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# Data Assimilation for Uncertainty Reduction Using Different Fidelity Numerical Models

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*"We propose a methodology that consists of generating and using efficient and effective lower-fidelity models (LFM) in data assimilation for uncertainty reduction."*

## Introduction

This text summarizes the paper published by Maschio et al. (2022) regarding the application of different fidelity numerical models in data assimilation (DA).

DA for uncertainty reduction based on reservoir simulation models is generally a high time-consuming process due to the number of uncertain parameters involved and the computational time required to run the flow simulation models. Depending on the degree of model description (fidelity), DA can take days or even weeks to be executed because it normally requires several hundred (or thousands) of reservoir simulations, even applying efficient DA methods. In this work, we propose a methodology that consists of generating and using efficient and effective lower-fidelity models (LFM) in DA for uncertainty reduction. The focus is to present a comprehensive and robust analysis of the DA process by assessing different model fidelities to achieve the best trade-off between computational time and quality of results.

The main motivation for this work is that the data assimilation process based on reservoir simulation models demands high computational effort and time. This problem implies the necessity of improving and accelerating the process, which can be solved by two complimentary ways: (1) applying efficient and effective DA methods; (2) using lower-fidelity models to reduce simulation time, balancing computational time and the quality of the results.

## Methodology

The methodology is divided into three main parts:

***1) Generation of the LFM:*** In this work, the lower fidelity models are generated by applying an upscaling process over the original fit-for-purpose model (FPM), named the medium-fidelity model (MFM) for practical purposes. The first step is building a structural model for each LFM based on the MFM, which is used as a basis for all LFM constructed.

***2) Data assimilation and results assessment:*** After the generation of the LFM, each different fidelity model is submitted, individually, to a data assimilation process to verify the consistency of the results. To accomplish this verification and assess the robustness of the results, we perform the following analysis: (1) history matching quality and computational time, (2) comparison of the variability of the solutions of the prior and posterior ensembles as well as the variability of the attributes.

***3) Selection of the fit-for-purpose model:*** To sum up the methodology, we introduce an innovative procedure to support the choice of the FPM. The proposed procedure consists of analyzing the quality of each fidelity against the computational time, pointing out directions to select the model fidelity that provides the best trade-off (balance between quality of the results and computational time).

## Application and results

We applied the methodology in a real and challenging field, named S-Field. S-Field is an off-shore turbidite reservoir located in Campos basin, Brazil. There are 2,359 days of history data from which 2,206 days (from 0 to 2,206, denominated history period) were used in the data assimilation, and the rest (from 2,207 to 2,359, denominated validation period) was used to validate the models regarding its predictive capacity. The field is produced by 8 producer wells (one of them is opened at the beginning of the validation period) and 4 water injector wells. The wells follow, predominantly, long horizontal trajectories. The reservoir is connected to a bottom aquifer, which is modeled numerically. The reservoir structure is modeled by means of a corner-point grid, and the reservoir fluid is modeled by a black-oil model. A second aquifer is modeled by the Fetkovitch analytical model.

Six different fidelities were used: the original fit-for-purpose model (MFM) and five LFM. For each fidelity model, we ran a DA process (of well data) and compared the results. In other words, the performances of the LFM are benchmarked against the MFM results.

Figure 1 summarizes the performance of the five LFM compared to the MFM. The prior and posterior ensembles are identified by 'pr' and 'pt', respectively. These plots show the number of filtered models (y-axis) against a cut-off value of NQD (absolute value of NQDS) considering all local objective functions (LOF) simultaneously (x-axis). Considering the LFM4, if we adopt a cut-off value of NQD equal to 5, there are 135 models for which all local objective functions simultaneously present an NQD value equal or less than 5. The more the curves tend to the left, the better the results are. We can clearly see two clusters of curves. The DA process was successfully applied for the six cases (MFM and the five LFM) because there is, in general, a significant improvement in the posterior ensembles for all of them.

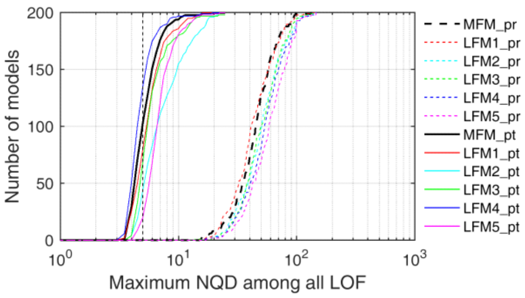


***Figure 1**: Global performance of the five LFM compared to the MFM.*

Figure 2 shows the performance of the six DA processes in terms of computational time and the number of filtered models using a cut-off value equal to 5. The smaller the score (total time divided by the number of filtered models), the better the relationship between cost (computational time) and benefit (quality of results), represented in this analysis by the number of approved (filtered) models.

