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Life Evaluation and Optimization Technology of Wind Turbine Generator Based on Big Data

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Abstract Although the global wind energy industry has made considerable progress in recent years, the complex systems and harsh working conditions of wind turbines have led to frequent failures. Therefore, how to use the operating unit operation and maintenance data to conduct overall research on the status of wind turbines, wind farm evaluation, intelligent operation and maintenance technology promotion, and optimizing operation and maintenance strategies are important issues that need to be resolved for the sound development of wind turbines. This paper studies wind turbine life assessment and optimization technology, and understands the relevant knowledge and theory of wind turbines based on literature data, and then designs the life assessment of wind turbines based on big data, and uses examples for experimental verification. The effectiveness of the proposed predictive algorithm is derived from experimental results, taking into account the duration of catastrophic failures. If the bearing runs for 34 days, the actual remaining life of the bearing is 0.2 days, the remaining life predicted by LRM is 0.8 days, and the remaining life provided by ILRM is 0.31 days. Therefore, compared with LRM, the prediction accuracy of ILRM is significantly improved.

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1. Introduction

Today, the development of human economy and society is subject to the dual constraints of resource and environmental protection issues, with the emphasis being reflected in the increasingly serious problems of resource scarcity and environmental pollution [1-2]. At present, countries all over the world are actively developing renewable energy projects to replace traditional energy sources such as fossil fuels and alleviate the resulting environmental pollution and resource scarcity problems [3-4]. Among them, wind power projects have the advantages of cleanliness, pollution-free, and increasingly mature production technology, and can be developed and implemented on a large scale. This solution is to use wind energy reasonably and efficiently, which is a good substitute for the current human energy shortage problem and fossil fuels [5-6]. Nowadays, all countries in the world regard wind energy TV as the main way to produce clean electric energy, especially in China, the sustainable development of wind power has a certain economic background and a certain social background [7-8].

Regarding the research on using wind energy to generate electricity, some researchers use the standard variable-pitch external total load analysis model to obtain the total load carried by the variable-pitch bearing under different wind conditions. Then, based on the terahertz contact principle, the finite element method is used to establish Finite element analysis model. Finally, by using the standard finite element analysis model for error evaluation of fatigue life type, support strength, step synchronization and flatness, etc., the load distribution of the stepped bearing and the fatigue life of the stepped bearing can be obtained, the calculation formula and the fatigue of the installation surface Influencing value, it can also analyze in detail the influencing factors of the bearing duration [9]. In addition, R&D personnel also use GH blade fan characteristic analysis software to measure the load of the blade during operation, use dynamic analysis to calculate the voltage-time curve of the dangerous part of the blade root, use the rainfall counting method to synthesize the voltage spectrum, and use the glass fiber SN curve for calculation. Before calculating the life of wind turbine blades, the effect of load interaction on blade fatigue life was determined [10]. And some researchers calculated the precise fan blade load with flat strip theory, obtained the maximum blade voltage and equivalent voltage with the finite element method, discussed the SN curve law of blade material, and discovered the theoretical method based on blade fatigue life estimation. However, the article does not verify the load balance, nor does it indicate that the output voltage range is in the dangerous part of the blade, and it is difficult to guarantee the accuracy of the life prediction [11]. Some researchers have proposed a method to determine the four coordinate system of a wind turbine, analyzed the load status of the wind turbine in this coordinate system, and further explored how to increase the load of the components of the wind turbine. However, this document only focuses on the static load of wind turbines, and cannot perform simulation calculations on wind turbine blades under complex conditions [12]. In summary, the research on wind turbines is mainly in two aspects, one is the study of the fatigue life of the bearing, and the other is the study of the fatigue life of the wind blade, but both of these are based on the analysis of the fatigue strength of the finite element. There is no fatigue strength prediction based on operating data.

This paper conducts research on the life assessment and optimization of wind turbines based on big data, analyzes the basic composition of wind turbines and monitoring data of wind turbines on the basis of literature data, and then conducts the life assessment of wind turbines based on big data, and design and verify the design with examples.

2. Wind Turbines

2.1 Wind turbine structure

The most widely used type of wind turbine on the market is a large (usually megawatt) horizontal shaft connected to a wind turbine network. Its basic structure is mainly composed of the following eight parts [13].

(1) Windmill: It is composed of three parts: blade, hub and step system. Wind turbines are also important components of wind turbines because they are the direct components that convert wind energy into mechanical energy.

