Uncertainty Quantification and Risk Analysis for Petroleum Exploration and Exploitation Projects

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Abstract

It is widely recognized that predictions of hydrocarbon recovery are uncertain. Despite this, engineers must answer several problems in this context: describe prior uncertainties, identify the ones that actually influence the oil production process, make safe production forecasts and optimize the reservoir production scheme. Since it is extremely difficult, if not impossible in most cases, to simulate reservoir performance in the laboratory, the oil production industry has been at the forefront of developing mathematical models of various recovery processes. As the model becomes more sophisticated, the computer runtime per case - and hence the cost of simulation – increases rapidly.

Thus, a statistical treatment that recognizes both the lack of knowledge and the uncertainty in the parameters involved in the forecasting of reservoir performance is desirable. Current stochastic-modeling approaches, such as Monte Carlo simulation and geostatistics, require extensive computational effort for realistic problems. There are numerous reasons for this, but the one that seems to present the largest impact is that reservoir prediction requires a large number of input parameters. A method that can identify the key parameters governing uncertainty in production and economic forecasting in the early phases of the study will significantly ameliorate the data acquisition program.

This paper presents the early stages of a research project, which focuses on investigating the application of an experimental design technique to the problem of uncertainty quantification and risk analysis for petroleum exploration and exploitation projects. The emphasis here is on the establishment of a workflow, preparation and description of the focal database representative of the real field scenario.

Introduction

Reservoir engineering requires to manage sources of uncertainty that can be classified in two categories: **A) uncontrolled uncertainties** on the physical reservoir description parameters; due to three major causes: 1) the model, because it is an imperfect representation of reality; 2) geologic parameters, because of a limited sampling in space and/or time, and 3) measurement errors in the experiments performed to determine inputs; and **B) controlled uncertainties** on the reservoir development scheme parameters (wells type: vertical or horizontal, well locations, surface separation capacity).

Historically, most reported post-analyses of field developments have revealed lower production rates and smaller reserves than pre-production forecast indicated. Pre-production uncertainties about reservoir characteristics, inadequate representation and lack of realistic geology in numerical models and unforeseen operational difficulties and constraints may have been the main causes of erroneous (optimistic or pessimistic) forecasts.

With rapid changes in political and economic conditions, it seems that smaller fields, geological more complex fields, smaller economic margins and less robust projects (EOR, infill drilling, thermal recovery) are typical petroleum engineering issues in many hydrocarbon producing regions of the world. For this reason, oil companies need a systematic method for quantifying the composite technical uncertainty (in production rates and reserves) and the compounded economic risk (NPV and other economic indicators) associated with field developments and incremental projects.

In the evaluation and planning of a reservoir development, the common approach is first to build the expected geological model, using the most representative set of dynamic parameters and then the best set of well locations given the geological model. The platform, in the case of an offshore environment, and production facilities are optimized (with respect to NPV) for this model. This combination of geological model, dynamic parameters and technical design constitutes the base (or reference) case. A reservoir simulation is then performed, giving the base case production profile and recovery factor. This production profile is finally combined with a fixed scenario for the future oil and/or gas prices and investment interests to obtain the economic indicators (NPV, PI, IRR) for the project.

One thing is certain: the final results from the base case are, not true. To study the influence of the various parameters that enter the process on the final results, a sensitivity study is usually performed. The most common approach was, and still is, to vary one parameter at the time, keeping all the other parameters at the base case value. For most parameters, two runs are required, with an optimistic and a pessimistic setting, respectively. The number of runs required for a full sensitivity study quickly becomes prohibitive. If there are:

- 5 gas sales scenarios,
- 5 handling capacities,
- 5 different number of wells,
- 2 different horizontal wells length,
- 2 vertical start positions, and
- 15 geological parameters with uncertainty

it will take 15 x 2 x 2 x 5 x 5 x 5 = 7,500 runs to perform such a sensitivity analysis. In addition, the joint effect of several parameters varying simultaneously cannot be investigated by varying one parameter at a time technique.

