The 8th European Congress on Computational Methods in Applied Sciences and Engineering
ECCOMAS Congress 2022
5 – 9 June 2022, Oslo, Norway

Data-Driven Reduced Order Modeling for Aerodynamic Flow Predictions

P. Bekemeyer[1] and D.A. Hines Chaves [2]

[1, 2] German Aerospace Center (DLR), Institute of Aerodynamics and Flow Technology, $C^2A^2S^2E$,
Lilienthalplatz 7, 38108 Braunschweig, Germany
[1] philipp.bekemeyer@dlr.de
[2] Derrick.HinesChaves@dlr.de

Key Words: *Reduced Order Modeling, Deep Learning, Data Fusion*

Aerodynamic data, no matter if performance values, handling qualities or loads, are an integral part of every aircraft design, optimization or certification program. The sheer amount of data needed typically results in relying on different data sources as well as different fidelity levels. However, continuous models are generally desirable to interact with other disciplines and drive design activities. Hence, data-driven models have been proposed to not only yield such models but also to enable the integration of data from various sources and fidelities. Besides long-standing conventional models, especially deep-learning approaches have gathered significant interest in the aerodynamics community [1]. However, even though several well-established deep-learning libraries are freely available, their applicability for physics-based problems on an industrial level remains unclear. Moreover, rigorous comparison to conventional techniques are only partially available at best [2]. Therefore, the GARTEUR group “Machine learning and data-driven approaches for aerodynamic analysis and uncertainty quantification” was initiated to bring industrial and academic experts together to evaluate the potential of emerging methods.

This work will provide an overview on ongoing DLR activities within the aforementioned GARTEUR group. It focuses on the application of reduced order modelling capabilities to the XRF-1 dataset. This dataset has been provided from Airbus and includes surface pressure distributions at various Mach numbers, angles of attack and Reynolds-numbers. Moreover, also different fidelity levels are available. Applied reduced order modelling approaches rank from conventional Proper Orthogonal Decomposition with latent space interpolation over more advanced subspace methods such as Isomap or Autoencoder to deep-learning based regression models including Multilayer perceptrons as well as graph convolutional networks. All methods are part of the DLR Surrogate Modeling for AeRo data Toolbox in python (SMARTy) which also features model selection algorithms. Data is consistently split into training, validation and test sets to ensure an unbiased model performance evaluation. Results will be compared with respect to prediction accuracy, model complexity and computational cost. Finally, a small insight will be given into fusing data with different spatial distributions as it is commonly the case when trying to combine wind tunnel measurements with computational fluid dynamics results. For this, the gappyPOD methodology is employed, as it has been recently extended towards a Bayesian perspective to provide variances for the fused results and to account for known measurement uncertainties.

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