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RESEARCH ON WTG POWER PERFORMANCE MONITORING METHODS OF REGIONAL WIND POWER GROUP

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Abstract- With growth of the wind power scale and the increasing of urgent requirement on operating life extension of units followed with which, how to monitor regional wind power group automatically and find recession performance of WTG power so as to take measures timely to restore the health condition and reduce power losses has become an important problem to be solved by wind farm operators. Horizontal and longitudinal performance comparison methods of the power characteristics for the same area and model units are proposed in this paper. Different real-time monitoring and analysis methods are used. The core technology of which is using wind speed partitioning technology and Wavelet analysis. Longitudinal power performance monitoring comparison method of single-unit is used as a further preferred aspect scheme of information fusion. Research results are verified by Matlab simulation platform. The study results integrated with the developed centralized monitoring system software, can improve the efficiency of wind farm operation and monitoring in large degree, further ensure the profitability production for wind farm plants.

Index terms: Regional wind power group, Bin method, Wavelet analysis, Horizontal and longitudinal comparison, Power performance monitor.

I. INTRODUCTION

With energy and environmental issues being concerned， wind energy has been developing rapidly as a clean and renewable energy in many countries. China has also focused on the energy strategy development of wind energy [1]. Due to the fact that wind fluctuations lead to instability of wind power output, more requirements are put forward to the grid control technology. Once a specific external environment is given, wind turbine power generation will depend on its power characteristics and wind energy utilization coefficient [2]. Currently, kinds of large-scale wind turbines in the wind farm are divided into three standard levels and a non-standard special level according to the relevant criterion [3], so as to choose the proper to match specific wind condition belong to different wind farms. Due to larger inconsistency between the actual wind farm conditions and local environmental conditions, besides the limited classification of wind turbines, the difference may be existed objectively between the actual operation conditions and design conditions for the unit. On the other hand, changes on factors such as structural parameters and working modes with field operation will also have impacts on the performances, resulting in actual operating characteristics different from that of original design of wind turbines, having an effect on the actual power generation [4].

Now, the size of the wind power development in China is still growing with the installation capacity increasing in many companies, and the same with the number of units. The growth of wind generation systems adds the proportion of the grid gradually, yet high penetration becomes a prominent issue, resulting in many types of faults [5]. In order to ensure generation systems run in reliable and secure. On-line diagnostic techniques in the maintenance schemes can be useful. Currently, some scholars have carried out some researches on fault diagnosis within the wind power system, and made some achievements. Literature [6] mentioned that by means of observation on LVRT fault happened at Texas area for a year, the performance characteristics of the fault was given by analysis. Stator voltage and current monitoring were used to diagnose faults in wind turbines [7]. Successively, more about fault diagnosis of wind generator were appeared in literature, Literature [8] presented that Recursive Maximum Likelihood Estimator was used to track the time-varying fault characteristics based on the generator stator current fault detection techniques and relevant decision support solutions and standards were proposed. Followed by which, some researchers made evaluations to those existed fault prognostic methods

[9]. These diagnose methods on faults are depended on field testing data. That is to say, sensors and detection equipment are essential.

Field test data can not only be used on fault analysis and diagnosis, can also be used to compare with performances for different wind turbines. In literature[10],by comparing the power quality with two wind farms which are equipped separately with FSIG+PMSG and DFIG, some conclusions about power quality, power characteristic, reactive power compensation and LVRT capability are given. In literature [11], the operation characteristics comparison between doubly-fed induction generator (DFIG) and direct-drive permanent magnet synchronous generator (PMSG) is illustrated by means of simulation. A conclusion is drawn that the voltage stability and frequency stability of DFIG wind farm are better than that of PSMG wind farm when power system faults happen.

On the other hand, we all know that when the wind power units are set in service for a period, operating performance will also be in a recession. More ever, many other uncertain factors also may result in running performance degradation. It is urgent for the wind power businesses to study and design a strategy to deal with the problem as fast as possible. To save costs and optimize configuration on spare parts, it is desirable to predict maintenance requirements as adequate as possible for the wind power system, so it is necessary to find unhealthy signs at an early stage to prevent the following breakdowns and ensure the continuity of power production. By obtaining the field monitoring data, the performance of the entire system can be evaluated.

Overall, the key issue is how to monitor the units dynamically to find those whose operating performance are decreased and give analysis, to take corrective measures timely so as to restore the operating performance of the unit, and improve the power output of wind farms, this is a significant topic and worthy of studying.

At the same time, scales of wind farms distribution are various in the world, the wind turbines quantity of units put into production ranges from dozens to hundreds, up to thousands within an area. So, it is unrealistic to acquire operating performance of wind turbines by manual means for an enterprise to accomplish the task of real-time monitoring. The developed monitoring system software can just cater for the function [12]. In recent years, kinds of message transmission equipment in smart were developed in order to facilitate centralized management of the dispersed wind farms on remote [13], centralized monitoring is established in succession by some plants to identify the performance and health of the units. In literature [14], aimed at the problems such as the production information collection, data consistency, data sharing, etc., monitoring and control approach with hierarchical optimization scheme are proposed on wind farm systems. The monitoring system used is capable of storing a huge amount of data and doing processing, helping engineers to do analysis efficiently and draw conclusions [15].

