Neural Networks for Wind Turbine Fault Detection via Current Signature Analysis

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Abstract – Cost-effective condition monitoring techniques are required to optimise wind turbine maintenance procedures. Current signature analysis investigates fault indications in the frequency spectrum of the electrical signal and is thereby able to detect mechanical faults without additional sensors. Due to the modern variable speed operation of wind turbines, fault frequencies are hidden in the non-stationary frequency spectra. In this work, artificial neural networks are applied to identify faults under transient conditions. The feasibility of the detection algorithm is demonstrated with a wind turbine SIMULINK model, which has been validated with experimental data. A framework is proposed for developing and training the algorithm for different rotational speeds. A simulation study demonstrates the ability of the algorithm not only to detect faults, but also to identify the strength of the faults as required for fault prognosis.

Keywords – Wind Turbine, Condition Monitoring, Fault Detection, Current Signature Analysis, Neural Networks, Variable Speed.

1 Introduction

With an increasing number of wind turbines (WTs) being installed in offshore and remote locations, there is a need for cost-effective maintenance. Predictive maintenance aims to detect condition changes early and enables maintenance teams to schedule the required work considering other limiting factors as e.g. weather conditions. For this reason, a reliable condition monitoring system (CMS) is required to detect and diagnose WT failures in their early stages.

In order to develop an effective CMS, the best solution for two characteristics of the system must be found:

- A signal providing information to describe the state of the monitored component.
- A technique to extract the condition state from the signal.

The most simple, but sufficient accurate solution has to be determined to reduce maintenance costs by giving reliable results and avoiding unnecessary equipment. Generally, the signals used in common WT CMSs include vibration, acoustic emission, strain, torque, temperature, lubrication oil quality, electrical output, and supervisory control and data acquisition (SCADA) system signals [1]-[2]. Among them, vibration is the most well-known signal used in a WT CMS [3]-[4]. However, analysis of electrical signals from the generator has been shown to have advantages over vibration signals for condition monitoring as the costs and complexity involved in current measurements are significantly lower [5-6]. Additional installation costs are avoided because current signals are already continuously measured in WTs [7].

Current Signature Analysis (CSA) utilises the knowledge that mechanical faults as rotor unbalance show up in increased amplitudes in the sidebands of harmonics of the fundamental frequency. However, it is a challenge to extract WT fault signatures from current measurements under variable speed operation. Moreover, the useful information in current measurements from a WT usually has a low signal to noise ratio, and thus it is very difficult to extract this information in a reliable way.

Extracting the fault signature from a monitored signal is commonly done by the well-known fast Fourier transform (FFT) and the short–time Fourier transform (STFT) [9]-[10]. However, in the case of variable speed WTs, FFT and STFT often fail to extract the required information which can vary in the time-domain, since the operation is predominately non-stationary due to variations in the wind speed.

The attractive feature of Artificial Neural Networks (ANNs) for condition monitoring is their ability to represent complex, nonlinear relationships through learned pattern recognition or signal regression. ANNs have been successfully used to identify changes in the relationships between SCADA signals that indicate the development of a failure [10].

In this work, the possibility of detecting mechanical faults in wind turbines by CSA is investigated. The application of Artificial Neural Networks (ANN) for detecting mechanical faults is proposed to automate the fault detection in the light of the limitations of spectral analysis in processing signals subject to transient effects. The diagnosis of rotor unbalance in a WT is used as an illustrative example. The simulation results demonstrate that the proposed method is effective in detecting mechanical faults in a variable speed machine.

2 Methodology

This research aims to develop a reliable technique to detect mechanical faults in a WT via the generator current signal. An ANN technique is proposed to automate the fault detection in a variable speed machine. The main purpose of using an ANN is to identify changes in the current signal which have non-stationary characteristics due to the variable-speed operating conditions of WTs, and to provide online fault detection in advance of catastrophic failures.

The data used in this work is based on a WT simulation model. The model is developed and validated with operational data of five 2.5MW turbines recorded by the SCADA system over the period of 1 year. The measured data recorded at 32Hz sampling frequency included wind speed, wind direction, pitch angle, rotational speed and three-phase power output. The model parameters used are detailed in Table 1.

