# Risk Assessment for Reservoir Development Under Uncertainty

D. J. Schiozer and E. L. Ligero
Departamento de Engenharia de Petróleo
Faculdade de Engenharia Mecânica - UNICAMP
PO. Box 6122
13081-970 Campinas, São Paulo. Brazil
denis@dep.fem.unicamp.br
eligero@dep.fem.unicamp.br

J. A. M. Santos
Petrobras
jams@petrobras.com.br

*Decision analysis applied to petroleum field development is always strongly related to risk due to the uncertainties present in the process. Methodologies to quantify the impact of uncertainties are still not well established due to the amount of variables that have to be considered. The complete analysis usually depends on geological, economical and technological uncertainties that have different degrees of impact in the recovery process and may affect the decision process at different levels depending on the problem, reservoir characteristics, recovery mechanism and stage of field development. This paper shows several details of a methodology that can be applied to complex and simple reservoirs in a reasonable amount of time, discussing especially the influence of the model used to predict recovery, choice of production strategies to be used in the process, number of attributes and type of information necessary to obtain reliable results. A discussion of data integration among geology, reservoir engineering and economic analysis also is presented in order to reduce the amount of information necessary and time for the process. Some results are presented to show the advantages of automation and parallel computing to reduce the total time of the procedure where reservoir simulation is necessary for reservoir performance prediction.*
***Keywords****: Petroleum, reservoir engineering, uncertainty, risk*

## Introduction

In the preparation of development plans, field management decisions are usually made using a deterministic approach. Probabilistic procedures are used in some cases for reserves assessment, considering geological uncertainties, or in the field evaluation, using Monte Carlo simulation or similar techniques to incorporate economic uncertainties. Some methodologies have been defined by several authors, such as, Newendorp (1975), Rose (2001) and Schuyler (2001). The use of probabilistic tools have been encouraged by Schuyler (1998) because they better capture expert judgments, better characterize uncertainty and provide a more accurate calculation result. However, when reservoir performance prediction is necessary, especially using numerical reservoir simulation, probabilistic approaches are often not used because of the amount of time and computational effort required.

Recent papers show that with current hardware and software, it is possible to incorporate more accurate production prediction in the process. Furthermore, for complex reservoirs and large fields, such step is not only possible but extremely necessary for production strategy definition.

In order to avoid excessive computation effort, some simplification is always necessary. The key point is to define the simplifications and assumptions that can be made to improve performance without loss of precision. In addition, in order to have methodologies that can be applied to a wide range of cases, it is necessary to build a flexible and easy to use technique.

One of the simplest approaches is to work with the recovery factor (RF) that can be obtained from analytical procedures, empirical correlations or previous simulation runs, Salomão and Grell (2001), when higher precision is necessary, or when the rate of recovery affects the economic evaluation of the field, using just the recovery factor may not be sufficient.

A more complete approach was developed by Steagall and Schiozer (2001). The entire process was integrated, including geological uncertainty, reservoir simulation and economic analysis. The disadvantages of this procedure are the large computational effort and time required.

The objective of this work is to show that some assumptions and simplifications can be used to reduce the computational effort and time without significant loss of precision. The impact of the simplifications for a few cases also is discussed. In addition, especial automated procedures and parallel computing can be used to reduce the total computing time.

When numerical simulation is used in the procedure, the production strategy must be included therefore it is necessary to include production strategy as an additional variable. Different production strategies can be incorporated in the analysis without adversely affecting the number of simulations. It was shown that different strategies are not even necessary in many cases.

An advantage of the use of reservoir simulation is that complete production data, injection rates and reservoir characteristics can be used for the economic analysis. In some cases, the level of details of the models can yield significant changes in the final decisions.

