Acoustic condition monitoring of wind turbines: tip faults

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Abstract

As a significant and growing source of the world's energy, wind turbine reliability is becoming a major concern. At least two fault detection techniques for condition monitoring of wind turbine blades have been reported in early literature, i.e. acoustic emissions and optical strain sensors. These require off-site measurement. The work presented here offers an alternative non-contact fault detection method based on the noise emission from the turbine during operation. An investigation has been carried out on a micro wind turbine under laboratory conditions. 4 severity levels for a fault have been planted in the form of added weight at the tip of one blade to simulate inhomogeneous debris or ice build up. Acoustic data is obtained at a single microphone placed in front of the rotor. Two prediction methods have been developed and tested on real data: one based on a single feature – rotational frequency spectral magnitude; and another based on a fuzzy logic interference using two inputs - spectral peak and rotational peak variation with time. Results show that the single spectral peak feature can be used to determine fault severity in ranges. The implementation of the fuzzy logic using a further input feature is shown to significantly improve the detection accuracy.

1. Introduction

As one of the worlds fastest growing renewable energy sources it is important to reduce costs of wind energy. In this way it can compete with already established energy sources [(1)]. Since wind turbines are commonly placed in remote areas and their structure is hard to access, the elevated cost of operation and maintenance has become a major issue. Furthermore, the wind turbine downtime tends to be long, which affects the availability of wind power directly because of its poor reliability [(2)]. Condition monitoring and fault diagnosis of wind turbines is therefore essential for wind energy's further development.

The work presented here explores an alternative method for the detection of wind turbine blade faults. In contrast to existing condition monitoring techniques for blades, such as Acoustic Emission, the proposed approach is a non-contact technique that aims to detect differences in the wind turbine noise. Measuring and predicting wind turbine noise is already a significant area of study in environmental impact [(3)].

The method proposed uses the acoustic signal emitted by the operating turbine to extract signal features that indicate the presence and progress of a blade fault. It is known that blades are primarily responsible for noise generation in wind turbines (4). For instance, when ice builds up at the tip of a turbine blade, it not only adds extra weight to that particular blade (potentially creating imbalance), but also alters the way in which the aerodynamic interaction with the tower happens. As a fault develops, differences in this signal indicate its progress through the various severity stages. The extraction and classification of acoustic signal features has already been shown as a powerful method to detect turbine condition in recent work presented by the authors (5).

This paper presents details of the measurement system and test methodology in the use of acoustic condition monitoring. Two simple features are extracted from the signal, namely the spectral amplitude of the rotational frequency and its variation in time. These are shown to be correlated with fault progression. Feature mapping of a single feature and the use of fuzzy logic to aggregate both features in the analysis of an unknown signal are shown to be successful in the detection and classification of blade faults.

2. Background

A wind turbine system can be divided into at least four subsystems. Given the difference in the mechanical nature of each subsystem, different condition monitoring and fault detection methods may apply for each case. The subsystems that compose the entire wind turbine can be classified as: gearbox and bearing; generators; power electronics and electric controls; rotors, blades and hydraulic controls (6).

2.2 Condition Monitoring of Wind Turbine blades

Composite blades often suffer delamination and cracks as a result of creep fatigue and corrosion fatigue of wind turbine rotors (6). Another common type of fault is the non-uniform accumulation of dirt, ice, moisture, etc. on the blades. Commonly, this can result in rotor imbalance and loss of energy capture efficiency due to blade's increased roughness. Imbalance can also occur as a result of manufacturing defects or accumulated damage to the rotor blades (7).

