Machine learning methods for the simulation of turbulent flows in turbomachinery

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Turbulence modelling represents a critical aspect in the prediction of the flow field in turbomachinery. Recently, high-fidelity simulations like Large Eddy Simulations (LES) or Direct Numerical Simulations (DNS) become possible thanks to the constant increase in computational power that has been achieved in the last decades. However, these simulations remain prohibitive for performance prediction during a design process because of the large number of configurations which must be investigated. For this reason, high fidelity simulations can be exploited to generate trustworthy solutions on representative test cases in order to understand the phenomena which govern the flow field. Furthermore, it is possible to exploit these results to improve the accuracy of low order models which can then be used for design purposes. In particular, Reynolds- averaged Navier-Stokes (RANS) models represent an efficient way to compute the average flow field but they can become quite inaccurate in the presence of separation or transition from laminar to turbulent flow. In this framework, machine learning strategies represent a possible approach to improve the predictive capability of existing RANS models starting from high-fidelity data obtained from LES or experiments [2]. Among the different algorithms, field inversion is a promising strategy. The approach, originally introduced by Paris et al., was exploited to improve RANS models for turbomachinery by Ferrero et al. The method relies on two steps: an optimisation procedure (the field inversion) and a regression performed by machine learning. The first step requires the definition of an optimisation problem where the goal function is represented by the error between the numerical prediction and the reference data: this error is minimised by finding an optimal field of corrections which alter the source term of the turbulence model. The solution of the optimisation problem contains a lot of information: in each point of the computational domain the local correction and all the fluid variables are known. This makes it possible to exploit machine learning algorithms to identify a correlation between some local flow features and the correction field. This regression step allows to generalise the results and to use the data-augmented RANS model for general predictions. Even if the first results of the field inversion strategy seem promising, several open questions remain. First of all, the reference data (experimental or from high-fidelity simulations) are affected by uncertainty and it propagates through the field inversion procedure up to the final data-augmented model. Furthermore, a significant modelling uncertainty is associated to the regression step: the selection of the flow features which should determine the local correction is not trivial. It is possible to follow some basic guidelines (nondimensional inputs, Galilean invariant inputs,...) but it is not clear how to demonstrate that the correlations captured by the regression analysis are based on a cause-effect principle. In this work Artificial Neural Networks and Random Forests are investigated as regression tools to find a correction to the Spalart-Allmaras RANS closure model for the flow in low pressure gas turbines. The correction acts as an intermittency model and allows to extend the original model to transitional low Reynolds number working conditions.