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Review

Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection

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ABSTRACT

This paper presents the research results of a comparison of three different model based approaches for wind turbine fault detection in online SCADA data, by applying developed models to five real measured faults and anomalies. The regression based model as the simplest approach to build a normal behavior model is compared to two artificial neural network based approaches, which are a full signal reconstruction and an autoregressive normal behavior model. Based on a real time series containing two generator bearing damages the capabilities of identifying the incipient fault prior to the actual failure are investigated. The period after the first bearing damage is used to develop the three normal behavior models. The developed or trained models are used to investigate how the second damage manifests in the prediction error. Furthermore the full signal reconstruction and the autoregressive approach are applied to further real time series containing gearbox bearing damages and stator temperature anomalies.

The comparison revealed all three models being capable of detecting incipient faults. However, they differ in the effort required for model development and the remaining operational time after first indication of damage. The general nonlinear neural network approaches outperform the regression model. The remaining seasonality in the regression model prediction error makes it difficult to detect abnormality and leads to increased alarm levels and thus a shorter remaining operational period. For the bearing damages and the stator anomalies under investigation the full signal reconstruction neural network gave the best fault visibility and thus led to the highest confidence level.

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1. Introduction

Condition monitoring of wind turbine components is of increasing importance. The size of wind turbines used nowadays has reached a level where the availability of the turbine is very crucial. Downtimes are very costly. It is therefore worth increasing the effort spent to monitor the turbine condition in order to reduce unscheduled downtime and thus costs.

Condition monitoring (CM) systems can be used to aid plant owners in achieving these goals. They aim to provide operators with information regarding the health of their machines, which in turn, can help them improve operational efficiency by allowing more informed decisions regarding maintenance [1].

The available CM systems mostly require high level knowledge about the problem domain. However, this knowledge is difficult to access and often does not exist. Physical models can thus seldom be built.

On the other hand there is a large amount of historical operational data available, which can be used to give an indication on the turbine condition. By application of advanced signal analysis methods, focused on trends of representative signals or combination of signals, significant changes in turbine behavior can be detected at an early stage [2].

Another possibility of identifying changes in signal behavior are model based approaches. Here the historical operational data is used to develop models capable of predicting a certain output signal, when given one or more input signals. For wind turbine signals these approaches are well suited, since many signals can be found to be correlated to other signals simultaneously measured, e.g. the wind speed or the power output.

One advantage of using normal behavior models to monitor wind turbine signals lies in the reduction of prior knowledge about the signal behavior. Another important property is that with normal behavior models the possibility of monitoring the signal is widely decoupled from the operational mode. In practice simpler monitoring approaches such as those by defining thresholds are difficult to establish due to the various operational modes, which cause signals to widely fluctuate. If thresholds are to be defined they must be specified for several operational modes individually.

The normal behavior models are developed at a stage where the turbine components can be considered healthy. Afterwards, the model is used to estimate a specific signal. The estimation error can give an indication of signal behavior changes and thus incipient faults.

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