Two main techniques have been used in the past for blade fault diagnostics, namely acoustic emission (AE) and optical strain sensors. AE focuses on measuring the rate and properties of sound waves that materials release when subject to strain or stress. Measurements can be taken using piezo-ceramic receivers placed strategically on the blade's surface (8). Optical strain sensors detect blade loading, thus strain, by measuring the slight bending of the blade. As the fibre bends with the blade, an alteration occurs in regards to reflection and refraction of light inside the optic-fibre. These alterations can be detected and quantified by measuring the light that arrives at the end of the fibre. Measurements can be done by either fiber-optic Bragg grating (FBG) or extrinsic Fabry-Perot interferometric (EFPI). FBG is most common (6, 9). Yuji and Bouno reported experiments where, for a small wind turbine, a piezoelectric impact sensor was used (10); in another report an AE sensor was used for detection of damaged blades in a small wind turbine (11).

2.2 Fuzzy Logic

Although the use of fuzzy logic in condition monitoring is scare in the literature, fuzzy logic has been widely considered particularly useful for process control [12, 13]. Most of the early implementation of fuzzy-based control processes has taken place in Asia, particularly in Japan. Applications include automatic train operation (Hitachi), vehicle control (Sugeno Laboratory at Tokyo Institute of Technology), robot control (Hirota Laboratory at Hosei University), speech recognition (Ricoh), universal controller (Fuji), stabilization control (Yamakawa Laboratory at Kumamoto University) [12] and others. Although applications of fuzzy logic are wide and are still growing [14, 15], poor literature exists on its applications on the engineering asset management aspects [16]. Yet, works exist (mainly in the conference realm) where fuzzy logic has been successfully applied for condition monitoring of machinery [16-28]. These references also suggest that fuzzy logic is particularly useful for fault detection purposes because of its ability to make 'human-like' decisions, based on vague information. When performing fault diagnosis, individual symptoms do not immediately suggest if an object is in 'good' or 'bad' condition. However, the combination of a number of them is able to give a clearer picture of the state of a particular fault. Additionally, examples of motor fault detection using neural networks and fuzzy-logic techniques can be found in [29] and [30]. All in all, fuzzy logic offers attractive advantages on applications such as automatic control, supervision, and fault diagnosis [31, 32].

3. Measurements

As mentioned before, a common fault in wind turbines is the non-uniform accumulation of dirt, ice, moisture, etc. at the tip of the blades. The present investigation simulates this fault in a small wind turbine. Sound pressure is captured at a single microphone placed in front of the turbine and analysed as described below.

3.1 Experimental Methodology

Measurements were carried out in a laboratory environment. The method uses the signal captured at a single, pressure sensitive, microphone. The turbine is driven a FHP-Motors electric motor (serial No UOZ 112 G 70 084159 3P 08159 390 FR 2053) controlled via software to allow accurate control of the drive speed. Driving the turbine with a motor enables a controlled constant speed of rotation while suppressing wind effects. The noise emitted by the rotating turbine is captured with a B&K 40AF Free Field Microphone (serial 15679) placed 1.1m straight ahead and upwind from the turbine. Power is supplied to the microphone with a B&K Type 2804 Power Supply (serial, 1848096). The corresponding audio signal is digitalized in an M-Audio MobilePre audio interface (PIN 9310-65011—00 Rev A), which is connected to the PC via USB. In the PC, Win-MLS software is used to gather the data. Data is collected for approximately 10 seconds per measurement and a wave file is created for later analysis in Matlab.

A fault has been planted on the tip of one blade in increasing amounts to simulate fault severity at different levels. The fault is introduced in the form of weighted (to a precision of 0.01g) pieces of 5gram bluetac. Measurements were taken starting from no added weights (baseline) to a total weight of 20g in 5g increments. For each fault severity, three 10-second length measurements were performed at 48kHz and 16 bit resolution, to a total amount of 15 measurement runs. Two measurement runs per fault severity are used to develop the classification model and one run is reserved to test the model. This will be referred to as the 'unknown' test data. The turbine's rotational speed is maintained at a relatively constant value of 367 rpm, which is equivalent to a rotational frequency (RF) of 6.12 Hz. Measurements where taken during quiet lab times to minimize background noise.

