Two-stage Scenario Reduction Process for Robust Optimization in Green Fields

Seyed Kourosh Mahjour

> *"Two important issues regarding the RS selection need to be considered: (1) the number of RS should be large enough to preserve the reservoir uncertainty space, and (2) the number of RS should be kept limited in order to decrease the computation costs."*

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Introduction

In this text, we present some highlights of the paper by Mahjour et al. (2020).

Recently, the scenario reduction methods have been widely used to accelerate robust optimization processes in green fields. In these methods, a subset of scenarios is normally selected representing approximately the features of the full ensemble. Hence, we call them representative scenarios (RS). The literature presents two main approaches to obtain reduced scenarios: (1) selecting representative geological realizations (RGR), and (2) selecting representative (simulation) models (RM). For this, two issues are important: (1) the number of RS should be large enough to preserve the reservoir uncertainty space, and (2) the number of RS should be kept limited in order to decrease the computation costs.

Previous work from UNISIM have shown some methodologies to select the RM. Here, we propose a two-stage scenario reduction to select the RGR and RM. This may be a practical workflow to perform efficient robust optimization in terms of preserving the overall reservoir uncertainty and reducing the computational costs in green fields with limited production history data.

Methodology

In Figure 1, the two-stage scenario reduction workflow is presented for field development purposes in green fields. The scenario reduction steps are highlighted by the green color.
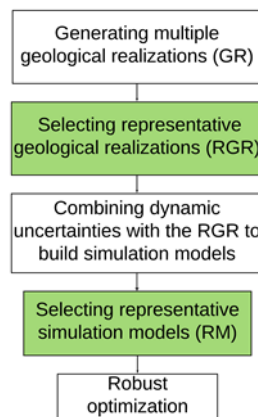
Figure 1: *Two-stage scenario reduction workflow*

In the first step of the scenario reduction process, we select the RGR using petrophysical reservoir features and without requiring forward reservoir simulation. To do so, distance-based clustering techniques can be employed based on the dissimilarity concept. These techniques are composed of three main steps: (1) distance (dissimilarity) matrix construction, (2) dimensionality reduction, and (3) clustering.

To build an N×N distance matrix, we use N geological realizations (GR), each containing hundreds to thousands of grid blocks. Hence, an efficient distance metric based on the petrophysical feature is significantly important.

The petrophysical property selected to measure the distance between two GRs should have a high correlation with the flow response. Generally, porosity and permeability, two important petrophysical properties,

have essential roles in fluid storage and flow, respectively. Hence, in this study, we used a parameter named reservoir quality index (RQI) to consider both properties together (Mahjour et al., 2019). RQI is deduced from the Kozeny and Carman equation and is defined by Equation 1.

$$RQI = 0.0314 \sqrt{\frac{K}{\varnothing}} \tag{1}$$

where the constant 0.0314 is the permeability conversion factor from μm2 to mD, K is the permeability in mD, and Ø is the total porosity in fraction.

After determining the RQI, we measure a distance indicator (S) between any pair of GR to be considered as the matrix elements. In this study, we measure the distance using the Euclidean distance, the most common metric in the literature.

Next, we use the multidimensional scaling (MDS) method to transfer the GR (with high dimensional data) into a 2D Euclidean space. The distance matrix built in the previous step is the input data to apply the MDS method. Finally, we perform the Kmeans-clustering and centroid sampling methods to classify the similar GR as the same group and select one single RGR from each group, respectively.

In the second stage of the scenario reduction process, we select the RM under dynamic and geological uncertainties (including all other uncertainties of represented in RGR) to be used in robust optimization. Meira et al. (2020) proposed a method named RMFinder as an optimization-based technique to select the RM. The method utilizes a metaheuristic algorithm considering the cross-plots (scatterplots) and cumulative distribution function (CDF) curves of the main simulation outputs (well and field indicators).

In the workflow, the number of RGR and RM are defined by users. To check the validity of the proposed workflow, we perform numerical simulation on the RM and the full set. For this purpose, the distribution of the defined simulation outputs obtained from the RM set and full set are compared and evaluated using the CDF.

Application and Main Results

The methodology is applied to the UNISIM-II-D benchmark case described at UNISIM website. In the uncertain simulation model, a cell with an average size of 100 m × 100 m × 8 m is used, yielding a total of 95,220 cells (41,151 active cells). The petrophysical properties are modeled and combined with four types of facies and represented by 500 GR. The required data for running the simulation is fully-explained at UNISIM website.

We selected 25 RGR out of 500 GR using the distance-based clustering. However, the number of RGR can be increased or reduced based on further analysis which will be applied in the next steps of the field development process. Figure 2 shows the 2D Euclidean space, in which the points show the GR. We categorized the all 500 GR into 25 clusters and selected one RGR from each cluster.

