Vibration Analysis for Fault Detection of Wind Turbine: New Methodology of Supervised Machine Learning Techniques

Javier Vives

Institute of Automatic and Industrial Informatics, Universitat Politècnica de València, Valencia 46022, Spain.
E-mail: javifus@posgrado.upv.es

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The implementation of supervised machine learning techniques classifiers is changing wind turbine maintenance. This automatic and autonomous learning methodology allows one to predict, detect, and anticipate the degeneration of any electrical and mechanical components present in a wind turbine. In this paper, two different failure states are simulated due to bearing vibrations, comparing frequency analysis and some machine learning classifiers. With the implementation of the KNN and SVM algorithms, we can evaluate different methodologies for supervision, monitoring, and fault diagnosis in a wind turbine. With the implementation of these techniques, it reduces downtime, anticipates potential breakdowns, and aspect import if they are offshore.

1. INTRODUCTION

In response to global warming and increased energy consumption, renewable sources of electricity are becoming increasingly popular. Wind energy production has grown by about 25 % in the past few years, and researchers and engineers have developed new techniques to maintain wind power plants. Through advanced monitoring and fault diagnosis, wind turbines can be made more reliable, safe, and profitable. Maintenance of wind turbines[1] have traditionally relied on spectral analysis and fault trees. However, through new technologies and advances such as connectivity, smart, and data generation, a shift is occurring towards artificial intelligence (AI). Data is becoming increasing available to the industry at this point, which affects important decisions in areas such as scheduling[2] ,maintenance management[3] and quality improvement.[4]

The impact of machine learning has been amplified in these areas due to new hardware and cloud-based solutions[5] . Wind turbines have many components working together, and vibration is a major cause of system failure. As well as gear and bearing defects, vibrations are usually an indication of mechanical or electrical faults. Bearings suffer wear mainly from their rolling elements, since their surface position changes continuously with respect to their load, due to the result of their rotation speed.

Aside from geometric imperfections, vibrations can also be caused by faults such as exterior and interior raceways, component failures, cage failure, and imbalances and misalignments.

There have been several studies on vibrations in structures and in rotating machines. The process used to detect bearing failure because of mechanical failure through frequency spectral analysis has been applied in many of the studies to date. Various diagnostic techniques have traditionally been used to detect faults in wind turbine generators and their structures in studies of wind turbines[6] . According to AI[7] , in this case Machine Learning, this type of methodology has worked perfectly and continues to work perfectly, but there are some limitations and drawbacks. With a series of maintenance methodologies, it is possible to anticipate, detect, and classify a malfunctioning component of a machine autonomously. With respect to Dhiman,[8] machine learning reduces response times and virtually eliminates error possibilities.

The availability of data management and analysis allows for feedback learning and flexible offshore implementation, according to Kreutz[9] . By analysing and preventing failures, AI methodology protects you against all types of failures that you desire to monitor. To implement these methods on an actual system without causing costly errors, they must be validated. The use of prototypes or test benches to develop new techniques, carry out studies, etc., is convenient when validating fault diagnosis techniques, and the prototypes are used to understand how these systems operate. Wind turbines that go down can cause considerable losses due to two factors: first, the cost of replacing them, and second, the energy that cannot be produced while they are offline, which may occur during peak energy production times. Due to the high repair and maintenance costs, especially in offshore wind farms, fault detection and diagnosis techniques are essential for the early detection of faults and stopping of the machine. Additionally, due to the lower costs associated with downtime and defective products, it is becoming increasingly important to manage maintenance activities efficiently. Through the application of algorithms designed to anticipate and prevent potential problems, we have developed a prototype that is able to detect, supervise, and anticipate failures compared to existing systems. In this paper, we propose a feature learning method for detecting different bearing failures autonomously using vibration analysis. We present an algorithm for monitoring and diagnosing faults in a prototype wind turbine in this article. A review of the literature is given in the next section. Next, we discuss the data collection process and the data set. Next, we evaluate the classification results. The study concludes with some relevant conclusions.

2. WORKING METHODOLOGY

Wind turbine failures due to vibrations in bearings are diagnosed and monitored using different methods, obtaining multiple characteristics of each bearing, and, therefore, the general characteristics of any individual bearing do not necessarily correspond to the fault characteristics. Of another bearing, following the same or different methodology. Using the characteristics extracted from vibration measurements, this study shows how machine learning can be used to improve accuracy and predict possible breakages.

