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An automated uncertainty reduction process coupled with geostatistical modelling

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One of the challenges to properly couple the reservoir characterization into data assimilation processes, is to automatize the whole procedure, since it involves reservoir models with different levels of fidelity. This work summarizes an automated uncertainty reduction process coupled with the geological modelling which focus on provide tools to this kind of process. The full content about the automated methodology can be access on Almeida et al. (2020).

Methodology

The data assimilation scheme is composed of 11 steps (Figure 1). The main contributions of this work are related to Steps 6 and 9. In Step 6, we estimate the similarity among scenarios and observed data. Under a multi-objective approach, the matching quality of the local-objective functions (LOF) are estimated through the Normalized Quadratic Deviation with Sign (NQDS). Moreover, we integrated two additional objective-functions: Productivity Deviation (PD) (Almeida et al. 2018 and Formentin et al. 2019) and Breakthrough Deviation (BD) (Almeida et al. 2018).

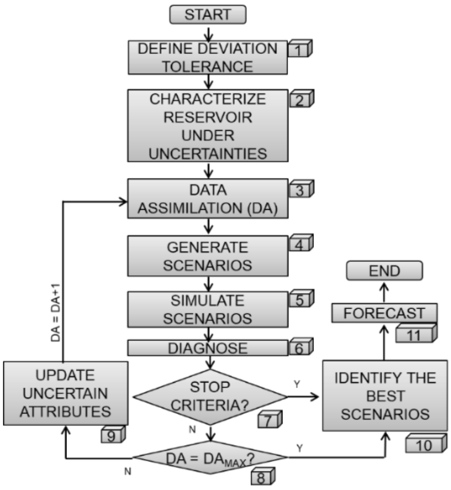

Figure 1: Methodology Flowchart

When the stop criteria (Step 7) is not reached and the maximum number of assimilations (8) is not achieved, the uncertainties are updated (Step 9). Each kind of parameters, scalar and spatial (grid properties) has a specialized process for uncertainties reduction. The main contribution is the update procedure focused on spatial uncertainties.

Spatial attributes updating process

Figure 2 summarizes the proposed process. The method follows a regional approach, which consists of identifying petrophysical realizations that provide the best match to data assimilated to each portion of the field.

The initial step of the process comprises the delimitation of the regions (Step A). Here, the regions are defined based on the wells positions, associating each block with the well that exhibits the lowest 3D Euclidean distance.

On Step B, the best petrophysical realization is identified per region observing two rules: (1) the highest percentage of local objective functions within the acceptance range; and, (2) the minimum absolute sum of the local objective functions.

On Step C, the best petrophysical property is kept for each region, in order to build a secondary data to be used as background information in the co-simulation to generate new realizations.

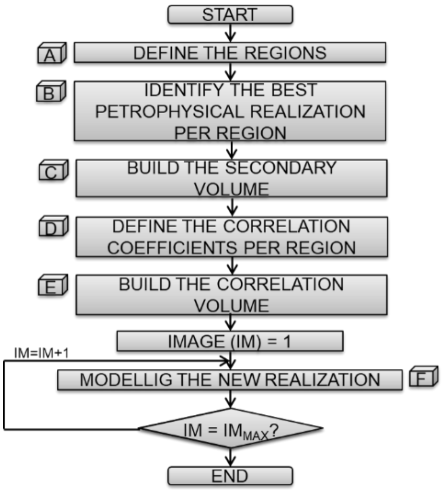

Figure 2: Methodology to treat the spatial uncertain attributes

To perform the co-simulation it is required to determine a correlation coefficient that will express how similar the new realizations must be in relation to the background information. Here, it is proposed define the correlation coefficient by region and as function of the measured misfit. In this sense, we propose a function to determine the correlation coefficient (CC) value (Equation 1).

$$CC_R = CCB - Iv * (DA_{max} - DA) + c * \left(\frac{PILOF_R^{SSR}}{100}\right) \quad \mathbf{(1)}$$

Three parts compound the function: (1) a base correlation coefficient (CCB) that indicates the reliability on the initial geological model; (2) a variability increase factor (*Iv*) to avoid limiting the search space since the initial assimilations; and (3) a correlation coefficient contribution (c) which is perturbed by the percentage of local objective function inside the acceptance range (*PILOF*) of the selected scenario (*SS*) for the region (*R*). Generated the correlation (Step E), the process employs the co-simulation to generate new petrophysical realizations (Step F). All data required on this process is generated externally employing Matlab, and is imported in a Petrel's workflow to properly generate the new realizations.

