When the process is repeated for many trials, a frequency distribution is generated, approximating the true probability distribution for the systems output.

Derivative Tree Technique: Steagall and Schiozer (2001) and Schiozer et al. (2004) used this technique. The uncertain attributes are discretized in levels of uncertainty and are combined according the branches of a tree. Each branch of the tree corresponds to a reservoir simulation model with an associated occurrence probability. The sum of the probabilities of all tree branches must be equal to the unity.

Numerical Flow Simulation: it is a reliable manner to predict the performance of petroleum reservoirs. Usually, a commercial Black-Oil simulator is used to obtain the objective functions: Cumulative Oil Production and consequent ly, the economic function, Net Present Value.

Experimental Design: another manner to predict the production of petroleum reservoir is through the experimental design and the response surface. The response surface is a collection of mathematical and statistical techniques to model and analyze problems in which a response of interest is influenced by several variables (Montgomery, 1997). The polynomial unknown coefficients of the response surface are estimated from some reservoir simulations, which are determined through experimental design. Usually, a response surface has linear, interaction and quadratic terms. However, it should be as simple as possible in order to avoid estimating unnecessary coefficients (Damsleth et al., 1991).

Combinations: Among the possible combinations presented in Figure 1, the following procedures can be considered: (1) Monte Carlo technique associated to Numerical Flow Simulation that should be the ideal combination, but it may not be viable due to the high number of simulations; (2) Derivative Tree technique associated to Numerical Flow Simulation is an alternative in substitution to Monte Carlo, however but precision can be a problem if a low number of discretization levels are used; (3) Monte Carlo technique associated to faster simulation models; (4) Derivative Tree technique associated to faster simulation models. In this work, the faster simulation models used in items (3) and (4) are obtained through the techniques Experimental Design and Response Surface. Automation of the process and parallel computing can be used to speedup the process (Ligero and Schiozer, 2002; Costa and Schiozer, 2004).

Critical Attributes
Before combining the uncertain attributes, it is usual to select the most important ones, called critical attributes, reducing the number of uncertain attributes to be considered in risk analysis and, consequently, the process time. Two methods are possible to be applied in order to select the most critical attributes: Sensitivity Analysis and Experimental Design.

Sensitivity Analysis: uncertain attributes are changed one by one in a base model constituted by all most probable attributes and this model has a characteristic of a deterministic model. For example, in a case with n uncertain attributes with three levels of uncertainty each one, the resulting number of reservoir models is equal to \( 2n+1 \). The advantages of the sensitivity analysis are: (1) to determine the effect of the different levels of an attribute in the objective function, (2) to verify if the type of influence of one attribute is linear or non-linear in the objective function and (3) to eliminate levels of uncertainty that do not influence significantly the process result.

The sensitivity analysis is also an initial step when experimental design will be used to select the critical attributes. The reason for this is, that in experimental design and response surface techniques, the optimistic value must be considered as +1, the pessimistic value must be considered as −1 and the probable one as 0. However, some uncertain attributes are represented by maps or tables and it is not possible to differ between optimistic and pessimistic levels without reservoir simulation. For this reason, it is necessary to determine their influence in the results of the objective function. The simulation of the models generated by the sensitivity analysis is a manner to determine if one attribute level is optimistic or pessimistic.

Experimental Design: the techniques used to select the most important uncertain attributes are usually factorial design \( 2^p \) and two-level fractional factorial design \( 2^{n-p} \), where p is the number of independent generators. Montgomery (1997) states that fractional factorial design is most used in the early stages of a project, when many attributes are considered. The factorial design results in a higher number of simulations than the two-level fractional factorial design.

Applications
The combinations of Figure 1, except Monte Carlo associated to Numerical Flow Simulation, were applied to offshore petroleum reservoirs located in deep and ultra-deep water. This work proposes to apply these combinations to quantify the risk in petroleum field development and to compare them in order to take into account the number of simulation runs and the difference in the risk curves. Two cases (Case 1 and 2) were studied.

The Case 1 represented a development field with 8 uncertain attributes: areas, dwoc, permx, permz, por, cpor, krog and pvt. All attributes had three level of uncertainty. In Case 2, the number of uncertain attributes were 5: dwoc, permx, por, krog and pvt. The discrete attributes (krog and pvt) were always discretized in 3 levels of uncertainty. However, the continuous attributes (dwoc, permx, por) were discretized in 3 or 5 levels of uncertainty. In both cases, the forecasting time was 7,300 days (20 years) and the objective functions analyzed were NPV and Np.

