The role of uncertainty in data-driven turbulence modelling

The role of uncertainty in data-driven turbulence modelling

Andrea Ferrero, Angelo Iollo, Francesco Larocca and Francesca Romana Pennecchi

Key words: Machine learning, field inversion, uncertainty, turbulence modelling, RANS

1 Abstract

Turbulence modelling represents a critical aspect in the prediction of the flow field inside aerospace propulsion systems. 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 [Sandberg and Michelassi(2019)]. 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

Andrea Ferrero
Politecnico di Torino, Corso Duca degli Abruzzi 24, Torino, Italy e-mail: andrea_ferrero@polito.it

Angelo Iollo
INRIA, CNRS, IMB and Université de Bordeaux, 351 Cours de la Libération, Talence, France e-mail: angelo.iollo@inria.fr

Francesco Larocca
Politecnico di Torino, Corso Duca degli Abruzzi 24, Torino, Italy e-mail: francesco.larocca@polito.it

Francesca Romana Pennecchi
INRiM, Strada delle Cacce 91, Torino, Italy e-mail: f.pennecchi@inrim.it

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 the high-fidelity data obtained from LES or experiments [Duraisamy et al(2019)]. Among the different algorithms, field inversion is a promising strategy. The approach, originally introduced by [Parish and Duraisamy(2016)], was exploited to improve RANS models for turbomachinery by [Ferrero et al(2020a)]. 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 [Ferrero et al(2020b)]. 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.

References

[Duraisamy et al(2019)Duraisamy, Iaccarino, and Xiao] Duraisamy K, Iaccarino G, Xiao H (2019) Turbulence modeling in the age of data. Annual Review of Fluid Mechanics 51:357–377

[Ferrero et al(2020a)Ferrero, Iollo, and Larocca] Ferrero A, Iollo A, Larocca F (2020a) Field inversion for data-augmented rans modelling in turbomachinery flows. Computers & Fluids 201:104,474

[Ferrero et al(2020b)Ferrero, Larocca, and Pennecchi] Ferrero A, Larocca F, Pennecchi FR (2020b) Uncertainty propagation in field inversion for turbulence modelling in turbomachinery. In: 2020 IEEE 7th International Workshop on Metrology for AeroSpace (MetroAeroSpace), IEEE, pp 303–308

[Parish and Duraisamy(2016)] Parish EJ, Duraisamy K (2016) A paradigm for data-driven predictive modeling using field inversion and machine learning. Journal of Computational Physics 305:758–774

[Sandberg and Michelassi(2019)] Sandberg RD, Michelassi V (2019) The current state of high-fidelity simulations for main gas path turbomachinery components and their industrial impact. Flow, Turbulence and Combustion 102(4):797–848