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# A Radial Basis Function Neural Network Approach for Detecting Wind Turbine Blade Damage via Embedded Accelerometer Data

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A significant number of wind turbines deployed across the Penghu Islands are exposed to challenging coastal and marine conditions. To address the operational risks associated with such environments, in this study, we introduce a real-time monitoring and fault detection framework aimed at identifying abnormal turbine behavior, particularly those linked to blade damage. The proposed system enhances turbine efficiency and reliability by continuously assessing blade integrity, swiftly detecting irregularities, and supporting near-instantaneous maintenance actions. This capability is especially vital in disaster-prone regions, where turbines may encounter conditions exceeding standard design specifications. The framework integrates sensor-based data acquisition—capturing input from accelerometers, anemometers, hygrometers, thermometers, and barometers—with signal processing and neural network techniques to analyze three-axis vibration data. By identifying distinct patterns associated with blade faults, the system enables timely detection and reporting of malfunctioning units, thereby facilitating effective repair and operational continuity.

## 1. Research Background

Enhancing the operational efficiency of wind turbines and minimizing maintenance expenses are the shared objectives among wind farm operators. However, much like the corrosive impact of seawater and harsh weather on offshore and coastal turbine systems, mechanical components remain prone to degradation, leading to reduced energy output. Despite the significance of these challenges, they have not been thoroughly addressed in a comprehensive manner.[(1–5)] Reducing operating costs by avoiding the unnecessary replacement of core components remains a top priority. However, to achieve this, early and accurate fault detection is essential alongside routine

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preventive maintenance. Blades, as a critical structural and aerodynamic element of wind turbines, play a decisive role in overall system reliability. Their durability and operational integrity are major concerns for both operators and manufacturers. Despite this, diagnostic assessments of blade condition are still heavily reliant on manual inspections, such as visual or acoustic evaluations conducted by trained personnel. These methods are inherently subjective and often inefficient. At present, there is a pressing need for objective, automated diagnostic solutions for blade condition monitoring.(1–5)

Recent research offers promising directions. Benbouzid *et al.* surveyed advancements in turbine condition monitoring, noting a shift from conventional analysis methods toward machine learning and data mining for predictive maintenance.(6) Complementing this, Natili *et al.* presented a multiscale modeling technique for detecting gearbox faults using industry-grade monitoring datasets.(7) In a separate effort, Papi *et al.* introduced probabilistic modeling frameworks to assess how blade damage impacts the performance of large-scale wind turbines. This approach, by treating damage as a stochastic variable, avoids biases tied to isolated case studies and supports more generalized insights.(8) Meanwhile, Santoramazza *et al.* applied machine learning to supervisory control and data acquisition (SCADA) system outputs to forecast anomalies in turbine operation. Their models, built using artificial neural networks, successfully detected faults in key components such as gearboxes and generators, and were validated on real turbine data from Italy.(9)

Maintaining full awareness of blade condition is fundamental to optimizing operational efficiency and minimizing costs, particularly as wind power becomes a leading renewable energy source. With the increasing deployment of wind farms—especially in offshore and island locations—equipment failures can lead to substantial losses if not addressed swiftly. Offshore infrastructure, although capable of continuous power generation, requires immediate attention during malfunctions. Delays in repair or diagnosis not only escalate costs but also jeopardize energy output.(1–5) These issues are further complicated in places like Taiwan, where maintenance is often handled by foreign contractors who may restrict access to proprietary maintenance procedures. While the broader implications of this practice extend beyond the scope of this study, the need for rapid, reliable fault detection in offshore wind farms remains clear.(1–5)

## 2. Study Overview

In this study, we developed a comprehensive mechanical condition monitoring system designed to track operational parameters such as vibration and noise from wind turbines. The system enables remote data collection, storage, and reporting, with the collected information organized into structured datasets. These datasets are analyzed through rule-based logic to identify signal patterns associated with varying degrees of blade damage severity. Unlike conventional manual inspection methods, this approach enables the automatic assessment of turbine health by continuously monitoring vibration behavior. The monitoring system offers near-real-time alerts for blade faults, allowing operators to proactively schedule maintenance and minimize turbine downtime. Unlike traditional predictive maintenance—which depends on scheduled interventions aimed at preventing failures—the proposed system activates upon detection of actual anomalies. For instance, conventional predictive strategies may prompt component replacement based on expected wear, which may sometimes lead to unnecessary intervention or even system errors. By contrast, the system introduced here delivers timely alerts upon detecting real damage, improving the precision and efficiency of maintenance responses. The proposed method supports responsive, unplanned maintenance through rule-based diagnostic predictions. When integrated into a fully operational monitoring platform, this mechanism enables maintenance teams to allocate resources more effectively, such as prepositioning spare parts or tools. In practice, this contributes to safer, more efficient turbine operation, lower maintenance costs, and enhanced system reliability.(1–5,10–14)

