

# Wind Turbine Intelligent Gear Fault Identification

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## ABSTRACT

This paper aims to present the development of a framework for monitoring of wind turbine gearboxes and prognosis of gear fracture faults, using vibration data and machine learning techniques. The proposed methodology analyses gear vibration signals in the order domain, using a shaft tachometer pulse. Indicators that represent the health state of the gear are algorithmically extracted. Those indicators are used as features to train diagnostic models that predict the health status of the gear. The efficacy of the proposed methodology is demonstrated with a case study using real wind turbine vibration data. Data is collected for a wind turbine at various time steps prior to failure and according to the maintenance reports there is enough data to form a healthy baseline. The data is classified according to the time before failure that the signal was collected. The learning algorithms used are discussed and their results are compared. The case study results indicate that this data driven model can lay the groundwork for a robust framework for the early detection of emerging gear tooth fracture faults. This can lead to minimisation of wind turbine downtime and revenue increase.

## 1. INTRODUCTION

Renewable energy generation capacity must be increased if the ambitious targets of climate protection and energy security are to be achieved. Wind energy harvesting has become a strong and fast growing renewable energy technology worldwide due to recent technological advances and commercial growth. To ensure wind energy is truly competitive with traditional fossil fuel and nuclear energy generation, ways of reducing the cost of energy cost must be investigated. A large proportion of the total cost of energy from wind in large wind farms is composed of operation and maintenance costs. These costs can be reduced if incipient machinery faults are successfully detected before they become catastrophic failures. Un-

expected failures of components directly translates to wind turbine downtime, loss of reliability and revenue reduction. Therefore, effective wind turbine condition monitoring (CM) that enables optimum maintenance actions is becoming critical (Crabtree, Zappalá, & Hogg, 2015).

The main two categories of maintenance for wind turbines are either corrective or preventive maintenance. Corrective maintenance concerns maintenance that is only performed once a component fails completely, whereas preventive maintenance is performed before the occurrence of a potential failure (Nielsen & Sørensen, 2011). Preventive maintenance can be further classified into scheduled maintenance and condition-based maintenance. Scheduled maintenance refers to maintenance that happens at a fixed frequency whereas condition-based maintenance involves continuous health monitoring of wind turbine components. This type of maintenance utilises an estimation of the current and future condition of a component in order to provide an optimised maintenance scheduling that prevents failures without resorting to over-maintenance (Verbert, De Schutter, & Babuška, 2017). This optimised maintenance scheduling offers extended machine lifetime, as well as reduced maintenance costs and downtime.

Current practice in the wind turbine industry involves scheduled maintenance, but owing to recent developments in the field of sensing and signal processing, modern wind turbines are equipped with CM systems for the active remote monitoring of their components (Byon, Pérez, Ding, & Ntaimo, 2011). CM systems provide signals (vibration or electrical) whose information is used to take suitable maintenance actions.

One of the most affected parts in a wind turbine in terms of reliability, is the wind turbine gearbox that bears alternating loads (Carroll, McDonald, & McMillan, 2015). Common failure modes include gear or bearing pitting and scuffing. If breakdown of the gearbox occurs it significantly increases the downtime and it is the most expensive component to maintain throughout the expected 20-year design life of a wind turbine. Effective health diagnosis of the gearbox is therefore vital in

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wind turbine fault detection and decision making. To achieve this, a robust predictive framework is required.

To this end, a multi-criteria condition monitoring framework is proposed that can be used as a basis for a robust condition-based maintenance tool. This framework combines several vibration signal features as input and returns the condition of the gear as an output.

Hence, this paper aims to present the development of a framework concerning the processing of vibration data and training of appropriate models for the condition monitoring of wind turbine gearboxes, focusing on specific failure modes. Section 1 introduces the paper's scope and motivation of research. Section 2 refers to the research background which involves the analysis of the vibration signals and the fault detection process, taking into account the variable speed of the turbine. In Section 3 the structure of a wind turbine gearbox is explained and the proposed methodology on vibration data analysis and model training is presented. Section 4 demonstrates the implementation and validation of the methodology in a case study concerning a real wind turbine gear fault. Section 5 presents the results of the case study and Section 6 concludes with the discussion and future research steps for the methodology development. The novelty in this paper lies in the combination of identification techniques used to detect the fault and train the prognostic model. A further element of novelty is the high quality vibration data and failure mode used to validate the techniques in the case study.