2.1. Machine Learning

In wind turbine fault detection, machine learning focuses mainly on two tasks: the first is the detection of anomalies, and the second is the classification of faults. By detecting failures promptly or anticipating them, this technique allows for corrective measures to be taken in a very short period, improving the system's reliability and security.

In the world of machine learning, there are two types of methods: supervised and unsupervised. The most common machine learning case, by far, is supervised machine learning.[10] With supervised learning, the output of your algorithm is already known while the output is unknown with unsupervised learning. To get in, on the way out, you only need to figure out the process. In most cases, the algorithms are "taught" from training data sets. Unsupervised learning, on the other hand, is a more complex process, because it relies only on the input data and binary logic that all computer systems use. No references whatsoever. To apply any type of learning, the data must first be classified.[11]

Different classification algorithms can be applied to this problem, where they take the functionality of an object and identify it by a limited number of categories or classes from the input information received from that object.

As a result, a classifier works in two phases:

- To achieve optimal performance, it must be trained, which means receiving a large amount of sample data and its correct classification, to adjust its parameters.
- When the algorithm has already been trained, it provides an output based on the input data it receives

2.2. Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning method based on statistical learning theory. It is a useful method for classification and regression in cases of small samples, such as fault diagnosis. A simple case of two classes is considered, which can be separated by a linear classifier. Figure 1 shows triangles and squares representing these two kinds of sample points. The hyperplane H is one of the planes of separation that separate the two classes. H_1 and H_2 (shown by dashed lines) are the planes that are parallel to H and pass through the sample points closest to H in these two classes. The margin is the distance between H_1 and H_2. The SVM attempts to place a linear boundary between the two different classes H_1 and H_2, and orient it in such a way that the margin is maximized, resulting in the smallest generalization error. The closest data points that used to define the margin are called support vectors.

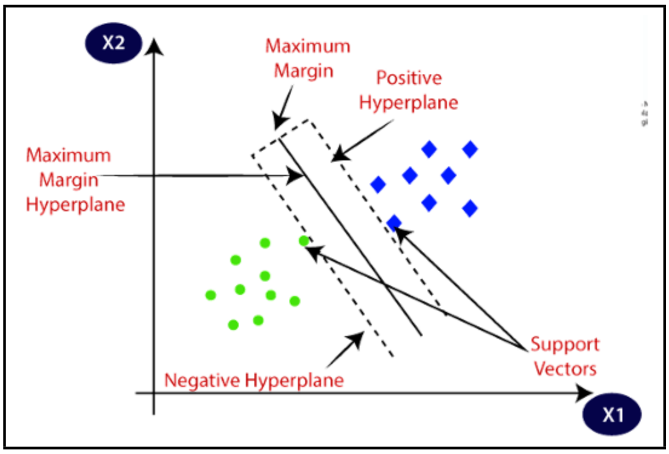

Figure 1. Optimal hyperplane for binary classification by SVM.

A quadratic function is minimized under linear inequality constraints by reducing it to convex optimization[12] . Assume we have a training set of samples $[(x_i, y_i)]$, where $i = 1$ to N, and N represents the total number of samples. To find the separation plane with the least generalization error out of each linear separation plane, we need to determine how to divide the input samples into two classes. It is possible to divide the samples into two classes: triangular and square. A triangle class has a $y_i = -1$ label. A square class has a $y_i = +1$ label. For non-separable data, slack variables are not considered (nor P 0). Using the following optimization problem, you can obtain the hyperplane for $f(x) = 0$ from the given data.

$$\text{Minimize} \quad \frac{1}{2}||w||^2 + C\sum_{i=i}^{N}\xi_i; \tag{1}$$

$$\text{Subject to} \quad \begin{cases} y_i(w^T x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0, i = 1, 2, \ldots N \end{cases}; \tag{2}$$

where C is a constant representing the error penalty. Introducing Lagrange multipliers to the optimization problem above leads to the following result:

$$\text{Minimize} \quad W(\lambda) = \sum_{i=i}^{N}\lambda_i - \frac{1}{2}\sum_{ij=i}^{N} y_i y_j \lambda_i \lambda_j (x_i x_j); \tag{3}$$

$$\text{Subject to} \quad \begin{cases} 0 \leq \lambda_I \leq C \\ \sum_{i=i}^{N} \lambda_i y_i = 0, \quad i = 1, 2, \ldots N \end{cases}. \tag{4}$$

Using the sequential minimum optimization (SMO) algorithm, the dual problem that results from SVM derivation can be efficiently solved. SMO breaks down the general QP problem into QP subproblems.

