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A Data-Mining Approach for Wind Turbine Power Generation Performance Monitoring Based on Power Curve

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Abstract

A new data-mining approach based on power curve profiles is put forward to monitor the power generation performance of wind turbines in this paper. Through assessing the wind-speed power datasets, the weakened power generation performance of turbines could be identified effectively by this approach. Shapes of power curve profiles over consecutive time intervals are constructed by fitting power curve models into wind-speed power datasets. In this research, we designed the Auto-adapt Optimal Interclass Variance algorithm, optimal constraint in each wind-speed power sub-dataset is explored for governing the data-driven method based on distance-based outlier detection and variance analysis model. The AOIV algorithm achieves the self-optimization of the threshold parameter and reaches a high degree of robustness to variations in wind-power generation performance monitoring. The blind industrial researches are conducted to validate the effectiveness of this approach, also indicates the decrease of error rates while detecting weakened power generation performance and the improvement of turbines' power output.

Keywords: *Wind turbine; Power curve; Data-mining; Performance monitoring;*

1. Introduction

Wind energy is a clean, efficient and renewable natural energy, which is considered to be one of the most potential energy sources in the world. And all over the world, many countries pay attention to it[1]. Wind power generation is a high efficiency, zero pollution transfer mode from wind energy to electricity, the application of wind power can promote the development and utilization of renewable energy. The wind turbine with great power generation performance, as the direct participants of wind power, is to ensure the stable development of wind power generation enterprises as well as planning management decision.

The power generation performance characteristics of wind turbines are by the response curve of output power. According to the definition of IEC61400-12-1, the power curve of wind turbine is the relationship curve of the output power of the generator with the average wind speed of 10 minutes, and which is an important indicator to measure the power generation performance of the wind turbine[2-4]. It not only reflects the performance of the wind turbine is in accord with the design of the product, but also embodies the characteristics of wind turbine actual

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operation[5].However, the power curve of wind turbine is often influenced by air density, system control, ambient temperature and so on. The original wind-speed power data collected by SCADA system often contains a variety of abnormal data[6-11].

The traditional data-mining methods which detect weakened power generation performance through building model training of historical datasets with certain ratio generally have inevitable prediction error, so the identification of the poor power generation performance of turbines is not accurately for the real-time data. Kusiak et al. [12] introduced non-parametric methods for modeling the wind power curve from industrial data and analyzed model fitting residuals to detect anomalies. Ustuntas [13]applied cluster center fuzzy logic modeling for power curve estimation. Kusiak and Li [14] investigated fault diagnosis through analyzing patterns of power curve fitting residuals. The philosophy of studies is to develop statistical boundaries for detecting outliers based on a derived reference power curve. Qiu et al. [15] and Feng et al. [16] presented physics-based data analysis methods for detecting anomalies of wind turbine assemblies and performing diagnosis with SCADA data. Besides, K-NN clustering and least square fitting method are usual used in the analysis of the power curve of wind turbine. But the process above mentioned methods is more complicated and not well be applied to the poor unit generation performance.

In this paper, a data mining approach is proposed to assess the wind power generation performance through analyzing the variation of wind power curves rather than individual data points. The power curve data of a wind turbine is partitioned into sub-datasets based on consecutive equal time intervals and each sub-dataset provides a power curve of the wind turbine over the time interval. And the outlier-detection approach and variance analysis model are used better to realize the self-optimization of the variance threshold parameter of each sub-dataset in the Auto-adapt Optimal Interclass Variance(AOIV) algorithm. The AOIV algorithm is effective applied to evaluate the performance of turbines with data in wind power company. The effectiveness of the proposed approach is demonstrated through some blind industrial studies. It can enhance the operation stability of the wind turbine and improve economic benefits of wind power enterprise.