## 2. RESEARCH BACKGROUND

The aim of health condition prognostics is to predict the equipment future health conditions and the remaining useful life, based on the condition measurements at each inspection point. Some prognostics methods are also capable of estimating the associated prediction uncertainties. The health condition prediction methods can be divided into model-based methods and data-driven methods. The model-based methods, also known as the physics-of-failure methods, perform reliability prognostics using equipment physical models and damage propagation models. Model-based prognostics methods have been reported for analyzing component reliability such as bearings (Marble & Morton, 2006) and gearboxes (Kacprzyński, Roemer, Modgil, Palladino, & Maynard, 2002), (Li & Lee, 2005). However, physics-of-failure models pose some limitations in building models and calculating dynamic responses in complex systems. On the other hand, data-driven methods directly utilize the collected condition monitoring data for health condition prediction, and do not require physics-of-failure models. Examples of the data-driven methods include the proportional hazards model (Banjevic, Jardine, Makis, & Ennis, 2001), the Bayesian prognostics methods (Gebraeel, Lawley, Li, & Ryan, 2005), and the ANN

based prognostics methods (Tian, 2012), (Tian, Wong, & Safaei, 2010).

Based on data-driven approaches, vibration analysis is one of the most commonly used mechanisms for condition monitoring of wind turbines, especially on gearboxes (Randall, 2011). Vibration signals produced by the rotating gears and bearings whose current health conditions need to be diagnosed are commonly analyzed either by broadband-based methods or spectral line analysis methods (Lu & Chu, 2010). In broadband analysis, parameters such as root mean square, or kurtosis are calculated based on the obtained output signals. Spectral line analysis methods measure the increase in the frequencies of the impulse signals and can indicate when a component failure is about to occur (Lu & Chu, 2010).

Vibration analysis requires the installation of acceleration transducers on the gearbox surface, which offers sensitivity in fault discovery. Different vibration analysis methods are evaluated and presented in (Sheng, 2012). In terms of diagnosis methods, spectral kurtosis has been used to detect a tooth crack in the ring gear of a wind turbine planetary gearbox (Barszcz & Randall, 2009). A demodulation analysis method based on ensemble empirical mode decomposition and energy separation to diagnose planetary gearbox faults is proposed in (Teng, Wang, Zhang, Liu, & Ding, 2014). Sideband energy ratio can be calculated from spectrum data and it is sensitive to amplitude and frequency modulation, giving an indication of the health state of the gear (Hanna, Hatch, Kalb, Weiss, & Luo, 2011).

A condition based maintenance method applied on a wind farm level is proposed in (Tian, Jin, Wu, & Ding, 2011), using Artificial Neural Networks. Support Vector Machines (SVMs) with different kernels are tested on wind turbine gearbox vibration data, examining imbalance and misalignment in (Santos, Villa, Reñones, Bustillo, & Maudes, 2015). SVMs are also used in (Leahy, Hu, Konstantakopoulos, Spanos, & Agogino, 2016) to diagnose wind turbine faults based on operational data.

A decision tree is a simple representation used for classifying. As shown in Figure 1 (Goodfellow, Bengio, & Courville, 2016), each node of the decision tree is associated with a region in the input space, and internal nodes (circles) break that region into one sub-region for each child of the node (typically using an axis-aligned cut). Space is thus sub-divided into non-overlapping regions, with a one-to-one correspondence between leaf nodes (squares) and input regions. Each leaf node usually maps every point in its input region to the same output.

## 3. METHODOLOGY

The methodology elaborated in this paper concerns the determination of the fundamental gear frequencies based on

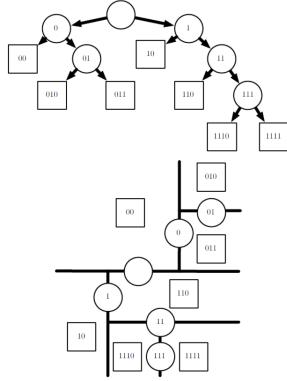


Figure 1. Diagrams describing how a decision tree works. Each node of the tree chooses to send the input example to the child node on the left (0) or the child node on the right (1) (Top). The tree divides space into regions (Bottom). (Goodfellow et al., 2016)

the wind turbine gearbox vibration signal, the angular re-sampling of the signal due to the variable speed, the feature extraction and the model training. This methodology was developed using MATLAB programming language and utilises the signal processing and classification libraries.

### 3.1. Wind Turbine Vibration Signal

In this section, the wind turbine gearbox structure, signal acquisition system and processing are presented.

