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A Data-Driven Approach to Performance Optimization and Lifetime Prediction for Wind Turbines

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Abstract. In order to solve the problem of poor performance stability of traditional wind turbines, a data-driven approach to optimize the performance and life prediction of wind turbines is proposed. Firstly, sensors are installed to collect the operating data of wind turbines; secondly, according to the working principle and operating characteristics of wind turbines, corresponding mathematical models are established, and multi-objective power generation optimization algorithms are designed; finally, the control system structure of the turbine is clarified, and the wind speed section is divided into full wind speed sections, and multi-objective power generation optimization is implemented in the full wind speed section. The experimental results show that: the closer the smoothing factor is to 0, the smoother the output power of the wind turbine is, and the better the multi-objective power generation optimization control effect is; the closer the smoothing factor is to 1, the greater the fluctuation of the output power, and the worse the multi-objective power generation optimization control effect is. Conclusion: After the proposed study is put into application, the power smoothing factor of each wind speed band of the generator set is lower, the output power fluctuation of the generator set is smaller, and the stability is significantly improved.

Keywords. wind turbine,power generation,full wind speed section,multi-objective,control

1. Introduction

With the transformation of global energy structure, renewable energy has become the key to future energy development [1]. Wind energy, as a clean and renewable energy source, is the key to energy development. As a clean and renewable energy source, wind energy has great potential for development [2]. As the main form of wind energy utilization, the power generation efficiency and stability of wind turbines directly affect the economic and social benefits of wind farms [3]. It is of great significance to realize multi-objective power generation optimization control in the full wind speed section to improve the operation efficiency and stability of wind turbines and reduce the energy cost [4].

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However, the wind turbine is located in a remote and harsh geographical environment, outdoor sun exposure coupled with lightning and rainstorms will contribute to the occurrence of mechanical or electrical failures, and the lack of wind farm technicians to understand the a priori knowledge of the wind turbine, resulting in high maintenance costs [5]. An important factor affecting the sustained and healthy development of the wind power industry is that most of the wind power equipment is set up in the sparsely populated remote areas or coastal areas, and the development of wind power equipment has always been to the trend of large-scale, wind blade diameter has also been increasing, so that there is an important role in the installation of equipment nacelle away from the ground farther and farther away, which makes the operation and maintenance of wind turbines is much more difficult, the wind turbine maintenance costs step by step, resulting in expensive operation and maintenance costs in the field. The maintenance cost of wind turbines is increasing, which eventually leads to the problem of expensive operation and maintenance cost in this field [6].

The expensive operation and maintenance cost of wind turbines is caused by the mode of operation and maintenance of wind power generation equipment, most of the wind farms still choose the way of regular maintenance, it is difficult to find out the possible failures in time, and the excessive maintenance for the non-faulty equipment will also enhance the operation and maintenance cost [7]. The general maintenance after the fact, regular maintenance will have an impact on the safety and stability of the wind turbine, economic operation. In view of this, the remaining service life of WTGs can be evaluated and predicted to accurately find out the possible failure time of each component. It is of practical significance to ensure the stable and reliable operation of WTGs and to reduce the maintenance cost of WTGs [8].

2. Literature review

With the rapid development of the wind power industry, performance monitoring and fault prediction of wind turbines have become the key factors to improve the operational efficiency of wind power stations and reduce maintenance costs [9]. The rise of big data technology provides a new way to solve this problem. In this paper, we will focus on the current status of big data application in the wind power industry, as well as the performance monitoring and life prediction of wind turbines based on big data to carry out in-depth research.

Xu, K et al. established a reliability mathematical model based on the performance characteristics of wind turbine, analyzed each evaluation index, obtained the weight value of each index based on principal component analysis, and derived the degradation of wind turbine using information fusion method [10]. The degradation threshold of each index is deduced through the principle of performance reliability, so as to derive the remaining service life of the wind turbine. The validity of the remaining service life model is verified by the wind farm SCADA data set. However, on the one hand, the traditional multi-objective power generation control method for wind turbine all-wind-speed section often focuses on the optimization of single or several performance indexes in practical application, while neglecting the optimization of the overall performance of the wind farm, which may lead to the wind farm failing to achieve the optimal operation effect in some cases. On the other hand, the traditional control method is sensitive to the internal parameter changes of the wind turbine and external environmental disturbances, which may not be able to fully utilize the wind energy, resulting in unstable or lower than optimal power generation.

In order to overcome these shortcomings, it is necessary to study the new multi-objective power generation optimization control method for the whole wind speed band. Therefore, this paper carries out a comprehensive and in-depth study on the optimal control of multi-objective power generation of wind turbines at all wind speeds, so as to contribute to the development of wind energy technology and optimization of energy structure.

