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Physics-based constrained reduced-order modelling of reacting flows

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Reduced-order models, incorporating proper orthogonal decomposition (POD) for dimensionality reduction and Gaussian process regression (GPR) for nonlinear regression, have significantly enhanced the computational analysis of complex combustion systems [1]. However, such surrogate models can yield physically inconsistent predictions, such as negative mass fractions. The linear transformation involved in dimensionality reduction via POD complicates the integration of underlying physical laws, while GPR lacks intrinsic constraints. This work presents a physics-based surrogate modelling framework that employs low-cost singular value decomposition (lcSVD) [2] to downsample high-dimensional data, which helps retain the original data's physical information in the reduced space and supports accurate, efficient reconstruction in the original space. To ensure physically consistent predictions, we embed the structure of the time-dependent, nonlinear Navier–Stokes and continuity equations into the GPR kernel. A linearized backward Euler time-stepping scheme [3] is incorporated to enforce species mass conservation directly within the regression process. We validate the proposed methodology by predicting unexplored thermo-chemical states of one-dimensional unsteady laminar NH_3/H_2 flames, with variations in equivalence ratio, H_2 molar fraction in the fuel stream, and inlet temperature. Results show that the model effectively enforces mass conservation while maintaining high predictive accuracy, highlighting its potential for reliable modelling of reacting flows.

References

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