Detection of pitch failures in wind turbines using environmental noise recognition techniques

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ABSTRACT

Modern wind turbines employ pitch regulated control strategies in order to optimise the yielded power production. Pitch systems can be subjected to various failure modes related to cylinders, bearings and loose mounting, leading to poor pitching and aerodynamic imbalance. Early stage pitch malfunctions manifest as impacts in vibration signals recorded by accelerometers mounted in the hub vicinity, as for example on the main bearings or nacelle frame, depending on the installed condition monitoring system and turbine topology. Due to the location of the above mentioned vibration sensors, impacts of various origin, such as from loose covers, can be generated, complicating the assessment of the impact nature. In this work, detection of pitch issues is performed by analysing vibration impacts from main bearing accelerometers and applying environmental noise and speech recognition techniques. The proposed method is built upon the following three processes. Firstly, the impacts are identified using envelope analysis, followed by the extraction of 12 features, such as energy, crest factor and peak to peak amplitude and finally the classification of the events based on the above features. Eighty nine impacts are analysed in total, where 60 impacts are categorized as valid and 29 as in-valid. It is shown that the frequency band of maximum crest factor presents the best classification performance employing K-means clustering, which is an unsupervised clustering technique. The highest correct classification rate reaches 90%, providing useful information towards coherent and accurate fault detection.

1. INTRODUCTION

Wind industry has been continuously growing over the past decades reaching new global total of 369.6GW at the end of 2014 (*Global Wind Report Annual Market Update*, 2014). In order to ensure system safety, profitability and uninterrupted operation, condition based maintenance (CBM) has been deployed by many owners and operators, especially in offshore wind turbines (Yang, Tavner, Crabtree, Feng, & Qiu, 2012). Condition monitoring (CM) is integrated part of CBM and specialized solutions are offered by condition monitoring system (CMS) suppliers and wind turbine (WT) manufacturers, mainly based on vibration analysis. Other non destructive techniques (NDT) which are applicable in monitoring specific subcomponents are oil debris analysis, temperature measurement, optical fiber monitoring and acoustic emission (Tchakoua et al., 2014). Regardless the condition monitoring technique, condition based maintenance is performed in the following steps: 1) data acquisition, 2) feature extraction, 3) diagnostics, 4) prognostics and 5) planning of maintenance activities (Coble & Hines, 2011).

CM systems target mainly drive train components, such as main bearings, gearbox and generator bearings, where accelerometers are mounted in strategic locations in order to ensure optimum vibration path and thus enhance fault detection. Furthermore, accelerometers are usually installed on the nacelle frame in order to record any excessive tower oscillation, due to blade, yaw and pitch related issues (Skrimpas et al., 2015). Although the pitch system is frequently subjected to a large number of failures resulting in increased downtime (Bi, Qian, Hepburn, & Rong, 2014), there is not any CMS solution able to detect these failures on time and prevent secondary damages. The latter could be possibly explained due to location of the pitch system in the nacelle hub and the nature of its function.

Modern wind turbines are equipped with pitch systems offering independent control of the three blades. A pitch cylinder is connected to each blade on one side and to the hub on the other side. The cylinder suspension system allows movement in two axes using slide bearings. Due to heavy operation, the suspension system can become loose, causing the pitch cylinder assembly to start moving irregularly leading to random impacts in early stage and one or two impacts per rotor revolution in late stage. The main issue of the above described jarring movement is damage to cables and hydraulics, improper pitching and poor power production. Furthermore, the replacement of the pitch system may cause substantial downtime especially in cases of extensive damage to the electric cables and hydraulic system failures (Skrimpas et al., 2015).

Considering a typical wind turbine drive train, accelerometers having adequate vibration path to the pitch system can be utilized aiming on the detection of pitch failures. Bearing in mind the sensor location described above, accelerometers monitoring the main bearings and tower are the ones closest to the pitch system. In this work, impacts captured by the accelerometer installed on the rotor-end (front) main bearing are analysed and correlated to pitch failures. The extracted features are adopted by speech, audio and environmental noise recognition methods, showing that techniques applied in sound applications can be also employed on the analysis of vibration signals. It has been observed that impacts generated by loose pitch suspension share common characteristics with gun-shots and glass breaks, which do not have any apparent substructures. Finally, the impacts are classified using K-means clustering, which is an unsupervised technique.

