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Research Article

Fault Warning Using Clustering Analysis Method on Wind Turbine Blade

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Abstract:

Background: In an attempt to solve the problem of internal damage and crack of wind turbine blades that are difficult to be evaluated, a method based on cluster analysis is proposed to study the fault warning of wind turbine blades using machine learning.

Aims: Developing an early warning method (fault warning) for explicit damage (including surface cracks and internal damage) to wind turbine blades by applying cluster analysis (K-Means) and unsupervised learning to short-term historical operational data.

Method: Firstly, 2 MW wind turbine was used to collect short-term historical operation data of wind turbine and perform data pre-processing. Secondly, the wind speed-power, wind speed-hub speed and wind speed-tip speed ratio were used to classify the parameters affecting the explicit faults of wind turbine blades by using the cluster analysis method, and the distance analysis was performed by using the combined weight method segmentation, and the axial vibration data of the abnormal data points were analyzed by using the Fourier series transformation. And then, establishing the wind turbine blade explicit fault evaluation rules based on the performance reliability theory. Lastly, the feasibility of the method is verified by cases.

Result: The results demonstrated that the method can quickly warning the wind turbine blade explicit faults, especially for evaluation of the wind turbine blade surface explicit cracks and internal explicit fault.

Conclusion: This work has achieved the fault warning of large components based on the wind turbine short-term historical operation data.

Keywords: Cluster analysis; Machine learning; Performance reliability; Wind turbine blade; Fault warning.

1. INTRODUCTION

Wind energy is a clean and renewable energy, wind power industry has developed rapidly in recent years. However, due to the harsh environment of wind farms and many other reasons to make wind turbine large parts damage on the wind power industry caused a large barrier, especially the blade cracking caused by downtime replacement Therefore, it is urgent to control the operating state of wind turbine blades.

A large number of scholars have conducted research around wind turbine blade fault diagnosis and have made stage progress: (Liu et al., 2026) used the IEA 15 MW and 22 MW reference offshore wind turbines, this study investigates post-fracture load mechanisms through aeroelastic simulations under turbulent wind conditions with an active emergency shutdown control strategy. (Ren et al., 2026) focused on the NREL-15MW reference floating wind-turbine, and develops a multi-physics coupled dynamic model of the floating wind turbine by integrating blade element momentum (BEM) theory with the OpenFAST model.

(X. Chen, 2025) explored virtual testing as a pathway to reduce or replace physical tests, focusing on static load certification of blades and their components. (Lyngby et al., 2019) addressed the challenge of assessing these uncertainties by developing a workflow using Abaqus and GPyTorch to develop probabilistic machine learning models to analyze the effects of manufacturing uncertainties. (Waldbjoern et al., 2025) required a robust structural failure assessment methodology, involving thorough experimental testing combined with non-destructive inspection (NDI) techniques for structural health monitoring (SHM). (Tian et al., 2024) failured during the start and brake processes of a 1.5 MW horizontal axis wind turbine blade was examined using a measured wind field with fluid-structure coupling.

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(Rogers & Ollson, 2025) showed debris traveled beyond 1.1 times the tip height had relatively low kinetic energy and would be extremely unlikely to cause injury to a person. (Chai et al., 2024) developed a conceptual framework for UGW-based SHM, and an experimental platform was established to embed piezoelectric (PZT) transducers into fatigue-prone sections of the WTBs using SMART Layer technology, thereby enhancing sensor integration and monitoring efficacy. (Abarca-albores et al., 2024) proposed methodology offers a new approach to early fault detection in wind turbine blades, highlighting the potential of integrating different computational learning techniques to enhance system reliability. (C. Zhao et al., 2024) used a novel Non-negative Matrix Factorization-Dynamic-inner Canonical Correlation Analysis (NMF-DiCCA) based on GRU and SSAE algorithm is proposed to solve this problem.

