Bearing Fault Identification for High-Speed Wind Turbines using CNN

Mohamed A. Hamid
Arab Academy for Science, Technology & Maritime Transport
Alexandria, Egypt
Eng.mhamed59@outlook.com

Rania A. Ibrahim
Arab Academy for Science, Technology & Maritime Transport
Alexandria, Egypt
rania_assem@aast.edu

Mostafa Abdelgeliel
Arab Academy for Science, Technology & Maritime Transport
Alexandria, Egypt
mostafa.geliel@aast.edu

Hussein Desouki
Arab Academy for Science, Technology & Maritime
Alexandria, Egypt
h.desouki@aast.edu

Abstract— Wind turbines condition monitoring and fault warning have significant importance in terms of reducing maintenance costs and improving operation levels of wind farms. Since high-speed shaft bearings account for a major share of wind turbine drivetrain failures particularly offshore ones, there is an urgent need to monitor the health status of wind turbine elements accurately. In this paper, Spectral Kurtosis (SK) data driven approach is utilized to provide a vibration-based prognostic and health monitoring methodology for wind turbine high-speed shaft bearing. Three data-driven machine learning models are applied: Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Random Forest (RF) to detect and classify remaining useful time in bearing through vibration condition monitoring. The results of the study carried out in this paper using actual wind turbine vibration dataset reveal that the CNN approach surpasses SVM and RF techniques in achieving higher accuracy and better classification performance.

Keywords—Bearing fault, wind turbine condition monitoring, CNN, Spectral Kurtosis, Support Vector Machine (SVM), Random Forest

I. Introduction

Wind energy provides a clean, environmentally friendly, and widely accessible power source. As appropriate locations for onshore wind farms become increasingly scarce, offshore wind farms have attracted considerable attention. Offshore wind farms can generate higher power, can be constructed in larger units that are easier to ship and deploy and are often built in larger spaces and permissible heights [1]. However, the cost of maintaining offshore wind turbines to ensure that they work optimally over their lifetime usually costs around 25% of the offshore installation [2]

Rolling element bearings are a key element that is utilized in a wide variety of applications in wind turbines which are subject to tremendous pressure at contact [3]. As the bearing rotates, Hertz contact stresses are generated in the bearing components due to cyclic loading at material contact points. This causes material fatigue and gradually reduces the machine's performance and availability. Since the wind turbine rotor and the gearbox shafts are all supported by bearings, bearing is thus a critical component of the mechanical system and its failure can either cause machine stalls or permanent damage. Typically, bearing failures account for more than 40% of the total wind turbine generator failures, resulting in unanticipated energy losses [4]–[6].

Since wind turbines work in a very challenging environment, condition monitoring techniques are urgently required to anticipate equipment condition by collecting data at regular intervals to reduce machine downtime and reduce maintenance costs. Therefore, prior knowledge of failing components will be useful for equipment stocking and scheduled maintenance. Numerous signals are acquired utilizing appropriate sensors for wind turbine condition monitoring such as vibration, acoustic emission, strain, torque, temperature, and electrical signals [7]. Commonly, bearing defects are diagnosed using vibration-based techniques, which necessitates a thorough understanding of the vibration signatures of bearings with flaws to successful failure detection. Typically, vibration signal analysis is carried out in time, frequency, and time-frequency based domains.

Regarding fault diagnosis, three methodologies exist which can be divided into: a) Modeling Based methods, b) Statistical-based approaches, and c) Data driven approaches [8]. Physical and modeling-based methods require a good understanding of the structure of the WT, but is hardly achievable with nonlinear systems. Statistical approaches are sensitive to the number of samples which may reduce their accuracy, especially with high dimensional data. Data driven approaches, on the other hand, map the relationship between inputs and outputs of the diagnostic model to characterize the fault, thus fault diagnosis accuracy is improved [9].

In recent years, Deep Learning (DL) algorithms for diagnostic purposes have been developed. Rather than artificial feature extraction with typical machine learning techniques, DL can automatically learn fault features from acquired data and is capable of extracting detailed features and patterns from the training dataset [4]. Hence, they attempt to provide end-to-end diagnostic models with high accuracy when handling the increasingly grown data due to their flexibility and self-organization [10]. CNN is among the most prominent DL networks, compared to machine learning techniques, CNN can automatically detect significant features, which is ideal in fault detection and diagnosis.

