

Uncertainty Quantification in Basin and Petroleum System Modeling with Case Study on Piceance Basin, Colorado

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Abstract

In this report we present work in progress from an interdisciplinary project that aims to 1) enhance the understanding of unconventional resources basin and 2) assess associated uncertainty in basin and petroleum system modeling discipline.

The first part of this project involved extensive study, and geological data compilation for the the Piceance basin for basin modeling, which will not be the main focus for this report. The second goal of this project, i.e. uncertainty assessment, will be the main focus of this report. We will start with the introduction of basin and petroleum system discipline, and discuss the importance of uncertainty quantification in basin and petroleum system modeling as well as review some previous studies in this topic. To address those challenges and improve the uncertainty quantification efficiency in this discipline, we will show our current proposal to construct a systematic workflow using a real world example.

The final part of this report would be some preliminary results of the implementation of the Generalized Sensitivity Analysis (GSA) method applied on 1D basin model.

The major contribution of this study would be the very first few systematic studies on uncertainty quantification and sensitivity analysis in basin and petroleum system modeling area. Also, this study will utilize a real world example (Piceance Basin) of unconventional resources basin to test the uncertainty quantification methods and thus we expect the conclusions from the study to be more attractive than using a synthetic case.

Introduction

Basin and Petroleum System Modeling

One of the major challenges in oil and gas exploration is to ascertain the presence, types and volumes of hydrocarbon in a prospective structure. With the assistance of seismic

interpretation technology, we may better delineate closed structures and identify potential subsurface traps, but this does not guarantee hydrocarbon or favorable fluids found in the traps. To further reduce the exploration risks, a robust methodology which effectively predict the likelihood of hydrocarbons resources in subsurface is required.

The early endeavors of generating this methodology started more than 50 years ago when geologists started to connect the past (a basin, the sediments and fluids that fill it, and the dynamic processes acting on them) to the present hydrocarbon discoveries, and made effort to developing methods to model these processes quantitatively. This area of study then becomes known as basin modeling. It is an integral method where people apply mathematical algorithms to solve coupled non-linear partial differential equations using seismic, stratigraphic, paleontologic, petrophysical, well log and other geologic information in order to reconstruct the evolution of sedimentary basins.

For oil and gas exploration activities, people are particularly interested in finding the next sweet spot and thus basin modeling study was first used by geochemists as a powerful tool for prediction of the petroleum generation potential of a lithologic unit in quantitative terms since the early 1970s. Then, sedimentary basin models as structural frameworks were used to capture the geochemical genetic correlations between hydrocarbons and source rocks. Several different names (e.g. oil system, hydrocarbon machine, petroleum system and independent petroliferous system) were given by scientist working on the notion and each of these terms emphasized different aspects of this multifaceted problem.

In this study, we utilized the term “petroleum system” and will conduct our study based on this concept. A petroleum system comprises a pod of active source rock and the oil and gas derived from it as established by geochemical correlation. Notice that this concept not only contains the elements such as the source rock, reservoir rock, hydrocarbon generated, etc, but also the process of the hydrocarbon generation, migration and accumulation. Thus, we can say that this concept embodies all of the geologic elements and processes needed for oil and gas to accumulate. The essential elements are an effective source rock, reservoir, seal and overburden rock; the last facilitates the burial of the others. The processes include trap formation and the generation, migration and accumulation of petroleum. These elements and processes must occur in the proper order for the organic matter in a source rock to be converted into petroleum and then to be stored and preserved. If a single element or process is missing or occurs out of the required sequence, a prospect loses viability.

Uncertainty Assessment in Basin and Petroleum System Modeling

From the definition of Basin and Petroleum System Modeling, integration of various sources of data is a key characterization in this concept. The modeling process covers very large spatial and temporal intervals with many of the input parameters highly uncertain and can yield very different results from different model inputs. Whenever constructing a specific model, we often assume the data is completely available and second that it is good quality. However, this is usually not the case in practice, and we tend to face in certain circumstances either lack of data or data with poor quality. Thus, an essential part of basin and petroleum modeling study should focus on better quantifying the associated risks resulted from various aspects. Hantschel and Kauerauf (2009) concluded three major types of questions raised in the risk analysis:

1. What is the impact of uncertainties in the input data on the model?
2. What are the important dependencies in our model?
3. Which set of input data leads to agreement when considering additional comparison data?

