IMPROVEMENT OF MEASUREMENT ACCURACY USING BAYESIAN INFERENCE - REDUCTION OF INSTRUMENTATION EFFORT IN AN AXIAL COMPRESSOR

Gonçalo G. Cruz
Ecole Centrale de Lyon, Laboratoire de Mecanique des Fluides et d'Acoustique ;
von Karman Institute for Fluid Dynamics

Xavier Ottavy
Ecole Centrale de Lyon, Laboratoire de Mecanique des Fluides et d'Acoustique

Fabrizio Fontaneto
von Karman Institute for Fluid Dynamics

ABSTRACT

As the next generation of turbomachinery components becomes more sensitive to instrumentation intrusiveness, a reduction of the number of measurement devices required for the evaluation of performance is a possible and cost-effective way to mitigate the arising of non-mastered experimental errors. A hybrid methodology that couples experimental techniques with modeling techniques through a Bayesian data-driven framework is employed to reduce the instrumentation effort. A numerical model is employed to provide an initial belief of the flow, which is then updated based on undersampled experimental observations by a Bayesian inference algorithm. The goal of the present work is to showcase the proposed hybrid methodology and demonstrate its application in reducing the instrumentation effort at the outlet of a low aspect ratio axial compressor stage representative of the last stage of a high-pressure compressor.

INTRODUCTION

Over the past few years, it has become evident that a leap forward in the typical testing procedures is required. Geared low-speed fans provide a smaller pressure ratio, leading to a marked sensitivity to instrumentation accuracy and intrusiveness. Intermediate and high-pressure compressors have seen a drastic reduction in their blade height as a consequence of the higher overall pressure ratio at which modern engines are and will operate.

With engine components becoming more sensitive to instrument intrusiveness in the flow, new data-driven approaches can suppress the excessive instrumentation effort required to evaluate with accuracy turbomachinery performance.

This work proposes a novel data assimilation methodology based on Bayesian inference for the performance characterization of turbomachinery components sensitive to instrumentation limitations [1]. It relies on numerical data, CFD simulations in the present work, and undersampled experimental measurements in a high-pressure axial compressor. The usage of Bayesian algorithms enables a fully propagated uncertainty assessment from the CFD and experiments on the evaluated machine performance.

RESULTS AND DISCUSSION

CFD RANS simulations are performed, creating a prior database of possible flow fields in a highly discretized domain. Random undersampled experimental measurements of the pressure field at the compressor outlet (33% of the complete experimental test) are assimilated in a Bayesian data-driven approach, based on Gaussian Processes [2], to infer the complete pressure flow field at the outlet of the compressor.

Figure 1 shows, on the left, the reference fully sampled experimental pressure field used to validate the methodology and, on the right, the inferred pressure field obtained with a 67% instrumentation effort reduction. A qualitative match between the full experimental flow field and the methodology inference is obtained with the main flow features being visible. A quantitative evaluation performed showed that the validation error against the fully sampled measurements is in the order of magnitude of the experimental uncertainty.

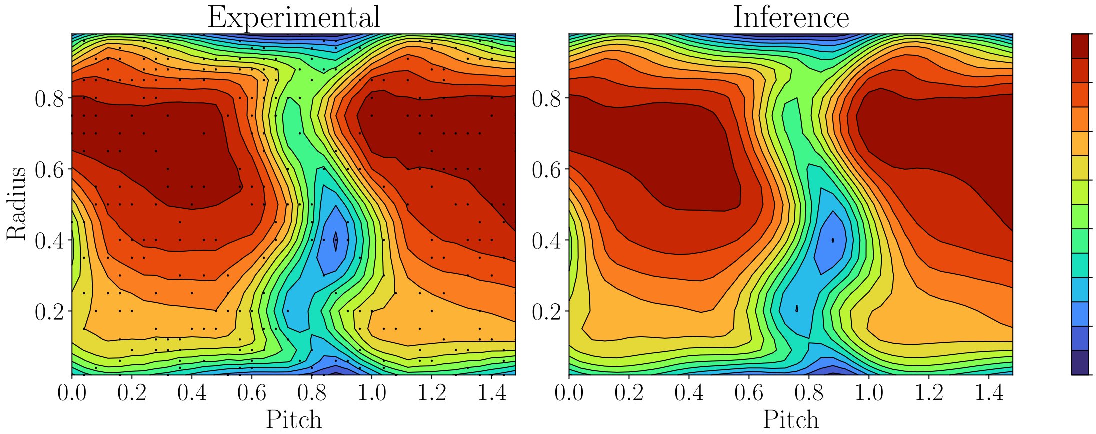

Figure 1. Fully sampled experimental reference (left) and inference of the total pressure map at the compressor outlet (right) with 33% experimental measurements sampled: Overall match of flow features; Error on the order of magnitude of the experimental uncertainty.

REFERENCES

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