Monte Carlo Simulation of production multiphase flow for better evaluation of project decisions

LP Fulchignoni[a]

[a]*Department of Energy Resources Engineering, Stanford University, United States of America*

ARTICLE INFO

Keywords:
Flow simulation
Uncertainty quantification
Monte Carlo simulation
Decision making

ABSTRACT

Offshore oil and gas production system projects have the challenging characteristic of involving large investments along with a high degree of uncertainty. It is clear that uncertainty quantification (UQ) allows for better Oil and Gas (O&G) project decision. Even though many techniques for UQ have been proposed over the last years, it is still common practice in the industry to consider the most likely parameters during project decision making. This paper computes the expected flowrate of a real reservoir, considering that the properties of the produced reservoir fluid are uncertain. It allows the estimation of the expected value of a project's revenue, which helps companies make new investment decisions. The uncertainty of the flow simulation model inputs was modeled through Gaussian probability densities. Based on the Monte Carlo simulation (MCS) method, it can be concluded that the production flowrate distribution is bimodal, and has an average value of 2960.3 m^3/d. The inputs sampling followed the Latin Hypercube Sampling (LHS) algorithm, in order to reduce computational processing time.

1. Introduction

Oil and Gas (O&G) projects are typically complex and expensive. Companies' investment decisions are based on the technical and economic viability of the exploration field. The financial evaluation of revenues is mainly dictated by petroleum production, *i.e.*, the oil and gas flowrate that the reservoir can provide. In this sense, the multiphase flow simulation is an essential tool in the production system's design phase. It involves several variables with different degrees of uncertainty. Therefore, it is wise to evaluate the production flowrate under a probabilistic approach and to quantify the uncertainty associated with its value. The consequence is that the revenue will also be a random variable, for which one can calculate the expected value and make investment decisions based both on risk and return.

The uncertainty of multiphase flow simulations arises from multiple sources. The physical behavior of the flow is constructed through mass, momentum and energy conservation equations. The formulation requires closure relations, which are usually proposed based on experiments. However, due to the impossibility of performing real scale experiments, those are commonly made on acrylic pipes of approximately 2" with water and air as the flowing fluids. It is clear thatthe flow model is a simplification of the true physical system. Besides, in Black Oil simulations, the behavior of the oil, gas and water phases as a function of pressure and temperature is given by empirical correlations. The densities of each phase, besides the Water Content (WC) and the Gas-Oil Ratio (GOR) are the only inputs needed to characterize the whole mixture behavior through a wide range of pressure and temperature.

The reservoir behavior is modeled through a Productivity Index curve, that relates well bottom hole pressure with flowrate. There is uncertainty involved in the model's selection and also in the model itself.Moreover, numerical methods are necessary to solve the system of equations which characterizes the simulation model. Uncertainty with this regard arises from the use of spatial numerical discretization and approximation errors.

Another source of uncertainty relies on the inputs of the simulation. Figure 1 summarizes the basic physical inputs for the construction of a Black Oil steady-state flow simulation model. Additional information, such as the boundary conditions, are necessary to actually run a simulation. It is impossible to measure the reservoir pressure on a frequent basis, for instance, even though it is a parameter that greatly impacts the flow simulation results. It is worth noticing that the uncertainty degree is a function of the input. The pipeline diameter, for example, is measured directly and, therefore, has a smaller uncertainty - associated with the measurement error.

This paper evaluates the uncertainty of the production flowrate through a Monte Carlo Simulation (MCS). The technique consists on sampling random inputs and using them to run realizations of the desired output. The key idea is that, after a sufficient number of realizations, the probability distribution of the output will converge its real shape.

