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Machine learning tools applied to gas turbine component design and asset monitoring

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With increases in both the quantity and quality of operational data in the gas turbine (GT) industry and the simultaneous expansion of the telecommunication infrastructure, the utilization of machine learning tools to reduce the maintenance cost and improve GT performance in real-time operation is becoming even more appealing from both an OEM and operator's perspective.

An important aspect of GT design has to do with the modelling of the heat transfer mechanisms occurring in the high pressure (HP) stages of the GT. For this purpose, machine learning techniques can be integrated with heat transfer and turbulence models to improve the prediction accuracy of the film cooling efficacy [1]. More accurate but numerically expensive techniques, such as large eddy simulations (LES), can be exploited to generate the data needed for algorithm training and verification. Therefore, with the adoption of machine learning in HP GT design not only a good accuracy can be achieved but also the computation time required by each design iteration can be significantly reduced.

However, such tools have not only been applied to turbomachinery design but are also particularly well suited for assessing GT operation (i.e., asset monitoring): classification-based machine learning algorithms have been proven to be particularly effective in GT fleet monitoring and fault detection. Starting from a set of data, classification algorithms are able to classify events into a given set of categories (e.g., faulty or normal operation) and understand whether the GT is running properly or anomalies are occurring. The algorithm is trained following a supervised process in which real test or field data labelled normal or faulty are fed to the algorithm, which learns to predict the output class based on the provided input.

Multiclass classification algorithms have been successfully applied to real-time GT combustion monitoring, proving to be more reliable and robust than conventional monitoring systems [2]: by monitoring GT exhaust temperature, nearly real-time information on the conditions in which combustors may be operating could be extracted. By doing so, anomalies and specific fault signatures in the Exhaust Gas Temperature (EGT) profile indicate to operators the presence of potential issues and, at the same time, provide hints on the problem root cause via the estimation of the EGT deviation. Quickly detecting and identifying combustion anomalies is crucial for the selection of the best recovery strategy and for this purpose ad-hoc machine learning techniques can be applied to reduce the maintenance cost (e.g., avoiding unscheduled down times) and increase GT availability.

Finally, one of the major challenges in the use of machine learning techniques is related to the scarcity of data needed for algorithm training and verification, two critical phases of the learning process. In case of missing fault condition data, machine learning tools can still be employed to predict normal conditions starting from the historical series of fault-free observations. By predicting deviation from measured values and detecting changes from reference conditions, early warning algorithms allow operators to see alarms much earlier and intervene faster than standard rules based on static thresholds.

References

[1] R. D. Sandberg *et al.*, "Applying machine learnt explicit algebraic stress and scalar flux models to a fundamental trailing edge slot," *J. Turbomach.*, vol. 140, no. 10, Oct. 2018, doi: 10.1115/1.4041268/401015.

[2] C. Allegorico and V. Mantini, "A Data-Driven Approach for on-line Gas Turbine Combustion Monitoring using Classification Models," *PHM Soc. Eur. Conf.*, vol. 2, no. 1, 2014, doi: 10.36001/PHME.2014.V2I1.1461.