3.2 Data Analysis

Feature extraction and classification has been performed in two of the three data series gathered. In order to extract features from the data, each data series has been segmented into 8 segments. Adequate low frequency information has been ensured by maintaining each segment long enough (about 2.7 seconds). Frequency resolution was maintained by zero padding each segment to its original length. Finally, to avoid the undesirable effects of spectral leakage, the segment was windowed using a Hanning window with 50% overlap between segments [33]. The process is represented in Figure 1. The signal features were determined using a Fourier Transform for each segment. Statistical indicators for each feature can then be determined and further analysis is possible on the data. Measurement data has been analysed according to two extracted features: the spectral magnitude of the rotational frequency – notated herewith as |RF| – and; the frequency variation of the RF – herewith named ΔRF.

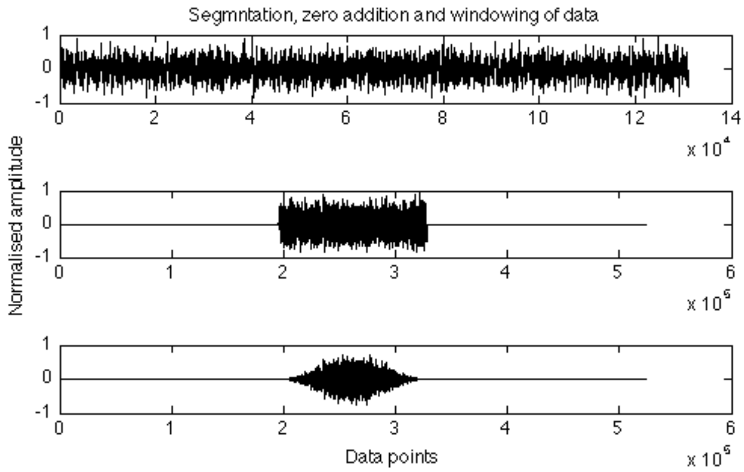

Figure 1: Segmentation process. a) One segment is cut from the main wave file information. b) Zeros are added before and after. c) Finally, the corresponding segment is windowed using a Hanning shape.

4. Feature Extraction and Simple Classification Model

Feature extraction and classification has been performed in two of the three data series gathered. In order to extract features from the data, each data series has been segmented into 8 segments. Adequate low frequency information has been ensured by maintaining each segment long enough (about 2.7 seconds). Frequency resolution was maintained by zero padding each segment to its original length. Finally, to avoid the undesirable effects of spectral leakage, the segment was windowed using a Hanning window with 50% overlap between segments [33]. The process is represented in Figure 1. The signal features were determined using a Fourier Transform for each segment. Statistical indicators for each feature can then be determined and further analysis is possible on the data. Measurement data has been analysed according to two extracted features: the spectral magnitude of the rotational frequency – notated herewith as |RF| – and; the frequency variation of the RF – herewith named ΔRF.

4.1 Condition Feature 1 – Spectral Amplitude of Rotational Frequency **(|RF|)**

The rotational frequency of the turbine is controlled from the driving motor and is thus prescriptive. Due to the aerodynamic interaction between the blades and the tower, impulsive noise is generated at the rotational and blade pass frequencies [34]. When the physical properties of one of the blades are changed, this interaction changes, which leads to a change in the spectral component of the RF [4]. As the severity of the fault is increased the magnitude of this peak should change accordingly. Figure 2 shows the obtained spectra for different fault severities. It is apparent that an increase in fault severity results in an increase on the amplitude of the rotational frequency (6.1Hz).