3. Methodology

3.1 Collecting wind turbine operation data

Appropriate locations are selected to install sensors to measure and collect operational data such as wind speed, wind direction, unit speed, and power of the WTGs [11]. These locations may include the tower, nacelle, blade and other key parts of the WTG. According to the parameters that need to be measured, the corresponding sensors are selected, as shown in Table 1.

Table 1. Sensor selection

parameters	Sensors
Wind speed	Wind speed sensors: hot-wire anemometers, ultrasonic anemometers, rotor anemometers
Wind direction	Wind sensors: photoelectric sensors, mechanical wind sensors
Temperature	Temperature sensor: thermistor, thermocouple
Humidity	Humidity sensors: capacitive hygrometers, resistive hygrometers
Stress	Pressure sensors: piezoresistive, capacitive

According to the type and characteristics of the selected sensors, they are appropriately calibrated and compensated to ensure the accuracy and stability of WTG operation data collection [12]. The selected sensors are installed in the selected WTG operation locations, and a stable power supply or signal transmission line is provided for them to be able to transmit the WTG operation data in real time [13]. Through data acquisition and analysis, the operational status, performance and potential problems of the WTGs can be understood in real time, providing a basis for the subsequent multi-objective power generation optimization control [14].

3.2 Designing a multi-objective power generation optimization algorithm

Firstly, define the objective of the optimization, which may include improving power generation efficiency, reducing load fluctuations, extending equipment life, etc. Ensure that the objectives are quantifiable and comparable so that the algorithm can find the optimal solution [15]. In the design process of optimization algorithm, according to the working principle and operating characteristics of WTGs, corresponding mathematical models are established, including the power output model, load model, and control model, which are used to describe the performance of WTGs under different wind speeds and operating conditions [16]. The mathematical model expressions are shown as follows.

$$P = \alpha \times V^3 \times R \times C_p \tag{1}$$

where P is the power output; α is a constant; V is the wind speed; R is the radius of the wind turbine; and C_p is the power coefficient. This formula is used to describe the relationship between the power output of the wind turbine and the wind speed and other parameters.

$$W = \gamma \times V^2 \times R \times C_l \tag{2}$$

Where W is the load on the WTG; γ is a constant; C_l is the load factor. The formula is used to describe the load distribution and maximum load limit of WTGs under different wind speeds and operating conditions.

$$\beta = \varphi \times (P/V) + \kappa \tag{3}$$

where φ and κ denote constants; β denotes the pitch angle. This formula is used to describe the pitch angle control strategy of the wind turbine to optimize the power output by adjusting the pitch angle. Through the above formula, it is possible to find a balance between multiple objectives and find the optimal solution [17]. According to the optimization objective of WTG power generation, the fitness function is designed as a criterion for evaluating the advantages and disadvantages of the solution, and the expression of the function is shown as follows.

$$F = w_1 \times P + w_2 \times W \tag{4}$$

Where, F denotes the adaptation value; w_1, w_2 both denote the weighting coefficients. Through this functional expression, the advantages and disadvantages of the solution are evaluated, and the two objectives of power output and load are considered comprehensively. According to the actual operating conditions of the wind turbine, the weight coefficients can be adjusted to balance the relationship between the two objectives.

3.3 Multi-objective optimal control of power generation in all wind speed bands

Based on the above multi-objective power generation optimization algorithm design, on this basis, the multi-objective power generation optimization control is implemented for the whole wind speed section of the wind turbine. First, the control system structure of the wind turbine is analyzed, as shown in Figure 1.

