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A new procedure for well productivity and injectivity calibration to improve short-term production forecast

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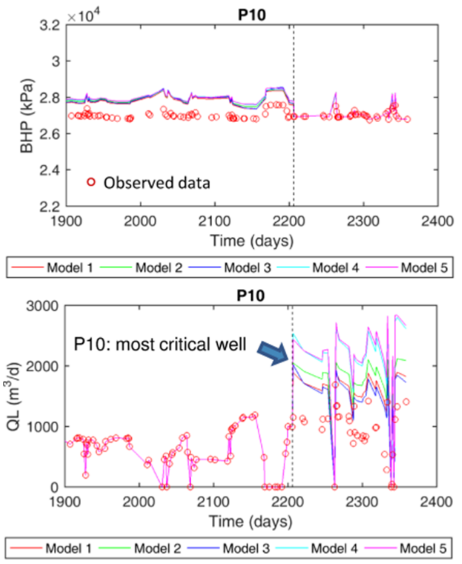
Introduction

This text summarizes the paper published by Maschio and Schiozer (2023) which present a new methodology for well productivity and injectivity calibration to improve short-term production forecast.

During data assimilation (history matching), wells are normally controlled by observed rates over the history period, typically liquid or oil rate for producer and gas or water rate for injectors. The well rates are imposed as target to be honored by the simulator. To perform production forecasts (immediately after the history period), wells control (operational conditions) must be changed to the forecast mode where wells are typically controlled by pressure. The target constraint imposed over the history period may hide productivity and injectivity issues that arise in the beginning of the forecast causing fluctuations in the transition from history to prediction. This work presents a simple and robust methodology to solve the history to prediction fluctuation issues improving the forecast quality of simulation models, especially for short -term forecasts.

Problem statement

Reservoir properties, such as absolute and relative permeability, and well model parameters, such as completion factor (FF), used to adjust the well index, act at the same time in the well productivity, making it very difficult to match all data simultaneously (rates, pressure and well productivity) in data assimilation, even using the productivity deviation (PD), proposed by Almeida et al. (2018) and Formentin et al. (2019), as objective function in the process. Figure 1 shows the bottom-hole pressure (BHP) and the liquid rate curves for 5 matched models. Note that the BHP curves are very well matched under the probabilistic point of view, because the NQDS are smaller than 1 for the 5 models. A NQDS equal to or smaller than 1 means that the curve deviation is smaller than the tolerance of 2.5%. However, despite the very good BHP matching, there are severe bias in the liquid rate curves after the transition from history to prediction periods, which jeopardize production forecast, especially short- and medium-term forecasting. Therefore, it is necessary to correct the well productivity issue before using the models in production forecasting.



BHP: Tol = 0.025   C = 0

Model	1	2	3	4	5
NQDS_BHP_P10	0.6693	0.7848	0.6718	0.8546	0.8700

***Figure 1**: Bottom-hole pressure (BHP) and liquid rate plots for 5 models selected from a set of models (posterior ensemble) after a data assimilation process.*

Methodology

Considering the difficulties in matching all data simultaneously, that is, well rates (oil, gas, and water), well pressure (bottom-hole pressure) and well productivities, this work proposes the division of the process into two major stages: (1) data assimilation, (2) refinement of the wells productivity (and injectivity) calibration considering the models selected in the first stage. The objective of this division is to isolate the influences of reservoir properties and well model parameters. The specific steps of the methodology are:

1) Perform the data assimilation process focusing on well fluid rates and bottom-hole pressure.
2) Apply a NQDS filter and select the best models from the Step 1.
3) For each model selected in Step 2, apply PI variations (ΔPI) to enable a linear fitting between ΔPI and ΔQ for each well. In other words, generate an equation of the form $\Delta PI = f(\Delta Q)$ for each well. Since the relationship between ΔPI and ΔQ is linear when the model is fixed, three points are sufficient. Therefore, for each selected model, three simulations are run to obtain the linear fitting for each well.
4) From the observed data and simulation results (for each selected model), obtain the target rate variation ($\Delta Q_T = Q_{model} - Q_{hist}$) in the last history time. To compute the ΔQ_T, we should invert the target constraint for the last history time from liquid rate to bottom-hole pressure to capture productivity issues in the transition from history to forecast.
5) Evaluate the linear fitting at the point ΔQ_T and obtain the desired PI multiplier for each well/model.
6) Simulate the selected models again by applying the new PI. The new PI is obtained by multiplying the old PI by the multiplier found in Step 5.

Figure 2 illustrates the PI multiplier determination using the target rate variation in the linear fitting.