The first two questions often involve with sensitivity study such as: how sensitive is the relationship between a given parameter variation and the resulting model variation? Not every uncertainty of an input parameter has an impact on uncertainty of each simulation result; so which parameter influences which result? How strong are the different influences? The third questions indicate the direction of value of extra information/data and often encountered in the problem of calibration. Very often additional calibration data are available which cannot be used directly for the modeling but can be compared to simulation results, efficiently utilizing these information to constraint our model, or even possibly reducing the uncertainty in the input data and excluding models related to simulation results which are not matching the calibration data. These type of questions are often listed under the keywords “inversion” or “calibration” and similar with the “history matching” problems in reservoir simulation area. We might apply those optimization techniques into basin modeling and should be an interesting aspect to explore in uncertainty assessment.

With the assist of more powerful computational resources, it allows us to assess multiple models in a reasonable time and thus makes it possible for uncertainty analysis in basin modeling. Previous work has been done on the uncertainty (Zwach and Carruthers 1998; Corradi et al., 2003; Wendebourg, 2003), the focus is mainly on traditional Monte Carlo

techniques which randomly draw values from statistical distributions of the input parameter and compare the difference in the result for each drawn input parameter. Figure 1-1 list several important risk parameters that industry had come up with (Wygrala 2008).

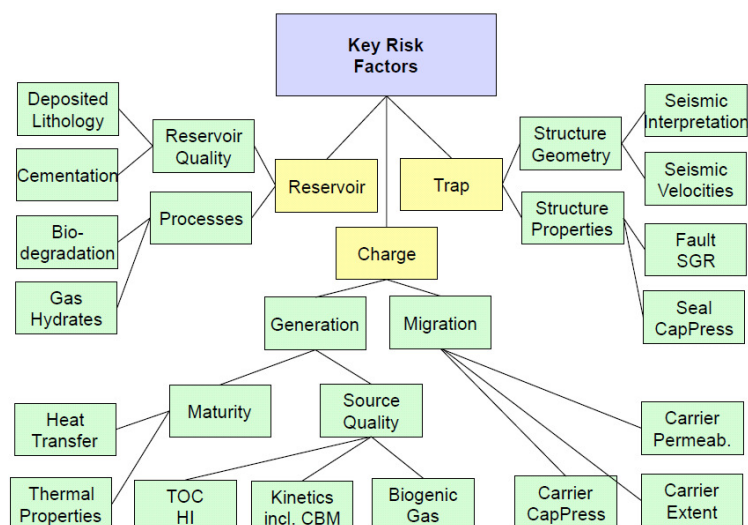


Figure 1: Important risk factors in basin modeling

In our study, we will not only explore the parameter uncertainty but also assess the joint spatial uncertainty which is usually ignored however lead significant uncertainty in basin and petroleum system modeling. Often, in earth sciences discipline, one seldom has either sufficient or accurate enough data to reveal the entire underlying subsurface conditions. Many of the inputs are inferred from sparse data inputs. Various spatial modeling techniques were applied to construct a better geological interpretation and understand the associated uncertainties. From previous study of (Jia 2010), the 1) structure and 2) facies model were identified as two major spatial uncertainty prospects: the structure model and the facies model.

Present-day structure model is the starting point for compaction analysis. In basin and petroleum system modeling, reproduce the burial history is key factor to characterize the evolution of basin. Usually, the structure models are built from picking and interpretation of seismic data constrained by well logs information. Well data is considered exact (hard data), while during each step of the seismic interpretation 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. From previous study, it is pointed out that the time-to-depth conversion uncertainty often represents 50% or more of the total uncertainty (Thore et al., 2002). Thus, we will first explore the uncertainty in time-to-depth conversion by using different velocity model to generate multiple horizons.

Facies map uncertainty is another key prospect worth investigating since the facies map will determine the geophysical and petrophysical properties of the rocks which are integrated into

facies definition and used in model building. In our study, we plan to use Multi-point geostatistical (MPS) method to generate multiple geological models with multiple facies properties and study the impact of those different geological scenarios on the model responses.

Methodology

From the previous discussion, we know that by nature Basin and Petroleum System Modeling discipline is an integrated approach which covers large spatial and temporal intervals and thus many of the input parameters are highly uncertain.

In order to improve the model robustness and reduce exploration risk, we would like to conduct a systematic investigation of uncertainty factors and study their impact on our basin model predictions. We will start with single In order to capture the uncertainties from parameters uncertainty on the model response, then study the spatial uncertainty to utilize advanced geostatistical method.

