Linking Geostatistics with Basin Modeling: Assessment of Structural Uncertainties

Bin Jia and Tapan Mukerji

Department of Energy Resources Engineering
Stanford University

Abstract

Basin and Petroleum System Modeling reconstructs the deposition and erosion history of a basin and models the thermal history and the associated generation, migration and accumulation of petroleum. The modeling process may cover a large geological time and spatial scale, and many of the input parameters are highly uncertain. While probabilistic approaches based on Monte Carlo simulations have been used to address this uncertainty, the impact of spatial uncertainty on basin modeling results remains unexplored. Present day structure models are the initial point for reconstruction and simulation and have major impact on the results. Two synthetic case studies are presented to demonstrate this impact and to explore the effects of spatial uncertainty. Seismic time-to-depth conversion uncertainty often represents more than 50% of the total structure uncertainties and must be quantified. This work proposes to use Bayesian Kriging for quantifying the uncertainty in the seismic depth conversion because of its stability on few observations. A complete workflow is proposed to quantify structural uncertainties using PetroMod® (Schlumberger) as the simulation software.

1. Introduction

Basin and Petroleum System Modeling (BPSM) is a key technology in hydrocarbon exploration that reconstructs deposition and erosion history and forward simulates thermal history and the associated generation, migration and accumulation of petroleum (Peters, 2008). The modeling process can cover very large geological time and space scale. Many of the input parameters are highly uncertain and a probabilistic approach is preferred (Corradi et al., 2003). While much work has been done on the uncertainty in BPSM, most focuses only on the Monte-Carlo simulations
of point-wise uncertainty, and spatial correlations are not taken into account.

In earth sciences, one seldom has sufficient data to accurately reveal the underlying subsurface phenomena. Spatial modeling techniques have to be used to make the best geological interpretation and understand the associated uncertainties. Geostatistical methods have been well developed and proven to be useful in mining, petroleum and other disciplines. We propose to combine geostatistical techniques with BPSM to account for spatial uncertainties.

Present-day structure model is the starting point for BPSM and has a direct impact on the model outputs. Structure models are usually built based on picking and interpretation of seismic horizons, and well data. Well data is considered exact, while each step of the seismic processing chain (acquisition, preprocessing, stacking, migration, interpretation, and time-to-depth conversion) has inherent uncertainty that must be evaluated and integrated into the final result (Thore et al., 2002). It is also pointed out that the time-to-depth conversion uncertainty often represents 50% or more of the total uncertainty (Thore et al., 2002). Therefore we will focus on the structural uncertainties resulting from seismic time-to-depth conversion and its impact on the results of BPSM. Bayesian Kriging is used for seismic depth conversion and a workflow is proposed to quantify the structural uncertainties in basin modeling.

The rest of this paper is organized as the follows. Section 2 reviews the BPSM process. Then in section 3, two synthetic examples are presented to demonstrate the impact of structural uncertainties in BPSM. Section 4 reviews Bayesian Kriging for seismic time-to-depth conversion and a workflow is presented in section 5 to quantify the structural uncertainties in BPSM. The discussion ends with preliminary conclusions and proposed future work.

2. Basin and Petroleum System Modeling

Hydrocarbon investigation can be divided into four levels: sedimentary basin, petroleum system, play and prospect. BPSM covers the first two of these and predicts locations of the pod of active source rock, thermal maturity of the source rock, migration pathways, and the timing of petroleum generation (Magoon and Dow, 1994).

BPSM involves solving coupled nonlinear partial differential equations with moving boundaries. The equations govern deformation and fluid flow in porous media, coupled with chemical reactions and energy transportation. The coupled system has to be solved numerically on discretized time and spatial grids with the integration of geological, geophysical, and geochemical input. PetroMod uses the finite element method to solve these equations. The workflow and key input parameters are summarized in Figure 1 (Peters, 2009).

