Methodology to Assimilate Multi-Objective Data Probabilistically Applied to an Offshore Field in the Campos Basin, Brazil

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Abstract

This work applies a new methodology to assimilate multi-objective data (production, injection and, pressure of all wells) based on five of the twelve steps described by Schiozer et al. (2015) using reservoir simulation and uncertainty reduction for a brown offshore field in the Campos Basin, Brazil. We use probabilistic techniques to assimilate all data simultaneously, improving the performance of the process. The 12-step methodology by Schiozer et al. is based on a closed-loop reservoir development and management process. Steps 1 and 2 construct the model under uncertainties and select the numerical model. Steps 3 to 5 assimilate history data in an iterative process proposed by Maschio and Schiozer (2016). At each iteration, a set of best-matched models is selected to update the probability distributions of the reservoir properties (parameters) based on a correlation matrix. Steps 6 to 12, comprising the decision analysis, were not included in this work. The results reflect a practical application of the methodology, considering a real reservoir with two zones and complex behavior that was captured during reservoir characterization using an uncertainty reduction algorithm. The reservoir was characterized through the probabilistic combination of uncertain variables, based on well logs and seismic data. The probabilistic characterization highlighted the geological variability under uncertainty. A set of three hundred geological realizations with associated porosity, net-to-gross ratio, and permeability distributions was generated for further combination with uncertain dynamic parameters. The method DLHG (Discretized Latin Hypercube combined with Geostatistics) was used during the entire process to build approximately 1000 uncertain scenarios allowing the review of reservoir parameters in any iteration. The data assimilation process was used to update the probability density function for each parameter according to the data match indicators. We significantly reduced the uncertainty and improved production forecast reliability. This paper integrated different areas including reservoir characterization, reservoir simulation and history matching with the associated uncertainty reduction. The methodology was successfully applied in a practical case with several uncertainties, indicating good potential for application in other fields. The matching quality was better than in previous approaches.
Introduction
The development and management of petroleum fields, especially offshore, is a complex and multidisciplinary task. Many times, the process carried out is based on empirical procedures associated with professional experience. However, empirical procedures can make formal documenting the process difficult, and do not facilitate the replication of the study in other cases. Therefore, a structured framework to guide the whole process is of great importance to increase efficiency and efficacy.

According to Jansen et al. (2009), closed-loop reservoir management (CLRM) is a combination of model-based optimization and data assimilation (computer-assisted history matching), also referred to as ‘real-time reservoir management’, ‘smart reservoir management’ or ‘closed-loop optimization’. Shirangi and Durlofsky (2015) presented a closed-loop field development (CLFD) under geological uncertainty involving three major steps: (1) optimizing the field development plan based on current geological knowledge, (2) drilling new wells and collecting hard data and production data, and (3) updating multiple geological models based on all available data.

As an alternative general approach, Schiozer et al. (2015) proposed an integrated model based decision analysis based on 12 steps. This methodology offers a structured framework to formally keep track of the development and management of petroleum fields. Steps 3 to 5 comprise the assisted history matching part (data assimilation) of the framework, which is the focus of this paper.

History matching (HM) consists of incorporating dynamic data, such as well pressure and rates and 4D seismic, in the reservoir modeling process to improve predictability of reservoir models. HM is an ill-posed problem due to issues such as observed data uncertainties (measurement errors for example), insufficient constraints and data. Thus, HM is a complex problem due to such non-unique solutions.

HM can be treated following either a deterministic or a probabilistic approach. Under the deterministic approach, the HM process is formulated as a minimization problem, by which one seeks minimizing an objective function (difference between simulation output and observed data) and finds one (or a set of) matched model(s). Under the probabilistic approach, the central idea is to use observed data to condition the process reducing reservoir parameter uncertainties, such as porosity, permeability etc. The idea is to find a posterior probability distribution constrained to the observed data, reducing the uncertainty in the reservoir parameters and, consequently, reducing production forecast uncertainty.

More details about history matching and uncertainty reduction can be found in Oliver and Chen (2011), Emerick and Reynolds (2012), Maschio and Schiozer (2016), Silva et al. (2017) just to name a few.

As the 12-step methodology was successfully applied in a benchmark case in Schiozer et al. (2015), it was time to test it in a real field, with real measured data, such as seismic, well logs, well tests, lab data and production history, and potential to receive an infill drilling project. The chosen field is located in Campos Basin, Brazil, and has approximately 10 years of production history.

Objective
The objective of this work is to apply a new methodology to assimilate multi-objective data (production, injection and pressure of all wells) based on five of the twelve steps described by Schiozer et al. (2015) using reservoir simulation and uncertainty reduction for a brown offshore field in Campos Basin, Brazil, using probabilistic techniques to assimilate all data simultaneously.

