

Abstract

In this thesis, we explore goal-oriented model order reduction to efficiently solve time-dependent partial differential equations. We introduce a novel, online-adaptive reduced-order modeling approach called MORE DWR (Model Orders Reduction with Dual-Weighted Residual error estimates), which combines space-time model order reduction with dual-weighted residual-based error control and on-the-fly basis enrichment through incremental proper orthogonal decomposition. The adaption of the reduced-order model is based on the rationale to use local error indicators extracted from the dual-weighted residual error estimates to refine the model. In an iterative process, the error in a goal functional is estimated during the simulation, allowing the reduced basis to be incrementally updated with new high-fidelity snapshots if the estimate exceeds a given threshold. This enables adaptive enrichment of the reduced basis in response to unanticipated changes in the solution behavior. As a result, there is no need for an expensive offline phase to explore the solution manifold, as the MORE DWR method automatically switches between reduced-order and full-order computation as needed. This method reduces the total number of full-order model solves compared to classical reduced-order modeling, provides robust estimation of the quantity of interest, and generates well-suited reduced basis spaces for the problem at hand.

We test our novel approach on heat and elastodynamics problems and subsequently extend it to poroelasticity. Finally, we apply the MORE DWR framework to time-dependent and parametrized partial differential equations, where it is used for efficient exploration of the solution manifold.

Keywords: adaptive model order reduction, incremental proper orthogonal decomposition, tensor-product space-time reduced-order modeling, goal-oriented error control, dual-weighted residuals