(2) Gearbox system: It is composed of three parts: main shaft, transmission gearbox, coupling, and mechanical braking system. The transmission device can transmit the rotor mechanical kinetic energy generated by the wind generator to the generator rotor, so that the wind generator rotates at the speed of the generator rotor.

(3) Generator: The electrical energy required by equipment that converts mechanical energy into electricity.

(4) Main engine and fuselage: The main engine is used to support the coupled transmission and generator, and at the same time transmit all the loads generated by the wind turbine and transmission system to the tower. The body cover is used to protect the components.

(5) Deflection control system equipment: When the deflection control system equipment is used to adjust the direction of the wind turbine against the wind, it is mainly composed of functional elements and mechanisms such as deflection bearings, drive motors, transmission mechanisms, and air brakes.

(6) Control and safety system: including step controller (divided into electric step and hydraulic step), converter, main controller, control unit safety chain, and various sensors. The management and safety control system mainly completes the management tasks from generator set signal monitoring, generator set starting to networking work and power generation to ensure the safe and reliable operation of the generator set.

(7) Tower and key components: The tower is the supporting component of the wind turbine, which mainly supports the weight of the entire engine and various dynamic loads generated during operation, and transmits these loads to the key components.

(8) Other parts: mainly including lightning protection system, etc.

2.2 Condition monitoring methods of wind turbines

As can be seen from the previous section, a wind turbine is a complex system composed of multiple components, and the failure of each component will affect the normal operation of other components, and even cause the entire unit to shut down. Therefore, monitoring the status of the key components of the wind turbine to detect early failures is of great significance to ensure the safe and reliable operation of the wind turbine. This paper briefly introduces the technology used to monitor the failure types and conditions of key components of wind turbines [14].

(1) Blade: The blade is exposed to harsh environments for a long time and bears complex alternating loads, and is prone to corrosion, cracking, deformation and other failures. The current condition monitoring technology is mainly based on the voltage and stress changes of the blade material under various forces to determine the blade fault status. Common state monitoring methods mainly include vibration measurement methods, transfer function and dynamic strain analysis methods, response comparison methods, and wave propagation analysis methods. At the same time, it can use the latest non-destructive testing methods to check the operating conditions, such as acoustic emission testing methods, infrared image testing methods, etc.

(2) Gear box: Under various working conditions and different load conditions, gear box failures are mainly divided into cone box failure and bearing type failure. Gear failures include tooth surface fatigue, adhesion and tooth fracture. The bearing type failures include fracture, shedding, perforation and damage. Vibration method is the most mature and commonly used error checking method in today's science and technology. By time-frequency analysis of

the incoming vibration information, the characteristic fault frequency can be regarded as the key index for predicting rolling bearing and gear errors, and more accurate fault inspection can be carried out, which greatly improves the accuracy of fault diagnosis. Time-frequency field analysis combines the dual information of time domain and frequency interval, and is suitable for processing unsteady vibration information. The most common analysis methods include EMD, particle analysis, and short-time Fourier transform. In addition, the temperature measurement method is a state recognition monitoring method based on the temperature changes of fan components. Because of its convenient measurement and operation, it is widely used in the state monitoring of gearboxes, generators and other components.

(3) Generator: Under high AC working conditions and a more complex electrical environment, the generator is prone to faults such as generator overheating, excessive vibration, short circuit, insulation rupture, etc, and monitoring can be taken according to pressure, current, and voltage. In addition, the linear and non-linear generator model generation technology can check the rotor eccentricity and other faults of the engine based on the characteristic fault analysis.

(4) Pitch system: The pitch system can use vibration monitoring to collect voltage and current signals to monitor the state of the pitch system.

(5) Electrical system: Common electrical system faults include short-circuit faults, over-current faults, and over-voltage faults. The status of each component of the electrical system can be monitored by voltage, current, temperature, etc.

(6) Bypass system: The main types of errors in the deflection system are gear wear, engine failure and improper installation. The available condition monitoring methods are approximate vibration monitoring, current monitoring and voltage monitoring.

3. Life Assessment and Optimization of Wind Turbine Generator Sets Based on Big Data

3.1 Monitoring signal analysis

During the operation of wind turbines, various types of signals are monitored, including many signals related to bearings [15]. The data in this article is based on the operation data of dual-power wind turbines monitored by wind farms in this city for one year. Table 1 shows the monitoring targets and sensor information. Table 2 shows the collected signals related to wind turbine bearings.