Methodology
12-step Methodology
This methodology is composed of 12 steps and was proposed to be used as backbone in the integrated decision analysis process related to petroleum field development and management. Each step contributes to an important part of the process taking into account reservoir simulation, risk analysis, history
matching, uncertainty reduction techniques, representative models and selection of production strategy under uncertainty. One of the characteristics of the methodology is the fact that there is no need to carry out all steps, rather only those relevant for the study.

The methodology uses reservoir simulation to directly reproduce field performance that can be used in complex and multiple reservoirs, different field stages, as well as in development and/or management.

It focuses on the use of static and dynamic data to reduce uncertainties that allow risk analysis. Thus, geological, economic, operational and other uncertainties yield a decision analysis based on reservoir simulation and risk return techniques.

Detailed information can be found in (Schiozer, Santos and Drumond 2015). The steps of the methodology are described below:

1. Reservoir characterization. This step consists of building a model, developing scenarios and estimating probabilities.
2. Building and calibrating the simulation model. This step is necessary to guarantee reliability of the model response, avoiding biased evaluation. In addition, the numerical model should be fast enough to allow a large number of simulation runs in an acceptable time span.
3. Verifying inconsistencies of the Base case with well dynamics data: correcting scenarios and uncertainties. This step is necessary to guarantee that the model response is compatible with field measured data.
4. Generating scenarios considering all possibilities.
5. Reducing scenarios with dynamic data. Several techniques (Armstrong M. et al., 2012; Maschio and Schiozer, 2015) can be used to reduce the number of possible scenarios that represent the case depending on its complexity and amount of data. The Base case must be selected, among the selected models, to be used in the next step where an initial strategy must be used. This initial strategy is not critical because it will be improved in the following steps.
7. First estimate of risk curve, considering production strategy, from Step 6, with all possible scenarios from Step 5.
8. Selecting Representative Models (RM) based on all input and output variables.
9. Selecting production strategy for each RM repeating step 6 for each RM.
10. Selecting production strategy under uncertainty including economic and other uncertainties, using a risk-return analysis, combining all possible strategies and all possible scenarios.
11. Potential improvements. This is focused on a detailed analysis of the production strategy selected in the previous step focused on identifying the potential for change to improve the chance of success.
12. Final risk curve and decision analysis.

The 12-step methodology has to be repeated whenever new important information are obtained and, therefore, it is a continuous process that must be used by the company.

**General History Matching Methodology**

The history matching methodology applied in this work is shown in Figure 1. This workflow is generic and can be used in traditional history matching or in uncertainty reduction processes. Uncertainty reduction re-characterizes the parameters considering observed data, including the probability redistribution and/or elimination of values. Traditional history matching seeks identifying the best matched models, normally using an optimization algorithm to minimize an objective function. Each step of the methodology is briefly described as follows:
- Step 1: comprises the definition of uncertain parameters, the discretization of their range of variation into values and the use a discrete probability distribution to represent each parameter.
- Step 2: defines the observed data tolerance for the normalized history matching quality computation.
- Step 3: normally involves choosing a traditional history matching or an uncertainty reduction process.
- Step 4: generate new simulation models according to the method chosen in Step 3.
- Step 5: run each simulation model.
- Step 6: check the history matching quality of all reservoir output (multi-objective) using the Normalized Quadratic Distance with Sign (NQDS).
- Step 7: using the NQDS indicator, assess if models are within the acceptance range or whether the process should be continued.
- Step 8: for models with unacceptable behavior, review simulation models to verify if the problem is related to the numeric model, for example, productivity index, improper boundary conditions, wells completed in wrong positions and so on.
- Step 9: if necessary, do the changes according to the assessment in Step 8.
- Step 10: parametrization is the key part of the process. The success (or failure) of any history matching process is highly dependent on a proper parametrization. Thus, if the objective is not accomplished, evaluate the need to change the parametrization.
- Step 11: this step normally involves changes in the variation range of parameters and the possibility of including new ones.
- Step 12: In uncertainty reduction process, parameter update implies probability redistribution. They are re-characterized (updated) conditioned to the observed data. The uncertainty reduction process is carried out under a probabilistic framework. If the process involves a traditional history matching, the parameter values are updated using an optimization algorithm (in an assisted HM process) or even manually, in a manual HM process.
- Step 13: at the end of the process, when the diagnostic indicates that it is possible to filter (select models that fit in a set of rules) acceptable models, it is possible to increase the number of combinations to improve the chance of filtering a greater number of models.
- Step 14: filter the best matched models to be used in the production forecast. The filter is applied to eliminate combinations that do not match the observed data according to some specific criteria.
- Step 15: use the filtered models for forecast and risk analysis.
Iterative Discrete Latin Hypercube (IDLHC)
Step 12 of the general HM workflow applied in this work is carried out using the IDLHC (Iterative Discrete Latin Hypercube) method, proposed by Maschio and Schiozer (2016). The idea consists of applying the Discrete Latin Hypercube (DLHC) method in successive iterations. After each iteration, a percentage of models is selected based on the history matching quality and a histogram is generated for each parameter. New probabilities are computed proportionally to the frequency of each uncertain value of each parameter. In this work, a special version of DLHC called DLHG (Discretized Latin Hypercube combined with Geostatistical realizations), proposed by Schiozer et al. (2017), was applied.

