WIND TURBINE FAULT MODELING AND CLASSIFICATION USING CUCKOO-OPTIMIZED MODULAR NEURAL NETWORKS

BABU PONNUSWAMY[1], CHRISTOPHER COLUMBUS[2], SREE RATHNA LAKSHMI[3], JEYANTHI CHITHAMBARAM[4]

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The wind turbine is rapidly becoming one of the world's most significant renewable energy sources. Wind turbines must be massive to increase amounts of electrical energy. The blades of a wind turbine are commonly made of fiber materials due to their low cost and low weight properties. However, blades are affected by gusts of wind, poor climate factors, uncertain wind loads, lightning storms, and gravity loads, resulting in a surface crack of the blade. As a result, it is important to monitor the state of each wind turbine and its location fault condition. In this research, a cuckoo-optimized modular neural network (COMNN) is proposed for detecting and classifying a crack in the blades of a wind turbine. The method is created using a piezoelectric accelerometer to calculate the blade vibration response when it is energized. Cuckoo optimization is applied to initialize and adjust the weight vector of the Modular Neural Network. The experimental result shows the COMNN accurately detects and classifies faults in an acceptable time. The proposed approaches classify the fault type with an accuracy 98.1 % higher than the existing techniques, such as convolutional neural networks (CNN), recurrent neural networks (RNN), and artificial neural network ANN + support vector machine (SVM) algorithms.

1. INTRODUCTION

Wind energy is one of the world's most significant energy sources. Its use has expanded significantly because of the current environmental problem and efforts to reduce environmental damage. Given its dependability and minimal vulnerability to climate change, it has become one of the finest alternative sources for the near future. It is critical in the energy industry, and all research indicates that the pattern will continue. Wind progress during the previous 18 years indicates that its significance will not diminish to rise in the future. Large and changing loads and extreme weather are typical with wind turbines (WT) [1]. As a result, the functional inability of WTs exceeds 4 % of their lifetime. For a wind farm, operation and costs can range from 20 % to 30 % of electricity cost, and a wind turbine can reach 40 % towards the end of its life. A high level of maintenance is required to ensure secure, expensive, and dependable power generation. This is especially important for wind farms off the coast, when wind turbines cannot be accessible because of poor weather [2,3].

In recent years, condition and structural health monitoring have been used to detect wind turbine defects [4]. The SHM approaches are founded on the concept that a variation in a structure's dynamic features will capture a change in its mechanical characteristics [5].

Sandwich materials, such as composite skins and a lightweight, isotropic core, are commonly used to make wind turbine blades. These materials were chosen due to the necessity to make blades with complex architecture, light density, and appropriate dynamic qualities [6]. It has a strong fatigue resistance, minimal thermal expansion, and thermal conductivity. Furthermore, increasing the blade size causes new challenges linked to loads and strains. Sandwich structures are made up of two outer skins that cover a lightweight inner material. This design has a high degree of stiffness and is relatively light. The core is thicker and has a lower density than the outer skins. The main purpose is to keep the skin from moving around.

Fault monitoring methods are separated into traditional and large-scale fault location strategies in practical application [7].

The majority of past research on fault location has used traditional approaches. Conventional methods use single-end, double-end, and multi-end power line data to locate the problem and monitor fault [8]. Traditional approaches in a large-scale power system require a minimum of one measuring at the end of the line device, but installing measurement equipment such as PMU at the end line is not cost-effective. Furthermore, if measuring instruments fail, which is unavoidable, conventional fault location methods make estimating problem location nearly impossible. As a result, it appears that wide-area measurement is more realistic in power systems. Wide-area monitoring systems are not useful in error detection of traditional systems due to the low sampling frequency of the measuring instruments. However, introducing wide-area measuring instruments, especially PMUs, has alleviated this difficulty by capturing the power system's dynamic behavior with a high sample frequency.

As a result, a novel cuckoo-optimized modular neural network is proposed in this research for the detection and classification of wind turbine blade cracks. Cuckoo optimization is applied to initialize and adjust the weight vector of the modular neural network. Experimental results show that COMNN accurately detects and classifies faults within an acceptable time. The proposed approaches classify the fault type with an accuracy of 98.1 %, which is higher than the existing methods such as convolutional neural network (CNN), recurrent neural networks (RNN), and artificial neural network (ANN) + support vector machine (SVM) algorithm.