Table 1. Monitoring target and sensor information

Type	Information
Motor model	Double-fed asynchronous generator (FYKS03)
Bearing Type	Deep groove ball bearing (SKF6322)
sensor type	Ordinary vibration acceleration sensor
Sampling frequency	2560Hz

Table 2. Signals related to wind turbine bearings

Category	Signal
Wind turbine bearing conditions Generator bearing status	Generator speed
	Generator output power
category	Generator bearing temperature
	Bearing vibration acceleration

In Table 2, the monitoring speed of the generator, the output power of the generator and the temperature of the generator bearing are the signals that reflect the operating status of the wind turbine bearing. The bearing acceleration signal of the bearing is the characteristic signal received by monitoring, which can reflect the deterioration of the bearing. It is greatly affected by operating conditions. Therefore, in order to receive vibration signals under the same operating conditions, it is necessary to divide the operating conditions of the wind turbine bearing. Vibration acceleration signals under the same working conditions are affected by internal and external interference. A large number of interference signals will be generated in the vibration acceleration signals to be monitored. Therefore, noise removal is required for the vibration signals to be monitored. Under the same operating conditions, it must have characteristics ground output the vibration signal after the noise is turned off to obtain the characteristic quantity that may reflect the change trend of the bearing life of the wind turbine.

3.2 Particle packet decomposition

This task briefly introduces the theory of ripple packet and demonstrates the process of ripple. Through the analysis of the characteristic frequency of the bearing defect, the corrugated package is used to realize the attenuation of the vibration signal to be monitored.

Turning off the vibration signal is to filter the noise from the observation signal infected by the noise. The noise may be caused by the malfunction of the signal detector and the monitor itself, or it may be caused by other interference. Noise is characterized by randomness, such as white noise and colored noise. Noise reduction is to minimize noise interference.

Under the influence of various factors, the large number of vibration signals that can be received by the running wind turbine bearing monitoring must contain certain noise. The existence of these noises inevitably reduces the reliability of the research results. In order to improve the reliability of the survey results, it is necessary to deactivate the vibration signal before extracting the characteristics of the vibration signal.

(1) Particle packet decomposition theory

The method of bulk packet noise reduction is to maintain a high time-frequency resolution while improving the signal-to-noise ratio. At the same time, according to the characteristics of the analyzed signal, the corresponding frequency band is adapted to match the signal spectrum. Assuming that the particle function y(t) and the scaling function φ(t) are given, let u(t)=φ(t), $u_1(t)$=y(t).

$$u_{2n}(t) = \sqrt{2}\sum_{k\in Z} h(k)u_n(2t-k) \quad (1)$$

$$u_{2n-1}(t) = \sqrt{2}\sum_{k\in Z} h(k)u_n(2t-k) \quad (2)$$

In the above equation, h (k) and g (k) are quadrature filters. One of the characteristics of wavelet packets is that they can completely decompose high and low frequency signals.

The particle packet decomposition method (as shown in Figure 1) divides each subband into two, and the one used for classification covers all frequency bands. In this way, the loss of effective signal information is reduced. Moreover, the wavelet packet can also automatically select the frequency band required by its information during the analysis process, which greatly improves the time-frequency analysis.

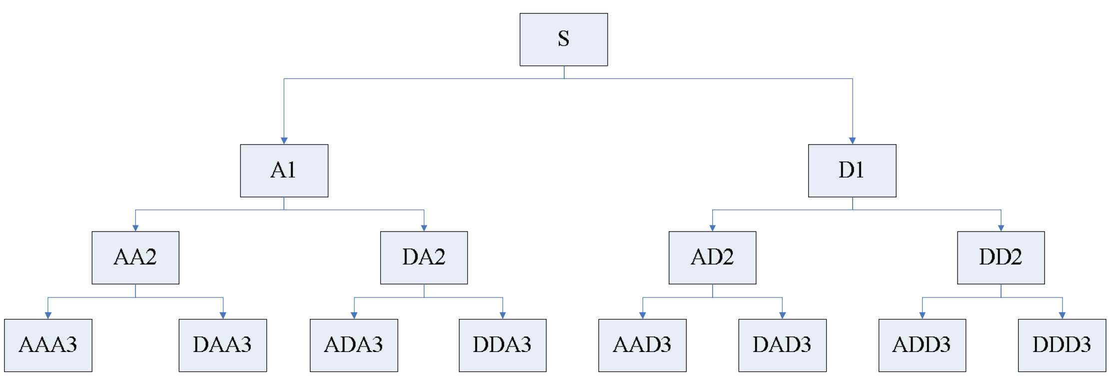

Figure 1. Particle packet decomposition

Particle packet decomposition applies g(k) and h(k) to the detail and approximation signals at the same time, and further decomposes to gradually improve the detail and approximation signals. Figure 2 shows the basic steps of using particle packet decomposition.