The key idea behind IDLHC method is the use of a correlation matrix to capture the influence of each parameter in all objective functions. The selection of the models to generate the histograms (used to compute the new probabilities) is based on a local objective function (LOF), which is composed of influenced reservoir responses identified with the aim of the correlation matrix. A cut-off value ($R_c$) is used to select the influenced responses based on the correlation coefficient. Thus, the models are selected based on these functions. Maschio and Schiozer (2016) showed that $R_c$ values that indicate moderate correlation are adequate.

The use of the correlation matrix ensures that, if a given parameter does not influence any reservoir output (objective function), the probability distribution of that parameter remains unchanged, or in other words, its variability is preserved. This is very important because it is possible that some parameters that do not influence reservoir behavior during the history period may become influential during the forecast period. Thus, preserving the variability of such parameters may avoid biasing the production forecast. More details about the IDLHC method can be found in Maschio and Schiozer (2016).

Normalized Quadratic Distance with Sign (NQDS)
NQDS is a normalized history matching quality defined as follows (Eqs. 1 to 4):
\( NQDS = \frac{QDS}{AQD} \)  

(1)

where

\[ QDS = \frac{\sum_{i=1}^{Nobs} (Sim_i - Hist_i)^2}{LD} \]  

(2)

\[ LD = \sum_{i=1}^{Nobs} (Sim_i - Hist_i) \]  

(3)

and

\[ AQD = \sum_{i=1}^{Nobs} (Tol*Hist_i + C)^2 \]  

(4)

where \( Tol \) is tolerance given by a percentage of the observed data (\( Hist \)) and \( C \) is a constant used to prevent division by zero when a data series (water rate in a producer well, for example) has observed data close to zero, which can occur with producer water rate. \( Sim \) is the simulated results and \( Nobs \) is the number of observed data for a given data series.

The parameters \( Tol \) and \( C \) represent measurement errors and reflect the reliability of the observed data. This choice is normally dependent on the type of data and may be based on engineering judgement. For example, gas rate is normally more difficult to measure and tends to have higher measurement errors. Data gathered using obsolete devices ("old data") tend to be less reliable. Thus, for these data, higher tolerance may be necessary.

The range \([-1, +1]\) in NQDS means that the deviation of the solutions (the deviation between the simulated and observed data) is of the same magnitude as the measurement errors. A slight increase in this range makes the acceptance criteria less strict. For complex cases, it is very difficult to match models in \([-1, +1]\) however it is possible to relax the criteria based on engineering judgement. Another guideline regarding the definition of this acceptance range may be related to the objective of the application of the matched models. For example, if the objective is a short-term production forecast, a stricter range may be necessary. On the other hand, for a long-term production forecast, a less strict range could be considered.

The NQDS has several objectives: (1) to provide a dimensionless quality match indicator that takes into account the reliability of the observed data, which can be expressed in terms of \( Tol \) and \( C \); (2) to allow the combination of different kinds of data (such as water and gas rates, water cut, pressure, among others) or data of the same kind but different magnitudes; for instance, the water rate of different wells can be so different that absolute error (without normalization) would not work well due to unbalanced error among wells with high rates and others with low rates; (3) to facilitate result visualization and analysis. In a single NQDS plot, it is possible to assess a big amount of data (several wells), saving the quantity of plots to evaluate the results; (4) to assess solution variability. The NQDS plots are very useful to check if the variability of the solution is biased or not, that is, if the ensemble of solutions encompasses or not the observed data. An ensemble that encompasses the observed data is better than one whose curves are all concentrated above or below the observed data (biased).
Field and uncertainty description

Field Description
The application case is a real offshore brown field, referred to herein as "Y Field". The Y Field is located in Campos Basin, Brazil, and consists of a sandstone reservoir from the Maastrichtian Age, which is divided in two main stratigraphic zones, referred to in this paper as ZP200 and ZP300.

The shallower zone (ZP200) has average porosity and permeability of approximately 25% and 1000 mD, respectively. It has, internally, some vertical flow barriers with great lateral continuity, and is modeled as a compound of several subzones (ZP210, ZP220 and ZP230). This subzone definition is based on all well log data, pressure logs (Repeat Fomation Tests - RFT) made after the beginning of production and 4D seismic data. These pressure logs indicated depletion of the upper regions, while pressures in the lower regions remained near the initial value.

The deeper zone (ZP300) is thinner (approximately 14 m of average net-pay against 30 m of ZP200) and has lower porosity and permeability (approximately 22% and 750 mD average). Although it is also divided into several subzones, all of them are hydraulically connected, thus their definition was made based on well log patterns.

