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Article

A Three-Level Service Quality Index System for Wind Turbine Groups Based on Fuzzy Comprehensive Evaluation

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Abstract: The maintenance and upkeep costs of wind farms and their internal wind turbines have been increasing annually. Therefore, a systematic evaluation of their operating status is of great importance in guiding reductions in maintenance and upkeep costs. In this aspect, this article proposes a three-level service quality index system of "key component–wind turbine–wind farm" based on the fuzzy comprehensive evaluation method. Firstly, raw data on the wind farm are preprocessed to avoid the impact of abnormal data on the evaluation results. Then, the data types are classified and the degradation degree of each indicator is calculated. Based on the entropy weight method, the weight of each indicator is weighted and summed to obtain the overall membership degree. Finally, the overall health level is determined according to the "maximum membership degree", which is the evaluation result. This article conducts an evaluation experiment based on the actual operating data of Gansu Huadian Nanqiu Wind Farm. The example shows that the proposed strategy can systematically evaluate the health level of wind farms and predict the future trends of health status changes. The research results can provide reference for the reasonable arrangement of unit scheduling, operation, and maintenance plans in wind farms.

Keywords: wind turbine group; service quality; fuzzy comprehensive evaluation; entropy weight method; state assessment

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1. Introduction

In recent years, the installed capacity of large-scale wind turbines in China has grown rapidly, resulting in escalating maintenance and repair costs. Therefore, conducting a systematic evaluation of the operating status of wind farms and their internal wind turbines is crucial [1–3]. This evaluation helps in achieving well-planned operation and maintenance strategies, accurately understanding the operational conditions of wind farms, optimizing maintenance procedures, and reducing maintenance costs for operational staff.

At present, the fuzzy evaluation method and analytic hierarchy process are primarily used for assessing wind farms and their wind turbines, and an evaluation index system is established by combining evaluation index weights [4–6]. Studies [7,8] establish a health status evaluation model for wind turbines based on the fuzzy evaluation method, the analytic hierarchy process, the variable weight method, the cloud model calculation method, etc. Wind farms and their wind turbines are significantly affected by various factors, such as mechanical, electrical, environmental, pneumatic, and thermal factors. The literature above only monitors and evaluates the status of certain factors at the wind turbine level, which presents issues such as a limited number of indicators and weak representativeness. The established indicator framework cannot effectively characterize the health and operational status of the entire wind farm. Therefore, it is necessary to propose a multi-level comprehensive monitoring and evaluation method.

In the field of wind power generation, with the increasing scale and service life of wind power devices, ensuring the service quality and operational efficiency of wind turbines has become particularly important [9,10]. As high-tech and complex engineering equipment, the service quality assessment of wind turbines not only affects the safety and reliability of the units, but also directly affects the economic benefits and sustainable development of wind power projects. Therefore, research on the service quality assessment of wind turbines has gradually become a key focus of attention in both academia and industry. At present, research on the service quality assessment of wind turbines mainly focuses on the following aspects: Firstly, based on data-driven methods, through real-time monitoring technology and big data analysis methods, how to track the operating status of the units in real time, as well as predict possible faults and failure risks, is considered [11,12]. Secondly, for the health status assessment of key components of wind turbines (such as blades, transmission systems, generators, etc.), vibration analysis, acoustic emission monitoring, ultrasonic testing, and other methods are used for fault diagnosis and life prediction [13]. Thirdly, using reliability engineering theory combined with historical data on wind turbine operation, reliability models have been studied and failure mode analyses of wind turbines undertaken [14]. Finally, with the continuous development of wind power technology, service quality assessment also needs to consider multidimensional factors, such as environmental factors, climate change, and operation and maintenance costs, to comprehensively evaluate the long-term stability and economy of wind turbines. Despite numerous research achievements, the assessment of the service quality of wind turbines still faces challenges, such as technical complexity, insufficient data, and environmental impact in practical applications. Therefore, how to further improve evaluation accuracy, reduce evaluation costs, and achieve intelligent and automated evaluation results remains an urgent research hotspot in the field of wind power.

On the basis of analyzing the composition of wind turbines and clusters, this article explores the implications of service quality in wind turbine clusters. It investigates and analyzes the impact of national/industry standards on the design and functioning of wind turbines (wind farm clusters), along with the regulatory obligations of national energy and environmental policies for wind power operations. It determines the connotations of service quality for wind turbines and clusters, as well as the functions, performance, reliability, safety, environmental adaptability, and economic utilization related to service quality. It also identifies the main relevant elements that affect these characteristics. According to the three-level analysis of "key component–wind turbine–wind farm", combined with the analysis results of the connotation elements of service quality, the importance of equipment/components is analyzed from top to bottom. The performance degradation and fault modes of components/equipment and their impact on the upper layer are analyzed from the bottom up. The "upward synthesis + upper layer addition" method is adopted. Based on the preliminary construction of a wind turbine service quality index system, a three-level service quality index system of "key component–wind turbine–wind farm" is constructed step by step through refinement, hierarchy, and standardization.

