Can Well Test Data Be Used to Reduce The Uncertainty in Geostatistical Realizations?

*Hamidreza Hamdi**
**University of Calgary*

Summary

The main objective of reservoir characterization is to generate some models that can effectively represent the underground reservoir. This task requires a comprehensive data integration plan to ensure all the available measured data is incorporated into the modelling workflow. Traditionally, the static data (e.g., core, logs) is employed to interpret and generate one (or a set of) reservoir model(s). However, in practice, the developed static models cannot truly represent the flow behavior of the subject reservoir because the measured *static* data that are the foundation of the modelling task are *local* (i.e., point measurements) and spatially sparse. The spatial sparsity of the static data requires some spatial interpolation techniques known as geostatistics to fill in the unsampled reservoir volume with properties such as facies, porosity, and permeability values. However, there is considerable uncertainty associated with geostatistical realizations because interpolation using a small amount of data is always erroneous. Additional *dynamic* data should be employed to validate the static models. The dynamic data is measured in time and contain the *volumetric* (as opposed to local) information about the reservoir structures and properties.
Online production data are the most frequent type of dynamic data that is used for validation purposes. However, in the exploration phase of the reservoir development (which is the subject of this study), only short flow tests, such as well test data, are normally available. The well test data is generally in the transient state, which means the recorded pressure data conveys important aggregated information about the heterogeneities encompassed by expanding volumes defined by the pressure diffusion process. Traditionally, analytical and/or simplified numerical methods are employed to gain additional insight about the reservoir from different interpretation techniques. Although these simplified modelling techniques are incredibly insightful, their role for seamless integration with reservoir characterization workflow is generally undermined. In particular, these modelling techniques rely on quick analytical, semi-analytical, or numerical methods to characterize homogenous or sometimes composite reservoirs. Complex geological structures cannot be easily integrated, and the resulting outcomes do not readily translate to detailed spatial geological heterogeneities.
The main objective of this study is to review and present some workflows for integrating the geostatistical methods and the well test data. The dynamic data is used to better represent the spatial petrophysical heterogeneities within the reservoir model. The uncertainty in the structural heterogeneities and the existence of sub-seismic structures below the resolution of the conventional 3D seismic acquisitions is not the subject of the current study.

Theory / Method / Workflow

Full integration of flow tests and reservoir modelling practice requires an inversion process called *geological well testing* (Hamdi 2012, Hamdi et al. 2014). A *meaningful* conversion of this inversion process is challenging because it needs to formulate complex spatial heterogeneities in terms of simplified mathematical functions. Otherwise, the validated model (i.e., a model that can produce the same flow response as the measured data) cannot preserve the original geological information.

Proper and adequate formulation of reservoir heterogeneities depends on the purpose of the inversion and the complexity of the underlying geological heterogeneities. Several methods exist to generate a functional form of the spatial distribution of the properties around the subject wells. Some of these methods include:

1. Engineering heuristics that help combine selected realizations (Hamdi et al. 2014)
2. The Gradual Deformation method and its variants (Roggero and Hu 1998, Hu et al. 2001, Heidari Sureshjani et al. 2020)
3. Semi-analytical methods relating the well test response to the heterogeneities within the investigated regions (Oliver 1990, Hamdi 2014)
4. Ensemble-based Assimilation Methods (Evensen 1994, Emerick and Reynolds 2013)
5. Statistical computer vision methods such as multi-resolution and dimension reduction techniques including Discrete Cosine Transform (Jafarpour and McLaughlin 2009) and Principal Component Analysis (Vo and Durlofsky 2015)
6. Machine learning methods such as Convolutional Neural Networks (Mohd Razak and Jafarpour 2020)
7. The Probability Perturbation Method (Caers 2004, Hoffman and Caers 2005, Hamdi and Costa Sousa 2016, Khani et al. 2017) and its variants