Oil properties vary both vertically and horizontally. ZP200’ simulation model is divided into two PVT regions, separated by a sealing fault, while ZP300’ model has only one PVT region. A black-oil with API Tracking model is used to represent vertical gradation in both zones. ZP200’ oil gravity, solution GOR and oil viscosity varies from 19 to 21° API, 29 to 39 m$^3$/m$^3$ and 11 to 21 cP, respectively. ZP300’ oil gravity, solution GOR and oil viscosity varies from 18 to 23° API, 31 to 53 m$^3$/m$^3$ and 6 to 32 cP, respectively. Viscosity data described above refer to oil saturation pressure ($P_{sat}$) condition.

The primary recovery mechanism in both zones is a mix of solution-gas drive (most significant) and partial-waterdrive (least significant). There is also use of waterflooding as secondary recovery, which helps lower production decline.

The initial production strategy consisted of four producer (PY33, PY34, PY38 and PY40) and three injector (PY27, PY28 and PY31) wells in ZP200 and one producer (PY36) and one injector (PY25) wells in ZP300. Production began in January 2007 and waterflooding in August 2007. One more producer well (PY48) was drilled in 2010 and began production in May 2011, draining ZP200 zone. All wells are connected directly to a FPSO unit.

All producer wells in ZP200, except PY48, are horizontal and produce only from the upper subzone, ZP210. All injector wells are horizontal but are completed in all subzones (ZP210, ZP220 and ZP230).

Figure 2, Figure 3 and Figure 4 show, respectively, the initial oil per unit area (total) map for each main zone with their producer and injector wells, a map of ZP200 zone showing the two PVT regions and plots of oil property values versus depth. In Figure 4, points represent fluid samples taken from a specific depth and vertical lines represent samples taken from a formation test with a perforation interval.
Figure 2—Initial Oil Unit per Area maps: (a) ZP200 on left and (b) ZP300 on right.

Figure 3—PVT Regions in ZP200: north (blue) and south (red), separated by sealing fault (dashed yellow line).

Figure 4—Oil properties versus depth from PVT Analysis: (a) Saturation Pressure ($P_{sat}$), on left, and (b) oil viscosity for ZP200, on center, and (c) oil viscosity for ZP300, on right.
Uncertainties

The number of parameters in a simulation model is usually very large, and all of which have associated uncertainties. One of the keys to the success of the whole process is selecting a good set of parameters and defining their uncertainties according to available data.

Y Field's simulation model was built using seismic data, well logs, well test results and lab test results. It was discretized into a corner point grid with 200x210x70 cells and a total of 222,282 active cells (156,889 from ZP200’ model and 65,393 from ZP300’). The simulation model was split by zone, generating two models, one for ZP200 and another for ZP300, in order to reduce computational cost of each simulation.

During geological modelling and grid construction, initial simulations were made in order to guarantee that the Base case was calibrated with dynamic data.

The uncertainties considered initially are described below and summarized in Table 1 and Table 2:

- 300 geostatistical realizations (images) of porosity, permeability and NTG, upscaled from the field's geological model.
- Vertical to horizontal permeability ratio.
- Relative permeability curve parameters (max values and exponents), water-oil capillary pressure (exponent), connate water saturation and residual oil saturation. Two flow units were defined for each model. The first one consists of grid blocks with permeability under 500 mD. The second one consists of grid blocks with permeability over 500 mD.
- Rock pore compressibility.
- Fault transmissibility multipliers (see Figure 5).
- Fault 2 reactivation pressure.
- PY48 partial completion factor.

![Figure 5—Grid Top map of zones with fault positions.](image-url)
Table 1—Uncertain parameters for ZP200 simulation model.