Determine Model response

We know from the modeling philosophy that each model been built has specific purpose and thus the uncertainty assessment should also closely tied to the model purpose. Usually, the model prediction behavior and corresponding outputs are what we called “model response”. Before conduct any uncertainty quantification, we need to determine what aspects are the response of interesting in our study. This is non-trivial question in basin and petroleum system modeling.

In the petroleum reservoir modeling discipline, people built the flow models are mainly built for predict the multi-phase flow in the subsurface and thus the model responses are usually chosen as well production rate data, saturation data or pressure data which resulted from the fluid flow dynamics within in a relative small drainage area. However, this is not as simple in basin and petroleum system modeling where we are interested not only the final (present-day) model output but also the process itself. Depending on the purpose of our study, we might choose different part of the model output or even the model process as our model response. For example, if we interested in determining the next sweet spot to drill, we might want to choose the accumulations location as model response; if we want to study the migration efficiency, we need to go into the model process and extract the hydrocarbon loss amount data as our model response.

Generally, the following aspects are categories which we may pick our model response from: 1) Oil/Gas Saturation; 2) Temperature; 3) Pressure; 4) Vitrinite Reflectance; 5) Oil/Gas Potentials; 6) Hydrocarbon properties: API, GOR, etc.

Parameter Uncertainty

We start our study with probabilistic approaches based on Monte Carlo simulations. Since the modeling process is mainly determined from three aspects: the trap formation, the reservoir rock and the charge system, we summarized the following list of parameters that represent the major uncertainties in the modeling process.

In the trap section, 3 parameter uncertainties may be investigated:

1. Erosion Thickness:

This parameter is for assigning an erosion thickness uncertainty to a specific layer. It is often challenging to quantitatively determine the erosion event and thus this parameter allows us to risk the erosion history. The present day geometry is not changed, only the amount of deposited and subsequently eroded material is varied.

2. Interpretation:

This parameter is important to quantify the structural uncertainty (e.g. resulted from poor seismic interpretation), it can be used for assigning a thickness uncertainty to a specific layer.

3. Capillary Pressure:

This parameter is used to assign a capillary pressure uncertainty for a specific lithology.

In the reservoir section, usually only lithology uncertainty will be taken into consideration.

1. Lithology:

Lithology is a key factor to determine many petrophysical properties and is the most sophisticated parameter in reservoir-scales models and characterization methods. Though basin model consider problems in a larger range, this parameter still allows us to substitute a particular lithology with a few of different lithologies. Unlike most other parameters, lithology substitution is not a continuously varying parameter. In current PetroRisk module, each simulation run will sample a lithology type from the indication of the proportion of particular lithology substitution would occur.

In the charge section, we have the largest numbers of the uncertainty parameters which resulted from source rock properties to boundary conditions. We summarized them into

1. Heatflow:

The heat flow trend of the model is a key boundary condition affect the thermal evolution of the basin and this parameter allow us to shift the trend by values drawn from a probability distribution. We can also specify the time frame where we want to put for this heat flow trend variation.

2. Heatflow Time shift:

This parameter allows us to only risk the heat flow trend of the model geological time according to a probability distribution.

3. SWI:

Another boundary condition which we can risk, this is also done by shifting certain values drawn from a probability distribution. A time frame for the SWI trend variation is also needed to be specified.

4. Thermal Conductivity:

This important physical property not only determines the thermal evolution of particular lithology and but also make impact on our model response.

5. Source rock Total Organic Carbon (TOC)

This parameter is one source rock property and measures the richness of the source rock. It usually comes from the Rock-Pyrolysis experiment and can be largely uncertain if no solid information available due to the lack of sample. We can vary the TOC value of certain facies according to a probability function. A TOC value needs to be assigned in the facies definition.

6. Source rock Hydrogen Index (HI)

Similar to the TOC property, HI is also the source rock property. When there's not enough information for the source rock, this value should be considered as an input for uncertainty analysis. The HI value also needs to be assigned in the facies definition.

7. Kinetic model

This parameter accounts various possible scenarios of kinetic models instead of a particular kinetic. This kinetic substitution is also not continuously varying parameter, and thus not described by a probability distribution but the indication of the possible scenarios with the

proportion of simulation runs in which any particular kinetic substitution should occur. The total amount must sum up to 100%.

8. Kinetic Activation Energy Shift:

This parameter is used to vary the activation energy of a kinetic according to a probability distribution.

9. Kinetic Sec. Crack. Activation Energy Shift:

This parameter is used to shift the secondary cracking activation energy of a kinetic.