2. The Three-Level Service Quality Index System for Wind Turbine Groups

Fuzzy comprehensive evaluation is a decision-making method used to address complex problems involving fuzzy information and concepts [15]. It is based on fuzzy logic theory, which processes fuzzy and uncertain input information through fuzzification, then uses fuzzy rules and fuzzy reasoning for processing, and finally produces fuzzy output results [16]. This method can effectively handle some difficult-to-quantify problems, such as sentiment analysis, expert systems, fuzzy control, and other fields. By considering uncertainty, fuzzy comprehensive evaluation can provide more flexible and robust decision-making solutions. This article introduces a three-level service quality index (QI) system of "key component–wind turbine–wind farm" based on the fuzzy comprehensive evaluation method. The overall evaluation process is illustrated in Figure 1.

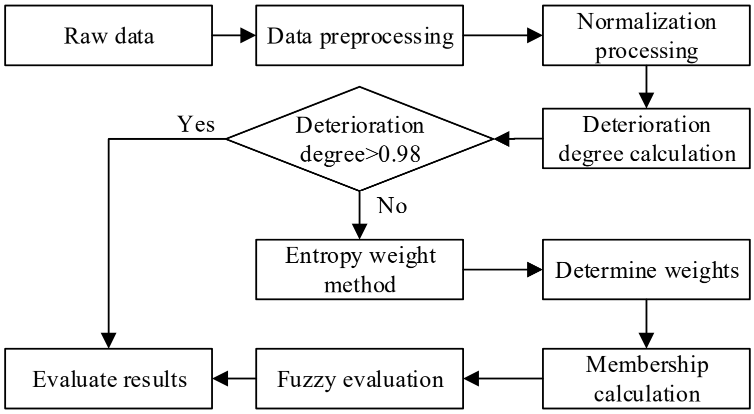

Figure 1. Overall evaluation process.

2.1. Establishment of Index System

This article comprehensively analyzes the significance of equipment/components from top to bottom based on the three levels of "fleet unit key components" and the analysis results of the essential elements of service quality. From bottom to top, the analysis focuses on the performance degradation and fault modes of components and equipment, as well as their impact on the upper layer. Using the method of "upward synthesis + upper layer addition", a three-level service quality index system of "key component–wind turbine–wind farm" is constructed layer by layer through refinement, hierarchy, and standardization based on the preliminary wind turbine service quality index system, as shown in Figure 2.

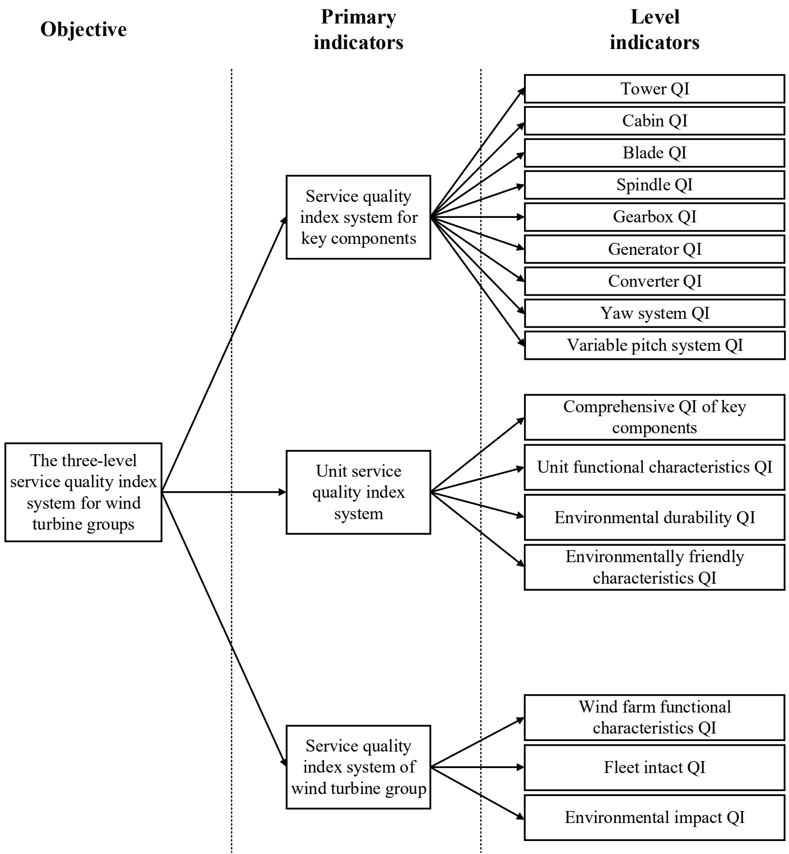

Figure 2. The three-level service quality index system of "key component–wind turbine–wind farm".

The selected parameter items in the three-level service quality index system of "key component–wind turbine–wind farm" integrate the operational requirements of wind power enterprises, demands from operation and maintenance departments, monitoring requirements of quality supervision departments, considerations from local communities near wind farms, and regulations from environmental protection departments for natural environment preservation, while also taking into account various national and industry standards.

2.2. Selection of Tertiary Indicators

Considering the three-level index of the service quality index system for key components, this article selects tower vibration and tower inclination angle to characterize the tower QI. Cabin vibration, temperature, and humidity were selected to characterize the cabin QI. Impeller speed, hub temperature, and blade cracks were selected to characterize the blade QI. Bearing temperature and spindle vibration were chosen to characterize the spindle QI. Gearbox oil temperature, gear vibration, and bearing temperature were selected as indicators to characterize the gearbox QI. Generator torque, generator speed, and bearing temperature were chosen to characterize the generator QI, where the generator bearing temperature specifically indicates the temperature of the internal bearings of the generator. Converter temperature and converter power were selected to characterize the converter QI. Yaw angle was selected to characterize the yaw system QI. Pitch angle was selected to characterize the variable pitch system QI.