#### 3.1.1. Wind Turbine Gearbox Structure

Thanks to the advantages of large transmission ratio and strong load-bearing capacity, planetary gearboxes are widely used in wind turbines. A typical wind turbine gearbox structure consists of three stages: one low speed planetary stage (PS) and two parallel stages, namely a high speed (HS) stage and an intermediate speed (IS) stage. The main shaft is connected to the planet carrier (PLC) and the HS pinion of the gearbox is coupled to the generator.

The gearbox internal structure is shown in Figure 2 and the characteristic gear mesh frequencies (GMF) are determined in Table 1.

Table 1. Fundamental Gear Frequencies

Gear Element	# Teeth	Speed	GMF
PS Planet Carrier		$f_a$	
PS Ring Gear	$Z_r$	Fixed	
PS Planet Gear	$Z_p$	$f_a \frac{Z_r}{Z_p}$	$f_a Z_r$
PS Sun Pinion	$Z_s$	$f_s = f_a (1 - \frac{Z_r}{Z_s})$	
LS Gear	$Z_l$		$Z_{ip} f_i$
IS Pinion	$Z_{ip}$	$f_i = \frac{Z_l}{Z_{ip}} f_s$	
IS Gear Wheel	$Z_{ig}$		$Z_h f_h$
HS Pinion	$Z_h$	$f_h = \frac{Z_{ig}}{Z_h} f_i$	

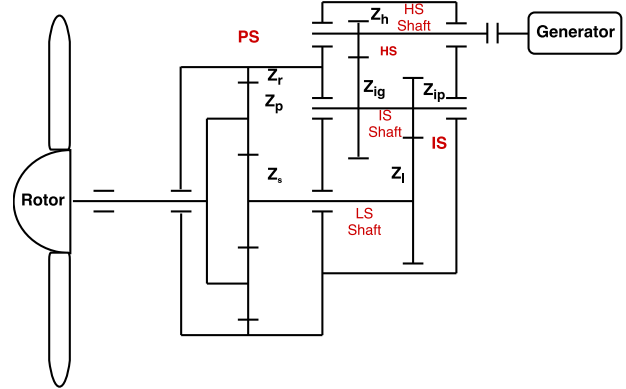


Figure 2. Gearbox Internal Nomenclature

#### 3.1.2. Wind Turbine Signal Acquisition

Vibration signals are obtained by accelerometers which are mounted on the gearbox surface. Each sensor has a different sensitivity and represents a different component of the gearbox. A tachometer pulse signal is usually provided as well, so that the equal time sampled data can be converted into equal shaft angular space data. The multi-channel vibration signals are collected and analysed in the frequency domain. The fundamental frequencies of the gears are computed according to Table 1.

#### 3.1.3. Data Pre-Processing: Angular Re-sampling

The required rotational speed of the wind turbine rotor is determined by the torque controller in response to the wind speed and therefore is not constant. In variable-speed rotating machinery, vibration signals are non-stationary due to speed alteration. Due to the rotor speed variation within the time window of the data acquisition, conventional signal processing techniques are insufficient because spectral leakage can occur in the frequency domain. The frequencies of the vibrations though, are proportional to the rotational speed and the constants of proportionality are the orders. By re-sampling the non-stationary vibration signals, it is possible to reconstruct cyclo-stationary vibration signals in the angular domain, to avoid the mismatch between angle and time information. Therefore, computed order tracking is used and its principles are explained in (Fyfe & Munck, 1997).

The data is recorded by the tachometer and constant time increments. Each pulse of the tachometer signal represents a once-per-shaft-revolution event, so that is used to measure the shaft speed and is the reference for measuring the vibration phase angle. The signal is then up-sampled and low pass filtered. The re-sampled signal is interpolated linearly into a uniform phase domain grid. Then, the Short-Time Fourier Transform of the interpolated signal is computed.

### 3.2. Fault Detection

When a gear has a local defect, such as a fatigue crack, the stiffness of the neighboring teeth is affected and this produces changes in the vibration signal. These changes are defined by amplitude and frequency modulation. The modulated gear meshing vibration is given by Eq. (1) (McFadden, 1986).

$$y(t) = \sum_{m=0}^M X_m(1 + a_m(t)) \cos(2\pi m Z f_s t + \phi_m + \beta_m(t)) \quad (1)$$

Where  $Z$  is the number of teeth on the gear,  $f_s$  is the shaft rotational frequency and therefore  $Z f_s$  is the mesh frequency,  $a_m(t)$  is the amplitude modulation function,  $b_m(t)$  is the frequency modulation function,  $\phi_m$  is the initial phase of amplitude modulation and  $m$  is the integer.

