Turbomachinery Research and Design: The Role of DNS and LES in Industry

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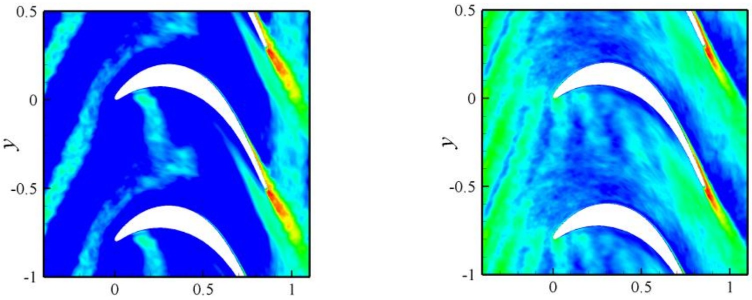
Gas turbine engines (GT) are the backbone of aircraft propulsion, power generation, and mechanical drive in a range of applications, and they will still be used in the foreseeable future. The main reason for GT success is their thrust and power per unit engine weight, their good efficiency and low emissions, and the ability to adjust to rapidly varying loads, as often required by the interaction with renewable resources. It is instructive to remind that in the US alone the GT natural gas and oil burn summed up to 27×10^{12} cubic feet and 6.3×10^{9} barrel of oil equivalent respectively in 2015 [1]. At current fuel prices, any small gas turbine performance improvement can result in a multi-billion-dollar economic impact. Moreover, this will also come with a significant CO_2 emission benefit.

In general, GT fuel burn can be better understood by observing how performance is governed by four different efficiencies [2]: *Thermodynamic efficiency*, which is directly proportional to pressure ratio and firing temperature, *Aerodynamic efficiency*, that measures the quality of the process of imparting and extracting energy from the working fluid, and guarantee operability range applied to compressor, high-pressure and low-pressure turbines, *Thermal efficiency*, that accounts for the internal and external cooling requirements and cavities purge of GT the firing temperatures of which are often above material capabilities, *Propulsive efficiency*, that applies specifically to GT for aircraft propulsion, measures the quality of the process of generating thrust and it is inversely proportional to the fan pressure ratio, and directly proportional to the volume flow.

In the engine component design phase, the prediction of efficiency, operability, cooling and purge systems, fan and nacelle aerodynamics is always heavily CFD assisted. Nowadays, the wide multidisciplinary range of turbomachinery design tools need to balance speed and accuracy. For aerodynamics, thermal, and aeromechanics CFD currently cannot compete with the speed of empirical 0D and 1D correlations. Such correlations, that condense proprietary company knowledge and experience, are and will be an essential part of the design process. Expensive testing is still required to improve design correlations as well as evolve and certify the design of both components and full engines. Tests essentially overcome the inherent weakness of simplified design correlations. In this scenario, it is partly due to the computer performance and availability improvement over the last decades that CFD evolved to become essential in turbomachinery design.

Despite its attractiveness due to the relatively low cost when comparing with design iterations assisted by testing, CFD potential is not fully exploited due to the well-known deficiencies and lack of thorough validation across the design space and operating conditions envelope [2, 3]. The flow in turbomachines is complex due its unsteady nature, both deterministic, due to alternating stages of stationary and rotating components, and chaotic due to turbulence, not to mention the large-scale unsteadiness that evolves in presence of stalls or shock-boundary layer interaction. The concerted action of deterministic and chaotic unsteadiness impacts aerodynamic performance, fuel burn, and reliability. Moreover, the different airfoil shapes, frame changes, range of Reynolds and Mach numbers, high temperatures and pressures as well as uncertainties due to manufacturing deviation from the design intent and transient missions make the analysis and validation of CFD prediction very challenging. Nevertheless, it is documented that RANS assisted design methods contributed and are still contributing to GT performance improvement and reduction in testing of high-pressure compressor [3]. Still, the current literature on the topic indicates that RANS and URANS model development has plateaued mostly because of shortcoming in the turbulence physics modeling approaches. Data taken in experimental testing may provide the “what”, namely the performance of a turbine stage, but not the “why” due to the inability to dissect the range of physical phenomena impacting a design. In addition, they cannot provide enough data to drive the development of computational models that should mimic the physical mechanisms governing aero-thermo-mechanical performance.

