Explainable AI for Intelligent Decision Support in Operations & Maintenance of Wind Turbines

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Abstract. As global efforts in transitioning to sustainable energy sources rise, wind energy has become a leading renewable energy resource. However, turbines are complex engineering systems and rely on effective operations & maintenance (O&M) to prevent catastrophic failures in sub-components (gearbox, generator, etc.). Wind turbines have multiple sensors embedded within their sub-components which regularly measure key internal and external parameters (generator bearing temperature, rotor speed, wind speed etc.) in the form of Supervisory Control & Data Acquisition (SCADA) data. While existing studies have focused on applying ML techniques towards anomaly prediction in turbines based on SCADA data, they have not been supported with transparent decisions, owing to the inherent black box nature of ML models. In this project, we aim to explore transparent and intelligent decision support in O&M of turbines, by predicting faults and providing human-intelligible maintenance strategies to avert and fix the underlying causes. We envisage that in contributing to explainable AI for the wind industry, our method would help make turbines more reliable, encouraging more organisations to switch to renewable energy sources for combating climate change.

1 INTRODUCTION

Condition based monitoring (CBM) has been of active interest to the wind industry, with the most popular approaches applying signal processing and numerical physics-based models [10]. Data-driven approaches have been also explored, with traditional ML algorithms including support vector machines, decision trees trees and probabilistic models being used for anomaly prediction [12, 1]. Some studies have utilised turbine power curves for identifying abnormalities in operation [5], but lack ability to provide component-level fault prediction (e.g. in gearbox). Deep learning algorithms have recently outperformed traditional ML methods in anomaly prediction in turbine operation, with the state-of-art studies utilising multi-layer perceptron and artificial neural networks [7]. The utilisation of more sophisticated architectures like recurrent neural nets has sadly been limited to a few studies applying long short-term memory models for power forecasting and fault diagnosis [8]. Some studies have proven effective in using computer vision for visual inspection via drones of external turbine sub-components (e.g. blades) applying convolutional neural networks [13], but are difficult to apply internally.

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2 PROBLEM STATEMENT AND PROPOSED APPROACH

While existing studies have demonstrated significant advances in making more accurate power forecasts and anomaly prediction, they lack transparency to provide human-intelligible causes and maintenance actions, which is essential for engineers & technicians to consider for averting (or fixing) faults. This makes the wind turbine operators reluctant to adapt data-driven approaches widely, which we aim to address in this project. The more interesting information which has mostly been neglected includes unstructured data on historical alarms which have occurred in the turbine. These alarm records are stored as event descriptions for the faults, which are basically natural language phrases providing detailed information about the faults. In this project, given a sequence of continuous numeric SCADA input features, we aim to **(1)** Predict a fault type and generate the alarm event description, with its possible causes. **(2)** Generate a maintenance action message to avert/fix the fault.[2] The maintenance actions to fix failures can either be authored by a human-domain expert, or learnt from documents such as maintenance manuals and work orders. This is a data-to-text generation problem, wherein, deep learning and natural language generation (NLG) models have shown success in domains such as weather forecast generation [11], spatial navigation [9] etc. Owing to the sequential nature of inputs (continuous SCADA time-series) and sequential nature of outputs (predicted alarm messages and maintenance actions), we believe that models such as Seq2Seq [6] and Transformers[2] can provide transparent decisions beyond accurate predictions of faults. The components of the proposed approach are briefly outlined below (refer Figure 1):-

- **Stage (a): Alarm message generation module:** The first component of the system utilises a NLG model, which takes in the sequence of continuous SCADA features, and outputs the internal status of the turbine in the form of predicted alarm messages. The NLG model, such as Transformer provides prediction of likely occurrence of faults in advance [4] (to assist in preventive maintenance), while also estimating the potential causes of the fault (through the attention weights). [3]
- **Stage (b): Maintenance action generation module:** Considering a fault predicted in any turbine component, we propose utilisation of a second NLG model such as Transformer, which takes as input a sequence of likely causes of the fault in Stage (a) along

[2] We aim to develop a scalable system through transfer learning techniques, wherein, faults can be predicted in new domains (e.g. new wind farms which have not been in operation for long) without additional labelled training data.

[3] This component is trained using historical SCADA data labelled with corresponding alarm messages through supervised learning.

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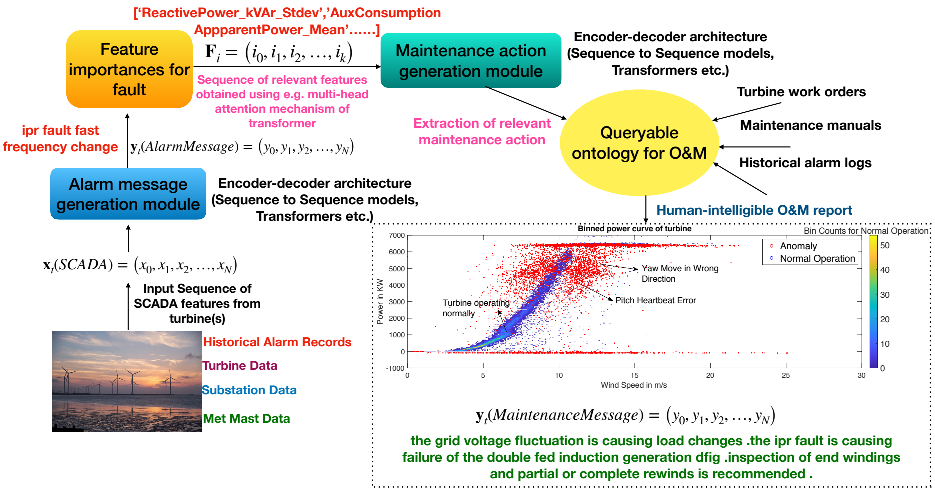

Figure 1. Our proposed intelligent decision support system for O&M of turbines.

with the identified alarm type, and generates the corresponding maintenance actions suitable for averting/fixing the fault. This is a content-selection problem, wherein, the most appropriate actions need to be selected from the available corpus [4].

3 PROGRESS AND RESEARCH PLAN

In the initial phase, we focused on obtaining SCADA data from an operational turbine [5], and its pre-processing. We established benchmarks on our dataset, and utilised various ML algorithms and deep learning techniques for comparison with existing work. At this stage, we developed a novel model utilising combination of a Long short-term memory recurrent neural network architecture for component-level predictions of faults and an XGBoost decision tree classifier to provide transparency to the black-box neural net. We also implemented transfer learning to port our model to an onshore wind farm, to predict faults without additional training data in a new domain [3]. Next, we extended our technique towards generating alarm messages and maintenance actions, utilising a dual-transformer NLG model for alarm type prediction and content selection [4]. At this point of submission, we are exploring development of a queryable ontology for O&M of turbines, by utilising maintenance manuals and other unstructured data. We are also considering the causal relationships in SCADA data to identify hidden relationships between features during various types of faults, through temporal causal graphs. Finally, we envisage that our approach will help facilitate intelligent decision support for the wind industry, by generating human-intelligible O&M reports in an accurate, scalable and transparent manner.

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[4] Content selection can be performed either through a collection of NLG templates authored by a domain-expert, or maintenance manuals etc.

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