In view of the above analysis, considering that power characteristics of wind turbines can response to the quality of operating performance in large degree, the application of centralized monitoring system is proposed in automatic real-time monitoring of power characteristics of wind turbine. Real-time alarm is given out once the performance of one unit is decline, reminding maintenance personnel taking measures to detect and restore the performance of the unit promptly, making sure that unit run on a healthy state and enhance the power output of wind farms.

II. POWER MONITORING AND HORIZONTAL COMPARISON

2.1 Overview of horizontal contrast and monitoring

The horizontal comparison is by monitoring over a certain period, putting operating parameters of a single unit on the same class units to identify those units with larger deviation, then to confirm the bias on the operating performance. Power characteristic curve is the foundation of the design of wind turbines, but also an important indicator on the assessment of the performance and the ability of generating units[16]. Therefore, horizontal comparison with the main operating parameters is equal to compare the power characteristic curves, including other auxiliary operating parameters (temperature, vibration, etc.). A comprehensive evaluation is shown to determine whether an unit is operating in a normal performance. For example, under the same wind conditions, power generated by the same type units may be in difference, some units may be below in a certain level. Once they are continue to fall over a certain magnitude, it is necessary to consider the abnormal of operating performance of these units. At the same time, under different wind conditions, if power output of the generation unit is kept down than the other units for a long time, it can also be sure that the performance of the unit is most likely in problem, and it must be checked. Due to that the horizontal comparison is comparing with each other, so the parameter values used do not need to be absolutely accurate, thus strength the feasibility and convenience of this method. For example, if there are requirements to compare the power characteristic curves, operating data may be used as a basis for comparison through real-time acquisition system. To the same area and the same type units, the methods of data acquisition and operating conditions are the same, so all the data are comparable.

2.2 Data acquisition and pre-processing

According to the IEC standard, the frequency of data collection should be above 0.5Hz, the total time for data preprocessing is from 30S to 10min. Here, wind farm data collection from all models is accomplished by self-developed centralized monitoring system. The collection frequency is 1Hz. According to IEC standards, the total time for the data pre-treatment is 10min. With data preprocessing being carried out, the main operating parameters (unit power, cabin wind speed, etc.) at every 10min are used to do average calculation and storage. Acquisition and pre-processing of data are stored in 1s-real time database and every 10min average database.

2.3 Data filtering

Data used in filtering are retrieved from the continuous measurement with 1s sampling period, filtering method is not the focus of this paper. Data groups on the case of the following should be removed from the database:

1) Wind turbine does not work;

2) Wind turbine in startup or shutdown;

3) Other special conditions.

In order to remove above data accurately from the experimental data, by means of analyzing the actual wind farm operating data, we can find that when wind turbines are in the case of rest or at startup or shutdown, they all have the same different characteristics from normal operating data, that is, wind power output is approximately zero and the pitch angle is about 90 degrees. According to the two characteristics of the data, they can be found out to filter.

By analyzing on actual data, we have found that when the external environment is close to the cut-in wind speed, the unit will always be in process of start or stop, and the power output is on relatively large deviation. In order to analyze performance of the unit more accurately, once the data collected is close to the cut-in wind speed, it is filtered. It is taken into account only the conditions of normal operating state, and monitoring the changes on performance.

2.4 Bin method wind partition

Although same model units installed on the same area, wind speeds on different cabin crew may be different at particular period of time (E.g. 10min). According to IEC61400-12 standard, wind data collected on-site should be cover at least the range from cut-in speed (-1 m / s) to a certain percentage of the rated power wind (1.5 ×85%m / s). To give out a simple, quick and real-time comparison on the power characteristics under certain same wind speed, referring to Bin method, wind section collected here are selected from 2m / s to 20m / s, the wind speed range is divided into several intervals (bin) by 0.5m / s space, the center value of each bin is 0.5 m / s multiply by an integer. Of course, each bin will contain a lot of wind scatters [17], shown in Figure 1.