(Mcwilliam et al., 2022) introduced a technique to automatically tune gradients with statistical methods and algorithms to calculate the Lagrange multipliers after an optimization. (Gigović et al., 2017) proposed evaluation indicators based on geographic information systems and multi-criteria decision analysis, considering economic, social and environmental factors for wind farm site selection. (Höfer et al., 2016) adopted the analytic hierarchy process in geographic information systems and proposed a comprehensive multi-criteria decision method for wind farm site selection assessment. (Vachaparambil et al., 2014) took a wind farm in India as the research object and obtained the optimal operating environment for wind turbines through satellite images. Took the geographical characteristics and meteorological information of a region in Greece as the research object, and used the weighted sum method to analyze the wind turbine industry benefits in that region. (Hajto et al., 2017) considered the investment and profitability of wind farms, and derived the optimal site selection by analyzing meteorological data. (Tsoutsos et al., 2015) adopted a multi-criteria method to develop a comprehensive assessment method for wind farm benefits, and classified them into grades of superiority and inferiority. (Chiang et al., 2016) raised the issues of landscape visual impact and investment cost, used ArcGIS to draw OWF site location maps, and highlighted the trade-off between investment and view. Used neural network methods to estimate the power generation performance of wind turbines using wind speed and air density. (Hendry et al., 2014) proposed the application of probabilistic methods in reliability analysis of complex engineering systems, collecting qualitative historical failure data to infer the failure probability of the system. (Habibi et al., 2018) improved the monitoring of wind turbine operating conditions through analyzing SCADA data for fault warning and performance degradation.

(Terensan et al., 2024) based on wind turbine performance indicators, proposed a normal allowable fluctuation range of actual output power compared with standard power during operation. (Han et al., 2018) combined the existing problems of wind farms to establish reliability assessment theory and procedures for wind turbines, improving the monitoring and control of wind turbine performance. (Hübler et al., 2018) studied wind turbine performance degradation and faults, and proposed an inference of failure probability based on historical operating data. When using Markov regenerative theory for analysis, the key is the selection of regeneration points; observing the system behavior at the moments of state changes exhibits the memoryless property, and such moments can be selected as regeneration points. (J. Zhang et al., 2026) used neural-network-based optimization methods to handle inverse problems and proposed parameters for functionally graded beams. (R. Chen et al., 2011) based on genetic algorithms, proposed a penetration probability test method to determine the parameters of the uncertain HJC equation for wind turbines.

(Ouyang et al., 2017) converted wind direction data into sine and cosine time series parameters, and proposed a method for extracting maximum wind energy within the yaw range of wind turbines. (Vera-tudela & Kühn, 2017) used neural grids to establish a monitoring system for wind turbine fatigue load prediction as a cost-effective alternative. (Yu et al., 2019) proposed spatiotemporal features describing the characteristics of spatiotemporal variation processes, mapped the data collected from wind turbines onto aircraft based on relative positions to generate scene graphs, and applied deep convolutional grids to predict wind turbine power generation. (Harrou et al., 2019) used the bagging method of decision trees for wind turbine power generation prediction, which has the advantage of combining multiple models to reduce overall error. (W. Zhang et al., 2011) computed sensitivity matrices to transform fuzzy formulas of uncertainty in inputs or outputs into identifiable formulas, then used the maximum likelihood principle to obtain the mean of location parameters, and finally obtained confidence intervals of solutions based on linearization and MCS to quantify uncertainty. (H. Zhao et al., 2018) proposed an adaptive threshold determined by extreme value theory, and used it as a rule for anomaly judgment. For random variables with known distribution forms, sampling is performed, and a large number of uncertain parameter sample points are used to continuously re-analyze the original problem to obtain sample points of the parameters to be identified (Knabe et al., 2013). Using known uncertain structural parameters, system inputs, and limited structural response values, developing computational inverse methods that consider model parameter uncertainty, and achieving effective evaluation of the influence of uncertainty on inverse parameters, has important theoretical significance and engineering value (Beven & Young, 2013). The implementation of hyperspectral imaging technology for wind turbine blade image acquisition, processing, defect identification, crack and erosion detection was proposed (Rizk et al., 2021).

(Tong & Wang, 2021) derived the wind turbine blade aerodynamic characteristic curves by applying the same deceleration frequency, slurry pitch amplitude and different initial angles of attack to the wind turbine blade. (Castro & Branner, 2021) combined two-dimensional finite element cross-sectional analysis and a continuum damage mechanics model to effectively predict the variation pattern of blade cross-sectional stiffness and intrinsic frequency with tunnel crack density. (Yang et al., 2021) used Otsu thresholding segmentation method to segment the leaf images and improved the accuracy of leaf defect detection using an integrated learning classifier based on random forest. (Evans et al., 2021) proposed an improved method for calculating the blade-fatigue spectrum of small wind turbines. An advantage of this method is that it does not require complex aeroelastic simulations or in situ measurements.