The structure of the paper is as follows. Section 2 describes the algorithm of impact identification which is divided into three processes, namely the identification of impacts, feature extraction and classification. Section 3 presents the results from 89 impacts classified as valid or invalid based on the feedback provided by the service crews. Finally, the discussion and conclusions are presented in sections 4 and 5.

2. METHOD DESCRIPTION

Traditionally, vibration based CMS consists of two main modules. The first step is the extraction of features from vibration signals which describe the condition of the component of interest and indicate a potential fault in case of progression or high levels. Typical features are the amplitude of spectral components associated to the operation of the monitored equipment, such as tooth mesh frequencies in gearboxes, or frequency bands which usually describes its overall status. The second block of a successful CMS is the capability of consistent alarming based on the level or progression of the related condition indicators. This stage can also provide an automated preliminary diagnosis of the fault and estimation of its severity.

Sound recognition systems are also composed of two stages, namely the extraction of features and classification (Dufaux, 2001). In the framework of evaluating solely impacts, a signal pre-processing stage is required in order to identify these events, shown in Figure 1 as impact detection. Although the core of any recognition system is the feature extraction, the effectiveness of the the impact detection is assessed to be critical on the performance of the proposed method.

A intermediate step not dispalyed in Figure 1 is the dimensionality reduction or feature selection. It refers to the algorithm that select the best subset of the input feature set in regards to class discrimination capabilities (Jain, Duin, & Mao, 2000).

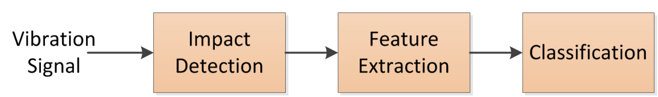

Figure 1. Method Description.

2.1. Impact Detection

The randomness, complexity and non-stationary nature of vibration impacts generated by wind turbine pitch system failures highlights the necessity of signal pre-processing for efficient feature extraction. Signal segmentation is used extensively as pre-processing stage in applications such as cardiac sound recognition (Choi & Jiang, 2008). Algorithms, such as normalized average Shannon energy and Hilbert transformation, are very effective techniques when detection of impacts is the main objective. In this work, the envelope of the signal high frequency bandwidth is utilized as signal segmentation tool. The envelope calculation process is executed in three discrete and simple steps illustrated in Figure 2. The signal passes through a bandpass filter in order to remove any low frequency noise and restrict the bandwidth to mitigate any aliasing effects. Typically low frequency (below 1kHz) spectral components in wind turbines are generated by multi-stage gearboxes and high speed generators. The vibrations created by these components are commonly recorded by accelerometers installed on the main bearings or nacelle frame due to the presence of weak vibration paths to them. In addition, vibrations from loose components of minor importance, such as covers, or structural micromovement could also produce noise and random impacts. The filtered signal is then rectified, shown as a diode in Figure 2, and the outcome is an unipolar signal. Finally, a low pass filter is applied in order to compute the envelope signal. Both filters are Butterworth and their settings are listed below. It is noted that the sampling frequency F_s is 25.6kHz in all presented waveforms.

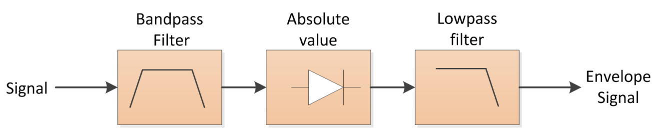

Figure 2. Calculation of envelope signal.

- Bandpass filter: 3^{rd} order. Bandwidth: 1kHz–10kHz
- Lowpass filter: 3^{rd} order. Cut–off frequency: 10Hz

Figure 3 shows the generated signals following the process described above from a vibration signal recorded in a multi-megawatt wind turbine.