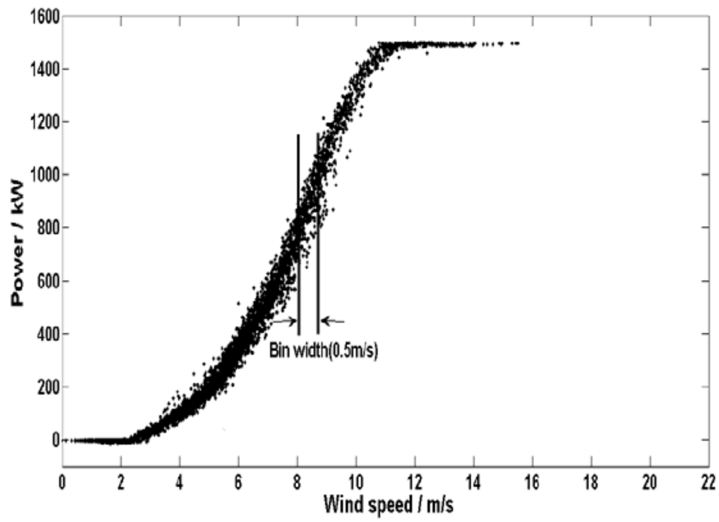

Figure 1 Bins statistics method schematic diagram

2.5 Data calculation

The following formula can be used to calculate average wind speed and average power value of each bin （V_i , P_i ） separately:

$$V_i = \frac{1}{n_i}\sum_{j=1}^{n_i} V_{ij} \quad (1)$$

$$P_i = \frac{1}{n_i}\sum_{j=1}^{n_i} P_{ij} \quad (2)$$

Where, n_i is the number of date pairs falling in i th bin, V_i is as average wind speed of the bin, P_i is as average power, V_{ij} is as the j th 10min average speed in the i th bin, P_{ij} is as the j th 10min average power in the i th bin. For example, when i =1, the corresponding wind speed interval is [2,2.5],if there are 20 units whose 10min average speeds are all situated in the bin, then n_i =20, V_i yet is arithmetic mean of the average wind speed of the 20 units. P_i is the 10min arithmetic mean of the average wind power of the 20 units.

The following formula can be used to calculate separately the 10min average power relative deviation σ_{ij} for each unit within each bin unit:

$$\sigma_{ij} = \frac{|P_{ij} - P_i|}{P_i} \times 100\% \qquad (3)$$

Where P_{ij} is the j th 10min average power in the i th bin. P_i is average power of the bin, relative standard deviation value can be determined empirically.

The expression (4) can be used to obtain factor α on behalf of bins proportion of abnormal performance to the total number.

$$\alpha = \frac{n_{bin}}{N_{bin}} \times 100\% \qquad (4)$$

Where n_{bin} is interval number appeared on abnormal performance, N_{bin} is total number of bin intervals, $N_{bin} = 36$, scale factor α can be determined as a thumb.

2.6 Power characteristics horizontal contrast

1) According to the above analysis, when 10min average power of certain unit in a certain bin is below the average of all units in a certain extent, it is need to consider the abnormal characteristics of the unit. The output of the unit is identified lower by judgment method as follows:

When $\sigma_{ij} > \sigma$ and $P_{ij} < P_i$, it is showed that wind power output is low, the cumulative number is added by 1.for the j th unit within the i th bin.

The cumulative number can be set artificially, once it is exceed the set value, it is considered that performance of the unit is abnormal on that bin and must remind electrical personal to pay close attention to the health of the unit by monitoring system.

By monitoring, the statistical number of bin intervals where performance appears abnormal is given out. Once the number exceeds the total intervals a certain proportion α, power characteristic of this unit is thought abnormal. At the same time, combined with other abnormal signal, such as temperature, vibration, etc., the voice alarm system gives alert to electrical maintenance personnel to check. For example, on the case caused by vertical wind, the wind turbine itself or transmission efficiency, etc..

2) When a 10min average power of certain unit is higher than the average within the bin of all units by a certain extent, the unit is regarded at abnormal characteristics. The power output of the

unit is confirmed deviated from the normal value higher. Correspond judgment condition is as follows.

When $\sigma_{ij} > \sigma$ and $P_{ij} > P_i$, it is showed that wind power output is higher, the statistical number is added by 1 to the j th unit in the i th bin.

The cumulative number can be set artificially, when it exceeds the set value, then it is considered that performance of the unit is abnormal in the bin and electrical personal must be reminded by the monitoring system to pay close attention to the health of this unit.

At the same time, combined with other critical monitor data, such as temperature, vibration, etc., electrical maintenance personnel are alerted to check by the voice alarm in time, for example, whether or not the measured anemometer is out of problem.

III. LONGITUDINAL COMPARISION ON SINGLE UNIT POWER.MONITORING FEATURES

3.1 Overview of monitoring longitudinal comparative

Comparison on vertical power characteristic monitoring is mainly with the curves of a same unit over the past two time periods to find unfavorable trends as early as possible so as to take appropriate measures to restore the health of the unit. Of course, in addition to the power characteristics, the change of other major operating parameters is also an adjunct on longitudinal comparative analysis.

When the unit is put in commissioning after installation, its initial power curve can be obtained based on actual operating data collecting. After a certain period (E.g. one month), the normal operational power curve is generated automatically by monitoring software. If the two curves can be analyzed in time, yet, the trends of wind turbine power characteristics can be monitored regularly.

3.2 Bin methods used in initial power curve

1) The initial power curve calculated

After the unit is installed and put into operation, further run a period of time (usually a year), with reference to the aforementioned bin method, its own cabin crew wind speed can be used on correcting wind power according to IEC standards. Equation (1) and (2) are used to calculate the average wind speed and average power within per bin.