(Wen et al., 2020) developed a fiber optic grating online monitoring system based on fiber optic grating (FBG) sensors and fiber optic rotary joints (FORJ). (Lyngby et al., 2019) proposed a measurement uncertainty estimation method based on the modular free size method (MFG). (Giefer & Freitag, 2020) proposed an in-situ defect detection system implemented on FPGA using quantized neural networks for automatic inspection of wind turbine rotor blade surfaces using an unmanned aerial vehicle (uav). (Q. Zhao et al., 2020) developed a competitive model for the failure probability of wind turbines under non-Gaussian wind loads. (Li et al., 2020) used the results of panel programs and Navier-Stokes solvers to compare the methods for modeling the bound vorticity of bent wing, straight flat dynamic wing and wind turbine blades. The research above mainly uses supervised learning and precision instrumentation measurements to achieve wind turbine blade fault monitoring. However, neural networks and other methods require high training data and precision instrumentation in-situ measurements is more expensive and time-consuming, which is not enough to be able to quickly and in advance to control the operating status of wind turbine blades.

In the light of the above deficiencies, this paper proposed an explicit fault warning using clustering analysis method on wind turbine blade. 2 MW wind turbine was used to collect one month of historical operation data of wind turbine and perform data pre-processing, and analyzed wind speed-power, wind speed-hub speed, wind speed-tip speed ratio and axial vibration data as parameters that affect the apparent failure of wind turbine blades. And then, the method of cluster analysis was used for segmentation categorization, and the combined weight method was applied for distance judgment, then the wind turbine blade explicit fault scoring rules were established based on the performance reliability theory. In the conclusion, the feasibility of the method was verified by example. The results have demonstrated that the method can provide early warning of wind turbine blade explicit faults, which is of great significance in wind turbine fault monitoring.

2. MATERIAL AND METHOD

Working principle of wind turbine

The wind turbine is driven by wind energy to trigger the rotation and the process of converting the mechanical energy of rotation into electrical energy by the principle of electromagnetic induction.

$$W = Pt$$

$$P = \frac{1}{2}\rho A V^3 C$$

In the formula, W is the wind turbine power generation in Kw · h; P is the wind turbine output power in Kw; t is the time in s; ρ is the air density; A is the wind area in kg/m^3; V is the wind speed in m/s; C is the wind energy utilization coefficient of wind turbine.

It can be seen that the power of a wind turbine can visually represent the performance of the wind turbine, and its corresponding performance parameters also include hub speed and blade tip speed ratio.

Wind turbine data pre-processing

In this study, the relationship between the rated wind speed interval and power of a 2 MW wind turbine was as follows:

$$P = \begin{cases} P_i, (3 \le V < 22) \\ 0, (0 \le V < 3) \end{cases}$$

In the formula, P is the wind turbine output power in Kw; P_i is the rated output power of the wind turbine in Kw; V is the wind speed in m/s.

Extracting the operating data of the wind turbine by the principle of operation of the wind turbine. However, data from wind turbines should be screened out when they were:

The power-limited state of the wind turbine;

Abnormal state of wind turbine;

Data outside the rated wind speed of wind turbine.

K-Means clustering algorithm model

The concept of K- Means algorithm is to divide the specified sample set into K categories, called K cluster trees. The model makes the sample sets in that category tightly connected and as far as possible from the sample data outside that sample set.

Cluster analysis was applied to compute the cluster center spacing values for each wind speed segment of the wind turbine's wind speed-power, wind speed-hub speed and the ratio of wind speed to tip speed. K-means can effectively calculate the spacing of cluster centers for two-class classification. DBSCAN can autonomously filter out discrete points. However, the model requires a focused analysis of these discrete points. Therefore, the DBSCAN model is not suitable for application in this paper.