<table>
<thead>
<tr>
<th>Parameter Symbol</th>
<th>Description</th>
<th>Value (probability)</th>
</tr>
</thead>
<tbody>
<tr>
<td>im</td>
<td>Geological realization</td>
<td>1 to 300 (equi-probable)</td>
</tr>
<tr>
<td>Cr</td>
<td>Rock pore compressibility ( (\text{kgf/cm}^2)^{-1} )</td>
<td>( 7 \times 10^{-4} ) (0.33); ( 9 \times 10^{-4} ) (0.34); ( 1.1 \times 10^{-4} ) (0.33)</td>
</tr>
<tr>
<td>Prf2</td>
<td>Fault 2 reactivation pressure ( (\text{kgf/cm}^2) )</td>
<td>No reactivation (0.25); 200 (0.25); 240 (0.25); 280 (0.25)</td>
</tr>
<tr>
<td>F5, f8, f19b, f30</td>
<td>Fault 5, 8, 19b and 30 transmissibility multiplier</td>
<td>0 (0.2); 0.001 (0.2); 0.01 (0.2); 0.1 (0.2); 1.0 (0.2)</td>
</tr>
<tr>
<td>Kz</td>
<td>Horizontal to vertical permeability ratio</td>
<td>0.05 (0.33); 0.15 (0.34); 0.25 (0.33)</td>
</tr>
<tr>
<td>Kro1</td>
<td>Maximum oil relative permeability from flow unit 1</td>
<td>0.35 (0.33); 0.575 (0.34); 0.8 (0.33)</td>
</tr>
<tr>
<td>Krw1</td>
<td>Maximum water relative permeability from flow unit 1</td>
<td>0.1 (0.33); 0.15 (0.34); 0.2 (0.33)</td>
</tr>
<tr>
<td>Pkro1</td>
<td>Oil relative permeability curve exponent from flow unit 1</td>
<td>1.8 (0.25); 2.4 (0.25); 3.0 (0.25); 3.6 (0.25)</td>
</tr>
<tr>
<td>Pkrw1</td>
<td>Water relative permeability curve exponent from flow unit 1</td>
<td>1.8 (0.25); 2.4 (0.25); 3.0 (0.25); 3.6 (0.25)</td>
</tr>
<tr>
<td>Ppc1</td>
<td>Water-oil capillary pressure curve exponent from flow unit 1</td>
<td>3.0 (0.33); 5.0 (0.34); 8.0 (0.33)</td>
</tr>
<tr>
<td>Swi1</td>
<td>Connate water saturation from flow unit 1</td>
<td>0.087 (0.33); 0.116 (0.34); 0.145 (0.33)</td>
</tr>
<tr>
<td>Sor1</td>
<td>Residual oil saturation from flow unit 1</td>
<td>0.22 (0.33); 0.3 (0.34); 0.38 (0.33)</td>
</tr>
<tr>
<td>Kro2</td>
<td>Maximum oil relative permeability from flow unit 2</td>
<td>0.75 (0.33); 0.825 (0.34); 0.9 (0.33)</td>
</tr>
<tr>
<td>Krw2</td>
<td>Maximum water relative permeability from flow unit 2</td>
<td>0.15 (0.33); 0.275 (0.34); 0.4 (0.33)</td>
</tr>
<tr>
<td>Pkro2</td>
<td>Oil relative permeability curve exponent from flow unit 2</td>
<td>1.8 (0.25); 2.4 (0.25); 3.0 (0.25); 3.6 (0.25)</td>
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<tr>
<td>Sor2</td>
<td>Residual oil saturation from flow unit 2</td>
<td>0.22 (0.33); 0.3 (0.34); 0.38 (0.33)</td>
</tr>
<tr>
<td>PY48f1</td>
<td>Partial completion factor for upper PY48 perforations</td>
<td>0.01 (0.33); 0.1 (0.34); 1.0 (0.33)</td>
</tr>
<tr>
<td>PY48f2</td>
<td>Partial completion factor for lower PY48 perforations</td>
<td>0.0001 (0.25); 0.01 (0.25); 0.1 (0.25); 1.0 (0.25)</td>
</tr>
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</table>
Table 2—Uncertain parameters for ZP300 simulation model.

<table>
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<th>Parameter Symbol</th>
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<td>Geological realization</td>
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<td>Cr</td>
<td>Rock pore compressibility ((kgf/cm²)⁻¹)</td>
<td>7×10⁻⁴ (0.25); 1.0×10⁻⁴ (0.25); 1.5×10⁻⁴ (0.25); 2.0×10⁻⁴ (0.25)</td>
</tr>
<tr>
<td>F13, f14, f16</td>
<td>Fault 13, 14 and 16 transmissibilities</td>
<td>0 (0.2); 0.001 (0.2); 0.01 (0.2); 0.1 (0.2); 1.0 (0.2)</td>
</tr>
<tr>
<td>Kz</td>
<td>Horizontal to vertical permeability ratio</td>
<td>0.05 (0.33); 0.15 (0.34); 0.25 (0.33)</td>
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<td>Kro1</td>
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<tr>
<td>Krw1</td>
<td>Maximum water relative permeability from group 1</td>
<td>0.1 (0.33); 0.15 (0.34); 0.2 (0.33)</td>
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<tr>
<td>Pkro1</td>
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<td>Pkrw1</td>
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<tr>
<td>Ppc1</td>
<td>Water-oil capillary pressure curve exponent from group 1</td>
<td>3.0 (0.33); 5.0 (0.34); 8.0 (0.33)</td>
</tr>
<tr>
<td>Swi1</td>
<td>Connate water saturation from group 1</td>
<td>0.20 (0.33); 0.22 (0.34); 0.24 (0.33)</td>
</tr>
<tr>
<td>Sor1</td>
<td>Residual oil saturation from group 1</td>
<td>0.22 (0.33); 0.3 (0.34); 0.38 (0.33)</td>
</tr>
<tr>
<td>Kro2</td>
<td>Maximum oil relative permeability from group 2</td>
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<tr>
<td>Swi2</td>
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<tr>
<td>Sor2</td>
<td>Residual oil saturation from group 2</td>
<td>0.22 (0.33); 0.3 (0.34); 0.38 (0.33)</td>
</tr>
</tbody>
</table>

The prior probability density function for all parameters had a uniform distribution. The methodology demands discretization of continuous attributes. The initial number of values for each was determined by the authors based on experience and knowledge of the field.