2) Data calculations to normal power curve

During normal operation, similar to the aforementioned methods, when running for some time (usually a month) after installation, bin date are acquired and the average wind speed and average power within per bin are calculated.

3) The relative deviation of the average power

By employing monitoring system software, period (usually one month) of date output is set manually, the relative deviation of average power within each bin between initial power curves and the normal case is calculated automatically for each turbine according to the formula (3).

3.3 Wavelet analysis used in initial power curve

The grid wind turbines often run under changing conditions as wind speed and direction, whose speed-power curve are different from specific operating conditions provided by technical manuals. It is important to get true wind speed-power curve so as to study interaction between wind farm and grid [18]. In fact, the wind turbines are installed originally in a particular environment, their initial power characteristic curves can be formed at that time. Once they are put into operation, due to the impact from a particular environment, the curve will be different from that supplied by manufacturers. As a stand-alone longitudinal comparison with power monitoring, it is more practical on guidance than theoretical power curve.

Generally, due to some factors, such as error of bins division, the variance of power signal and noise, method of bin partitions that used in the average power calculating can’t represent the unit power characteristic curve accurately. To draw the initial power characteristic curve accurately, wavelet analysis is considered on signal analysis for that it can be processed not only in time domain but frequency domain [19]. It can distinguish the mutated ingredient of the signal and noise better, preventing some "interference point" from unit power characteristics.

To be able to calculate group power characteristic curve quickly and easily, a fixed threshold approach is used due to that signal energy is concentrated on some limited coefficients in the wavelet domain and where the energy of noise is distributed, which is shown in Figure 2.

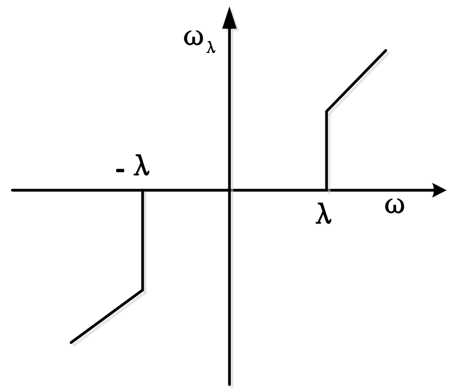

Figure 2 Hard Threshold Function

When wavelet decomposition is done, wavelet transform coefficient signal is greater than the wavelet coefficients of noise. By setting a threshold value $w_{j,k}$, if $w_{j,k}$ is less than a certain threshold, then the signal is rounded down, if greater than this threshold, then remained unchanged. The coefficient is picked out as formula (5):

$$f(x) = \begin{cases} w_{j,k}, & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases} \quad (5)$$

Here λ is the threshold value.

3.4 Data acquisition and processing

Data collected by the monitoring system are filtered by the aforementioned methods. Due to the tasks of comparing and analyzing on power characteristic curves or monitoring overall trends are all done to the same unit, the operating data acquired are ignoring the effects of wind direction on the power characteristics, yet not considering amending velocity. But for the same wind speed, due to other factors such as air temperature, humidity and etc., the air density can be different on same unit from time to time, so powers generated are vary greatly with environment. According to the IEC standards, when local air density deviation from the standard air density exceeds ± 0.05, the power should be amended. The output power of wind turbine is proportional to the air density. Under standard conditions, air density $\rho_0 = 1.225\, kg/m^3$, temperature $T_0 = 288.15K$, pressure $P_0 = 101.33kpa$, air density is calculated as follows:

$$\rho = 1.293 \times \frac{273}{273+t} \times \frac{p - 0.0378\varphi \cdot p_b}{0.1013} \quad (6)$$

Wherein: ρ ——air density; kg/m^3 ;

p ——Full wet air pressure, Mpa ;

p_b ——The partial pressure of saturated water vapor air at t ; Mpa ;

φ ——Relative humidity of the air, %.

According to the relationship that power output is proportional to the air density, it can be converted into standard conditions by the calculation formulation (6).

$$P_0 = \frac{\rho_0}{\rho} P \qquad (7)$$

3.5 Wavelet de-noising data calculation

1) The initial power curve calculated

When the unit is installed, put into operation and run a period of time (usually a year), its own cabin crew wind speed can be used to correct wind power. Wavelet analysis is used to draw the initial power curve of the unit.

Firstly, hard-threshold function is used on power signal de-noising. The sym4 wavelet is selected in the original signal decomposition [20], the decomposition level is 5. Results are shown in Figure 3 and Figure 4. Figure 3 is shown with power point signal noises, and Figure 4 is a signal after wavelet de-noising. By comparing the two figures, it can be found that using wavelet de-noising has a good effect, the smoothness of the resulting waveform is better, reflecting the initial power characteristic curve of the unit better. But in a few local singular points, where Gibbs shock is produced, yet accompanied by waveform distortion, so not smooth enough after de-noising.

