Label Extraction, Feature Generation and Machine Learning Approaches to the Detection of Clogged Radiator Coolers on Offshore Wind Turbines

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Abstract

As a part of the effort to drive down the cost of wind energy, there is a desire to reduce unscheduled maintenance on wind farms. Some estimate this to be 75% of total maintenance costs on a wind turbine [1]. This goal has led to the substantial growth of the value of condition and prognostic modelling through data mining and machine learning.
Effective application of machine learning classifiers to wind turbine SCADA data for fault detection relies heavily on data availability, quality of labels and feature generation and selection. For reasons of commercial sensitivity, it can be difficult for researchers to access large databases of wind farm data. At least four papers in the past five years have based their analysis on only one wind turbine [2-5]. Other recent papers derive their results from outdated turbine models or from a period of only a few weeks or days [6][7].

This paper will focus on models developed to detect faulty cooling radiators at three different locations on a wind turbine. These radiators are susceptible to getting clogged by debris over time and require cleaning to restore their cooling capacity. Effective operation of these components is essential for keeping the wind turbine's components in good condition. Hundreds of 3MW class wind turbines and over three years of data including SCADA, workorders and annual service data were available to the authors.

In the paper, it will be demonstrated that three models developed with different machine learning algorithms can be adopted to detect this fault using SCADA data, workorder and annual service histories. These approaches will include an assortment of different pre-processing steps including data-labelling and feature generation procedures. Furthermore, the paper will discuss the handling of uncertainty regarding information extracted from workorder datasets and how modelling approaches must be adapted to take this into account.

The first model was applied to converter cooler one and utilised a rule extraction process based on generating decision tree classifiers. Almost a thousand candidate classification rules were generated and then assessed using a scoring metric to determine the best rule for the model. Several of the rules were able to achieve 100% recall on the training and validation sets. A final detection rule was selected based on its ability to characterise the fault.

The second model was applied to the gearbox cooler and used principal component analysis

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with k-means clustering to classify turbines and detect where the fault was present.

The final model was applied to converter cooler two and used an isolation forest to detect outlying datapoints. Temperature thresholds were then applied to the data points to determine their final classification.

Each of the models were tested for a period of over 3 months on a large set of over one hundred wind turbines and a sample of positive detections were confirmed by site visits.

All three modelling approaches were then applied to the same cooling radiator. This allowed for a direct comparison of the three approaches in terms of their precision, recall and lead-time capability to assess each model's relative strengths and weaknesses.

References

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