Neural Networks for Wind Turbine Fault Detection via Current Signature Analysis

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1. Introduction

With an increasing number of wind turbines (WTs) being installed in offshore and remote locations, there is a need for cost-effective and predictive maintenance. 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 a reliable CMS, there is a need for information to describe the state of each monitored component and a reliable technique for fault feature extraction and fault diagnosis. In other words, the most important elements of a WT CMS are the measured signal and the technique to extract useful features from the measured signal. If this can be done effectively, this could lead to reduced maintenance costs, the avoidance of damage to hardware and less unscheduled downtime. Generally, the signals used in 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].

Generator electrical signal analysis has been shown to have advantages over vibration signals for condition monitoring in terms of accessibility, cost, implementation, and reliability [5]-[6]. The costs and complexity involved in current measurements are significantly lower than many other signals such as vibration, because the current signals are already and continuously measured in WTs and thus no additional sensors are required [7]. However, it is a challenge to extract WT fault signatures from non-stationary current measurements, due to variable-speed operating conditions of WTs. 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 without a reliable method.

Generally, condition monitoring and fault detection involves some method to extract fault signatures from the monitored signal. The fast Fourier transform (FFT) and the short–time Fourier transform (STFT) are perhaps the most well-known methods of spectral analysis used to process signals for condition monitoring and fault diagnosis [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. They 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 electrical signal and particularly current signature analysis (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 stochastic 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.

1. Approach

This research in this paper 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 in this paper with operational data of five 2.5MW turbines were recorded by the SCADA system over the period of 1 year. The measured data (SCADA data) were recorded at 10-min intervals and 32Hz sampling frequency including wind speed, wind direction, pitch angle, rotational speed and three-phase power output. The model parameters used are detailed in Table 1. The phases were taken in this paper are illustrated Table 2.

Table 1: Model parameters.

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

2. Main body of abstract

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

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 data recorded by 2.5MW 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 to measured generator speed. It is clear the model is in good agreement with the measured data.

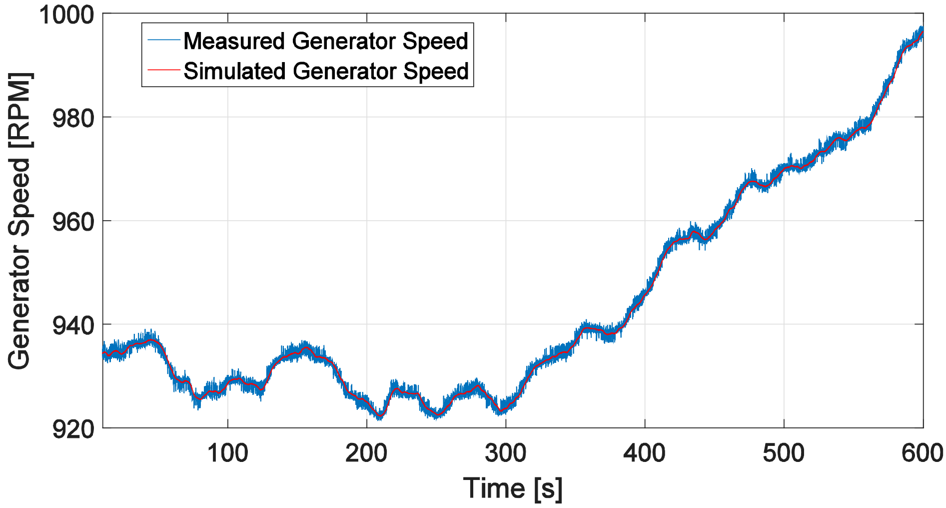

Figure 1: Example of model validation considering generator speed.

Rotor eccentricity is used as an illustrative example to investigate the use of an ANN with the aim of developing knowledge based fault detection method for performing online fault detection in variable speed WTs. During rotor eccentricity, certain sideband harmonics around the fundamental frequency in the machine current signal occur and their amplitude increases proportionally with the fault level. It was experimentally proven [5] that rotor eccentricity faults actually 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 components, 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. Components with frequencies at 60 Hz and 34Hz are intentionally simulated to be present in the healthy machine spectrum as a dynamic eccentricity. Other spectral components are labelled and identified by the equation (1) which are generated by the rotor eccentricity faults.

