Condition monitoring by neural network modelling of drive train temperature

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INTRODUCTION

- Up-scaling and significant technology improvements have reduced wind energy costs in the last decades.
- Operational costs, where the fuel is effectively ‘free’, are dominated by maintenance actions.
- Unscheduled maintenance particularly offshore results in high costs as accessibility is restricted by weather and availability of vessels.
- Advanced maintenance strategies based on actual condition rather than using corrective or preventive maintenance can reduce these costs.
- Evaluation of operational data recorded by the Supervisory Control And Data Acquisition (SCADA) system of a wind turbine shows promise for the purposes of condition monitoring as the cost of additional sensors is avoided.

METHODOLOGY

Monitoring temperatures for mechanical failures:

If a drive train temperature is higher than the ambient temperature, energy is lost. Energy losses are load dependent. If the relative temperature increases, the condition of the system is altered due to wear or a failure [1].

Why simple temperature thresholds do not work:

Example of transient drive train temperature time series. The temperature is influenced by the ambient temperature and the operational level of the turbine. Condition changes are not detectable in the absolute temperature trend.

Normal Behaviour Modelling – predicting the temperature while assuming the part operates normally:

Detecting imminent failure in increasing residual of measured minus modelled value:

Different approaches of data-driven modelling are investigated.

Artificial neural network are one powerful option:

Feed-forward architecture with 4 inputs and 6 neurons in one hidden layer. Neural networks have been used for drive train temperature modelling e.g. in [2-4].

Novel approach to consider system inertia in modelling:

Layer recurrent network architecture

Layer output is fed back to the inputs to enable dynamic response of the network. The recurrent connection has a specified delay.

CASE STUDY

US wind farm with more than 100 variable speed turbines with a rated power of 1.5 MW:

- 6 months of SCADA data with mean values of temperatures and control parameters.

Comparison of feed-forward and layer recurrent neural networks in normal behaviour modelling:

- 52 days for training
- 69 days for blind testing
- Two-fold cross-validation
- Modelling of bearing temperature and generator winding temperature.

Evaluation of prediction performance in different metrics:

- Coefficient of Determination $R^2$
- Mean absolute error (MAE)
- Root mean squared error (RMSE)

The average performance in the farm is given with the median value.

CONCLUSION AND OUTLOOK

- Normal Behaviour Modelling of drive train temperatures as a way of condition monitoring is investigated.
- Feed-forward and layer recurrent architectures of neural networks are compared.
- In a case study with real data from a wind farm with more than 100 turbines two different drive train temperatures are modelled.
- The layer recurrent architecture results in better modelling performance for only one of the two investigated temperatures.
- Further studies comparing Normal Behaviour Modelling based on linear models, neural networks, support vector regression, Gaussian process regression and adaptive neuro-fuzzy inference systems will be presented at TORQUE 2016.
- The impact of the selected inputs for modelling will be studied.
- Uncertainties have to be discussed to assess the general validity of findings.
- Eventually, the detection of failures with Normal Behaviour Modelling shall be discussed with real data containing failures.

REFERENCES


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