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"A full uncertainty analysis demands a comprehensive exploration of the uncertain input parameter space of the reservoir model."

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Emulation based Uncertainty Analysis: Method and Concepts

Carla Janaína Ferreira; Ian Vernon

Introduction

Reservoir simulation is essential in the development and management of oil reservoirs, as it is used to forecast the reservoir behaviour, which is vital in the decision-making process. However, the actual properties of the sub-surface are highly uncertain, and thus so are the appropriate choices of the reservoir model input parameters and the predictions based on these models. Therefore, to obtain a reliable production forecast, reservoir models consistent with the dynamic data available from field production are identified in a process known as data assimilation. However, it can be too expensive computationally to perform a full comprehensive uncertainty analysis. A successful method within this context is that of uncertainty reduction via Bayes linear emulation, which solves the speed problem and facilitates a detailed exploration of input parameters and a robust subsequent uncertainty analysis.

This work describes the iterative emulator-based Bayesian uncertainty analysis methodology and concepts used. See Ferreira et al. (2019) for further information.

Optimization *versus* Exploration

Many methods seek to optimise the match between reservoir simulator output and history data and hence produce one or a relatively small number of optimised reservoir simulator evaluations (Figure 1a). In many cases, this approach does not lead to adequate uncertainty analysis. In fact, a full uncertainty analysis demands a comprehensive exploration of the uncertain input parameter space of the reservoir model, to identify all input parameter configurations that would lead to acceptable matches between reservoir simulator output and history data (Figure 1b and Figure 1c).

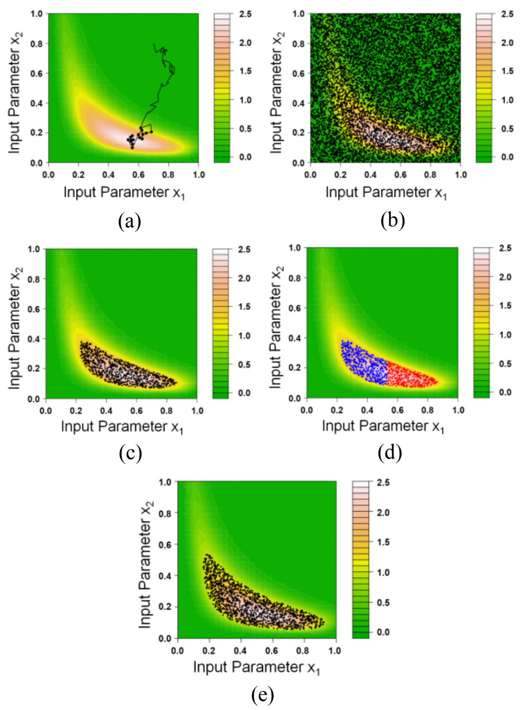

Figure 1: 2D input space coloured by likelihood such that high values are desirable: (a) optimisation approach, (b) full analysis - a vast number of input configurations considered, (c) full analysis - acceptable matches using simulator, (d) two different subsets of the acceptable set (red/blue) (e) full analysis - acceptable matches using emulation.

Usually, a vast number of simulation runs to perform the uncertainty analysis is required, which becomes a critical issue. The challenge needs to be addressed considering the possible drawback of identifying only a partial subset of the input parameters consistent with observed data (red and blue points in Figure 1d). Critically, these subsets will result in unjustifiable forecasts that are both biased and overconfident, which directly lead to sub-optimal decision making. Figures 1d and 2 demonstrate this principle: the blue points and red points lie in different parts of the acceptable input space. Both are consistent with the history data, but the forecasts from the blue points or red points on their own are biased high/low while simultaneously being overconfident. This problem is even worse when the acceptable input space is composed of disconnected regions, in which case optimisers will often get stuck in one of these regions, again leading to biased, overconfident forecasts.

A full exploration of the input space is, therefore, critical. Hence, we construct emulators and employ iterative uncertainty analysis to reduce the reservoir uncertainty for given observed data carefully. The slight inaccuracy of the emulator causes the difference between the exploration final result using emulation (Figure 1d) and simulation (Figure 1c), that in turn is a computer model which is not a perfect representation of the real system. The iterative process used allows to obtain more detailed emulators at each iteration and reduce such difference.

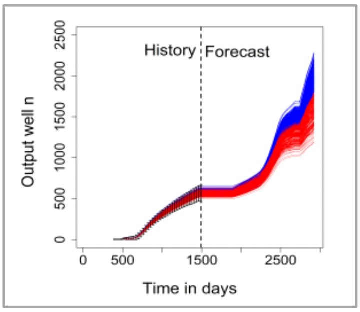

Figure 2: Schematic production data from Figure 1d subsets (red lines - red points, blue lines – blue points, black error bars – historical data) .

Emulation

An emulator is a statistical construct that seeks to mimic a complex physical model, such as the reservoir simulation model, but which is several orders of magnitude faster to evaluate. The emulator provides an understanding of the structure of the model's behaviour and can replace the simulation model in many complex calculations. An emulator provides not only an estimate of the simulator model output at an unexplored input location but also an associated uncertainty statement regarding that estimate.

The emulator is a vector function represented by:

$$f_i(x) = \sum_j \beta_{ij}\, g_{ij}(x_{A_i}) + u_i(x_{A_i}) + \delta_i(x) \qquad (1)$$

where the vector x is the list of reservoir input parameters such as water-oil contact and the vector $f(x)$ is the list of model outputs, such as fluid rates at different production times, with individual outputs denoted by $f_i(x)$. The subset of the inputs x that are most influential for output $f_i(x)$ is the vector of active inputs x_{Ai} for each output i.

