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# Risk analysis of petroleum fields using Latin hypercube, Monte carol and derivative tree techniques

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A risk analysis can be applied to several phases of the development of a petroleum field. A typical analysis requires many realizations. Selection of the realizations is usually made in a way that maximizes the coverage of anticipated range of input parameters while requiring the minimum number of simulation runs. Techniques such as Latin Hypercube, Statistical Design, Derivative Tree and Monte Carlo can be used in this process. Alternatives to speed up the process are the reduction of the number of attributes and their discretization levels or the substitution of the conventional reservoir modeling by faster techniques (proxy models). The main objective of this paper is to apply and compare the precision of the results using three different techniques. Derivative Tree, Monte Carlo, Latin Hypercube. The idea is to reduce the number of simulation runs maintaining the precision of the results. The case studied represents a field with 4 main uncertain attributes: horizontal and vertical permeability, porosity and net pay. The objective functions analyzed are net present value, oil recovery factor, water production and oil production. It is shown that the choice of the right technique in this paper allows a reduction in the number of simulations, maintaining the precision of the risk curves. It is shown that the results were very satisfactory with the application of the Latin Hypercube Technique. The results showed that, in this case, this technique is more adequate than Derivative Tree and Monte Carlo considering the required number of simulatins.

Keywords: Risk Analysis, Latin Hypercube, Statistical Design, Simulations.

#### INTRODUCTION

The methodologies required in a risk analysis related to the development of petroleum fields depend on the level of uncertainties, which vary according to the field development phase. The total number of models to be simulated depends on the number of uncertain attributes and the treatment of each of them.

Some methodologies in the literature present good results but, in some cases, they are not feasible because

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#### ABREVIATION

MC, Monte Carlo; HCL, Latin Hypercube; DT, Derivative Tree; ,Np, Cumulative Oil Production; NPV, Net Present Value; Wp, Cumulative Water Production; RF, Oil Recovery Factor; SIM, Simulation. the number of simulations is high. Most publications use the Monte Carlo Technique to combine the possible scenarios. The Monte Carlo Technique allows the generation of values for uncertain attributes for the model input variables. When the process is repeated, a frequency distribution is generated. The total number of models (N) obtained is the same number of trial values for each attribute, and the probability of each model is (1/N).

The Latin Hypercube Technique was incorporated in the process of risk analysis in an attempt to minimize this limitation. This technique divides the distribution in intervals and selects values from each interval. Although more complex and less used than Monte Carlo, the Latin Hypercube Technique is more precise for random samples because the full range of the distribution is sampled more evenly and consistently( Vose, 2000). The process of sampling in Monte Carlo is the generation of



**Figure 1**. Example of triangular distribution for MC and HCL techniques with 200 trials.



**Figure 2.** Example of triangular distribution for MC and HCL techniques with 9000 trials.

random numbers (Hammersley and Handscomb, 1983). In this method, the process of generation of random values is sometimes repeated, resulting in various scenarios for a problem. All scenarios result in a band of the possible solutions, some of which are more probable than the others (Rubinstein, 1981). A smaller number of scenarios is necessary to have the same accuracy as the Monte Carlo Technique (Figures 1 and 2).

Some works applied in oil field management use a system that combines the Derivative Tree, Response Surface and Monte Carlo Techniques in the analysis of the information value in the decision of the real field development (Floris and Peersmann, 2000). The statistical theory and especially the statistical (experimental) design approach are well-suited to determine the most uncertain parameters, to evaluate the impact of uncertainty on production forecasts, and to help in making a decision during the reservoir development (Venkataraman, 2000; White and Royer, 2003). A method for predicting reservoir performance using a simple model that can approximate the reservoir simulator over a given range of some important input parameters is a good approach to provide the means of

comparison and preliminary predictions without resorting to numerical simulation (Prada and Cunha, 2008). The purpose is to use statistical design techniques to develop a response surface that can predict performance without the expense of doing simulation (Prada and Cunha, 2008). The application of statistical design techniques in reservoir engineering studies is not new: numerous applications can be fond in the technical literature, especially when the aim is to map the uncertainty of some variable that measures the reservoir performance (Prada et al., 2005). The Statistical Design Technique, coupled with response surface methodology, was an efficient way to accurately quantify the impact of reservoir uncertainties on production forecasts. The statistical design was used to obtain the proxy models (Narahara et al., 2004). Thus, it was possible to use Monte Carlo combined with the proxy models.