## 3. Condition Monitoring Systems and Methods

In this section, we outline the development of condition monitoring systems, focusing on both remote and server-side architectures. Because the remote monitoring units are physically installed on the turbine's structural foundation, a brief overview of wind turbine components is first provided for context. A typical wind turbine consists of several key systems: control units, transmission assemblies, generators, power converters, blades, towers, electrical cabling, and transformers. Within the transmission assembly, critical elements include the wheel hub and yaw system.

Turbine performance varies by model and is heavily influenced by environmental factors at the installation site. Harsh weather conditions or natural disasters can impair turbine functionality, leading to unexpected failures that must be addressed through predictive maintenance strategies. Beyond environmental stressors, turbines may also suffer from internal design limitations—such as incompatible specifications, subpar build quality, or misalignment between design and local site conditions—that increase the likelihood of operational instability and premature wear, particularly in components such as the blades.

Blade failures generally stem from two main categories: internal and external causes. Internally, degradation may result from prolonged mechanical stress, leading to the deformation of structural elements. During standard operation, the tower structure itself is subject to shifts and displacements depending on the load, foundation integrity, and operational dynamics. Externally, severe weather events such as typhoons or earthquakes can inflict substantial, often unpredictable, damage to the blades. While these external incidents are unplanned, their impacts can be systematically addressed using the fault detection and diagnostic tools proposed in this study.

## 4. Condition Monitoring System Hardware

The remote monitoring system is built around ADLINK's USB-2405 module, which serves as the primary data acquisition unit. This device supports dynamic signal capture through a 24-bit USB interface and includes four analog input channels, each capable of simultaneous sampling at rates up to 128 kS/s. It features a BNC connector for signal input and supports both

AC and DC coupling. Additionally, it incorporates an integrated electronic piezoelectric sensor interface, providing a precise 2 mA excitation current for connected sensors.

In this configuration, each input channel can be linked to either an accelerometer or a microphone, allowing for the accurate detection of vibration and acoustic signals. Specifically, the setup employs P.C.B. 601A01 accelerometers, which have a sensitivity of 100 mV/g and operate within a frequency range of 0.27 to 10,000 Hz. The system also integrates an anemometer for monitoring wind speed as part of the broader environmental data collection effort.

Anemometers are an essential tool for meteorologists studying weather patterns. They are also crucial to the work of physicists who study the movement of air. Figure 1 shows a wind speed line chart of the environment where the wind turbine is located. Wind speed refers to the speed of air movement relative to a fixed location on Earth. In daily life, we call the movement of air wind. Wind speed is commonly used to measure the speed of outdoor air movement. There are also situations where measuring the indoor air flow rate is necessary, but these are relatively rare. Wind speed plays a vital role in our daily lives: weather forecasting, aviation and navigation operations, construction, and civil engineering all require reference to wind speed. High wind speed will cause adverse consequences, and for specific levels of high wind speed, we will use appropriate terms to identify them, such as strong wind, gale, storm, and hurricane. Anemometers are instruments used to quantify wind speed, typically providing measurements in units such as knots (kn), meters per second (m/s), or kilometers per hour (km/h).

Figure 2 shows a wind direction–time line chart in the environment where the wind turbine is located. Wind is often described in terms of its intensity and direction. Differences in air pressure cause the wind. Air flows from regions of higher pressure to those with lower pressure, generating winds that vary in speed depending on the pressure gradient. The Coriolis force deflects the airflow on a rotating planet outside the equator. Globally, the two main drivers of large-scale winds are the heating difference between the equator and the poles and the planet's rotation. Large-scale winds tend to reach geostrophic equilibrium at high altitudes beyond the

