UNISIM ON-LINE
Year 15, Number 2 | 137th edition | February, 2020

“Two important issues regarding the selection of RMs: (1) the number of RMs should be large enough in order to preserve the uncertainty space, (2) the number of models should be kept limited in order to decrease the computation time for simulation purposes.”

Specials interests:

- UNISIM
- UNISIM Publications
- Reservoir Simulation and Management Portal
- Previous Issues

Links:

- UNICAMP
- Cepetro
- Petroleum Engineering Division
- School of Mechanical Engineering
- Petroleum Sciences and Engineering

Graduate:

Petroleum Sciences and Engineering: interested in Masters and PhD in the Simulation and Oil Reservoir Management area click here.

Using an integrated multidimensional scaling and clustering method to reduce the number of scenarios based on flow-unit models under geological uncertainties

Seyed Kourosh Mahjour

Introduction

This text presents some highlights of the paper of Mahjour et al. (2020) [1].

Representative models (RMs) have widely been used to speed up the reservoir management. RMs are a small subset of models that represent approximately the features of the full ensemble. Consistent with this, two important issues should be jointly taken into account to select RMs: (1) the number of RMs should be large enough in order to preserve the uncertainty space, and (2) the number of models should be kept limited in order to decrease the computation time for simulation purposes. Previous works from UNISIM have shown methodologies to select RMs after simulation runs. In this study, we present a statistical solution to select the RMs under geological uncertainties based on measuring the similarity between 3D flow-unit models without the need of previous simulation runs. The proposed method includes the integration of multidimensional scaling and cluster analysis (IMC). IMC can be applied to the models before the simulation process to reduce computational time.

Methodology

The proposed methodology starts with a novel scheme of measuring the similarity between available 3D flow-unit reservoir models [2] including (1) smoothing 3D models (Figure 1), (2) converting 3D models into 1D arrays (Figure 2), (3) measuring the pairwise distance between the models using the simple matching coefficient (SMC) (Figure 3).

SMC is the number of similar grid cells between two models divided by the number of total grid cells for a model. According to a set of “*m*” models and a dissimilarity function δ, where δ = 1- SMC, between any two models calculated from the previous step, a *m x m* distance matrix is built comprising the dissimilarity function between any two models (models I and j) δ_{ij} (Figure 4). In the next step, the generated distance matrix is used to map all models into a Euclidean space using multidimensional scaling (MDS) where each point in this map indicates a model. The points in the Euclidean space are then grouped using different types of clustering algorithms (hierarchical and K-means) to compare and select different RMs.

In this study, to define the number of clusters Elbow method is used. Finally, a single representative point from each cluster is selected using centroid sampling to select RMs (Figure 5).

To check the validity of the methodology a numerical simulation run and then uncertainty quantification are carried out on the RMs and the full set. For this purpose, the cumulative distribution functions (CDF) and visual inspection of the RMs and the entire set of models are compared for the field and well objective functions.

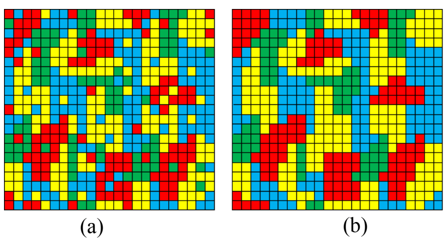

Figure 1: A model before (a) and after (b) smoothing process.

Application

The methodology is applied to a benchmark case named UNISIM-II-D [2]. Mahjour et al. (2019) [3] extended the model and built a flow-unit model based on UNISIM-II-D features.

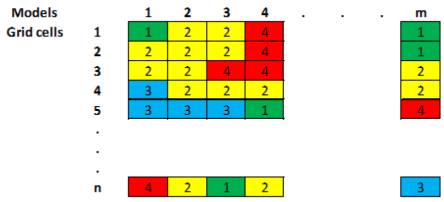

*Figure 2: **m** 3D models organized into **m** 1D arrays with **n** grid cells in each.*

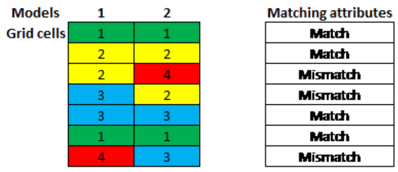

Figure 3: Example of a simple matching coefficient (SMC) for two models with seven grid cells in each.

