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Uncertainty quantification in inverse spatial-temporal problems of porous media flow modelling

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Uncertainty is an inherent feature of our understanding of the explored reality. Mathematical models describe our vision of reality in the analytical form. Model uncertainty is associated with the lack of our knowledge about natural systems. Uncertainty in the model definitions/parameters reflects our prior knowledge about the phenomenon (e.g. spatial correlation range, variability, connectivity, stochastic non-uniqueness, etc.). Therefore, there is a diversity of possible model realisations, which result in a spread of the model predictions. On the other hand we can observe the reality by collecting the data in space and time, which are also subject to uncertainty. The problem of calibrating the model based on our prior knowledge to the data, usually, has inverse nature and is ill-posed. It can be solved by a range of optimisation or assimilation methods, which provide an ensemble of multiple good fitting solutions.

The challenge of quantifying uncertainty in inverse problems is in obtaining the ensemble of good fitting model solutions. This task is especially difficult with natural system models, which are highly complex and, usually, highly parametric. Thus, the optimisation/assimilation is performed in high dimensional space of the model parameters and becomes computationally expensive with multiple forward solutions to compute, e.g. flow simulations in porous media. Usually, we can afford to run a limited number of flow simulations corresponding to the set of spatial distributions of porous properties. Therefore, there is a need for an adaptive fast converging algorithms to solve inverse optimisation problem in high dimensional space of models.

Any optimisation method used for solving an inverse problem must be fast in navigating high dimensional search space and efficient in finding multiple good fitting models with a limited number of simulations. The importance of the optimisation algorithm choice and tuning becomes essential when we try to estimate tens or even hundreds of parameters in the presence of multiple local minima. Stochastic population based algorithms are seen as good candidates to solve history matching problems.

We use adaptive stochastic sampling algorithms to explore high dimensional model space and concentrate on the regions with the high likelihood models that fit the data better. Advanced evolution algorithms, such as particle swarm optimisation, differential evolution, etc., are able to find effectively multiple good solutions, which correspond to local minima of the optimisation problem. Diversity of the found solutions is the one of the key components of the representativeness of the ensemble of models and, therefore, the robustness of the forecast. Contemporary stochastic evolutionary population-based algorithms are capable of solving multi-criteria optimisation problems, which improve computational efficiency and reliability in obtaining solutions for inverse problems. Uncertainty assessment using Bayesian inference provide a way to quantify posterior probability of the model predictions and associated uncertainty of the model parameters.