Results
Case 1 – Critical Attributes

(1) Sensitivity Analysis
Figure 2 illustrates the sensitivity analysis for the objective function NPV for a case with 8 uncertain attributes with tree levels of uncertainty, called Case 1. The advantage to eliminate some levels of attributes it is clear from Figure 2, such as pessimistic levels of permx and areas and the optimistic level of krog. Only 17 reservoir simulations were required for the sensitivity analysis.

The non-linear behavior of some attributes of Case 1 can be observed in Figure 3. The –1, 0 and 1 levels represent the pessimistic probable and optimistic levels, respectively. The high non-linearity of the attributes por, permx and dwoc confirm their elevate importance as shown in Figure 2.

The attributes which levels were presupposed as optimistic were pessimistic through the analysis of Figure 2. The opposite was also observed to levels presupposed as pessimistic. The same behavior was observed regarding the NPV function.

The experimental design was capable to produce almost the same results than the factorial design when the effects of pure attributes were considered for the NPV (Figure 4).

Another advantage of the experimental design was the possibility of determining the effect of interaction between the attributes. However, this technique did not allow eliminating a level of uncertainty of an attribute.

(2) Experimental Design

In the Case 1, the two-level fractional factorial design required only 32 simulation models \(2^8 - 3\), while the factorial design required 256 simulation models \(2^8\). However, the two-level fractional factorial design was capable to produce
The Figure 6 illustrates the percentile values (P10, P50 and P90) for NPV stabilized from the addition of the sixth attribute. The same occurred for Np. Figure 6 shows too the exponential behavior of the number of simulation runs as the number of attributes increases.

![Figure 6](image1.png)

Figure 5: Risk curves obtained through the combination-Derivative Tree Technique and Numerical Flow Simulation: (a) NPV and (b) Np (Ligero et al., 2005).

![Figure 5](image2.png)

Figure 6: Use of gradual combination of attributes for NPV (Ligero et al., 2005).

(2) Derivative Tree Technique and Response Surface

The experimental design called composite central design, which requires $2^n + 2n + 1$ reservoir simulation models, was used to obtain the response surface to NPV and Np (Figure 7). The response surface was obtained by three different manners: only linear terms, linear and interaction terms and linear, interaction and quadratic terms.

![Figure 7](image3.png)

Figure 7: Risk curves obtained through the combination-Derivative Tree Technique and Response surface: (a) NPV and (b) Np (Ligero et al., 2005).

In Figure 7, the reference curve was also considered the derivative tree with 8 attributes and 6,561 simulations. The surface response with linear, interaction and quadratic terms was the most adequate to represent the risk curve for NPV and Np. Response surfaces with linear, interaction and quadratic terms required only 273 reservoir simulations.

(3) Monte Carlo Technique and Response Surface

For each attribute, it was selected 16,000 values through Monte Carlo technique. These values were combined in order to be used in the response surface.

The same response surface with linear, interaction and quadratic terms used in Figure 7 (273 reservoir simulations)
was substituted in Monte Carlo combinations in order to generate the risk curves for NPV and Np (Figure 8).

Figure 8. Risk curves obtained through different techniques to evaluate the risk: (a) NPV and (b) Np (Madeira, 2005).

Case 2 – Risk Curves

In this Case like Case 1, the combinations: (1) Derivative Tree Technique and Numerical Flow Simulation; (2) Derivative Tree Technique and Response Surface and (3) Monte Carlo Technique and Response Surface were also considered. In this case besides the composite central design, the Box-Behnken was employed.

Box-Behnken design has several advantages. When compared to a three level full-factorial design, it reduces the number of required experiments. This reduction becomes more significant as the number of attributes increases (Box-and Behnken, 1960).

The reference risk curve was also obtained through the combination of Derivative Tree Technique and Numerical Flow Simulation. The 5 critical attributes were discretized in 3 levels, resulting in 243 simulation runs. The adopted procedure to obtain the other risk curves taking into account the Monte Carlo Technique and the Experimental Design can be better understood through Figure 9. Three types of experimental design were employed to calculate the response surfaces: Box-Behnken, Factorial Design and Central Composite Design.

Figure 9. Case 2 - Combinations to risk assessment.

(1) Experimental Design - Box-Behnken

Besides the reference risk curve (Derivative Tree and Numerical Flow Simulation), two others curves were obtained: Derivative Tree and Monte Carlo Technique combined to a response surface generated by Box-Behnken. The risk curves for NPV and Np are in Figure 10.