## Nomenclature

NPV = Net present value
OIP = Oil in place
RF = Recovery factor
Cr = Rock Compressibility
Kh = Horizontal permeability
Krw = Relative permeability of water
Kz = Vertical permeability
M = Medium case
n = Number of attributes
O = Optimistic case
P = Pessimistic case
Por = Porosity

## Uncertainty

Decisions related to field development and reservoir management are always related to risks involved because of the uncertainties that are present in the process. The process is even more critical because most of the investments are made during the stage when the uncertainties are greater. Figure 1a is a typical curve of uncertainty related to a field development process. Even for a mature field, uncertainties are still present but the decisions are not very critical.

There are many uncertainties that can influence the success of an exploration and production project. The most common uncertainties occur in the geological model: volume in place, continuity, faults, etc. The recovery factor is a function of the reservoir properties and production strategy and the economic model is principally composed of prices. There are also other uncertainties such as technological, operational and political but they often have a secondary role.

Methodologies to measure the impact of uncertainties are frequently not well defined because the impact of these uncertainties varies with time and the amount of information available, Fig. 1b. Most of studies about risk measurement are related to exploration phase where the uncertainties due to reservoir performance prediction have small impact and where probabilistic treatment combined with Monte Carlo techniques may be sufficient to reach the required precision (Newendorp, 1975; Garb, 1988).

Nevertheless, the importance of considering uncertainties in the decision making process is unquestionable. Recently, it is becoming more common the necessity of better accuracy in the process. Better accuracy is possible due to advances in the hardware and software and geological modeling. The use of reservoir simulation in the process is also increasing because it increases the reliability, improves the quality of the results and provides the output of other important variables such as water and gas production, pressure, detailed production strategy, etc. Figure 2 shows a typical uncertainty data from cumulative production.

## Risk Analysis

The types of development risks that have to be considered in the decision making process are related to opportunity loss, uncommercial development and suboptimal development, Demirmen (2001).

Basically, development risk is function of geological, economic and technological uncertainties, as in Fig. 3. However, the quantification of the risk is affected not only by such uncertainties but also by the production strategy model and the management decision process. Especially for complex reservoirs, a precise risk assessment requires a level of detail in the reservoir production prediction that is only obtained by numerical simulation.

In the exploration stage, volumes in place and recovery factors are sufficient in the risk analysis. However, in the field development stage, it is also necessary a detailed information about the speed of recovery, the necessary investments, number of wells, water and gas production, operational costs, etc. In some cases, these parameters may be not necessary but in many other cases, an incorrect development model can yield significant suboptimal development.

The methodology proposed by Loschiavo et al. (2000) and implemented by Steagall and Schiozer (2001) is based on the numeric flow simulation of several possible scenarios of the reservoir, combining the uncertain attributes, as in Fig. 4.

Other example of this type of application has been presented by Jensen (1998). Each final branch of the tree results in a simulation model that is built automatically. The probability of each final model is equivalent to the product of the conditional probability of its attributes. In this work some additional steps were:

1. Construction of geological model;
2. Definition of Base Case composed by the most probable values of all input variables;
3. Selection of important uncertain attributes;
4. Definition of the uncertainty of attributes and associated probabilities;
5. Sensitivity analysis to select the most critical attributes;
6. Automatic assembly of simulation models through a derivative tree technique;
7. Simulation runs using parallel (distributed) computing;
8. Statistical treatment of the results obtaining production forecast with uncertainty and risk;
9. Selection representative models (few models that can represent the geological uncertainty).