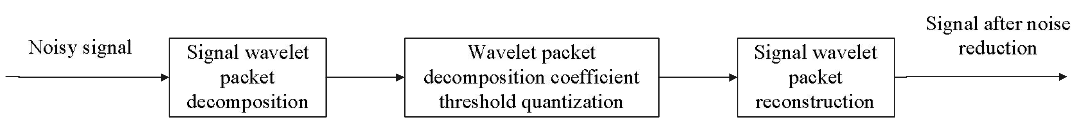

Figure 2. The basic steps of particle packet decomposition

3.3 Feature extraction

After the signal is decomposed, the decomposition result contains more error information, and then the features are extracted to obtain the input data of the classification model.

(1) Sensitive IMF selection

A sensitive IMF is an IMF that contains a large amount of error information, and its sensitivity is determined based on its curvature and related indexes. Kurtosis is a dimensionless function in the time domain. Its value is only related to the impact of the bearing failure when the signal is collected, and has nothing to do with the size of the bearing, the type of bearing tested and the load carried by the bearing, and it is more suitable for surface damage.

(2) Time-frequency domain output characteristics

The time-domain characteristics of a signal can be roughly divided into two-dimensional characteristic parameters and non-dimensional characteristic parameters according to various physical characteristics. General dimensional parameters such as peak value and average value will vary with operating conditions such as load and speed, but the dimensionless characteristic parameters are relatively constant. Frequency domain characteristics include average frequency, center frequency, root mean square frequency and standard signal frequency deviation. The time-domain and frequency-domain attribute configuration for generating attribute vectors can take into account the stability and accuracy of error diagnosis. If the time sequence of the signal is (x(1),...x(N)), the Fourier change of the signal gets the frequency sequence (x[(1)],...x[(N)]), and the output signal time domain is 7 characteristics in the frequency domain.

3.4 Life prediction algorithm

In this paper, PCA and ILRM's four-point spherical bearing residual life prediction method is adopted. By selecting simulation partners and revising the model itself, the accuracy of predicting the residual life of the model is greatly enhanced. The specific process is as follows.

(1) Selection of functional parameters: Extract the time domain, frequency domain, and time-frequency domain attributes of the entire life cycle from the bearing vibration data, filter the effective attribute parameters, and form a vector attribute set.

(2) Construct a set of relatively large dimensions. Select the characteristic quantity of a bearing in a normal period and take the average value, and divide the total life data of the characteristic by the average value to obtain the relevant characteristic. Obtain the relative characteristics of each active characteristic parameter used to construct the mixed sector.

(3) Principal component analysis: Principal component analysis is to analyze a group of relatively large characteristics of the mixture, and select the principal components with a cumulative contribution rate of more than 95%.

(4) Model structure: Calculate model parameters based on the selected effective key elements and create ILRM.

(5) Life prediction: Use the test group bearing data and refer to the program in the training group method to select model variables, and evaluate the safety of the roller bearing by calibrating the ILRM, so as to make an estimate of the remaining life.

4. Simulation Experiment

4.1 Life prediction

According to the above-mentioned ILRM and LRM life prediction methods, the remaining life of the four-rolling bearing of the wind turbine is calculated, and the results are shown in Table 3:

Table 3. Life expectancy of ILRM and LRM

Bearing status	Normal period	Early failure	Recovery period	Mid-term failure	Severe failure period
Time (days)	30.4	32.5	33.2	33.9	34.1
Remaining life	3.98	1.89	1.19	0.49	0.29
LRM	8.36	3.52	2.92	1.23	0.85
Prediction error	4.38	1.64	1.77	0.74	0.56
ILRM	6.39	3.22	2.01	1.03	0.32
Prediction error	2.41	1.34	0.83	0.19	0.04