Figure 10. Case 2 – Risk Curves: (a) NPV and (b) Np. All attributes discretized in 3 levels of uncertainty (Risso et al., 2006).
The risk curves in terms of NPV and Np obtained by Derivative Tree associated to reservoir simulator or Box Behnken were very closer one of the other. In the first combination, the number of simulation runs was 243 and for the second, it was only 41 simulations. The curves generated by Monte Carlo (16,000 combinations) associated to Box Behnken required also 41 simulation runs. The curves of Monte Carlo were a little distant from the others due to all combination possess the same occurrence probability.

(2) Experimental Design – Factorial Design
The risk curves obtained by Derivative Tree and Numerical Flow Simulation continued to be the reference curves. The other curves for NPV and Np were obtained by Derivative Tree and Monte Carlo Technique combined to a response surface generated by Factorial Design (Figure 11).

![Figure 11: Case 2 – Risk Curves: (a) NPV and (b) Np. All attributes discretized in 3 levels of uncertainty (Risso et al., 2006).](image)

(3) Experimental Design – Central Composite Design
The risk curves obtained by Derivative Tree and Numerical Flow Simulation continued to be the reference curves. The other curves for NPV and Np were obtained by Derivative Tree and Monte Carlo Technique combined to a response surface generated by Central Composite Design (Figure 12).

The curves obtained by Central Composite Design combined with Derivative Tree or Monte Carlo presented practically almost the same behavior. The Central Composite Design required 43 simulations. The reference curves in terms of NPV and Np (Derivative Tree combined to Numerical Flow Simulation) were distant from other curves due the smaller number of discretization levels of the attributes (only 3).

![Figure 12: Case 2 – Risk Curves: (a) NPV and (b) Np. (dwoc, permx and por - discretized in 5 levels and pvt and krog - 3 levels) (Risso et al., 2006).](image)

Discussions
For Case 1, the Derivative Tree Technique with 6,561 simulations represented all scenarios for 8 attributes with 3 levels of uncertainty (Figure 5) with an elevated computational effort required; this option was used as the one with the highest reliability and precision. For a lower precision, the Derivative Tree with gradual addition of attributes could produce risk curves with a much lower...
number of simulations. For the objective functions Np and NPV, the Derivative Tree with 6 attributes resulted in 486 simulation runs. If a lower precision should yet be accepted, the Derivative Tree with gradual addition of attributes could produce risk curves with a much lower number of simulations.

For the Derivative Tree Technique with 8 attributes and Monte Carlo both associated to response surface technique (Figures 7 and 8), the simulation runs were reduced to 273 and were good representations of curves compared to the reference curves (Derivative Tree Technique with 6,561 simulations). Therefore, if it is necessary to consider more than 5 or 6 critical attributes, the response surface is recommended due to the number of simulations is reduced significantly. The curves obtained through response surface (273 simulations) were equivalent to those obtained through Derivative Tree with gradual addition (486 simulations). If the required precision is not high, the risk curves can be obtained with a lower number of simulations.

In Case 2, it is shown that the type of experimental design is important in order to have reliable risk curves. The application of Box-Behnken technique required 41 simulations (Figure 10), while the Factorial Design and the Central Composite Design both required 33 and 43 simulation runs, respectively (Figures 11 and 12). The response surface with quadratic terms presented better results than the surfaces with only linear terms.

The response surfaces were capable of substituting the simulator in risk curves elaboration, however, for a specific case (specific simulation run), the response surface may to substitute the reservoir simulator accurately (Figure 13).

Figure 13. Case 1 - Comparison between simulation and response surface for Np (Ligero et al., 2005).

Conclusions

Although, the experimental design can be useful and a fast tool in order to obtain the risk curves, it is necessary to have a good knowledge of both risk analysis process and experimental design techniques in order to obtain reliable results and with a reduced number of simulation runs.

Monte Carlo and Derivative Tree Techniques can be used with similar performance to assess risk in the field development process but several simplifications are necessary in order to have efficient processes.

Nomenclature

- areas: Structural model
- cpor: Rock compressibility
- CCD: Central Composite Design
- DT: Derivative tree
- dwoc: Water-oil contact
- krog: Oil-gas relative permeability
- L: Level
- MC: Monte Carlo
- n: Number of attributes
- Np: Cumulative oil production
- NPV: Net present value
- P: Percentile
- p: Number of independent generators
- permx: Absolute permeability in x direction
- permz: Absolute permeability in z direction
- por: Porosity
- pvt: PVT analysis
- RS: Response surface
- SIM: Simulation

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References


