Reduced Order Modelling of a Reynolds number 10^6 jet flow using machine learning approaches

Amal Roy Murali[1], Vasily Gryazev[2], Umberto Armani[2], Annabel P. Markesteijn[2], S. Elnaz Naghibi[3], Vassili Toropov[2], Marc C. Jacob[1], Sergey A. Karabasov[2], and Vladimir Riabov[4]

[1]Univ Lyon, Ecole Centrale de Lyon, CNRS, Univ Claude Bernard Lyon 1, INSA Lyon, Laboratoire de Mécanique des Fluides et d'Acoustique, UMR5509, 69130, Ecully, France
[2]School of Engineering and Material Science, Queen Mary University of London, London
[3]School of Architecture, Computing and Engineering, University of East London, London
[4]Department of Complex Systems, Future University Hakodate, Hakodate, Hokkaido, Japan

Keywords: Reduced Order Modelling, Jet flow, Artificial Neural Networks, Genetic Programming

Introduction

The extraction of the most dynamically important coherent flow structures using reduced order models (ROM) is a challenging task in various fluid dynamics applications. In particular, for high-speed round jet flows, the axisymmetric pressure mode of interest is known to be responsible for sound radiation at small angles to the jet axis and dominant contribution to the jet noise peak. In this work the axisymmetric pressure mode of the Navier-Stokes solution at low frequency of a typical high speed jet flow is reconstructed from simulation data using two Machine Learning (ML) methods, whose output can later be exploited for data-driven design of effective turbulent acoustic source models. The data used as input for the ML techniques are derived from the Large Eddy Simulation database obtained by application of the high-resolution CABARET method accelerated on GPU cards for flow solutions to NASA Small Hot Jet Acoustic Rig (SHJAR) jets. The SHJAR simulation database is fed to two variants of POD, one time-based[1] and the other frequency based[2], and the resulting time coefficients of the turbulent pressure fluctuations are the targets of the two machine learning methods put to the test in this work. The first Machine Learning method used is the Feed-forward Neural Networks technique, which was successfully implemented for a turbulent flow over a plunging aerofoil in the work of Lui and Wolf[3]. The second method is based on the application of Genetic Programming, which is a symbolic regression method well-known in optimisation research, but it has not been applied for turbulent flow reconstruction before.

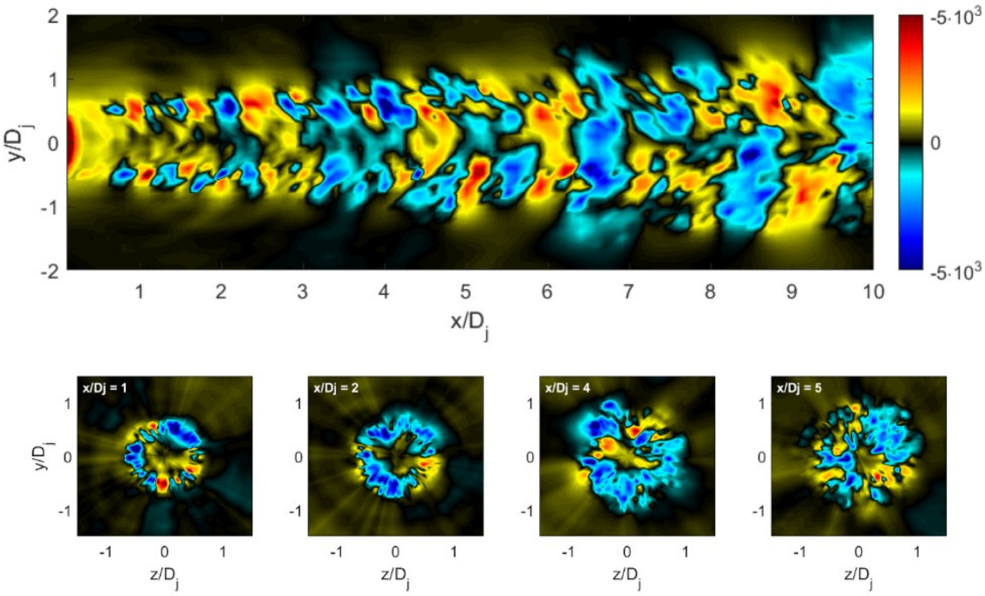

Figure 1: Instantaneous snapshots of fluctuating pressure p' in the symmetry plane (top) and several cross planes at streamwise locations x/Dj=1,2,4,5 (bottom), extracted from the SHJAR dataset for M=0.9.

Case studies and preliminary results

From the SHJAR dataset, the data corresponding to isolated unheated static jet is extracted for this study. The jet Reynolds number based on the nozzle exit diameter is around one million and the acoustic Mach number is 0.9. Only the first azimuthal mode (axisymmetric) is used for this study in order to attempt capturing the most dominant flow characteristic. The modal decomposition of this dataset in time domain using Spectral Proper Orthogonal Decomposition (SPOD) yields the spatial and temporal components as shown in Figure 1. The ANN and GP algorithm is then trained on the temporal components using the first 1000 time steps. After training, the algorithms are then used to predict the signals from the initial time. This prediction for the case of ANNs and for the case of two values of the filter parameter α = 0.0 and 0.99 are as shown in Figure 2. Correponding predictions for the GP algorithm are shown in Figure 3.