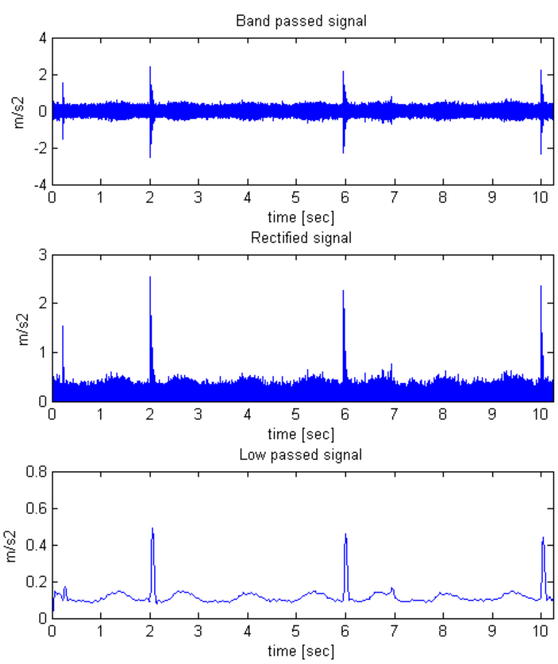

Figure 3. Computation of envelope signal. The upper subplot shows the outcome of the bandpass filter. The middle subplot displays the rectified signal. The lower subplot presents the envelope signal.

The envelope signal shows the presence of three large impacts, one minor impact in the beginning of the signal and a moderate modulation matching three times the main shaft speed. In order to extract only the large impacts, a limit is defined above which the signal is segmented and characterized as impactive. Following trial and error method, a global satisfactory limit value was found to be 1.5 times the energy of the envelope signal. Figure 4 shows the envelope signal along with the limit for this case. Finally, Figure 5 shows the extracted impacts and segments. It can be seen that the event in the first segment does not have the required energy to be identified as impactive compared to the rest of the signal characteristics.

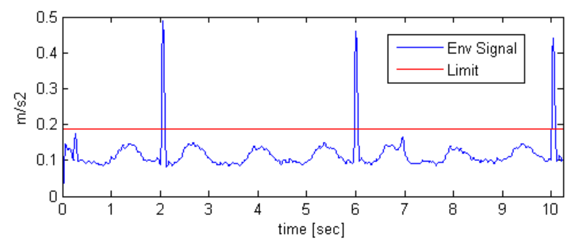

Figure 4. Envelope signal and limit.

2.2. Feature Extraction

The most critical part of any recognition system is the effectiveness of the extracted features in discrimination between different classes. One of the main objectives is to improve the signal to noise ratio in order to maximize the information. There is an arsenal of features which have been studied extensively in audio, such as music and speech, and environmental sound recognition applications. Time domain features, such as zero crossing rate, spectral features, such as spectral centroid and Mel-frequency cepstral coefficients (MFCCs), and joint time-frequency characteristics have been traditionally used as features (Ghoraani & Krishnan, 2011).

The basis of this work is to utilize the features applied to sound signals in vibration time waveforms. The following subsection present the features which are extracted from each impactive segment, as the ones illustrated in Figure 5.

- *Peak* value of a signal $S(n)$ defined as the maximum positive amplitude of a time waveform.

$$A_{pk} = max(S(n)) \quad (1)$$

- *Peak to peak* (P2P) is the difference between the maximum positive and the maximum negative amplitudes of a signal $S(n)$. In the current application, the main purpose of evaluating both peak and peak-to-peak is the identification of malfunctioning sensors which often present unipolar time waveforms