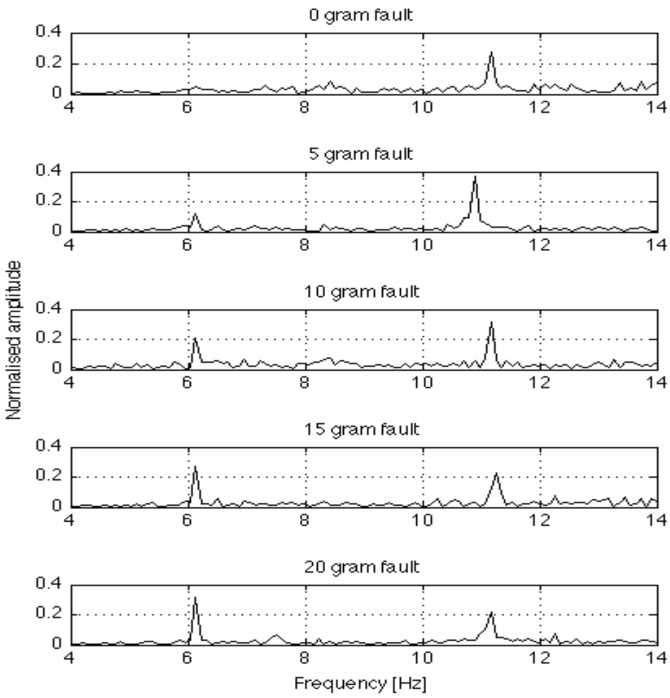

Figure 2: Spectral magnitude for different fault severities. The rotational frequency component in the spectrum increases consistently with the increase of the fault amount.

An ANOVA has been performed within each repeated measurement to check for significant differences on this feature between sets. No significant differences have been found between the data sets ($p>0.05$), hence data from both data sets has been grouped in order to define the feature levels for each fault severity. A further ANOVA has been carried out to test for significant differences between each fault severity level. The ANOVA results are shown in Table 1.

Table 1: Results from ANOVA analysis

Source	SS	df	MS	F	Prob>F
Columns	0.0027422	4	0.00068555	21.8255	5.6677e-12
Error	0.0023558	75	3.141e-05		
Total	0.005098	79			

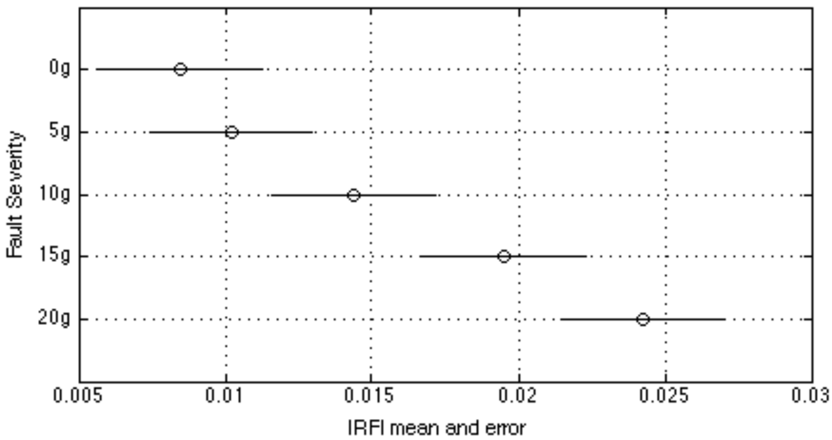

Figure 3: Multiple comparison from ANOVA analysis. Results show that while no significant difference can be found between neighbouring groups, a significant and consistent difference is found as the fault severity increases.

Clearly there is a highly significant effect of fault severity on the data (*p<<0.01*). Significant differences can be found among fault severity groups, although not among neighbouring faults. A multiple comparison between all fault cases is shown in Figure 3 to help visualise this. Faults 0g and 5g are not significantly different from each other but 0g is significantly different from faults at 10g, 15g and 20g; Fault 5g is significantly different from 15g and 20g, and so on. Thus, it becomes clear that the added weight fault significantly causes |RF| to increase. This feature may thus be used to detect the fault.