At the three-level indicator level of the unit service quality index system, this article selects the QI of each key component to characterize the comprehensive QI of key components. Phase voltage, phase current, active power, reactive power, power factor, and grid frequency were selected to characterize the operational features of the unit's QI. The phase voltage of the wind turbine refers to the AC voltage output by the generator. The phase current refers to the current passing through the generator winding. The active power refers to the actual power output by the wind turbine, while the reactive power refers to the power component generated by the wind turbine with a phase difference of 90 degrees from the active power. The power factor of the wind turbine refers to the ratio of the useful power output to the total power. The grid frequency refers to the periodic changes in the frequency of AC power in the power system. Monitoring and controlling these parameters helps ensure a stable connection between the wind turbine and the grid, maximizing their efficiency of connection. Utilizing wind energy for power generation, corrosion resistance and de-icing capability were selected to evaluate the environmental durability QI. The corrosion level of wind turbines is typically influenced by factors such as humidity, salinity, chemicals, and climate in the environment. Common types of corrosion include atmospheric corrosion, salt spray corrosion, and chemical corrosion. In order to reduce the impact of corrosion, wind turbines typically implement anti-corrosion measures, such as using corrosion-resistant materials, conducting regular inspections and maintenance, and applying protective coatings when necessary. The de-icing capability of wind turbines refers to the maintenance of the surface cleanliness of wind turbine blades in low-temperature environments, especially under freezing conditions, to ensure the normal operation of wind turbines. The de-icing system usually includes mechanical de-icing, heating de-icing, and chemical de-icing methods. These systems can ensure their reliability through regular inspection and maintenance, effectively removing ice and snow accumulation on the blade surface when needed to prevent any negative impact on the performance and safety of wind turbines. Noise level and oil leakage were chosen as indicators to assess the environmentally friendly characteristics of the QI. The term "unit noise" of wind turbines refers to the sound generated during their operation. This noise mainly comes from factors such as friction between wind turbine blades and air, the internal mechanical operation of the generator, and the structural vibration of the wind turbine. In order to minimize the impact of unit noise on the surrounding environment and personnel, wind turbines usually implement sound insulation measures, such as using noise-absorbing materials, optimizing blade design, and adjusting operating parameters. Oil leakage refers to the unintentional discharge of lubricating oil or hydraulic oil during the wind turbine's operation. This issue may be caused by oil seal failure, loose pipeline connections, oil pipe wear, or abnormal system pressure. Oil leakage may affect the operation and safety of the unit. Therefore, wind turbines are usually equipped with oil collectors, oil pump monitoring systems, and other equipment. Regular inspection and maintenance procedures are also implemented, including the replacement of seals when necessary, to minimize the risk of oil leakage.

For the three-level index of the service quality index system for wind turbine groups, this article selects the active power and reactive power of wind farms, the low-voltage crossing ability of wind farms, and the adaptability of wind farm operation to characterize the functional characteristics of wind farm QIs. The active power of wind farms refers to the actual power output from the wind farm to the grid, while the reactive power refers to the power component generated by the wind farm with a phase difference of 90 degrees from the active power. This reactive power is essential for maintaining grid stability and regulating voltage. The low-voltage ride-through capability of a wind farm refers to its ability to maintain stable operation and provide power to the grid when the grid voltage drops or fluctuates. This usually involves the electrical and control systems of the wind farm equipment to ensure that the wind farm can promptly respond and adjust the generator output power to maintain grid stability when the grid voltage fluctuates. The operational adaptability of wind farms refers to their ability to adapt to different meteorological conditions and grid operation requirements. Wind farms typically use advanced wind turbine control systems and electrical equipment to adjust to real-time wind speed and grid demand. Wind turbines can also endure harsh weather conditions and emergencies, guaranteeing the dependability and stability of wind farms. Wind farms have various environmentally friendly characteristics. Wind energy is a clean energy source with zero emissions. Wind power generation does not produce greenhouse gases or other pollutants, and it has no negative impact on the atmospheric environment. Additionally, wind energy is a renewable resource, and wind farms harness this energy for power generation without depleting resources, thereby reducing dependence on finite energy sources. Moreover, wind farms are land-use efficient, typically occupying relatively small areas that can be built on farmland, wasteland, or offshore locations. Compared with traditional energy power plants, wind farms reduce land occupation. They also contribute to ecological protection by implementing measures to safeguard the habitats of wild animals and plants during construction and operation, thereby minimizing their impact on the local ecosystem. The intact QI of the fleet is characterized by selecting the functional characteristics of each unit and determining the number of units that can be fully utilized. Additionally, the environmental impact QI is defined by selecting the environmentally friendly characteristic QI, ecological impact index, and climate impact index of each unit. The ecological impact index and climate impact index are indicators used to evaluate the environmental impact of wind farms. The ecological impact index includes the degree of damage to wildlife habitats, interference with bird migration routes, and the impact on groundwater and soil. These indicators can be evaluated through environmental impact assessments to ensure that the impact on the ecosystem is minimized during the construction and operation of wind farms. The climate impact index includes the impact of climate change, as well as the impact on surrounding climate factors such as temperature, wind speed, and humidity. Wind farms have a positive impact on reducing greenhouse gas emissions and replacing fossil fuels. However, they may also have certain effects on the local climate, such as the formation of microclimate changes around wind farms. These impacts need to be evaluated and managed through simulation and on-site monitoring.