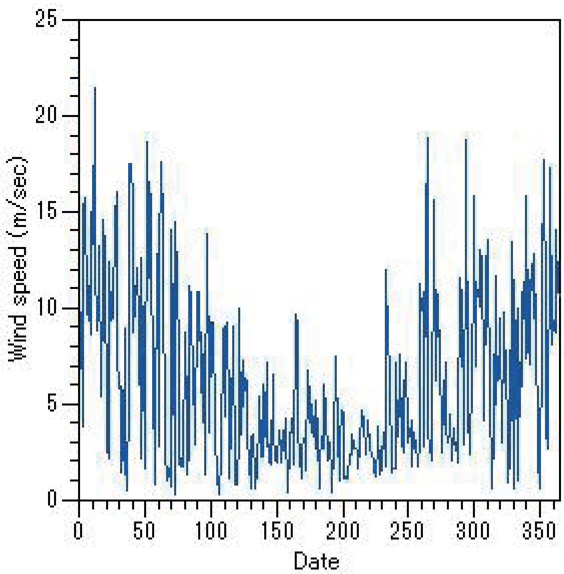


Fig. 1. (Color online) Time-series chart depicting wind speed conditions at the wind turbine installation site.

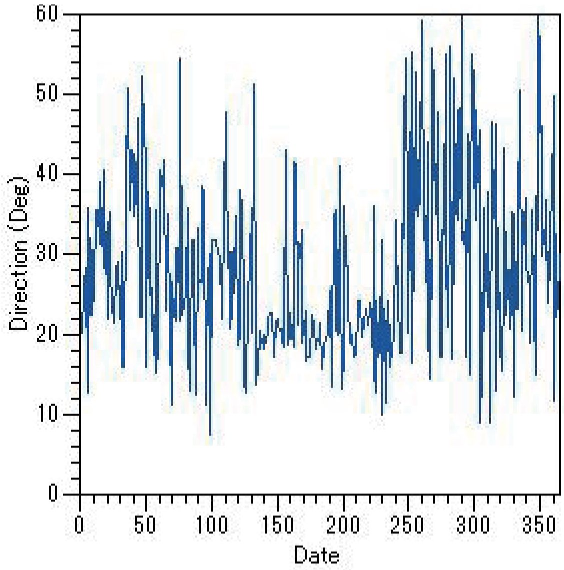


Fig. 2. (Color online) Wind direction–time line chart in the environment where the wind turbine is located.

equator, unaffected by ground friction. On Earth's surface, friction causes winds to slow down gradually. Surface friction also pushes more wind into low-pressure areas.

Figure 3 shows a time-series graph illustrating temperature variations at the wind turbine site. Temperature represents the physical measure of how hot or cold a substance is. On a microscopic level, it reflects the average kinetic energy associated with molecular motion. Since temperature cannot be measured directly, it is inferred through the properties of materials that vary with temperature. The system used to quantify temperature is referred to as a temperature scale, which defines both the reference point and the unit of measurement. The theoretical high point of temperature is the Planck temperature, and the theoretical low point is absolute zero. The Planck temperature and absolute zero cannot be reached through finite steps. The most widely adopted temperature measurement systems worldwide include the Celsius (°C) scale, the Fahrenheit (°F) scale, the Kelvin (K) thermodynamic scale, and the International Practical Temperature Scale. Temperature manifests the average kinetic energy between molecules in an object.

Figure 4 shows a humidity–time line chart of the environment where the wind turbine is located. In the measurement system, we used a hygrometer, which is a device designed to quantify the moisture content or water vapor present in the atmosphere. Humidity generally refers to air humidity in meteorology, which is the content of water vapor in the air. Air without water vapor is called dry air. Since water vapor in the atmosphere can account for 0% to 4% of the air volume, when the components of various gases in the air are listed, they generally refer to the components in dry air.

Figure 5 shows a time-series chart of atmospheric pressure conditions at the wind turbine site. The monitoring setup includes a barometer, an instrument specifically used to measure ambient air pressure. Observing changes in barometric pressure is useful for forecasting short-term weather patterns. Surface pressure data also plays a key role in identifying meteorological

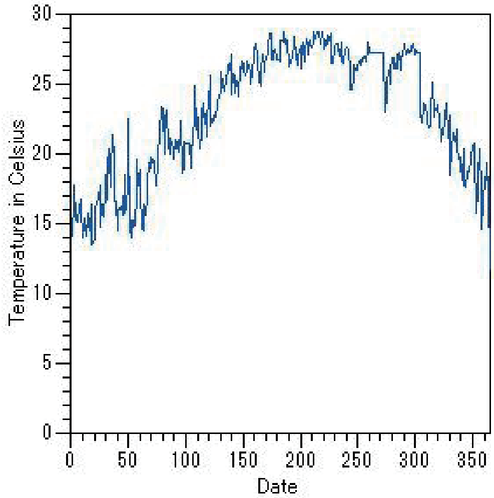


Fig. 3. (Color online) Temperature–time line chart of the environment where the wind turbine is located.