With the Latin Hypercube Technique, a smaller number of trials achieve the same accuracy as a large number of Monte Carlo trials. The Latin Hypercube Technique is less used than other techniques in the literature.

The main objective of this paper, is to compare the

precision of the results using different Techniques: Derivative Tree, Monte Carlo and Latin Hypercube and their application in the risk analysis.

#### **Derivative Tree Technique**

Some works (Steagall and Schiozer, 2001; Schiozer et al., 2004), used the Derivative Tree Technique. The uncertain attributes are discretized in levels of uncertainty and are combined according to 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. The main limitation of this technique is the high number of simulations required when a large number of uncertain attributes must be considered.

#### Monte Carlo Technique

The Monte Carlo Technique consists in the generation of random values of uncertain attributes in agreement with the distribution and associated probabilities. The number of simulation runs does not depend on the number of attributes. However, good results require simulations on the order of  $10^4$ , which is not feasible due to high computation cost (Srikanta, 1998). The number of simulations is critical in this case because many simulations are required to reproduce the representative distribution of the attributes.

The alternative is then to combine Monte Carlo with proxy models that substitute the simulator. The number of simulation runs to generate proxy models depends on the number of attributes but it is generally lower; consequently, there is a cost and time reduction (Narahara et al., 2004). This alternative to use this technique with proxy models shows good results, but it can present difficulties in complex cases where the proxy models can have difficulties in adequately representing the reservoirs.

A possible drawback is the precision of the proxy models compared with simulation models and can be an issue for complex reservoirs.

#### Latin Hypercube Technique

The Latin Hypercube Technique is characterized by the division of the uncertainties range in sub-regions and the sampling of each one of these regions.

The trials number can be defined by the following method: the trials number in each region is defined proportionally to the probability of the specific region and the occurrence probability of each model is defined by 1/N, where N is the total number of trials.

#### **Risk Curves**

The risk curves can be generated by the Derivative Tree, Latin Hypercube and Monte Carlo Techniques. The values of each model (trial or combination) can be calculated by the simulation or proxy models that substitute the simulator. These curves are useful in the decision-making process.

#### **Proxy Models**

Recent progress in computational hardware and software development has opened new frontiers in reservoir modeling. However, for many workflows in uncertainty quantification and optimization with application to reservoir simulation the availability of computing resources is still seen as a limiting factor. Therefore, engineers are still looking for a ways to reduce the computational load related to simulation studies, so application of computationally efficient proxy models gains a lot of attention (Zubarev, 2009; Yeten et al., 2005).

The statistical design is specified. The number of runs and levels of variables used in the simulation work are defined depending on the number of input variables and the type of analysis aimed at. In experimental design (statistical design) variables control the result of the experiment and levels are the values those variables are assigned to during the experiment. In a reservoir simulation study, the variables would then be the input parameters of a numeric reservoir simulator the expert believes are ruling the result of any reservoir simulation cases. The ultimate purpose, when the set of cases is run, is the determination of the space variation of the reservoir performance variable due to the variations in the input parameters of a reservoir simulation model (Prada and Cunha, 2008). It is necessary to define the attributes and the type of statistical design to be used to obtain the proxy model. In this work, the Statistical Design Box-Behnken was used.

A quadratic proxy model is generated for each matrix of statistical design (Schiozer el al., 2008). It was observed (Risso et al., 2006) that the best proxies were generated by a quadratic response surface and that the linear response surface did not present good results.

In order to verify the consistency of the results obtained by the Proxy Model, some statistical analyses are realized. Consistency of the acceptable solutions is verified with simulation (Van Elk et al., 2000). The statistical tests are: variance analysis and also the graphs of cross-correlation between the results to verify the consistency of the proxy. It is possible to use the validated proxy for the calculation of the objective functions and the risk curves through the studied techniques.