Assuming that the sample set was $D = \{x_1, x_2, \ldots x_m\}$, the output clusters were classified as $C = \{C_1, C_2, \ldots C_K\}$, the minimization of the squared error were used to determine the value of K:

$$E = \sum_{i=1}^{k} \sum_{x \in C_i} \left\| x - \mu_i \right\|_2^2$$

$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x$$

Where μ_i was the center of mass of C_i.

Upon determining the number of clusters in the sample set, assuming that the data points within the same cluster were $\{x_1, x_2, \ldots x_i\}$, The distance between the sample and the center of this cluster was：

$$d_{ij} = \left\| x_i - \mu_i \right\|_2^2$$

Measuring the validity of the clustering results by contour coefficient. Assuming that the average distance of sample i to the other sample points within the cluster was a_i, the average distance of sample i to other sample points in other clusters was A_i, defining $A_i$as the inter-cluster dissimilarity of sample i :

$$A_i = \min\{A_{i1}, A_{i2}, \ldots A_{ik}\}$$

The contour factor was Q_i.

$$Q_i = \frac{a(i) - A(i)}{\max\{A(i), a(i)\}}$$

$$Q_i = \begin{cases} 1 - \dfrac{a(i)}{A(i)}, a(i) < A(i) \\ 0, a(i) = A(i) \\ \dfrac{a(i)}{A(i)} - 1, a(i) > A(i) \end{cases}$$

From the above equation, it was clear that the contour coefficient was an important parameter for assessing the number of clusters, as a way to evaluate the reasonableness of the number of clusters, and also to determine the accuracy of the clustering algorithm.

Figure 1 illustrated the K-Means clustering model, where 10,000 data were randomly generated and the number of clusters is set to 3.

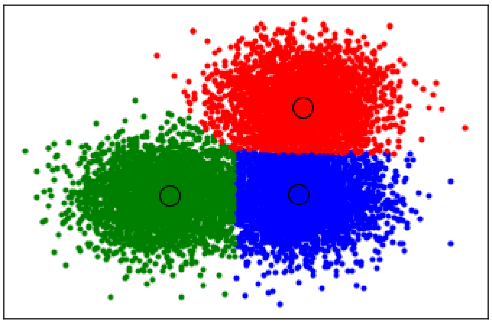

Figure 1. Schematic diagram of K-means clustering analysis

Rules for scoring explicit fault warnings for wind turbine blades

The wind speed-power, wind speed-hub speed, the ratio of wind speed to blade tip speed, and second-level vibration data were used as the evaluation criteria by comprehensively analyzing the working principle of wind turbine and the influence on wind turbine operation data under the explicit blade fault.

Extraction the data for a period of continuous operation of the wind turbine, which can be one month, three months or a longer period of time. Analyzing the hub speed-generator torque first and ensuring that the control system was working properly, the wind speed-power, wind speed-hub speed, the ratio of wind speed to tip speed, and second-level vibration data were analyzed using Section 2.3, and scored separately as $T = T_1 + T_2 + T_3 + T_4$. The scoring criteria for wind speed - power, wind speed - hub speed, and the ratio of wind speed to blade tip speed are the same. As an example of wind speed-power, the wind speed interval was divided into N_I, which $i = 1,2,3 \ldots n$, Supposing that the upper and lower values of cluster center coordinates for a certain wind speed interval were (x_1, y_1) and (x_2, y_2), this wind speed section was rated as T_{1i} , the total score T_1 was:

$$T_{1i} = \begin{cases} 1, 0.2 < \dfrac{|y_1 - y_2|}{y_2} \le 1 \\ 0, 0 < \dfrac{|y_1 - y_2|}{y_2} \le 0.2 \end{cases}$$

$$T_1 = \begin{cases} 1, 0.25 \le \dfrac{\sum_{i=1}^{n} T_{1i}}{n} < 0.75 \\ 0, others \end{cases}$$

The wind speed-power, wind speed-hub speed and the ratio of wind speed to tip speed of wind turbines were assessed as described above, the Fourier series transformation of the second-level axial vibration data of wind turbines and the assessment criteria were shown below:

$$X(\omega)=\int_{-\infty}^{\infty}x(t)e^{-j\omega t}dt$$

$$X(k)=\sum_{n=0}^{N-1}x(n)W_N^{kn}$$

In which the finite length discrete signal $x(n)$, N was the number of data collection: $n = 0,1,2,\ldots,N-1$.

$$W_N = e^{-j\frac{2\pi}{N}}$$

In which $k = 0,1,2,\ldots N-1$.