Recent research and applied projects focus on the study and application of experimental design techniques [1,2,3] for the quantification of uncertainty present in oil and gas production prediction. Basically, experimental design is a smart sampling technique that is used to extract the maximum information about a process with minimum cost. This will cause several parameters to be varied simultaneously according to a predefined pattern. The technique gives the possibility of obtaining the same information as the one parameter at a time method with significantly fewer simulation runs, and to obtain some understanding of possible interactions between the parameters.

An experimental design is simply a recipe describing the different settings of each of a number of input parameters in a series of simulation runs. The theory of experimental design describes how to construct these settings so that maximum information can be obtained from a minimum number of simulation runs.

The most popular experimental design is the Fractional Factorial Design (FFD)[4]. FFD can be used to simplify and improve studies from the planning to the analysis phase. A subcategory of FFD is the screening design. This is primarily used to identify the n key parameters ($n \ll N$) that most influence the response very early in the study. For example the economics of oil production from an offshore reservoir depend on a large number of parameters (N>10) ranging from geological characterization, to fluid and flow properties, to well locations and completions and to surface facilities. Usually, screening design is a 2-level (high and low) design, which allows efficient estimation of main (linear) effects of all the factors being explored, ignoring the factor interactions.

If significant interactions and/or curvature are expected in the response, a screening design may not be sufficient for a thorough analysis. In these situations the screening design may then be used only to rank the *n* significant parameters in order of their influence on the response. Subsequently a 3 level design is prepared using the *n* significant parameters identified by the screening design. The 3 level design evaluates every parameter at a low, median and high value in an attempt to model the curvature in the response.

More recently, a work performed by Leuangthong and Deutsch [5] describes a methodology to determine a design matrix for sensitivity analysis for any generic case.

This paper presents the early stage of an on-going research project. The primary objective consists of the application of an experimental design technique for the determination of a design matrix for sensitivity analysis. The secondary goal is to use this knowledge to improve the quantification of uncertainty and risk analysis processes associated with petroleum exploration and exploitation projects.

Next section describes the construction of the focal dataset that mimics a real field scenario. Characterization of the main uncertain variables associated with the geological, geophysical and engineering data is illustrated and preliminary results are presented. This is followed by a discussion on some future considerations and research directions.

Case Study – Problem Description

The main effort in this on-going project is to investigate the advantages and limitations of an experimental design technique when applied to the quantification of uncertainty in a performance production forecast for a real reservoir. To achieve this goal, a synthetic model that mimics a real reservoir complexity was built. The proposed scenario considers an offshore exploration block in which a pioneer well discovered a heavy oil accumulation. In this virtual scenario, although the fluid properties of the discovery are not favorable, the magnitude of the standard oil in place justifies a closer look at the accumulation. The main geological/geophysical and engineering characteristics and uncertainties of this synthetic case are described below.

Geological and Geophysical Data

The reservoir considered here resembles an offshore anticline. The depth of the main portion of the reservoir lies between –2800 m and –3100 m, with an oil-water contact well defined at –3000m. The total thickness of the reservoir varies from 20 m to 180 m.

It was assumed to consist of very clean unconsolidated turbiditic sandstone with average porosity around 27%. Based on this average value and assuming uncertainty on porosity values determination, it was decided to consider three scenarios for porosity in the simulations: 24% (pessimistic), 27 % (most probable), and 32% (optimistic).

Three sets of absolute permeability values were considered: 1500 mD horizontal/750 mD vertical in the optimistic case, 500 mD horizontal/250 mD vertical in the pessimistic case and 1000 mD horizontal/500 mD vertical in the most probable case.

A very weak correlation between porosity and permeability was assumed. Therefore, they were considered independent, and no special care was taken during the construction of the cases to be simulated.

The areal extent of the reservoir was determined from the combined analysis of open-hole logs and seismic. Based on the fact that the validity of estimating the area process is mostly dependent on the seismic data quality, resolution and the ability to distinguish lithofacies as calibrated by the open hole log data, most probable, optimistic and pessimistic value were chosen due to imperfect seismic resolution. For example, based on different cut-off values of seismic amplitudes the most probable, medium and small maps of the reservoir could have been obtained.