10. Kinetic Frequency Factor Shift:

This parameter is used to vary the frequency factor of a kinetic according to a probability distribution.

11. Langmuir Volume Shift:

This parameter allows us to vary the Langmuir volume of a kinetic that uses the Langmuir bulk adsorption model.

12. Langmuir Pressure Shift:

This parameter is another on in tuning the kinetic that uses the Langmuir bulk adsorption model.

13. Desorption Energy Shift:

This parameter is used to vary the Desorption energy of a kinetic that uses the Langmuir bulk adsorption model.

14. Permeability:

Using this parameter, we can define a permeability uncertainty for a specific lithology.

15. Mobility:

Using this parameter, we can shift the petroleum mobility factor, which is entered in the Simulator interface (this is a new parameter added since PetroMod 2012 version)

One thing we would like to address here is that these parameters might not be as important and even may not present in some models, thus, depending on our model complexity and purpose, we may have different parameter of interest and only conduct the uncertainty quantification among those parameters of interest.

Spatial Uncertainty

From the previous part, we have summarized the parameters in basin and petroleum system modeling and will study the quantification of these uncertainties in the next section using real world example. However, we know that there is another important spatial uncertainty remain un-tackled. In this study, we will utilize advanced geostatistical methods and investigate the impact of spatial uncertainty mainly resulted from the following two aspects:

Structure Uncertainty

The integrated natural of basin and petroleum system modeling requires data from various resources, and geological maps are one of the most essential input. However, the depth maps are often come with seismic interpretation with large uncertainty in velocity modeling process. From the previous study, the time-to-depth conversion uncertainty often represents 50% or more of the total uncertainty (Thore et al., 2002). Thus, we will first explore the uncertainty in time-to-depth conversion by using different velocity model to generate multiple horizons and thus obtain realizations with various layer depth for present-day and study the impact of these spatial uncertainty on the basin model response, especially the hydrocarbon accumulation type and amount which are the primary interests for oil and gas exploration. In our study, we will investigate the following 3velocity scenarios in our 3D model to assess the structural uncertainty.

1. Uniform velocity across the basin and unconditioned to the well location to generate the depth maps.
2. Regional-vary velocity profile obtained from average the velocity information from wells.
3. Depth maps from time-to-depth conversion while condition on the exact well picks information.

Facies Uncertainty

In this section, we will investigate how facies uncertainty affect the basin modeling process. Faceis maps control the lithology and many geophysical and petrophysical. We will use Multi-point geostatistical (MPS) method to generate multiple geological realizations.

In this part, we will need to use SGeMS to first generate the facies distribution outside the

PetroMod and then load each model into the PetroMod Builder module. Current challenge for this can be:

1. How to efficiently generate facies model and load into PetroMod?
2. Scale problem. Since SGeMS is widely applied to reservoir scale model, how to generate facies model for basin scale need our investigation. e.g. PetroMod usually has 1km by 1km cell, will it geologically presentable to assign same lithology in such big scale?

Global Sensitivity Analysis (GSA) Method

Recently, a new generalized sensitivity analysis method was refined and successfully applied on a West Africa reservoir model case by Stanford Center for Reservoir Forecasting (SCRF). This method is typically applicable in the engineering of complex reservoir systems, however, also shows application potentials in the many other area of engineering, such as groundwater, CO2 sequestration, earth sciences model etc.

Since in these modeling processes, one critical factor is to find which model parameters (including combinations) have a significant impact on the decision variables.

We know that many parameters need to be considered in all aspects (geophysical, geological, and engineering) for the basin modeling process. Some of them are continuous, others discrete, and others have no intrinsic value and are scenario-based.

The proposed generalized sensitivity analysis approach (GSA) method classifies the model response /decision variables into a limited set of discrete classes using clustering method. Then, the analysis starts from the following principle: if the parameter frequency distribution is the same in each class, then there is no sensitivity, while deviation in the frequency distribution would indicate sensitivity. Based on this simple idea, a new general measure of sensitivity is developed, along with ways to quantify and understand the interaction between model parameters based on class-conditional distribution models. The detail discussion and example can be found in the reference.

Preliminary Results

In this section, we will show the application of Generalized Sensitivity Analysis (GSA) on the 1D basin model and illustrate the potential advantages of implementing this method to assist in identifying sensitive parameters in basin and petroleum system modeling.