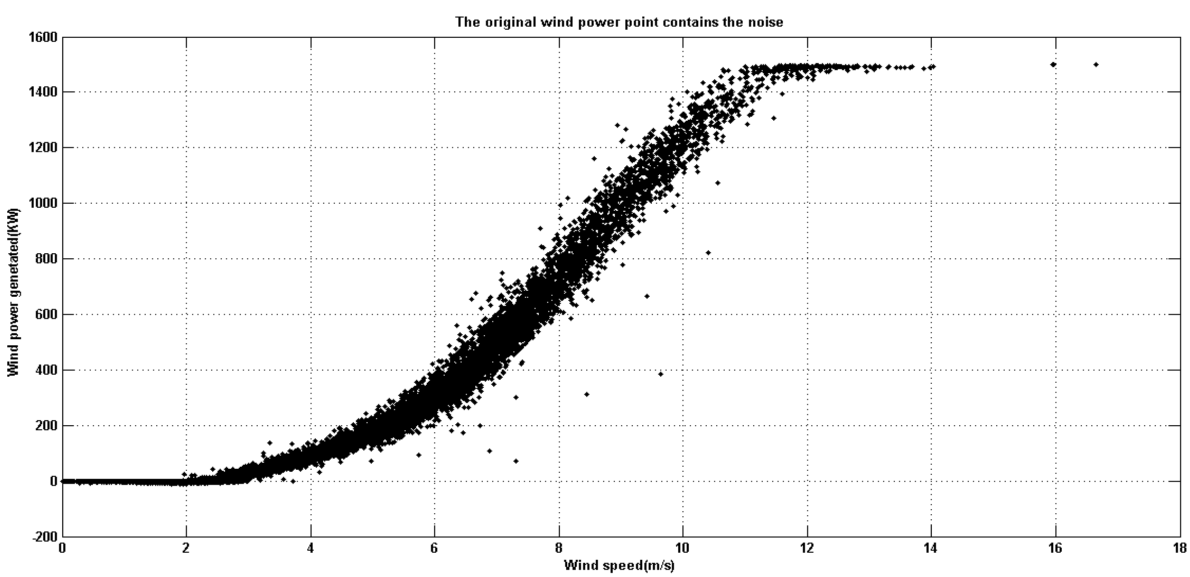

Figure 3 Original wind power points containing noise

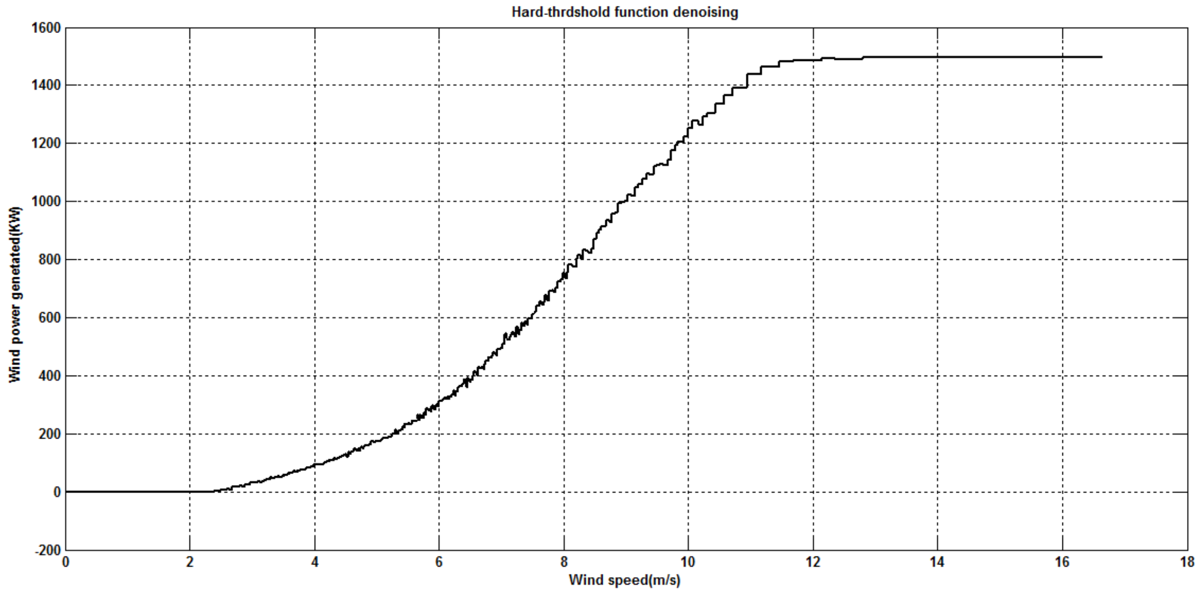

Figure 4 Hard-threshold function denoising

In order to restore the power curve of the unit accurately, sine curve is used to fit the wavelet data. It is shown in Figure 5. As can be seen from the figure, the shape becomes more smooth, local shock phenomenon does not exist.