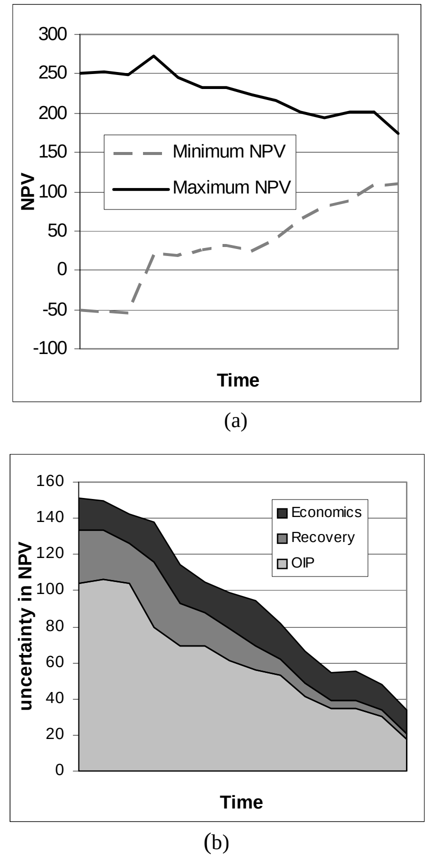


**Figure 1. (a) Typical uncertainty in NPV. (b) Typical uncertainty due to oil in place, recovery factor and economic model.**

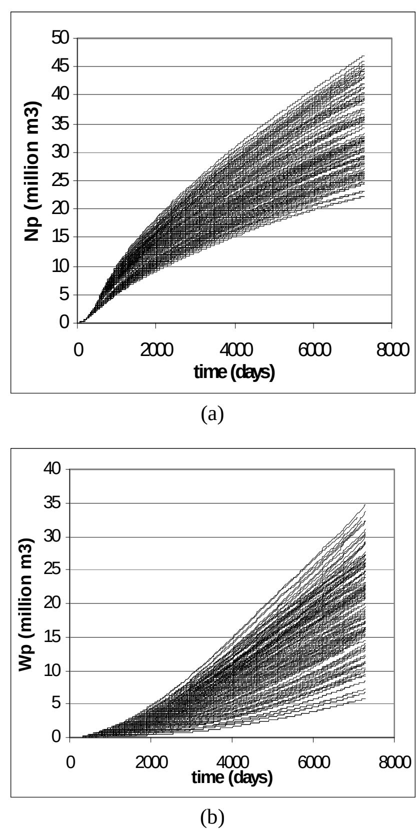


**Figure 2. Typical uncertainty in the cumulative production of (a) oil and (b) water.**

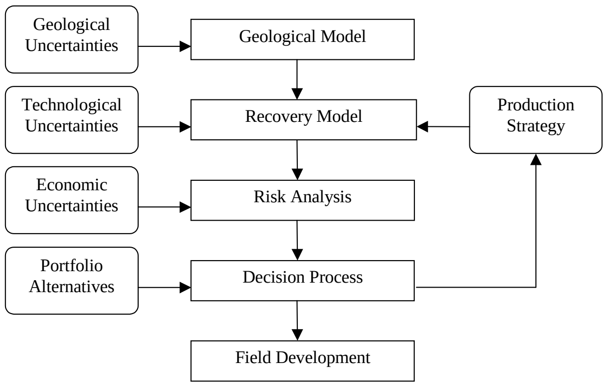


**Figure 3. Reservoir management decision process under uncertainty.**

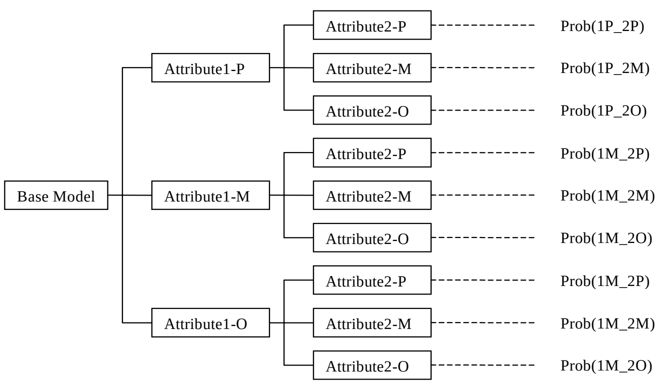


**Figure 4. Example of derivative tree with 2 attributes and three levels (P, M and O).**

The total number of simulation runs is defined by the number of attributes and the number of discretization levels. The usual approach is to start with 3 levels for each attribute, usually a medium (M), a pessimist (P) and an optimist (O) case. Assuming "n" attributes, 3n simulation runs are required. Depending on the type and importance of the attributes, it is possible to reduce or increase the number of levels, as shown in the next sections. Each "final" model has a probability of occurrence, as in Fig. 5.