Base Case Scenario

In this example, the base case scenario is simply the 1D basin model constructed at Mobil Oil T-52-19-G well location where the source rock been buried deepest and thus ideal for us to study of maturation of Cameo Coal source rock. By incorporate geological information from various resources, we were able to reconstruct the burial and erosion history at the well location and predict the source rock maturation (vitrinite reflectance) and the transformation ratio of source rock (amount of source rock been 'cooked'). Those parameters are commonly used to evaluate the source rock quality and quantity which will in turn largely effect the hydrocarbon generation and accumulation within a basin.

Among all input parameters, we started our investigation by exploring the sensitivity in three key parameters which usually identified as important however largely uncertain ones. They are basin basal Heat Flow value (HF), source rock Hydrogen Index (HI), source rock Total Organic Carbon (TOC).

In the base case model, we used the value given in the following table:

Base Case Scenario	
Heat Flow [mW/m ²]	60
HI [mgHC/gTOC]	150
TOC	50%

Uncertainty Parameters and Model Responses

To assess the sensitivity of the above three key uncertainty parameters, we conducted the GSA workflow and tested on 2 model responses. In the first case, we chose present-day vitrinite reflectance (R_o , commonly used index for source rock maturation) as our model response. In the second case, the Cameo Coal source rock transformation ratio at present day was chosen as model responses.

In both cases, 50 combinations of the above 3 parameters were generated by sampling the uncertain parameters from normal distribution. Then, 50 basin models were simulated and model responses were clustered into 3 groups. Prior empirical cdf and class-conditional pdf were compared and used to identify both single way and multi-way parameter sensitivities. The detail analyses are explained in the next section.

Generalized Sensitivity Analysis

Case 1: Vitrinite Reflectance (Ro) Response

The 50 simulated Ro values are clustered into three groups, of sizes 19, 18 and 13, with each group corresponding to mid, low, high value of Ro and corresponding to mid, low, high level of source rock maturity.

Pareto plot of the standardized measure of sensitivity for each single parameter is given in the figure below:

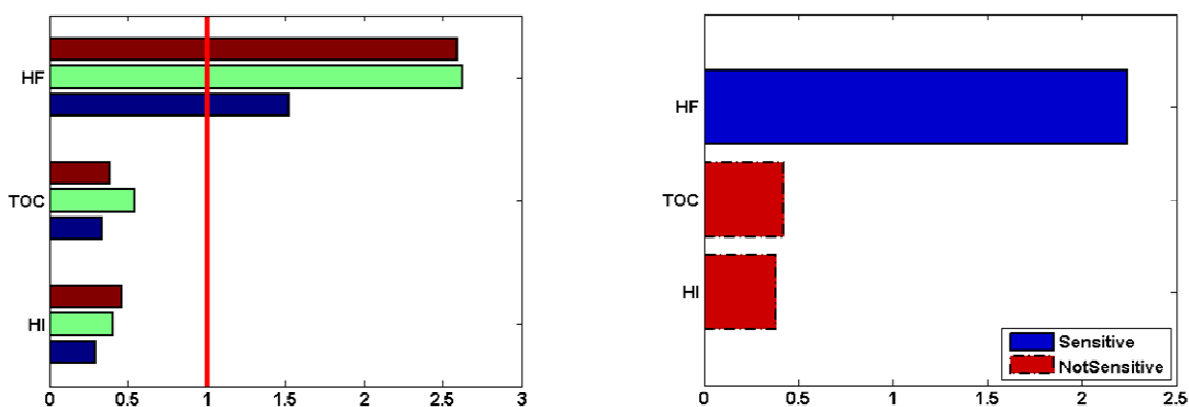


Figure 2: Pareto plot of the standardized measure of sensitivity for each single parameter on Vitrinite Reflectance Response

In this case, we found that the vitrinite reflectance value is most sensitive to Heat flow value since among the three total clusters, 2 classes reject the hypothesis and have a standard sensitivity measurement greater than 1.

Besides the single-way sensitive analysis, one advantage of GSA method is the capability of conducting multi-way parameter interaction sensitivity analysis, meaning that one parameter might not be sensitive to the model response in that the highly nonlinearity of the model, however, the correlations between certain parameters might result in sensitivity and thus could be identified by test the differences from prior empirical distribution and class-conditional distribution.

In this case, there are totally 6 interactions between these 3 parameters. From the GSA

algorithm, one response is insensitive to certain combination of 2 parameters if there's no significant difference between the class-conditional distribution of a single parameter and the class-conditional distribution of the parameter additionally conditioned to a second parameter.