2. General Power Curve Properties

2.1. Wind Energy and Power Curve

Wind power refers to the kinetic energy of wind. The wind turbine is capable of absorbing the wind energy through blades, then converting it into rotating machinery to drive the generator to generate electricity, so as to realize the conversion of the energy[16]. When the wind speed through the impeller is V, the theory wind energy on the blade at the time of the unit is E:

$$E = 0.5\rho_0 AV^3$$
(1)

Where E is the theoretical wind energy; ρ_0 is the reference air density; A is the swept area of the blade; V is the wind speed;

Due to the restriction of aerodynamic characteristics, wind turbine blades can only absorb part of the wind energy[17]. According to Baez theory, the maximum power of the blade can be obtained from the wind energy is $P_{\max}$ in the ideal condition:

$$P_{\max} = 8\rho_0 AV^3 / 27$$
(2)

Thus, the theoretical maximum efficiency of the wind turbine generator is C_p:

$$C_p = P_{\max} / E = 2P_{\max}\rho_0 / AV^3 \approx 0.593$$
(3)

C_p also known as theoretical wind energy utilization coefficient, the ideal blade can only absorb a portion of its energy from the natural wind, and other non absorption parts can be interpreted as the rotational kinetic energy left in the wake flow. Power curve of wind turbine under the ideal operation state shown in Figure 1.

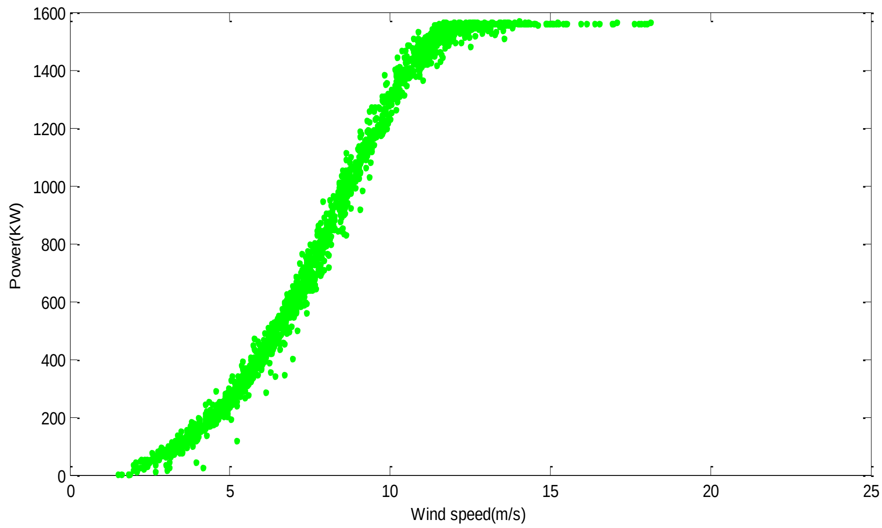


Figure 1. Ideal Power Curve

2.2. Betz Theory and Power Curve

For the actual wind turbine, the blade structure of the wind turbine is not satisfied with the ideal conditions, and the transmission system and the generator and other energy conversion links are lost. So the actual wind energy utilization coefficient is lower than the theoretical wind energy, that is $C_P \leq 0.593$ [18].The useful power output of wind turbine actually obtained can be expressed as formula (4):

$$P = 0.5\rho_0 AV^3 C_P$$
(4)

The relationship of wind energy utilization coefficient C_p and pitch angle β and tip speed ratio ϕ is in (5):

$$\begin{cases} C_p(\phi,\beta) = c_1(\frac{c_2}{\phi_i} - c_3\beta - c_4)e^{\frac{-c_5}{\phi_i}} + c_6\phi \\ \frac{1}{\phi_i} = \frac{1}{\phi + 0.08\beta} - \frac{0.035}{\beta^3+1} \end{cases}$$
(5)

Where the ϕ is the tip speed ratio, and the β is the pitch angle of wind turbine, $c_1 = 0.5176$, $c_2 = 116$, $c_3 = 0.4$, $c_4 = 5$, $c_5 = 21$, $c_6 = 0.0068$; The change curves C_p for $\beta = 0^\circ$ is shown in Figure 2.