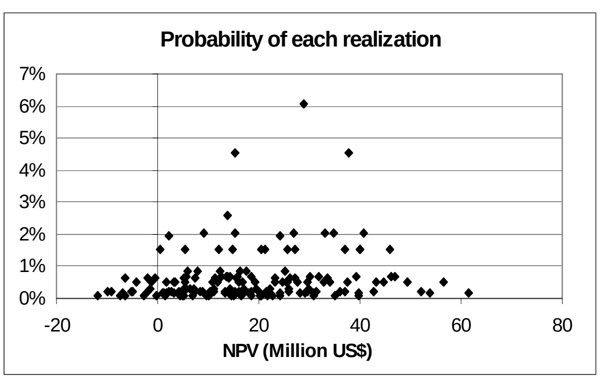


**Figure 5 Probability of realizations for 5 attributes.**

## Applications

The results shown in this work were generated by running several examples related to Brazilian offshore fields. Reservoir and production data are restricted to the information of the appraisal and development phases.

## Production Prediction under Uncertainty

The use of analytical or simpler models to predict production is not enough for most of the objectives of risk analysis in the appraisal and development phases. The use of numerical simulators is important:

- To predict speed of recovery (which with high intern rates of return can affect significantly the economic results),
- To dimension adequately the size of production facilities,
- To monitor other variables such as filed pressure, water and gas production, etc.

One possible difficulty encountered in the use of numerical simulators is that they need the definition of the production strategy, which should be a function of the model. Therefore, the production could be one of the uncertain parameters. Another option would be an iterative procedure. However, both options would yield a significant increase in the number of simulations.

Santos and Schiozer (2003) showed that an optimized production strategy originated by the Base Case could be a good approximation. A higher or smaller number of wells could be used in the optimistic and pessimistic structural models. If a better precision is required, the optimization of the strategy for the representative models is enough.

Figure 6 shows an example of the difference of some output variables between the Base Case and the representative models for on of the examples tested. Similar results can be generated for other variables of interest, for instance, investment, water production, etc. Normally, greater differences are expected for the pessimistic cases. These differences are also more critical because than they can yield a reduction of attractiveness if compared with the Base Case or the P50 Case.

## Sensitivity Analysis

The most effective way to reduce computational cost in a risk analysis process is to reduce the number of variables. The choice of the important (or most critical) attributes can be performed through a sensitivity analysis, as in Fig. 7.

Figures 8 and 9 show the difference in the risk curve as the number of attributes increase. It can be observed that from 4 to 5 attributes, the difference is very small and the number of simulations is three times bigger. The ideal number of attributes varies but normally there are 4 to 7 attributes that are critical and can be used to represent the uncertainty. The best procedure is to add one attribute at a time so the process can be interrupted when the required precision is reached. If the number of attributes is higher than 7, other tools have to be used in order to limit the computational time.

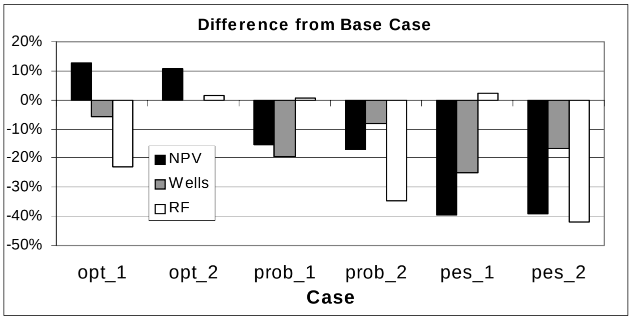


**Figure 6. Variation (difference to Base Case) of NPV, number of wells and recovery factor after optimization of representative models (optimistic, probable and pessimistic models).**