As the modulation is periodic with the gear shaft rotation frequency  $f_s$ , these functions may be represented by discrete Fourier series, as in Eq. (2, 3).

$$a_m(t) = \sum_{n=0}^N A_{mn} \cos(2\pi n f_s t + a_{mn}) \quad (2)$$

$$b_m(t) = \sum_{n=0}^N B_{mn} \cos(2\pi n f_s t + \beta_{mn}) \quad (3)$$

Note that the modulation functions may differ with  $m$ .

In the frequency domain, the Fourier transform  $Y(f)$  will comprise the fundamental and harmonics of the meshing frequency surrounded by modulation sidebands. Multiple frequencies in the modulation cause multiple sidebands to appear in the spectrum. These sidebands occur at frequencies of  $Z f_s \pm k f_s$  where  $k$  is an integer of 1 or higher.

The signal analysis is performed through the MATLAB signal processing toolbox. Spectral line analysis is used to diagnose the health state of the vibration signals. After the application of order tracking, the spectrum has clear distinct frequency components which allows for an automatic procedure of algorithmic order peak detection. The health indicators used to diagnose the state of the gear are computed on the second harmonic of the gear mesh frequencies of the vibration signals:

- Sideband Energy Ratio (SER)
- Sideband Average Power (SAP)
- Narrowband Kurtosis (KUR)

The SER algorithm sums the amplitudes of the first six sideband peaks on each side of the center mesh frequency  $\sum_{i=-6}^6 A_{SB,i}$  and divides by the amplitude of the center mesh frequency  $A_F$ , as in Eq. (4).

$$\text{SER} = \frac{\sum_{i=-6}^6 A_{SB,i}}{A_F} \quad (4)$$

For a healthy gear mesh the sidebands have a small amplitude compared to the center mesh frequency. As damage develops on a gear tooth, the sideband rise in amplitude which results in a larger SER value.

The SAP algorithm calculates the total power of the first six sidebands rising around the center mesh frequency. The power is normalised with the length of the data segment.

$$\text{SAP} = \frac{\sum_{i=1}^N |A(i)|^2}{N} \quad (5)$$

Where  $N$  is the length of the narrowband data segment and  $A$  is the Amplitude of the signal.

Kurtosis is a measure of how outlier-prone a distribution is. Assuming that the part of the spectrum that includes the center mesh frequency and a frequency interval of up to six multiples of the shaft rotational speed represents a distribution, then the kurtosis is calculated. If the kurtosis has a high value it means that the distribution is quite sharp and most values are concentrated in the center frequency. In case of a fault development, sidebands have increased amplitude in a spectrum, which means that the values are more distributed towards the tails, so the kurtosis is lower.

$$\text{KUR} = \frac{\frac{1}{N} \sum_{i=1}^N (A(i) - \bar{A})^4}{(\frac{1}{N} \sum_{i=1}^N (A(i) - \bar{A})^2)^2} \quad (6)$$

Lastly, the model should take into account that loading conditions affect the gear vibration signature to a great extent. Thus, the reference torque is calculated based on the produced electrical power  $P$  and generator speed  $\omega$  and is normalised with the rated torque  $T_R$ .

$$\text{Ref. Torque} = \frac{P}{\omega T_R} \quad (7)$$

### 3.3. Fault Prediction Model

The final aim of the methodology is to train fault prediction a model based on the extracted features. The features are labeled as 'healthy' or 'faulty' based on whether the gearbox eventually failed within a time frame of 2 months. The features considered for the model training are presented in Table 2. These include the health indicators but also the reference torque, so as to distinguish any signal variations due to loads from the variations due to faults.

A decision tree classifier is trained based on historic data. It's a non-parametric supervised learning method used for classification and its goal is to create a model that predicts the value

Table 2. Input features and equations.

Input Feature	Equation
SER	$\sum_{i=-6}^6 A_{SB,i}$
SAP	$\frac{A_F}{\sum_{i=1}^N  A(i) ^2}$
KUR	$\frac{\frac{1}{N} \sum_{i=1}^N (A(i)-\bar{A})^4}{(\frac{1}{N} \sum_{i=1}^N (A(i)-\bar{A})^2)^2}$
Ref. Torque	$\frac{P}{\omega T_R}$

of a target variable by learning simple decision rules inferred from the data features.