2) Data calculations to normal power curve

During normal operation, similar to the aforementioned methods, when running for some time (usually a month) after installation, nacelle wind speed and corrected power generating are employed to obtain operating power curve of the unit.

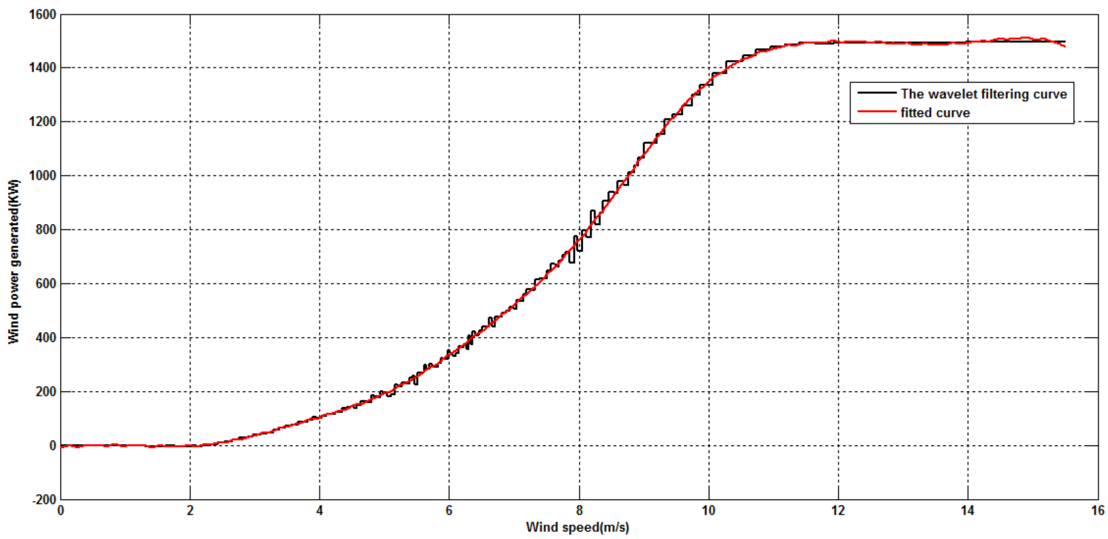

Figure 5 Graph of sine curve fitting initial power

3) The relative deviation of the power curve

To measure the degree of deviation of the normal power curve from the initial power curve, the correlation coefficient is introduced. The correlation coefficient is a statistical indicator used to reflect the degree of correlation between variables, which is calculated as equation (8).

$$r = \frac{N\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{N\sum x_i^2 - (\sum x_i)^2}\sqrt{N\sum y_i^2 - (\sum y_i)^2}} \quad (8)$$

In Formula 8， the correlation coefficient r shows correlation between curve *X* and *Y*, where *x* is the data points

Table 1 Correlation coefficient and degree

Correlation coefficient(r)	0.8-1.0	0.6-0.8	0.4-0.6	0.2-0.4	0.0-0.2
Degree of correlation	Most strong correlation	Strong correlation	moderate correlation	weak correlation	no correlation

in the curve *X*, *y* is the data points in the curve *Y*, *N* represents the number of data points. Generally, related strength is determined in the range by the variables as shown in Table 1.

Considering the actual application, if the case operation of the unit is judged according to the correlation as described in the table 1.it may be not reach the actual precision needed. So the correlation coefficient criterion is given out combined with practical experience, as shown in Table 2.

Table 2 Correlation coefficient criterion

Correlation coefficient (r)	0.9990-1.0000	0.9900-0.9990	<0.9900
Unit status	Normal	Abnormal	Failure

By means of monitoring system software, and time period (usually a month, be set artificially), correlation coefficients for each turbine power curve and initial operation of the power curve can be calculated automatically based on the formula (8).

3.6 Power characteristic longitudinal comparison

1) Comparison based on bin method

After the data contained in two curves are calculated by the method aforementioned, the relative deviation values within the range each bin are calculated. When the deviation within a certain bin is greater than a set value, it is taken granted that the units fall too more in power characteristics within this bin range. Similar to horizontal comparison, when the counts of decline occur on power characteristics bin intervals exceed a certain percentage of total by α, automatic alarm system reminds inspection personnel to take further action. Meanwhile, power characteristic curve of each unit is produced by the monitoring system automatically according to a set length (usually a month), which is drawn in a same figure for the same unit, the growth trend of which can be found directly.

2) Comparison based on Wavelet analysis

When the data to be formed two curves are processed by wavelet filtering method, correlation coefficient of the two curves is calculated, and the results are evaluated according to that in Table 1, the relevance between normal running power curve and the initial power curve is determined. Once the degree between the two is less than strong correlation, the automatic alarm system reminds inspection personnel to take further action. Meanwhile, power characteristic curve of each unit is produced by the monitoring system automatically according to a set length (usually a month), which is drawn in a same figure to the same unit, so the growth trend can be found directly.