Plotting the wind speed-power scatter diagram of wind turbine to locate the point with the largest offset, and selecting the time of the data point. And then using the time period as the intermediate time to extract the axial second vibration data before and after a total of 60 minutes, then to carry out the Fourier transform, the number of axial second vibration data was not less than 8000.

$$T_{amplitude(\max)} \geq 0.2, \text{abnormal vibration}$$

$$T_{amplitude(\max)} < 0.2, \text{normally vibration}$$

In conclusion, combined with performance reliability theory and statistical principles, the scoring rule adopted the one-sided performance reliability theory and allowed a one-sided lower limit of 10% floating, with the following rules for its ultimate warning conclusion:

$$\begin{cases} 2.88 \leq T \leq 3.6, \text{blade crack} \\ 2.16 \leq T < 2.88, \text{blade most likely crack} \\ 1.44 \leq T < 2.16, \text{blade possibly likely crack} \\ 0 \leq T < 1.44, \text{blade normal} \end{cases}$$

As different models of wind turbine blades exhibited different interval segments for explicit faults, abnormal data for one or more interval segments may occur occasionally when the wind turbine blades were normal.

Overall, the scoring rule can cover all models and screen out outliers, and it has good applicability.

Wind turbine blade explicit fault warning model

Extracting one year of operating data of a wind turbine with explicit blade fault by studying 2 MW wind turbine. And the site was found in December 2025 with an obvious apparent blade fault, by intercepting operational data from September 2025, in which parameters included: running time, wind speed, ambient temperature, power, hub speed and generator torque. The data pre-processed according to Section 2.2 at the first, then the data with ambient temperature below 5°C was screened out to prevent the influence of blade icing on the explicit fault of the wind turbine.

The working principle of a wind turbine involves a wind speed-power control system, where power control is typically implemented with a wind speed interval width of 0.5 m/s. Reducing the width of the wind speed segment would introduce power instability. Therefore, the wind speed segment interval is set to 0.5 m/s.

To warrant the accuracy of the clustering analysis, the wind speed interval setting to 0.5 m/s, where a wind speed segment was randomly selected to run the K-Means model in Section 2.2 for the wind speed-power data. The cluster-profile coefficients for this wind speed segment were shown in Figure 2, and the classification diagram for this wind speed segment was shown in Figure 3.

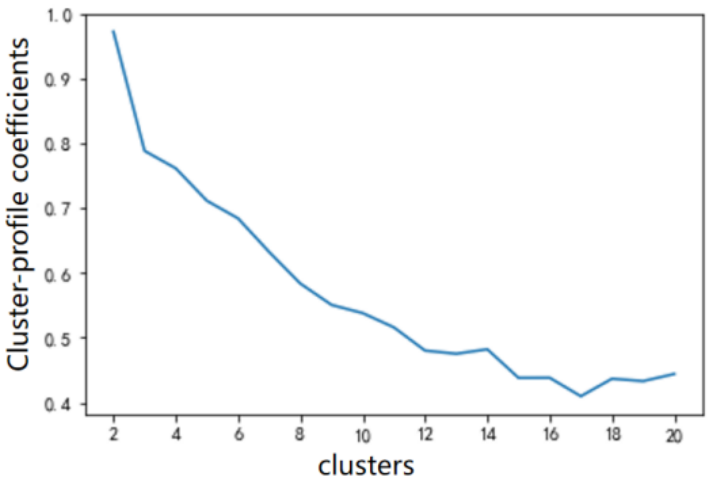

Figure 2. Score plot for cluster number determination in K-means clustering analysis

As can be seen from Figure 2, the hub factor of 0.5 m/s interval was close to 1, which showed the optimal performances.