The rest of the paper is formatted in this method. Section 2 contains a review of the research used as a reference. Section 3 discusses the proposed hierarchical framework. The proposed approach's graphical outputs, performance evaluation, and accuracy are discussed in section 4. The conclusion is found in section 5.

2. LITERATURE SURVEY

This part shows how several studies have been conducted throughout the years to classify faults in wind turbines. This

[1]Department of Electronics and Communication Engineering, PSN Engineering College, Tirunelveli, India, Email: babup@psncet.ac.in
[2] School of Computer Science and Engineering, VIT Chennai, India, Email: christopher.columbus@vit.ac.in
[3] Department of Electronics and Communication, Agni College of Technology, Chennai, India, Email: sreerathnalakshmi.ece@act.edu.in
[4] Department of Electronics and Communication, PSN Engineering College, Tirunelveli, India, Email: jeyanthi@psncet.ac.in

paper reviews and provides an overview of current developments in fault detection.

Zare *et al*. [9] presented the autonomous data-based defect detection algorithm developed using a multilayer deep neural network. The simulation result showed that the introduced method could robustly classify the fault and has high accuracy.

Cho *et al*. [10] presented the Kalman filter that determines the valve spool and the pitch angle location with readings from the sensors system, and a neural network was used for fault diagnosis. The fault diagnostic technique is based on a supervised training artificial neural network technology capable of detecting a specified fault type. The result showed that the introduced method has high accuracy for fault.

Guo *et al*. [11] developed the fault detection technique for wind turbine gearboxes with coupling faults. The RI-MPCNN diagnoses all types of fault conditions components in the wind turbine gearbox. Results showed that the introduced technique increases accuracy and accurately detects the faults in wind turbines.

Nithya *et al*. [12] found the fault in the wind turbine system using an artificial neural network (ANN). Increased mechanical element degradation, a significant function of asset reduction, and an increase in the expense of regular maintenance can all result from system faults. Differences in blade angle and pitch mismatch are two possible flaws in a wind turbine system. The result showed that the introduced method directly improves a system issue.

Jiang *et al*. [13] developed an MSCNN structure where adaptive fault detection of WT gearbox in diverse operational situations has been developed. In terms of feature learning, the ability to withstand noise, and performance in classification, the MSCNN greatly outperforms the traditional CNN in the evaluations.

Liu *et al*. [14] presented a fault detection approach using generative adversarial nets with synthetic fault data (GANs). GAN was developed to address the fault results revealed caused by small real-world fault sample data. The result indicated that the method was effective in their performance because of the SCADA data.

Xiang *et al*. [15] presented a convolutional neural network used to find flaws in a wind turbine (CNN). A wind turbine real-time monitoring system is utilized to create a CNN architecture that extracts dynamic changes in data. The findings showed that the suggested method has a higher systematic evaluation index, reduces false positives, and significantly supports decision-makers.

Miao *et al*. [16] presented the improved maximum correlated kurtosis deconvolution and eliminated various sounds in the encoder signal. Real experimental cases validated the encoder signal as an alternate tool for defect diagnosis of wind turbine gear.

Wang *et al*. [17] presented a selection that is a variable approach based on principal component analysis with numerous criteria for selection for selecting a collection of fault signals while retaining the original dataset's data variation. Results showed that the model has a high forecast accuracy and the ability to identify and estimate the severity of the issue.

Agasthian *et al*. [18] presented cuckoo search optimization (CSO) as the application of a support vector machine (SVM) in a wind turbine to lower operating costs and enhance accuracy. According to the results, the CSO model based on the SVM algorithm achieved precise defect identification.

From the above literature review, different traditional networks detect cracks in the blades of a wind turbine. Still, they have some drawbacks, such as reduced efficiency, lost energy production, and less accuracy and specificity. The proposed work uses MNN to detect a crack in the blades of a wind turbine, but it needs more accuracy. So, the proposed cuckoo-optimized modular neural network is used to identify cracks in wind turbines. Experiments show that this method effectively detected the faults and improved the accuracy.