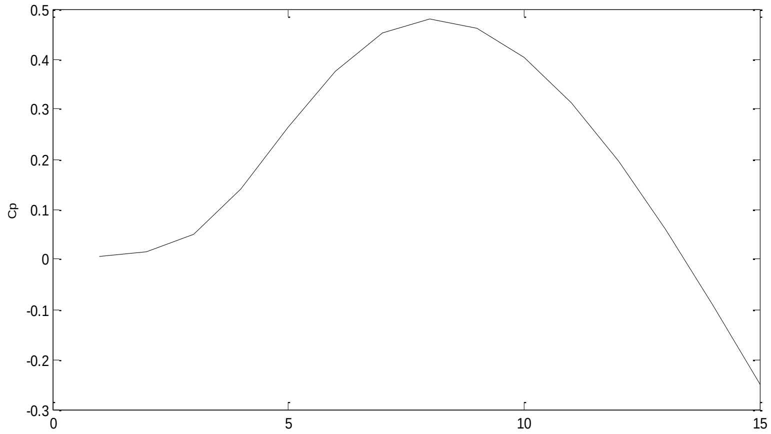


Figure 2. Changing Curve of C_p

3. Data-Mining Based on Power Curve

3.1. Data Preprocessing

Before mining the power curve profiles, the data are preprocessed according to the methodology used in wind power generation enterprise of China. That encompasses the three following steps: 1) validity check, 2) data range check, and 3) missing data processing. Moreover, these anomalies should be removed to make a separate analysis if necessary. Actually, the simplified rules as follows are often used when taking into account time and high-efficiency.

a)wind speed < cut-in speed—the cut-in speed is the wind speed value at which the turbine starts operating; pitch angle about 90^o.

b)wind speed between cut-in speed and cut-out speed—power output zero or negative.

c)wind speed > cut-out speed—the cut-out speed is the wind speed value at which the turbine stop generating available power; pitch angle about 90^o.

The data satisfied above rules should be removed. The preprocessing result of sample turbine is shown in Figure 3.

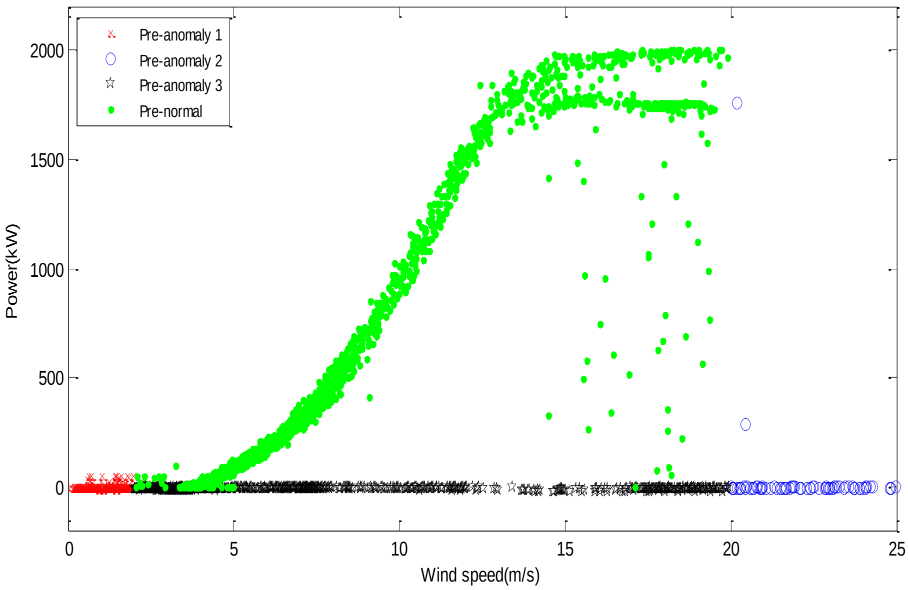


Figure 3. Power Curve Preprocessing

3.2. Data-Mining with AOIV Algorithm

Data mining with the AOIV algorithm is the core of detecting anomalies based on power curve in wind turbine power generation performance monitoring.

(1) OIV Algorithm

The optimal interclass variance(OIV) algorithm based on the power curve is a simple and efficient data-mining method for the power curve analysis of wind turbines, and which detects anomalies by combined with the initial variance threshold. The specific cleaning process of the algorithm is as follows.