This paper's primary objective is therefore to investigate wind turbine high speed shaft bearing degradation during run-to-failure testing utilizing a SK -based feature extraction system. Based on the computation of a kurtosis spectrogram, the acquired samples are classified into two classes: short and medium life expectancy, thus reflecting the bearing condition and need for maintenance or replacement. Three distinct machine learning classifiers are tested and compared among which the classifier attaining the highest accuracy and performance is highlighted.

II. Data Driven Bearning Fault Diagnosis

Wind energy is currently recognized as one of the most rapidly expanding renewable energy sources. However, the wind industries continue to experience difficulties due to their premature failure of components, which has a direct impact on their operation [11]. Wind turbine components can either be monitored by offline or online tools that rely on sensors to record data continuously [12]. However, the large amount of collected data has paved the way to use data driven approaches using machine learning and DL techniques for fault classification and prognosis.

Regarding machine learning algorithms, extensive literature exist. Authors of [13] employed SVM to anticipate wind turbine bearing failures and the remaining service life by analyzing high-frequency vibration data, however, low prediction accuracy has been reported. The work in [14] classified and diagnosed various types of bearing faults using an SVM classifier which has been trained using frequency domain features derived from a fast Fourier transform. Acoustic emission signals were used in [15] where time, frequency, and spectral characteristics of the faulty signal where classified using different learning models. In [16], a condition-based monitoring strategy based on SVM algorithm was adopted to optimize the maintenance arrangement of offshore wind turbines by studying the correlation between components. In [17] a feature vector was provided to an RF classifier for fault diagnosis using variational mode decomposition. The experimental findings demonstrated that the proposed approach achieved higher accuracy compared to the conventional SVM, genetic algorithm based SVM, and particle swarm based SVM with less time.

Deep learning approaches have recently gained researchers' attention, particularly for the purpose of overcoming limitations of conventional machine learning ones. Limitations such as sensitivity to outliers in the data being processed, solving multi-classification problems, processing a large number of samples, and overfitting due to noise, are commonly associated with vibration signals acquired from wind turbine data. CNN and DL are therefore ideal to overcome the aforementioned problems. Authors in [18] can directly input vibration signal, extract features through the CNN, and identify vibration signal thus avoids the subjectivity of feature extraction process. In [19], a CNN with 4 convolution-pooling layer pairs are employed and the raw data are transformed into spectrograms. Results showed high accuracy and outperforming those of the linear SVM with particle swarm optimization, and the conventional SVM. The work in [20], [21] both presented an acoustic emission-based bearing fault diagnosis system. The work in [20] trained a CNN to classify the bearing acoustic emission signal as normal or faulty, yet with some limitations with low frequency features. In [21], authors have addressed the problems associated with vibration signals in low-speed rolling bearings faut identification and using and subspace embedded feature distribution alignment along with acoustic signals. A neural network approach for bearing fault diagnosis with continuous temperature monitoring was proposed in [22] where the model is previously trained during normal operation of the wind turbine to estimate the expected temperature values of turbine critical components under various conditions. The work in [23] developed a CNN based methodology with variational mode decomposition algorithms that can directly interpret raw vibration signals, taking into account environmental noise and variable loading. Wind turbine high speed bearing prognosis was carried out by authors in [24], [25] for the same dataset using SK. Authors in [24] used exponential degradation model for remaining useful life estimation, while the work in [25] used a one-dimensional CNN for fault classification.

Based on the literature work, various signals have been utilized to determine the fault and life expectancy of rolling bearings in wind turbines such as vibration, acoustic and temperature signals. Due to their high capabilities in detecting incipient faults with less complex signal processing, vibration monitoring is well suited for wind turbine bearing condition monitoring systems. On the other hand, vibration signal analysis in time domain might not be a viable option especially in early-stage detection, and for this reason, time-frequency analysis is more preferrable. For higher degree of accuracy, DL algorithms show higher classification accuracy compared to machine learning models in various literature. Compared to other work using the same dataset, the work of [24] used a fit exponential degradation model which requires complex analysis and prior knowledge for fault prediction. On the other hand, the work in [25] only studied the use of a single classifier with possible enhancement in results.