2.3. Selection of Secondary Indicators

This article proposes a service quality index system that is based on the importance of components and the measurability of relevant data. On the basis of the service quality index of key components, a comprehensive quality index of key components is formed. This is combined with the overall functional characteristic quality index, environmental durability quality index, and environmentally friendly characteristic quality index of the unit to jointly form the service quality index system of the unit. On the basis of the service quality of each wind turbine unit in the wind turbine group, considering factors such as the overall functional characteristic index of the wind farm, the intact quality index of the turbine group, and the environmental impact quality index, a service quality index system for the wind turbine group is constructed.

3. Fuzzy Comprehensive Evaluation Model

This section provides a detailed introduction to the fuzzy comprehensive evaluation model used in this article. Firstly, the raw data of the wind farm are preprocessed to remove outliers and noise data, ensuring data quality and avoiding misleading effects of abnormal data on the evaluation results. Next, the processed data are classified according to different data types, and corresponding degradation indicators are calculated for each type of data, reflecting the degree of degradation of wind farm equipment or system performance. Subsequently, the entropy weight method was used to allocate weights to various degradation indicators, taking into account the importance and information content of each indicator to ensure the scientific and rational evaluation process. Next, by using the weighted sum method and combining the weights and degradation levels of various indicators, the overall membership value of the wind farm is obtained. Finally, according to the principle of "maximum membership degree", the health level with the highest membership degree is selected as the final evaluation result, thus achieving a comprehensive evaluation of the health status of the wind farm.

3.1. Normalization of Evaluation Indicators

Normalization is a data processing technique aimed at converting data of different scales, units, or ranges into a unified standard or similar scale. This helps eliminate the dimensional influence between different data, allowing them to be compared, analyzed, or combined. Normalization typically involves scaling data to a specific range, such as mapping the data to a range between 0 and 1, or converting the data to a standard normal distribution with a mean of 0 and a standard deviation of 1. Normalization helps to improve the efficiency and accuracy of data processing, especially in fields such as machine learning and data mining, which are widely used.

The various indicators in the three-level service quality index system of "key component–wind turbine–wind farm" proposed in this article have specific physical meanings and reasonable ranges. In order to comprehensively analyze and calculate these indicators, it is necessary to normalize each indicator. This article utilizes the calculation method of relative degradation degree, which converts the corresponding data into intervals based on the actual operating status of wind turbines, as indicated by each indicator. The smaller the value, the better the operating situation. The formula used to calculate the degree of degradation in this article is shown below.

3.1.1. The Smaller the Factor, the Better the Type

In the calculation of degradation degree, the "smaller the better" type factor refers to evaluating the degradation degree or quality of the object, and the smaller the value, the better the quality. This type of factor is usually used to measure the extent of adverse effects or losses, such as the number of product defects, system failure rate, service delay time, etc. In these cases, smaller values represent higher quality, fewer problems, or less impact, so smaller values are preferable. The formula for calculating the degree of degradation is as follows:

$$f(x) = \begin{cases} 0, & x < x_{\min} \\ \frac{x - x_{\min}}{x_{\max} - x_{\min}}, & x_{\min} \le x \le x_{\max} \\ 1, & x > x_{\max} \end{cases} \tag{1}$$

Among them, x is the actual value of the indicator, $[x_{\min}, x_{\max}]$ is the reasonable range of the indicator, and $[x_a, x_b]$ is the optimal range of the indicator.

3.1.2. Intermediate Factors

In the calculation of the degradation degree, intermediate factors refer to the presence of an intermediate range or state that represents the optimal situation when evaluating the degree or quality of degradation of an object. This type of factor is typically used to measure specific performance indicators or characteristics, such as the efficiency of a product's functionality, system availability, service response time, etc. In these cases, there is an intermediate range where higher or lower values indicate poor performance, while the intermediate value represents the optimal scenario. Therefore, intermediate factors play an important role in evaluating the performance of objects when calculating the degree of degradation. The formula for determining their degradation degree is as follows:

$$f(x) = \begin{cases} 1, & x < x_{\min} \\ \frac{x_a - x}{x_a - x_{\min}}, & x_{\min} \le x < x_a \\ 0, & x_a \le x \le x_{\mathrm{b}} \\ \frac{x - x_{\mathrm{b}}}{x_{\max} - x_{\mathrm{b}}}, & x_{\mathrm{b}} < x \le x_{\max} \\ 1, & x > x_{\max} \end{cases} \tag{2}$$

Among them, x is the actual value of the indicator, $[x_{\min}, x_{\max}]$ is the reasonable range of the indicator, and $[x_a, x_b]$ is the optimal range of the indicator.