3. **PROPOSED METHODOLOGY**

Wind energy is the quickest renewable source in the world. Because of the current generation of wind turbines' large size and remote locations, operational accessibility of wind turbines is becoming more and more crucial. Figure 1 displays the proposed COMNN for detecting and classifying the crack on wind turbine blades. This research aims to propose a COMNN for fault detecting and classifying the cracks on wind turbine blades.
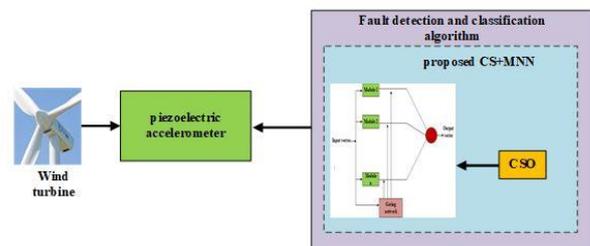

Fig. 1 – Proposed method for cuckoo-optimized modular neural.

3.1. DATASET DESCRIPTION

This work's data collection, which included 725 high-resolution camera images of blades, was gathered from wind farms in eastern China [19], as shown in Fig 2. During maintenance, four defects are inspected: edge erosion, coating flaws, fiber defects, and cracks. These four categories of defects comprise five classes in the data set, including the healthy state. Expert annotations on each faulty region's location and classification are ground realities.

Fig. 2 – Sample images of cracked wind blade images.

3.2. DESIGNED MNN FOR WIND TURBINE FAULT DETECTION AND CLASSIFICATION

A modular neural network (MNN) is a DNN with learning that has a separate sequence of intermediary components that comprise a module that operates under a specific design. This intermediate receives Individual network module output as input, which aids in the computation of the final output, which is resolved using a tangential activation function. MNN aspires to shrink a big network into a smaller, more manageable one. It improves efficiency by connecting units in a way that grows exponentially when more separate networks are added. While this complicates the network, it increases computing productivity by minimizing computational time on

specific activities allocated to divided modules, and tasks are done in parallel with module rearrangement to improve system adaptability and flexibility.

The design of the proposed Modular Neural Network. Recurrent neural networks with random connections make up an expert and gating network. The number of expert networks defines the gating network's output units, and the signals of at least one of these output units must be nonzero and equal to one. We employ the "SoftMax" activation function to meet these requirements; precisely, the activation of the gating network, denoted h_i, is

$$h_i = \frac{e^{w_i}/_t}{\sum_{j=1}^{x} e^{w_j}/_t},$$ (1)

where w_i stands for the weighting factor of unit i inputs, t for temperature, and x for the number of expert networks. P is the entire system's output vector

$$P = \sum_{i=1}^{x} h_i P_i.$$ (2)

The i-th expert network is denoted by P_i. Using the backpropagation technique, the expert and gating networks are modified together during learning to optimize the cost function.

$$\ln N = \ln \sum_{i=1}^{x} \frac{h_i}{\sigma_o} \|P^* - P_i^2\|.$$ (3)

The architecture's purpose is to simulate the dispersion of training patterns. The log-likelihood function is used to achieve this by using gradient ascent. We show that this derivation is given by using the chain rule (1).

$$\frac{\partial \ln N}{\partial w_i} = s_i - h_i.$$ (4)

The likelihood a network of experts creates the target vector is given by s_i:

$$s_i = \frac{\frac{h_i}{\sigma_o} \|P^* - P_i^2\|}{\sum_{i=1}^{x} \frac{h_i}{\sigma_o} \|P^* - P_i^2\|}.$$ (5)

Consider the log probability gradient about the output of the ith expert network. In L is differentiated about P_i to give

$$\frac{\partial \ln N}{\partial P_i} = \frac{s_i}{\sigma_i^2} (P^* - P_i).$$ (6)

Finally, we calculate the log probability gradient about σ_i^2 the i-th expert network's variance. In N is differentiated to produce

$$\frac{\partial \ln N}{\partial \sigma_i^2} = \frac{S_i}{2\sigma_i^4} (\|P^* - P_i\| - \sigma_i^2).$$ (7)

This expression means that the parameter σ_i^2 is weighted by the likelihood a posteriori and adjusted toward the sample variance $\|P^* - P_i\|$.

3.3. CUCKOO SEARCH OPTIMIZATION

The CSO is applied to initialize and adjust the MNN weight vector. Due to its unusual lifestyle and aggressive reproduction method known as brood parasitism, CSA was inspired by a bird species known as cuckoo birds [19]. CSA is boosted by Lévy flights, which provide more capability than the existing method, rather than random walks like other algorithms [20].