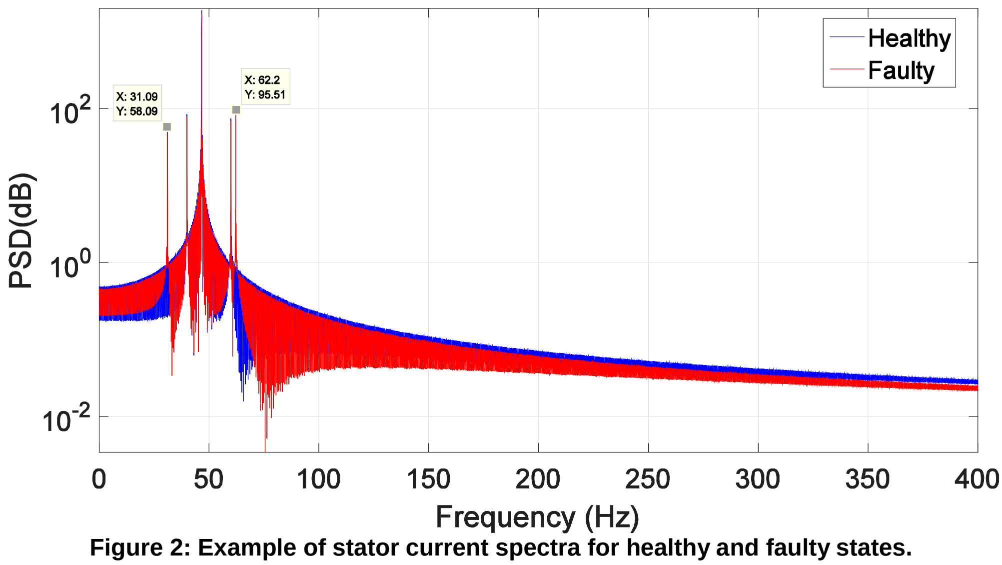

Figure 2: Example of stator current spectra for healthy and faulty states.

Automated fault detection with Artificial Neural Networks

The WT model is run at variable speed under both healthy and faulty rotor conditions. For each condition, data are recorded for 600 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.

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 finding non-linear relationships and automated processing. With data-driven training, the network learns 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.

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 is selected with the information of the rotational speed extrema.

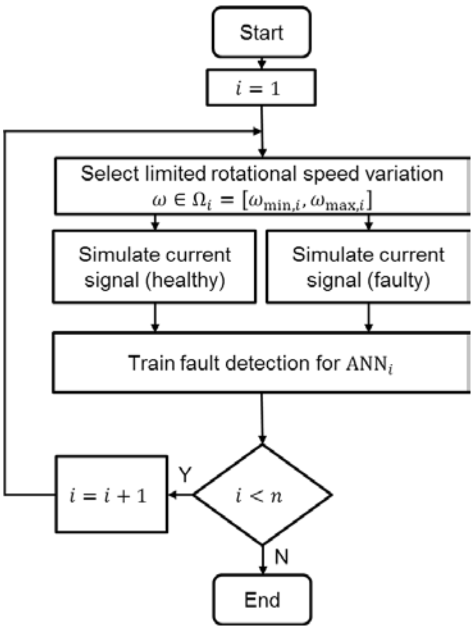

Figure 3: Workflow for training of fault detection algorithm.