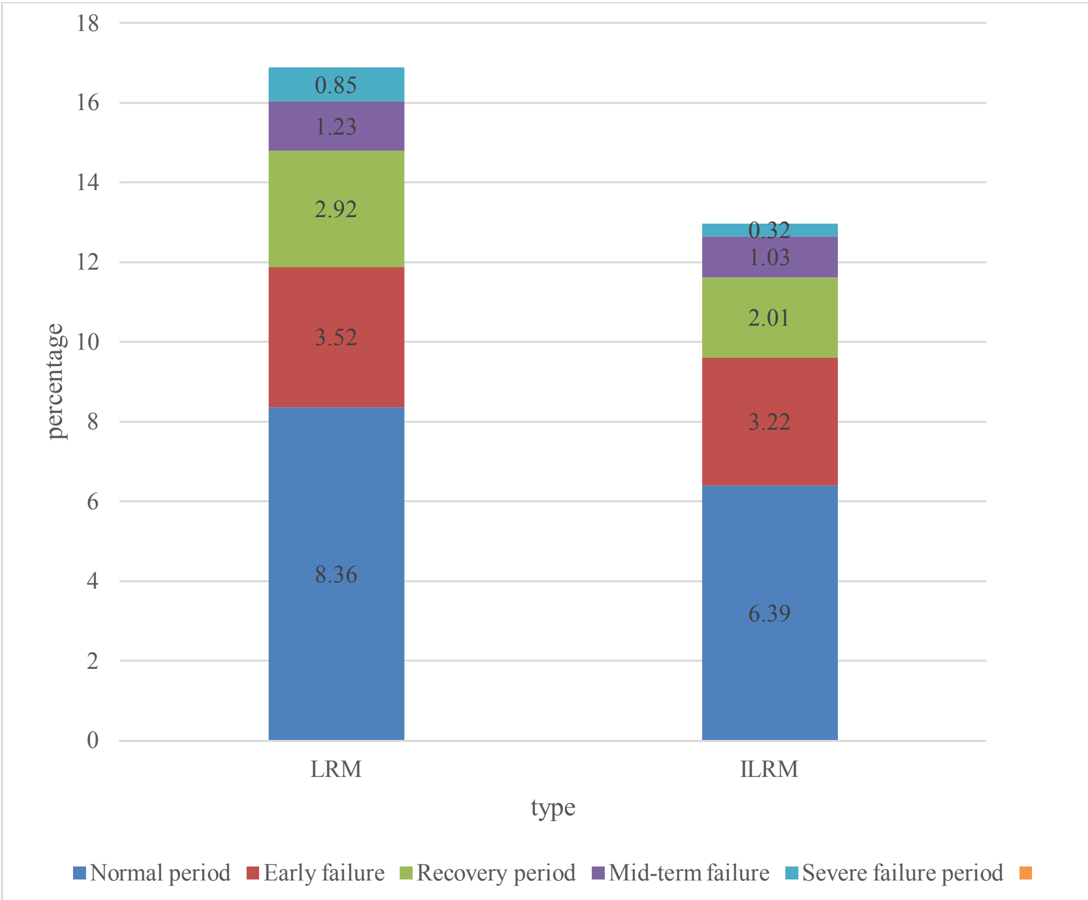

Figure 3. Life expectancy of ILRM and LRM

It can be obtained from the above Figure 3 that the accuracy of the residual life of ILRM is much higher than that of LRM. Therefore, the duration of catastrophic failure must be considered. If the bearing industry operates on the 34th day, the actual remaining life of the bearing type is 0.2 days, while the actual remaining life predicted by LRM is 0.8 days, and the actual remaining life provided by ILRM is 0.31 days. Therefore, compared with LRM, the forecast accuracy of ILRM has been significantly improved.

4.2 Optimal design of structural parameters

In practice, bearings need to have a longer service life, higher load-carrying capacity and lower rotational torque. In order to meet this requirement, the objective function of the optimized design model is to select the dynamic load rating, static load rating and friction moment of the bearing, namely:

$$F(X) = \min_{X \subset D} F(C, C_o.M) \quad (3)$$

In the expression, D is the possible area of the objective function.

In this paper, the linear weighting method is used to determine the objective function of the multi-objective optimization problem. Bearing static load rating and dynamic bearing rating are the biggest issues, and bearing friction torque is the smallest issue. The objective function is:

$$F(X) = -\omega_1 \mathrm{C} - \omega_2 \mathrm{C}_o + \omega_3 M \quad (4)$$

In the formula: ω_1, ω_2, ω_3 --weight, which depends on the impact of the objective function on the bearing performance.

4.3 Comparison of mechanical properties of bearings after optimization

View the simplified finite element model of the 4-point ball bearing with bolted connection with the optimized structural parameters, and perform the ultimate load experimental analysis on it. Table 4 shows the experimental results of applying ultimate load to the 4-point contact bearing.