Given a sample dataset of turbines $U=\{(x_1,y_1),(x_2,y_2),...,(x_n,y_n)\}$,and satisfy $y_i<y_{i-1}$, $i\in(2,n)$, x represents wind speed, y is expressed as power, and n is the total number of sample points. The profile for depicting the characteristic of the power curve contained in U is λ if and only if λ satisfies (6).

$$\lambda=\arg\max\{\sum_{\lambda=2}^{n}(\frac{1}{\lambda}*\sum_{j=1}^{\lambda}(y_j-\overline{y_\lambda})^2)<S\}$$

(6)

Where y_j is the jth power value; $\overline{y_\lambda}$ is the average of first λ power value; λ is constant; S is initial threshold.

Let t index U , $t=1,2,...,W$,a set of power curve profiles, λ can be obtained through (6). W is the total number of sub-datasets, and the interval of wind speed is 0.5m/s by default. Particularly the downtime data points are not considered here. In certain sub-dataset, the abnormal data can be successfully detected by obtained λ that only if satisfies (7) and (8).

$$U_n(t)=\{(x_i,y_i)\,|\,(x_i,y_i)\in U(t),1\le i\le\lambda\} \quad (7)$$

$$U_l(t)=\{(x_i,y_i)\,|\,(x_i,y_i)\in U(t),(x_i,y_i)\notin U_n(t)\} \quad (8)$$

Where the $U_n(t)$ represents the normal data in the sub-dataset; $U_l(t)$ represents the abnormal data in the sub-dataset.

At last, the data processing results of power curve of each sub-dataset are classified and sorted, the normal and the abnormal data sets are obtained in (9) and (10).

$$V_n = \{U_n(1), U_n(2), ..., U_n(W)\} \tag{9}$$
$$V_l = \{U_l(1), U_l(2), ..., U_l(W)\} \tag{10}$$

Where the V_n is the power curve data for power generation performance normally. V_l is the power curve data for the lower power generation performance.

OIV algorithm block diagram is as follows.

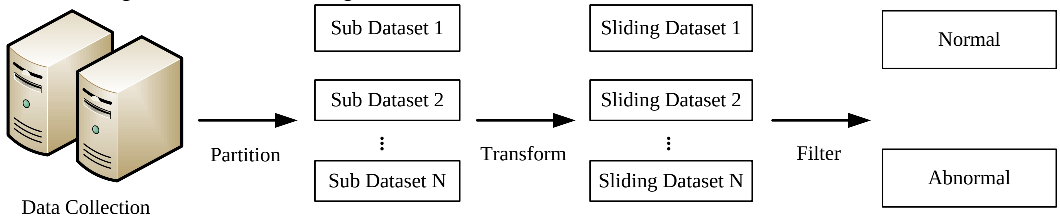


Figure 4. Block Diagram of OIV Algorithm

(2) AOIV Algorithm

The auto-adapt optimal interclass variance(AOIV) algorithm is proposed to enhance the accuracy with the combination of the outlier detection and the optimization of the variance threshold in this research.

A. The Detection of Outliers

The outlier detection approach based on the distance is effective to detect power curves with different curvature. And the detected outlier should be removed and belongs to the category of the abnormal dataset. $u_i = (x_i, y_i)$ represent a data point in the sample set U , The distance between two points is defined:

$$d_k(u_i, u_{i-1}) = (|x_i - x_{i-1}|^k + |y_i - y_{i-1}|^k)^{1/k} \tag{11}$$

If k=1, then

$$d_1(u_i, u_{i-1}) = |x_i - x_{i-1}| + |y_i - y_{i-1}| \tag{12}$$

At this time ,the distance is the absolute value distance.

If k=2,then

$$d_2(u_i, u_{i-1}) = (|x_i - x_{i-1}|^2 + |y_i - y_{i-1}|^2)^{1/2} \tag{13}$$

At this time, the distance is the Euclidean distance.

Definition 3.1 For any point $u_i = (x_i, y_i)$ in U , given a relative small positive number ε , if any point $u_i = (x_i, y_i)$ in data set U satisfy with condition: $d_k(u_i, u_{i-1}) < \varepsilon$, so u_{i-1} is the ε -proximal point of u_i , and the set of all ε -proximal points is ε -neighborhood of u_i .