Figure 1 shows a 3-D view of the reservoir for the greatest reservoir area. Figures 2a and 2b show structural and thickness maps for the greatest reservoir area. Figures 3a and 3b show structural and thickness maps for the most probable reservoir area and Figures 4a and 4b show structural and thickness maps for the smallest reservoir area. As can be seen from these maps, the differences between the three cases are important. The number of active blocks decreases from 8100 in the optimistic case, to 6120 in the most probable case and to only 4516 in the pessimistic case.

Engineering Data

In the reservoir environment created here, one of the main concerns is the quality of the oil. It is assumed that only a sample of dead oil was recovered during a production test and analysis of this sample revealed very heavy oil, with API 13^o. Given the oil and gas properties, the PVT behavior was estimated using Standing correlations for bubble point pressure, oil volume factor and gas-oil ratio, Vasquez-Beggs correlations for oil compressibility and Vasquez-Robinson for dead and live oil viscosity. Table I shows the complete estimate of the PVT (P – pressure, R_s – solution ratio, B_o – oil volume factor, B_g – gas volume factor, μ_o and μ_g – oil and gas viscosity, respectively).

Table I – Estimated PVT table for oil with API 13^o

P	R_s	B_o	B_g	μ_o	μ_g
kPa	m^3/m^3	rb/stb	rcf/scf	cp	cp
101.3	0.24	1.0834	1.3215	38.8388	0.014180
567.9	0.80	1.0845	0.2349	37.2821	0.014211
1,034.5	1.44	1.0858	0.1284	35.6225	0.014252
1,501.1	2.13	1.0871	0.0882	33.9606	0.014301
1,967.6	2.87	1.0886	0.0670	32.3392	0.014355
2,434.2	3.63	1.0901	0.0540	30.7801	0.014414
2,900.8	4.43	1.0917	0.0451	29.2938	0.014476
3,367.4	5.25	1.0933	0.0387	27.8852	0.014543
3,834.0	6.10	1.0950	0.0339	26.5550	0.014612
4,300.5	6.96	1.0968	0.0301	25.3022	0.014685
4,767.1	7.85	1.0985	0.0271	24.1242	0.014761
5,233.7	8.75	1.1003	0.0246	23.0176	0.014840
5,700.3	9.66	1.1022	0.0225	21.9788	0.014921
6,166.8	10.59	1.1041	0.0208	21.0037	0.015005
6,633.4	11.54	1.1060	0.0192	20.0885	0.015092
7,100.0	12.50	1.1079	0.0179	19.2292	0.015181
11,830.0	22.85	1.1293	0.0106	12.9246	0.016218
16,560.0	34.10	1.1530	0.0075	9.3380	0.017488
21,290.0	46.03	1.1788	0.0059	7.1281	0.018998
26,020.0	58.51	1.2063	0.0050	5.6716	0.020766
30,750.0	71.46	1.2355	0.0043	4.6585	0.022821

It was estimated that the saturation pressure of the oil is 7100 kPa, and the values of Rs, Bo, μo, and oil compressibility at saturation pressure were the following: 12.5 m3/m3, 1.1079 m3/m3, 19.23 cp and $6.2x10^{-5}$ $(kgf/cm^2)^{-1}$.

Other engineering data that always have a lot of uncertainty are the relative permeability and capillary pressure curves. The capillary pressure curve was modeled by a constant value of zero, that is, the water-oil contact is sharp. The uncertainty in the initial water saturation of the reservoir was taken into account by assigning the following values to it: 11% and 18%.