Results

Steps 1, 2 and 3 of the methodology proposed by Schiozer et al. (2015) were described in section "Field and uncertainty description". The following steps (4 and 5) and the results are shown below.

Step 4
In step 4, 900 scenarios for each zone were generated, using the prior probability distributions, described in Table 1 and Table 2.

Step 5
The uncertainty reduction process starts with the simulation of the initial scenarios. The history matching quality indicator, NQDS, was calculated per well and for each of the following observed data:

- Producer wells: oil rate (Q_o), water rate (Q_w), liquid rate (Q_l) and bottom-hole pressure (BHP)
Injector wells: water injection rate ($Q_{wi}$) and bottom-hole pressure (BHP)

Tolerance was defined as 10% for all objective functions, except PY48 oil rate, the tolerance of which was defined as 20%, due to lower reliability of the measured data.

The IDLHC method was then used to update probability distributions of parameters. As described in section "Methodology", the process consists of successive iterations. Each follows several steps, some of which automated and others done manually:

1. Generation of scenarios from probability distributions of parameters using DLHG. This step is automated by software MERO, DHLG module, developed by UNISIM Team.
2. Generation of simulation models (*.dat files) from step 1 results. Automated by software MERO, GAS module.
3. Simulate all models and get results. Automated by software MERO, DSGU module. MERO generates output files in an internal format, *.UNIPRO.
4. Calculate NQDS from *.UNIPRO files and *.HIST file, which contains observed data. The output is a csv file containing NQDS per scenario (model) per objective function (data included in *.HIST file).
5. Calculate correlation matrix and new probability distributions, which would be used in the following iteration. This step is done manually.

20 and 14 iterations were made for ZP200 and ZP300, respectively. The necessary number of iterations depends on the case, and it is a decision that involves a compromise between time spent and quality of results. During the process, new parameters (see Table 3 and Table 4) were included and more levels (values) were added to the existing ones. In addition, the number of scenarios per iteration was increased to 1200 after iteration 5. For ZP300, in the last iteration 2000 scenarios were generated, in order to filter a larger number of matched models.

Table 3—Uncertain attributes included during IDLHC process for ZP200.

<table>
<thead>
<tr>
<th>Added in iteration</th>
<th>Parameter Symbol</th>
<th>Description</th>
<th>Value (probability)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>f3, f6, f23</td>
<td>Fault 3, 6 and 23 transmissibility multipliers</td>
<td>0 (0.2); 0.001 (0.2); 0.01 (0.2); 0.1 (0.2); 1.0 (0.2)</td>
</tr>
<tr>
<td>9</td>
<td>multkp210, multkp220, multkp230</td>
<td>Subzones ZP210, ZP220 and ZP230 permeability multipliers</td>
<td>0.3 (0.142); 0.5 (0.142); 0.8 (0.142); 1.0 (0.148); 1.1 (0.142); 1.4 (0.142); 1.8 (0.142)</td>
</tr>
<tr>
<td>9</td>
<td>multiphzp210, multiphzp220, multiphzp230</td>
<td>Subzones ZP210, ZP220 and ZP230 porosity multipliers</td>
<td>0.7 (0.142); 0.8 (0.142); 0.9 (0.142); 1.0 (0.148); 1.1 (0.142); 1.2 (0.142); 1.3 (0.142)</td>
</tr>
<tr>
<td>9</td>
<td>Por-aquifer</td>
<td>Porosity of analytical aquifer</td>
<td>0.05 (0.2); 0.1 (0.2); 0.15 (0.2); 0.2 (0.2); 0.3 (0.2)</td>
</tr>
<tr>
<td>9</td>
<td>Perm-aquifer</td>
<td>Permeability of analytical aquifer</td>
<td>10 (0.2); 50 (0.2); 100 (0.2); 500 (0.2); 1000 (0.2)</td>
</tr>
<tr>
<td>9</td>
<td>Rratio-aquifer</td>
<td>Ratio of the aquifer's external radius to that the reservoir's effective radius</td>
<td>1 (0.2); 2 (0.2); 2.5 (0.2); 3 (0.2); 4 (0.2)</td>
</tr>
<tr>
<td>16</td>
<td>multiPY27, multiPY28, multiPY31</td>
<td>Injectivity index multiplier for wells PY27, PY28 and PY31</td>
<td>0.001 (0.125); 0.01 (0.125); 0.05 (0.125); 0.1 (0.125); 0.2 (0.125); 0.5 (0.125); 0.8 (0.125); 1.0 (0.125)</td>
</tr>
</tbody>
</table>
Table 4—Uncertain attributes included during IDLHC process for ZP300.