Definition 3.2 For any point $u_i = (x_i, y_i)$ in U , given a relative small positive number ε ,select an empirical critical value N_0 . Assume that the number of ε -neighborhood of u_i is N_i , if $N_i < N_0$,The point u_i is called an isolated point of U .

B. The Optimization of Variance Threshold

The improved model of variance analysis is effective to achieve the optimal variance threshold for each sub-dataset. Given a set of sliding variance samples is $Z = \{z_1, z_2, .., z_k\}$, k represents the total number of sample points. To define the value range of S is $[s_1, s_2]$, and satisfy with $S \in N_+$. The default value is $s_1 = 1, s_2 = 500$. The sample set Z is divided into two groups by selecting different values of S in turn, and the following calculation is performed if and only if there are two groups of data, otherwise should be ignored and reselect the S value. Assume that the two groups of data in an specific S are $Z_1 = \{z_1, z_2, .., z_\lambda\}$ and $Z_2 = \{z_\lambda, z_{\lambda+1}, .., z_k\}$, and the internal error and external error between Z_1 and Z_2 is calculated in (14) and (15).

$$\sigma = \sum_{j=1}^{\lambda} (z_j - \overline{Z}_1)^2 + \sum_{j=\lambda+1}^{k} (z_j - \overline{Z}_2)^2 \tag{14}$$

$$\omega = (\overline{Z}_1 - \overline{Z})^2 * \lambda + (\overline{Z}_2 - \overline{Z})^2 * (k - \lambda) \tag{15}$$

Where σ presents external error; ω presents internal error; z presents sliding variance; $\overline{Z}_1$ presents the mean value of data set Z_1; $\overline{Z}_2$ presents the mean value of data set Z_2; $\overline{Z}$ presents the mean value of the sliding variance sample Z; The value S is the optimal variance threshold for the sub-dataset when only satisfy with formula (16).

$$S = \arg\max\left(\sum_{S=s_1}^{s_2} \sigma_S / \omega_S\right) \tag{16}$$

In order to avoid the effect of the algorithm on the data distribution in the normal operation mode of the wind turbine., S usually need to join a certain threshold supplementary quantity μ which not less than minimum variance values of normal running mode of wind turbine.

$$S' = S + \mu \tag{17}$$

Where S' presents the variance threshold after the update;

The principle diagram of the auto-adapt optimal interclass variance(AOIV) algorithm is as follows:

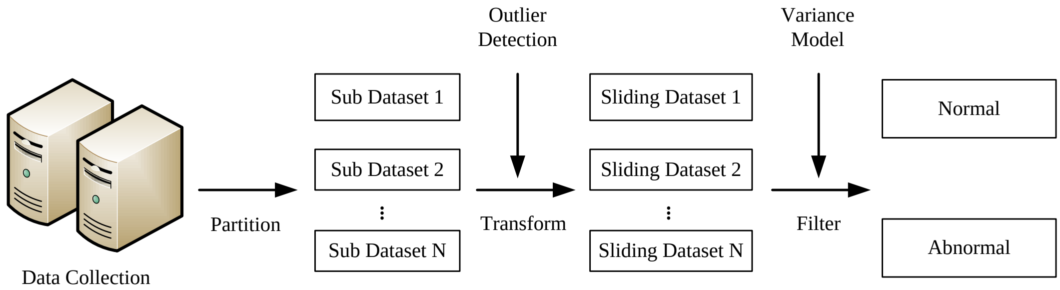


Figure 5. Block Diagram of AOIV Algorithm

4. Industrial Studies

4.1. Data Preprocessing

In order to verify the effectiveness of the approach and the application of the power generation performance monitoring, this paper investigates the 10-min

SCADA data of 33 wind turbines collected from May 31, 2013 to May 8, 2013 in a 100MW Class wind farm in China. The collected data contained values of wind turbine performance parameters, wind conditions, as well as the fault logs. And the basic parameters of the turbine are shown in table 1.