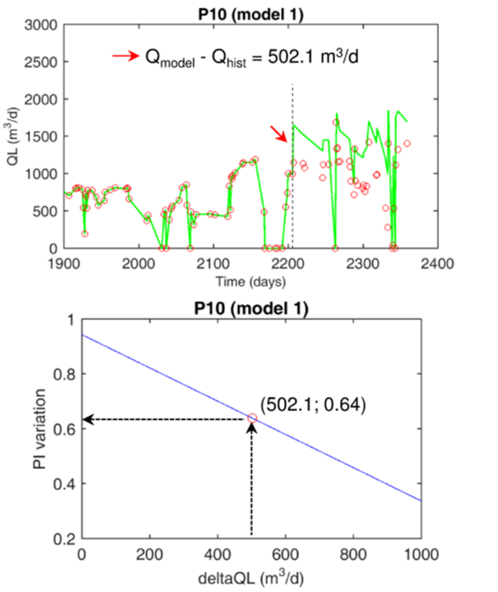


***Figure 2**: Illustration of PI multiplier determination from the linear fitting.*

Application and results

The proposed methodology was applied to a real field from Campos basin (Brazil), named S-Field. Figure 3 shows the liquid rate curves comparing the models before and after PI calibration (green). The severe bias in the liquid production estimates is totally corrected after the application of the proposed methodology. Note that the transition from the history to the forecast (green curves in bottom-right plot) is smooth, without any fluctuation.

Figure 4 shows well-by-well NQDS (for liquid rate) computed over the first month after the beginning of the validation period (NQDSv). The gray and blue markers represent the prior and posterior ensemble, respectively. The magenta markers represent the filtered models before the PI correction and the green markers represent the filtered models after the PI correction. The horizontal bars in the plot represent the range of NQDS between -1 and 1. The improvement after the application of the proposed method is remarkable.

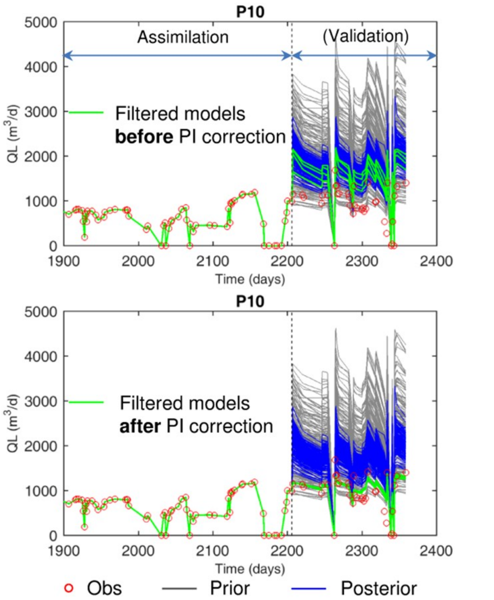


Figure 3*: Liquid rate comparing the models before and after PI calibration (green). Gray and blue represent the prior and posterior ensemble, respectively.*

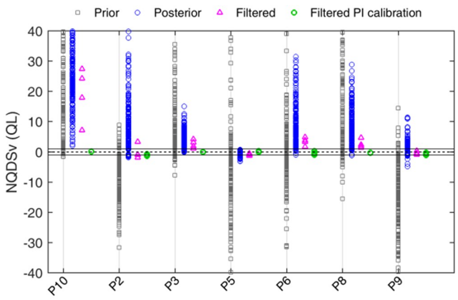


Figure 4*: Liquid rate NQDS computed over the first month after the beginning of the validation period (NQDSv). The horizontal lines represent the range of NQDS between –1 and 1.*

Conclusions and final remarks

- There is intrinsic complexity in matching all data (well rates and pressure, and well productivity) simultaneously in probabilistic history matching approaches due to concurrent influences among reservoir properties and well model parameters in the well productivity.
- It was showed that, despite a good general matching (rates and pressure) obtained during the data assimilation, the matched models may not be suitable for production forecast, especially short-term forecast.
- For reliable short-term forecasts, it is necessary to calibrate the wells productivity to avoid fluctuations in the transition from history to forecast periods.
- The proposed methodology enabled the correction of severe bias in fluid rates, allowing smooth transition from history to forecast (without any fluctuation). The matching quality in the assimilation period (oil and water rates and pressure) was preserved after the PI calibration.
- The proposed methodology is very easy to implement and represent an important contribution to improve the applications of reservoir simulation models in short-term decision-making processes.

Although this work is primarily focused on short-term forecast, we also presented in the full version of the paper additional analysis about the effect of PI calibration in long-term forecast for the filtered models. We have showed that the production deviation in the beginning of the forecast normally ends up being accommodated in long-term due to global material balance. However, when the differences with and without PI corrections are more pronounced, meaning that the productivity deviation is too high (which is the case of P10, for example), the impact in the well-level can be critical even in long-term. Therefore, even in long-term forecasts is recommended the PI calibration for more reliable predictions.

More details and results can be found in Maschio and Schiozer (2023).

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