According to the degree of deterioration of various indicators, the overall level of deterioration of the wind farm can be calculated using the weighted sum method. The calculation formula is as follows:

$$f = \sum_{i=1}^{n} \omega_i \cdot f_i \tag{3}$$

Among these factors, ω_i is the weight of the i th indicator, f_i is the degree of degradation of the i th indicator, f is the overall degradation level of the wind farm, and n is the total number of indicators.

3.2. Calculation of Indicator Weights

When it comes to multi-indicator decision-making, determining the weights of each indicator is crucial. The calculation methods for weights can mainly be divided into the expert experience method and the data statistics method. The expert experience method determines the weight of each indicator through the consensus of the expert team or the judgment of individual experts, usually employing expert questionnaires, discussions, and other methods. The advantage of this approach is its simplicity and ease of implementation, relying on expert experience and judgment. It can flexibly adjust weights according to specific situations. However, the disadvantage is that it is easily influenced by subjective factors, such as personal preferences and subjective errors, and thus lacks objectivity and scientific rigor. The data statistics method is based on historical data or empirical research, using mathematical or statistical methods to calculate the weights of various indicators. Common methods include the entropy weight method [17], principal component analysis, etc. The advantage of this approach is that it is relatively objective and quantifies the importance of each indicator through data, without being influenced by personal subjective preferences. However, the disadvantage is that there is a high requirement for data quality, and there may be limitations when dealing with indicators that have high correlation, which can result in high computational complexity. The expert experience method emphasizes the subjective judgment and experience of professionals and is suitable for situations with insufficient data or complex relationships between indicators. On the other hand, the data statistics method focuses on objective data and statistical analysis, making it suitable for decision-making analysis that requires more objective and scientific methods. Choosing the appropriate method depends on factors such as the specific situation of the decision, available data, and time resources.

This article employs the entropy weight method as a data statistics method to calculate the weight of each indicator according to its degree of degradation. The entropy weight method is a multi-indicator decision-making approach that determines the weight of each indicator via comprehensive evaluation using the concept of information entropy. This method involves several steps. First, it determines the indicators that require weight calculation and collects corresponding data. The second step is to normalize the data of each indicator, and then use the concept of information entropy to calculate the relative entropy value of each indicator. The third step is to calculate the weight of each indicator based on its relative entropy value. The fourth step is to normalize the calculated weights to a total of 1, in order to facilitate the subsequent use and comparison of weights. Finally, the meaning of the weights is explained and they are applied to specific decision-making problems. The core idea of the entropy weight method is to determine the weight of each indicator by measuring its uncertainty or information content. This approach aims to reflect the importance of each indicator in decision-making objectively. The entropy weight method has proven to be effective in multi-indicator decision-making problems, especially in decision-making scenarios that require a comprehensive consideration of multiple factors. The advantages of this approach include effectively reflecting the importance of each indicator, as well as being relatively simple and easy to implement. Overall, the entropy weight method has a wide range of applications in multi-indicator decision-making, evaluation, and ranking.

3.3. Analysis of Membership Function

Membership degree is a fundamental concept in fuzzy logic, used to indicate the degree to which an element belongs to a fuzzy set [18,19]. Unlike the binary property in traditional set theory, where elements must either belong to a certain set or not belong to it, fuzzy sets allow elements to belong to a set to varying degrees. The value of membership degree is usually defined between 0 and 1, where 0 indicates that the element does not belong to the fuzzy set at all, whereas the value of 1 indicates full membership in the fuzzy set. Any value between 0 and 1 represents the varying degree to which the element belongs to the fuzzy set. This flexible membership relationship enables fuzzy logic to better handle uncertainty and ambiguity in the real world.

The overall operating status of a wind turbine group is a gradual and ambiguous process, making it challenging to quantitatively analyze the overall operational status of the wind turbine group. The design of the membership function should ensure that it covers the entire range of degradation values and has an appropriate distribution at each degradation level to accurately reflect the state of the evaluation object. This article uses a ridge distribution membership function to determine the overall operating status by assessing health levels. The operational status of the three-level service quality index system of "key component–wind turbine–wind farm" is categorized into five health levels ranging from excellent to extremely poor: excellent, good, average, poor, and extremely poor. The membership degree of the wind farm corresponding to different health levels can be calculated based on the weighted sum of the degradation degrees of each indicator. The calculation formula for the ridge distribution membership function of each health level is as follows:

$$r_{Excellent}(f) = \begin{cases} 1, f = 0 \\ \frac{1}{2}\left[1 - \sin\left(\frac{f-0.1}{0.2}\right)\pi\right], 0 < f < 0.2 \\ 0, f \geq 0.2 \end{cases} \quad (4)$$

$$r_{Good}(f) = \begin{cases} 0, f = 0 \\ \frac{1}{2}\left[1 + \sin\left(\frac{f-0.1}{0.2}\right)\pi\right], 0 < f \leqslant 0.2 \\ \frac{1}{2}\left[1 - \sin\left(\frac{f-0.35}{0.3}\right)\pi\right], 0.2 < f < 0.5 \\ 0, f \geq 0.5 \end{cases} \quad (5)$$

$$r_{Average}(f) = \begin{cases} 0, f \leq 0.2 \\ \frac{1}{2}\left[1+\sin\left(\frac{f-0.35}{0.3}\right)\pi\right], 0.2 < f \leqslant 0.5 \\ \frac{1}{2}\left[1-\sin\left(\frac{f-0.65}{0.3}\right)\pi\right], 0.5 < f < 0.8 \\ 0, f \geq 0.8 \end{cases} \tag{6}$$

