A Goal-Based Parameterised Non-Intrusive Reduced Order Model demonstrated on a Geothermal Reservoir

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ABSTRACT

An approach to optimise the accuracy in the geothermal production predicted by a Parameterised Non-Intrusive Reduced Order Model (PNIROM [1]) is presented herein. The optimisation is based on a goal and uses the approximation of an adjoint solution ('importance map') to move the geothermal information backwards through time. We use the importance map to weight the initial condition for each snapshot, thereby optimally generating snapshots in such a way that they contribute maximally to the goal.

Importance maps [2] are defined as regions in space and time of importance for a particular goal e.g. an observation point within the domain. They are calculated from solutions of the forward model generated from perturbed initial conditions. The importance map approaches an adjoint solution if the perturbations of the initial condition are small and the number of ensemble members is large.

Non-Intrusive Reduced Order Modelling [3] is a branch of reduced order modelling in which the discretised governing equations are approximated using only the snapshots and basis functions. Machine learning techniques can take this information and build up an approximation to the governing equations, having the advantage that the forward model source code need not be modified.

The forward model is solved in an integrated open-source code, the Imperial College Finite Element Reservoir SimulaTor (IC-FERST) [4]. The goal, in this case, is the geothermal energy extraction from a well (i.e. the quantity of hot water produced). We demonstrate that without using this approach, for unseen cases, one obtains poor performance.

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