III. Feature Extraction & Spectral Kurtosis

Wind turbines are complex and have flexible operating conditions. Thus, feature extraction stage is used to compress high-dimensional time series (such as sensor signals) by keeping their main characteristics intact while discarding noise and removing correlations [2].This should speed up model training and produce better outcomes than when applied to the original, raw data.

Feature extraction/signal processing stages can be divided into time, frequency, and time-frequency domain analysis [26]. The time domain analysis involves extraction of statistical features such as peak, root-mean square (RMS), crest factor, and kurtosis for fault diagnosis. The frequency domain analysis utilizes fast Fourier transform (FFT), envelope analysis, and spectrum analysis, whereas time-frequency domain analysis can be divided into WT, Hilbert–Huang transform (HHT), Wigner–Ville distribution (WVD) and Short-Time Fourier Transform (STFT).

Spectral kurtosis (SK) is a statistical metric that indicates frequency dependance of signal's impulsivity. As faults in bearings give rise to a series of short impulse as the rolling elements strike faults on the races, the spectral kurtosis may be useful when determining the frequency bands dominated by the bearing fault signals, which typically contains resonance due to faults. STFT can be used to define SK in a 3-D diagram with time and frequency, allowing it to be used as a filter to select out the most impulsive portion of a signal, and significantly reducing noise and enhancing the diagnostic abilities [27].

IV. PROPOSED FRAMEWORK

The framework proposed in this work can be found in flowchart of Fig. 1 and is based on the run to failure data of high-speed wind turbine bearing. This paper compares the performance of three machine learning based classifiers that classify each sample into two classes: a) Short lifetime Class (faulty condition) and, b) Medium Lifetime Class (normal condition). The former represents bearing life expectancy less than 15 days while the latter represents more than 15 days of life expectancy. Fault features are extracted from the given dataset in both time and time- frequency domain, with nine signal-based statistical features extracted in the time domain. Furthermore, kurtosis spectrogram is computed using STFT to convert the sinusoidal time-domain signal to non-cyclic frequency domain in order to differentiate between the fault classes. Classifiers compared in the work are CNN, SVM and RF.

A. Dataset and Acquisition:

The dataset used in this analysis if for a 2MW high-speed shaft driven wind turbine which can be found in [24], [25] which is driven by a pinion gear. The bearing is a component of the gearbox that is responsible for coupling the electrical generator with the rotor. The vibration signal acquired was recorded daily for a duration of 50 days at scan frequency of 97656 Hz, and the recording period is carried out every 6 seconds. Over the course of the 50 days, a defect in the inner race fault led to the bearing's failure.

B. Data Preprocessing & Inspection

The total number of collected and recorded data entries is 29,286,800, which is complex to process. Initially, data is preprocessed by removing duplicated and unnecessary entries and zero records. In addition, date information versus vibration data is generated. The 50-day vibration signal is plotted in time-frequency domains for further exploration and visualization. STFT is applied to plot the vibration signal spectrogram.

C. Feature Extraction

In this step, a collection of statistical features derived from time-domain signal and spectral kurtosis are to be extracted. Time domain features include, date, mean, standard deviation (STD), peak to peak (P2P), root mean square (RMS), crest factor (CF), shape factor (SF) and impulse factor (IF). These feature are necessary in quantifying the impulsiveness of the signal. Besides the time domain features, SK is considered powerful tool for wind turbine prognosis in frequency domain. Statistical features of the spectral kurtosis, such as mean, standard deviation, skewness (Skp) and kurtosis (K) are also being extracted to create feature table.

D. Bearing fault diagnosis using CNN & ML

This step entails evaluating and comparing several ML classifiers to evaluate their diagnostic capability when implemented in the classification stage. This involves CNN, SVM and RF classifiers to distinguish between normal and faulty bearing condition, After Kurtosis is computed using STFT, samples are classified as either a) Short lifetime Class (faulty condition) and, b) Medium Lifetime Class (normal condition). Each class represents the bearing life expectancy. The three constructed models are tested over 20% of the samples, yet preserving the amount of records per sample such that the dataset is divided into a training set (80% of the data) and a testing set (20% of the data). For the CNN model training, batch size is 32 with 30 training epochs and loss function of cross entropy is selected. To lower computation burden, Adam optimizer is used for parameter tuning.