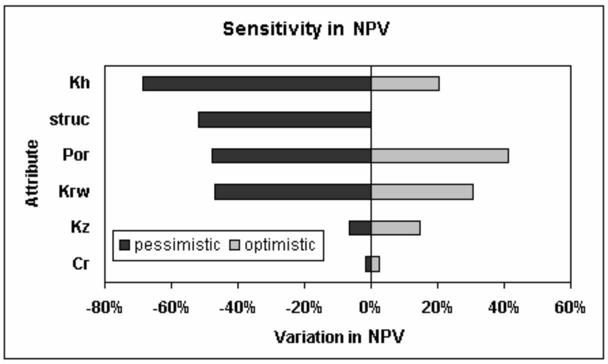


**Figure7. Sensitivity Analysis (structural model, has only two possible realizations in this case).**

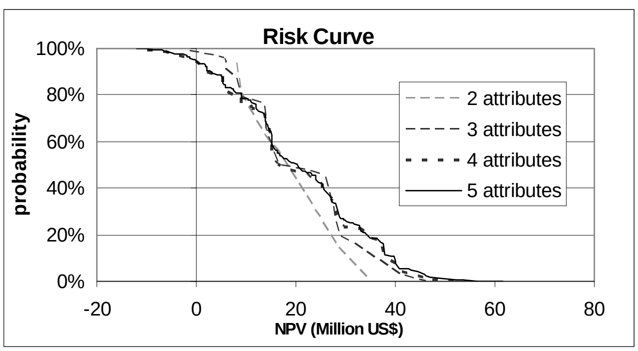


**Figure 8. Risk curve for different number of attributes.**

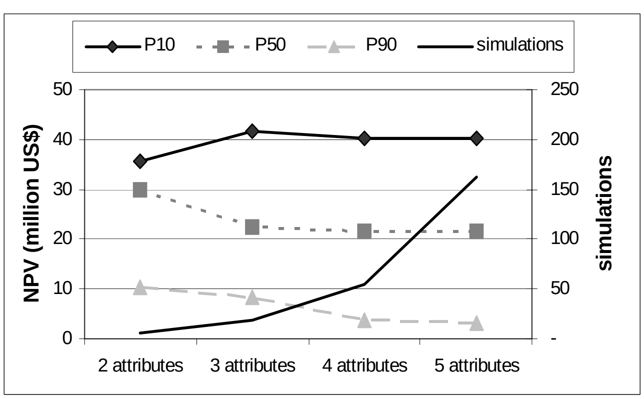


**Figure 9. Variations in P10, P50, P90 and number of simulations as number of attributes increases.**

## Other Possible Simplifications

The consideration of one or a few production strategies and the use of sensitivity analysis to eliminate uncritical attributes are the most effective and common simplifications that can be used in the process. Several other simplifications are possible to avoid large computational effort. Some examples that can be implemented are:

1. Use of simpler simulation models which can be obtained for instance by simpler formulation (for example, streamline model) or fewer blocks as Ligero et al. (2003); Subbey and Christie (2003) and Ligero and Schiozer, (2001).

2. Use of fewer levels of uncertainties for attributes that are not critical, Costa and Schiozer 2002 and 2003).

3. Aggregation of several attributes in the analysis, Costa and Schiozer (2002 and 2003).

Every simplification or assumption in the process can lead to a less accurate response compared with an ideal. However, if the simplifications are applied carefully, in a correct way, the results are very good, as observed in several different cases tested (some of the results are presented here).

## Speedup

In order to speedup the process, automation and parallel computing are necessary. The amount of time that is necessary for building the data sets for simulation, running the simulations and analyzing the results can be very significant and it is necessary to have tools that allow executing all steps automatically.

Flexibility is also important to avoid spending unnecessary time in the process. Many times, it is always necessary to add attributes, to change the economic model, to change the probability distribution of attributes, etc. Most of these options don't require modifications in the simulations and can be executed rapidly.