$$A_{pp} = max(S(n)) - min(S(n)) \quad (2)$$

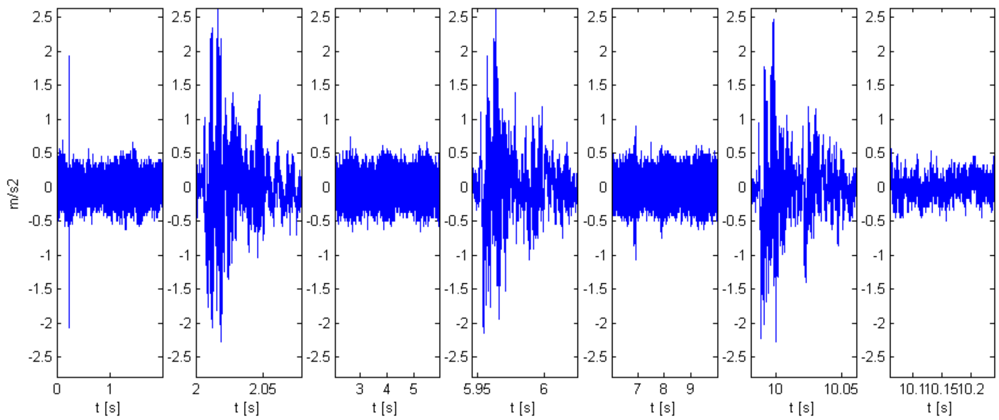

Figure 5. Segments extracted from the initial signal using envelope analysis.

- *Energy* E_S of a discrete signal $S(n)$ is a measure of signal strength. It is defined as:

$$E_S = \frac{1}{N} |S(m)w(n-m)|^2 \tag{3}$$

where $w(m)$ is a window of size equal to the signal length

- Impact duration T is the time duration of each extracted impactive events using the process described in section 2.1

- *Power* of a signal is given by the following ratio:

$$P_S = \frac{E_s}{T} \tag{4}$$

- *Zero crossing rate* (ZCR) occurs when successive sampes have different signs (Chu, Narayanan, & Kuo, 2009). It is given by:

$$Z_n = \frac{1}{2} \sum_m |[sgn(S(m)) - sgn(S(m-1))]| w(n-m) \tag{5}$$

where

$$sgn|x(n)| = \begin{cases} 1 & x(n) \geq 0 \\ -1 & x(n) < 0 \end{cases} \tag{6}$$

- *Standard deviation* (Std) is a measure of how spread is a distribution. It is equal to

$$\sigma = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (S(n) - \mu)^2} \tag{7}$$

where the mean value μ is equal to $1/N \sum_{n=1}^{N} S(n)$

- *Kurtosis* is a typical measure of signal peakdeness. It is equal to:

$$K = \frac{1/N \sum_{n=1}^{N} (S(n) - \mu)^4}{(1/N \sum_{n=1}^{N} (S(n) - \mu)^2)^2} \tag{8}$$

- *Spectral centroid* (SC) measures the brightness of a sound. The higher the centroid, the brighter the sound (Chu et al., 2009). It is equal to

$$SC = \frac{\sum_{m=1}^{M} m \cdot F(m)}{\sum_{m=1}^{M} F(m)} \tag{9}$$

where F stands for the Fourier Transformation of signal S.

- *Spectral flatness* (SF) quantifies the tonal quality, i.e. how much tone-line the sound is as opposed to being a noise (Chu et al., 2009). I is given by:

$$SF = \frac{exp(\sum_{m=1}^{M} \log F(m))}{1/M \sum_{m=1}^{M} F(m)} \tag{10}$$

- *Crest factor* (CF) is the ratio of peak value to the signal RMS (root mean square) value. It is commonly used in vibration analysis for bearing wear.

$$SF = \frac{S_{pk}}{S_{rms}} \tag{11}$$

- *Maximum crest factor frequency band*. (Max CF band) It is a joint time-frequency feature, which corresponds to the frequency range of 500Hz bandwidth yielding the maximum crest factor.

2.3. Dimensionality Reduction

Dimensionality reduction is defined as the selection of a feature subset of size m, out of a set of d features, which leads to the smallest classification error (Jain et al., 2000). The most straightforward is to examine all (dm) combinations and select the subset with the lowest classification error. Although the risk of exhaustive search is apparent, the small number of features permits this method to select the feature subset. Reference (Jain et al., 2000) presents a complete list of dimensionality reduction methods, where the most popular and commonly used are principal component analysis (PCA) and Fisher's Linear Discriminant. Bishop discusses the use of these techniques showing that Linear Discriminant Analysis shows usually better characteristics in classification problems compared to PCA.

