Incremental-learning-based Non-intrusive model order reduction

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ABSTRACT

Model Order Reduction (MOR) technique can provide compact numerical models for fast simulation. Different from intrusive (physics-based) MOR methods, non-intrusive MOR does not require access to the full order model (FOM), especially the system matrices. Since non-intrusive MOR methods strongly rely on the snapshots of the FOM, constructing good snapshot sets becomes crucial. A good snapshot set should contain sufficient number and diversity of the FOM observations. However, in the field of non-intrusive MOR, the relevant research is missing.

To deal with this problem, a novel greedy approach is proposed. The key components of this algorithm include a validator based on Probably Approximately Correct (PAC) learning [1] and an error estimator based on the error snapshots. By predefining the desired confidence and accuracy of the reduced order model (ROM), this algorithm will iteratively build a training dataset which contains input-output observations of the FOM. With the help of the data-driven error estimator, after each iteration, the additional snapshots will be taken at the positions where the current ROM is expected to be the least accurate.

This greedy algorithm is independent to the ROM identification method, and in this research, the algorithm is integrated with ANN [2] and OpInf [3] respectively. The performance of the whole workflow is tested by a numerical model of a vacuum radiation furnace.

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