In this simple example, the comparisons between distances are easy to visualize using the following empirical cdf shown in Figure 3 as below:

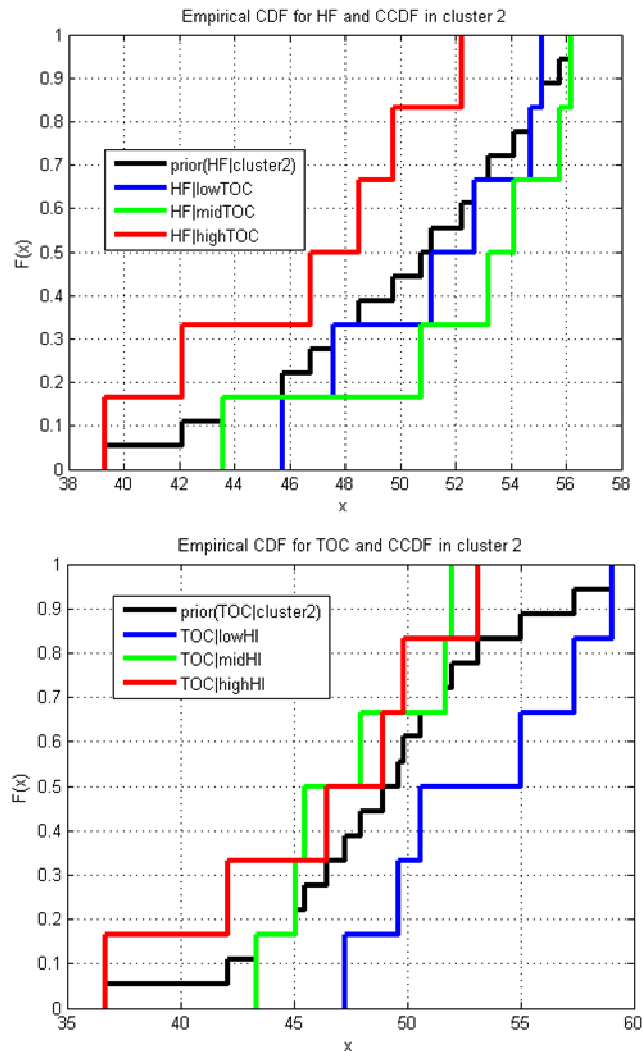


Figure 3: Empirical CDFs show parameter interactions in Ro sensitivity

In both upper and lower Figure 3, the black curves show the empirical distribution of one single parameter in certain cluster. The red, green and blue curves are empirical cdfs of this parameter additionally conditioned to a second parameter.

For example, the black curve of the upper chart of Figure 3 shows the empirical distribution of Heat Flow value in Ro response cluster 2. The red, blue and green curves are empirical cdfs of Heat Flow value given low, middle and high TOC value respectively. We can observe that the

red and black curves have the largest differences and from our algorithm, this distance is statistically significant. Thus, we identified that the parameter combinations represented by the red curve is most sensitive to the model response (in this case, the R_o value).

Similarly, in the lower chart of Figure 3, the combination of parameters representing by the blue curves shows the largest statistically significant distance away from the black curve. This indicates that TOC conditioned on low HI value most sensitive to the R_o model response.

Figure 4(left) displays the distance measures of the sensitive interactions for each class. The stacked bars show the contribution of the distance for each bin. Figure 4(right) shows the average measure of sensitivity for the parameter interactions as determined by the GSA algorithm.

From the figure, a direct interpreting would be that: sensitivities in the multi-way interactions can be identified in the second cluster (in which we have low R_o model response):

- Low HF correlated with High threshold values of TOC together sensitive to the low R_o value
- High TOC correlated with Low value of HI may also impact the low R_o value