DNS and LES do help by providing “virtual test data” with accuracy and details appropriate to provide the “why” and guide both design improvements and CFD model maturation. This lecture will illustrate how GE is focusing on improvements to the CFD ecosystem with the help of scale-resolving CFD, like DNS and LES, to analyze the flow physics in Low-Pressure-Turbines, investigating the impact of a range of design parameters [4, 5], like Reynolds number, aerodynamic load, flow coefficient, reduced frequency, axial gaps, and the impact they may have on performance and unsteady excitation. For example, Figure 1 shows two phase-locked averaged snapshots of the turbulent kinetic energy in an LPT blade passage with two combinations of flow coefficient, ϕ, and reduced frequency, F_{red} which impact losses, proportional to local production of turbulent kinetic energy, and unsteadiness, proportional to the residual incoming wake strength.



Low F_{red}, medium ϕ. High F_{red}, low ϕ.

Figure 1. Turbulent kinetic energy production in the vane of a low-pressure turbine; impact of design choices (ϕ=flow coefficient, F_{red}=reduced frequency) [4].

The analysis extends to High-Pressure-Turbines tackling the problem of loss generation and heat transfer [6, 7] in the critical pressure trailing edge cooling region. Figure 2 shows a snap-shot of the instantaneous temperature field in an idealized pressure-side slot geometry with cooling ejection, typical of small high-pressure-turbines trailing edges, predicted by LES. The LES results compare well with measurements, and they are also used to improve Reynolds averaged models by introducing non-linear constitutive laws machine-learnt from the LES data-base, as shown in Figure 2 bottom.

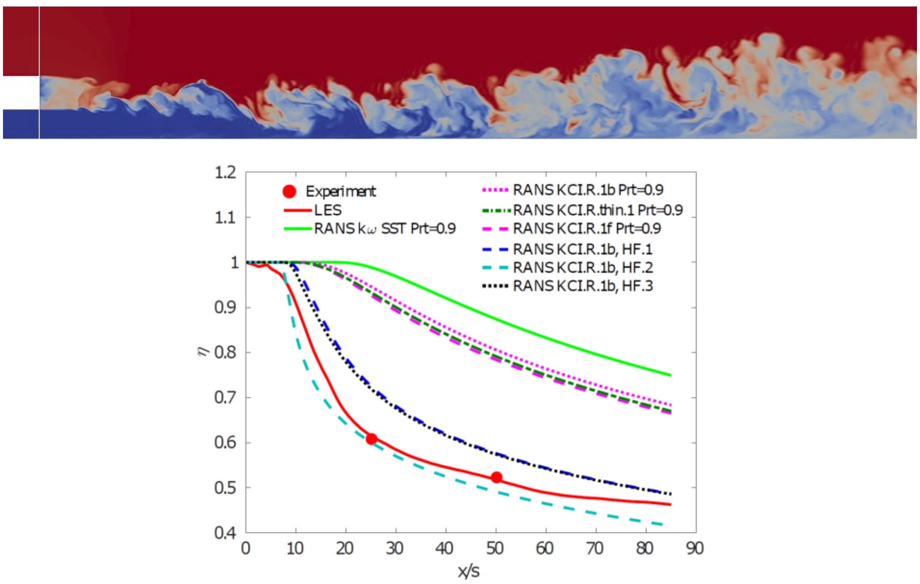


Figure 2. Snap-shot of the temperature flow field in an HPT trailing edge slot-like geometry in presence of cooling ejection predicted by LES (top), and adiabatic effectiveness (η) prediction improvement by LES and Machine-Learnt RANS models (bottom) [7].

Axial compressor flows are also of critical, in particular the prediction of off-design performance that controls the overall operability range of a GT. The prediction of the flow in axial compressors at off-design conditions was investigated in [8]. Figure 3 shows a snap-shot of the instantaneous span-wise vorticity for positive incidence with a clear tendency of the suction side boundary layer to develop intermittent separations. LES loss predictions agree well with data, as well as RANS (see Figure 3) suggesting that for the compressor midspan section a simple turbulence model is probably adequate to predict the main flow features.

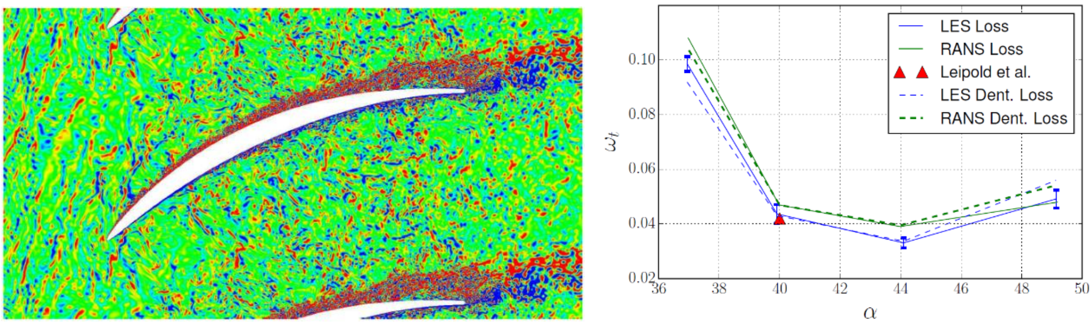


Figure 3. LES of an axial compressor at positive incidence (left) and loss predictions for a typical incidence range from test, LES and RANS (right) [8].