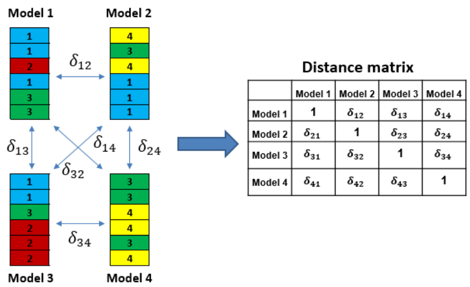

Figure 4: Example of building a distance matrix for four models.

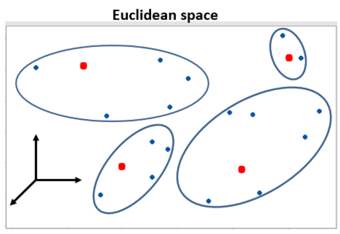

Figure 5: Example of cluster representation where each circle representes a cluster and the red dot representes the center of the cluster.

In the coarse grid 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) with the estimates of porosity and permeability properties. The petrophysical properties are modeled and combined with seven flow-units. According to geological uncertainty variables, 200 models are generated by Latin Hypercube sampling.

Results

The results are related to the steps of the methodology. Likewise, the first step of the IMC method is to smooth the flow-unit models using median filtering. Next, the 3D filtered models are organized into the 1D arrays. The SMC is then calculated as a similarity distance between the pair of models. The 200 × 200 distance matrix is built using the similarity distance. Subsequently, the distance matrix defined formerly is considered to map all the flow-unit models into a 2D Euclidean space using multidimensional scaling.

> “The proposed methodology is used to select the RMs under geological uncertainties before the simulation process which results in reducing computational time and costs.”

The clustering and sampling techniques are then performed in the Euclidean space. According to the Elbow method, the best cluster number is 18 (9 % of the total existing models). In this work, K-means and hierarchical clustering (HC) are used to group similar models. We test different linkage functions to apply HC method including average, centroid and complete linkages and then, centroid sampling is carried out to check different RM from each cluster. Figure 6 displays 2D Euclidean space and different clustering methods to group all models into 18 clusters. In the figure, the RMs are defined by black points.

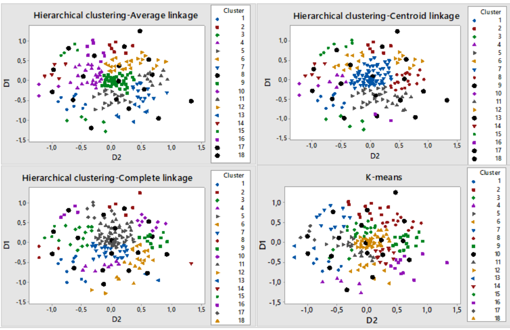

Figure 6: *Clustering and sampling in 2D Euclidean space.*

To validate the results, the uncertainty space of output simulation of the obtained RMs from different clustering algorithms are compared with the entire set of models using CDF curves. To do so, it is necessary to define a production strategy. We defined 20 wells (Figure 7) during 30 years of (forecast) simulation time.

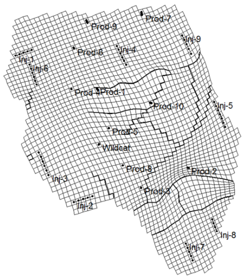

Figure 7: *Location of the wells for the applied production strategy.*

Based on four clustering methods, the CDF curves for OIP, WIP, NPV, and ORF have been plotted, and the results show that there is a good match between the RMs and total (full-set) models CDF curves for all objective functions based on the average linkage HC compared to the other clustering and linkage methods (Figure 8).