The cross validation method used to assess the performance for the model is *k*-fold cross validation with 5 folds. The validation accuracy calculated then is the average mean squared error between the observations in a fold when compared against predictions made with a tree trained on the out-of-fold data. The model is trained recursively 10000 times in order to ensure consistency in the results. The average model accuracy is calculated based on the mean value of all the trained model accuracies.

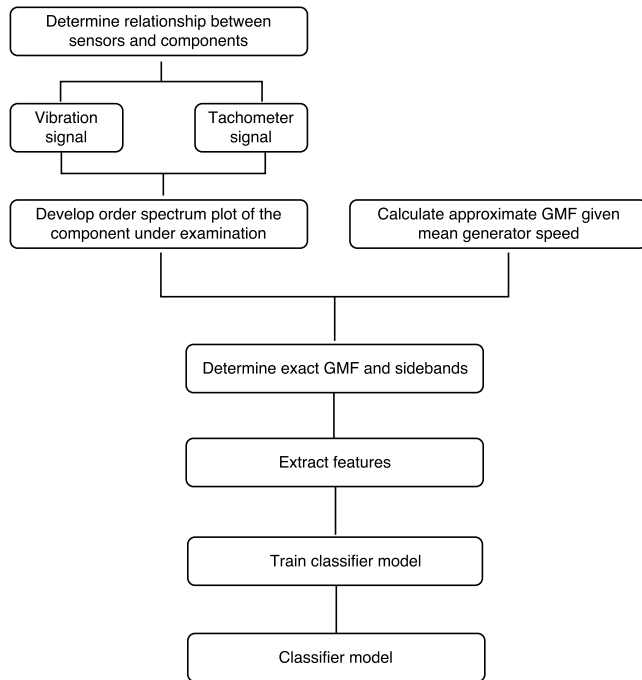


Figure 3. Methodology flowchart.

**4. CASE STUDY**

To validate the suggested methodology, a case study on vibration data from the same type of gearbox but for three different wind turbines is presented. The wind turbines considered in this study are rated at between 1.5 and 3 MW. The vibration data acquisition system consists of eleven accelerometers and a tachometer on the high speed shaft. The generator

speed, the wind speed and the power produced by the turbine are also recorded. The acquisition time of the signal is between 10 and 11s and the sampling frequency is over 25kHz. Ranges are provided for the rated power, sampling period and sampling frequency for confidentiality reasons.

This failure occurs on the pinion tooth of the intermediate stage of the gearbox. The tooth issue has been recorded as a gear tooth tip and flank fracture, as shown in Figure 4. Root cause analysis of this gear tooth issue has not yet been completed by the OEM and is out with the scope of this paper.

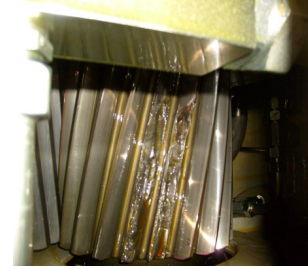


Figure 4. Broken pinion on intermediate shaft

Data is collected for the wind turbines at various time steps prior to failure. The oldest dataset dates back to 2.5 years prior to failure and according to the maintenance reports the gearbox at this time is in a healthy state.

The data is classified as ‘faulty’ 2 months prior to failure, as this is the time when the sidebands are highly prominent (see Section 5) and at the same time is a sufficient period to schedule maintenance activities.

**5. RESULTS**

The signals obtained from the sensor on the intermediate speed shaft are collected and order tracking is applied. The order domain spectra of the vibration signals at different acquisition dates prior to failure is shown in Figure 5. The order number axis shows the high speed shaft order, where the tachometer pulse is located. The vibration signal from gears depends highly on load and therefore the signatures plotted belong to similar loading conditions (Ref. Torque=0.8). The rising of sidebands around the center mesh frequency (order 8.6) becomes more prominent in time steps closer to failure, as expected.

To further illustrate the difference between healthy and faulty vibration signatures, Figure 6 shows order spectra for the same gearbox, which eventually failed, at 2 years (healthy) and 2 weeks (faulty) before failure respectively.

As such, the features explained in Section 3 are extracted from each vibration signal. The health indicators as a function of the reference torque are shown in Figure 7. The data is classified according to the time before failure that the signal was collected.