<table>
<thead>
<tr>
<th>Added in iteration</th>
<th>Parameter Symbol</th>
<th>Description</th>
<th>Value (probability)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>Multkzp300</td>
<td>ZP300 permeability multiplier</td>
<td>0.3 (0.142); 0.5 (0.142); 0.8 (0.142); 1.0 (0.148); 1.1 (0.142); 1.4 (0.142); 1.8 (0.142)</td>
</tr>
<tr>
<td>7</td>
<td>Multphizp300</td>
<td>ZP300 porosity multiplier</td>
<td>0.7 (0.142); 0.8 (0.142); 0.9 (0.142); 1.0 (0.148); 1.1 (0.142); 1.2 (0.142); 1.3 (0.142)</td>
</tr>
<tr>
<td>7</td>
<td>multiPY25</td>
<td>Injectivity index multiplier for well PY25</td>
<td>0.01 (0.142); 0.05 (0.142); 0.1 (0.142); 0.2 (0.142); 0.5 (0.142); 0.8 (0.142); 1.0 (0.148)</td>
</tr>
</tbody>
</table>

It is important to note that not all parameter probability distributions must be changed during the process, but rather only the ones that, in any iteration, had significant influence on any objective function. Figure 6 and Figure 7 show examples of parameters whose probabilities changed and more levels added, while Figure 8 shows an example of a parameter that did not.

Figure 6—krw2 (ZP200) uncertainty reduction

Figure 7—kz (ZP300) uncertainty reduction.
Figure 9 shows NQDS plots for the first, an intermediary and the last iterations. It is possible to notice that NQDS variability for most of the objective functions dropped. Another aspect to note from Figure 9 is how easy iterations can be compared and objective functions can be visualized together with few plots. The evolution of results can also be seen by using plots depicted in Figure 10, which shows the number of models versus the maximum NQDS. In these plots, each point represents the number of models for which all objective functions have NQDS smaller than the corresponding value on the abscissa. The more the curves tend to the left, the better the results. For example, comparing the initial and the last iterations, there were almost no models with NQDS values for all OF (objective functions) lower than 10 in the first one, but in the last one more than 30% (ZP200) and 60% (ZP300) of the models had NQDS under 10.
After the last IDLHC iteration, it is necessary to define NQDS filters to get the best-matched models. The ideal filter is range [-1, +1]. However, as explained in section "Methodology", in complex cases it is very difficult to match models within this range for all objective functions. Thus, a more relaxed filter was defined with acceptable results, summarized in Table 5 and Table 6. Those filters resulted in 21 and 34 matched models for ZP200 and ZP300, respectively. Figure 11 to Figure 22 show production curves for ZP200, ZP300 and wells with history data from the last iteration. Each curve, except water cut, was normalized using a specific factor.

### Table 5—NQDS filters for producer wells.

<table>
<thead>
<tr>
<th>Well</th>
<th>Ql</th>
<th>Qo</th>
<th>BHP</th>
</tr>
</thead>
<tbody>
<tr>
<td>PY33</td>
<td>[-1, 1]</td>
<td>[-5, 5]</td>
<td>[-2, 2]</td>
</tr>
<tr>
<td>PY34</td>
<td>[-1, 1]</td>
<td>[-2, 2]</td>
<td>No filter</td>
</tr>
<tr>
<td>PY36</td>
<td>[-1, 1]</td>
<td>[-1, 1]</td>
<td>[-6, 6]</td>
</tr>
<tr>
<td>PY38</td>
<td>[-1, 1]</td>
<td>[-2, 2]</td>
<td>[-3, 3]</td>
</tr>
<tr>
<td>PY40</td>
<td>[-1, 1]</td>
<td>[-2, 2]</td>
<td>No filter</td>
</tr>
<tr>
<td>PY48</td>
<td>[-1, 1]</td>
<td>[-2, 2]</td>
<td>No filter</td>
</tr>
</tbody>
</table>

### Table 6—NQDS filters for injector wells.

<table>
<thead>
<tr>
<th>Well</th>
<th>Qwi</th>
<th>BHP</th>
</tr>
</thead>
<tbody>
<tr>
<td>PY25</td>
<td>[-1, 1]</td>
<td>[-1, 1]</td>
</tr>
<tr>
<td>PY27</td>
<td>[-1, 1]</td>
<td>[-3, 3]</td>
</tr>
<tr>
<td>PY28</td>
<td>[-1, 1]</td>
<td>[-1, 1]</td>
</tr>
<tr>
<td>PY31</td>
<td>[-1, 1]</td>
<td>[-3, 3]</td>
</tr>
</tbody>
</table>
Figure 11—Production curves for ZP200 with history data and 21 filtered models.

Figure 12—Production curves for ZP300 with history data and 34 filtered models.
Figure 13—Production and pressure curves for PY33 well with history data and 21 filtered models.

Figure 14—Production and pressure curves for PY34 well with history data and 21 filtered models.
Figure 15—Production and pressure curves for PY36 well with history data and 34 filtered models.