The acquired data was used to develop a classification model for the detection of the fault. Feature mapping was obtained by defining a range within the variance values for each fault severity level. A 3rd order polynomial regression has been fitted at these extremes defining the fault area shown in Figure 4. A data series containing an unknown fault can now be examined and its feature level (i.e. the mean |RF|) mapped in the classification model. Clearly this will result in a predicted fault range defined at the points where the measured |RF| intersects the fault area.

To test the classification model the third independent data series obtained from our measurements has been used. The determination of |RF| is carried out in the same way as has been discussed in Section 4. A single mean value obtained by segmenting the unknown data is used. The individual values for |RF| according to the unknown cases are shown in Table 2.

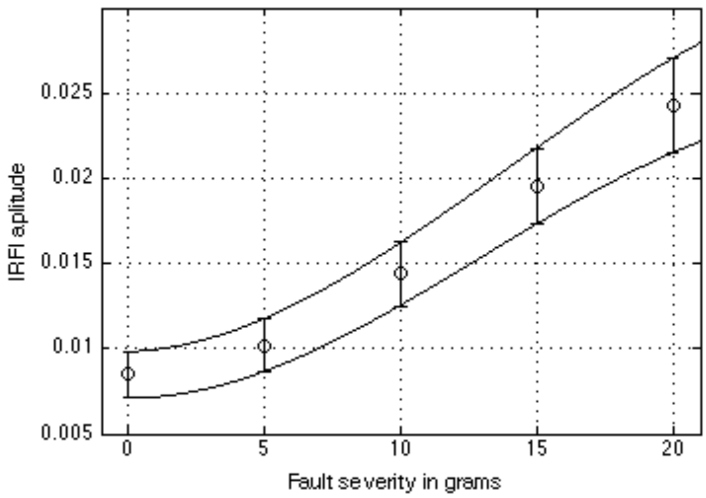

Figure 4: |RF| peak magnitude mean and variance of individual fault groups. Two polynomials are fitted at the extremes of the variance of each group. This gives an area in which the peak magnitude can be evaluated for fault detection.

Table 2: Third measurement |RF| peak magnitude data, used for testing

	Baseline	5 gram	10 gram	15 gram	20 gram
1.	0.0122	0.0240	0.0290	0.0404	0.0378
2.	0.0117	0.0105	0.0146	0.0225	0.0266
3.	0.0065	0.0073	0.0288	0.0221	0.0265
4.	0.0065	0.0119	0.0256	0.0179	0.0250
5.	0.0068	0.0066	0.0326	0.0220	0.0271
6.	0.0136	0.0127	0.0235	0.0065	0.0269
7.	0.0053	0.0051	0.0080	0.0166	0.0274
8.	0.0051	0.0103	0.0262	0.0135	0.0198
Mean	0.0085	0.0110	0.0236	0.0202	0.0271

Table 3 shows the results for each ‘unknown’ data set presented in terms of fault severity.

Table 3: Comparison between actual and predicted results

Fault Severity (g)	Output (g)
0	0 - 5
5	4 - 8
10	17 - 24
15	14 - 18
20	>20

It can be seen that fault mapping is fairly accurate with most unknown faults matching to the correct range of fault prediction values. The 10-gram fault however is overestimated and, apart from contamination of a transient noise existent in the data series at about 3 seconds from the start, we could not find a reason for this discrepancy. Further work is being carried out to investigate this.

4.2 Condition Feature 2 – Variation of Rotational Frequency (ΔRF)

Large scale wind turbines have a fixed rotational speed, whilst in micro turbines the rotational speed varies with wind speed. In our case, it is desirable that the rotational speed is kept fixed in order to extract fault detection features such as |RF| described in section 4.1. This is also in keeping with the principle of operation of large scale turbines. In our tested system, the drive from the electric motor replaces wind energy, constantly injecting energy into the system and overcoming damping forces that would eventually bring it to a stop. The turbine is driven at a constant speed, nevertheless, small variations in the rotational speed of the turbine are expected, depending on a number of complex phenomena (i.e. electrical, electronic, mechanical, external, etc.) among which the moment of inertia is significant. This aspect may be easily understood when considering the example of an engine's flywheel, a heavy circular disk which helps to maintain uniformity in the rotational motion generated by piston strokes in the engine [35, 36]. In a similar way, as mass is added to a turbine blade the rotational inertia is increased. This tends to stabilize fluctuations in the rotational speed and one can expect fewer variations over time, as long as the added mass does not create significant imbalance.