The required phases of the algorithm development and testing for an online fault detection tool are given in Table 2.

Table 1: Model parameters.

Parameter	Value
Cut-In, Rated, Cut-Out Wind Speed	3 m/s, 12 m/s, 25 m/s
Rated Tip Speed	80 m/s
Rotor Diameter	90 m
Gearbox Ratio	1:77.4
Line-Line Voltage (RMS)	690V
Frequency	50Hz
Pole Pairs	3
Rated Generator Speed (RPM)	1000

Table 2: Phases of the project.

Phase	Task
1	Development of simulation tool providing current signal
2	Validation of simulation with experimental data
3	Training and testing of automated fault detection with simulation
4	Validation of fault detection with experimental current signal
Final	Online fault detection with current signal

In the following, the methodology behind the simulation model, CSA and the ANN fault detection are presented.

2.1 Wind turbine SIMULINK model

A general model for representation of variable speed wind turbines was implemented in MATLAB/Simulink, including wind speed, rotor, pitch control system, drivetrain and generator model [11]. The model has been developed to facilitate the investigation of condition monitoring and effective algorithm development for fault detection. The measured wind speed recorded by a wind turbine SCADA system has been used as model input to validate the response of the wind turbine model. Figure 1 shows the response of the model compared with measured generator speed. It is visible that the model is in good agreement with the measured data.

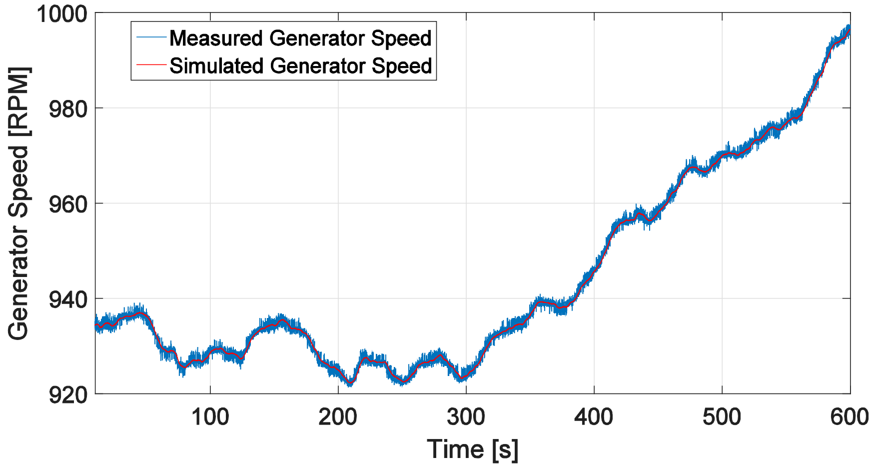

Figure 1: Model validation considering generator speed.

Rotor eccentricity is used as an illustrative example to investigate the use of the proposed fault detection algorithm in variable speed WTs. During rotor eccentricity, certain sideband harmonics around the fundamental frequency in the machine current signal occur with increased amplitudes proportionally to the fault level. It was experimentally proven [5] that rotor eccentricity faults give rise to a sequence of such sidebands given by:

$$f_C = \left(1 \pm \frac{2k-1}{p}\right) f \qquad (1)$$

where f_C and f are the rotor fault and fundamental frequency, respectively, k is an integer ($k = 1, 2, 3, \ldots$) and p is the number of pole pairs. The fundamental frequency in a variable speed WT with a permanent magnet synchronous generator (PMSG) is proportional to the rotational speed, i.e. the characteristic of the signal is varying with time.

Figure 2 shows the stator current spectra for a faulty and healthy machine for fixed rotational speed. Components with frequencies at 60 Hz and 34Hz are intentionally induced in the healthy machine spectrum to represent machine-specific noise close to the fault frequencies. The fault frequencies identified by the equation (1) are labelled in Figure 2.

2.2 Automated fault detection with Artificial Neural Networks

A simple detection threshold for the fault frequencies is not feasible due to the variable speed operation and accordingly shifting frequencies.