Details about the theory involving statistical design



**Figure 3.** Reservoir Representation Including the Production Strategy.

techniques and response surface methodology appear in (Myers and Montgomery, 1995), among others.

#### METHODOLOGY

Three Techniques (Derivative Tree (DT), Monte Carlo (MC) and Latin Hypercube (HCL)) were tested and compared. The main objective was to verify the influence Of the trial numbers to obtain the risk curves. Three numbers of trials were tested: 9000, 3000 and 200.

In order to obtain risk curves, using the Derivative Tree, 625 simulations with 5 levels and 81 simulations with 3 levels were necessary. For the Monte Carlo and Latin Hypercube Techniques, a proxy model generated by the proxy-model (statistical design Box-Behnken) was used; 25 simulations (Box and Behnken, 1960) were necessary.

The objective functions studied were:

- Np = Cumulative Oil Production of the field;
- Wp = Cumulative Water Production of the field;
- RF = Oil Recovery Factor;
- NPV = Net Present Value.

The proxy-model is an approximation of the existing numerical reservoir model. It should be able to mimic the highly non-linear response of the real model, be easy to build, and be simple in its application. Every proxy-model is individually estimated, based on responses from a particular reservoir simulation model. The type of proxymodel applied in this study in reservoir simulation is Polynomial regression model.

Polynomial regression models are commonly referred to

as response surface models in the statistical literature. They were first proposed for analysis of physical experiments and later adopted for computer experiments as well. Even though this type of model does not exactly approximate the experimental data, polynomial regression models have been widely adopted in petroleum industry due to their ease of understanding, flexibility, and computational efficiency. The general formulation for quadratic polynomial regression model can be given as

$$y(x) = \beta_o \sum_{i=1}^{nd} \beta_i x_i + \sum_{i=1}^{nd} \sum_{j=1, j>1}^{nd} \beta_{ij} x_i x_j + \sum_{i=1}^{nd} \beta_{ii} x_i^2$$

(1)

Where x is a vector of input variables of length  $n_d$ ,  $x_i$  is a linear term,  $x_i x_j$  is a cross term,  $x_i^2$  is a quadratic term and  $\beta_o$ ,  $\beta_i$ ,  $\beta_{ij}$ ,  $\beta_{ii}$  represent unknown regression coefficients for constant, linear, cross and quadratic terms respectively. Beta terms are estimated with a least squares approach.

Estimation of the polynomial regression model includes selection of the terms to be included into the model and Calculation of the regression coefficients.

#### Applications

The application presented in this study is a synthetic model (Becerra, 2007) with 4 main uncertain attributes (porosity, horizontal and vertical permeability and net pay). The model is a reservoir with high heterogeneity and complexity, where a sand of low quality is crossed by



Figure 4. Risk Curves for 9000 trials: (a) Np (b) Wp (c) RF (d) NPV.

canals of high permeability (Figure 3). The model is composed of 6 layers, each one with different geophysical properties. The simulation model has 43x55x6 vertical blocks and 12 wells.

## **Production Strategy**

The production strategy of the field is composed of 7 producers and 5 injectors, as shown in Figure 3. The operation conditions of the producing wells are:

- Minimum pressure: 110 Kgf/cm<sup>2</sup>;
- Maximum liquid production: 1800 m<sup>3</sup>/day;
- Closing of production interval when the water and liquid total reaches more than 90%;
  - The operation conditions of the injector wells are:
- Maximum injection of 1800 m<sup>3</sup>/day;
- Maximum pressure: 400 Kgf/cm<sup>2</sup>.

### **Economic parameters**

The economic objective function (NPV) is obtained based on the following parameters:

- Oil price: US\$50,00/barrel;
- Discount rate: 13% year;
- Government take: 45% on the gross revenues and 15% on the liquid revenues;
- Platform Investment: US\$ 250 million; Investment drilling and completion: US\$ 20

million/well;

- Oil production cost: US\$6,0/bbl;
- Water production cost: US\$2,0/bbl;
- Water injection cost: US\$ 1,0/bbl;

## RESULTS

A study to compare the Latin Hypercube and Monte Carlo Techniques was performed and presented the risk curves obtained using both techniques (with 9000, 3000 and 200 trials).