E. Performance Evaluation:

The effectiveness of the three different ML classifiers has been verified using numeric simulations based on an actual wind turbine dataset. A set of statistical indices have been utilized in this work to assess the diagnostic accuracy and to comprehensively compare the performance of each of the three ML techniques employed. These indices include accuracy, sensitivity, precision, specificity, and F1-score which can be computed using the following (3-5):

$$Accuracy = \frac{TP+TN}{TN+FP+FN+TP} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$F1-Score = \frac{2 \times TP}{2 \times TP+FP+FN} \quad (5)$$

where, TP, TN, FP, and FN are identified as the true classified positive and negative predictions and the false classified positive and negative predictions.

V. EXPERIMENTAL RESULTS & VALIDATION

To validate the effectiveness of the proposed framework in detecting bearing faults at an early stage, the proposed framework is evaluated using actual vibration signal obtained from a commercial 2 MW, high speed wind turbine. Several The suggested model was constructed using Python packages, including Keras, and native TensorFlow.

As mentioned earlier, vibration signals have been collected for 50 days and analyzed in both time and frequency domain in order to visualize and extract required features that will be helpful in building successful fault diagnosis. Fig. 2 shows a plot of the vibration signal in time domain. It can be noted that time domain spectrum demonstrate an increasing trend of the signal's impulsiveness, which can be observed in the amplitude variation of the acceleration signal. Accordingly, time domain features are extracted, including date, mean, standard deviation, P2P, RMS, CF, SF and IF and are tabulated in table 1. For a more insightful analysis, the vibration signal is further analyzed in the frequency domain where SK is applied using STFT. To visualize the spectral kurtosis changes along time, a plot of SK values as a function of frequency and the measurement sample are presented in Fig. 3. As the bearing state deteriorates, it is observed that the SK value near 10kHz rises. Statistical features of the SK, such as mean, STD, Skp and K are calculated accordingly and updated in Table 1 which shows a sample of 5 entries.

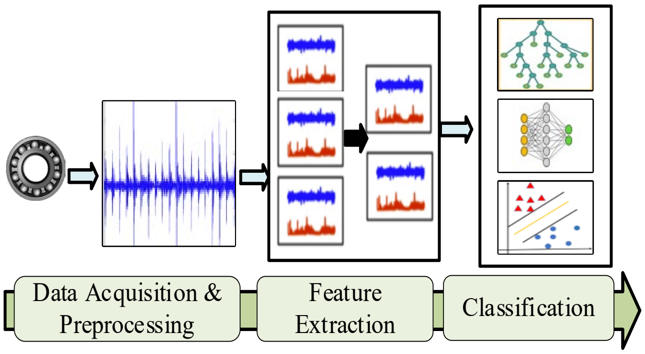

Fig. 1. Proposed Framework

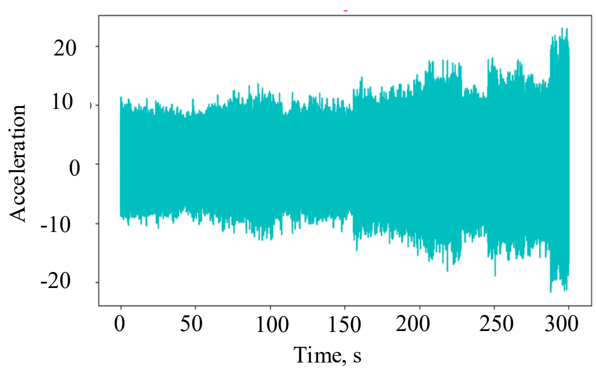

Fig. 2. Acceleration with Time

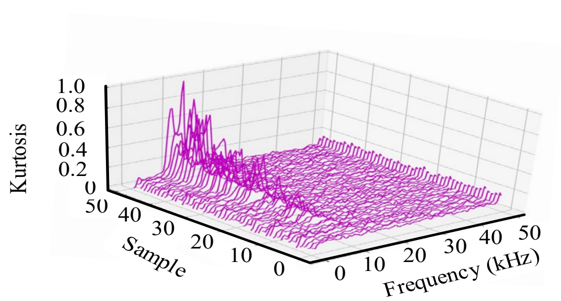

Fig. 3. Kurtosis Spectrogram

TABLE.1 EXTRACTED FEATURES

Parameter	0	1	2	3	4	5
Mean	0.346	0.244	0.218	0.213	0.215	0.293
STD	2.270	2.062	2.103	2.008	2.060	2.079
Skp	0.003	0.003	-0.001	0.001	0.001	-0.008
K	2.995	3.019	3.022	3.041	3.044	3.017
P2P	21.621	19.309	21.474	19.520	21.216	20.049
RMS	0.003	0.002	0.002	0.002	0.002	0.002
CF	3762.055	3760.6	3991.38	4046.27	3831.73	3671.60
SF	0.008	0.011	0.012	0.012	0.012	0.009
IF	32.618	41.794	50.417	49.947	48.194	34.332