*(Time/n_mod)x60

| Model | Time (hours) | n_mod (NQD ≤ 5) | Score* |
|---|---|---|---|
| MFM | 68.4 | 103 | 39.8 |
| LFM1 | 18.6 | 80 | 14.0 |
| LFM2 | 7.8 | 44 | 10.6 |
| LFM3 | 9.6 | 69 | 8.3 |
| **LFM4** | **8.4** | **135** | **3.7** |
| LFM5 | 6 | 20 | 18.0 |

***Figure 2**: Performance of the six DA processes. The **new** FPM (selected based on the trade-off) is highlighted in blue.*

Figure 3 shows the NQDS plot comparing LFM4 with MFM (the other 4 LFM are similar). This plot reveals three important aspects: 1) in general, there is a good agreement between the prior distributions from LFM and MFM; 2) overall, all DA processes were successfully accomplished since the posterior variability was significantly reduced when compared to the prior one, and the posterior models are well distributed around the observed data, that is, there is no bias in the posterior ensembles; 3) the third, and more important aspect, is that the matching quality from the five LFM is in good agreement with the MFM solution, showing consistent and reliable results.

Figure 4 shows oil rate curves for one producer well (P9) comparing LFM4 and MFM. Note that there is a high

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*"It is recommended to adopt a 'controlled fidelity', named fit-for-purpose model (FPM), which permits to accelerate the reservoir simulation studies without losing the quality of results."*

degree of similarity between the results.

Figure 5 shows the NQDS computed in the validation period comparing the results from the LFM4 with the MFM ones. First, it is possible to note the uncertainty reduction in the posterior ensemble. Second, although some minor differences exist in some wells, overall, the NQDS distributions for both prior and posterior ensembles present similar trends when comparing the LFM4 with the MFM.

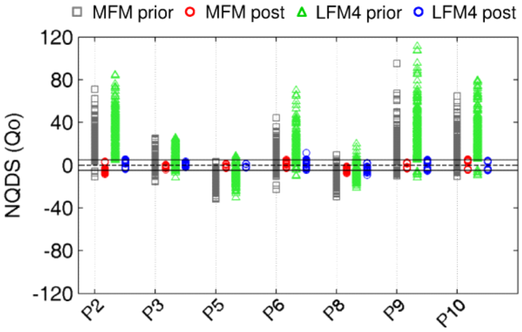


***Figure 3**: NQDS plots for all producers (oil rate) comparing the prior and posterior ensembles (LFM4 x MFM).*

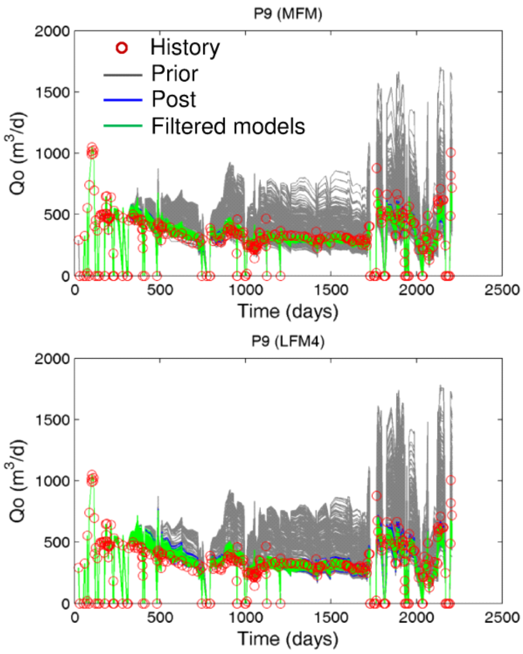


***Figure 4**: Oil rate curves comparing MFM and LFM4 for 1 out of the 7 producers (P9).*

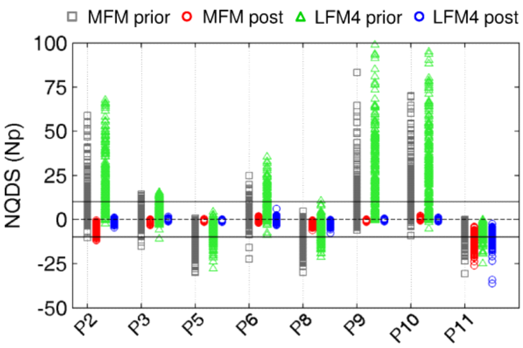


***Figure 5**: NQDS computed in the validation period (comparing MFM and LFM4) for cumulative oil production (Np) .*

## Conclusions and final remarks

- We presented a methodology using lower-fidelity models to accelerate the DA process while maintaining the consistency and the quality of results, overcoming the difficulties associated with higher computational time. We showed a comprehensive and robust analysis of the DA process in a real and challenging field by evaluating several degrees of model fidelities to establish a trade-off between computational cost and quality of results after the DA procedure.
- We showed that, for the case studied, the DA process using LFM reduced the computational time from days to hours, being up to about 11 times faster than the process using the original FPM with similar or even better results, making it clear the advantage of building, evaluating and selecting a lower-fidelity model based on the purpose of the study. The proposed approach allowed us to choose a new FPM for the field studied, much faster than the original with the same (or even better) results.
- Higher-fidelity models tend, in general, to better represent the reservoir. However, much higher computational demands are involved and more grid properties need to be updated, making the reservoir simulation studies (especially the DA process) more difficult and slow. Therefore, it seems more interesting to adopt a 'controlled fidelity', named fit-for-purpose model (FPM), which permits to accelerate the reservoir simulation studies without losing the quality of results.
- It is very important to dedicate some extra analysis in the DA stage to select a reliable reservoir model that matches the historical data within acceptance criteria (understanding more about the reservoir as the data is assimilated) in order to save time and increase the productivity in both the DA process itself and the reservoir development and management.

More details and results can be found in the full version of the paper.

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## Reference

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