Study Case

The methodology was tested in UNISIM-I-M benchmark case, built for studies related to decision-making analysis in the management phase (Gaspar et al., 2016). The benchmark has also a reference case (UNISIM-I-R) which represents the "True Answer" (https://www.unisim.cepetro.unicamp.br/benchmarks/en/unisim-i/overview).

Twenty-five wells (14 producers and 11 water injectors) constitute UNISIM-I-M exploitation strategy. The case presents some challenges to the assimilation, especially due to 85% of the wells present less than 600 days of historical data.

The acceptable deviation was 31 days for BD, 10% for

"Fully automated uncertainty reduction process coupling numerical reservoir simulation and geological modeling."

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the LOFs (Oil rate, gas rate, water injection rate, bottom-hole pressure and productivity deviation), 20% only for water production rate. In total, six scalar uncertainties (Rock compressibility, Water-Oil Contact, PVT, Water relative permeability curves, Vertical Permeability Multiplier, and Well Index Multiplier) and three spatial uncertainties (Porosity, Permeability, Net-to-Gross) were treated.

Results

Seven iterations were necessary to achieve the stop criteria. Here, we call Best Scenarios (BS) the best fifty scenarios as final output of assimilation.

The best scenarios displayed more than 95% of traditional LOFs assessed inside the acceptance range (Figure 3).

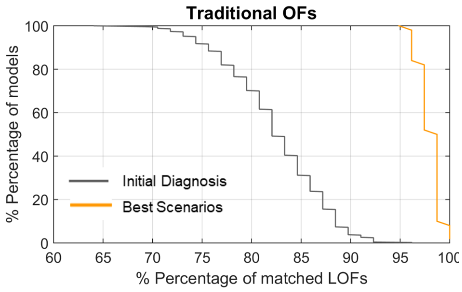

Figure 3: Comparison between the percentage of matched LOFs

The scalar attributes had the uncertainty diminished without collapsing to a deterministic level. Furthermore, they presented the center of the final distribution encompassing the reference values. The reduction provided matched scenarios capable to reproduce the behavior seen in the reference case. The BS provided a closer VOIP distribution to the reference value (Figure 4), overcoming the bias visualized in the initial diagnosis. Also presented a closer behavior to the reference response in the forecast period (Figure 5 and 6). A detail description of the wells behavior can be found in Almeida et al. (2020).

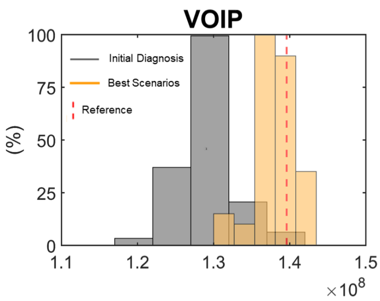

Figure 4: Volume of oil-in-place

Final Remarks

The automatic procedure assimilated the data in an iterative process resulting on reduced deviations. The consistent forecasts showed the potential of the procedure. Despite the increase on time-consumption, due the addition of the modelling steps, the proposed methodology is a robust process to increase the chance of obtaining results with geological consistency. In addition, the introduced procedure is a practical methodology to handle both types of uncertainty (scalar and spatial), employing simultaneously uncertainty reduction processes in an integrated manner. In future studies, we will test 4D Seismic data assimilation with the presented methodology.

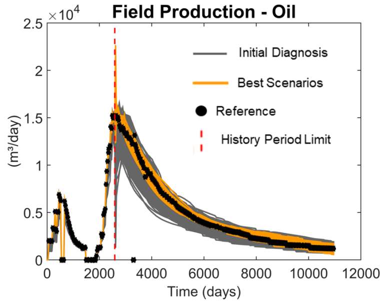

Figure 5: Field oil production

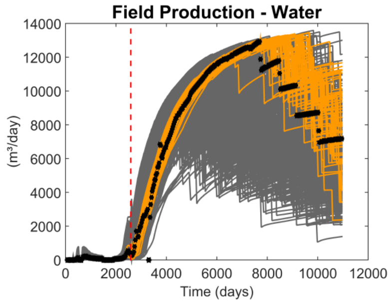

Figure 6: Field water production

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