In a further attempt to improve RANS, GE is also focusing on analytic turbulence model assessment [9, 10], model improvement by Machine-Learning applied not only to high-pressure turbines [7], but also to the prediction of the wake decay in low-pressure turbines [11], and on the application of non-conventional post-processing to scale-resolved simulations by POD [12] to extract information of the physics that drives the growth of irreversibility. Figure 4 shows a typical POD mode decomposition of the unsteady flow in a low-pressure turbine with discrete incoming wakes generated by moving bars, and how it is possible to associate losses to each mode in specific flow regions of interest. Such analysis is of importance to understand the details of the loss generation mechanism and to drive attention to efficiency top offenders.

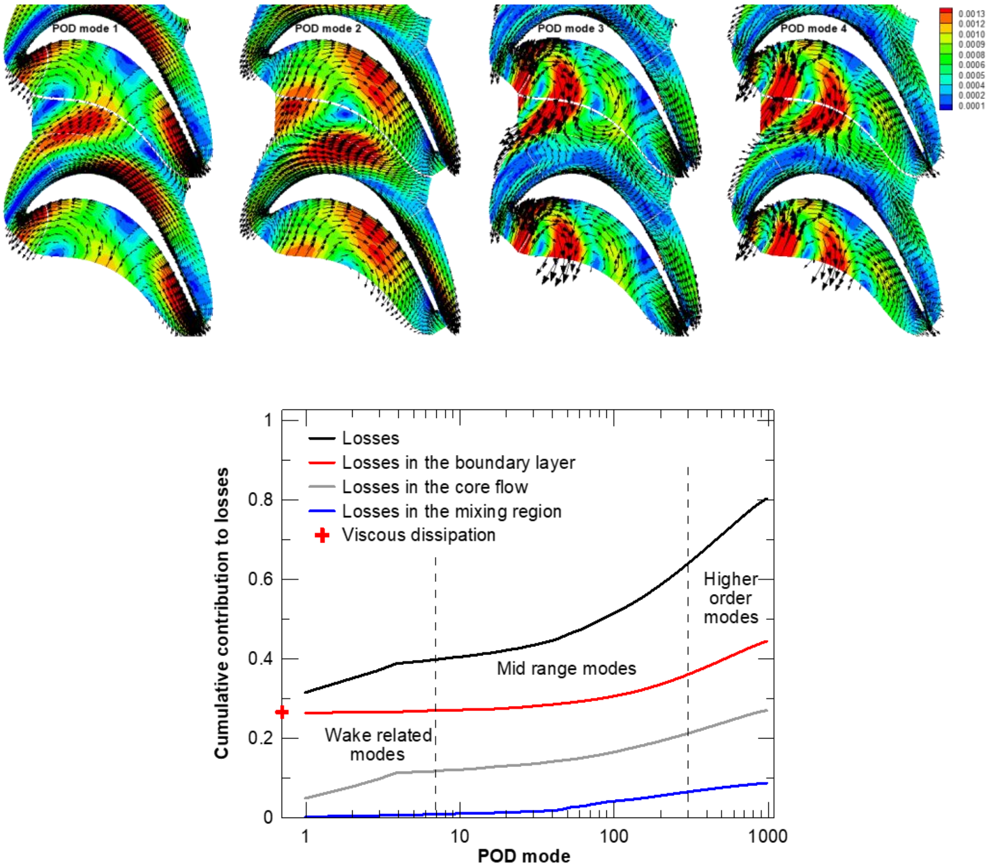


Figure 4. POD mode decomposition of the flow in a low-pressure-turbine with discrete incoming wakes (top), and cumulative contribution to losses split in different flow regions (bottom) [12].

In conclusion, there is a broad range of areas in turbomachinery design where scale-resolved computer simulations are having a significant impact, through better understanding of the complex flow field and by improving lower order turbulence models, that are routinely used in the design phase.

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