The speedup caused by automation is difficult to be measured but easily perceptible. An example of speedup caused by parallel (distributed) computing is presented in Fig. 10. If implemented correctly, for a typical network of 10 to 15 workstations (or processors) the process can be executed 10 times faster. For dedicated parallel networks, which today have a reasonable price, the benefits are even greater.

Ligero and Schiozer (2002) showed the some advantages of an automated methodology to perform risk analysis during appraisal phase using reservoir simulation.

## Representative Models and Economic Uncertainty

Due to the high number of uncertainties, the integration of all variables in a unique process may not be always practical. Steagall and Schiozer (2001) showed that in the process of quantification of impact of geological uncertainties, representative models can be selected to be used in the quantification of other types of uncertainties.

They have shown that such models must be selected based on volume in place, recovery factor and net present value. The criteria for selection of these models must be further investigated and it seems to be case dependent. Figure 11 shows an example of a case where 8 models were selected. The necessary number of representative models may vary with objectives of the study, characteristics of the geological model and computer time required for the simulation runs.

A sensitivity analysis based on these models considering economic uncertainties is recommended and it doesn't require additional simulations. Representative models production data can even serve as input for current economic evaluation and portfolio tools.

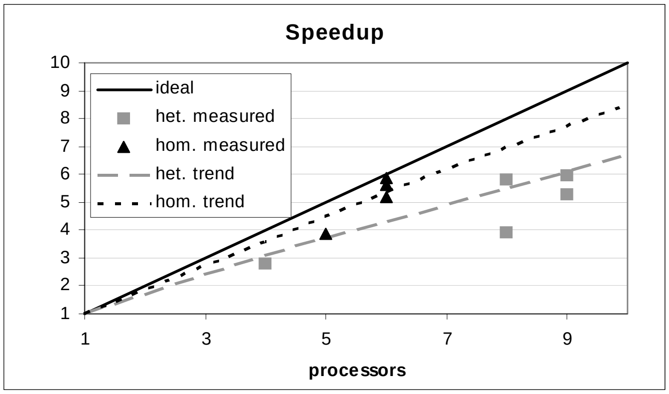


**Figure 10 Speedup measured and trend for homogeneous and heterogeneous network.**

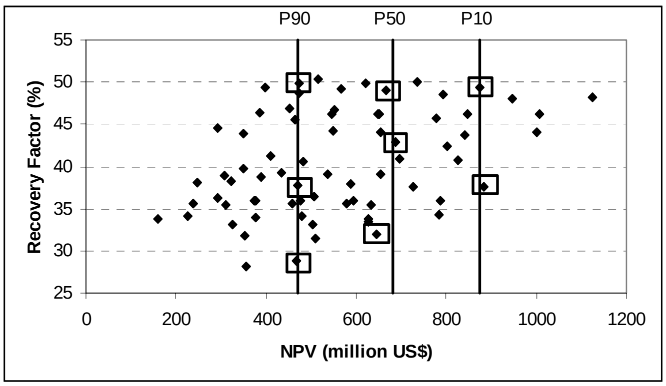


**Figure11. Example of 8 representative models selected based on NPV and RF.**

## Discussion and Conclusions

It is important to include probabilistic approaches to quantify the impact of uncertainties in the field development process. Current hardware and software tools are sufficient to perform such task with adequate accuracy even when complex geological models are required.

Reservoir simulation can be used to improve the quality of the results. Other advantage of using simulation is that other output variables that can play an important role in the decisions and can be included in the probabilistic prediction.

For complex models that require long simulation runs, several simplifications can be applied to the process, based on the required precision. Most typical and usual are selection of critical variables through sensitivity analysis, use of production strategies as function only of the structural models, aggregation of variables, etc. In such cases, representative models can also be very useful in the integration of geological and economic uncertainties. Automation and parallel computing is strongly recommended.

It is very important to have a default methodology for risk analysis in order to have a similar procedure applied to all cases which eventually will be compared in portfolio analysis.

## Acknowledgments

The author would like to thank PETROBRAS and FINEP-CTPETRO for the financial support to the project that lead to the results and conclusions of this paper.