For relative permeability curves, 16 Corey models were used based on four types of rock wettability (strong oil-wet, weak oil-wet, strong water-wet and weak water-wet) and four types of rock consolidation (fractured reservoir, well sorted consolidated sandstone, poorly sorted unconsolidated sandstone, cemented sandstone or oolitic limestone) [3]. The end-point saturations and relative permeability for each case are listed in Table II. The equations used to build the relative permeability curves are listed below:

Table II - Relative permeability model

Model			k_{rwro}	k_{rocw}	k_{roeg}	S_{wcon}	S_{wcr}	S_{orw}	S_{oirw}	N_w	N_{ow}	N_g	N_{og}
1	Strong Oil-wet	Fractured Reservoir	0.50	0.60	0.60	0.10	0.10	0.55	0.55	1.0	1.0	1.0	1.0
2		Well sorted - consolid	0.50	0.60	0.60	0.10	0.10	0.55	0.55	3.0	3.0	3.0	3.0
3		Poor sort - unconsolid	0.50	0.60	0.60	0.10	0.10	0.55	0.55	3.5	3.5	3.5	3.5
4		Cemented sandstone	0.50	0.60	0.60	0.10	0.10	0.55	0.55	4.0	4.0	4.0	4.0
5	Weak Oil-wet	Fractured Reservoir	0.60	0.50	0.50	0.15	0.15	0.45	0.45	1.0	1.0	1.0	1.0
6		Well sorted - consolid	0.60	0.50	0.50	0.15	0.15	0.45	0.45	3.0	3.0	3.0	3.0
7		Poor sort - unconsolid	0.60	0.50	0.50	0.15	0.15	0.45	0.45	3.5	3.5	3.5	3.5
8		Cemented sandstone	0.60	0.50	0.50	0.15	0.15	0.45	0.45	4.0	4.0	4.0	4.0
9	Strong Water-wet	Fractured Reservoir	0.10	0.90	0.90	0.20	0.20	0.30	0.30	1.0	1.0	1.0	1.0
10		Well sorted - consolid	0.10	0.90	0.90	0.20	0.20	0.30	0.30	3.0	3.0	3.0	3.0
11		Poor sort - unconsolid	0.10	0.90	0.90	0.20	0.20	0.30	0.30	3.5	3.5	3.5	3.5
12		Cemented sandstone	0.10	0.90	0.90	0.20	0.20	0.30	0.30	4.0	4.0	4.0	4.0
13	Weak Water-wet	Fractured Reservoir	0.20	0.80	0.80	0.30	0.30	0.20	0.20	1.0	1.0	1.0	1.0
14		Well sorted - consolid	0.20	0.80	0.80	0.30	0.30	0.20	0.20	3.0	3.0	3.0	3.0
15		Poor sort - unconsolid	0.20	0.80	0.80	0.30	0.30	0.20	0.20	3.5	3.5	3.5	3.5
16		Cemented sandstone	0.20	0.80	0.80	0.30	0.30	0.20	0.20	4.0	4.0	4.0	4.0

For $S_w < S_{wcr}$, $k_{rw} = 0;$ (1a)

For $S_w \geq S_{wcr}$, $$k_{rw} = k_{rwro}\left(\frac{S_w - S_{wcr}}{1 - S_{oirw} - S_{wcr}}\right)^{N_w};$$ (1b)

For $S_w > 1\text{-}S_{orw}$, $k_{row} = 0;$ (2a)

For $S_w \leq 1\text{-}S_{orw}$, $$k_{row} = k_{rocw}\left(1 - \frac{S_w - S_{wcon}}{1 - S_{wcon} - S_{orw}}\right)^{N_{ow}};$$ (2b)

For $S_g < S_{gcr}$, $k_{rg} = 0;$ (3a)

For $S_g \geq S_{gcr}$, $$k_{rg} = k_{rgro}\left(\frac{S_g - S_{gcr}}{1 - S_{gcr} - S_{oirg} - S_{wcon}}\right)^{N_g};\qquad (3b)$$

For $S_g > 1\text{-}S_{org}\text{-}S_{wcon}$, $k_{rog} = 0$; (4a)