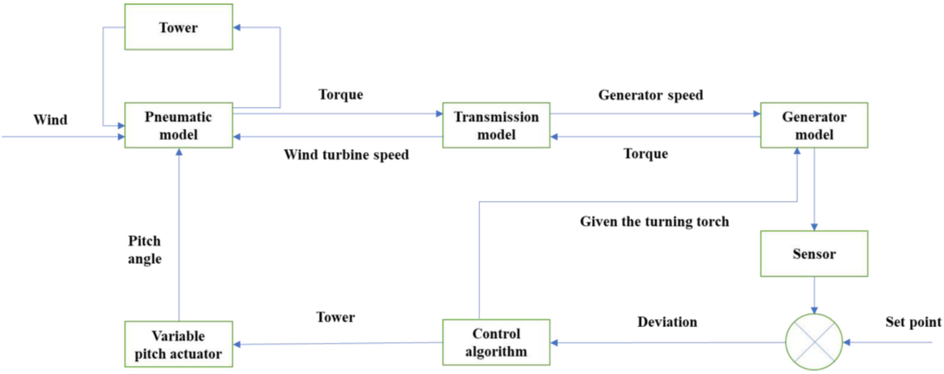

Figure 1. Structure of wind turbine control system

As shown in Figure 1, the main controller of the wind turbine is mainly responsible for the logic control of the power generation operation of the wind turbine. The pitch controller is responsible for adjusting the pitch angle of the WTG blades, so that the WTG can maintain the maximum wind energy capture efficiency in the low wind speed section. The torque controller is responsible for realizing the variable speed and constant frequency control of the WTG to achieve the maximum constant power output. After mastering the control system structure of WTGs, due to the power generation optimization control of WTGs is a complex process, in order to achieve the optimal power generation control objective, this paper firstly divides the full wind speed section of WTGs for the general situation, see Table 2.

Table 2. Classification of wind turbines into full wind speed bands

Serial number	wind speed segments	Wind speed threshold/(m/s)
V1	Low wind speed segments	V<5
V2	Low and medium wind speed bands	5≤V<12
V3	High wind speed segments	12≤V<20
V4	Ultra-high wind speed section	V>20

In Table 2, the thresholds for each wind speed band are exemplary and can be adjusted according to specific WTG models, geographic locations, and climatic conditions. Based on the above wind speed bands, the corresponding power generation optimization control strategies are designed as follows.

Low wind speed section (V1): In this wind speed section, WTGs are usually adjusted to capture more wind energy by adjusting the pitch angle. The pitch angle is the angle between the WT blades and the wind direction, and by changing this angle, WTs can better adapt to different wind conditions, so that they can maintain stable operation at low wind speeds. First, the pitch angle is adjusted to adapt to the low wind speed to increase the wind energy capture efficiency. Secondly, according to the wind speed and generator status, it is decided whether to start or stop the WTGs. Finally, based on this, the vibration and load of the WTGs are monitored to ensure safe operation. The expression of the control function for power generation optimization is as follows.

$$P_{\mathrm{v1}} = 0.5 \times \pi \times R \times V^2 \times C_{p(V)} \times \rho \tag{5}$$

Where P_{v} denotes the power output of WTG in low wind speed section, $C_{\mathrm{p(V)}}$ denotes the wind energy utilization coefficient, and ρ denotes the air density. This type of regulation enables the WTGs to maintain the optimal operating efficiency under changing wind speeds, thus maximizing the utilization of wind energy.

Low and medium wind speed section (V2): When the wind speed increases into the low and medium wind speed section, the WTGs increase the power output by increasing the rotational speed to adapt to the low and medium wind speed conditions. Load and power limitation is implemented to prevent overloading. Optimize generator control to improve energy conversion efficiency. The expression of the generator optimization control function is shown as follows.

$$P_{\mathrm{V2}} = 0.5 \times \pi \times R \times V^2 \times C_{p(N)} \times \rho \tag{6}$$

In the formula, P_{v2} represents the power output of WTG in low and medium wind speed section; $C_{\mathrm{p(N)}}$ represents the torque power coefficient of WTG.

High wind speed section (V3): When the wind speed enters the middle and high section, in order to ensure the safety and stability of the wind turbine and avoid the occurrence of overloading, this paper adopts a technology called maximum power point tracking, real-time monitoring of the operating status of the wind turbine, and make corresponding adjustments to ensure that it operates under the optimal blade tip speed ratio. The tip speed ratio is the ratio between the rotational speed of the blade and the wind speed, and this ratio directly affects the power output of the wind turbine. Through the maximum power point tracking technology, the wind turbine can automatically adjust the pitch angle and rotational speed according to the current wind speed and power output to ensure that it operates under the optimal blade tip speed ratio, so as to maximize the use of wind energy and prevent overloading. The optimized control function is expressed as follows.

$$P_{\mathrm{V3}} = 0.5 \times \pi \times R \times V^2 \times C_{p(\lambda)} \times \rho \tag{7}$$

Where, P_{V3} represents the maximum power output of the wind turbine in the high wind speed segment; $C_{p(\lambda)}$ represents the wind energy utilization coefficient under the optimal tip speed ratio. The application of this technology can significantly improve the operation efficiency and stability of wind turbines, and also provide an important guarantee for the reliability and safety of the entire wind power system.