For our condition monitoring problem, a second feature has been extracted from the data in order to detect and classify fault severity. This feature is related to the variation of the rotational frequency (ΔRF) which was found to vary up to 4Hz when extracted over various segments of a measurement data series. The classification data for ΔRF was quantified from the variance of 16 data segments (8 segments for each 10 second measurement) for each fault severity. ΔRF is shown to decrease significantly with fault severity as shown in Figure 5.

Since the feature itself is related to the spread (variance) of a data series, the derivation of confidence intervals that allow more robust statistical analysis of the data is not trivial. Furthermore the necessity of defining membership functions for the *fuzzyfication* stage in a Fuzzy Logic Interference (described in more detail in section 5) requires an estimation of the spread of the data – i.e. the variance of the variance. To estimate this parameter, one can use a maximum likelihood approach. This thus provides us with an unbiased estimation of the variance.

Given the above, the estimated variance of ΔRF may be defined according to the standard error of the sample variance. This can be estimated using

$$\sigma_{(\hat{\sigma}^{ML})^2} = \sigma^2\sqrt{2/k} \qquad (1)$$

where σ^2 is the variance and k is the number of samples (in this case 16) [37]. The sub-index $(\hat{\sigma}^{ML})^2$ denotes the maximum likelihood estimator of the variance. This approach assumes that errors are distributed as a gaussian function, which are reasonable assumptions in the present case. Figure 5 shows the calculated ΔRF and its corresponding (estimated) variances, plotted for each fault severity.

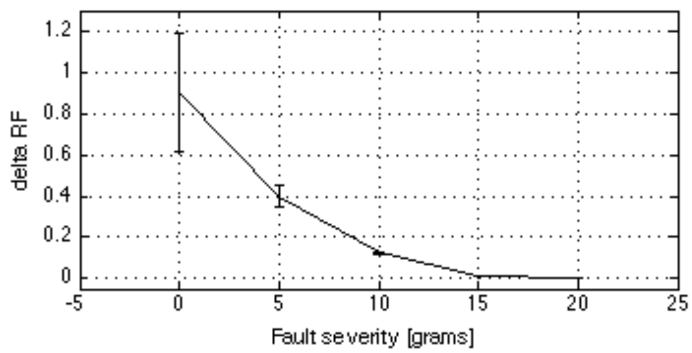

Figure 5: ΔRF and estimated variance. This is useful for defining the spread of the corresponding gaussian membership functions in the FIS.

5. Fuzzy Logic Classification Model

A detection algorithm has been built based on a fuzzy logic interference system (FIS). Fuzzy logic has been widely employed in control systems because it is able to deal with data features that have no clearly defined boundaries. Analysis systems based on fuzzy logic are fundamentally dependent on the definition of fuzzy sets [38], which represent data sets with no clearly defined boundaries, containing elements whose membership might be only partial. The degree to which data elements belong to a set is measured by membership functions ranging between 1 (full belongingness) and 0 (non-belongingness). Fuzzy logic is therefore effective at dealing with imprecision taking imprecise (fuzzy) observations for inputs and delivering precise and clear values for outputs [39, 40]. Three main components govern the FIS structure: input variables, decision making logic (rules) and output variables. The identification and definition of input variables and their ranges is often called fuzzyfication which leads to the definition of the MFs. The decision making logic is guided by a knowledge database often guided by experience. The output decision, commonly termed *deffuzyfication*, is the process of defining a single figure, crisp output. The most popular method is the calculation of the centroid returning the centre of gravity of the area under the curve identified by the FIS. Our FIS uses two inputs, namely |RF| and ΔRF, and outputs a prediction of fault severity from an unknown data series.