Figure 9 shows that the RMs are well-distributed into the full-set. In this figure, the Gp, Np, Wp, and Winj curves are shown for one producer “PROD-3” and one injector “INJ-3” as samples.

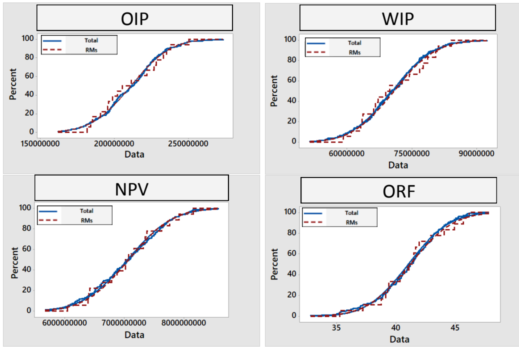

Figure 8: *CDFs of field objective functions for all 200 models (blue line and 18 obtained RMs from average linkage-HC (red line) for 10957 simulation days.*

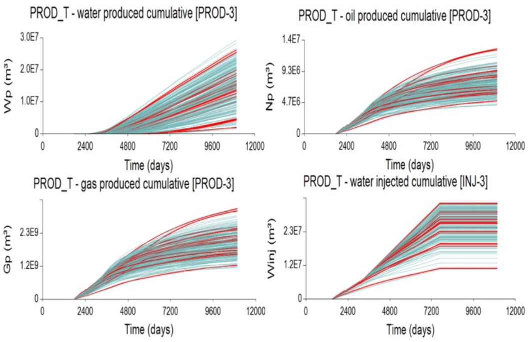

Figure 9: *Well objective functions of “PROD-3” and “INJ-3” wells for all 200 models (blue line) and 18 RMs (red line) for 10957 simulation days.*

Conclusions

We applied a statistical method including the integration of multi-dimensional scaling and cluster analysis (IMC) to select 18 RMs from 200 geostatistical models before the simulation process. Hence, we present an alternative way to select RMs without running any simulation which results in reducing computational time. Different clustering algorithms were tested.

We then performed a numerical flow simulation for the RMs and the full-set to validate the methodology. The simulation output showed that the HC method with average linkage function is the most suitable method given the similarity distances of the models. Hence, the RMs can be sufficient for the uncertainty quantification if appropriate similarity measures and clustering methods are used.

References

[1] Mahjour, S. K., Correia, M. G., de Souza dos Santos, A. A., and Schiozer, D. J. (2020). Using an Integrated Multidimensional Scaling and Clustering Method to Reduce the Number of Scenarios Based on Flow-Unit Models under Geological Uncertainties. ASME. Journal of Energy Resources Technology. 142(6), 063005.

[2] Correia, M. G., Hohendorff, J., Gaspar, A. T. F. S., Schiozer, D. (2015). UNISIM-II-D: Benchmark Case Proposal Based on a Carbonate Reservoir. SPE Latin American and Caribbean Petroleum Engineering Conference held in Quito, Ecuador, 18–20, November.

[3] Mahjour, S. K., Correia, M. G., Santos, A. A. S., Schiozer, D. J. (2019). Developing a Workflow to Represent Fractured Carbonate Reservoirs for Simulation Models under Uncertainties Based on Flow Unit Concept. Oil & Gas Science and Technology - Rev. IFP Energies nouvelles 74, 15.

About the author:

Seyed Kourosh Mahjour is a PhD student in Petroleum Science and Engineering at UNICAMP.

UNISIM opportunities:

If you are interested in working or developing research in the UNISIM Group, please contact us.

For further information, click here.

Research in Reservoir Simulation and Management Group

Petroleum Engineering Division - Energy Department
School Of Mechanical Engineering
Center for Petroleum Studies
University of Campinas
Campinas - SP

Phone.: 55-19-3521-1220
Fax: 55-19-3289-4916

unisim@cepetro.unicamp.br