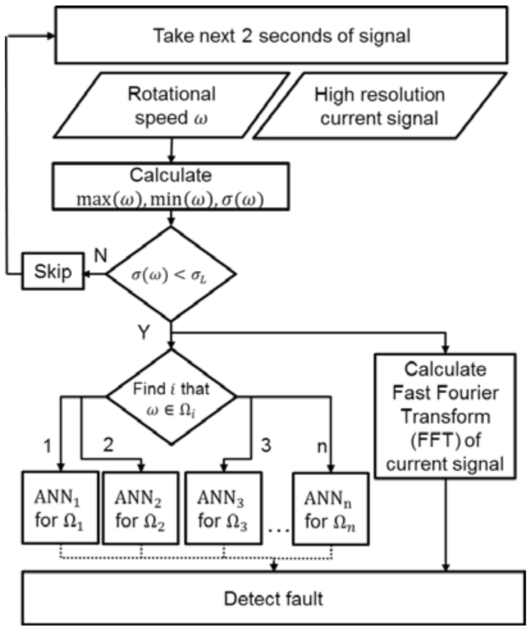

Figure 4: Workflow for fault detection after training.

In this paper, the feasibility of the framework is discussed by investigating the training of one network for a limited rotational speed variation between 924 and 937 rpm in 300 seconds' operation, as shown in Figure 5. The current signal is simulated for healthy and faulty conditions based on the same rotational speed variation. Subsequently, the signals are split in each 150 data sets of 2 second periods. Data sets from healthy and faulty conditions are mixed and randomly split in training and testing. The inputs for ANN fault detection consist of 250 frequency components provided by FFT from each 2 second period. A simple classification as 'healthy' or 'faulty' was achieved with scaled conjugate gradient backpropagation. The number of neurons and training samples were varied in a sensitivity study. Network training was repeated a number of times to investigate the impact of the random selection of training samples.

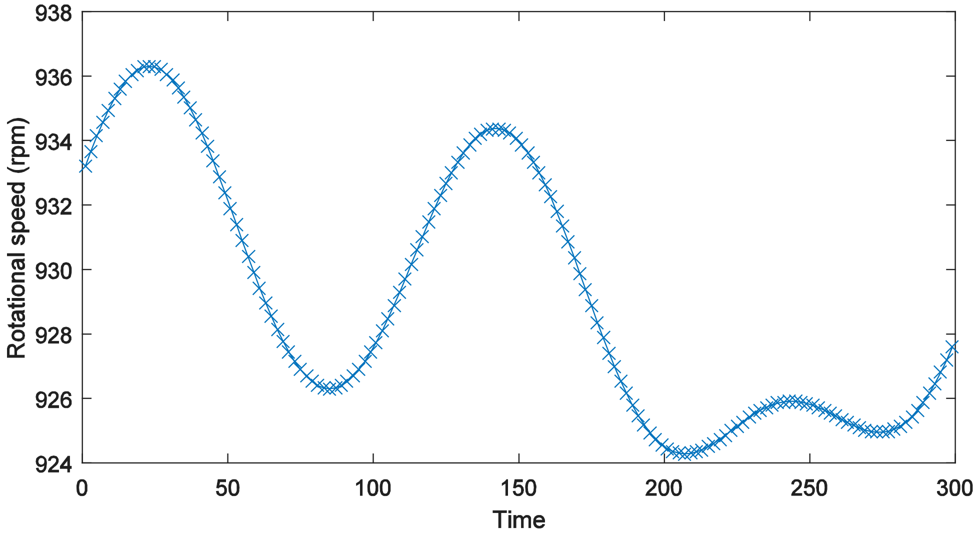

Figure 5: Rotational speed variation in simulation study.

Results of simulation study

The results of the simulation study with current signals from healthy and faulty conditions are presented in Table 3 considering accuracy as correct classifications of both ‘healthy’ and ‘faulty’ conditions. 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.

ANN configuration:	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 neurons	93.5	96.7	98.0
5 neurons	94.5	96.7	98.0
10 neurons	95.5	97.3	98.0
25 neurons	95.5	97.3	98.0
50 neurons	95.0	97.3	98.0

3. Conclusion

A technique to detect mechanical faults in variable speed WTs via the current signal and neural networks is proposed. A simulation study of a rotor imbalance demonstrates the ability to detect faults with a high accuracy. The full paper will present the results of detecting fault levels, i.e. to forecast the expected degree of deterioration over a particular time frame. The results of detecting transient and permanent faults will also be presented.

4. Learning objectives

This paper demonstrates how an ANN can be used to detect fault signatures in current signals under challenging non-stationary conditions.

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