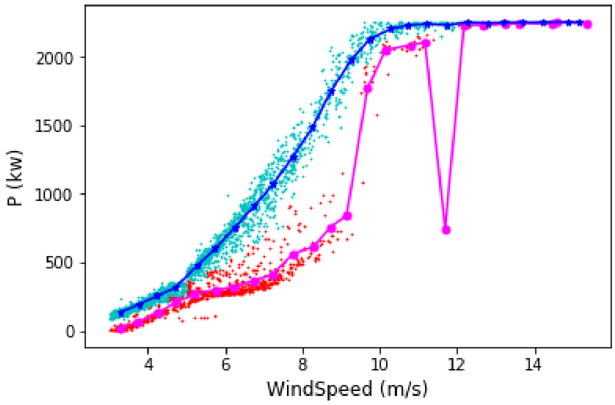

Figure 3. The classification chart of wind speed - power

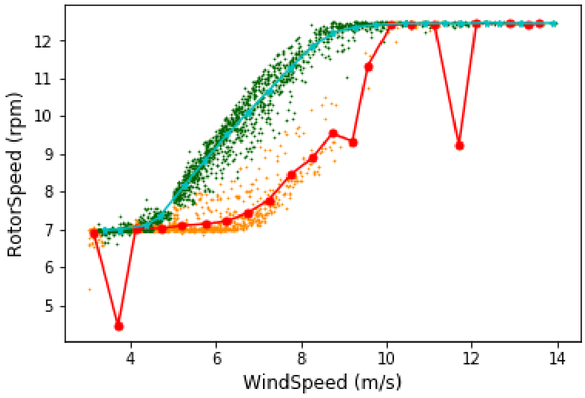

Figure 4. The classification chart of wind speed-hub speed

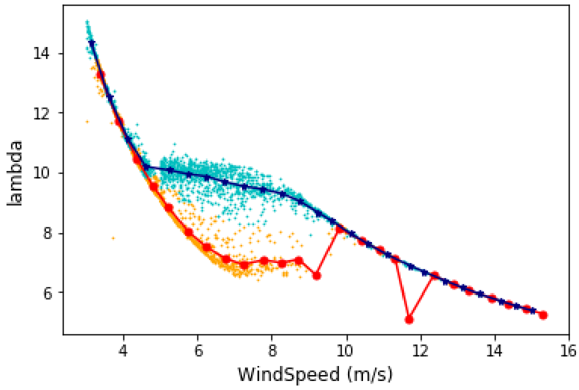

Figure 5. The classification chart of the ratio of wind speed to blade tip speed

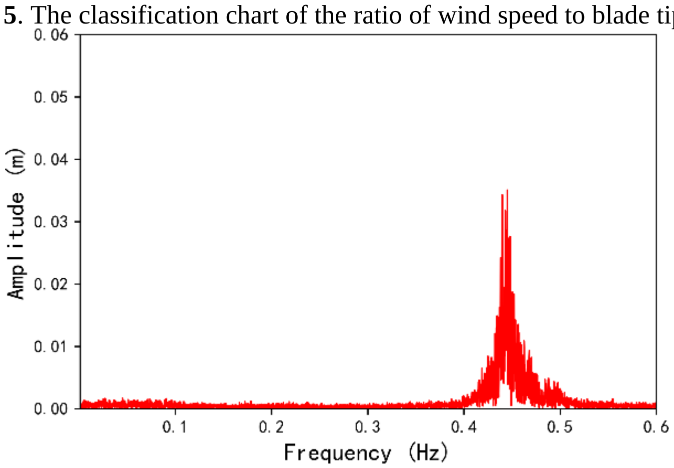

Figure 6. Scatter plot of Fourier transform of second-level data of axial vibration

From Figure 3, Figure 4, Figure 5 and Figure 6, we can clearly see that there was a big difference between the operational data of wind turbine blades during explicit fault and normal data comparison, and the following conclusions could be deduced from the wind speed-power, the ratio of wind speed to tip speed, and wind speed-hub speed data of wind turbine blades of different models with explicit faults were abnormal in different wind speed sections, the abnormal wind speed interval segments account for about 25% to 75% of the total wind speed segments.