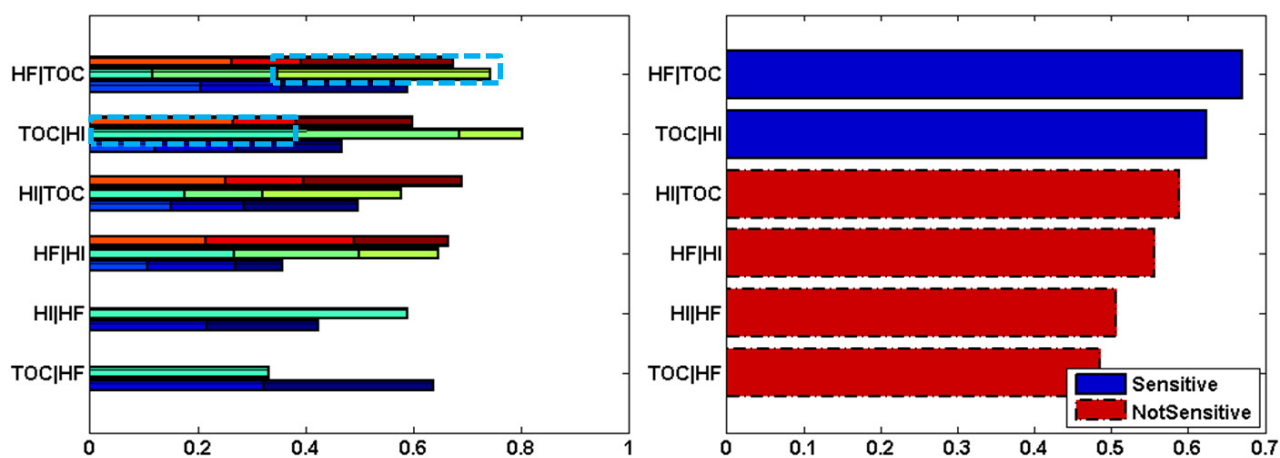


Figure 4: Pareto plot of the standardized measure of sensitivity for parameter interaction

However, interpreting these interactions and linking these information to geological knowledge are not trivial.

In our simple 1D model, we may interpret the first sensitivity interaction is the HF|TOC where we have a combination of low heat flow value with higher TOC value. A geological interpretation of this scenario would be a cooler basal heat flow (low HF) with a larger amount of source rock scenario. Under this circumstance, it is reasonable for us to expect a lower source rock maturation (Low R_o value) under similar thermal history.

Case 2: Source Rock Transformation Ratio Response

Similarly, 50 runs were conducted and simulated transformation ratio (TR_ALL) values are clustered into three groups, of sizes 16, 16 and 18 based on low, mid high value.

Figure 5 show the Pareto plots of the standardized measure of sensitivity for each single parameter and indicate that source rock transformation ratio is most sensitive to both Heat Flow value and Hydrogen Index.

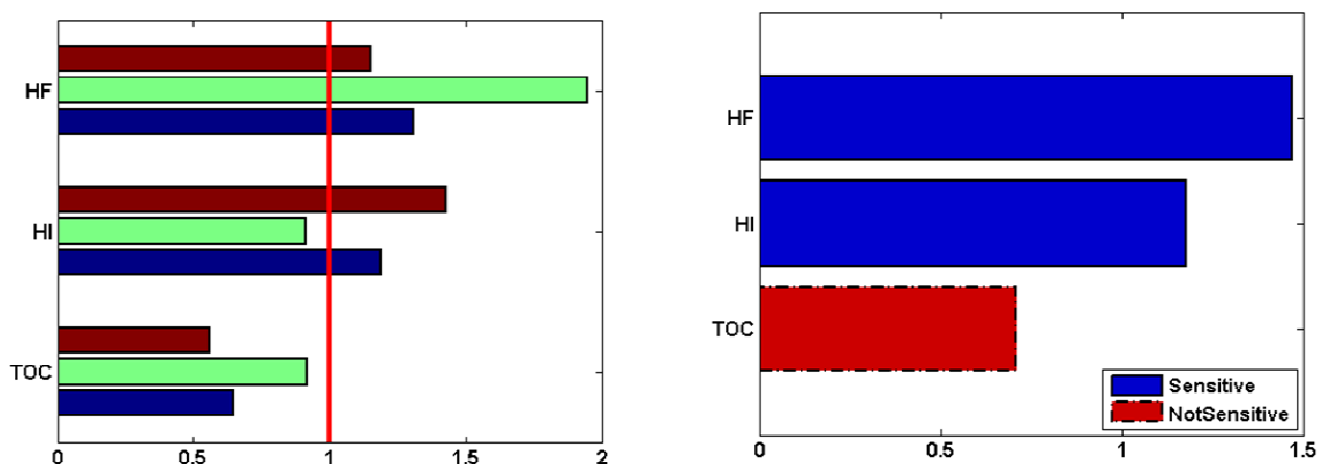


Figure 5: Pareto plot of the standardized measure of sensitivity for each single parameter on Transformation Ratio Response

A reasonable geological interpretation of the single way sensitivity for this case would be that the thermal history which represented by the heat flow value and source rock hydrogen index are most crucial factor for determine the source rock transformation ratio.

