POD-BASED ANALYTICS AND PREDICTION IN SUPPORT OF THE CALIBRATION PROCESS OF FAST-RESPONSE AERODYNAMIC PROBES

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ABSTRACT

Modeling, analysis and control of flow-fields are key enablers of sustainability in mobility and energy sector. Towards this goal, robust and effective calibration of sensing tools is the backbone that supports the translation and correction of raw measurement data to useful insights. Despite the necessity of calibration data to the proper translation of such raw measurement data, time-constraints and increasing complexity reduce the amount of data that are a priori available or adaptively created. To address this issue, calibration data production is supported using proper orthogonal decomposition and classic point-prediction models, aiming to perform field-predictions of the flow-area of interest. The resulting field-prediction tools is applied to enhance the calibration process of a 4-sensor probe, aiming to effectively take into account the Mach field distributions, without compromising the speed of the overall process.

INTRODUCTION

Point-prediction models such as polynomials, regression-based models and Kriging, are well-know and extensively used in several fields of engineering, accelerating, design and optimization processes. However, flow characterization problems are inherently connected to field-data, which are usually expensive, in respect to time, to derive. For this reason, classic techniques used in fluid modal analysis and image processing coupled to classic point-prediction model became popular as an alternative solution to reconstruct and produce field-data in an one-off basis. Among a general family of techniques, Proper Orthogonal Decomposition (POD), originated from turbulence fields decomposition [1], demonstrates more extensive use and future potential in the flow characterization field. POD uses classic linear algebra theory and matrix decomposition to identify the directions of maximum variance in field data, associate these directions with modes, and finally use the above to perform a lower-rank reconstruction of the field. To extend the capabilities of POD to prediction, established point-prediction models are used to interpolate known-value of calculated modes, aiming to reconstruct unseen flow-field data. In the current study, the coupling of classic POD formulations with SVR models [2] is investigated as a tool to produce unseen field-data.

RESULTS AND DISCUSSION

The coupled POD-SVR model is used an inherent part of a calibration process of a 4-sensor FRAP (FRAP-4S) [3]. As said, the final aim is to systematically produce flow-field data. The data are produced in a request-based process, while the differentiating parameter between the various flow-fields is the Mach number. To enable the training and validation of the POD-SVR tool, an initial database for various Mach numbers is created. A first version of the POD tool, is tested on the database, described above, in terms of decomposition and reconstruction. Figure 1 illustrates the error fields of such reconstructions regarding the pressure field readings of the FRAP-4S in two different Mach numbers of the database. The results show the high quality of the reconstructions, based on POD, while demonstrating a clear increase of the error values for the higher Mach number. The rest of the analysis will present and quantify the predictive capabilities of the POD-SVR tool, focusing on the approximation errors, the initial size of the necessary database, and the final results of the calibration process.

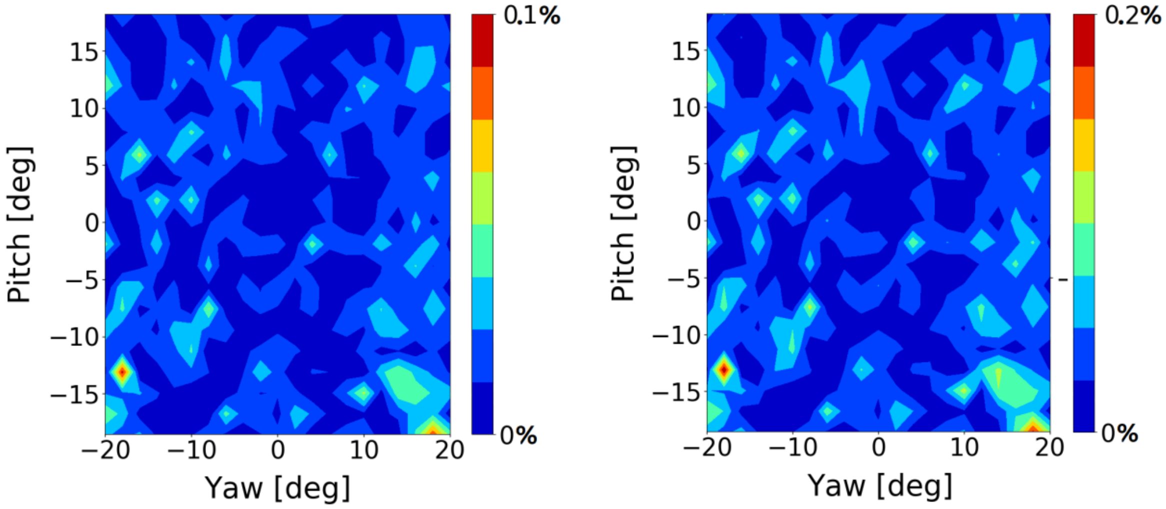

Figure 1. Error fields for POD-based reconstruction for two different Mach numbers: 0.1 (left) and 0.6 (right)

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