Use of Artificial Intelligence Techniques in Turbomachinery Aero-thermodynamics

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Abstract

The use of Artificial Intelligence (AI) in engineering is expanding rapidly, with both in-house and commercial solutions now offering AI-assisted simulation (CFD and FE). However, its technology readiness level (TRL) is currently low and its application across aerospace industry needs better focus and coordination. Although great strides have been achieved with the use of Large Language Models (LLMs), the focus of this presentation is on the following areas:

1) Improving the accuracy and speed of the CFD simulations
2) Improving the performance, accelerating the design cycle (by analysis) & reducing lead-time
3) Addressing the manufacturing variation issues related to the engine (e.g. test bed) performance
4) More-time on the wing – end of life, residual life prediction and prognosis

1. Introduction

Over the past three decades, the use of advanced simulation tools coupled with high performance computing (HPC, mainly Intel chips) has played a major role in the design and validation of aero engines and their derivatives. The use of HPC allows highly complex CFD and FE analyses to be performed. Advances in numerical tools coupled with computing parallelisation have allowed large scale and high fidelity 3D modelling and faster computations. In a modern engine 1% fan efficiency can lead to 100s of millions of pounds cost reductions for a fleet of aircraft [1].

The aerodynamic design of the fan, multi-stage core compressors, turbines, combustion and aero-thermals, engine noise, installations and fluid systems can only be competitive through very advanced and complex CFD computations. Moreover from a mechanical integrity perspective, the engine extreme event and impact simulations require significant use of HPC. Over the past ten years, Rolls-Royce has been pioneering test simulations, in particular, the replacement of core compressor strain gauge engine tests by analyses. These simulations reduce engine costs during development but require significant use of HPC. Over the past decade, significant progress has also been made in the development of analysis automation, robust design [2, 3] and optimisation capabilities addressing the *curse of dimensionality* [4, 5]. However, these advances will bear little fruit in the absence of adequate computing capability and better, i.e. more accurate, simulation capability.

In the discussion section of this paper, a definition of AI is first provided and the advantages of coupling it with CFD articulated, e.g. to produce a *functional-inspection* of on-the-wing components, throughlife estimation - leading to more accurate shop visits and scheduling. Improvements to the CFD accuracy and its improvements to predict the gas temperature and the HP turbine blade stress, can also lead to increase component life & better robust design optimisation.

2. Definition of AI

AI is a multidisciplinary topic that enables machines, devices, and computers to think and make decisions in a way that would seem intelligent. AI helps machines and programs make smarter decisions by learning and improving in an iterative process based on the information they collect. However, as also shown in Figure 1, there are four different nested fields related to AI, a key question is which of these will benefit the turbomachinery industry most and in the short to medium term, e.g., more time on the wing, reduce design time, increase profit margin in years to come.

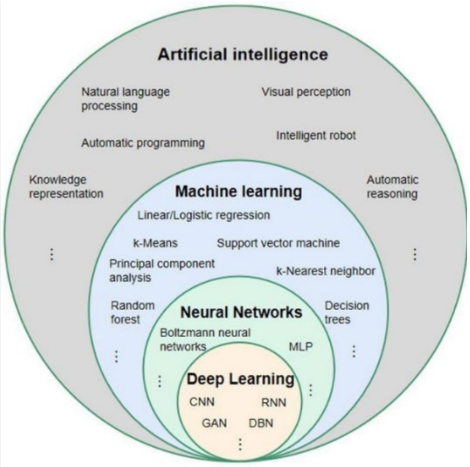


Figure 1: *AI Methodologies.*

Although, rapid advances in AI have created a frenzy of industry and academic activities, it has also increased concerns about ethics and its safety. Generative AI has recently captured popular imagination, creating text, images, audio and codes comparable to humans.

3. CNN/UNET to support instant CFD

Convolutional Neural Network (CNN) based on UNET [6] architecture for computer vision application has the potential to reproduce the flow field instantly in different aircraft engine components after an initial training with a large dataset of images which represent complex aerodynamic interactions. The classical usage of these networks can assist with the prediction of the size and binary segmentation of the flow features. This code has been modified to predict the RGB contours from a binary image. The model has been trained on a compressor intake under cross wind with a time-dependent solution, with the predictions closely resembling the ground truth (middle image) and with a Structural similarity index >99% (See Figure 2).