The modeling process often covers a long geological time (millions of years) and
large spatial extent (tens to hundreds of kilometers) and each step has its inherent uncertainties. Zwach et al (2003) evaluated the use of stochastic techniques in BPSM. Wendebourg (2003) studied the uncertainty of petroleum generation using methods of experimental design and response surface. However most of these works only studied the point-wise uncertainties and the spatial correlation between data are not considered.

Present-day structural models seem to be an ideal example for spatial uncertainty studies because they are the starting point for the modeling process and require the integration of geophysical data, well data and geological interpretations. Structural models along with other inputs are used to reconstruct the burial and thermal history of the basin, based on which the forward modeling is run to simulate the petroleum generation, migration and accumulation. In the next section, we will demonstrate the impact of structural uncertainties with two synthetic case studies using a simple sensitivity analysis.

Figure 1: Basin and Petroleum System Modeling Workflow (Peters, 2008)
3. Impact of structural uncertainties

Figure 2 shows a simple 2D basin model with nine layers and two faults. Layer_8 is the main source rock with kinetics of the type Burnham_T3 (Burnham, 1989), so mainly gas will be produced. Layer_6 is the main trap formation where the generated gas will migrate and accumulate. For our base case the average thickness for the source rock layer Layer_8 is 291 m and the resulting accumulation of gas is 27.51 Mm$^3$. We now want to know how the size of the final gas accumulation will differ if the source rock layer structure is changed.

![Figure 2: Model for the synthetic case study. Layer_8 is the main source layer and Layer_6 is the main reservoir rock.](image)

The source rock was perturbed manually to demonstrate the simplest structural uncertainties and seven models were generated with average source layer thickness varying from 210-370 m. All of these models were simulated in PetroMod by keeping all other input parameters the same. Figure 3 shows the simulated gas accumulations for the different models. The Y-axis is the gas accumulation in million cubic meters.
Some observations and remarks:

1. Final accumulation increases monotonically with the increase of average source rock thickness. This is reasonable simply because more source rock generates more hydrocarbons.

2. There is a sharp change in accumulation size between source rock thickness 280 m and 290 m which indicates that the underlying numerical method is very sensitive to changes in the structure model in some cases. This is another reason why we need to better understand these uncertainties and their impact.

3. The accumulation reaches a constant value when the average thickness increases above 290 m, beyond which the accumulation seems not to increase with the increasing of source rock thickness. This occurs because at thickness 290 m, the maximum accumulation capacity of the reservoir rock (Layer_6) is reached. Any additional gas generated by increasing thickness cannot be trapped.

Figure 4 shows the impact of the reservoir rock capacity on the final accumulation. The structure model was perturbed manually to have a larger (left) and a smaller (right) drainage area. This insignificant local variance caused a significant change in the final accumulation output, 35.76 Mm$^3$ for the large trap and 11.25 Mm$^3$ for the small trap. Therefore, the structural uncertainties of reservoir rock need to be carefully studied.
With the two simple synthetic examples above, we have shown that structure uncertainties have direct and significant impact on BPSM results. The data used for structural model building are often uncertain; therefore, it is desirable to incorporate the associated uncertainties into the model output. As mentioned before, the seismic time-to-depth conversion accounts for more than 50% of the total uncertainty. The next section shows one approach for seismic depth conversion using Bayesian Kriging, and a workflow to quantify the structural uncertainties in basin modeling.

4. Bayesian Kriging for Seismic Depth Conversion

Structural models for a basin are usually constructed based on depths determined from two-way seismic travels times supplemented by depths from well logs. The well data are accurate to within a few meters, but are usually available at only a few locations. Seismic travel times are usually available on a spatially extensive grid which allows an almost continuous but inexact description of the lateral depth trends. Many geostatistical methods have been developed to combine the exact well measurements and seismic travel time data to make the best prediction of the structure model and quantify the associated uncertainties. Abrahamsen (1996) compared different methods and concluded that Bayesian Kriging is one of the more suitable approaches for depth prediction because all data are included and all intercorrelations between subsurfaces and interval velocity fields are considered.

