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Using data science and probabilistic methods to determine the optimal safe operational life of gas turbine components

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Maximising the life of assets and minimising the need to manufacture new assets has been identified as a critical aspect of realising net-zero [1]. For gas turbines (GTs) as well as many other assets, this can be achieved using data science. These approaches can not only help make GTs more reliable and cost-effective as a key power generation technology for enabling the transition to net-zero, but they can also make them more sustainable by maximising the life of components. These components include those in the hot gas path which require energy intensive manufacturing and the use of valuable rare elements.

Historically, GTs would often utilise more simplistic life prediction strategies with increased inspections and larger margins of error and conservatism. However, with the digital age in full swing we are seeing more and more data science methods being used and developed in industry and academia to help realise operational and environmental benefits in the GT industry. We will touch on some of these methods and ideas in this short article.

There is a wide range of service data that is monitored and recorded for the safe operation of GTs and a constantly growing range of methods to utilise this data for component life prediction approaches. These life prediction methods range from traditional deterministic modelling like Paris' law, Miner's rule, and creep laws, to probabilistic modelling approaches and entirely data-driven approaches such as neural networks.

With the growing amount of data captured from GT assets operating in the field, there are numerous opportunities to utilise this data to better understand the actual damage a specific asset or component has incurred, although doing this effectively is always easier said than done.

The simplest methods are often purely deterministic models, which represent a degradation mechanism such as creep. However, no two batches of material are the same, and degradation mechanisms have a habit of behaving differently depending on their interactions with things like environmental contaminants and other degradation mechanisms. Therefore, GT life prediction approaches now increasingly combine a conventional deterministic life model with a probabilistic framework, using methods like maximum likelihood optimisation or Monte Carlo simulations [2] [3] to understand the uncertainty and bounds of a model. These approaches not only predict the expected life, but also provide a probability distribution of the predicted life, which directly relates to the risk of failure, and gives a better understanding of how uncertainty in component life can influence the risk profile (refer to Figure 1).

Bayesian inference has been demonstrated as a powerful statistical tool which can be used to infer the likelihood of an event based on previous observations. This approach can help engineers understand the significance of different engine operational parameters for given outcomes, such as damage or unfavourable modes of operation [4]. Furthermore, Bayesian inference can be combined with in-service inspection data to provide more accurate life predictions for critical components, based upon their current and predicted future damage state.

Data science packages are increasingly available across numerous open source and commercially available programming languages. We can use combined deterministic and probabilistic methods to inform an artificial intelligence (AI) or machine learning (ML) approach, where models are optimised and updated as new data is acquired (refer again to Figure 1). A useful review of machine learning approaches and AI applied to GTs was published in a recent review in Energies [5].

Additionally, neural networks can be used to interrogate data sets and understand where correlations and relationships exist between operation and an outcome such as high damage or an undesirable mode of operation. This topic will be discussed in detail in the next blog article from the ETN Young Engineers Committee.

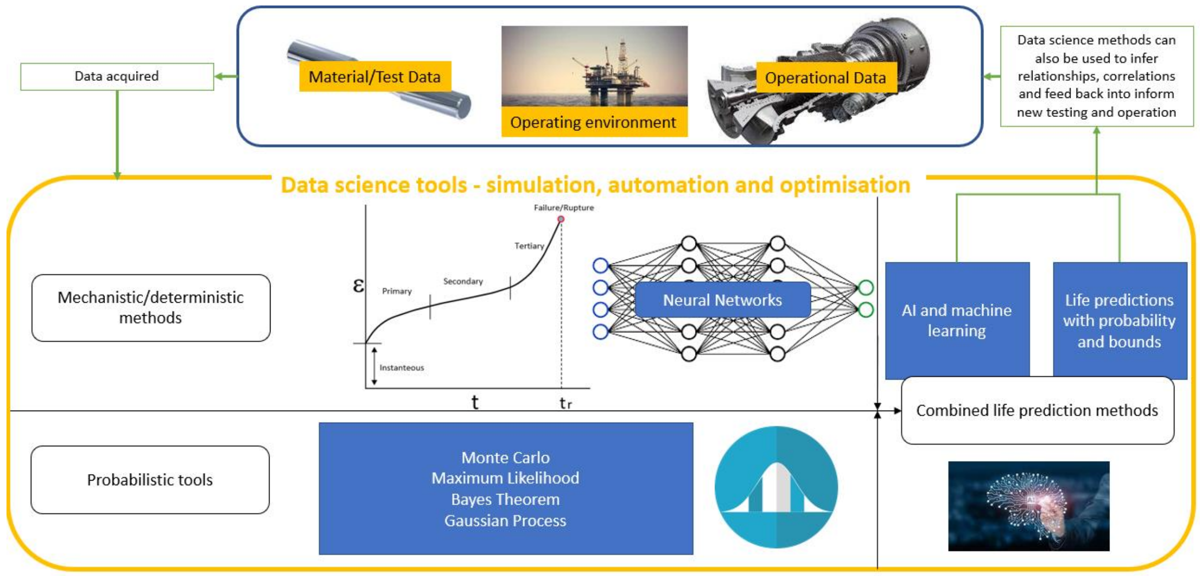

Figure 1: Examples of how deterministic and probabilistic methods can be used to inform component life prediction in GTs

References

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