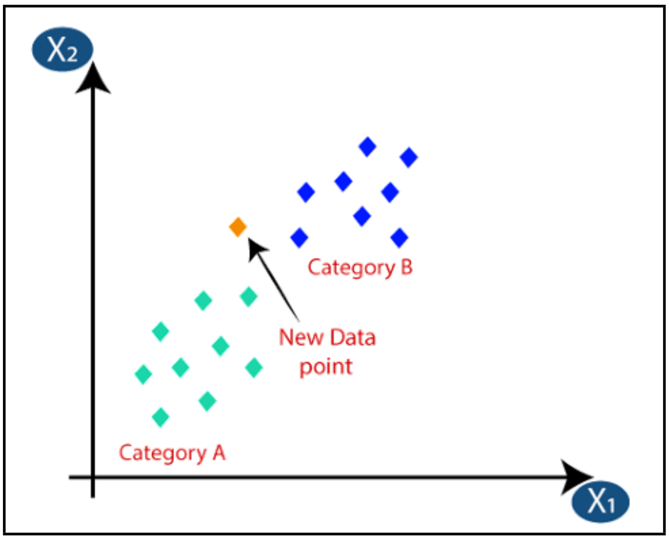

Figure 2. K-NN diagram with different samples.

2.3. K-Nearest Neighbour (KNN)

Learning algorithms based on these principles can help users determine how several instances within a data set experience similar characteristic.[13] Learning occurs while the test data is tested, so that rather than create a model from learning with training data, the model is created automatically. Lazy learning is another name for this algorithm type.

Its operation is very simple, for a given training group of classified instances $T = [(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)]$, where x_i is the vector of characteristics of the unlabelled instance, y_i is the label $y_1 = c_1, c_2, \ldots, c_K, i = 1, 2 \ldots N$. Using a given distance metric, the k-NN algorithm finds the k closest instances to a training sample (x, y). N_k represents the area where these k instances are located. As a result, it is possible to calculate the test sample label x from the decision rules:

$$y = argmax_{cj} \sum_{x_i \eta N_k(x)} I(y_i = c_j), \quad i = 1, 2, \ldots N; \quad j = 1, 2, \ldots K; \tag{5}$$

where I is the indicator function.

According to Fig. 2, by analysing what an unclassified instance's closest neighbours are, we can extract its tags.

Three basic concepts make up the k-NN algorithm: how many instances were measured, the classification decision rule, and how many measured instances there were.

3. SYSTEM DESCRIPTION

In this section, we describe the industrial environment within which the system will operate and list each component it comprises. It also describes the distribution of the sensors. The document also discusses the features of a data acquisition card, which measures signals and its connections.

3.1. Prototype

The prototypes for small wind turbines, as shown in Fig. 3, are very useful for diagnosing problems with the components.

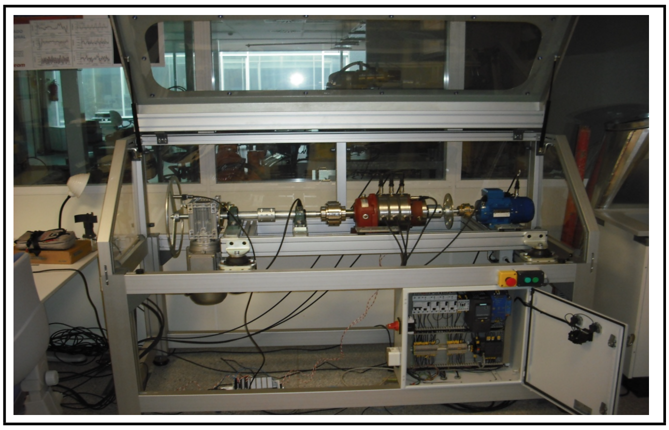

Figure 3. Component distribution in the prototype.

