CALIBRATION DATA AUGMENTATION THROUGH POD-BASED SURROGATES AND GAPPY POD METHOD

Georgia Komatsiouli **Panagiotis Tsirikoglou**
Limmat Scientific AG
Mühlegasse 18, Baar 6340, Switzerland

Paschalis Oikonomou **Anestis I. Kalfas**
Aristotle University of Thessaloniki
Laboratory of Fluid Mechanics and Turbomachinery
Department of Mechanical Engineering
GR-54124, Thessaloniki, Greece

ABSTRACT

Modeling, analysis and control of flow fields are key enablers of sustainability in mobility and energy sectors. Despite the significant advancement of numerical methods in the last years, experimental approaches are still necessary to provide ground-truth data and validate new concepts. Calibration of sensors in such experimental campaigns are the backbone of raw-data translation to meaningful insights. However, obtaining the calibration data under various conditions is a non-trivial, time-consuming process, while ad-hoc production of new calibration data in unseen conditions can increase the flexibility and applicability of the sensing equipment. To achieve this, and keep time requirements for calibration within limits, the current work presents augmentation of calibration data through proper orthogonal decomposition (POD) based prediction models and iterative, gappy POD method. In the context of this work, the developed pipeline is applied to enhance the aerodynamic calibration process of a 5-hole pneumatic probe, and a 4-sensor, fast-response aerodynamic probe, by generating new calibration data for unseen Mach number values, and refined measurement grids.

INTRODUCTION

Focus of the current work is placed on pressure-based techniques, and particularly experiments that incorporate miniaturized, multi-hole and multi-sensor pressure probes able to derive a full flow-field characterization. The aerodynamic calibration of such probes is a data intensive process, involving measurements in multiple Mach numbers over measurements grids. To extract the measurement quantities on a potential application of the probe, prediction models are used to create response surfaces and mimic the dynamics of the reverse calibration process, thus having as inputs, parameters that are known during a measurement campaign i.e. Mach number, pitch and yaw angles. Considering the described process, a data augmentation pipeline can extend the applicability of the pressure probes to unseen input parameters, while minimizing the required amount of original calibration data. The proposed data augmentation pipeline comprises two main sections. First, POD is coupled to point-prediction models to achieve field prediction in unseen Mach numbers. Various surrogate models are compared based on the resulting prediction error fields. Second, the augmented data are combined and used as the basis of an iterative, gappy POD method to refine grid data, i.e. generate unseen data in respect to yaw and pitch angles. Key point of the presented analysis is a comparison of initialization approaches and their impact on the accuracy of the iterative POD method. Finally, a section of this work is dedicated on the configuration of the overall data augmentation pipeline, to assess its performance in respect to key parameters, and enhance overall reproducibility of the results.

RESULTS AND DISCUSSION

The main sections of the data augmentation pipeline are implemented and tested, showing that POD-based surrogates can achieve a mean prediction error of 3% to 5%, while Gappy POD achieves comparable error metrics depending on the grid refinement ratio and the Mach number (see figures below). It is in the scope of this study to further provide an exhaustive analysis of the prediction performance of the pipeline in respect to its parameters e.g. number of grid points considered in refinement and size of the feature basis.

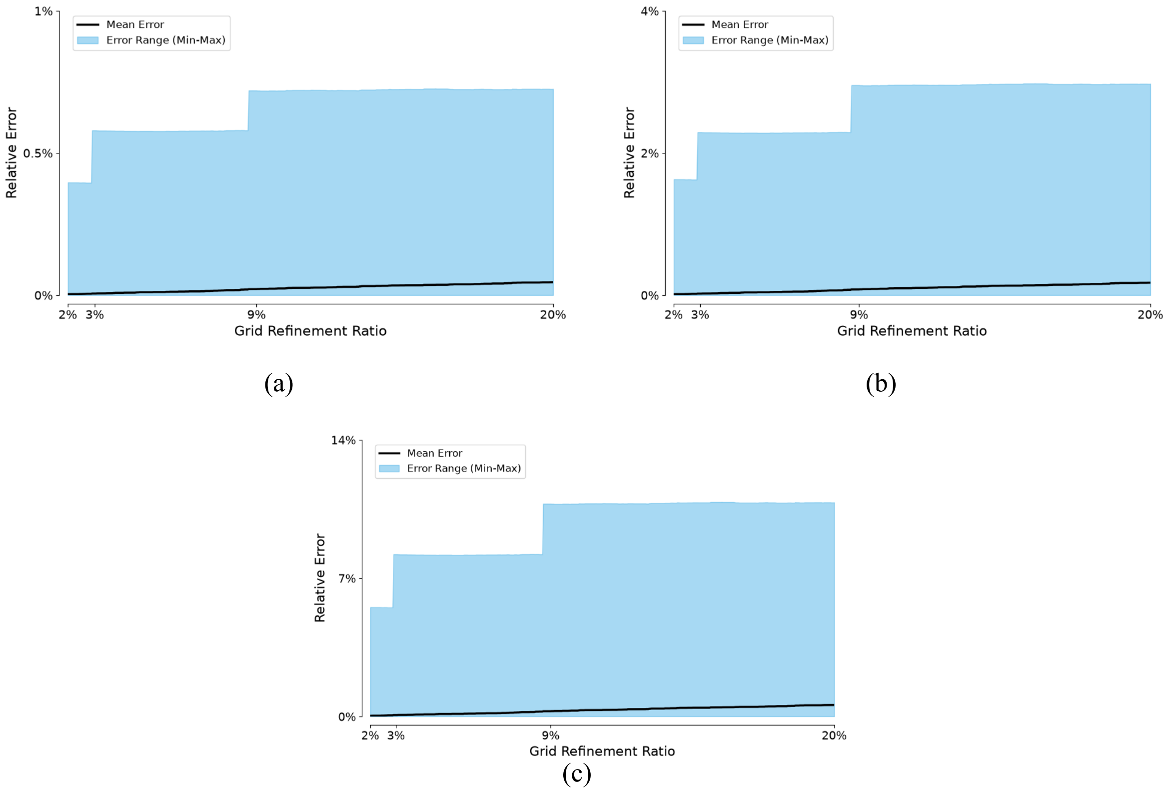

Figure 1: Prediction accuracy of Gappy POD method in respect to various measurement grid refinement ratios. The calibration data illustrated correspond to absolute pressure of hole 1 in a five-hole pressure probe for Mach number 0.15 (a), 0.3 (b) and 0.6 (c)