Ultra-high wind speed section (V4): In the high-speed wind speed section, in order to ensure the safe operation of WTGs, it is necessary to limit the input power of WTGs, optimize the blade design and control, and reduce the impact of turbulence. On this basis, vibration and load monitoring should be strengthened to provide early warning and take countermeasures. The optimized control function expression is shown as follows.

$$P_{\mathrm{V4}} = 0.5 \times \pi \times R \times V^2 \times C_{p(\varphi)} \times \rho \tag{8}$$

Where, P_{v4} represents the power limit output of the wind turbine in the ultra-high wind speed segment; $C_{p(\psi)}$ represents the wind energy utilization coefficient under the restriction of tip speed ratio.

Through the above functional expression, the multi-objective power generation optimization control can be realized in all wind speed bands to improve the overall power generation efficiency of the wind turbine and reduce the load fluctuation, so as to obtain a better performance of the wind turbine.

3.4 Life dynamics prediction methods

In actual operation, due to the different maintenance cycles and maintenance methods of different components, the degradation process and life cycle of different components are different, so the wind impact and state evolution of components in different life cycles are also different. Under the complex uncertainty scenario, it is difficult to guarantee the accuracy of the remaining life prediction only by the component reliability model.

In order to improve the accuracy of the remaining life prediction of wind turbine components under the time-varying uncertainty scenario, the parameters in the remaining life prediction model are corrected and updated by utilizing the real-time monitoring data of the components, so as to reduce the prediction error while decreasing the prediction uncertainty, and then obtain the dynamic prediction value of the remaining life of the components. The steps of the dynamic prediction of the remaining life of components are as follows.

1) Correction and updating of wind impacts. Based on the actual wind shocks in different years and months, the initial wind forecast shocks are corrected, and the wind arrival rate χ' in the next time interval is dynamically updated by taking into account the seasonality of the wind shocks and the future forecast information.

2) Correct and update the component state probability distribution matrix. The preventive maintenance strategy of the component can improve the reliability of the component, so that the probability distribution of the state of the component can be regressed to the probability distribution at a moment before t. If there is maintenance activity at time t, the component state probability distribution matrix at time t is corrected to $\pi'(t)$ according to the different maintenance methods, as shown in equation (9).

$$\boldsymbol{\pi}'(t) = \boldsymbol{\pi}(t - T_{\varepsilon}^{w}) \tag{9}$$

where:$T^{w\varepsilon}$ is the fallback time due to maintenance method w.

3) Correct and update the state transfer matrix. The state transfer matrix is corrected according to the deviation value between the actual state evaluation probability of the current component and the initial prediction probability, so as to obtain the elements of the state transfer matrix P′ at the future moment, as shown in equation (10).

$$\begin{cases} p_{xx}' = p_{xx}^*(t) - (p_x(t) - p_x^*(t)) \\ p_{xl}' = p_{xl}^*(t) + \dfrac{p_{xl}^*(t)}{\sum_{l'=x+1}^{n_x-1} p_{xl'}^*(t)}(p_x(t) - p_x^*(t)) \end{cases} \tag{10}$$

where:$p_x(t)$, $p^{*x}(t)$ are the predicted probability and actual evaluation probability of state x in $\pi(t)$, respectively; $p^{*xx}(t)$, $p^{*xl}(t)$ are the probability that state x maintains the current state and the probability that it transfers to other states in the corrected initial state transfer matrix at moment t, respectively; p_{xx}', p($_{xl}'$ are the probability of state x maintaining the current state and the probability of transferring to other states in the modified future state transfer matrix at moment t, respectively.

4) Update the state assessment results based on fault type learning. There are many types of faults in WTG components, and the severity of faults varies under different fault types. In addition, in order to improve the accuracy and reasonableness of the condition assessment results under different fault types, a set of parameters ψ_s consisting of the influence of fault type s on the condition assessment is set, and the set of parameters ψ_s is updated continuously with the increase of the running time of the component and the accumulation of fault information. The influence of different fault types on condition assessment can be expressed by equation (11).

$$S'(t) = (1 + \psi_s(t))S(t) \tag{11}$$

where:S′(t) is the updated S(t).

5) Based on the current component state evaluation results, wind impact monitoring data and maintenance information, the component degradation failure rate λ^* t) and reliability R^* t) at time t are corrected. Based on χ', $\pi'(t)$, P′, and S′(t), the predicted values of component reliability R′(t) are obtained by updating the wind

impact quantity and the component state value in the future, and the dynamic predicted value of residual life F_t' is thus obtained, and its distribution function $F_t'(L)$ is as follows.

$$F_t'(L) = P(T_t \leqslant L) = P(t_s - t \leqslant L) = P\left(\frac{t_s \leqslant t+L}{t_s > t}\right) = 1 - P\left(\frac{t_s > t+L}{t_s > t}\right) = 1 - \frac{R'(t+L)}{R^*(t)} \quad (12)$$

Where:L is the remaining life value.