$$r_{Poor}(f) == \begin{cases} 0, f \leqslant 0.5 \\ \frac{1}{2}\left[1+\sin\left(\frac{f-0.65}{0.3}\right)\pi\right], 0.5 < f \leqslant 0.8 \\ \frac{1}{2}\left[1-\sin\left(\frac{f-0.9}{0.2}\right)\pi\right], 0.8 < f < 1 \\ 0, f = 1 \end{cases} \tag{7}$$

$$r_{Extremely\ poor}(f) = \begin{cases} 0, f \leqslant 0.8 \\ \frac{1}{2}\left[1+\sin\left(\frac{f-0.9}{0.2}\right)\pi\right], 0.8 < f < 1 \\ 1, f = 1 \end{cases} \tag{8}$$

Among them, f is the degree of deterioration and $r(f)$ is the membership degree corresponding to each health level. The schematic diagram of the ridge distribution membership function for each health level is shown in Figure 3:

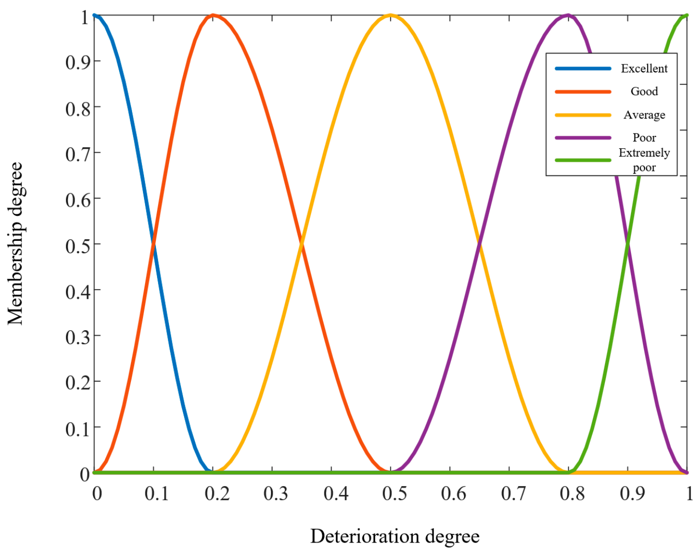

Figure 3. Schematic diagram of ridge distribution membership function.

As shown in Figure 3, when the membership degree is greater than 0, the degradation degree range for an excellent evaluation level is 0–0.2; for a good evaluation level, it is 0–0.5; for a general evaluation, it is 0.2–0.8; for a poor evaluation level, it is 0.5–1; and for extremely poor evaluation, it is 0.8–1.

4. Case Study

This article takes some actual operating data of Gansu Huadian Nanqiu Wind Farm in March 2024 as an example to verify the effectiveness of the method proposed in this article. Gansu Nanqiu Wind Farm is located in Dingxi City, southeastern Gansu Province, China. It is situated at the northern foot of the Qilian Mountains and is a typical area with abundant wind energy resources. To simplify calculations, 13 indicators were selected for simulation. These include grid phase A voltage, grid phase A current, active power, power factor, cabin position, pitch angle, impeller speed, gearbox oil temperature, gearbox bearing temperature, generator speed, generator drive-end bearing temperature, generator non-drive-end bearing temperature, and cabin temperature.

4.1. Data Preprocessing

Among the 13 indicators selected in this article, 8 indicators—grid phase A voltage, grid phase A current, active power, power factor, cabin position, pitch angle, impeller speed, and generator speed—belong to the intermediate-type factor. The other five indicators—gearbox oil temperature, gearbox bearing temperature, generator drive-end bearing temperature, generator non-drive-end bearing temperature, and cabin temperature—belong to the smaller and more efficient category. To improve the accuracy of subsequent calculations, abnormal data were excluded from the operation data of a wind farm unit for the entire day. This article simplifies the calculation by sampling data every two hours throughout the day, resulting in 12 sets of data, as shown in Tables 1 and 2.

Table 1. Intermediate factor operation data.

15 March 2024	Phase Voltage	Phase Current	Active Power	Power Factor	Cabin Position	Pitch Angle	Impeller Speed	Generator Speed
00:00:00	618.9	840.5	954.2	89.7	435.2	7.8	1703.2	1805.7
02:00:00	620.1	783.5	889.1	89.8	447.2	−0.4	1692.7	1784.3
04:00:00	616.0	108.5	124.6	91.6	436.9	1.0	1048.5	1121.6
06:00:00	613.2	0.8	0.0	91.6	469.0	85.6	6.9	15.0
08:00:00	623.8	754.3	853.7	89.9	213.1	10.8	1696.7	1800.0
10:00:00	625.0	838.5	935.0	89.9	215.9	4.6	1690.4	1800.4
12:00:00	622.5	527.0	596.8	89.3	215.8	1.2	1684.1	1802.8
14:00:00	617.1	495.3	567.6	89.4	203.6	2.1	1686.7	1805.0
16:00:00	615.4	772.0	883.0	89.8	201.5	−0.4	1702.3	1798.0
18:00:00	616.1	360.3	408.6	89.7	203.8	−0.5	1472.8	1575.0
20:00:00	616.6	734.8	826.2	92.3	232.0	2.3	1702.6	1793.6
22:00:00	619.8	326.0	367.8	95.0	248.0	−0.5	1422.1	1528.0

Table 2. The smaller the factor, the better the operating data of the factor.