ORCID(s):

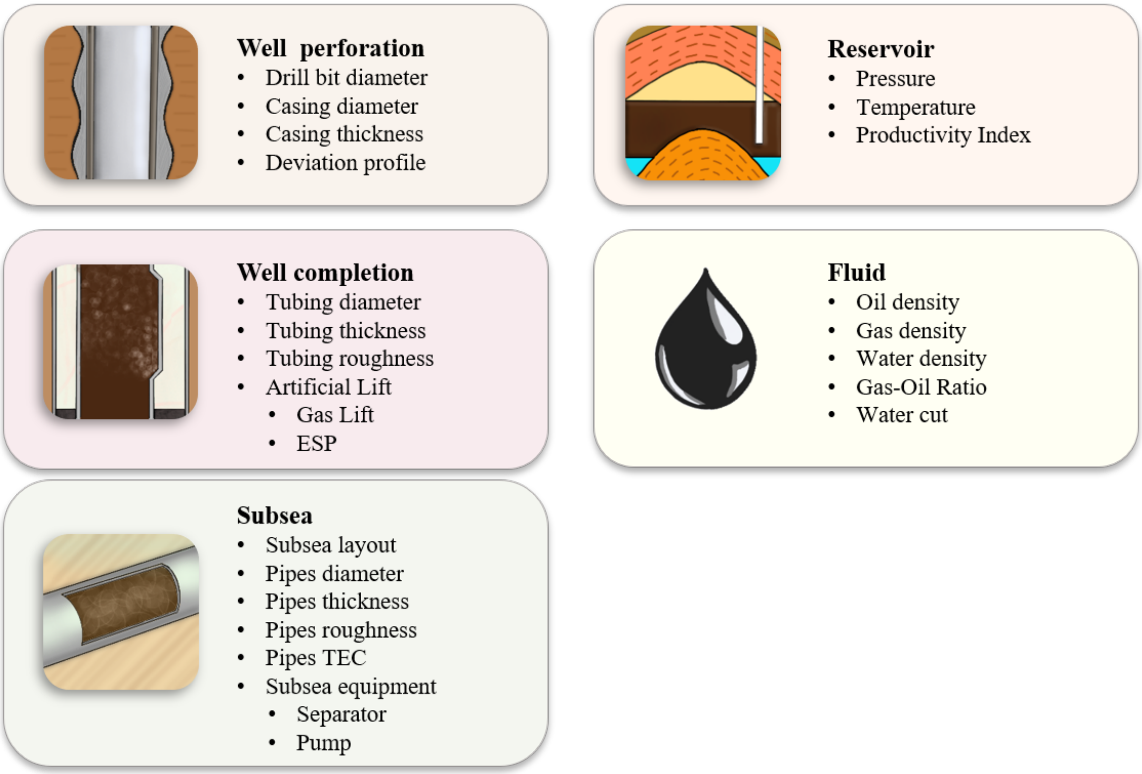

Figure 1: Basic physical inputs for modelling a Black Oil steady-state flow simulation

According to Kroese, Brereton, Taimre and Botev (2014), MCS is still one of the most useful approaches to scientific computing due to its simplicity and general applicability.

In particular, this paper considers the uncertainty of the inputs related to the oil and gas properties, namely: the oil density, the gas density, and the gas-oil ratio. The goal is to generate a probability distribution of the petroleum production flowrate. From that, one can compute the expected flow rate and, consequently, the expected revenue since there is a close relation between the two values. Other random input parameters, including those of the water phase, will be included in future work. Quantification of the uncertainty related to the other aspects of the simulation model (mentioned before) are also on track for future work.

Different studies followed a similar approach when evaluating uncertainty in the O&G industry. Cremon, Christie and Gerritsen (2020) used MCS to quantify the geological uncertainty in reservoir simulation, giving special attention to the evaluation of the number of realizations needed for convergence. Rotondi, Nicotra, Godi, Contento, Blunt, Christie et al. (2006) performed a MCS to investigate hydrocarbon production forecast. Tipping, Medvedev, Kovyazin and Valencia (2008) also considered MCS to determine the P10, P50, and P90 recoveries for a production development plans. Caers, Srinivasan, Journel et al. (1999) used MCS for geostatistical reservoir characterization.

2. Methodology

The oil density, the gas density, and the gas-oil ratio are the random variables in the simulation model, *i.e.* the sources of uncertainty. The uncertainty on these variables was modeled through a Gaussian probability density function (PDF).