Figure 16—Production and pressure curves for PY38 well with history data and 21 filtered models.
Figure 17—Production and pressure curves for PY40 well with history data and 21 filtered models.

Figure 18—Production and pressure curves for PY48 well with history data and 21 filtered models.
Figure 19—Injection and pressure curves for PY25 well with history data and 34 filtered models.

Figure 20—Injection and pressure curves for PY27 well with history data and 21 filtered models.
General discussions

Usually, it is difficult to use probabilistic approaches for history matching in real fields with long production history. This occurs because the longer the history, the stronger the influence of local heterogeneities in production, demanding great effort from reservoir engineers and geoscientists to calibrate these heterogeneities in reservoir model. The Y Field, presented in this paper, has a 10-year production and injection history. Besides that, as explained in section "Field and uncertainty description", the reservoir has
aspects that strongly affect fluid flow, especially the ZP200 zone, making this case even more difficult than standard turbidites.

Despite all these aspects, results shown in section "Results" demonstrate that the application of the IDLHC method was successful, reducing uncertainties of several attributes and generating a set of matched models (not just one) to be used in the following steps of the 12-step methodology. Each model has a different geological image, which means that forecasts will not only consider dynamic parameter uncertainties, but also static ones. It is a great advance because of the improvement of risk curves reliability for future projects. Considering that geological model is consistent, all matched models are geologically consistent too.

In addition, the fact that we can easily change parametrization (by adding new parameters or new values to existing ones) in the middle of the process without losing the previous results is a great advantage, avoiding wasting time. Ideally, the initial parametrization should be enough to reach an acceptable history matching. However, in complex cases, it is sometimes necessary to include new information during the process, and it is not desirable to restart from the beginning every time it happens.

Regarding the case presented in this paper, the results helped improve the understanding of the reservoir dynamics. Some examples are described below:

- ZP200 model considers total isolation between subzones by continuous shale layers. Results of breakthrough on PY33 (Figure 13) and BHP on PY34 and PY40 (Figure 14 and Figure 17, respectively) suggest that may be a hydraulic communication between these subzones. In other words, the shale layers may be not as continuous as considered. A parameter that could have compensated the lack of volume communication is multiphizp210 (see Table 3). Its final probability distribution, showed in Figure 23, tended to greater values in upper levels, increasing ZP210 porosity and consequently ZP210 oil volume.

- Matching injector wells BHP was only possible by including Injectivity Index multipliers. However, even the filtered models in the end of the process showed a noticeable variability (see Figure 19 to Figure 22). The most probable explanation is that injection pressure was always above reservoir fracture pressure. This means that, during all injection history, the reservoir was hydraulically fractured by injector wells, and this effect was not included in simulation model.

![Figure 23—multiphizp210 (ZP200) uncertainty reduction.](image)

**Conclusions**

This paper presented the application in a real brown field of a multi-objective data assimilation methodology, proposed by Maschio and Schiozer (2016), following five of the 12-steps methodology described by Schiozer et al. (2015).

The application of DLHG method is worthwhile as it uses a probabilistic approach and includes geological uncertainties. Along iterations, parameters’ probabilities are updated and more matched models
can be filtered, until an acceptable result is reached. After that, optimization under uncertainties and probabilistic forecasts can be performed using directly the results of the study.

The methodology revealed flexibility, allowing changes, as reparametrizations and corrections, during the process without the need to restart the whole process from the beginning.

Initially, 900 scenarios (models) per zone were generated and 20 iterations for ZP200 and 14 iterations for ZP300 were adequate for the problem studied. Although some results could be improved, the methodology was able to reduce reservoir parameter uncertainties strongly, helping us understand reservoir dynamic behavior, and generate matched models for the following steps (optimization, decision analysis).

Finally, the main contribution of this work is to point out that the five initial steps of the 12-step methodology and IDLHC method were successfully applied to a real complex case and can be easily applied to other fields.

**Acknowledgements**
The authors would like to thank PETROBRAS and UNISIM/CEPETRO/DE-FEM/Unicamp for supporting this work.

**Nomenclature**

- **HM** = History matching
- **AQD** = acceptable quadratic distance
- **C** = constant added to production data to compute AQD
- **Hist** = observed data
- **LD** = linear deviation
- **Nobs** = number of observed data
- **NQDS** = normalized quadratic distance with signal
- **Rc** = cut-off value for the correlation matrix
- **Sim** = simulated results
- **Tol** = tolerance applied to production data to compute AQD
- **GOR** = gas-oil ratio
- **RFT** = Repeat Formation Test
- **P_{sat}** = Oil saturation pressure
- **FPSO** = Floating, Production, Storage and Offloading
- **PDG** = Permanent Downhole Gauge
- **Q_o** = Oil Rate
- **Q_w** = Water rate
- **Q_l** = Liquid rate
- **BHP** = Bottom-hole pressure
- **Q_{wi}** = Water injection rate
- **TORQUE** = Terascale Open-Source Resource and Queue Manager

**References**