Figure 5. Order Spectra of Intermediate Speed Shaft Acceleration for Varying Times Prior to Failure

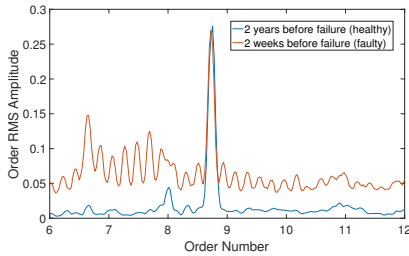


Figure 6. Order Spectra of Healthy and Faulty Signal

The input features of the prediction model are given in Section 3.3.

The performance of the classifier is visualised in the confusion matrix shown in Figure 8. Faulty condition can be translated as up to 2 months prior to failure. The probability density function of the model’s accuracy after the 10000 runs is shown in Figure 9. The mean value is 95.6% and the standard deviation is 0.011.

Out of the 27 healthy samples only 1 is detected as faulty and out of the 18 faulty samples only 1 is detected as healthy. Overall, 95.6% of the predictions are correct and 4.4% are wrong classifications.

The downside of predicted faulty but actually healthy is a redundant inspection. The downside of predicted healthy but actual faulty is more severe because it can lead to critical failure.

Practically, this means that the model can either diagnose that a gear is healthy or predict that the gear is 1-2 months before complete failure. With continuous monitoring, this can give sufficient time for maintenance actions and/or changes in operation to extend lifetime.

## 6. CONCLUSIONS

This paper aims to present a framework for wind turbine vibration data processing and fault identification and prognosis on component level. First, an overview of the current state of research in wind turbine condition monitoring was presented. Then, proposed methodology was presented and elaborated

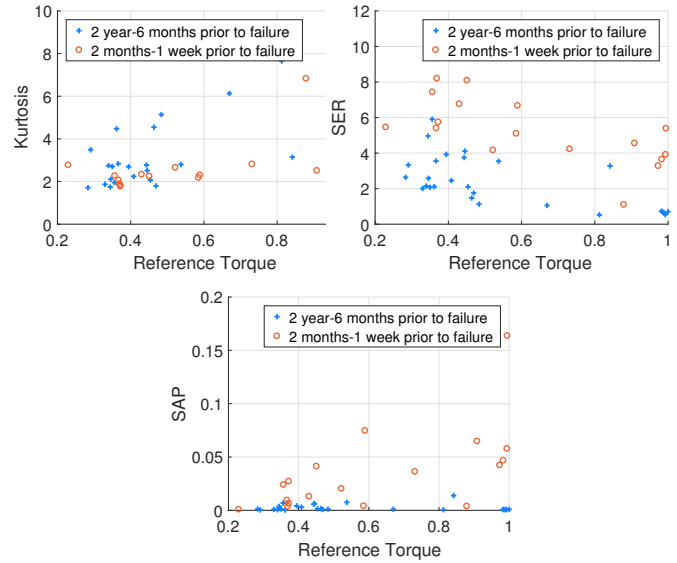


Figure 7. Health indicators as a function of the reference torque. Narrowband kurtosis (top left), SER (top right) and SAP (bottom).

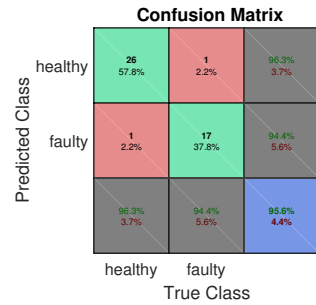


Figure 8. Confusion Matrix

through a case study using real wind turbine vibration data. The case study validated the model performance and effectiveness. According to the results, SAP, SER, narrowband kurtosis and a decision tree algorithm can be used to correctly classify healthy or faulty data in discrete time ranges. These indicators have some dependence on the loading conditions and therefore the torque is taken into consideration in the model training.

Future research steps include further model verification using datasets from more wind turbine fleets, so that model robustness is increased. Testing other types of learning algorithms will also be considered.

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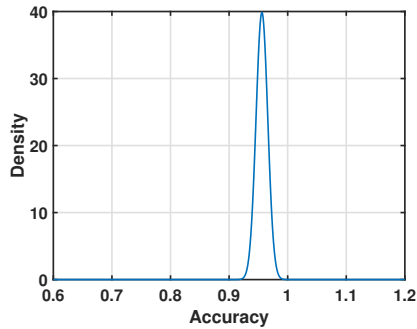


Figure 9. Probability Density Function of Classification Model Accuracy

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