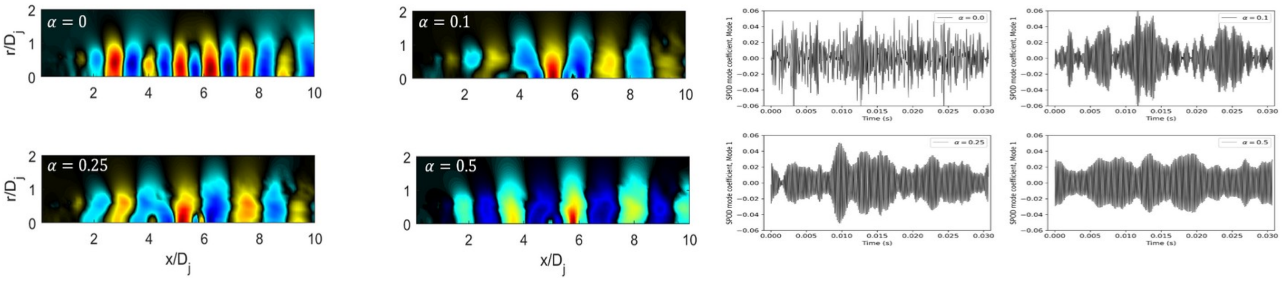

Figure 2: First Spatial modes (left) and corresponding temporal coefficents (right) of the time-domain SPOD, ψ1(x,r), for the Fourier azimuthal mode m=0 of the fluctuating pressure p' computed for four values of filter strength α= [0.0, 0.1, 0.25, 0.5].

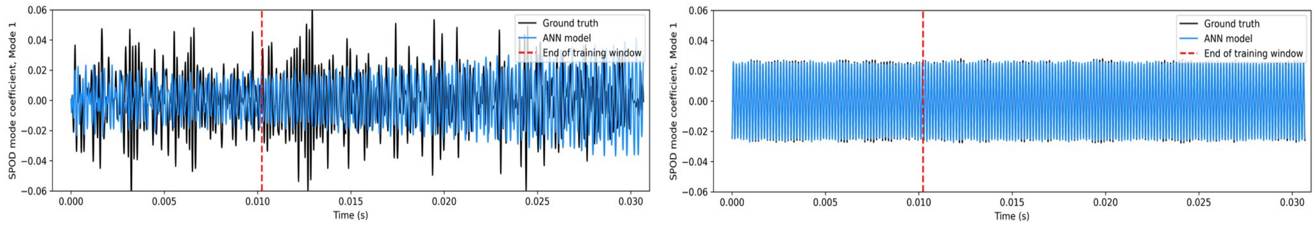

Figure 3: Comparison of the ANN reconstruction of the POD time coefficient b1(t) at filter strength 0.0(left), and 0.99(right) with the reference signal. The end of the training time window is shown by a vertical red line.

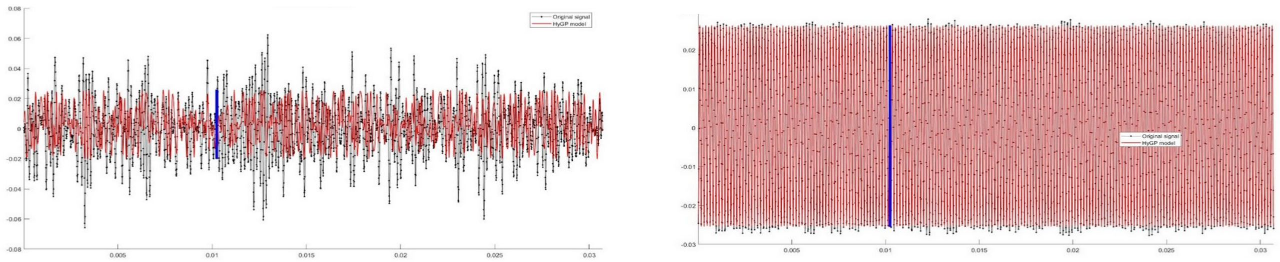

Figure 4: Comparison of the GP reconstruction of the POD time coefficient b1(t) at filter strength 0.0(left), and 0.99(right) with the reference signal. The end of the training time window is shown by a vertical blue line.

Futher development

Further results to be presented in the full version of this article will include the results of the same exercise for signal generated from second type of SPOD algorithm where the Fourier Transform is employed instead of the filtering of the correlation matrix. From the preliminary analysis, it has been inferred that Genetic programming approach has stronger stability characteristics, which enable it to obtain non-diverging signal in any case. Hence, the prediction using GP approach will be subjected to further statistical analysis. Additionally, stability and dependency of the two ML algorithms on the smoothness and the sampling rate of the underlying turbulent flow signals will also be examined.

References

[1] M. Sieber, C. O. Paschereit, and K. Oberleithner, "Stochastic modelling of a noise-driven global instability in a turbulent swirling jet," Journal of Fluid Mechanics 916, A7 (2021).

[2] Towne, A., Schmidt, O.T., Colonius, T.: "Spectral proper orthogonal decomposition and its relationship to dynamic mode decomposition and resolvent analysis," Journal of Fluid Mechanics 847, 821–867 (2018).

[3] H. F. Lui and W. R. Wolf, "Construction of reduced-order models for fluid flows using deep feed-forward neural networks," Journal of Fluid Mechanics 872, 963–994 (2019).