15 March 2024	Gearbox Oil Temperature	Gearbox Bearing Temperature	Drive-End Bearing Temperature	Non-Drive-End Bearing Temperature	Cabin Temperature
00:00:00	50.9	63.4	54.6	70.5	25.9
02:00:00	54.7	67.2	56.1	69.2	27.5
04:00:00	51.9	63.0	50.2	55.5	26.4
06:00:00	48.7	53.4	44.8	50.5	18.6
08:00:00	50.7	62.5	52.9	68.8	24.1
10:00:00	51.7	62.5	55.8	70.6	25.7
12:00:00	53.8	66.0	56.6	66.5	28.1
14:00:00	52.7	65.2	54.5	59.8	24.7
16:00:00	51.2	64.3	51.5	54.6	22.2
18:00:00	54.0	66.8	48.7	52.2	24.3
20:00:00	54.4	66.9	49.7	52.4	24.0
22:00:00	52.4	65.9	48.9	52.2	23.6

Under normal operation in wind farms, intermediate indicators such as phase voltage, phase current, and active power typically exhibit certain fluctuations. Most of these fluctuations are caused by external environmental factors, such as changes in wind speed, meteorological conditions, etc., and these fluctuations have a certain degree of periodicity and randomness. The fluctuation of wind speed directly affects the power output of wind turbines, leading to fluctuations in power generation. Generally speaking, as the wind speed increases, the power generation will correspondingly increase, but due to the instability of wind speed itself, the power generation often exhibits fluctuating fluctuations. In addition, the load factor of wind farms is also affected by changes in wind speed, exhibiting a relatively smooth fluctuation trend. Overall, these fluctuations are usually unavoidable features of wind farms during normal operation. The smaller the size, the better the performance indicators (such as gearbox oil temperature, drive-end bearing temperature, cabin temperature, etc.), which usually reflects the health status and operating efficiency of the fan equipment. The fluctuations in these indicators should be kept within a small range, as excessive fluctuations may indicate a malfunction or unstable operation of the fan. When these indicators fluctuate too much, it may be due to overload, wear and tear, uneven airflow of the fan, or improper system scheduling. In an ideal situation, the fluctuations of these indicators should be kept within the preset normal range. Small fluctuations indicate that the wind farm is running smoothly and the equipment performance is good, thereby ensuring power generation efficiency and equipment lifespan.

4.2. Normalization Processing Calculates Degradation Degree

Based on the processed samples, the reasonable and optimal range for each indicator can be determined. Subsequently, we calculated the degradation degree of each indicator using the formula outlined in Section 2.1 for the 12 sets of data presented in Tables 3 and 4.

Table 3. Intermediate factor degradation degree.

15 March 2024	Phase Voltage	Phase Current	Active Power	Power Factor	Cabin Position	Pitch Angle	Impeller Speed	Generator Speed
00:00:00	0.00	0.61	0.60	0.05	0.93	0.47	0.50	0.28
02:00:00	0.00	0.49	0.48	0.00	0.98	0.59	0.24	0.00
04:00:00	0.33	0.75	0.74	0.20	0.93	0.00	0.98	0.99
06:00:00	0.71	1.00	1.00	0.20	1.00	1.00	1.00	1.00
08:00:00	0.41	0.42	0.41	0.00	0.13	0.70	0.33	0.12
10:00:00	0.55	0.61	0.56	0.00	0.00	0.24	0.18	0.13
12:00:00	0.26	0.00	0.00	0.47	0.00	0.00	0.02	0.20
14:00:00	0.18	0.00	0.00	0.32	0.63	0.05	0.09	0.26
16:00:00	0.41	0.46	0.47	0.00	0.74	0.59	0.47	0.07
18:00:00	0.31	0.09	0.07	0.04	0.62	0.59	0.30	0.28
20:00:00	0.25	0.38	0.36	0.27	0.05	0.06	0.48	0.00
22:00:00	0.00	0.18	0.17	0.60	0.11	0.59	0.38	0.35

Table 4. The smaller the size, the better the deterioration degree of the factor.

15 March 2024	Gearbox Oil Temperature	Gearbox Bearing Temperature	Drive-End Bearing Temperature	Non-Drive-End Bearing Temperature	Cabin Temperature
00:00:00	0.56	0.63	0.83	0.92	0.83
02:00:00	0.97	0.92	0.95	0.86	0.95
04:00:00	0.67	0.60	0.48	0.29	0.86
06:00:00	0.32	0.00	0.06	0.08	0.28
08:00:00	0.54	0.56	0.70	0.85	0.69

Table 4. *Cont.*

15 March 2024	Gearbox Oil Temperature	Gearbox Bearing Temperature	Drive-End Bearing Temperature	Non-Drive-End Bearing Temperature	Cabin Temperature
10:00:00	0.65	0.56	0.92	0.92	0.81
12:00:00	0.87	0.83	0.98	0.75	0.99
14:00:00	0.75	0.77	0.82	0.47	0.74
16:00:00	0.59	0.70	0.59	0.25	0.55
18:00:00	0.89	0.89	0.37	0.15	0.71
20:00:00	0.94	0.90	0.45	0.16	0.68
22:00:00	0.72	0.82	0.38	0.15	0.65

To prevent a severely degraded indicator from being masked by other indicators with low degradation, this article stipulates that if the degradation degree of a particular indicator exceeds 0.98, the evaluation outcome of this group will automatically be classified as extremely poor.