The risk curves for Np, Wp, RF and NPV are presented in Figures 4, 5, 6 and 7.

The risk curves for 9000 trials: (a) Np, (b) Wp, (c) RF and (d) NPV are presented in Figure 4.

The risk curves for 3000 trials: (a) Np, (b) Wp, (c) RF and (d) NPV are presented in Figure 5.

It can be observed, in the Figures 4 and 5, that the risk curves obtained through the Derivative Tree Technique were equivalent to those obtained through the Latin Hypercube and Monte Carlo Techniques for 9000 and 3000 trials.

The risk curves for 200 trials: (a) Np, (b) Wp, (c) RF and (d) NPV are presented in Figure 6.

In the Figure 6, it can be observed that the risk curves obtained through the Monte Carlo Technique were not equivalent to those obtained through the Latin Hypercube and Derivative Tree Techniques for 200 trials. For Monte Carlo Technique the variation in the number of trials



Figure 5. Risk Curves for 3000 trials: (a) Np (b) Wp (c) RF (d) NPV.



Figure 6. Risk Curves for 200 trials: (a) Np (b) Wp (c) RF (d) NPV.



Figure 7. Risk Curves for 200 trials (Proxy and Simulation): (a) Np (b) Wp (c) RF (d) NPV.

influences the quality of the results.

The risk curves obtained with 200 trials (in Figure 6) was very close to the risk curves obtained with 9000 and 3000 trials (Figures 4 and 5), for Latin Hypercube Technique. It can be observed, in this case, the number of trials did not yield alteration in the results.

The results presented by the Monte Carlo Technique, with 9000, 3000 and 200 trials, (Figures 4, 5 and 6) had only been satisfactory for cases with a high number of trials. It can be observed that the number of trials influences the quality of the results.

Therefore, the results presented by the Latin Hypercube Technique, the variation in the number of trials had a small impact on the quality of the curves. It can be observed in the risk curves in the Figures 4, 5 and 6.

The comparison between the values obtained by simulation and proxy using 200 trials is done by risk curves: (a) Np, (b) Wp, (c) RF and (d) NPV that are presented in Figure 7.

The Monte Carlo and Latin Hypercube Techniques presented equivalent results for a high number of trials.

This condition does not occur when a low number of trials are used. In this situation, the best results are obtained by the Latin Hypercube Technique.

For example, for the Derivative Tree Technique with 8 attributes, 6561 simulations are necessary, while the

Latin Hypercube Technique requires only 200 simulations, independent of the number of attributes.

For the Monte Carlo Technique, the number of trials had impact on the quality of the risk curves. The method is effective but not efficient. The combination of Monte Carlo and numerical simulation is not feasible due to the great number of simulations and is recommended for cases combined with response surface.

#### CONCLUSIONS

The results show that risk analysis of petroleum fields can be performed with all three techniques presented in this paper. However, Latin Hypercube Technique presented the best results considering precision and number of simulations.

The Derivative Tree technique simplifies the statistics. It yields non smooth curves for a low number of attributes and it is not a good technique for a large number of attributes because of the number of simulation runs that increases exponentially with the number of attributes and and levels of uncertainty.

The risk curves obtained through the Derivative Tree were equivalent to those obtained through the Latin Hypercube Technique. The results presented by the Monte Carlo Technique had only been satisfactory for cases with a high number of trials. The variation in the number of trials had a small impact on the quality of the curves obtained by the Latin Hypercube Technique. For Monte Carlo, the number of trials directly influences the quality of the results.

The combination of the Statistical Design, Proxy Models and Monte Carlo is also a possible solution but it simplifies the tool (reservoir represented by a proxy model) and this simplification must be verified along the process to guarantee the quality of the results.

Based on the presented results, it can be observed that the Latin Hypercube Method is more efficient and it can be used with a lower number of trials (simulation) and with no need of proxy models (although it can also be combined with proxy models). Furthermore, the benefits are expects to increase as the number of attributes and level of uncertainties increase.

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