3. RESULT AND DISCUSSION

3.1 Results

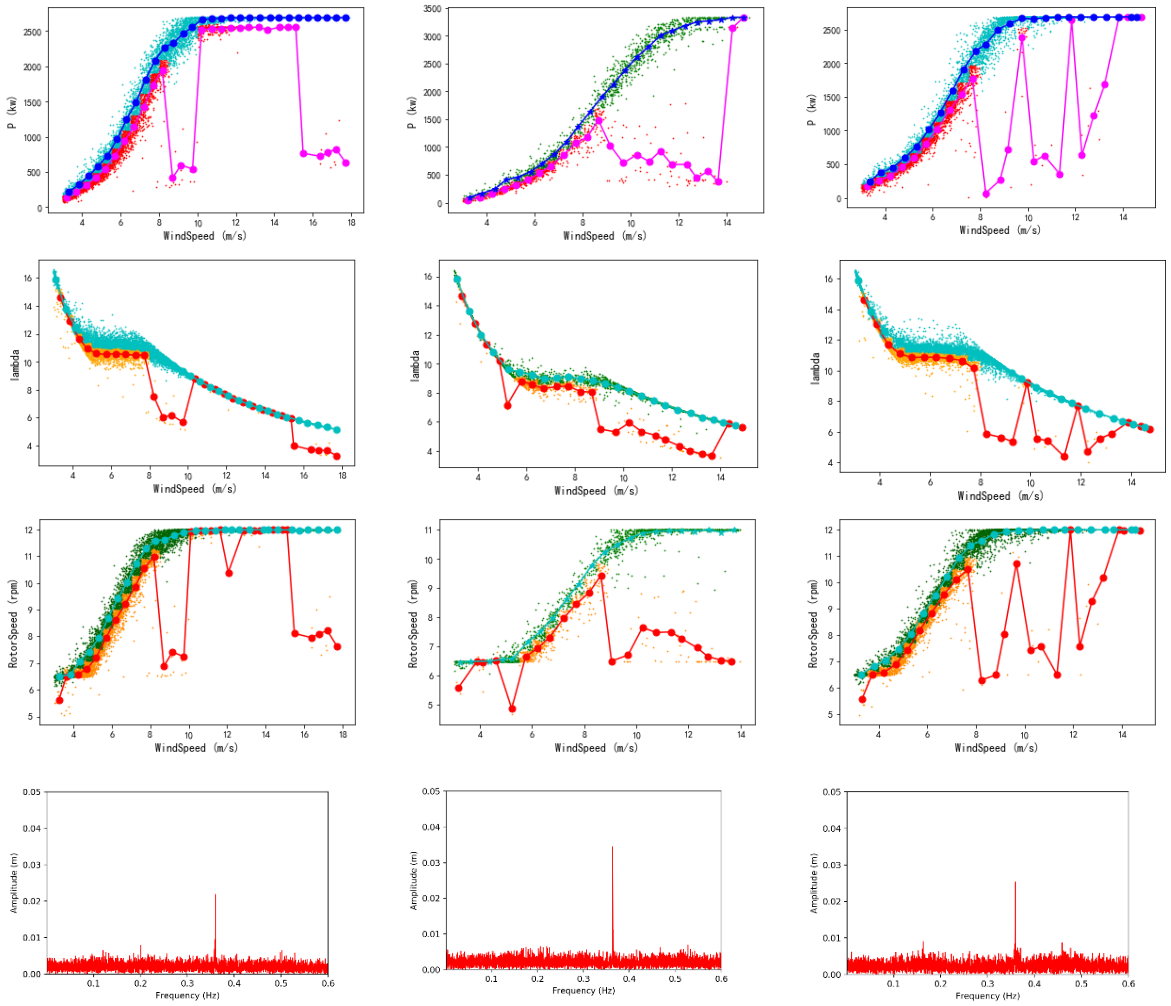

Figure 7. The classification plots of wind speed-power, the ratio of wind speed to tip speed, wind speed-hub speed for three wind turbines and fourier transform of the second-level axial vibration data

Thirty wind turbines from a wind farm in the south of China were selected to investigate the blade explicit faults of different wind turbine models, which consisted of 2MW, 2.5MW and 3.2MW models, three of which had varying degrees of blade explicit faults. Data from 1 month, 3 months and 5 months of operation were randomly extracted for analysis.

The data pre-processed firstly to screen out the operating data in abnormal conditions, and then the wind speed-power, wind speed-hub speed, the ratio of wind speed to tip speed, and axial second-level vibration data of the wind turbine were respectively extracted.