4.3. Entropy Weight Method for Determining Weights

This article is based on the entropy weight method, which calculates the weight corresponding to each indicator by preprocessing the samples. The calculation results are shown in Table 5.

Table 5. Weight of each indicator.

Index	Weight	Index	Weight
Phase voltage	0.00000748	Generator speed	0.000250921
Phase current	0.085211613	Gearbox oil temperature	0.000770457
Active power	0.085266848	Gearbox bearing temperature	0.042690068
Power factor	0.0000744	Drive-end bearing temperature	0.001083506
Power factor	0.031073611	Non-drive-end bearing temperature	0.00402718
Cabin position	0.703328461	Cabin temperature	0.002370901
Pitch angle	0.043844593		

4.4. Membership Calculation

Firstly, the comprehensive degradation degree of each data group is calculated based on the degradation degree of each individual data group and the corresponding weights of each indicator. Then, the comprehensive degradation degree is substituted into the formula in Section 2.3 to obtain the membership degree of each group of data corresponding to each health level, as illustrated in Table 6.

Table 6. Membership degree of each group of data.

15 March 2024	Excellent	Good	Average	Poor	Extremely Poor
00:00:00	0.00	0.00	1.00	0.00	0.00
02:00:00	0.00	0.00	0.94	0.06	0.00
04:00:00	0.00	0.00	0.00	0.00	1.00
06:00:00	0.00	0.00	0.00	0.00	1.00
08:00:00	0.00	0.00	0.77	0.23	0.00
10:00:00	0.00	0.80	0.20	0.00	0.00

Table 6. *Cont.*

15 March 2024	Excellent	Good	Average	Poor	Extremely Poor
12:00:00	0.00	0.00	0.00	0.00	1.00
14:00:00	0.70	0.30	0.00	0.00	0.00
16:00:00	0.00	0.00	0.94	0.06	0.00
18:00:00	0.00	0.01	0.99	0.00	0.00
20:00:00	0.25	0.75	0.00	0.00	0.00
22:00:00	0.00	0.01	0.99	0.00	0.00

4.5. Fuzzy Evaluation to Obtain Evaluation Results

This article is based on the principle of “maximum membership degree” and uses a fuzzy evaluation method to determine the corresponding health level of each group of data based on the membership degree. The evaluation results are shown in Table 7.

Table 7. Health level of each group of data.

15 March 2024	Health Grade	15 March 2024	Health Grade
00:00:00	Average	12:00:00	Extremely poor
02:00:00	Average	14:00:00	Excellent
04:00:00	Extremely poor	16:00:00	Average
06:00:00	Extremely poor	18:00:00	Average
08:00:00	Average	20:00:00	Good
10:00:00	Good	22:00:00	Average

According to Table 7, the health levels of the third and fourth groups of data are both extremely poor. Additionally, Table 3 shows that there are already six indicators in the fourth group of data with a deterioration degree of 1, indicating severe deterioration at this time. However, operation and maintenance personnel can predict a deterioration trend in the health status two hours in advance based on the health level of the third set of data. They can then take appropriate measures to prevent further deteriorations in health status.

5. Conclusions

The maintenance and operational costs of wind farms and their turbines have been rising steadily each year. As a result, conducting a systematic evaluation of their operational status is crucial for optimizing maintenance efforts and reducing costs. To address this challenge, this article introduces a three-level service quality index system of “key component–wind turbine–wind farm” based on the fuzzy comprehensive evaluation method. The process begins with preprocessing the raw data from the wind farm to mitigate the influence of abnormal data on the evaluation outcomes. Next, the data are classified, and the degree of degradation for each indicator is calculated. Using the entropy weight method, the weights of each indicator are determined and aggregated to compute the overall membership degree. Finally, the health level of the wind farm is assessed based on the principle of “maximum membership degree”, which serves as the evaluation result. An evaluation experiment is carried out using real operational data from the Gansu Huadian Nanqiu Wind Farm. The results demonstrate that the proposed method can effectively assess the health status of the wind farm and predict future trends in its operational condition. The findings offer valuable insights for optimizing unit scheduling, operational planning, and maintenance strategies for wind farms.

There are some limitations to the quality assessment of wind farm services, including dependence on high-quality data, subjectivity in selecting evaluation indicators and setting weights, as well as the computational complexity and resource consumption issues faced in large-scale wind farms. In addition, existing evaluation methods have poor adaptability to the dynamic changes in the long-term operation of wind farms, making it difficult to respond promptly to sudden failures or changes in the operating environment. Future research can focus on the application of artificial intelligence and big data technology, improving evaluation accuracy and real-time performance through machine learning and deep learning. At the same time, building a more comprehensive and dynamic multidimensional evaluation system, combined with real-time monitoring and early warning systems to enhance the reliability of wind farms, will ultimately promote the standardization and universality of evaluation methods.

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