Proceedings of the Canadian Society for Mechanical Engineering International Congress
32nd Annual Conference of the Computational Fluid Dynamics Society of Canada
Canadian Society of Rheology Symposium
CSME-CFDSC-CSR 2025
May 25–28, 2025, Montréal, Québec, Canada

Sparse Bayesian Physics-Informed Neural Network model for nonlinear aeroelastic prediction

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For computational efficiency in nonlinear aeroelastic modeling, the nonlinear aerodynamic forces and moments are often represented semi-empirically using a set of nonlinear ordinary differential equations. Naturally these simplified models often struggle to capture the full complexity of aerodynamic phenomena at hand. To model wind-tunnel aeroelastic data recorded from an elastically mounted airfoil undergoing pitching limit cycle oscillations, aerodynamic forces and moments are represented using simplified differential equations in our previous studies. These models often define the aerodynamic moment as a polynomial expansion of the pitch angle and pitch velocity, incorporating elements such as linear aerodynamic stiffness and damping terms, as well as Duffing- and van der Pol-type nonlinear stiffness and damping terms in the nonlinear aeroelastic oscillator. While these models have some physical underpinning, they rely on numerous simplifying assumptions. Notably, they lack any explicit representation of nonlinear effects stemming from Reynolds number variations and flow separation. Such limitations introduce modeling errors, making it difficult to accurately capture complex aerodynamic behaviors. To improve predictive accuracy and quantify uncertainty (UQ), we have previously leveraged hybrid physics-informed models that integrate both physics-based and data-driven components within the framework of classical Bayesian state and parameter estimation and model selection . In the presence of significant modeling error, the predictive performance of such models degrades. To address these issues, we leverage an optimal sparsity structured Bayesian physics-informed neural network (OSS-BPINN) that automatically induces sparsity in the network parameters based on the principle of Occam's razor. The OSS-BPINN is selected by seeking the optimal network structure that explains the data well, but reduces the model complexity, thereby reducing overfitting and improving generalization capability to unseen data. We aim to demonstrate how this framework enables the accurate representation of the aerodynamic behavior despite the presence of model error. The results highlight the potential for OSS-BPINN predictions to generalize across a wide range of Reynolds numbers for effective nonlinear aeroelastic computation and uncertainty quantification.