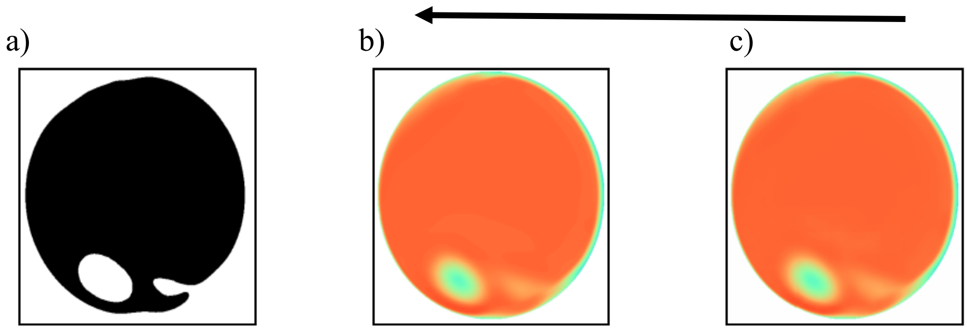


Figure. 2: *Aspirated intake in ground proximity with a ground vortex ingested, a) Stencil of the distortion field b) Ground Truth from CFD computation C) AI generated flowfield using the modified UNET architecture*

With 500 solutions as a training data set, the overall training time was 40 minutes, and the code is able to detect flow features (ground vortex and lip separation) in real time. Afterwards, the same architecture has been applied to results from in-house RANS CFD simulations carried out on conventional high-pressure turbine blades with service degradation (spallation and TBC loss). Sixty-seven blade sections were provided, and the dataset was augmented by using rotation, crop, roll and inversion, generating an additional 2800 images for the training. The resulting flow contours are shown in figure 3c.

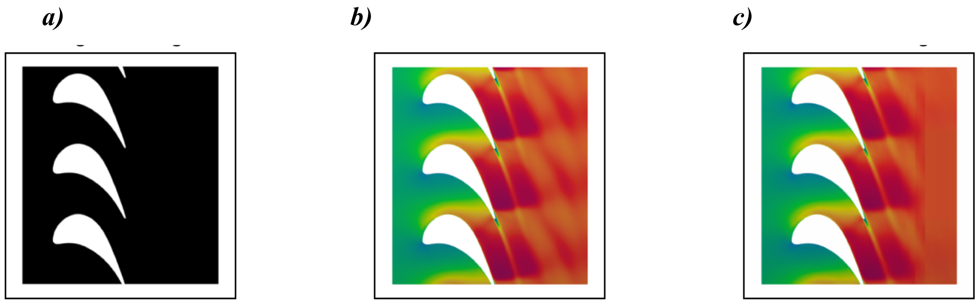


Figure 3: *HP Turbine blade – Mid-span Po contours shown a) reference stencil image of the aerofoil, b) Ground truth from hi-Fi CFD and c) is the AI predicted image. (Images NOT to scale)*

Typically, 85% - 90% of the images were used for training, the rest for validation and testing purposes. The CNN framework enabled the prediction of the two-dimensional flow field including the presence of manufacturing defects and coolant holes. Further details can be found in the NextAIR EU Horizon R&T program.

4. AI to Improve the Accuracy of CFD Simulations

DNS in fluid mechanics, although regarded as very accurate and of the highest fidelity, is very expensive for realistic flight Reynolds numbers. Hence, the effect of turbulence is usually modelled, often at the expenses of accuracy, i.e. using RANS is still the most common approach in the aerospace industry. Hence, advanced Machine Learning algorithms (able to generate large amount of data) were combined with high-fidelity CFD calculations, to find correlations and relate turbulence behaviour to mean flow features [7]. The output of the process is a data-driven turbulence closure that can easily be implemented in a CFD solver (e.g. Hydra) and provide more accurate flow predictions, at the same cost of a traditional RANS calculation, See examples shown in Fig 4. Several closures were identified as part of this PhD research and most importantly, a framework was put in place to facilitate new derivations in the future [8].