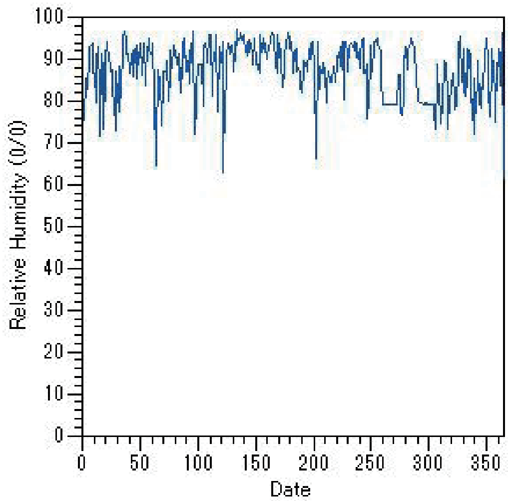


Fig. 4. (Color online) Humidity–time line chart of the environment where the wind turbine is located.

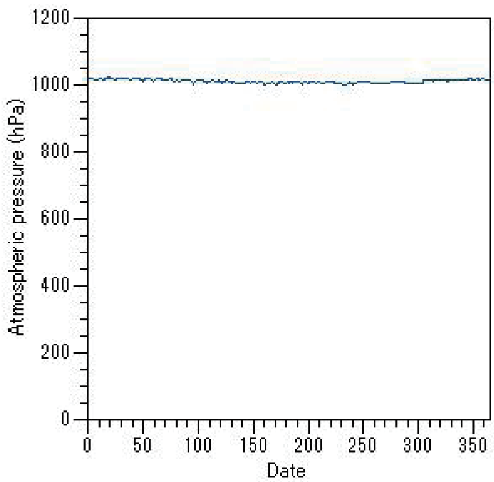


Fig. 5. (Color online) Air pressure–time line chart of the environment where the wind turbine is located.

features such as troughs, pressure systems, and frontal zones. Atmospheric pressure—commonly referred to as air or barometric pressure—represents the force exerted by Earth's atmosphere. A standard atmospheric pressure is defined as 1013.25 hectopascals (hPa).

Figure 6 shows the voltage–time line graph generated by wind turbines. In the measurement system, we used a voltmeter, which is a device used to measure the voltage or the electrical potential difference between two points in a circuit, and it is connected in parallel with the component being measured. It usually has high resistance, drawing negligible current from the circuit.

Figure 7 shows the current–time polyline generated by wind turbines. Electric current is the average directional movement of charges in an electric field or semiconductor. Current direction is defined as the direction in which positive charges move; the current size is called current intensity, which refers to the net charge transfer amount through a specific section of the wire per unit time.

Figure 8 shows the power–time polyline generated by wind turbines. Power is defined as the energy conversion or use rate, expressed in terms of the amount of energy per unit time, which is the rate of work done. The international standard power unit is the watt (W), named after the eighteenth-century steam engine designer James Watt. The rate at which a light bulb transforms electrical energy into heat and light over time is represented by its power output. The higher the wattage, the higher the capacity or power per unit of time.

## 5. Utilizing Radial Basis Function (RBF) Neural Networks for Diagnosing Faults in Wind Turbines

Machine learning first appeared in 1949, when Hebb developed a learning mechanism based on neuropsychology, using machine learning as a learning method to solve various problems. An

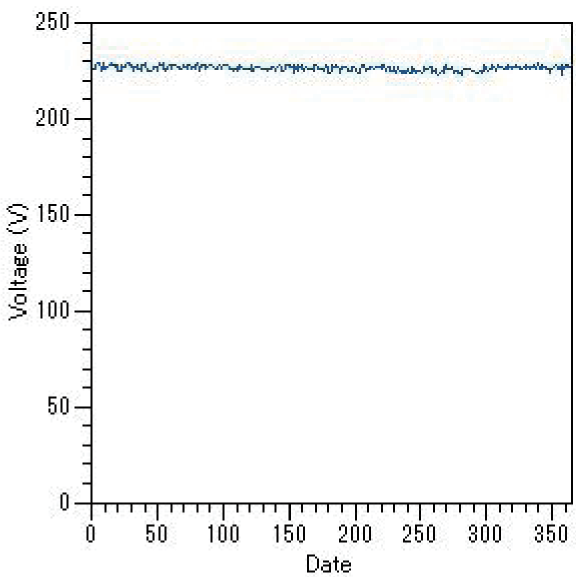


Fig. 6. (Color online) Voltage–time line graph generated by wind turbines.

