Reservoir Forecast Optimism – Impact of Geostatistics, Reservoir Modeling, Heterogeneity, and Uncertainty

W. Scott Meddaugh, W. Terry Osterloh, and Nicole Champenoy
Chevron, Houston
scottmeddaugh@chevron.com

Summary
The oil and gas industry uses static and dynamic reservoir models to assess volumetrics and to help evaluate development options. The models are routinely generated using sophisticated software. Very elegant geological models are often generated without a full understanding the limitations imposed by the available data or of the underlying stochastic algorithms. Key issues facing reservoir modelers that have been evaluated include use of reasonable semivariogram model parameters (e.g. range, form, and nugget), model grid size, and model complexity. Within the last decade there has been increased recognition that incorporating uncertainty into reservoir modeling yields better business decisions, generally decreases project cycle time, and enables better understanding of the impact of reducing specific uncertainties through additional data acquisition. The robust incorporation of a reasonable uncertainty description in static and dynamic models significantly improves business decisions. The use of stochastic earth models combined with well placement optimization workflows is likely to yield significantly optimistic forecasts. Well placement optimization should be based on property distributions derived via appropriate estimation methods rather than stochastic methods. The oil and gas industry is in general moving away from an “honor the data” paradigm to an “honor the data and respect/incorporate uncertainty” paradigm for reservoir modeling.

Introduction
Reservoir forecasts tend to be optimistic – a statement made but not provable, at least with data in the public domain. Yet, conversations at technical meetings, the absence of publications highlighting extended forecast accuracy, the continued growth of papers related to building more detailed and hence, more complicated reservoir models (presumably to yield better forecasts), as well as the increased numbers of papers focused on uncertainty assessment and/or risk management all suggest that The oil and gas industry could improve its reservoir performance forecast accuracy (Meddaugh et al, 2011). The industry regularly uses static and dynamic reservoir models to develop forecasts that will ultimately be used to choose or justify a development option for an asset at a particular time (e.g. primary, infill, IOR, EOR) in the asset’s history. The models are routinely generated using sophisticated software – sophisticated both in terms of the user interface as well as the underlying algorithms. Consequently, very elegant geological models can be generated without a full understanding the limitations imposed by the available data (quality, quantity, areal and vertical/stratigraphic distribution) or even the limitations of the underlying stochastic algorithms.
Discussion

Many of the stochastic algorithms that are used to populate reservoir models typically use the semivariogram as a measure of spatial continuity. For carbonate reservoirs, a survey of internal and published studies suggests that a reasonable semivariogram range is on the order of 1500 m for a full field model. A 2006 full field study of the Wafra First Eocene Reservoir located in the Partitioned Zone (PZ) between Saudi Arabia and Kuwait gave semivariogram models with range values of 1100-2400 m for porosity for individual stratigraphic layers (Meddaugh et al., 2007). Studies in progress using a very dense data set (56 wells including 4 full cores in a 40-acre area) from the Large Scale Steamflood Project or LSP (Al-Yami et al., 2009) in the First Eocene reservoir give a semivariogram range on the order of only 120-280 m for porosity for individual stratigraphic layers. The issue faced by the reservoir modeler is what semivariogram range should be used for a full field model? The range derived from the full field data set or the pilot project or some combination of the two via a nested semivariogram, for example? Analysis of models generated using the full field and pilot derived semivariogram models shows that the smaller semivariogram range yields models that have a higher recovery factor for some recovery processes (e.g. waterflooding) but little, if any, impact on other recovery processes such primary and steamflooding (Meddaugh, 2010).
Figure 2. Cross sections from models generated for the EOR pilot. The red square shows the location of the 4.5 million cell model cut out of the full 73 million cell EOR area model. The historical, full field primary wells shown on the full field data section are generally 400-500 m apart. As expected, the models generated using the SVM appear much more heterogeneous than the models generated using the LVM. Note that there is not much visible difference in the models constrained by all wells (including the densely spaced EOR pilot wells) vs. the models generated using only the “sparsely” spaced historical, full field primary wells (after Meddaugh et al., 2010).

Figure 3. Plot showing recovery factor (RF) vs. pore volume injected (PVI) for EOR pilot area streamline-based waterflood simulation. Two way analysis of variation (ANOVA) showed with >95% confidence that after 1 PV injection, the recovery factor (RF) obtained by 3D streamline simulation for SVM models are about 2 RF units higher than those obtained for LVM models. Note that the absolute spread between the highest RF for SVM models and lowest RF for LVM models is about 4 RF units at 1 PVI (after Meddaugh et al., 2010).
Studies have also shown that areal grid size, which has minimal effect on primary recovery, may significantly impact the recovery forecast for displacement processes (Meddaugh, 2006a). Models generated using large areal grid cells (e.g. more than 25 m) or with fewer than 10-20 cells between wells produce optimistic results for waterflooding or steamflooding compared with models generated with small areal grid sizes (e.g. less than 10 m) and at least 10 cells between wells. Although more studies on other reservoirs are needed to confirm these observations, it is clear that basic static modeling parameters such as the semivariogram parameter and grid size do impact forecasts, particularly for some IOR/EOR processes.

