

14<sup>th</sup> World Congress on Computational Mechanics (WCCM XIV)

8<sup>th</sup> European Congress on Computational Methods in Applied Science and Engineering (ECCOMAS 2020)

July 19- 24, 2020, Paris, France

## **DATA-DRIVEN AND MACHINE LEARNING FOR TURBULENCE, FLUID LOADS, AND FLUID-STRUCTURE INTERACTION**

**TRACK NUMBER (1700)**

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**Key words:**Data-Driven,Machine Learning,Turbulence Modeling ,Fluid-structure Interaction

### **BSTRACT**

Artificial intelligence (AI) is an active research topic in recent years, which has been successfully applied to many disciplines of science and engineering. Big Data generated in computational simulation or experiment measurement are inherently huge with complicated information. Learning dynamics based on large data and sparse regression has also successfully discovered the underlying nonlinear dynamics governed by ordinary or partial differential equations. How to use these big data through data-driven and machine learning techniques to model, predict, control, and optimize complex fluid systems is a new and promising research direction. The development of multidisciplinary and multi-physical models with respect to fluid mechanics is required in many engineering applications, like aerospace, renewable energy, and marine engineering. This will involve the modeling of multi-field coupling problems, multi-disciplinary intelligent optimization design and adaptive flow control.

At the theoretical and methodological level, main research topics can cover the mechanization of governing equation derivation, machine learning of turbulence modeling, and the intellectualization of dimensional, scaling analysis, as well as numerical simulation. For example, neural network and deep learning have been introduced to develop and calibrate turbulence models or reduce the uncertainty of turbulence modeling. Based on AI techniques, there is also an urge to develop the intellectualization of flow feature extraction and multi-source data fusion. The combination of data from multiple sources, with different fidelities and costs, has been considered in developing multifidelity models that are useful in multi-query problems like optimization, inference, and uncertainty quantification. Model reduction based on machine learning to represent aerodynamic systems that are coupled with structure or control systems has accelerated the simulation of multiphysical problems like aeroelasticity or flow control. Aerodynamic optimization design has already benefited from the reviving of machine learning, where neural network and feature extraction have been used in surrogate model construction and shape parametrization.

In this mini-symposium, the new data-driven and machine learning techniques, research directions and applications in turbulence modeling, unsteady fluid and aeroelastic loads prediction, active flow control, aerodynamic optimization, biological flows and fluid-structure interaction simulation will be discussed .

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