Table 4. 4 Experimental results of ultimate load of point contact bearing

	After optimizing the structure	Before optimizing the structure
Maximum load of raceway 1	83803.3	59514.8
Maximum load of raceway 2	86573.6	61482.2

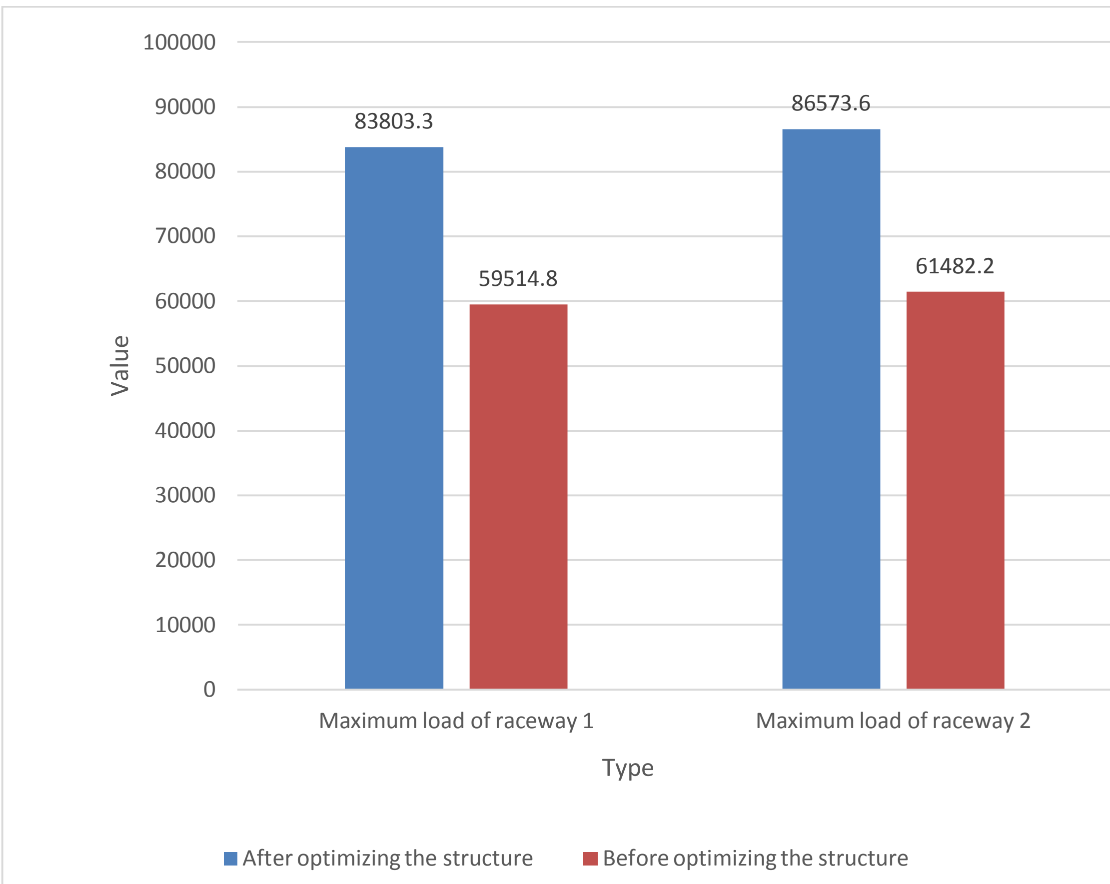

Figure 4. 4 Experimental results of ultimate load of point contact bearing

It can be seen from Figure 4 that the optimized structure has a maximum load of 83803.3N for the No. 1 raceway and a maximum load of 5,9514.8N for the No. 2 raceway. After optimization, the maximum load of the No. 1 raceway is 85673.6N, and the maximum load of the No. 2 raceway is 61482.2N. After structural optimization, the maximum contact load on Highway 1 and Highway 2 was reduced. No. 1 raceway is reduced by 2772.4N, the maximum load of No. 2 raceway is reduced by 1967.5N, and the maximum load is reduced by 3.20%.

5. Conclusions

This paper studies wind turbine life assessment and optimization technology, analyzes the relevant theoretical knowledge of wind turbines on the basis of literature data, and then designs the life prediction of wind turbines based on big data, and carries out an example of the model. The calculation results show that the remaining life accuracy of ILRM is much higher than that of LRM, and then the bearing structure parameters are optimized. After the optimized structure, the maximum contact load of raceway 1 and raceway 2 is reduced.

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