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Use of Emulator Methodology for Uncertainty Reduction Quantification

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1. Introduction

Reservoir simulators are computer implementations of high-dimensional mathematical models for reservoirs, where the inputs are physical parameters and the outputs are observable characteristics (production pressure and fluid movement). The uncertainties are always present in the reservoir characterization process, so: some input and output parameters are usually uncertain.

Identifying the input parameters for whose outputs match the observed data (history matching) can be a difficult task, because simulation models can take a long time to run. Emulators can be used to deal with the large number of iterations commonly encountered in such context.

The emulator (low fidelity model) is a mathematically defined function that replicates the simulation model output for selected input parameters. Inputs and operational conditions affect the simulation outputs. For the history matching the operational parameters are informed and the emulation technique aims to identify the unknown input parameters, within a search space, whose outputs match the observed data.

2. Objective

Describe a workflow to use the emulation technique in a history matching procedure, evaluating the capacity of production data to identify uncertain inputs over the production period.

3. Methodology

The methodology is divided into six steps. A brief description of the main steps is presented as follows (Ferreira *et al.,* 2014).

3.1. Input Data Set Sampling. The Latin Hypercube can be used as a sampling method. Scenarios are generated using the sampled input parameters and are simulated to obtain the outputs. The sampled input parameters and resulting outputs are then used to construct the emulator.

3.2. Emulator Design. The emulator is represented by a vector function, taking inputs *x* represent the vector of reservoir input parameters, and return the output parameter reservoir input parameters, and return the output parameter $\hat{f}(x)$. The emulator both suggests an approximation to the function and also contains an assessment of the likely magnitude of the error of the approximation. The form for emulation of output component is

$$\hat{f}_i(x) = \sum_j \beta_{ij}\, g_{ij}(x) + u_i(x), \qquad (1)$$

where *i* is the output being emulated, *j* is the number of function elements, *β* are unknown scalars, *g* are known deterministic functions of *x* and *u* express local variation with constant variance. In this work multiple linear regression was used to determine *β*, *g* and *u*.

3.3. Implausibility Analysis. This step determines the input parameters whose outputs match the observed data. The implausibility value (*I*) is determined for each set of input parameters by

$$I_i^2(x) = \frac{\left(z_i - E[\hat{f}_i(x)]\right)^2}{Var[\hat{f}_i(x)]}, \qquad (2)$$

where z_i is the observed data, $E[\hat{f}_i(x)]$ is the expected value output from the emulator and Var $[\hat{f}_i(x)]$ is the variance.

Large values of *I* suggest that it is implausible that the input *x* results in an output that matches the observed data. The maximum acceptable *I* value can be defined based on various considerations as discussed in Vernon *et al*. (2010).

4. Application

The methodology was applied to a synthetic five-spot case. The uncertainty reduction was determined to two different production periods: 1000 and 3500 days. The observed data was obtained through a reference model that represents the reality. The reference model has a high-permeability channel, whereas the base model has constant porosity and permeability.

5. Results

The parameters that make up the vector x are: Cartesian coordinates of the center of the channel, angle, width, length and permeability of the channel and permeability of the reservoir. The outputs are: BHP, time for water breakthrough and water production at production wells.

The Latin Hypercube was used to sample 200 vectors of inputs x and simulated to obtained the corresponding outputs. The sampled input parameters and resulted simulation outputs were used to estimate the emulator.

A search in the initial input space was performed to identify the 'non-implausible' parameters. A comparison between the number of points evaluated and the number of 'non-implausible' input parameters obtained is presented in Table 1.

Table 1: Number of inputs

Analysis Phase	Period (days)	
	1000	**3500**
Initial Inputs	800 E+06	
'Non-Implausible' Inputs	2698	364
Time for evaluation (min)	485	1116

The number of 'non-implausible' inputs at the beginning of production is higher. Some of them will be discarded as more data is added to the process.

The number of non-implausible parameters was a small set of the initial input space. The time for a single run using the simulator software was 10s. The time for evaluation using emulation in both cases is lower than the necessary to run 800E+06 runs.

Figure 1 shows the cumulative oil (Np) for production well 3, as an example, for the initial input data set (red lines), scenarios obtained after the uncertainty reduction at 1000 (green lines) and 3500 (cyan lines) days, with the reality model shown as a single dark blue line.

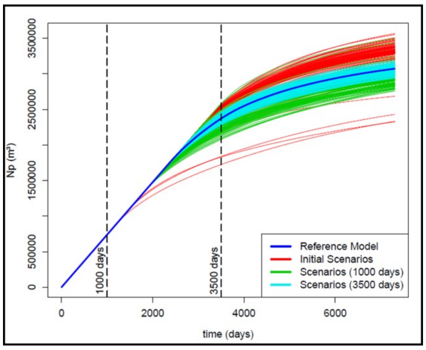

Figure 1: Uncertainty reduction: Np

6. Conclusion

The use of emulation technique was effective to the case studied. Its use was justified because a high quantity of inputs was evaluated to determine the 'non-implausible' ones. The linear regression model was successfully used, due to the simplicity of the model. However, a more sophisticated technique is necessary for complex models, because of possible nonlinear relationship between variables.

7. References

VERNON, I.; GOLDSTEIN, M.; BOWER, R. G. Galaxy Formation: a Bayesian Uncertainty Analysis. In: International Society of Bayesian Analysis, 2010.

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