The sampling technique followed the Latin Hypercube Sampling (LHS) algorithm. It was used, instead of the standard random sampling, in order to reduce the number of experiments needed for a reasonable result from the MCS. The LHS consists on dividing the PDF into equal partitions, and sampling a random data point in each partition.

Flow simulations were run on Petrobras' in-house simulator Marlim®. The model configuration file is a text file with a *.mr2 extension. The simulation results are stored in this same file, at its end. Once the simulation finishes, the

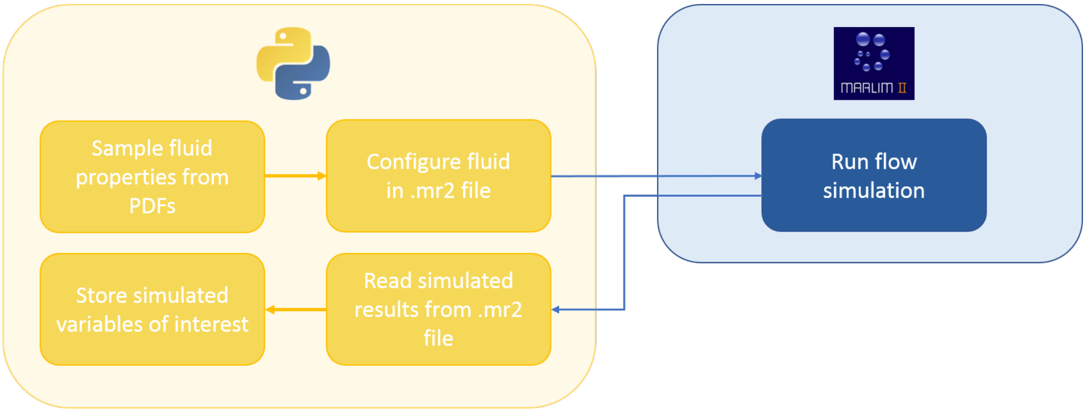

Figure 2: Schematic algorithm

flowrate is located in the text file and stored. The methodology is summarized in Figure 2.

Once all the simulations were run, a Gaussian Kernel Density Estimator (KDE) was used to fit the distribution profile of the flowrate. Different bins were tested for the KDE, and the one with higher fitting score was chosen as the best fit. Finally, the expected value of the flowrate was computed.

3. Production system characterization

The case study uses a real offshore production system, located in Campos Basin, Brazil. The reservoir produces oil, gas, and water. Fluid are modeled according to the Black Oil approach. The relevant fluid properties for the purposes of this study are described in Table 1 in terms of the Gaussian PDF parameters.

Table 1
Summary of the oil and gas properties.

Property	Average	Standard deviation
Oil density (-)	0.94	0.05
Gas density (-)	0.61	0.03
Gas-oil ratio (Sm^3/Sm^3)	163	8

4. Results

A total of 18071 realizations were performed for the MCS. The quantity of interest, the production flowrate, presented the distribution profile plotted in Figure 3. It is worth noticing that the distribution is bimodal, which may sound counter intuitive at first, given that all the random input parameters followed Gaussian distributions. The bandwidth that gave the best fit was 1. The descriptive statistics associated with the flowrate are described in Table 2. If the flow simulation considered only the average oil density, gas density and gas-oil ratio, the deterministic expected flowrate would be $2811.4m^3/d$. This would not be a representative estimate if considered alone.

From that, one could compute the expected revenue associated with such production system. Considering the oil barrel price of \$37.14 (WTI crude oil), the expected daily revenue is \$109,946. Moreover, if the project's lifespan is 20 years, the expected revenue (undiscounted) is \$803 MM. The difference from the deterministic approach represents a significant revenue of \$1 MM.