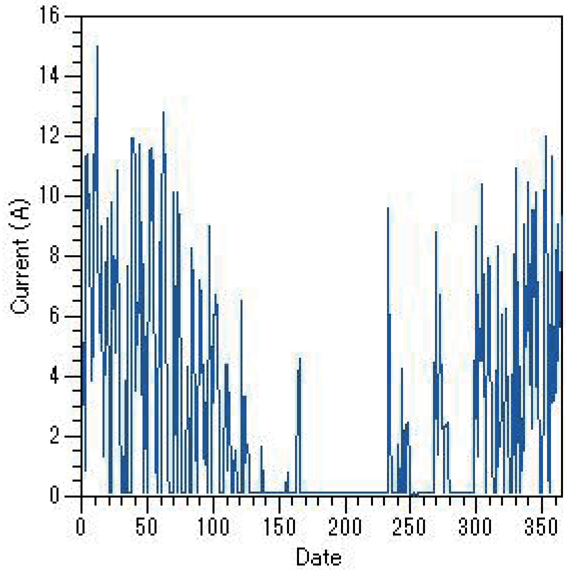


Fig. 7. (Color online) Current–time polyline generated by wind turbines.

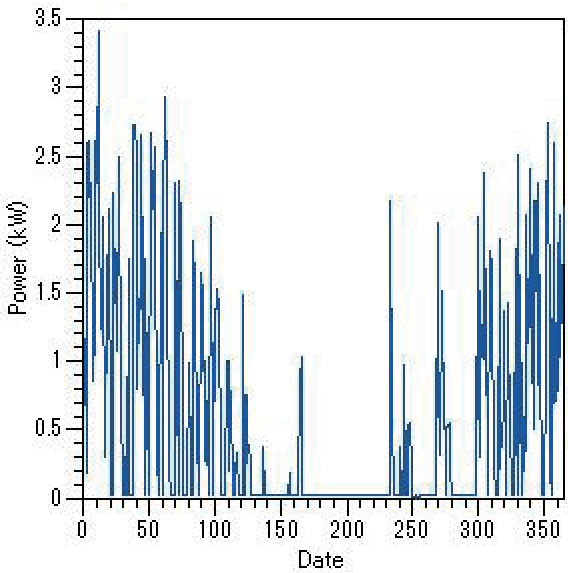


Fig. 8. (Color online) Power–time polyline generated by wind turbines.

neural network typically follows a three-layer feedforward architecture. The input layer consists of source nodes that simply pass data forward without modifying it. The hidden layer, whose number of neurons is determined on the basis of a specific application, employs Gaussian functions as activation mechanisms to perform nonlinear mapping of the input space. Finally, the output layer processes the signals from the hidden layer using a linear activation function, producing the final output through a weighted sum of the hidden layer responses. After years of development, it has been applied to multiple branches of artificial intelligence, but each learning algorithm for each machine has advantages and disadvantages. The wind turbine is one of the most common types of power generation equipment in modern production and is widely used in various fields. As a mechanical power equipment, its operating status directly affects the working status of the equipment. However, the working conditions of wind turbines are very harsh, so the possibility of failure is relatively high. In this example, a probabilistic neural network is used to establish a classification model, and the vibration signal of the wind turbine is collected as input to detect whether there is a fault and to determine the fault type. The status detection of wind turbines can promptly detect and effectively predict and eliminate faults, enhance the safety of wind turbines, increase service life, and is of great economic significance for reducing maintenance costs and avoiding significant accidents. We have many years of experience in mechanical equipment diagnostic technology. Owing to the simplicity of sensing equipment, fault diagnosis mainly relies on information obtained by experts using their senses and simple instruments—fault judgment based on experience and the rise of artificial intelligence technology. With the continuous development of sensor technology, the acquisition of fault signals has gradually become standardized and accurate. With the complexity of equipment and instruments, correct analysis of collected signals has become the key to fault diagnosis, so intelligent diagnosis can simulate the human thinking process and significantly improve the diagnosis process. Fault diagnosis of wind turbines can be abstracted into a classification problem.