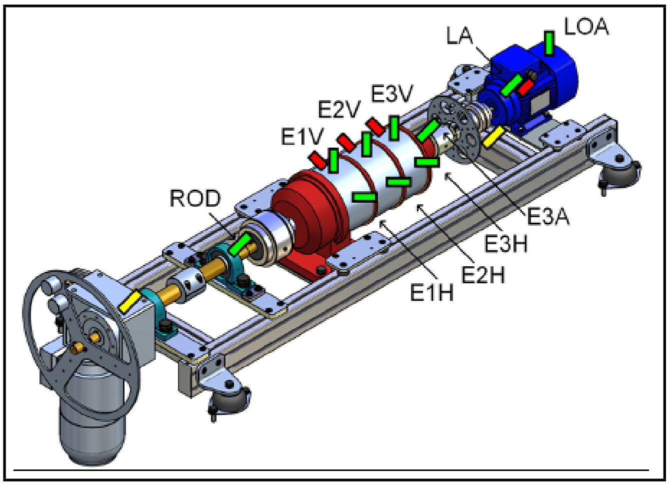

Figure 4. Position of the accelerometers in the system.

As an example, it can be used to identify deterioration and wear on its parts and determine what effects it has.[14] This system was designed to allow for easy interchange of parts without having to wait for deterioration to occur and can thus test diagnostic techniques without waiting for deterioration.

We measured the vibration of the generator, gearbox, and bearings. For a generator, vibration sensors should be positioned at the fast shaft coupling to measure the vibrations. Considering the multiplier, the techniques used for monitoring the machine state and the design of the machine required that each stage have its own sensor, allowing measurements to be taken of how the signal propagates between devices as well as how component failures affect vibrations. The following distribution of 10 accelerometers was thus decided, based on the above considerations:

3.2. Data-Connection Acquisition Card

Vibrations were measured by accelerometers. They came with 2-pin MIL-C-5015 NI connectors ideal for general purpose accelerometers. The acquisition card PCI-4472B[15] was used, optimized for vibration measurements. As explored previously, the acquisition system relies on two PCI-4472B modules because the prototype had a total of 8 inputs and ten accelerometers.

Table 1. Comparative of KNN and SVM algorithms.

	KNN	SVM
Advantages	Robustness to nosy data Can be used for both classification and regression Easy to implement Good overfitting	Can handle high-dimensional features Robust to overfitting and noise High sorting accuracy Fast sorting speed
Limitations	Needs a lot of storage space The selection of k influences the classification Great computation Slow sorting speed	Binary classifier No physical meaning Low efficiency for big data

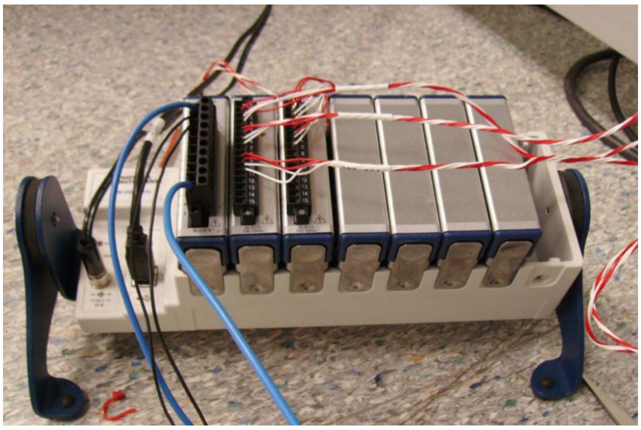

Figure 5. Connection of accelerometers to the data acquisition card.

Figure 6. System Vibration Detection.

4. RESULTS

In this section, we compare traditional methods with artificial intelligence methods. Traditionally, vibrational motion is measured using spectral analysis. The simulation executes successfully. In the image below, you can see the output of 10 accelerometers around the wind turbine prototype. The prototype can be rotated at 5 different speeds between 0 and 1500 rpm. In this case, a medium speed of 300 rpm is used. For each sensor analysed, an average of 5000 samples are obtained and graphically represented using a sampling frequency of 1 KHz.

Using automated learning systems, wind turbine failures can be tracked, diagnosed, and prevented using traditional vibration analysis methods. Automated learning systems can track, prevent, and diagnose wind turbine failures. To make a correct prediction, the algorithm must first be trained to get feedback, so that it can analyse and classify the data independently once it has experienced feedback. To ensure that we get reliable results, this section describes how to train and teach the algorithm. During training, two states of analysis were simulated, breakage and imbalance, and we think that has sufficient feedback for prediction. The algorithm was trained about eight times.