5.1 Defining Membership Functions (MF) from classification data

In our condition monitoring problem the MFs for input and output variable have as many membership functions as the number of fault severity levels measured. The first input variable to the FIS is |RF|, and its feature map has been defined in section 4.1. The membership functions (MF) for this variable have been modelled as Gaussian functions. The highest MF value for each fault is located at the mean value of |RF| and the spread of each Gaussian function is defined according to the corresponding variance of each fault level. The 0g and 20g membership functions are modelled as sigmoids since they model the boundaries of the data sets. The generated MFs for |RF| are shown in Figure 6.

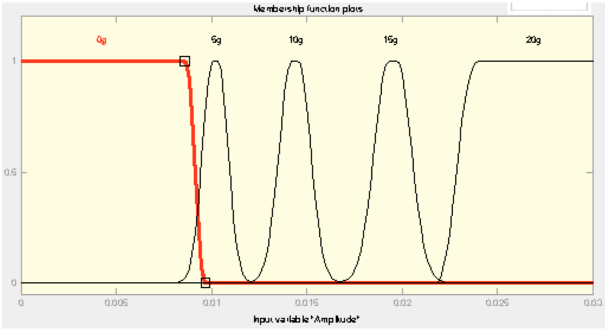

Figure 6: |RF| membership functions (first input variable)

The definition of MFs for the second input variable follows the same principle. That is, they are defined as maximum at the value of mean ΔRF extracted from each fault level in the classification data and their Gaussian spread is determined by the estimated variance of the variance (as described in section 4.2).

The output of our FIS is also based on 5 Gaussian membership functions with maximum values corresponding to each fault severity level [0g, 5g, 10g, 15g, 20g]. This is shown in Figure 7.

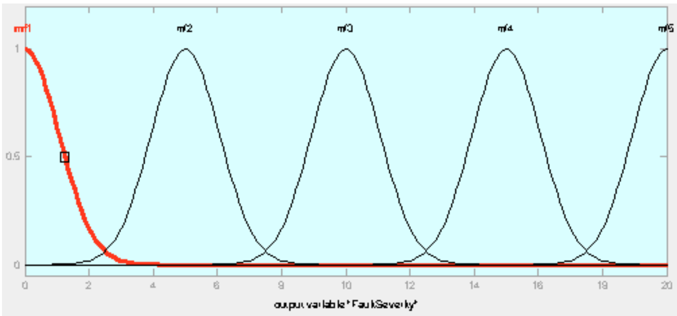

Figure 7: FIS output membership functions.

5.2 Defining decision making logic

The decision making logic in this case is fairly simple and could in, future iterations of the system, be improved. The fuzzy set of decision rules has been constructed as follows.

- 1. If (|RF| is 0g) or (ΔRF is 0g) then (FaultSeverity is 0g) (1)
- 2. If (|RF| is 5g) or (ΔRF is 5g) then (FaultSeverity is 5g) (1)
- 3. If (|RF| is 10g) or (ΔRF is 10g) then (FaultSeverity is 10g) (1)
- 4. If (|RF| is 15g) or (ΔRF is 15g) then (FaultSeverity is 15g) (1)
- 5. If (|RF| is 20g) or (ΔRF is 20g) then (FaultSeverity is 20g) (1)

Each defined rule may be associated with a weight or relative importance. In this case all rules have full weight, indicated as a (1) at the end of each line.

5.2 Testing the Fuzzy Interference System

The following plot shows the mapping between the two input functions and the output.