Determining whether a fault is a two-classification problem and judging a specific fault type is a multiclassification problem. We have defined six failure modes of wind turbine blade damage: 0 blades, 0.5 blades, 1.0 blade, 1.5 blades, 2.0 blades, 2.5 blades, plus 3.0 blades under normal conditions, a total of seven modes. Time domain accelerometer signals are used as input samples. Therefore, the probabilistic neural network model for wind turbine fault diagnosis includes input samples, classification patterns, and probabilistic neural network structures. Each node corresponds to an input training sample with six classification modes. Implementing wind turbine fault diagnosis uses six modes to represent the wind turbine's working status and realizes the modes' classification. The diagnosis process is shown in Fig. 9.

## 6. Formulation and Discussion of Rules

After preprocessing and cleaning the collected data sets, the first stage involves visualizing the source time domain data sets to make preliminary comparisons. For this purpose, server-side vibration data sets were sampled and calculated for wind turbine setups of 3.0 blades (all blades), 2.5 blades, 2.0 blades, 1.5 blades, 1.0 blade, 0.5 blades, and 0.0 blades. These simplified visual representations are used to highlight the distinguishing features among various blade failure


Fig. 9. (Color online) Fault diagnosis process.(15,16)

scenarios and to formulate rule-based criteria for automatic classification. The diagram below offers a clear comparison, facilitating the identification of blades operating under faulty conditions in contrast to those under normal conditions. On the basis of these results, the blades on the wind turbine are judged to be 0 blades, 0.5 blades, 1.5 blades, and 2.5 blades. Under normal operating conditions, all blades function as expected, allowing for the development of an accurate diagnostic model. By applying the established rules, both intact and damaged wind turbine blades can be effectively characterized. The simplicity and low computational demand of these rules enable rapid fault identification and timely alert generation, which greatly supports reactive maintenance efforts and enhances operational efficiency in wind farm management. The Pacific Rim is an area prone to supertyphoons, with wind speeds reaching over 150 kilometers per hour. Wind turbine blades breaking or falling off completely is not news to anyone. In addition to typhoons, earthquakes represent another unpredictable but significant source of turbine damage in the study region. Given their sudden nature, integrating predictive diagnostic mechanisms alongside routine maintenance protocols is advisable—even under otherwise manageable weather conditions. Although such events are sporadic, incorporating even a partial diagnostic component into the turbine's blade assembly can enhance overall operational efficiency. This approach contributes to a more comprehensive and integrated maintenance strategy, helping reduce costs and better accommodate unplanned repair needs in wind farm operations. Figure 10 shows the prediction results of different blade failure speeds using time domain data. Figure 11 shows the absolute error for different sample sizes using time domain data. The maximum absolute error is. Figure 12 shows the results of predicting various blade failures using frequency domain data. Figure 13 shows the absolute error for different samples using frequency domain data. The maximum absolute error is $1.0395 \times 10^{-10}$. Figure 14 shows the prediction results for various wind speeds using time domain data. Figure 15 shows the absolute error for different samples using time domain data. The maximum absolute error is $6.2528 \times 10^{-13}$. Figure 16 shows the absolute error for different samples using time domain data. Figure 17 shows the results of predicting various wind speeds using frequency domain data. The maximum absolute error is $1.0128 \times 10^{-8}$. Unlike conventional SCADA-based diagnosis systems,(6–9) our model uses raw accelerometer time- and frequency-domain data to classify

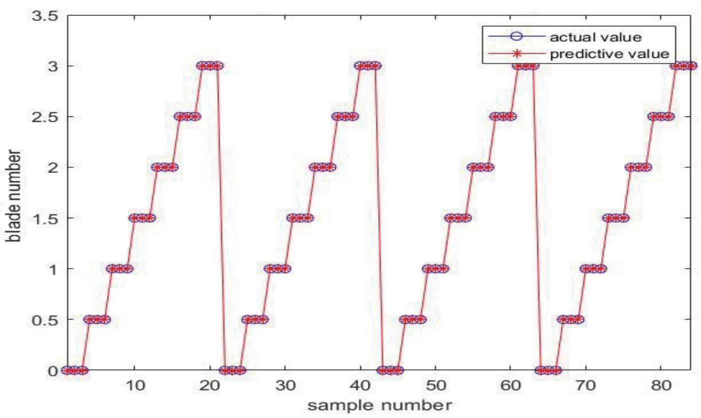


Fig. 10. (Color online) Prediction results of various blade failure speeds using time domain data.