## References

Costa, A.P.A., Schiozer, D.J., 2003, "Treatment of Geological Attributes in Risk Analysis Applied to the Appraisal Phase of Petroleum Fields", Canadian International Petroleum Conference, Calgary, Canada, June.

Costa A.P.A., and Schiozer, D.J., 2002, "Escolha de Atributos na Análise de Risco em Campos de Petróleo na Fase de Desenvolvimento", 9th Brazilian Congress of Thermal Engineering and Sciences (ENCIT), Caxambu, MG, October 15-18.

Demirmen, F., 2001, "Subsurface Appraisal: the Road from Reservoir Uncertainty to Better Economics", SPE 68603, SPE Hydrocarbon Economics and Evaluation Symposium, Dallas, 2-3 April.

Garb, F. A., 1988, "Assessing Risk in Estimating Hydrocarbon Reserves and in Evaluating Hydrocarbon-Producing Properties", Journal of Petroleum Technology, June, p. 765-778.

Jensen, T. B., 1998, "Estimation of Production Forecast Uncertainty for a Mature Production License", SPE Annual Technical Conference and Exhibitions, New Orleans, USA, SPE 49091, September.

Ligero, E.L., Maschio, C. e Schiozer, D.J., 2003, "Quantifying the Impact of Grid Size, Up scaling and Streamline in the Risk Analysis Applied to Petroleum Field", 17th Reservoir Simulation Symposium, SPE 79677, Houston, USA, February.

Ligero, E.L. e Schiozer, D.J., 2002, "Exploration and Production Risk Analysis- Automated Methodology and Parallel Computing to Speedup the Process", Second Meeting on Reservoir Simulation, Buenos Aires, Argentina, November.

Ligero, E.L., and Schiozer, D.J., 2001, "Importância da Escala do Modelo de Simulação de Reservatórios de Petróleo na Análise de Incertezas em Projetos de Exploração e Produção", I Congresso Brasileiro de P&D em Petróleo e Gás, Natal/RN.

Loschiavo, R., Steagal D., and Schiozer D.J., 2000, "Estudo do Impacto de Incertezas no Desempenho de Reservatórios de Petróleo", 8th Brazilian Congress of Thermal Engineering and Sciences, Rio Grande do Sul.

Newendorp, P. D., 1975, Decision Analysis for Petroleum Exploration, Penn Well Publishing Co., Tulsa, Oklahoma, 1975.

Rose, P., (2001), Risk Analysis and Management of Petroleum Exploration Ventures, AAPG Methods in Exploration Series, No 12, Tulsa, Oklahoma, USA.

Salomão, M.C. and Grell, A.P., 2001, "Uncertainty in Production Profiles on the Basis of Geostatistic Characterization and Flow Simulation", SPE Latin American and Caribbean Petroleum Engineering Conference, Buenos Aires, Argentina, SPE 69477, March.

Santos, J.A.M. e Schiozer, D.J., 2003, "Quantifying Production Strategy Impact in Risk Analysis of an E&P Project using Reservoir Simulation", 17th Reservoir Simulation Symposium, SPE 79679, Houston, USA, February.

Schuyler, J., 2001, Risk and Decision Analysis in Projects, Project Management Institute Inc., Pennsylvania, USA.

Schuyler, J.R., 1998, "Probabilistic Reserves Lead to More Accurate Assessments", SPE Annual Technical Conference and Exhibition, Louisiana, USA, SPE 49032, September.

Steagall, D.E. and Schiozer, D.J., 2001, "Uncertainty Analysis in Reservoir Production Forecast during the Appraisal and Pilot Production Phases", SPE Reservoir Simulation Symposium, Dallas, USA, SPE 66399, February.

Subbey, S. and Christie, M., (2003). A Strategy for Rapid Quantification of Uncertainty in Reservoir Performance Prediction, SPE79678, 17th Reservoir Simulation Symposium, Houston, USA, February.