To further identify the classification results of the testing phase, the confusion matrix diagrams of the three ML models are presented in Fig. 4. The vertical axis indicates the actual sample label, while the horizontal axis represents the predicted label such that a zero value represents a medium lifetime class (normal condition), and 1 represents short lifetime class (faulty condition). The corresponding performance metrics are accordingly calculated in Table 2.

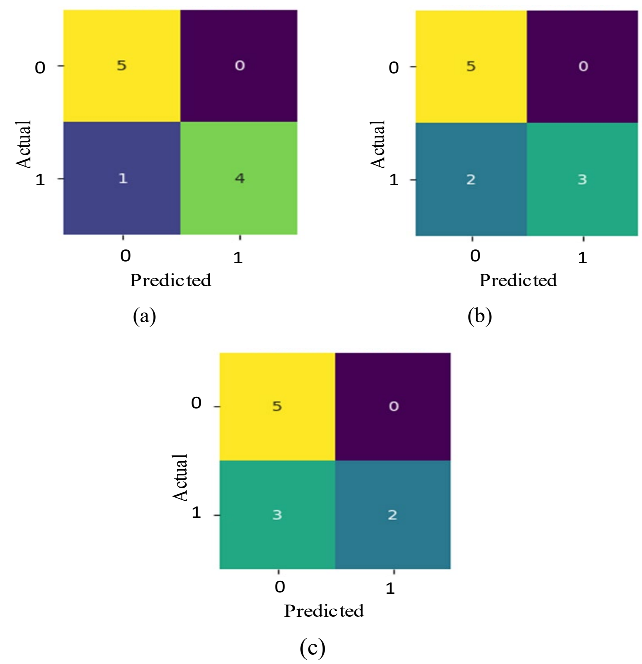

Fig. 4. Confusion Matrix a) CNN, b) RF, c) SVM

As demonstrated in Table 2, the specificity and precision of the three ML classifiers are 100%. The CNN measurements attained 90% accuracy, 83.33% sensitivity and 90.9% F1-ccore. For RF, the performance metrics are 80%, 71.42% and 83.33% for accuracy, sensitivity and F1-score respectively, and those for the SVM classifier were 70%, 62.5% and 76.92%. Results of Table 2 demonstrate that CNN is superior to RF and SVM in predicting bearing fault and remaining useful life.

Compared to the work of [24], [25] using the same dataset, in [24] authors have provided a statistical based exponential degradation model to predict the bearing remaining useful life, which might be non-deterministic as it depends on set of statistical assumptions [28]. On the other hand, the calculated accuracy, sensitivity and F1-score in [25] are 84%,76%, and 87% respectively, compared to the proposed work of 90%, 83.33% and 90.9% respectively. This demonstrates the superiority of the proposed methodology in achieving better performance results when compared to counterpart.

TABLE. 2 PERFORMANCE METRICS

	Accuracy	Sensitivity	Specificity	Precision	F1-Score
CNN	90%	83.33%	100%	100%	90.9%
RF	80%	71.42%	100%	100%	83.33%
SVM	70%	62.5%	100%	100%	76.92%

VI. Conclusion

Rolling bearings are one of the most commonly utilized rotating parts in mechanical equipment and also the most prone to damage and failure. This paper investigates the framework for intelligent fault diagnostic SK-derived features-based approach to extract the bearing vibration characteristics from raw vibration signal, which can address the problem of high probability of mechanical bearing defects in wind turbines. Comparative studies utilizing various ML techniques were carried out to classify the bearing's remaining useful life into two categorial classes: short and medium life expectancy. Results for remaining useful life estimation based on CNN show superiority compared to SVM and RF.