Multi-way parameter interactions (totally 6 interactions between these 3 parameters) were also conducted in this case. Figure 6 are the Pareto plots of the standardized measure of sensitivity for parameter interaction. Figure 6(left) displays the distance measures of the sensitive interactions for each class. The stacked bars show the contribution of the distance for each bin. Figure 6(right) shows the average measure of sensitivity for the parameter interactions as determined by the GSA algorithm. From these 2 charts, one parameter interaction can be identified as sensitive in the second cluster: the combination of Low HI with middle threshold values of TOC together is sensitive to the transformation ration value.

Geological interpretation of the sensitivity on source transformation ratio is even challenging in that the transformation ratio calculation depending on multiple parameters and non-linear

model. A possible geological reasoning of this would be the source rock transformation ratio is sensitive to the 2 main source rock property, hydrogen index and total organic carbon. Notice that this type of relationship will only be identified using the GSA algorithm since the previous single-way sensitivity analysis indicates that the TOC is not a sensitive parameter.

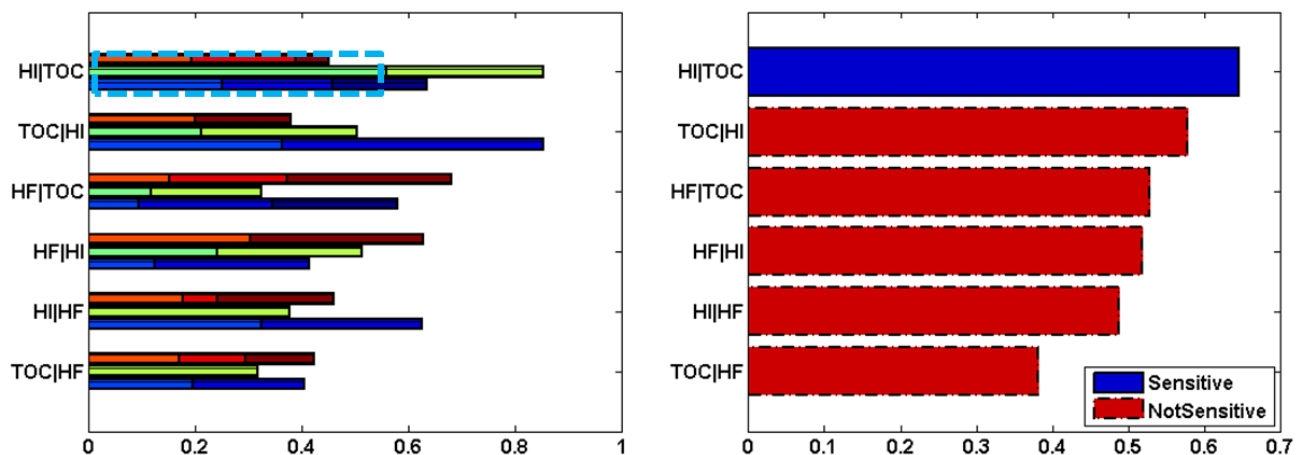


Figure 6: Pareto plot of the standardized measure of sensitivity for parameter interaction

Discussion and future work

From this illustration example, we showed several advantages of GSA algorithm. It can not only identify single-way sensitivity of parameters but also the interactions between parameters and their impact on the model response. This unique feature can be used to distinguish sensitivity parameters and identify correlation that may be ignored using other methods such as experimental design.

Another nice feature we found from GSA algorithm is that it purely based on measurements of the distance between models and generally applicable for discrete parameters and even scenarios uncertainty. Thus, in the future 3D model study, we may utilize this method to identify the sensitivities on both one-way parameter and multi-way parameter interactions. Moreover, we will analysis these sensitivity results and combine the geological knowledge so that we can get a better geological interpretation of certain model scenario. We believe that by combining this quantitative method with integrated geological knowledge, our approach will provide a robust way for quantitative sensitivity analysis of the complicated basin modeling process.

To identify the sensitivity parameters is not our final goal. The question we would like to answer also includes how to capture the wide range of uncertainty. Our current proposed idea is to construct multiple representative models from the combination of those most sensitive parameters (may vary depending on various modeling response choices). Then, by simulating those representative models, we will get the model responses which capture the possible uncertainty range without running a large number of models. This is especially attractive for complicated basin models for which one single 3D model can take days or weeks to simulate.

With all the above steps, we will be able to answer the questions raised in the previous section and establish a workflow for uncertainty quantification in basin and petroleum system modeling discipline.

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