ANNs are useful for automated processing and finding non-linear relationships. With data-driven training, ANNs learn to weight different inputs in a way to deliver the required output. Problem-specific settings have to be found in particular for the number of neurons and the amount of training required.

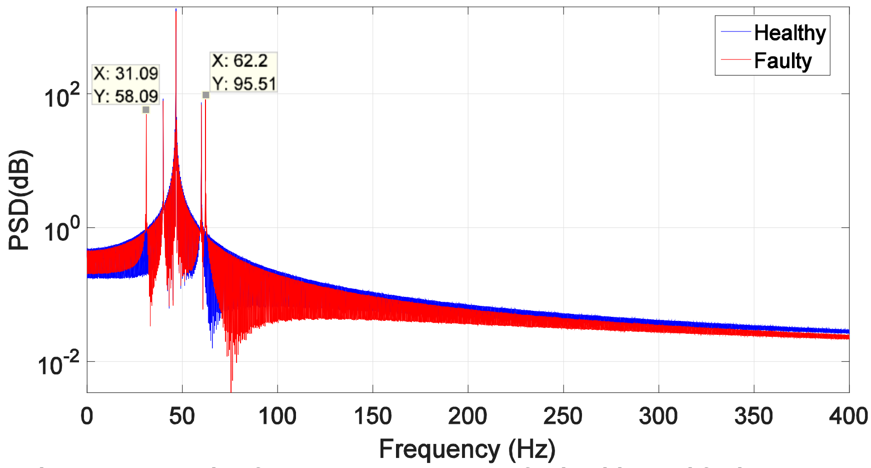

Figure 2: Example of stator current spectra for healthy and faulty states.

The rotational speed ω of a PMSG turbine varies significantly. Fault detection for all possible rotational speeds is not feasible with a single ANN. A framework is proposed, in which different networks are used for different ranges of rotational speeds, as sketched in the workflows in Figure 3 and Figure 4. In the training phase, n sets of different rotational speeds (Ω) with defined limits $\omega_{\min}$ and $\omega_{\max}$ are used for simulation of the current signals. The sets are selected in a way that all possible speeds are covered. For each of the sets, an ANN is trained to detect a fault. In the detection phase, maximum (max), minimum (min) and-standard deviation (σ) are calculated for each two second record. If the variation in the rotational speed is relatively high, the frequency spectrum becomes indistinct. Accordingly, the standard deviation of the set has to go below a defined limit σ_L to allow further processing. The appropriate ANN for fault detection with the FFT of the current signal is selected with the information of the rotational speed extrema.

In this paper, the feasibility of the framework is discussed by investigating the training of one network for a limited rotational speed variation.

2.3 Simulation study

In a first simulation study the ability to differentiate between healthy and faulty stages is tested. The second study investigates fault degree detection with different fault strengths where the fault level has been simulated by increasing the magnitude of the sideband harmonics as an indication to the fault with higher level.

2.3.1 Fault classification

The WT model is run for healthy and faulty condition with a selected variable speed variation between 924 and 937 rpm as shown in Figure 5. Analysis of the real SCADA data suggested such a variation in 5 minutes.

For each condition, the current signal is recorded for 300 seconds at 5 kHz sampling frequency. Periods of two seconds of data are selected for analysis using the Fast Fourier Transform (FFT) algorithm. This window length is identified as the shortest possible with a sufficient resolution to capture all harmonics of interest. The frequency spectrum of each window consisting of 250 amplitudes acts as a 'sample' for ANN fault detection. All samples from healthy and faulty stages are mixed and randomly split in training and testing. A classification as 'healthy' or 'faulty' is trained with scaled conjugate gradient backpropagation. The number of neurons and training samples are varied in a sensitivity study. Network training is repeated a number of times to investigate the impact of the random selection of training samples.

