Proceeding Series of the Brazilian Society of Computational and Applied Mathematics, v. 10, n. 1, 2023.

Trabalho apresentado no XLII CNMAC, Universidade Federal de Mato Grosso do Sul - Bonito - MS, 2023

Proceeding Series of the Brazilian Society of Computational and Applied Mathematics

Identification of the Sound Field Produced by Turbulent Jets Through the Use of a Neural Network.

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The development of quieter aircrafts is a strong requirement to achieve the social and ecological targets imposed on the modern aeronautical industry. To accomplish this task, it is necessary to use experimental and numerical methods in order to identify all important noise sources in the aircraft structure, allowing for the designers to intervene in the noise generating mechanisms to reduce noise emission and, as a result, conceive quieter aircrafts. Among a bunch of aircraft noise sources acting at typical operational conditions, turbulent jets are prominent source of noise [1].

Turbulent jet noise has been recognized to behaviour as non-compact acoustic line source that produces a characteristic sound directivity pattern in the acoustic far field region, i.e., at the observer location [2]. In this study, we propose to employ a machine learning-based methodology to identify the characteristic noise produced by turbulent jets. The idea is to employ the Cross-Spectral Density matrix (CSD), virtually measured by a microphone array, as the signature of a jet sound source to be recognized by a machine learning-based computational algorithm. Input databases for a great number of combinations of observer and source relative positions, jet flow Mach numbers, hydrodynamic wavenumbers, wavepacket and coherence lengths, respectively, will be employed to train the developed algorithm to identify the acoustic signature of turbulent jets. The turbulent jet noise source proposed by Cavalieri and co-workers [3–5], which takes into account the effect of turbulent flow coherent decay on sound radiation at subsonic convection velocities and has shown good agreement with experimental data, is adopted in this study.

The neural networks became a really common way to use machine learning to resolve complex problems like multiclass classification problems. The feedforward models with backpropagation learning and cost functions were vastly used in the last two decades, but the interactive tuning of the network parameters can sometimes bring a lot of problems if not done correctly. The extreme Learning Machine (ELM) neural network model [6, 7] offers a lot of advantages when compared to the Square Vector Machine (SVM) model, or the Least Square Vector Machine (LSVM) model [8]. Whenever the interactive tuning is not required, there is no need of previous information to determinate the optimum weights and biases values of the single hidden layer neurons.

However, the application of machine learning to the identification of sources of sound induced by turbulent flow is still in a very early stage, but raises as a promising technique to boost the already existing numerical and experimental fronts in the aeroacoustic field. In this study, we follow the increasing tendency of applying strategies for training artificial intelligence systems to identify the behaviour of multiphysics systems with strong applications in engineering. In a first step, the training process will be applied to identify the acoustic spectra from acoustic fields produced by free turbulent flows. Since the calculation of a cross-spectral matrix is an intermediate step for the implementation of a bemaforming algorithm, this study can be generalized for the mapping of turbulent jet noise sources based on a beamforming algorithm aided by a proper a machine learning strategy.

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A computer algorithm will be implemented to numerically simulate a neural network devoted to the identification of turbulent jet sound source. This step opens a room to compare the performance of new tendencies in neural network applications, such as the extreme Learning Machine neural network model, with traditional methods commonly applied to a large branch of engineering problems. The neural network training process will be supported by numerical data from a parametric study conducted by a partner student (FAPESP grant n° 2021/12698-9). Based on the output data, we intend to be able to assess the performance of the neural network in identifying the salient features of a turbulent jet, such as source superdirectivity and its dependence on hydrodynamic wave and convective Mach numbers.

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