Conducting Section 2.4 to analyze 30 wind turbines for the wind farm. After clustering analysis and wind turbine blade explicit faults of the scoring criteria to achieve three wind turbines are determined as blade explicit faults. The classification of wind speed-power, the ratio of wind speed to tip speed, and wind speed-hub speed classification charts for these three wind turbines were shown Figure 7.

The method adopted in this paper is based on analyzing multiple factors such as the working principle and performance parameters of wind turbines. An unsupervised learning approach is used for blade fault diagnosis of wind turbines. Unsupervised learning does not involve labeled data, metrics such as recall are not applicable. The accuracy was evaluated by monitoring 30 wind turbines across several wind farms. Three turbines were identified as having blade faults, and the results were verified to be consistent with the model output. Therefore, the tested model achieved 100% accuracy.

The results showed that the wind farm has three wind turbine blade explicit faults, and the accuracy rate of the evaluation is 100%, one 3.2MW wind turbine achieved 2 months in advance blade explicit fault warning.

3.2 Discussion

3.2.1 Implications

The method based on cluster analysis proposed to the fault warning of wind turbine blades using machine learning, it can be seen that the abnormal data segments presented by different models of wind turbine blade explicit faults were quite different, the feasibility of the wind turbine blade explicit fault warning method based on cluster analysis has been initially verified, and the advanced warning has been realized, especially for the evaluation of the wind turbine blade internal explicit faults which are difficult to be observed by naked eyes.

3.2.2 Research contribution

In an attempt to solve the problem of internal damage and crack of wind turbine blades that are difficult to be evaluated, a method based on cluster analysis is proposed to study the fault warning of wind turbine blades using machine learning.

The methond use wind speed-power, wind speed-hub speed and the ratio of wind speed to tip speed were used to classify the parameters affecting the explicit faults of wind turbine blades by using the cluster analysis method, and the distance analysis was performed by using the combined weight method segmentation, and the axial vibration data of the abnormal data points were analyzed by using the Fourier series transformation. Establishing the wind turbine blade explicit fault evaluation rules based on the performance reliability theory.

This study has achieved the fault warning of large components based on the wind turbine short-term historical operation data.

Common approaches include machine learning and computer vision. However, blade faults in wind turbines are rare events with enormous economic losses, resulting in a limited amount of fault data, making it difficult to acquire sufficient data for machine learning models. Moreover, computer vision methods cannot identify internal cracks in the blades.

Therefore, this paper innovatively analyzes the failure mechanism of wind turbine blades and extracts operational parameters for unsupervised learning.

3.2.3 Limitations

Several limitations should be acknowledged. Wind turbines are expensive to manufacture, and blade faults are extremely low-probability events. Consequently, the number of wind turbines with blade faults is very small. In future work, the operational parameters of wind turbines will be continuously monitored. The operating environment of wind turbines is relatively harsh, which can lead to fluctuations in the accuracy of some sensors. These fluctuations are minor and unavoidable. However, they are so small that although they may cause some deviations in the results, they do not affect the final outcome.

3.2.4 Suggestions

Future research should focus on increase the number of parameters related to wind turbine blade failures, with a particular focus on analyzing sensor data values that exceed the normal range. In the coming period, the author will continue to conduct research on wind turbine blade failures.

4. CONCLUSION

(1) Proposing a clustering analysis-based wind turbine blade explicit fault warning method, combining statistics and performance reliability theory to establish wind turbine blade crack assessment rules.

(2) Collecting the operating data of 30 wind turbines of a wind farm with different models, the data were firstly pre-processed to screen out the abnormal operation data of wind turbine. Next, cluster analysis is applied to respectively classified hub speed-hub torque, wind speed-power, wind speed-hub speed, the ratio of wind speed to tip speed and vibration by cluster analysis, and calculated the cluster center interval distance of each interval segment separately. At last, the possibility of explicit faults of wind turbine blades was evaluated according to its assessment rules.

(3) The feasibility of the explicit fault warning method of wind turbine blade based on cluster analysis was verified by study, especially for wind turbine blade internal damage can be advanced warning. The method is of great significance for the advance warning in large-scale component damages of wind turbine.

5. ACKNOWLEDGEMENT

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6. AUTHOR CONTRIBUTION STATEMENT

Yuli Guo is responsible for all tasks including data cleaning, model construction, and model test. Yirui Qiao is responsible for data collection.

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