2.4. Classification

A simple unsupervised classification technique used in many application is K-means clustering. K-means clustering groups a data set consisting of N observations $x_1, ..., x_N$ of dimension D into K clusters, where the inter-point distances between them is minimized (Bishop, 2006). A binary index r_{nk}, where $n = 1, ..., N$ and $k = 1, ..., K$ is assigned to each data point when the sum of the squares of the Euclidean distances between the cluster centres and the data is minimized, as shown in Eq. 12. Hence, each data point is assigned to the closest cluster centre.

$$r_{nk} = \begin{cases} 1 & \text{if argmin} \sum_{k=1}^{K} \sum_{n=1}^{N} ||x_n - \mu_{\mathbf{k}}||^2 \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

K-means clustering is based on the Expectation-Maximization (EM) algorithm, where the Expectation step corresponds to clustering the data points based on equation 12 and the cluster centres $\mu_{\mathbf{k}}$ are updated at the Maximization step. The initial clustering and cluster centres can be arbitrarily selected, given a known number of clusters K. The process is terminated after a predefined number of iterations or when a desired convergence is achieved.

3. DETECTION OF PITCH FAILURES

Detection of pitch failures is performed in multi megawatt wind turbines, whose topology is depicted in Figure 6. In addition, the installed CMS sensors are represented by red rings, where the blue ring shows the position of the speed sensor. It is shown that the front and rear main bearing accelerometers (Brüel and Kjær Vibro AS-70) are placed at the bottom and top of the bearings respectively in order to take into account the stress applied on the shaft due to the rotor weight. The recorded vibration signals are processed by the Wind Turbine Analysis System Type 3652 (WTAS Type 3652) which calculates scalar values and streams them to central servers every one hour for long time trending and alarming. Furthermore, 10.24 second vibration signals recorded by the accelerometers mounted on the generator bearings, gearbox and main bearings sampled at 25.6kHz are delivered to the central servers every one or two days for detailed spectral analysis.

It is assessed that the vibration path from the pitch cylinders to the front main bearing accelerometer is the clearest, and thus this sensor will be utilized as indicator for pitch related issues.

The test set consists of 89 impacts from 35 wind turbines, where 60 impacts from 20 turbines and 29 impacts from 15 turbines are marked as valid and invalid respectively regarding the presence of a fault in the pitch cylinders or pitch suspension. The verification of an actual fault depends highly on the provided feedback from the service technicians troubleshooting the corresponding alarms. Therefore, there is a error margin on what is classified as loose suspension based on the technicians' assessment.

Normalization of the extracted features is essential in order to obtain more consistent and effective classification. A random feature f can normalized using the following equation:

$$f_{norm} = \frac{f - \mu_f}{\sigma_f} \quad (13)$$

where μ_f and σ_f are the mean and standard deviation of the feature population respectively.

In many cases, it is useful to obtain two- or three- dimensional projection of the features offering a visual examination of the data. The features described in section 2.2 are clustered in pairs as shown in Table 1. It is shown that the best classification performance is seen when one of the utilized features is the frequency band of maximum crest factor, reaching 90% in almost all cases. It is also important to note that the aforementioned feature provides the same results when it is the only one used. Furthermore, moderate results in the vicinity of 70% are recorded using other features, where spectral flatness and spectral centroid are among them.