Figure 7. Broken bearing.

The faults and conditions introduced are:

- Bearing break failure
- Imbalance

A final comparison is conducted between the two states for each of the two classification methods, the first Support Vector Machines (SVM) Fig. 8 and the second K-Nearest Neighbour (KNN) Fig. 9. We divided it into 4 phases to obtain it. In the first phase, the data was obtained via the PCI-4472B acquisition card, then filtered and processed. For the analysis to be stable, it is essential to transform the signal into something non-random. When applying machine learning algorithms to these types of signals, appropriate conditioning and efficient processing are crucial to extracting patterns from them. For this method to function correctly, another key aspect is that the signal's time variation makes it difficult to process and to learn from. For the algorithm to function correctly, this first stage of signal conditioning and filtering is crucial. In this first point, the signal processing should be such that the algorithm reads invariant characteristics in time.

To determine the fault threshold or the prescribed condition for each fault or condition, feature extraction must be done. Let us examine each of these phases in more detail. To calculate the arithmetic mean, each example taken is added together (for each predetermined issue condition) and separated by the absolute number of tests considered. Principal component analysis is then used to reduce the size of the data set. In this method, the number of new variables is reduced to the minimum number possible to represent the old ones.

We can then make future decisions based on an understanding of our current state, as well as what is happening. Based on the results of the two previous phases, we can determine the

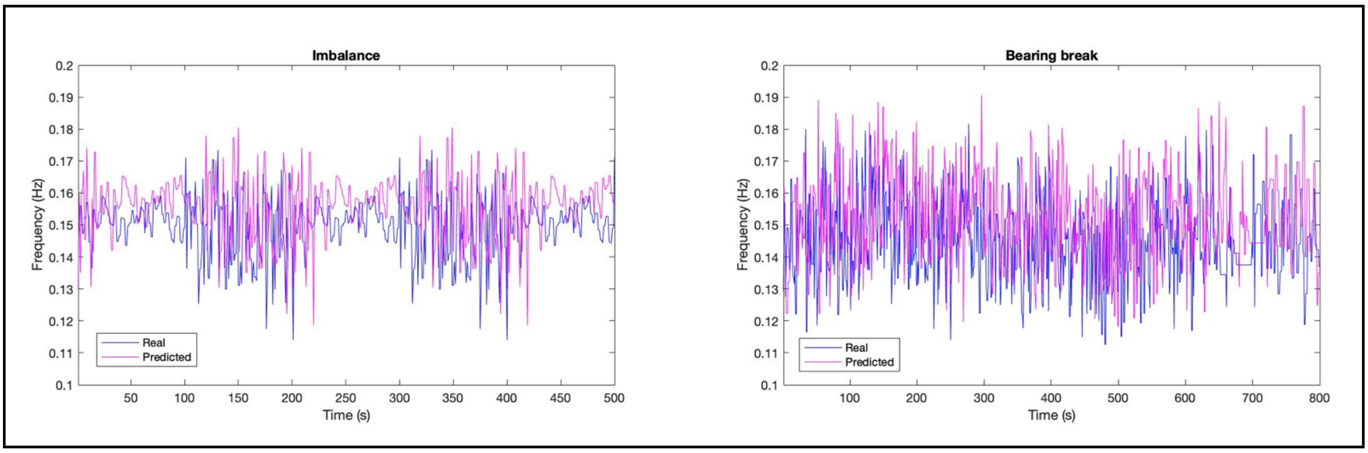

Figure 8. Real vs predicted output Support Vector Machines (SVM) algorithm.