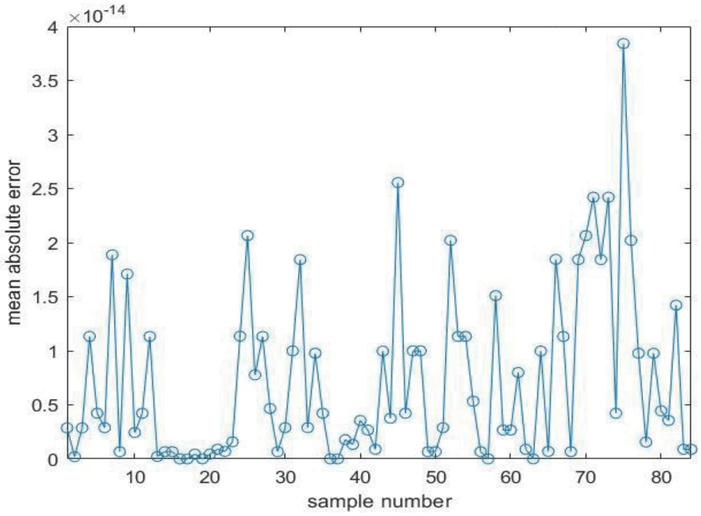


Fig. 11. (Color online) Absolute error for different numbers of samples using time domain data.

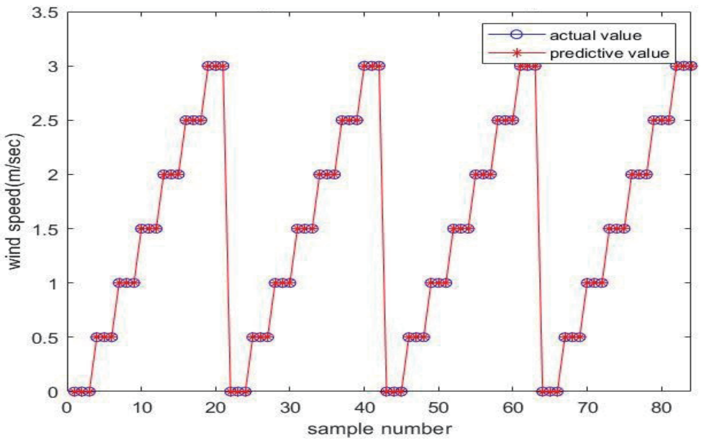


Fig. 12. (Color online) Results of using frequency domain data to predict various blade failures.

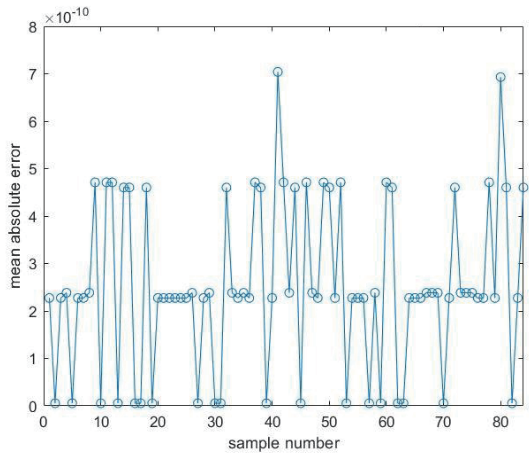


Fig. 13. (Color online) Absolute error for different numbers of samples using frequency domain data.

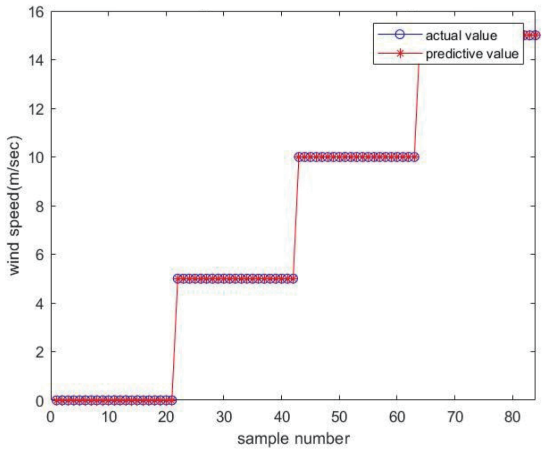


Fig. 14. (Color online) Prediction results for various wind speeds using time domain data.