Some of these methods are developed with a premise of unimodal (single facies) reservoir models with Gaussian distribution of the reservoir properties (e.g., assimilation, Gradual Deformation, and dimension reduction techniques). The perturbation is usually conducted directly on the *real space* of the generated realizations. For example, the Gradual Deformation approach combines multiple Gaussian realizations to generate new Gaussian realizations. The combination iterations continue until a match with measured well test data is achieved. However, in many practical cases, the underlying reservoir is a realization of a complex multi-facies random process with discrete facies boundaries. Multiple-point statistical (MPS) simulations are more favorable to fill in the reservoir volume sequentially in such situations. Analog patterns (known as the training image), spatial trends interpreted from seismic data (i.e., soft data), and multiple well data measurements (i.e., hard data) are among the most critical pieces of information fed into the MPS process. MPS techniques heavily rely on the probability concept, which can generate realizations within the *probability space*. As a result, methods like the Probability Perturbation Method (PPM) are introduced to perturb any facies' probability before generating the realizations in the real space. The benefit of this method is that the continuity, statistics, and the information content of the original geological interpretation will be preserved. In addition, and more importantly, the probability perturbation can be conducted systematically by changing a single real number (r_D) between 0 and 1. Any slight change in this parameter will result in a different probability matrix, which can generate a substantially different realization in the real space. This approach will be helpful to match the well test data by changing the spatial distribution of the facies around the well. **Figure 1** shows the overall workflow of the PPM.

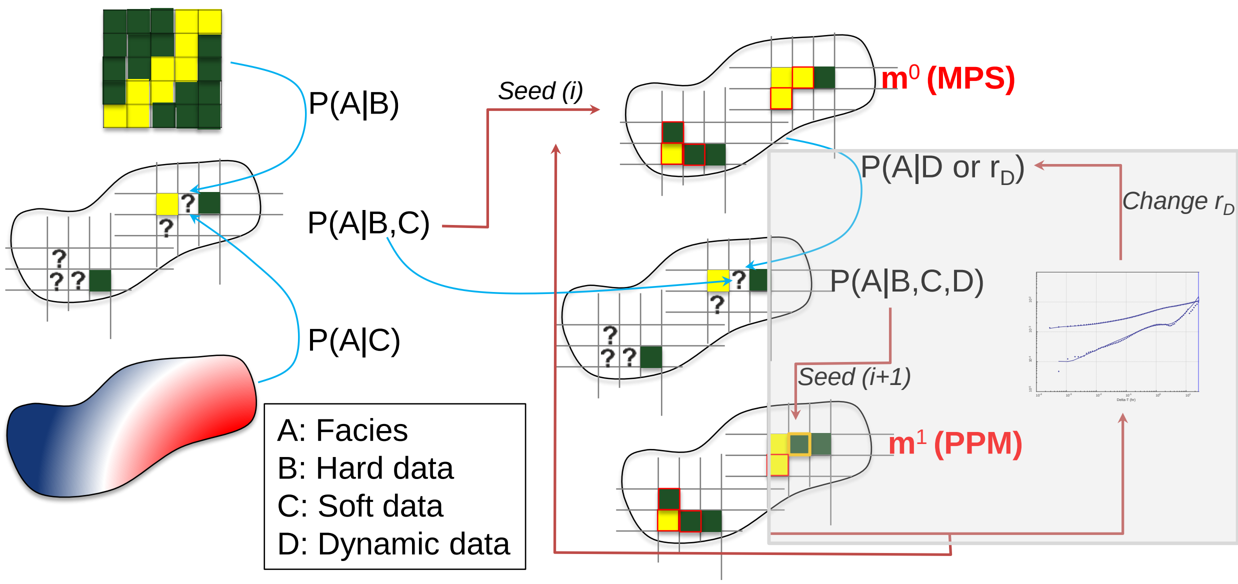

Figure 1. *A general workflow for employing the PPM to calibrate the MPS realizations using the well test data. The realizations are generated sequentially by combining the probability of occurring the facies given the probability of available hard and soft data. Perturbation occurs in the probability space and the sequential sampling is used to sample from the local probabilities to generate facies realizations in the real space.*

To showcase the usefulness of the PPM, an initial multi-facies reservoir model (**m_0**) is generated using some assumed well log data (hard data), a multi-scale fluvial training image (digitized from a modern river analog), and a specific seed number. This initial model serves as a truth case in the analyses. The generated facies model is populated with some reservoir properties (i.e., porosity and permeability data). A drawdown-buildup test is then simulated by placing and flowing a well in the middle of the truth reservoir model. The resulting flow test is used to condition the geostatistical realizations during the calibration process.
Further, this initial reservoir model is smoothed dramatically to provide some global trend maps of the existing facies (soft data). These trend maps represent some attributes that are routinely constructed in practice from the available seismic data interpretations. After the initial truth case is generated, the training image, simulated flow test, and the soft/hard data are employed to generated realizations that can hopefully match the static and dynamic (transient well test) behavior of the truth case. The seed number of the truth case is kept aside and is not used in the calibration process. The numerical flow simulations are conducted using tNavigator, which could help to dramatically reduce the simulation run time.