Next, we combined the selected RGR with the dynamic uncertainties using the Latin hypercube with geostatistical realizations (DLHG) method. We generated 75 simulation models. The ratio between the number of RGR and scenarios is 1 to 3.

We then used the RMFinder method to select the

RM using the simulation outputs. We obtained the outputs based on a well-pattern with wide reservoir coverage and with no restrictions related to the production system named production evaluation zero (PE0). The PE0 was defined by the five-spot well patterns (28 vertical production wells and 28 vertical injection wells) considering water flooding as the recovery mechanism. Note that to define the PE0, we didn't perform optimization. Furthermore, the final simulation time (forecast) was 30 years. We selected nine RM using seven field outputs and 56 well outputs.

To check the validity of the proposed workflow, we compared the CDF curves of simulation outputs obtained from nine RM set and 1500 simulation models as the full set. To generate the full set, all 500 GR along with dynamic uncertainties were considered. Figure 3 represents the CDF curves for four field outputs as examples: OIP, WIP, NPV, and ORF. The results show that there is a good match between the CDF curves of the RM and the full sets. Figure 4 also illustrates that the RM set are well-distributed into the full-set. In this figure, the curves for Gp, Np and Wp for one random production well "p06", and Winj for one random injection well "i06" are shown. Furthermore, the percentage difference of the NPV average for the full and the RM sets is 2 % showing the close dynamic behaviour of the sets.

Conclusions

We proposed a workflow to reduce the number of scenarios for robust optimization in green fields with the limited production history data. According to the proposed workflow, we gradually reduced the number of scenarios in two stages: (1) selecting the RGR using petrophysical data, and (2) selecting the RM using the simulation outputs. In the first stage, we selected the RGR based on distance-based clustering and without requiring forward reservoir simulation, while in the second stage, the reservoir simulation was required to select the RM. To check the effectiveness of the proposed workflow, we compared the distribution of the simulation outputs obtained from nine RM and the full set with 1500 models using the CDF curves. The results showed that there is a good match between the CDF curves of the RM and the full sets for the defined objective functions.

To sum up, the proposed workflow could significantly reduce the number of scenarios while the reservoir uncertainty space is preserved. This can reduce the computational costs in the field development phase for the green fields.

One important observation is that this methodology was used to green fields and it is not yet recommended for brown field because the variability of the full ensemble of the geological representation may me important in the data assimilation processes. However, it is possible that the methodology can applicable after the data assimilation but we still need to test it to verify the applicability.

References

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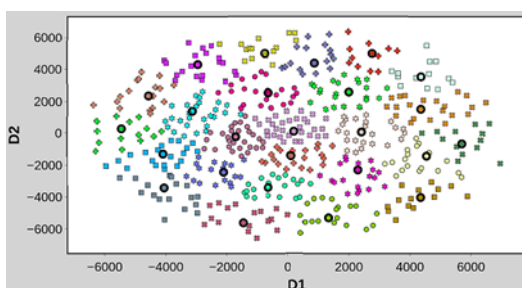
Figure 2: *Transformation of 500 GR into 2D Euclidian space. 25 clusters are defined and the RGRs are shown by the black points.*
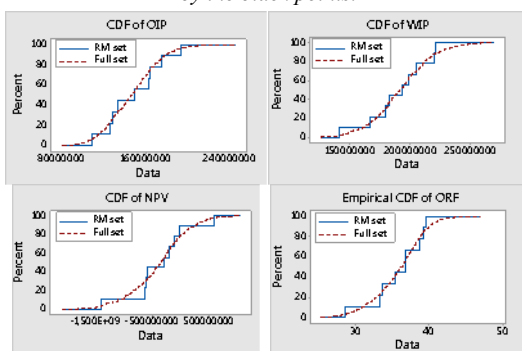
Figure 3: *CDF of field objective functions for all 1500 models and 9 selected RM.*
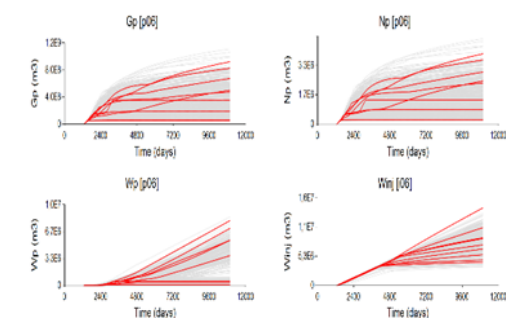
Figure 4: *Well objective functions of "P06" and "i03" wells for all 1500 models (grey line) and 9 selected RM (red line).*

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