Modelling and Control of near wall Turbulence: from physical understanding to Machine Learning approaches

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Nowadays, experimental and numerical simulations progressively provide an unprecedented **volume of extremely detailed data**, which need to be examined and interpreted. There is therefore an increasing urgency of refined investigative tools for appropriate statistical analyses and data mining. **Machine-learning (ML) algorithms** offer a new path for investigating high-dimensional, nonlinear problems, such as near-wall Turbulence. The development of ML methods, associated with the abundance of data and combined with **solid background in Turbulence**, offer an unique opportunity for achieving major breakthrough in terms of advances in wall-bounded flows and their control. The key objectives of this research programme, by using a large spectrum of statistical analysis combined with various ML approaches, is to nail the **boundary-layer theory** down and derive **models** that are able to predict relevant physical characteristics and the response to **forcing near-wall Turbulence** for both incompressible and compressible flows, where density variations are caused by pressure or temperature fluctuations or both. The other objective is to provide solutions for **reducing drag** and, in the case of a thermal boundary layer, to **maximise the heat transfer**, whilst keeping losses as low as possible.

Societal context: Turbulent flows dictate the performance characteristics of numerous industrial equipment and environmental applications. One important consequence of Turbulence is high friction drag on surfaces, the increase relative to laminar conditions easily reaching factors of 10-100, depending on the Reynolds number of the flow. In many applications, the friction drag is extremely influential to the operational effectiveness of the device or process. This applies especially to transport, involving either self-propelling bodies moving in a fluid or fluids being transported in ducts and pipes. The United Nations' International Civil Aviation Organization (ICAO) expects aviation emissions to roughly triple by 2050, at which time aircraft might account for 25% of the global carbon budget (ICCT). There is, therefore, significant pressure to **reduce transport-related emissions, of which friction drag is a major constituent**. On the other hand, enhancing the turbulent fluxes within the wall-bounded region, is generally beneficial for the heat transfer at walls. Thus, in the case of heat exchangers, a balance need to be found between drag-induced losses and the heat transfer. With the development of renewable energy, increasing the efficiency of heat exchangers is a fastgrowing field of research, especially for solar receiver.

Scientific challenges: In contrast with many scientific fields (brain functioning for instance), fluid mechanics is in the enviable position of having a first principle equation, the Navier-Stokes (NS) equations, to describe flows. In principle, the flow motions can be perfectly predicted by solving these equations (Laplace's determinism). However, the NS equations prove to be extremely complex and even impossible to resolve in some cases, mainly because of its non linearity. For any viscous fluid in motion relative to a solid, the velocity decreases to zero at the wall inducing a shear layer. The flow produced by this shear layer creates chaotic turbulent structures within a wide spectrum of length and time scales. The stronger the shear layer is, richer and more complex is the dynamics, which renders the study of near-wall Turbulence extremely fascinating and challenging. Since Prandtl at the beginning of the last century, near-wall flows have intensively been studied, however more than two centuries after equations governing turbulent flows were introduced, our **understanding of near-wall Turbulence remains pitifully modest**. This is all more true since as the Reynolds numbers increases turbulent flow becomes more and more complex as new families of coherent structures are produced and enrich the flow dynamics (see Fig. 1). Without a sufficiently detailed understanding of turbulent flows, most control strategies remain sub-optimal. Thanks

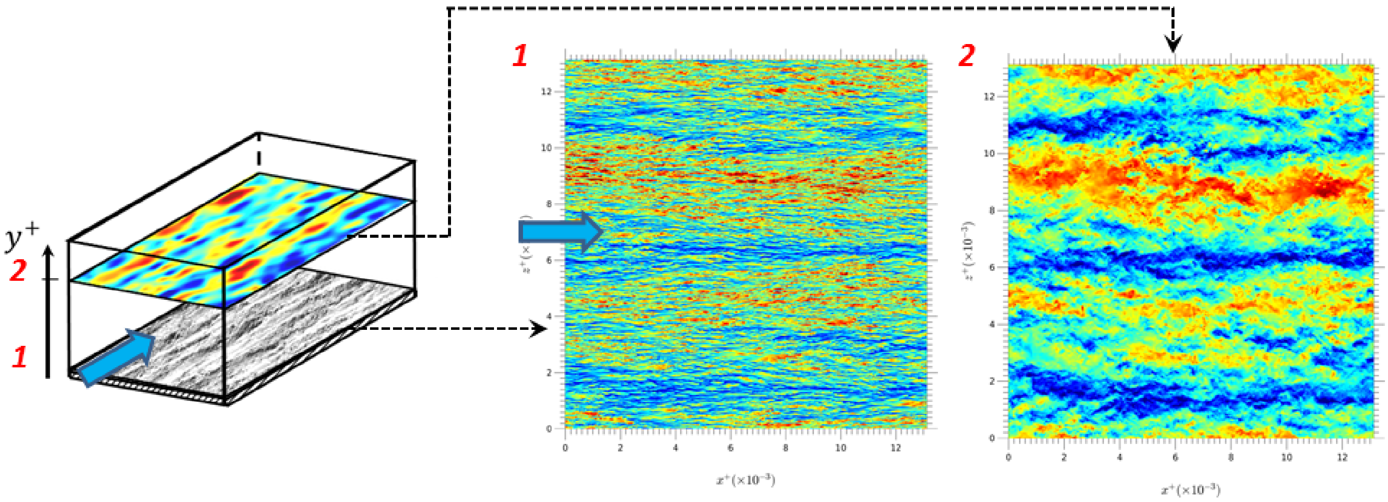

Figure 1: Streamwise velocity field for $Re_\tau \approx 4200$. 1: in the viscous sublayer and 2: in the outer flow (mid-height of the log law).

to recent advances in metrology, and the drastic reduction in computational costs, both the number and the size of database have undergone substantial growth in fluid mechanics. This abundance of data poses new challenges for the postprocessing that requires appropriate tools. Thankfully, many techniques have been developed by the **Machine Learning (ML) community** that are readily applicable to spatiotemporal fluid data, and are sustained by the recent advances in hardware (development of GPU/TPU platforms), algorithms and open-source libraries. By definition, ML is the field of study that gives computers the ability to learn without being explicitly programmed. In this project, Machine Learning algorithms will not aim to replace knowledge from physics (evolution laws for instance) with data, but rather to **use models and data in synergy**. Indeed, it would be completely nonsense to get rid of centuries of scientific knowledge or proven models. The applicant will therefore use Machine Learning methods as complements to traditional approaches by imposing, for example, symmetry properties or known evolutionary models.

The identification of the phenomena driving the flows dynamics remains one of the major challenges of physics and engineering today. This complexity has traditionally been addressed by statistical Turbulence models, but these are proven to have only limited generality, even in the case models are based on the most elaborate transport equations for the second moments of the turbulent fluctuations. The recent developments of **Machine Learning** methods for the **modelling of large-scale problems and their control** prove to be a promising way forward. Based on our current knowledge of turbulent flows, and from the many progress which still to be made using Machine Learning techniques, one can expect to introduce more effective new control methods. Moreover, any efforts towards unravelling the nature of structures populating boundary layers, and towards understanding their dynamics, are crucial to progress towards **universal modelling of Turbulence**, and contribute for deriving effective **control systems** that are compatible with the requirements of industrial applications. After years of in-depth analysis of boundary layer dynamics in compressible and incompressible regimes, and his recent studies using Machine Learning algorithms, the applicant believe that significant progress in understanding near wall flows and their control can only be achieved by making the best use of a solid background in Turbulence and new approaches offered by Machine Learning.