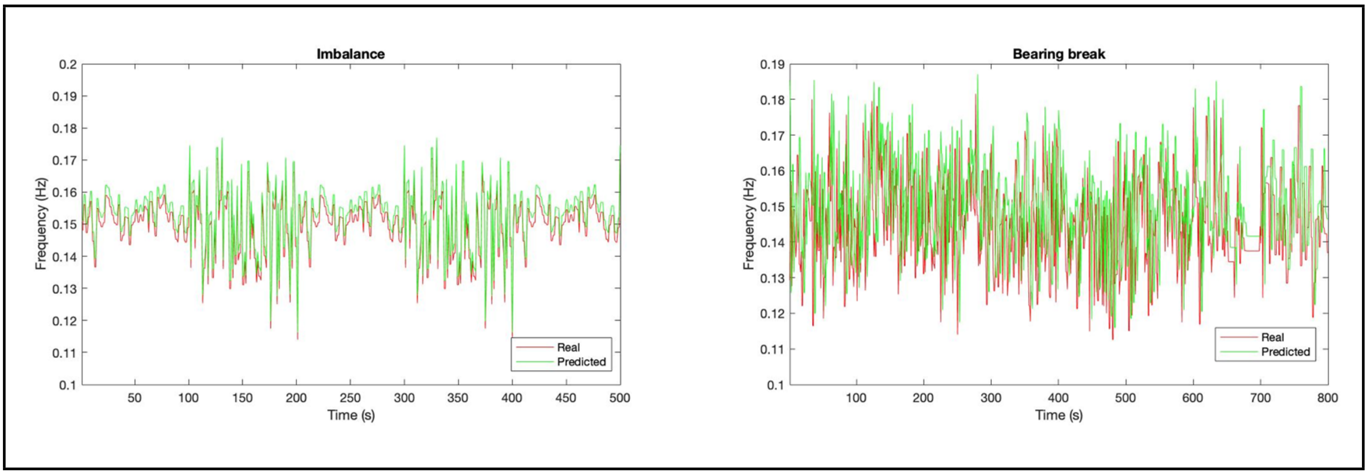

Figure 9. Real vs predicted output K-Nearest neighbour algorithm.

standard deviation of each of the stipulated failure conditions. The data presented in it demonstrate variation or dispersion. Several states have a relatively low standard deviation, which indicates that most points are close to the average, which is why it should work. These three stages are used by both classifiers. To classify the data, both methodologies of the two algorithms are used. Afterwards, the data have been properly conditioned.

A few training rounds follow this entire process so that the algorithm can be made self-operating in the future. Several training sessions are enough for the algorithm to work; it only needs new data. This new data is analysed and classified using a specific method to help predict the process being controlled.

Here's a breakdown of each state. Firstly, both classifiers follow the same pattern, but in this case, in the SVM algorithm the results are slightly out of date due to the limitations used in this case. Eventually, it turns out that the failure was caused by a broken bearing race, which changed the behaviour of both algorithms. The KNN produces more grouped data than the SVM, due to the different techniques used for sorting and classifying the data, since they do not follow a strict pattern. Furthermore, in both cases, both algorithms are highly accurate and like the actual and predicted outputs for either failure condition. It is observed that both classifiers produce quite similar results.

For example, let us focus on the imbalance variable. This variable is correctly classified in 96 % of cases, while it is incorrectly classified in 4 % of cases. A total of 95 % of true positives and just 5 % of false positives were detected. KNNs achieved a 94 % success rate, while Support Vector Machines (SVMs) reached 95 %. Due to this, both KNN and SVM are thought to have many similarities with the wind turbine prototype, which enables us to accurately predict the turbine's failure.

Regarding the results obtained, it should be noted that both classifications implemented in this simulation, KNN and SVM, have been characterized by being quite robust to interference (noise). In addition, KNN was characterized by allowing it to be implemented as a regression classification, while SVM by its handling high-dimensional features. Regarding the classification speed, the SVM was much faster than the KNN, but as mentioned earlier, both were quite accurate in their predictions.

5. CONCLUSIONS

To enable the successful and effective function of artificial-intelligence, data acquisition and classification are vital. Machine learning improves the accessibility and reliability of fault detection, monitoring, and diagnosis for wind turbines. This document examines several approaches to diagnose and preventfailures in wind turbine bearings based on vibration analyses and the use of artificial intelligence techniques.

The KNN and SVM models have been used to summarize the fault diagnosis for bearings from a theoretical and practical perspective. They both feature high processing speeds, robustness, and precision, which are important for this kind of research. Methods such as spectral analysis, which were traditionally used, are increasingly obsolete due to its advantages and its ease of classification and prediction. Using the proposed technique, the specified failure conditions could be predicted highly accurately, allowing it to be applied to other mechanical components of the prototype to prevent or anticipate possible breakdowns.

These possibilities can be used to evaluate, develop, and validate new methods of fault diagnosis and supervision. Using prototypes of wind turbines before they are installed in offshore places is very helpful in terms of reducing costs and time, and improving accuracy and reliability by verifying, adjusting, and correcting their design.

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