The first term on the right-hand side of eq. (1) express the global variation of $f_i(x)$, where β_{ij} are unknown scalar coefficients and g_{ij} are known deterministic functions of x_{Ai}, a common choice being low order polynomials. The term $u_i(x_{Ai})$ is a Gaussian process over x_{Ai} that expresses the residual local variation in $f_i(x)$ not captured by the trend, and the nugget $\delta_i(x)$ is an uncorrelated term that models the effects of inactive variables as white noise.

“We seek to remove parts of the input space that would lead to unacceptable matches between model and observed data.”

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Figure 3 presents the schematic process to construct an emulator. A set of simulation runs is designed considering the uncertain inputs and then simulated using computer software. We use both inputs, and correspondent model outputs to construct the mathematical equation that relates them, which is then used as a substitute for the reservoir model depending on the objective of the project.

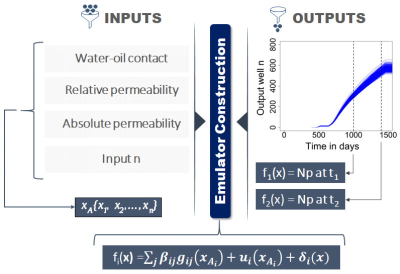

***Figure 3**: Schematic process to construct an emulator.*

Figure 4 shows an example of a 1D emulator for the function , for which six model evaluations have been performed, given by the black dots. The emulator expectation evaluated over a large number of input points is given by the blue line, while the green lines give the emulator credible interval. We note that even after only six evaluations, the emulator expectation mimics the shape of the sine function well. Also, we see that the credible interval is large in-between model evaluations where the emulator is less informed, but shrinks to zero close to the evaluations as is desirable for a deterministic function.

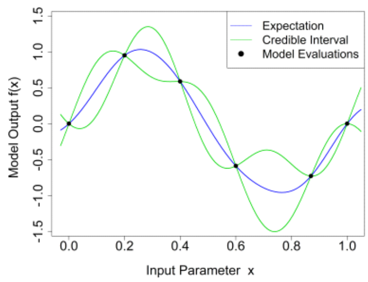

***Figure 4**: An example of a 1D emulator.*

The emulator expectation and variance are used to compute implausibility measures required for the global parameter search, as presented below.

Uncertainty Reduction via Bayes Linear Emulation

Our approach to uncertainty reduction is based on the use of Bayesian emulators to evaluate the input space efficiently and implausibility measures to determine which part of the input space can be discarded from further investigation i.e. deemed implausible.

Figure 5 shows an example of the first wave of an uncertainty reduction via Bayes linear emulation as applied to the function. Figure 5a has the same emulator as that of Figure 4, but now a single observation has been included (solid black line). The error bars on this observation are represented as the black dashed horizontal lines. The implausibility calculated is represented by the coloured bar along the *x*-axis, with implausible *x* input coloured in red, borderline coloured yellow, and non-implausible inputs coloured green. We note that even for such a simple emulator and after a single wave, most of the input space is red and hence ruled out, and therefore does not warrant further investigation via additional model runs.

However, as there is substantial emulator variance throughout much of the non-implausible region, we know that a wave 2 will be beneficial. Figures 5b to 5d show the results of adding three runs, sequentially. We see that the point included in Figure 5b, is highly informative, and the emulator variance has significantly been reduced. Including the next two points as shown in Figures 5c and 5d provide much less dramatic improvements and result in a more modest reduction of the non-implausible region. Figure 5d also highlights that the emulator variance is now much smaller than the observation error variance (as the green lines are narrower than the horizontal dashed lines), and hence that further runs of the model would not provide further input space reduction. Hence the stopping criteria is reached and the process terminates.

This process is usually very effective at input space reduction because it uses a fast statistical construct of the reservoir, focuses on identifying non-implausible inputs instead of directly chasing acceptable ones, perform the parameter search iteratively and naturally identifies disconnected regions of acceptable inputs.

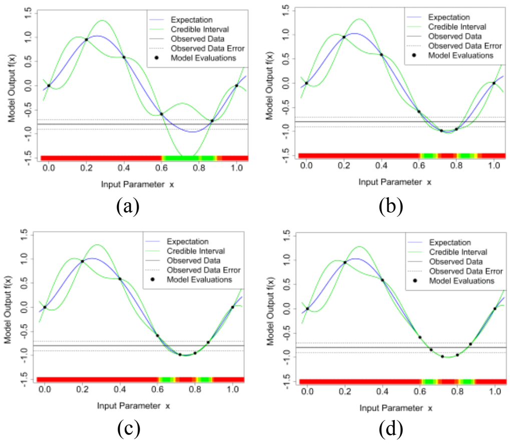

***Figure 5**: Uncertainty reduction via Bayes linear emulation as applied to the toy example: (a) the six model evaluations in the first wave, (b)-(d) the three evaluations in wave 2, included sequentially.*

Conclusion

Reservoir simulation is an essential tool for decision making, as it is used to forecast reservoir behaviour. Therefore, appropriate treatment of available historical data and reservoir uncertainties is necessary to provide reliable simulation models to be used in reservoir development and management. However, it can be too expensive computationally to perform a full comprehensive uncertainty analysis of the reservoir model. This work presented the description of the Uncertainty Reduction via Bayes Linear Emulation methodology, which is one way to solve the speed problem and enable a detailed exploration of input parameters and robust subsequent uncertainty analysis.

References

[1] Ferreira, C. J.; Vernon, I.; Caiado, C.; et al. “Efficient Selection of Reservoir Model Outputs Within an Emulation Based Iterative Uncertainty Analysis”, OTC Brasil, 29-31 Outubro, Rio de Janeiro, Brasil, 2019.

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