5. Conclusions

This research aimed to compute the uncertainty associated with the expected production flowrate, and, consequently, with the reveue, of a new O&G project. Initially, the uncertainty of the flow simulation model inputs was

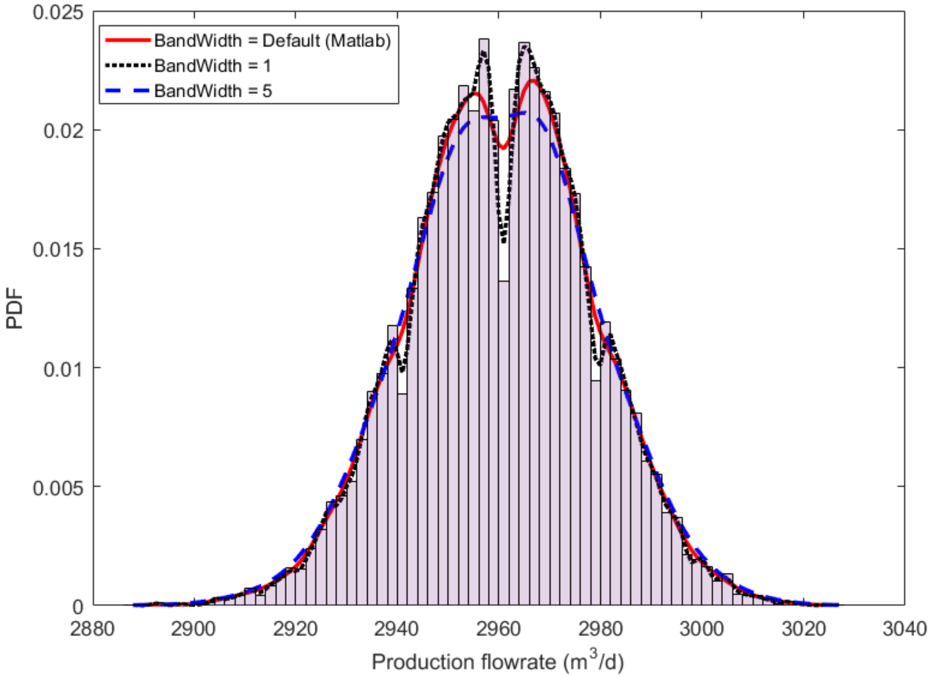

Figure 3: Distribution of the production flowrate

Table 2
Descriptive statistics of the flowrate distribution.

Mean (m^3/d)	2960.3
Standard deviation (m^3/d)	17.8
Minimum (m^3/d)	2887.9
Maximum (m^3/d)	3027.3
25% (m^3/d)	2948.4
50% (m^3/d)	2960.4
75% (m^3/d)	2972.3

modeled through probability densities. Based on a Monte Carlo Simulation, it can be concluded that the production flowrate distribution is bimodal, and has an average value of 2960.3 m^3/d. from this value, the annual revenue of the project is expected to be $803 MM. This is an essential metric for the investment decision making. If a deterministic approach had been followed, the computed flowrate would be $2811.4 m^3/d$.

References

Caers, J.K., Srinivasan, S., Journel, A.G., et al., 1999. Geostatistical quantification of geological information for a fluvial-type north sea reservoir, in: SPE Annual Technical Conference and Exhibition, Society of Petroleum Engineers.

Cremon, M.A., Christie, M.A., Gerritsen, M.G., 2020. Monte carlo simulation for uncertainty quantification in reservoir simulation: A convergence study. Journal of Petroleum Science and Engineering 190, 107094.

Kroese, D.P., Brereton, T., Taimre, T., Botev, Z., 2014. Why the monte carlo method is so important today. Wiley Interdisciplinary Reviews: Computational Statistics 6, 386–392.

Rotondi, M., Nicotra, G., Godi, A., Contento, F.M., Blunt, M.J., Christie, M., et al., 2006. Hydrocarbon production forecast and uncertainty quantification: A field application, in: SPE Annual Technical Conference and Exhibition, Society of Petroleum Engineers.

Tipping, D., Medvedev, A.L., Kovyazin, D., Valencia, R., 2008. Minimising risks of a siberian field development with major reservoir uncertainties.