Traditionally the time-to-depth conversion is performed for each layer independently. Abrahamsen (1993) proposed an approach to integrate all subsurfaces and the estimated velocity field in one consistent model using Bayesian Kriging as described in Omre and Halvorsen (1989). The approach is briefly summarized here.

The travel time $t_l(x)$ is considered as an average of an area, so the ‘true’ travel time to the reflector $l$ is modeled with a residual as

$$T_l(x) = t_l(x) + R_l(x),$$
The interval velocity is modeled with a lateral trend and residual as

\[ V_l(x) = \sum_{p=1}^{P} A_l^p g_l^p (x) + R_l^r (x), \]

where \( A_l^p \) are the prior coefficient parameters, \( g_l^p \) are the known regression functions which are typically interval velocities from stacking velocities or functions of interpreted travel times. The model can be formulated as

\[ Z(x) = \sum_{l=1}^{L} \sum_{p=1}^{P} A_l^p g_l^p (x) \Delta t_l (x) + \sum_{l=1}^{L} R_l^r (x) \Delta t_l (x) + R_l^z (x). \]

where \( Z(x) \) is the depth to subsurfaces. The Bayesian Kriging predictor and the corresponding variance are

\[ Z^*(x) = f(x) \cdot \mu_0 + k_z(x) K_z^{-1} (Z - F \mu_0) \]

\[ \sigma^*(x) = k_z(x) - k_z(x) K_z^{-1} k_z^T (x), \]

where

\[ f(x) = \sum_{l=1}^{L} g_l(x) \Delta t_l (x). \]

\( \mu_0 \) is the prior mean of coefficient parameters \( A \), \( k_z(x) \) is the prior variance of \( Z(x) \), \( k_z(x) \) is the prior covariance between \( Z(x) \) and the data vector \( Z \), and \( K_z \) is the covariance matrix.

The key advantage of Bayesian Kriging is that unlike Kriging with Trend, it is stable for any number of coefficients and data, including cases without well observations (Abrahamsen 1996). This is important for basin structural modeling because it is usually done at an early stage of exploration when very few well data are available.

5. **Workflow to quantify structural uncertainties**

We now can construct a complete workflow to integrate all input and to quantify the structural uncertainties in the BPSM process as shown in Figure 5.
Figure 5: Workflow to quantify the structure uncertainties in BPSM.

Unlike the typical BPSM process, the output model is not perturbed to match the calibration data. Because we can generate multiple realizations with stochastic simulation, we simply include those models that match the calibration data into the final assessment. If not enough models match the calibration data, one might try to modify the prior coefficient parameters, regression function for the lateral trend or even the model itself as long as the hard data are honored. Once we get enough models that match the well data and calibration data, we can begin to quantify the uncertainties in these models.

The workflow is general and can be applied to other aspects that are important in BPSM, such as facies modeling. One only needs to modify the input parameters and
the algorithms used to generate the model realizations.

6. Conclusions

Structural uncertainties significantly impact the output of basin and petroleum system modeling. Seismic time-to-depth conversion uncertainty represents more than half of the total structural uncertainties. Bayesian Kriging is used to estimate the uncertainties in the seismic depth conversion. A workflow is proposed to quantify the structure uncertainties, which can also be applied to other aspect such as facies modeling. BPSM relies heavily on the rock physical properties and these properties are normally directly linked to the facies assignment. Therefore it is crucial to model the facies accurately and incorporate the associated uncertainties. The novel aspect in this workflow is the inclusion of spatial uncertainty in the BPSM process.

7. Acknowledgement

The authors would like to thank Andre Journel, Allegra Scheirer, Kenneth Peters and Mohammad Maysami for their comments and suggestions on this work.

8. References