References

[1] O. Attallah, R. A. Ibrahim, and N. E. Zakzouk, "CAD system for inter-turn fault diagnosis of offshore wind turbines via multi-CNNs & feature selection," *Renew Energy*, vol. 203, pp. 870–880, Feb. 2023, doi: 10.1016/j.renene.2022.12.064.

[2] A. Stetco *et al.*, "Machine learning methods for wind turbine condition monitoring: A review," *Renew Energy*, vol. 133, pp. 620–635, Apr. 2019, doi: 10.1016/j.renene.2018.10.047.

[3] M. A. Vishwendra *et al.*, "A Novel Method to Classify Rolling Element Bearing Faults Using K-Nearest Neighbor Machine Learning Algorithm," *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, vol. 8, no. 3, Sep. 2022, doi: 10.1115/1.4053760.

[4] H. Li, J. Deng, S. Yuan, P. Feng, and D. D. K. Arachchige, "Monitoring and Identifying Wind Turbine Generator Bearing Faults Using Deep Belief Network and EWMA Control Charts," *Front Energy Res*, vol. 9, Nov. 2021, doi: 10.3389/fenrg.2021.799039.

[5] R. A. Ibrahim, K. H. Ahmed, B. W. Williams, M. S. Hamad, and Y. G. Dessouky, "Improved ride-through of PMSG wind turbine during symmetrical voltage dip using a magnetic amplifier," in *2nd IET Renewable Power Generation Conference (RPG 2013)*, Institution of Engineering and Technology, 2013, pp. 3.51-3.51. doi: 10.1049/cp.2013.1857.

[6] R. Assem, M. F. Moussa, Y. G. Dessouky, and B. W. Williams, "Parameters determination of grid connected interior permanent magnet synchronous generator," in *2012 15th International Power Electronics and Motion Control Conference (EPE/PEMC)*, IEEE, Sep. 2012, p. DS1c.5-1-DS1c.5-6. doi: 10.1109/EPEPEMC.2012.6397228.

[7] W. Qiao and D. Lu, "A Survey on Wind Turbine Condition Monitoring and Fault Diagnosis—Part II: Signals and Signal Processing Methods," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 10, pp. 6546–6557, Oct. 2015, doi: 10.1109/TIE.2015.2422394.

[8] M. M. Youssef, R. A. Ibrahim, H. Desouki, and M. M. Z. Moustafa, "An Overview on Condition Monitoring & Health Assessment Techniques for Distribution Transformers," in *2022 6th International Conference on Green Energy and Applications (ICGEA)*, IEEE, Mar. 2022, pp. 187–192. doi: 10.1109/ICGEA54406.2022.9791900.

[9] T. Sun, G. Yu, M. Gao, L. Zhao, C. Bai, and W. Yang, "Fault diagnosis methods based on machine learning and its applications for wind turbines: A review," *IEEE Access*, vol. 9, pp. 147481–147511, 2021, doi: 10.1109/ACCESS.2021.3124025.

[10] J. Fu, J. Chu, P. Guo, and Z. Chen, "Condition Monitoring of Wind Turbine Gearbox Bearing Based on Deep Learning Model," *IEEE Access*, vol. 7, pp. 57078–57087, 2019, doi: 10.1109/ACCESS.2019.2912621.

[11] A. Y. Jaen-Cuellar, D. A. Elvira-Ortiz, R. A. Osornio-Rios, and J. A. Antonino-Daviu, "Advances in Fault Condition Monitoring for Solar Photovoltaic and Wind Turbine Energy Generation: A Review," *Energies*, vol. 15, no. 15. MDPI, Aug. 01, 2022. doi: 10.3390/en15155404.

[12] A. Dhanola and H. C. Garg, "Tribological challenges and advancements in wind turbine bearings: A review," *Engineering Failure Analysis*, vol. 118. Elsevier Ltd, Dec. 01, 2020. doi: 10.1016/j.engfailanal.2020.104885.

[13] A. Turnbull, J. Carroll, S. Koukoura, and A. McDonald, "Prediction of wind turbine generator bearing failure through analysis of high-frequency vibration data and the application of support vector machine algorithms," *The Journal of Engineering*, vol. 2019, no. 18, pp. 4965–4969, Jul. 2019, doi: 10.1049/joe.2018.9281.