IV. DATA SIMULATION RESULTS ANALYSIS

Based on the above theoretical analysis, actual operating data from 70 sets of GE1.5 units of a wind farm in the past year are adopted and analyzed on MATLAB simulation. In the power characteristics of monitoring system, 10min average power relative standard deviation value is set to 20 %, the cumulative count is set to 12, α is set to 20%, bins range is selected from 4m / s to 20m / s. The simulation result is as shown in Figure 6, which shows accumulated statistics of abnormal performance obtained with time on before and after data filtering. From the figure we can see clearly that filtering can remove dates where larger errors happened due to some other reasons, such as start and stop.

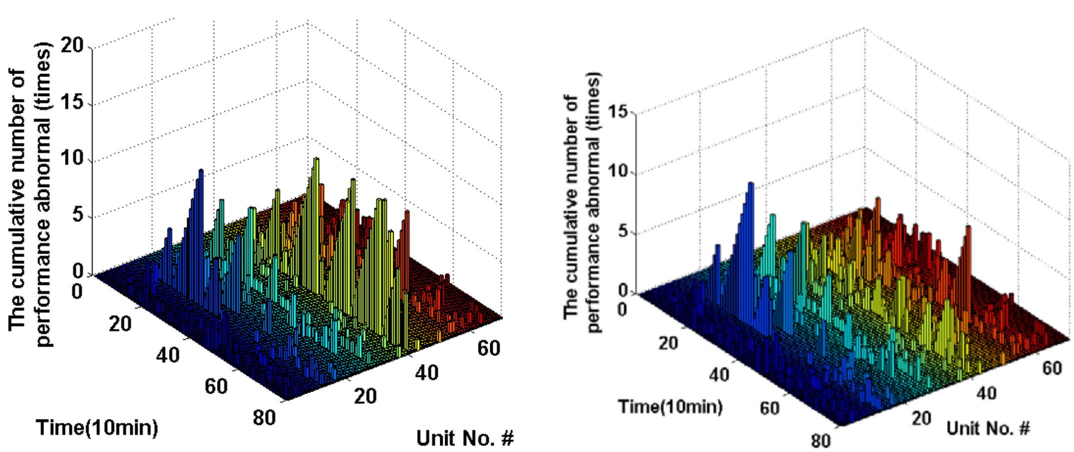

Figure 6 Accumulated statistics of abnormal performance obtained before and after data filtering

4.1 Abnormal statistical analysis and horizontal contrast

Figure 7 shows the number of bins statistics whose output are appear abnormal. We can see from the figure that performance degradation is appeared a total of five times of 43 # unit, respectively in 1th,3th,5th,6th,8th bin, namely $n_{bin} = 5$.By the formula (4), it can be obtained $\alpha = 15.6\% < 20\%$. Then the monitoring system must warn the personnel to pay close attention to the health of this unit. While for 51 #, it can be seen from the figure that performance degradation appeared a total of several times, respectively in 5th,6th,7th,8th,16th 17th,19th bin, namely $n_{bin} = 7$ .By the formula (4), it can obtained $\alpha = 21.9\% < 20\%$. At this point, the voice alarm monitoring system is triggered to alert engineers to check the abnormal unit. Test results show that some are by environmental factors such as topography and wake effects, and some are caused by such equipment factors as the vane deviation.

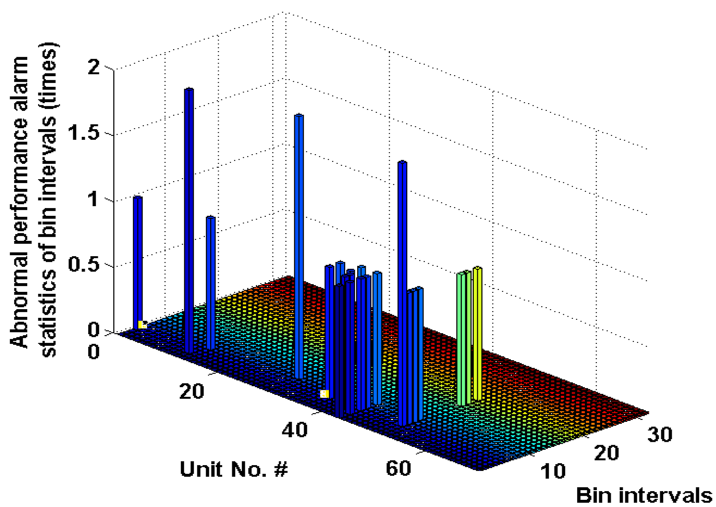

Figure 7 Alarm statistics of abnormal bins

In order to get the performance in each bin more accurately, it is helpful to resort to a statistical analysis for the low output cumulative counts in the each case bin of unit.