Figure 7 illustrates the initial classes using spectral flatness and maximum crest factor band on the left, and the recalculated classes based on K-means clustering on the right. The red squares represent the data corresponding to pitch failures and the blue diamonds to negative feedback from the service technicians. The black stars on the right figures represent the new cluster centres. In this case, approximately 90% of the data are assigned to their initial classes. The class separation is maximized in terms of distance between the cluster centres as compared to Figure 8, where spectral flatness and spectral centroid are used. At this point, it is important to note that the misclassified points are mainly related to actual faults which are assigned to the "no-fault" cluster. However, the above phenomenon could be linked to the the presence of both valid and invalid impacts in the same analysed time waveform. The effectiveness of maximum crest factor band

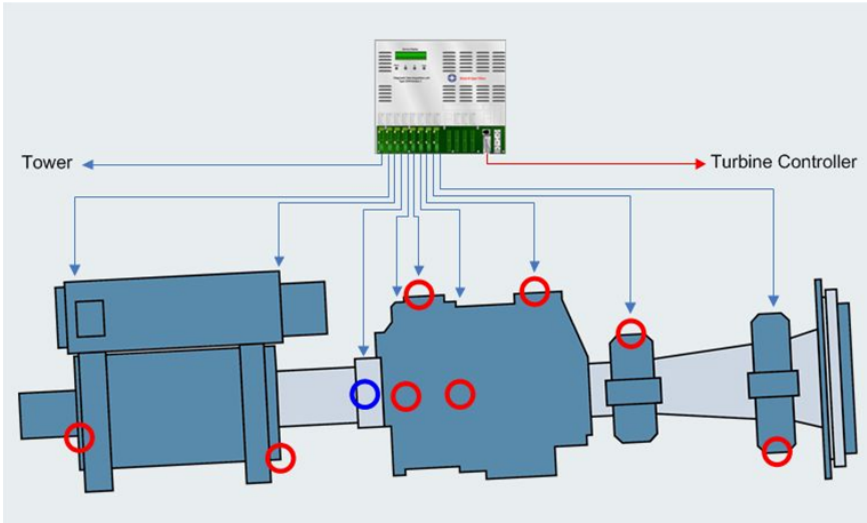

Figure 6. Wind turbine topology and CMS sensor location.

	Peak	P2P	Energy	Duration	Power	ZCR	SC	Std	Kurtosis	SF	CF	Max CF band
Peak	40.67	40.67	35.28	72.26	35.28	40.67	53.95	40.67	41.84	70.22	62.04	90.32
P2P	40.67	40.67	35.28	72.26	37.97	40.76	53.95	40.67	41.84	70.22	62.04	90.32
Energy	35.28	35.28	35.28	63.00	35.28	57.25	63.20	37.97	38.63	70.22	62.70	90.32
Duration	72.26	72.26	63.00	35.28	57.25	59.79	54.25	48.25	68.54	71.09	61.92	90.32
Power	35.28	37.97	35.28	63.00	35.28	57.25	58.32	37.97	39.14	70.22	62.70	90.32
ZCR	40.67	40.67	57.25	59.79	57.25	59.28	54.25	48.25	67.52	68.39	62.70	90.32
SC	53.95	53.95	63.20	54.25	58.32	54.25	71.95	53.95	70.43	70.94	73.63	82.74
Std	40.67	46.06	37.97	48.25	37.97	48.25	53.95	48.25	41.84	70.22	59.85	90.32
Kurtosis	41.84	41.84	38.63	68.54	39.14	67.52	70.43	41.84	35.94	70.22	56.13	90.32
SF	70.22	70.22	70.22	71.09	70.22	68.39	70.94	70.22	70.22	70.22	66.71	90.32
CF	62.04	62.04	62.70	61.92	62.70	62.79	73.63	59.85	56.13	66.71	72.11	88.14
Max CF band	90.32	90.32	90.32	90.32	90.32	90.32	82.74	90.32	90.32	90.32	88.14	90.32

Table 1. Correct classification percentage when reclustering the extracted features in pairs.

as classifier is also displayed in Figure 9 where it is the only used feature.

In order to investigate the optimum feature subset which yields the lowest classification error, all combinations were examined as discussed in section 2.3. No improvement has been observed, whereas in many combinations moderate to high increase of misclassified data was registered. As for example, Figure 10 depicts the clusters when spectral flatness, spectral centroid and maximum crest factor band are used. The proper classification percentage in this case was approximately 87%.