In mathematics, Lévy flights characterize the random process. The performance of the levy flight is provided while creating a new solution $m^{(n+1)}$.

$$m_i^{(n+1)} = m_i^n + \beta \cdot \text{levy}(\pi),$$ (8)

where β is a positive step with a size that changes depending on the optimization model, and n is the current gene ratio. Lévy distribution can be conceptualized as

$$\text{levy} \sim e = n^{-\pi} \ (0 < \pi < 4).$$ (9)

The Levy flight combines Levy distribution and the step value stated in (7). Setting the parameter values is another significant benefit of the CSO method. As a result, we need to adjust the crucial parameters P_a, and n. The outcome shows the convergence rate is unaffected by the parameters utilized. This means that CSA does not require fine-tuning.

4. RESULT AND DISCUSSION

This part demonstrates and evaluates the COMNN technique. The test was performed using MX-POWER in a 50 W, 14 V variable wind turbine. The proposal is evaluated using simulated signals. Table 1 lists the characteristics of a wind turbine. Vibration signals are gathered using an accelerometer of the piezoelectric variety.

Regarding defect detection, its frequency sensitivity is strong [21,22]. As a result, accelerometers are commonly used in health monitoring. A 500 g uniaxial accelerometer with a 100 mV/g sensitivity and a resonance frequency of roughly 40 Hz was utilized in this experiment. Using the COMNN technique, the piezoelectric accelerometer was installed on the turbine close to the wind turbine hub to record the vibration data displayed in Table 1.

Table 1
Characteristics of a wind turbine

Model	FP-50W-14V
Rated power	50 W
Rated rotating rate	900 rpm
Cut in wind speed	3.6 m/s
Rated voltage	14 V
Cut out wind speed	51 m/s
Start-up wind speed	2.9 m/s
Rated wind speed	13.6 m/s
Rotor diameter	1058 mm
Blade materials	Carbon fiber
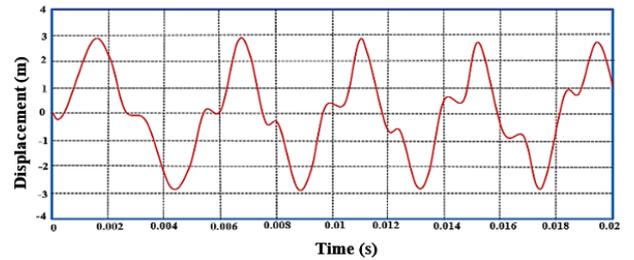
(a)
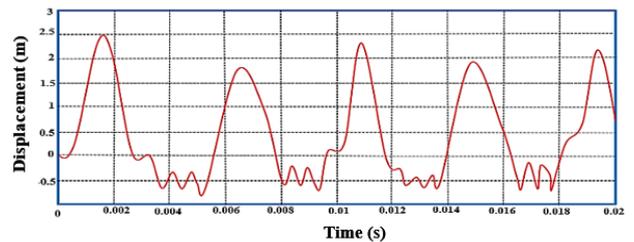
(b)

Fig. 3 – a) Healthy blade; b) cracked blade.

The wind turbine is positioned on a fixed steel platform. The wind tunnel has a speed range of 5 to 15 m/s and is used to turn on the turbine. The wind speed was adjusted continually to imitate the real world's wind conditions.

Figure 3 shows the healthy and cracked blade. The time-variant cracked blade generates a vibrational response with the frequency content varying with time. In this paper, COMNN is used for crack detection in wind turbines.