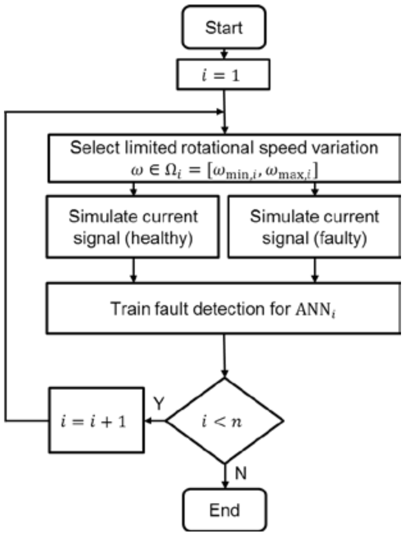

Figure 3: Workflow for training of fault detection algorithm.

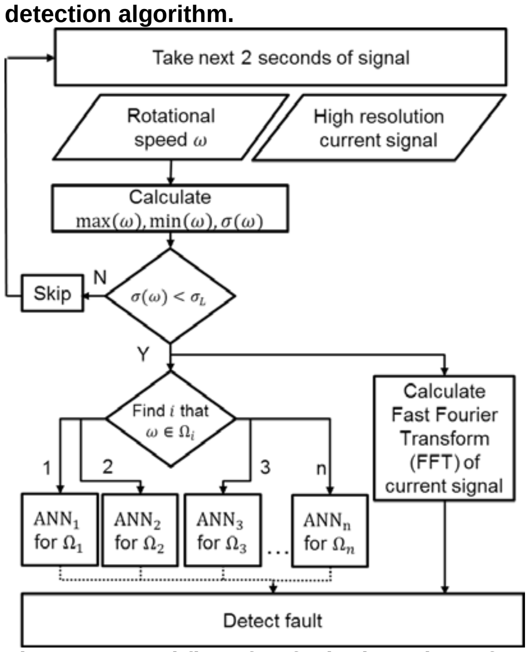

Figure 4: Workflow for fault detection after training.

2.3.2 Fault degree detection

Additional to the above described two simulations representing permanent healthy and faulty condition, two further runs are used to investigate fault development. The first simulation applies a linear increasing fault during 300 seconds. In the second run a fault occurs only at a certain point in the simulation.

A fitting neural network with a tansig transfer function in the output layer is used to predict a fault degree between 0 and 1. All samples from the first simulation plus 100 randomly selected samples of the linear increasing fault simulation are used for training the ANN. Network training is repeated with identical data to illustrate differences resulting from suboptimal training.

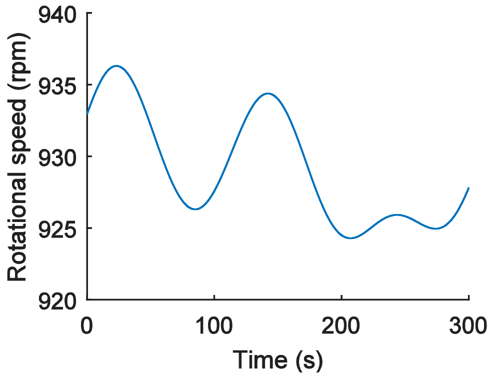

Figure 5: Rotational speed variation in simulation study.

3 Results of simulation study

3.1 Fault classification

The results of the simulation study with current signals from healthy and faulty conditions are presented in Table 3 considering accuracy as correct classification of both ‘healthy’ and ‘faulty’ stages. The median detection accuracy between 93.5 and 98 % for different ANN and training length configurations distinctly higher than random classification (50 % accuracy) shows that ANN fault detection using current signals under non-stationary conditions is feasible.

Table 3: Accuracy of ANN condition detection from frequency spectrum given as median percentage from 250 training repetitions.

Number of neurons used:	Training with 100 samples, testing with 200 samples	Training with 150 samples, testing with 150 samples	Training with 200 samples, testing with 100 samples
2	93.5	96.7	98.0
5	94.5	96.7	98.0
10	95.5	97.3	98.0
25	95.5	97.3	98.0
50	95.0	97.3	98.0

3.2 Transient and variable fault detection

Results of the transient and variable fault detection are presented in Figure 5 and 6. Although the significant differences between three ANNs trained with the same input indicate that further optimisation of training and algorithm settings might be reasonable, the general fault development is successfully detected. Unsurprisingly, the fault degree detection is less accurate than the simple healthy or faulty classification. Regardless, even the rough detection of the strength of a fault enables better monitoring of condition changes.

