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

Parameter estimation and model comparison of nonlinear aerodynamic models for limit cycle oscillations using Bayesian Inference

David Clarabut[1], Brandon Robinson[1], Rimple Sandhu[2], Mohammad Khalil[3], Chris L. Pettit[4], Dominique Poirel[5], Abhijit Sarkar[1]

[1]Department of Civil and Environmental Engineering, Carleton University, Ottawa, ON, Canada
[2]National Renewable Energy Laboratory, Boulder, CO, United States of America
[3]Sandia National Laboratories, Livermore, CA, United States of America
[4]Department of Aerospace Engineering, United States Naval Academy, Annapolis, MD, United States of America
[5]Department of Mechanical and Aerospace Engineering, Royal Military College of Canada, Kingston, ON, Canada

ABSTRACT

Leveraging experimental data, a comparison of nonlinear aerodynamic models is undertaken using Bayesian physics-based machine learning to model the complex aeroelastic dynamics of limit cycle oscillations. The experimental setup under consideration consists of a rigidly mounted airfoil whose base is free to rotate about a pitching axis, constrained by a torsional spring. We consider two classes of semi-empirical aerodynamic models to capture the limit cycle oscillations observed during experiments. In the first model, the nonlinear aerodynamic load is expressed semi-empirically by the pitch angle and its time derivatives. The second class of models involves nonlinear aerodynamics expressed by the so-called effective angle of attack. While the former class has been extensively studied and shown to model limit cycle oscillations reasonably well, the latter approach enables a more effective representation of the aeroelastic dynamics, both in terms of physics of aerodynamics and computational efficiency of Bayesian machine learning. Despite their apparently useful features, a poorly represented aerodynamic model may lead to an issue called overfitting, leading to a large uncertainty in predictions away from the training data space. Although some terms in the overly complex nonlinear aerodynamic models are significant, other terms may be irrelevant to the system dynamics, leading to overfitting. To this end, we seek to discover the optimal representation of the aerodynamic model which minimizes overfitting based on (noisy) wind tunnel data. Considering quasi-steady and unsteady aerodynamic models, the nonlinear sparse Bayesian learning (NSBL) algorithm is first leveraged in order to identify the optimal sparse representation of aerodynamic models, thereby reduce overfitting.

While known priors can be assigned to parameters whose significance to the system's physics is known a priori, NSBL also leverages the concept of automatic relevance determination priors to induce sparsity among the remaining parameters. Using wind-tunnel data, the evidence-based Bayesian model selection is carried out using the semi-analytical NSBL framework to select the optimal sparse representations of the aerodynamic models, demonstrating their predictive capabilities in reducing uncertainty (by alleviating overfitting).