![Figure 4](image_url)

**Figure 4.** Impact of grid size on waterflooding recovery factor. Results are shown for single realization of each grid size (5 m, 10 m, and 20 m). Note that as grid size increases results become more optimistic as the recovery factor at 1 PVI increases from about 0.195 for the 5 m grid to 0.235 for the 20 m grid.

Model complexity is a significant issue. Larger, more detailed static models take significantly more time to build and review. Very detailed models may also incur a significant up front data analysis and interpretation cost. The added expense and project cycle time may be worthwhile particularly when making decisions at the single well level, but complex models may have limited impact at the full field decision level. A published study (Meddaugh, 2006a) incorporating results from a Permian-age carbonate reservoir in New Mexico, an Eocene-age shallow water clastic reservoir in Venezuela, and an Upper Miocene deepwater clastic reservoir in California suggest that simple workflows that use only essential stratigraphic and geological constraints are as good in capturing overall reservoir fluid flow response as complex, highly constrained workflows that use detailed stratigraphic and facies constraints. This and other published studies suggests that for reservoirs with moderate to high net to gross (e.g. greater than about 30%) or with only small differences in the porosity vs. permeability trends of individual facies or rock types that reservoir models generated using simple workflows are adequate (Larue and Hovadik, 2008). Detailed models may be important for reservoirs with significant permeability heterogeneity, particularly for displacement processes.
Another important issue surrounds the impact of up-scaling on fluid flow response. Vertical up-scaling by factors commonly used for full field simulation models has little impact on fluid flow response as long as significant permeability contrasts (e.g. barriers, baffles, and thief zones) are preserved during up-scaling. However, some recent preliminary studies have shown that areal up-scaling of models initially generated using a very fine areal grid significantly alters the fluid flow characteristics (e.g. tends to make response to water injection more optimistic) and warrants additional study (Meddaugh, 2006a, b). A common practice for well planning in the industry is to use a single realization from the scaled up geologic model (usually what is considered to be a P50 scenario) to do detailed well planning for forecast generation and thus economics. A study was conducted using a hypothetical data set in order to test the idea that optimizing well locations on a single realization is introducing significant upside bias given the way these models are generated.

Figure 5. Plot showing nearly identical distribution of recovery factors from each of the 15 realizations generated from the three workflows of increasing complexity for the Permian-age carbonate reservoir in New Mexico. The geological constraints range from simple stratigraphy to stratigraphy + depositional facies + lithology (after Meddaugh, 2006).

Figure 6. Average porosity maps for two of the 25 P50 realizations generated for the hypothetical reservoir used for the well optimization study. Note the significant difference in the porosity distribution in the two realizations. Hypothetical well locations shown by black circles (after Meddaugh et al., 2011).
In the past few years there has been increased recognition that incorporating uncertainty into reservoir modeling, both static and dynamic, yields better business decisions, generally decreases project cycle time, and enables better understanding of the impact of reducing specific uncertainties through additional data acquisition. Routine use of design of experiments (DoE) based workflows to incorporate and analyze the impact of volumetric and connectivity uncertainty is growing. A generalized DoE-based includes the following key steps: (1) develop a list of appropriate static and dynamic uncertainties; (2) assign low and high end values (and by definition a mid value) for each of the uncertainties; (3) build an appropriate set of models based on a DoE design such as Plackett-Burman (PB) screening (Placket and Burman, 1943), folded PB, d-Optimal, space filling, etc.; (4) evaluate and statistically analyze the response of the models to obtain P10, P50, and P90 values for recovery and in place volumetrics; and (5) build “final” P10, P50, and P90 models using appropriate combinations of the key, high impact uncertainties recognizing that key, high impact uncertainties may change over time. Forecasts from the “final” models are used as input to the economic models used to make reservoir management decisions. What is needed now are tools and workflows to reduce “inherent bias” (aka – geological and engineering “optimism”) so that the full range of uncertainty in both what is “known” and “unknown” can be better incorporated in DoE-based workflows (Meddaugh et al., 2009). The robust incorporation of uncertainty, particularly permeability heterogeneity both vertically and areally, in static and dynamic models may significantly improve business decisions.

Summary/Conclusion
Although more studies on other reservoirs are needed to confirm these observations discussed above, it is clear that basic static modeling parameters such as the semivariogram parameter and grid size do impact forecasts, particularly for some IOR/EOR processes. The robust incorporation of uncertainty, particularly permeability heterogeneity, in static and dynamic models may significantly improve business decisions. Tools and workflows are needed that reduce the “inherent bias” of modelers so that the full range of uncertainty in both what is “known” and “unknown” can be better incorporated in uncertainty-based workflows. The oil and gas industry is in general moving away from an “honor the data” paradigm to an “honor the data and respect uncertainty” paradigm for reservoir modeling.
References


Meddaugh, W. Scott Osterloh, W. Terry; Champenoy, Nicole, 2011. Impact of Carbonate Reservoir Heterogeneity on Reservoir Forecasts: Why Are Production Forecasts Too Optimistic and Can Anything Really Be Done to Eliminate Forecast Bias? AAPG, (Houston, April 2011)