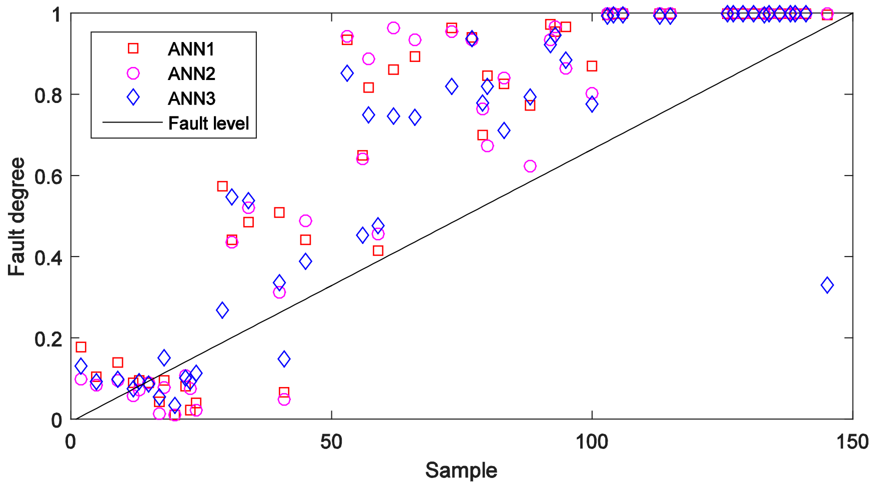

Figure 5: ANN fault degree detection of a linear increasing fault.

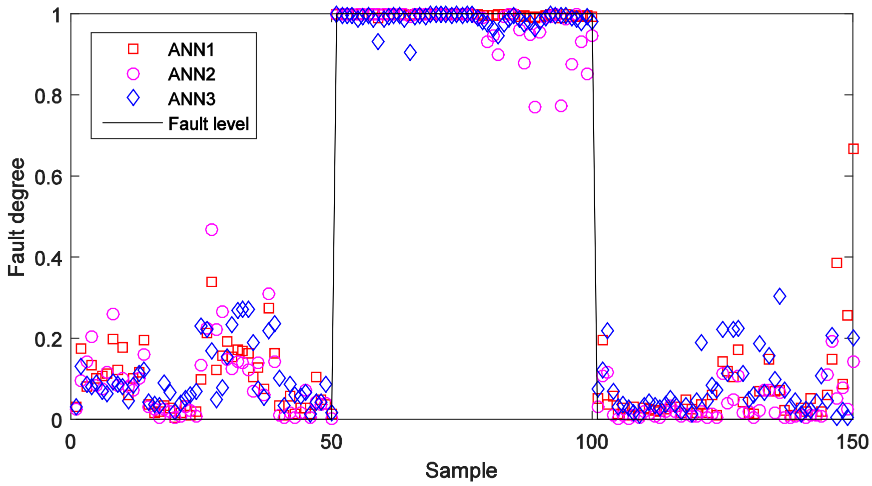

Figure 6: ANN fault detection of a transient fault.

4 Conclusion

A technique to detect mechanical faults in variable speed WTs via the CSA and ANN is proposed. A framework is discussed for training of fault detection with simulated signals from faults for later online detection in real WTs. For each set of limited rotational speed variation a separate ANN will detect the fault.

In a simulation study of a rotor imbalance under varying rotational speed as expected in 5 minutes operation the feasibility of the fault detection approach is demonstrated. Simple classification of healthy or faulty condition is achieved with a high accuracy. In a further step towards fault prognosis, the severity of the fault is successfully detected.

Future work has to be done to validate the fault detection algorithm with experimental data. A full test of the proposed framework has to be conducted including different sets of rotational speed variation. In terms of fault prognosis, optimisation of the ANN settings might increase the fault degree detection accuracy.

Acknowledgement

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