3.5 Experimental analysis

In order to verify the effectiveness of the proposed method, this paper selects a large wind farm as the test sample object. There are 20 wind turbines in this wind farm, distributed in different wind resources and terrain conditions. The models, parameters and operation data of each WTG are different, which are diversified and representative. During the test, the operation data of each wind speed band in the past one year were collected from the wind farm, and the average value was taken as the test sample, details are shown in Table 3.

Table 3. Sample data of wind turbine operation in full wind speed section

wind speed segments	Power generation/kW-h	Power fluctuation/%	Mechanical load/N
Low wind speed segments	1000	5	200
Low and medium wind speed bands	2500	8	400
High wind speed segments	3500	15	800
Ultra-high wind speed section	2000	20	1000

The wind turbine operation data in Table 3 covers the operation in different seasons, different wind speed bands and different weather conditions, which ensures the richness and authenticity of the data. Through the processing and analysis of these data, the features related to the control parameters can be extracted. On this basis, the multi-objective power generation optimization control method proposed in this paper is applied to carry out experimental tests.

4. results and discussion

In this test, the introduction of comparative analysis of the experimental method principle, the above-mentioned multi-objective power generation optimization control method proposed in this paper is set as a test group, the distributed DC grid-connected converter bus voltage stability analysis and motor efficiency optimization and control, the probability of large-scale wind power access to the power system of the small perturbation stability analysis and optimization of the proposed conventional control method proposed conventional control method are set as a control group, respectively. The proposed conventional control method is set as control group 1 and control group 2 respectively, comparing the optimization control effect of wind turbine power generation after the application of the three methods. The power smoothing factor of the wind turbine in the full wind speed section is chosen as the evaluation index for this test, and the index is used to measure the smoothness of the output power of the wind turbine, and the calculation formula is shown as follows.

$$\delta = (P_u - \overline{P})/(P_{max} - P_{\text{mant}}) \tag{13}$$

where P represents the current output power of the wind turbine.$\overline{P}$P $_{max}$ represents the average value of WTG output power in a period of time; P $_{max}$ represents the maximum value of WTG output power in a period of time; P $_{min}$ represents the minimum value of WTG output power in a period of time. The closer the smoothing factor is to 0, the smoother the output power of the WTG is, the better the optimization and control of multi-objective power generation is; the closer the smoothing factor is to 1, the bigger the fluctuation of the output power is, the worse the optimization and control of multi-objective power generation is. By calculating the smoothing factor, the operational status of WTGs can be evaluated. The comparison results of the power smoothing factor of WTGs in the whole wind speed section are shown in Fig. 2.

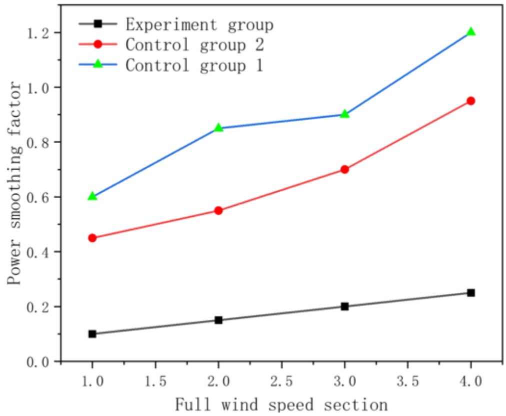

Figure 2. Comparison results of power smoothing factor

As can be seen from the comparison results in Fig. 2, after the application of the multi-objective power generation optimization control method proposed in this paper for all wind speed bands, the power smoothing factor of the generator set in each wind speed band is significantly lower than that of the control group, which indicates that the output power of the wind turbine of the experimental group fluctuates less and is more stable. This test comparison proves that the test group has obvious effect in reducing power fluctuation and improving the stability of wind farm.

5. Conclusion

This paper proposes a data-driven wind turbine performance optimization and life prediction method. As the main form of wind energy utilization, the power generation efficiency and stability of wind turbines directly affect the economic and social benefits of wind farms. Therefore, the study of multi-objective power generation optimization and control of wind turbine at all wind speeds has important theoretical significance and practical value. The research in this paper not only helps to improve the operation efficiency and stability of wind turbines, but also provides new ideas and methods for the economic and efficient operation of wind farms. The test results show that the method can significantly improve the stability of wind turbine power generation in the full wind speed band. Although the method proposed in this paper has achieved good results in the test, it still needs to be further verified and improved in the practical application.

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