Here α is set to 16.7%, take the unit 7 as an example, which is shown in Figure 8. It can be seen that within the bin from 2.5m / s to 7m / s and from 11.5m / s to 14.5m / s, average power appears larger deviation, in turn, the cumulative number of abnormal performance up to 12 from 4.5m / s to 5m / s and from 13.5m / s to 14m / s, so the abnormal bin intervals is 2. It can be obtained by the formula (4), $\alpha = 5.6\% < 16.7\%$, Then the monitoring system must warn the personnel to pay close attention to the health of this unit. With unit running, once the scale factor $\alpha > 16.7\%$, the voice alarm monitoring system will alert officers to check the abnormal unit. Referring to the actual operation, the phenomenon can be caused either by environmental or the other equipment performance.

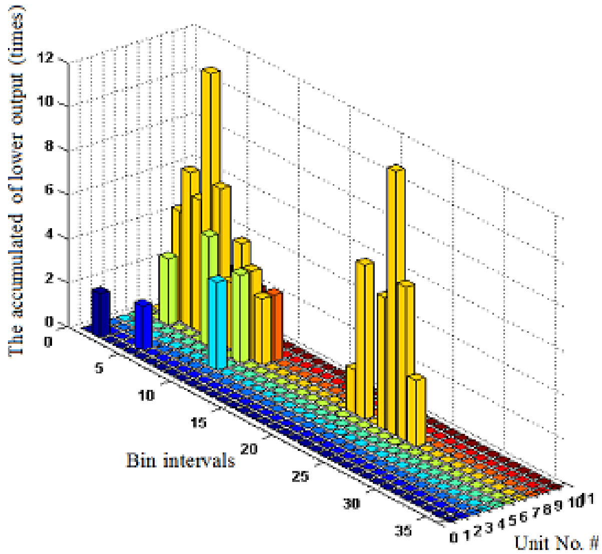

Figure 8 Horizontal contrast simulation results

4.2 Wavelet analysis and longitudinal contrast

In the simulation of the power characteristic longitudinal monitoring contrast, the power characteristic longitudinal monitoring is done and evaluated, production data in the first year are used to generate the initial power curve. Then the actual six months operational data four years later is simulated by MATLAB, the result is shown as in Figure 9.

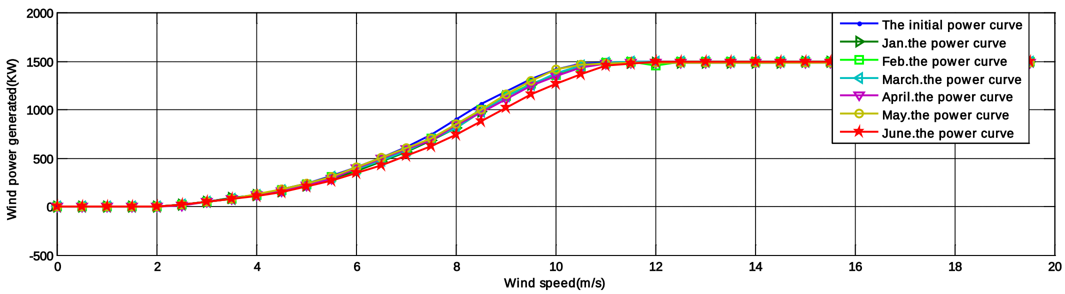

Figure 9 Longitudinal comparison of simulation results

Where the blue curve represents the initial power curve, and the rest are the power characteristic curves from January to June of a single unit. It can be seen from the figure, with the extension of unit operation time on, power characteristics curve is declined compared with the initial power curve. In order to measure the decline more accurately to the unit power characteristic curve, Equation 8 is used to calculate the correlation coefficient(r) to the initial power curve, the results is as shown in Table 3.

Table 3 Correlation coefficient to the initial power curve

Time	January	February	March	April	May	June
Correlation coefficient(r)	0.9993	0.9995	0.9993	0.9992	0.9998	0.9960

We can be seen from Table 3,from January to May, correlation control to the correlation coefficient r between the power characteristic curve and the initial power characteristic curve is greater than 0.9990,refer to Table 2, the unit is thought operated in normal. While in June, correlation coefficient is 0.9960, so the unit is thought in abnormal.

Similar to horizontal contrast, the voice alarm monitoring system must alert engineers to inspect the unit. Case in actual operation shows that some surrounding environmental (new crew wake effects) may cause the phenomenon, of course other reasons such as the device itself can also do.

V. CONCLUSIONS

It is of great significance to discover recession of wind turbine with the power characteristics and improve the power output of wind farms in time. The paper presents horizontal comparison method of the same area, the same model power characteristics of quasi-real-time monitoring of units. Meanwhile, longitudinal comparative monitoring method is proposed to provide an intuitive and effective method for single unit power characteristics of different periods for the automatic monitoring trends of wind turbine. Especially in conjunction with system software development for large-scale regional centralized monitoring center, software can be utilized automatically to calculate, analyze, alarm, improving greatly the efficiency of wind farm operation and monitoring, which is an effective means to reduce the loss of power and increase revenue generation.

ACKNOWLEDGEMENTS

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