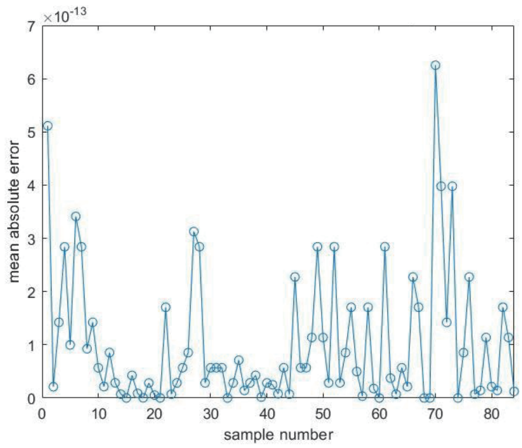


Fig. 15. (Color online) Absolute error for different numbers of samples using time domain data.

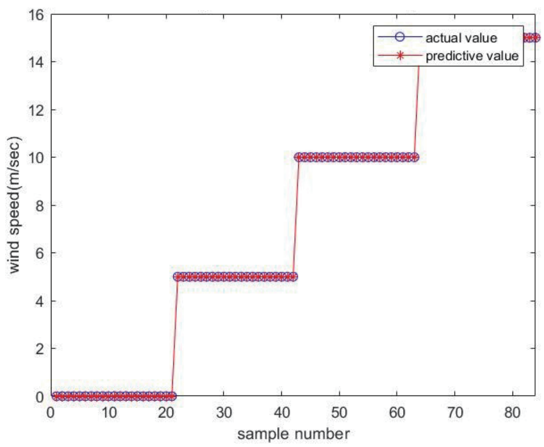


Fig. 16. (Color online) Results of predicting various wind speeds using frequency domain data.

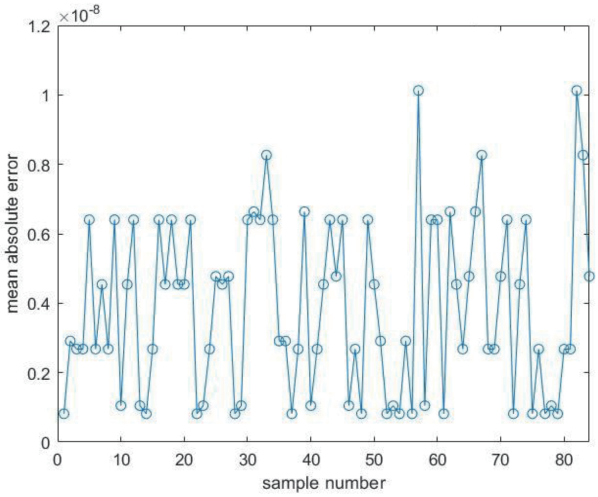


Fig. 17. (Color online) Absolute error for different numbers of samples using frequency domain data.

multiple levels of blade damage using RBF neural networks, allowing near-instant fault localization and predictive alerts.

## 7. Conclusion

In this study, we demonstrated a practical sensor-integrated approach using time–frequency analysis and machine learning to achieve real-time wind turbine fault diagnostics. Future work will aim to deploy the proposed system on operational turbines to validate its scalability and robustness under real-world conditions. With the construction and operation of more and more wind farms worldwide, the practical value of wind turbine status monitoring and fault diagnosis for reducing maintenance costs and improving wind farm operation efficiency is increasing. As market competition intensifies, wind farm operators are under growing pressure to lower both operational and maintenance expenditures to boost profitability and sustain long-term competitiveness. This economic imperative demands that maintenance approaches be not only efficient but also highly reliable. In response, the implementation of condition monitoring systems and early-stage fault detection has become standard practice across the industry, as these methods enhance both the reliability and productivity of wind energy systems. Among the various components, wind turbine blades pose particular challenges during the operational and maintenance phases owing to their susceptibility to failure. Monitoring blade integrity has become increasingly important, especially given the distinct structural characteristics associated with different turbine models and manufacturers. To address this, it is essential to leverage real-time, high-resolution data and develop robust diagnostic methods tailored to blade-specific failure modes. Experimental investigations in this study revealed that vibration signals serve as a key medium for detecting mechanical anomalies. By interpreting these signals, it is possible to trace the origins of specific failures. However, our laboratory trials also indicated that relying on conventional plausibility frameworks—originally designed for generator diagnostics—is inadequate for identifying blade faults in remote turbine configurations, highlighting the need for customized diagnostic strategies in such contexts. Therefore, regulatory standards for detecting fault conditions must be reconsidered. We determine the damage type of wind turbine blades on the basis of the accelerometer's time and frequency domain signals and choose the wind speed when the wind turbine blades are operating. Frequency and time domain signals determine which blades the wind turbine is operating under.

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