For $S_g \leq 1\text{-}S_{org}\text{-}S_{wcon}$, $$k_{rog} = k_{rocg}\left(1 - \frac{S_g - S_{gcon}}{1 - S_{org} - S_{wcon} - S_{gcon}}\right)^{N_{og}};\qquad (4b)$$

where:

k_{rwro} - Relative permeability to water at residual oil saturation
k_{rocw} - Relative permeability to oil at connate water saturation
k_{rgro} - Relative permeability to gas at residual oil saturation (constant = 0.08)
k_{rocg} - Relative permeability to oil at connate gas saturation
S_{wcon} - Connate water saturation
S_{gcon} - Connate gas saturation (constant = 0.04)
S_{wcr} - Critical water saturation
S_{gcr} - Critical gas saturation (constant = 0.04)
S_{orw} - Residual oil saturation during a water flood
S_{org} - Residual oil saturation during a gas flood (constant = 0.3)
S_{oirw} - Irreducible oil saturation
S_{oirg} - Irreducible gas saturation (constant = 0.3)
N_w - Water relative permeability exponent
N_{ow} - Oil relative permeability exponent in the water – oil curves
N_g - Gas relative permeability exponent
N_{og} - Oil relative permeability exponent in the gas – oil curves

Water properties were estimated based on correlations. Water viscosity at reservoir conditions is 0.42 cp, water compressibility is equal to $4.13\text{x}10^{-5}$ $(\text{kgf/cm}^2)^{-1}$, and water density was set to 1057 kg/m^3. Rock compressibility was set to $9.8\text{x}10^{-5}$ $(\text{kgf/cm}^2)^{-1}$. The initial pressure at the water – oil contact was recorded as 313.6 kgf/cm^2.

In order to maximize recovery, two reservoir development schemes were considered: vertical or horizontal producers and injectors. Flow simulation estimated the productivity of vertical wells around 4 $\text{m}^3/\text{day/kgf/cm}^2$. In the case of horizontal wells, the productivity was imposed to the flow simulator in values of 8, 20 and 50 $\text{m}^3/\text{day/kgf/cm}^2$ depending on the scenario. This is considered because the productivity of horizontal wells is severely affected by the effective length and the damage ratio, and these situations are difficult to simulate in simple flow models as the one that was conceived.

In summary, there are 6 parameters with a high level of uncertainty:

1. area of accumulation (3 possible values)
2. porosity (3 possible values)
3. absolute permeability (3 possible values)

4. rock wettability and rock consolidation with the resultant uncertainty in relative permeability curves (16 possible values)
5. oil PVT behavior (2 possible values)
6. well type (1 vertical + 3 productivity index for horizontal wells = 4 possible values)

The combination of these parameters will give a total of 3,456 cases to be simulated. The assembly of the simulation models and the results of these simulation runs are described in the next sections.

Flow Simulation

IMEX [6] black-oil simulator will be used in the flow simulations. A corner-point grid was used with blocks having 200 x 200 m in size for *x* and *y* directions, and variable size for the *z* direction. The grid dimensions were 70 x 35 x 4, with a total number of grid blocks of 9,800. It was decided to keep fixed the grid dimensions having a variable number of active grid blocks according to the scenario being studied (pessimistic, most probable and optimistic). In the pessimistic case there 4,516 active blocks, in the most probable case there are 6,120 active blocks, and in the optimistic case there are 8,100 active blocks. The considered reservoir model for the optimistic case is shown in fig. 4. The average execution time for a single simulation was about four minutes on a computer with a Pentium IV 2.5 GHz processor and 1024 MB RAM.

Two well configurations were used to develop the field. In one configuration, the field was developed only with vertical wells, and in the other, the field was developed mainly with horizontal wells. For all the maps the well configuration was kept fixed. The wells were located in the main portion of the field that corresponds basically to the central area of the pessimistic map. There is no doubt that the well configuration could be optimized to provide better results, but this would be beyond the scope of this study. In both well configurations, the field was developed through two fixed platforms (TLP's), the production wells were produced with a minimum bottom hole pressure (BHP) of 125 kgf/cm^2 and maximum flow rate at the surface of 1,500 m^3/day, the injection wells were also controlled by a maximum BHP of 360 kgf/cm^2 and maximum flow rate of 2,000 m^3/day.