The piezoelectric accelerometer is used to collect the vibration signals. The subsequent issues were replicated on a single blade, with the remaining blades remaining in superior shape, and the corresponding vibration signals were documented. Their corresponding vibration signals are shown in Fig. 4.
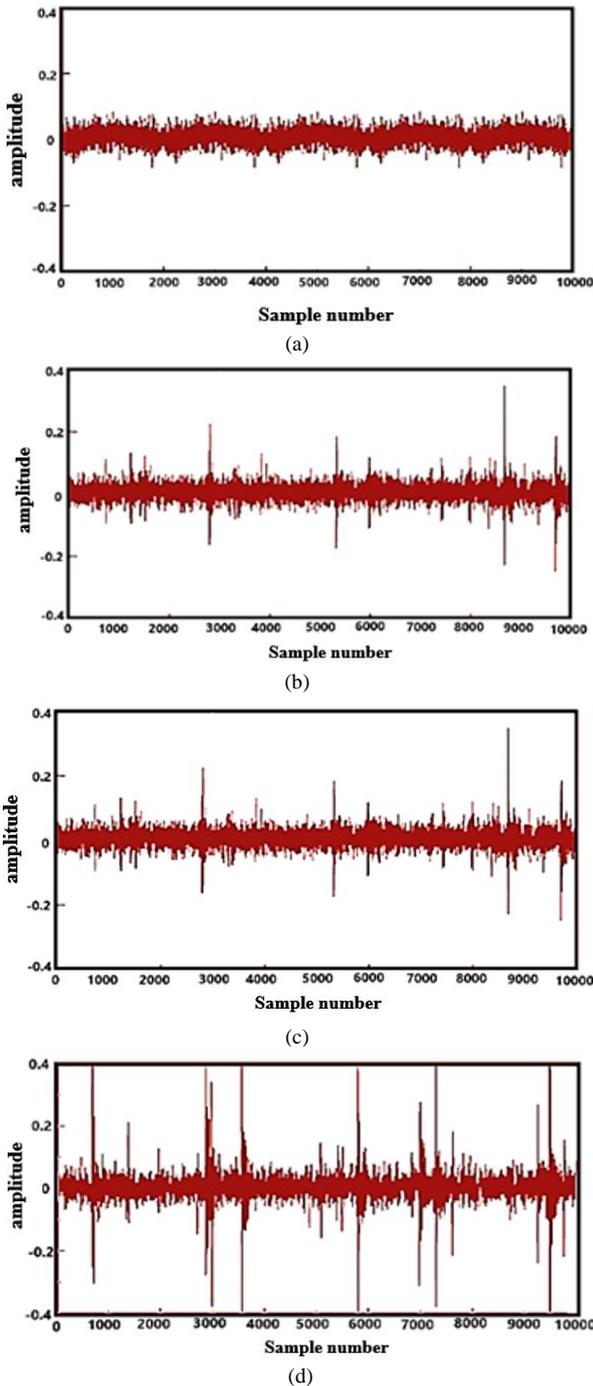

Fig. 4 – Vibration signal of the blade (a) good signal (b) fault signal for blade root crack (c) fault signal for a blade's mid-span crack (d) fault signal for blade tip crack.

The vibration signals of a wind turbine blade produced at 900 rpm from different crack situations are shown in Fig. 5. A blade in good condition, a blade with a root crack fault, a blade with a mid-span crack fault, and a blade with a tip crack fault are all displayed on the vibration signal plot (sample number vs amplitude). This results a rudimentary notion of the magnitude of obtained vibration signal changes time in relation to simulated fault.
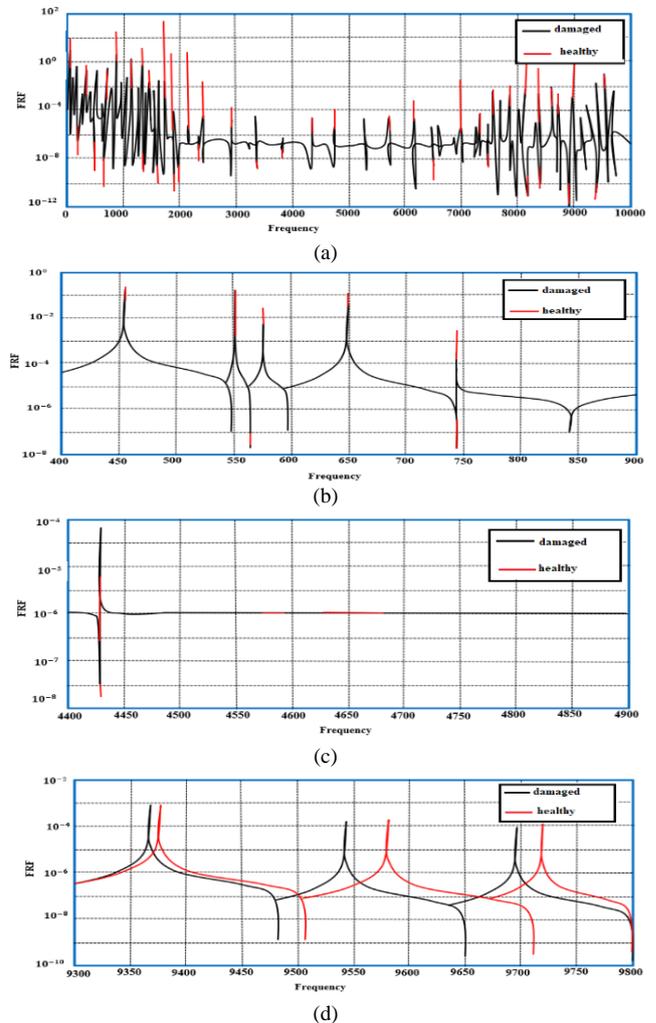

Fig. 5 – Frequency response function of the blade; a) overall range; b) low frequency range; c) mid-frequency range; d) high frequency range.