Results, Observations, Conclusions

The calibration process is started and iterated by varying r_D, and the reservoir properties. The seed number is also changed when the convergence is slowed. After a few hundreds of iterations, a match to the truth case data is obtained. The calibration process is repeated a few times to reduce the effect of randomness in the matching process. Interestingly, the connectivity of the facies (only if it is influential on the well test signature) is preserved in the matched model. Having additional flow tests in different locations in the reservoir can significantly improve the resulting model. It is important to notice that since only the well test data is considered in the calibration process (i.e., no inter-well injection data is available), the facies connectivity in distant areas may not be perfectly preserved. This is mainly because the well test signature in later times comes from larger investigated volumes. In other words, the test data provides less information about the accurate position of the heterogeneities in later times.

After the calibration process, additional samples are generated using a quasi-uniform sampling approach (with the seed number of the matched case) to conduct some sensitivities. The relevant samples are used to train a Gaussian process model as an accurate proxy to perform the global sensitivity analysis. The usefulness of the global sensitivity analysis is to better understand which part of the well test data is more influenced by the uncertain variables (i.e., matching parameters). The results indicate that at the early times, when the diffusion front has not reached the reservoir and facies boundaries, the well test response is more sensitive to the reservoir properties of the nearby hosting rock. However, at later times, when the diffusion front senses more boundaries, r_D (i.e., facies configurations) becomes the dominating factor guiding the matching process.

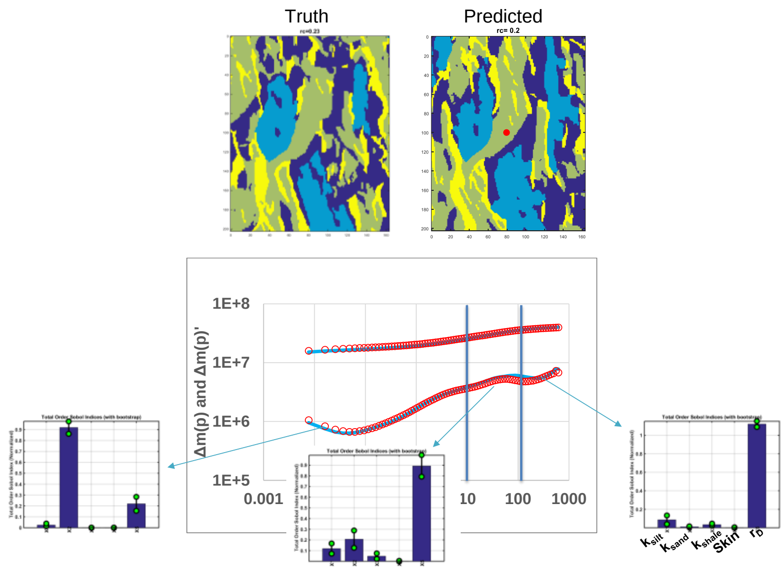

Figure 2. *The results of calibration process. The predicted facies realization closely follows the truth case particularly in near wellbore areas (top). The simulated well test response also matches the signatures of the truth well test (bottom). The global sensitivity analyses for each segment of the well test signature (the histograms) show the importance of each variable on the well test signature changes with time.*

Additive Information

This study provides a review of some important quantitative data integration methods that can be employed to condition the geostatistical realizations using the available measured well test data. The PPM is used to showcase the importance of flow tests in reservoir characterization workflows.

Acknowledgments

Hamidreza Hamdi would like to thank Rock Flow Dynamics Inc. for supporting his independent research and the use of tNavigator for conducting the reservoir simulations

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