4. DISCUSSION

The method described in the previous sections is the first approach by the authors to correlate single or repetitive vibration impacts recorded from the front main bearing accelerometer in wind turbines to failures related to the pitch assembly. The validity of the technique and results depends highly on two factors; the provided feedback from the field and the extracted features. The human factor and thoroughness on reporting the presence of a fault is a parameter which can-

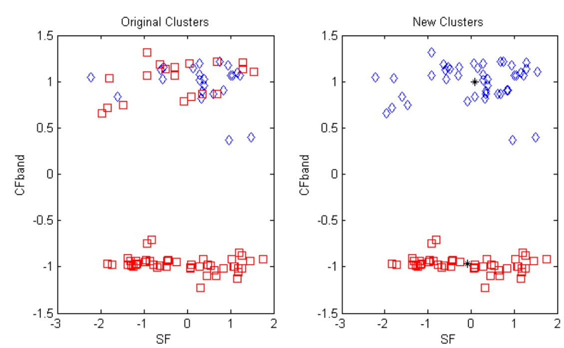

Figure 7. Original and news clusters using spectral flatness and maximum crest factor band. Correct classification is at 90.32%.

not be explicitly quantified and it will always add uncertainty on the method. The feature extracted in the time-frequency domain presented the best performance compared to conventional spectral or temporal features, suggesting that the correct classification percentage can be further improved if more features are tested. Furthermore, the impact population un-

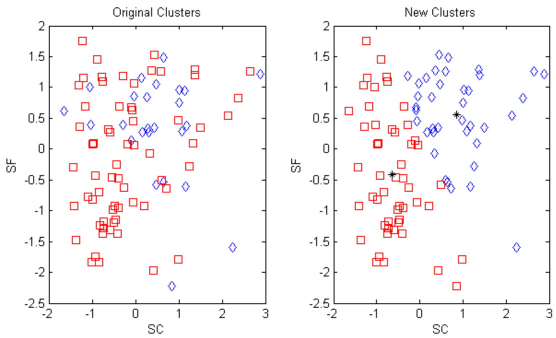

Figure 8. Original and news clusters using spectral flatness and spectral centroid. Correct classification is at 70.94%.

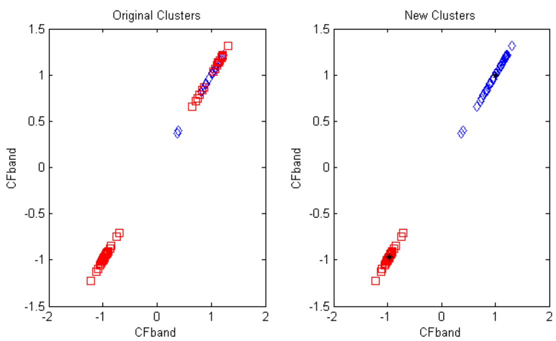

Figure 9. Original and news clusters using only maximum crest factor band feature. Correct classification is at 90.32%.

der investigation, i.e. 89 impacts, is considered relatively limited so as to serve as a platform for establishing a data base or training set. The limited number of confirmed impacts has been the main motivation for using an unsupervised clustering technique and not employing advanced classification methods, such as space vector machine (SVM), Gaussian mixture models (GMM) or neural networks (NN).

An important aspect of the impact classification method is the lack of severity estimation. Although the evaluation of the remaining useful lifetime of the pitch assembly is assessed to be challenging, the proper identification of the issue could assist the maintenance organization to plan its troubleshooting more efficiently. Based on the nature of the described failure mode, a single impact over 10.24s, i.e. approximately three rotor revolutions, is usually an early failure indicator, whereas the presence of repetitive impacts matching the rotor running speed suggests severe looseness of the pitch suspension or cylinders. It is the belief of the authors that a more complete impact database could potentially offer the ground for holistic condition monitoring of pitch systems in wind turbines.