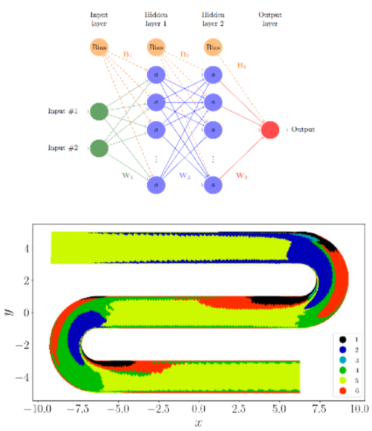
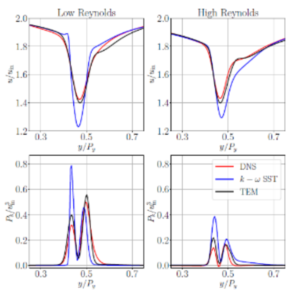
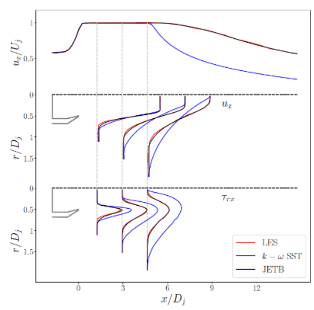


Figure 4: *Automatic identifications of clusters based on flow characteristics (to train Structure of the neural network)*



a) the ML model to improve turbine wake prediction



b) ML model to improve jet prediction

While being very promising, several challenges remain. These are: a) generating high fidelity data for representative engine configurations b) blending together different models, or automatically selecting one over the other based on the type of flow (e.g., turbines, compressors, jets), c) extending the framework to turbulence modelling for URANS, d) further automating the framework to generate new turbulence closures, e) improving the machine learning algorithm, enforcing physical constraints. The author & his colleagues will continue this R&D work through a newly started Horizon EU program called ROSAS [9].

5. Image segmentation using Borescope data

Here, an industry standard code – Yolov8 (You only look Once) from Ultralytics is used [10]. A small dataset of 55 end-of-life blades was used for training and an additional 11 blades for testing. Using this CNN architecture, the code was able to rapidly predict the damaged sections of the blades, see figure 5. Advanced segmentation features such as SAHI (Slicing Aided Hyper Inference), where the images are sliced and the predictions are performed yielding better results.

a) b) c)

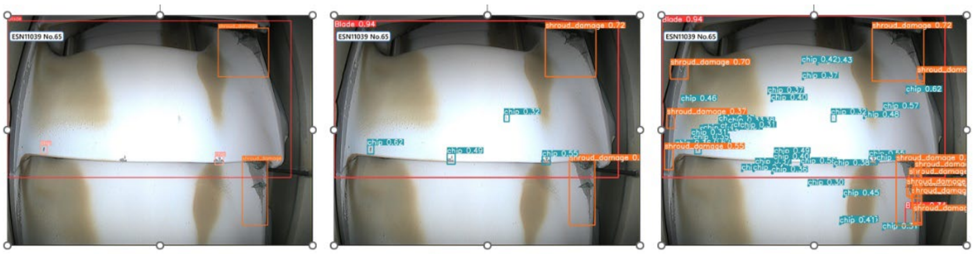


Figure 5: *Video images of a borescope of a Turbine blade with areas of large damages identified for taking b) the code detects similar unseen damages c) this can be enhanced with additional AI software for TBC loss [10]..*

6. Conclusions

The author has kept the enterprise wide usage of LLM like *ChatGPT* (and what it can do for engineering), and its link to *Digital Twin* out of the scope of this short paper. Focus has mainly been on HPC enabled AI applications and opportunities in aerothermal engineering. In the Author's experience so far, the performance and the actual success of AI usage is very much related to **four factors**: 1) The hardware that they are run on, e.g. GPUs offer an order of magnitude speed up for most AI codes developed, thanks to the gaming industry exponential growth in the usage & graphic processing speed improvements. The amount of RAM memory and storage also plays a key role here 2) Availability of vast "good" data – Good refers to clean data where it is "consistent", ideally noise free and clearly labelled and the meta data seamlessly made available to the user 3) Physics-based reasoning where the results are enhanced and agree with the well-known physical laws, such as thermodynamic laws, conservation of the mass, momentum and energy fluxes 4) Allowing expert knowledge to be injected to the solution, e.g. for turbomachinery, interesting facts are also available, like the flow in a single passage of stator or rotor should be periodic, a prediction of a flow which is not clearly periodic? needs reinforcement learning, other flow features like wakes, stagnation points, secondary-flows behavior are all well-known features to an expert aerodynamicist.

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