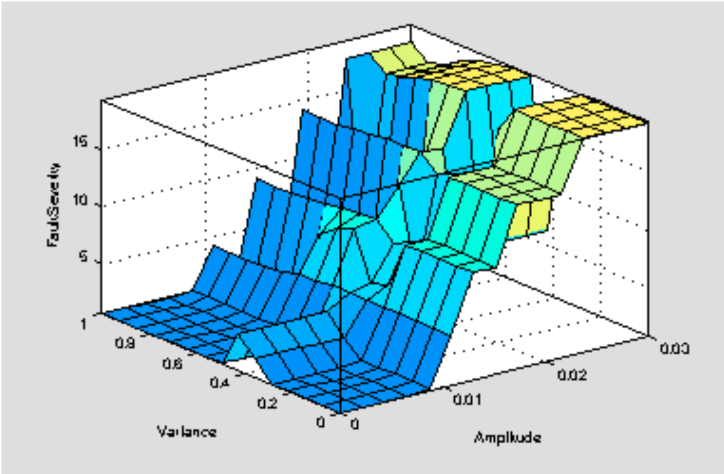

Figure 8: Surface plot of the FIS model. The two input functions (|RF| and ΔRF) are plotted in the horizontal plane and the output (predicted fault severity) on the vertical axis.

The process of testing the FIS model is similar to that reported in section 4.1. The third independent measurement (containing 'unknown' data) is segmented enabling 8 |RF| and ΔRF values to be extracted. The mean |RF| is averaged (see Table 3) and ΔRF is calculated as described in section 4.2. A summary of the unknown fault input data is shown in table 4.

Table 4: Summary of input data for the FIS per fault severity

Fault Severity (g)	Magnitude	Variance
0	0.0085	0.3160
5	0.0110	0.0142
10	0.0236	0.2006
15	0.0202	0.5770
20	0.0271	0.0066

The output of the FIS model, rounded to the nearest integer, is shown below.

Table 5: FIS model output

Fault Severity (g)	Output (g)	Error
0	1	1
5	5	0
10	19	9
15	15	0
20	19	1

Most faults levels have been predicted with accuracy, except the 10g fault, which again is erroneous. It is nevertheless important to note a few important points:

1. The predicted values for an FIS are, by definition, single valued and based on a centroid calculation of the resultant output universe of discourse.
2. The output MFs for the FIS system have been defined to match the 5 fault levels planted in the turbine.

It is therefore expected that a decision making system (the FIS) will naturally converge to values where its MFs are maximum thus matching almost exactly the planted fault. We expect that where unknown data with faults planted at levels other than the classification data (i.e. 0,5,10,15 and 20 grams) the prediction errors will be larger.

5. Conclusions

A study has been conducted on the use of acoustic monitoring for fault prediction on the tip of a wind turbine blade. Fault detection and classification is based on two simple signal features, namely the spectral magnitude of the rotational frequency and its variation in the data series. The feature mapping has been obtained from 'training' data measured with a single acoustic probe positioned upwind from the turbine in a controlled environment. The 'test' data was obtained in the same circumstances.

It has been shown that, as a single feature, the spectral magnitude of rotational frequency is indicative of the condition of the blade and is able to distinguish between fault severities. Detected faults are output in ranges rather than single figures predictions.

A further classification model has been developed based on a fuzzy logic interference system using the two features as inputs. The membership functions have been modelled using the variance obtained from the classification data. Although we have used rather simple features for the fuzzy logic model, it has been demonstrated that its use affords a reasonable prediction of fault level. It allows the aggregation of the various input features to improve on classification accuracy over simple single features.

Our interest in this initial investigation on the use of fuzzy logic for condition monitoring is that it is intuitive to implement in such condition monitoring problems and may easily be altered to include different input features and other decision making logic routines.

Authors are now working on the extraction of other signal features for a more robust model. Other methods being investigated include empirical mode decomposition, wavelet analysis, cepstrum analysis (5, 6, 41).

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