In the optimistic case, the vertical well configuration consists of 42 wells, 18 being injectors and 24 producers, distributed in a 5-spot pattern (Figure 5). For the other two cases, the numbers of wells are 21 producers, 16 injectors for the most probable case and 16 producers, 13 injectors for the pessimistic case. The wells are located in the best portion of the reservoir, and the water injection is started at the same time as production in order to maintain reservoir pressure. Keeping the pressure as close as possible to initial pressure will have the effect to maintain the gas in solution, which will result in relatively small viscosity for the oil. The drainage radius of each producer is approximately 1000 m.

Although two platforms are still required to develop the field with the horizontal well configuration, fewer wells are required because of the increased productivity of the horizontal wells. All wells are designed to have 600 meters of effective length. The boundary conditions at the wells are the same as for the vertical well configuration. All horizontal wells are located at the top of the structure. The well disposition was chosen in such a way that the predicted lateral displacement from the predicted drilling location to the end of the horizontal section was not greater than 3,000 meters.

In this synthetic case, the use of wet Christmas-trees (sub-sea tree valve) was not predicted because a more careful study about flowing of this oil in low-level sea temperatures is necessary to decide what are the best options for this case. All wells produce directly to the platform to avoid this kind of problem.

Future Work

The total combination of these parameters will give a total of 3,456 cases to be simulated. With an average CPU time per run of 4 minutes, that means 230 hours. As the total time for each flow simulation is not excessive, the idea is to run all possible cases. The results will be ranked by the accumulated oil production corrected by an annual discount rate. This will allow the visualization of the STOOIP overall variation as well as, the identification of the most influential parameters in the variation of the STOOIP. The planned simulation production time for each run is 30 years.

In order to make the process more automatic for the user, the current task in this project is to develop a computer program using Pascal compiler to automatically change the simulator input file. The computer program will consist mainly of a series of loops, in which the uncertain parameters will be assigned values corresponding to the optimistic, most probable and pessimistic case scenarios. For each combination of the uncertain parameters in the input file, the program will call the simulator and run the realization. From the output file the program will select the result of interest, i.e. the cumulative oil production – surface condition - after 30 years corrected by an annual discount, and write it in a new file together with the uncertain input parameters corresponding to that particular realization.

The next step in this work would be to run a Monte Carlo simulation with these results to determine what is the probability associated with each outcome of the simulation and the Bootstrap technique to assess the uncertainty in the mean of this probability distribution.

The project will continue with the implementation of an experimental design approach in order to select relevant models, record factor settings for models, create data files, control execution, gather summary data and create the response model. The purpose of *Response surface methodology (RSM)* is to approximate a process over a region of interest, often called operating region. The goal is to define a performance measure of the process called response (i.e. cumulative production over 30 years of production) and some input variables X_1, X_2, X_3,…, X_n called factors, that are assumed to influence the response (areal extent of the reservoir, porosity, permeability,..). RSM provides tools for identifying the factors that are influential on the response, and for building a regression model linking the response to the influential factors, such as illustrated below:

$$\mathrm{Re}\,sponse = a_0 + a_1 X_1 + a_2 X_2 + \ldots + a_n X_n + a_{12} X_1 X_2 + \ldots + a_{n-1,n} X_{n-1} X_n + a_{11} X_1^2 + a_{22} X_2^2 + \ldots + a_{nn} X_n^2 \tag{5}$$

where $a_0, a_1, \ldots, a_{nn}$ are constant coefficients obtained by fitting a set of numerical simulations. The main advantage of the RSM model is its negligible cost to estimate new values of the response compared to CPU time-consuming reservoir simulations. This regression model can then be used to make safe predictions of the process over the uncertain domain and to generate probabilistic distribution of the response using Monte-Carlo sampling technique. A sufficient number of response values corresponding to different sets of factor values is required in order to fit this model. Depending on the objective of the study: screening or modeling (risk analysis) a simple first-order or a more complete second-order models are used.

The experimental design technique coupled with the response surface methodology (RSM) looks like an efficient and rigorous methodology to accurately quantify the impact of reservoir uncertainties on production forecast.

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