The frequency response curve in the $f = 2\,500$–$6\,500$ Hz range is typically flat at most frequencies, as shown in Fig. 5a. The modulation bandwidths emerge because of the frequency response function's peaks changing and the value of the frequency response changing at the pump rate, according to the sideband estimations from the method, which depend on the principle of opening and closing cracks.

Figure 5b contains many peaks and a slope that is frequency-dependent. It is challenging to disentangle the relationship between the curvature of a healthy blade and that of a damaged one.

Figure 5c has fewer peaks at first. Furthermore, the curves are flat for most of this range. As a result, finding a side band with a modulated signal would be challenging.

Figure 5d displays the frequency response curve in a frequency range suitable for frequency probing selection. The frequency strongly influences the frequency response characteristics, and there is a significant variation in the

curves of the healthy and injured blades. According to this result, the probing frequency should be carefully selected to achieve nonlinear modulation efficiently.

4.1. EVALUATION METRICS

The results are analyzed using the confusion matrix, which has four primary parameters: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The confusion matrix has been used to investigate accuracy (Ac) and specificity (Sp) metrics. These metrics are as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+TF}, \quad (10)$$

$$\text{Specificity} = \frac{TN}{FP+TN}. \quad (11)$$

Ac denotes the COMNN accuracy and additional fault detection techniques, whereas specificity denotes the correct/incorrect classification proportion. It is indeed important to note that these measurements can help with fault detection evaluation.
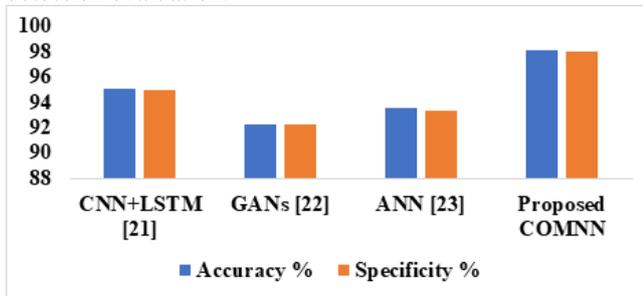

Fig. 6 – Comparison of faulty detection of the proposed method with existing method.

Table 2
Comparison of the proposed method with existing method

Techniques	Accuracy %	Specificity %
CNN+LSTM	95.1	95
GANs	92.3	92.2
ANN	93.5	93.3
Proposed COMNN	98.1	98

The performance of the concurrent techniques (*i.e.*, CNN, RNN, and ANN+LSTM) using the same simulation parameter of our research work. Table 2 illustrates that traditional networks such as CNN, RNN, and ANN+LSTM have less accuracy and specificity than the COMNN method. The COMNN technique maintains 98.1% and 98 % accuracy and specificity. Figure 6 shows the COMNN approach improves the overall accuracy by 3 %, 5.8 %, and 4.6 %, and specificity of 3 %, 5.8 %, and 4.7 % better than CNN, RNN, and ANN+LSTM, respectively**.** From the above comparison, the COMNN model has higher accuracy and specificity than existing models.

5. **CONCLUSION**

Wind turbines are critical components in the extraction of wind energy. This paper presents a piezoelectric accelerometer-based classification of vibration signals for evaluating wind turbine crack detection and classification using a cuckoo-optimized modular neural network (COMNN). It describes three wind turbine faults: blade root crack, blade mid-span, and blade tip crack. The proposed approach is compared with several traditional techniques,

such as CNN, RNN, and ANN +SVM algorithms. The proposed method effectively detects blade cracks in the wind turbine. As well as the proposed approach proved to be superior in classifying the faults. The result showed that the COMNN has 98.1 % accuracy and high specificity. We aim to enhance the generality of the proposed method and develop it in the future in the presence of limited visibility.

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