DISTRIBUTED COMPUTING FOR PHYSICS-BASED DATA-DRIVEN REDUCED MODELING AT SCALE

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ABSTRACT

High-performance computing (HPC) has revolutionized our ability to perform detailed simulations of complex real-world processes. A prominent contemporary example is from aerospace propulsion, where HPC is used for rotating detonation rocket engine (RDRE) simulations in support of the design of next-generation rocket engines; however, these simulations take millions of core hours even on powerful supercomputers [1], which makes them impractical for engineering tasks like design exploration and risk assessment. Reduced-order models (ROMs) address this limitation by constructing computationally cheap yet sufficiently accurate approximations that serve as surrogates for the high-fidelity model. In this presentation, we discuss a new distributed algorithm [2] that achieves fast and scalable construction of predictive physics-based ROMs trained from sparse datasets of extremely large state dimension. The algorithm learns structured physics-based ROMs that approximate the dynamical systems underlying those datasets. This enables model reduction for problems at a scale and complexity that exceeds the capabilities of existing approaches. We demonstrate our algorithm's scalability using up to 2,048 cores on the Frontera supercomputer at the Texas Advanced Computing Center [3]. We focus on a real-world three-dimensional RDRE for which one millisecond of simulated physical time requires one million core hours on a supercomputer. Using a training dataset of 2,536 snapshots each of state dimension 76 million, our distributed algorithm enables the construction of a predictive data-driven reduced model in just 13 seconds on 2,048 cores on Frontera.

REFERENCES

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