Explainable AI for wind turbine fault detection

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Introduction

Operations and Maintenance (O&M) activities make up a significant proportion of the lifetime costs of wind farms, with up to 35% reported for some offshore developments [1]. Maintenance represents a large portion of O&M effort, cost and risk. It is increasingly important for wind farm owners and operators to optimize the maintenance strategies of their assets in order to reduce O&M costs. Condition based maintenance (CBM) aims to foresee when a certain equipment might fail and to identify when is the right time to perform a maintenance intervention. This can be achieved through increased monitoring and analysis of operational data. The economic benefits of implementing preventive CBM strategies are substantial, in terms of maintenance costs minimization, operational performance and safety improvement, and reduction of the number and severity of in-service failures. There is increasing interest in applying deep learning techniques to predict faults and anomalies in wind turbines for CBM [2]. However, an important shortcoming of deep learning models is their lack of transparency. They operate as black boxes and typically do not provide rationales for their predictions, which can lead to a lack of trust in predicted outputs. This has been recognized as one of the main factor currently limiting the adoption of such data-driven decision making approaches in practical applications in wind energy [3]. Explainable AI (XAI) models have been shown great potential for responsible and trustworthy decision making [4]. XAI can contribute to improved performance of AI models as explanations help trace issues and pitfalls in datasets and the behavior of features, while also assisting O&M engineer to better trust predictions made by such models. Despite its enormous potential, the wind industry has seen very limited applications of XAI so far, which mainly focus on turbine power prediction, while limited attention has been received in the area of fault prediction.

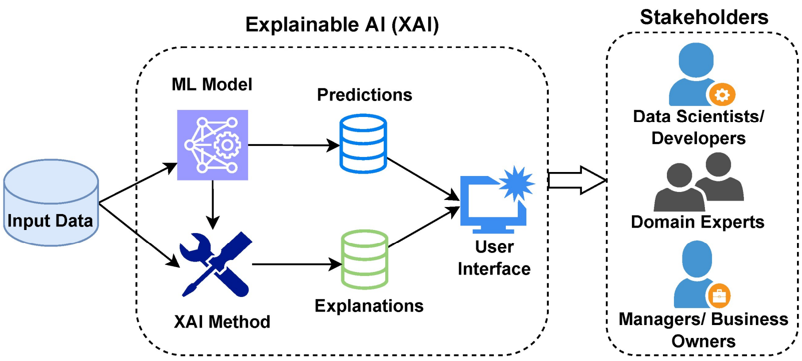

Figure 1: The concept of explainable AI. Figure credited from Mach. Learn. Knowl. Extr. (2023) [5].

Objectives

The goal of this master thesis is to propose an XAI method for fault detection on wind turbine components. This includes the following:

- Choose a set of suitable AI architectures to accurately predict failures in wind turbine components and implement the methods with open access SCADA data from 5 wind turbines.
- Add explainability to the chosen methods by generating feature importance analyses, to better understand and trust the decisions of the algorithms. Other approaches, like for example model simplification, will also be considered, if time allows.
- Evaluate the models and draw conclusions about performance and transparency. Compare the methods to identify the most sensitive and reliable approach.

References

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