[14] S. E. Pandarakone, Y. Mizuno, and H. Nakamura, "Evaluating the Progression and Orientation of Scratches on Outer-Raceway Bearing Using a Pattern Recognition Method," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 2, pp. 1307–1314, Feb. 2019, doi: 10.1109/TIE.2018.2833025.

[15] M. Altaf *et al.*, "Automatic and Efficient Fault Detection in Rotating Machinery using Sound Signals," *Acoust Aust*, vol. 47, no. 2, pp. 125–139, Aug. 2019, doi: 10.1007/s40857-019-00153-6.

[16] J. Kang, Z. Wang, and C. Guedes Soares, "Condition-Based Maintenance for Offshore Wind Turbines Based on Support Vector Machine," *Energies (Basel)*, vol. 13, no. 14, p. 3518, Jul. 2020, doi: 10.3390/en13143518.

[17] T. Han and D. Jiang, "Rolling Bearing Fault Diagnostic Method Based on VMD-AR Model and Random Forest Classifier," *Shock and Vibration*, vol. 2016, pp. 1–11, 2016, doi: 10.1155/2016/5132046.

[18] Z. Xiaoxun, Z. Jianhong, H. Dongnan, and H. Zhonghe, "Research on mechanical rotor condition monitoring based on VCNN," *Energy Procedia*, vol. 158, pp. 6393–6398, Feb. 2019, doi: 10.1016/j.egypro.2019.01.208.

[19] W. Zhang, F. Zhang, W. Chen, Y. Jiang, and D. Song, "Fault State Recognition of Rolling Bearing Based Fully Convolutional Network," *Comput Sci Eng*, vol. 21, no. 5, pp. 55–63, Sep. 2019, doi: 10.1109/MCSE.2018.110113254.

[20] J. Kim and J.-M. Kim, "Bearing Fault Diagnosis Using Grad-CAM and Acoustic Emission Signals," 2021, pp. 527–534. doi: 10.1007/978-981-15-9837-1_46.

[21] R. Chen, L. Tang, X. Hu, and H. Wu, "Fault Diagnosis Method of Low-Speed Rolling Bearing Based on Acoustic Emission Signal and Subspace Embedded Feature Distribution Alignment," *IEEE Trans Industr Inform*, vol. 17, no. 8, pp. 5402–5410, Aug. 2021, doi: 10.1109/TII.2020.3028103.

[22] P. Teimourzadeh Baboli, D. Babazadeh, A. Raeiszadeh, S. Horodyvskyy, and I. Koprek, "Optimal Temperature-Based Condition Monitoring System for Wind Turbines," *Infrastructures (Basel)*, vol. 6, no. 4, p. 50, Mar. 2021, doi: 10.3390/infrastructures6040050.

[23] Z. Xu, C. Li, and Y. Yang, "Fault diagnosis of rolling bearing of wind turbines based on the Variational Mode Decomposition and Deep Convolutional Neural Networks," *Appl Soft Comput*, vol. 95, p. 106515, Oct. 2020, doi: 10.1016/j.asoc.2020.106515.

[24] Mathworks, "Wind Turbine High-Speed Bearing Prognosis." https://www.mathworks.com/help/predmaint/ug/wind-turbine-high-speed-bearing-prognosis.html (accessed Apr. 17, 2023).

[25] Eric Bechhoefer, "Wind Turbine High Speed Bearing Prognosis Data," *Creative Commons Attribution-Non Commercial-ShareAlike 4.0 International License*, 2020. https://creativecommons.org/licenses/by-nc-sa/4.0/ (accessed Apr. 14, 2023).

[26] M. H. Mohd Ghazali and W. Rahiman, "Vibration Analysis for Machine Monitoring and Diagnosis: A Systematic Review," *Shock and Vibration*, vol. 2021. Hindawi Limited, 2021. doi: 10.1155/2021/9469318.

[27] R. B. Randall, N. Sawalhi, and R. B. Randall, "The application of spectral kurtosis to bearing diagnostics." [Online]. Available: https://www.researchgate.net/publication/267700692

[28] W. Zhang, J. Vatn, and A. Rasheed, "A review of failure prognostics for predictive maintenance of offshore wind turbines," *J Phys Conf Ser*, vol. 2362, no. 1, p. 012043, Nov. 2022, doi: 10.1088/1742-6596/2362/1/012043.