5. CONCLUSIONS

The present work shows an effective technique to diagnosticate pitch assembly malfunctions, an area which has re-

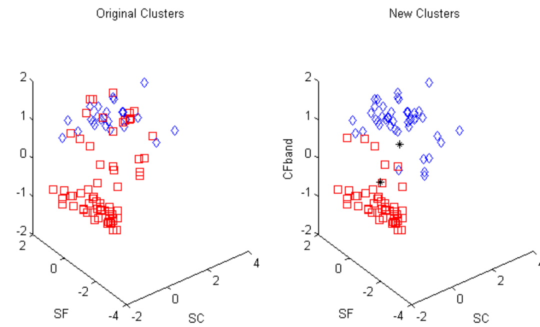

Figure 10. Original and news clusters employing three features, namely spectral flatness, spectral centroid and maximum crest factor band.

ceived little attention, by analysing vibration signals recorded in wind turbine main bearing accelerometers. The proposed impact recognition scheme consists of three blocks, namely impact detection, feature extraction and classification, inspired by research areas not related to machinery diagnostics, such as in environmental noise and speech recognition systems. Consistent impact recognition is achieved using envelope analysis, where the limit for assigning an event as impact was found to be equal to 1.5 times the envelope signal energy. The maximum correct classification percentage reaches 90% in a test sample of 89 impacts. Out of the 12 extracted features, the best classification characteristics are seen on a joint time-frequency feature representing the spectral bandwidth of maximum crest factor. Conventional spectral and temporal features present poorer class discrimination tendency ranging from 30% to 70%.

REFERENCES

Bi, R., Qian, K., Hepburn, D. M., & Rong, J. (2014). A survey of failures in wind turbine generator systems with focus on a wind farm in china. *International Journal of Smart Grid and Clean Energy*, 366–373.

Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer New York.

Choi, S., & Jiang, Z. (2008). Comparison of envelope extraction algorithms for cardiac sound signal segmentation. *Expert Systems with Applications*, *34*, 1056–1069.

Chu, S., Narayanan, S., & Kuo, C.-C. (2009). Environmental sound recognition with time–frequency audio features. *IEEE Transactions on Acoustics Speech and Signal Processing*, *17*, 1142–1158.

Coble, J., & Hines, J. W. (2011). Applying the general path model to estimation of remaining useful life. *International Journal of Prognostics and Health Management*, *2*, 1 – 13.

Dufaux, A. (2001). *Detection and recognition of impulsive sounds signals* (Unpublished doctoral dissertation). Institute of Microtechnology, University of Neuchatel, Switzerland.

Ghoraani, B., & Krishnan, S. (2011). Time–frequency matrix feature extraction and classification of environmental audio signals. *IEEE Transactions on Acoustics Speech and Signal Processing*, *19*, 2197–2209.

Global wind report annual market update (Tech. Rep.). (2014). Rue d'Arlon 80, 1040 Brussels, Belgium: Global Wind Energy Council.

Jain, A. K., Duin, R. P. W., & Mao, J. (2000). Statistical pattern recognition: A review. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*, 4–37.

Skrimpas, G. A., Marhadi, K., Hilmisson, R., Sweeney, C., Mijatovic, N., & Holboell, J. (2015). Advantages on monitoring wind turbine nacelle oscillation. In *American wind energy association (awea).*

Tchakoua, P., Wamkeue, R., Ouhrouche, M., Slaoui-Hasnaoui, F., Tameghe, T. A., & Ekemb, G. (2014). Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges. *Energies*, *7*, 2595–2630.

Yang, W., Tavner, P., Crabtree, C., Feng, Y., & Qiu, Y. (2012). Wind turbine condition monitoring: technical and commercial challenges. *Wind Energy*, *17*, 673–693.

BIOGRAPHIES

Georgios Alexandros Skrimpas received the Diploma in electrical and computer engineering from the Aristotle University of Thessaloniki, Greece, in 2009 and the M. Sc. in wind energy from the Technical University of Denmark (DTU) in 2012. He joined Brüel and Kjær Vibro in 2012 and since 2013 he is pursuing the Industrial Ph.D. degree at the Centre of Electric Power and Energy at DTU in cooperation with Brüel and Kjær Vibro. His research interests are diagnosis and prognosis of electrical and mechanical faults in wind turbines.

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