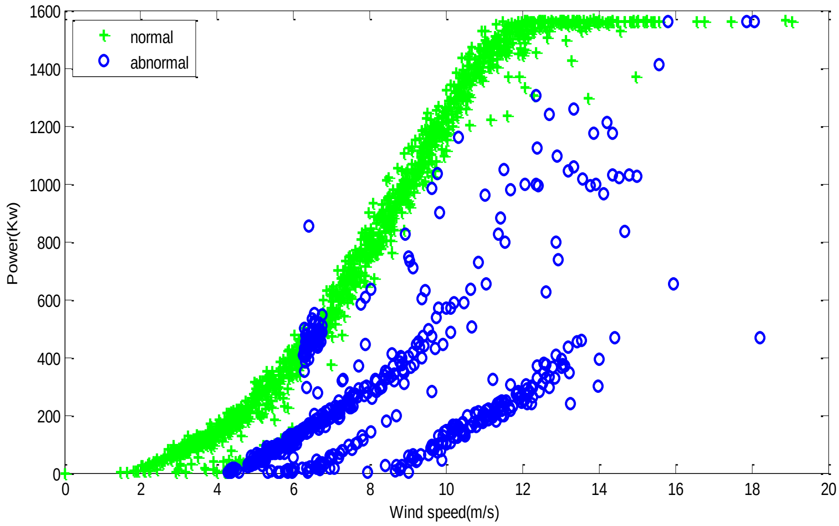
Table 1. Wind Turbine Parameter Table

Turbine Parameter	Value
Rated power /kw	1500
Power adjustment mode	Variable pitch, variable speed
Impeller diameter /m	70
Hub height /m	68
Cut-in wind speed (m.s-1)	2
Rated wind speed(m.s-1)	12
Cut-out wind speed (m.s-1)	25
Maximum wind speed (m.s-1)	60

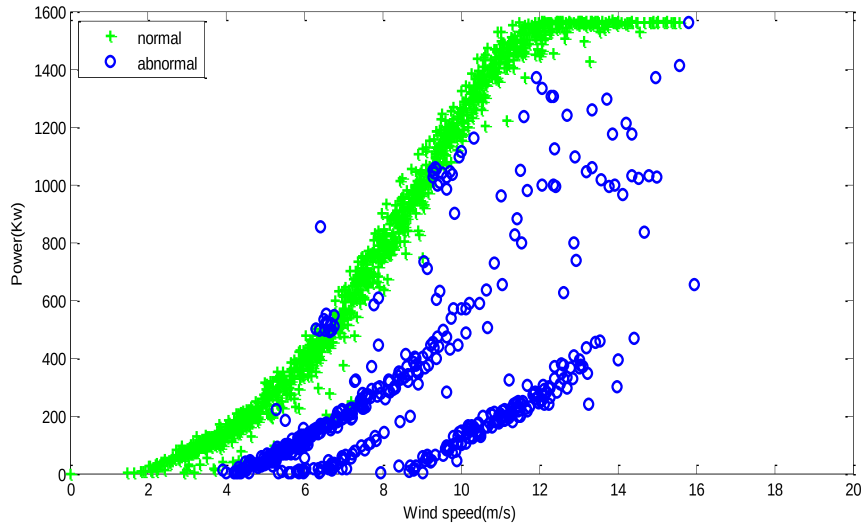
4.2. Contrastive Analysis between Algorithms

To compare the data-mining effect between two algorithms in chapter 3, this section presents some industrial studies based on turbines' 10-min SCADA data which collected randomly from a wind farm in China.

Two kinds of different variance thresholds are selected to inspect the OIV algorithm. Meanwhile, the threshold supplementary quantity value in the AOIV algorithm is 30 that usually determined by turbine's type. The results are shown in figure 6 and figure 7.



(a)



(b)

Figure 6. Processed Power Curve with OIV Algorithm

As shown in Figure 6, (a) express the processed results of the OIV algorithm with the variance threshold of 50, (b) express the processed results of the OIV algorithm with the variance threshold of 85. From the above results we can see ,in the wind speed range of 6-8m/s, the existence of outlier greatly reduce the data-mining accuracy of OIV algorithm. While the increase of the variance threshold value, this impact has a varying degree of reduction. But the data-mining effect of the whole unit is poorer. This is due to the threshold values in each wind speed range is different.

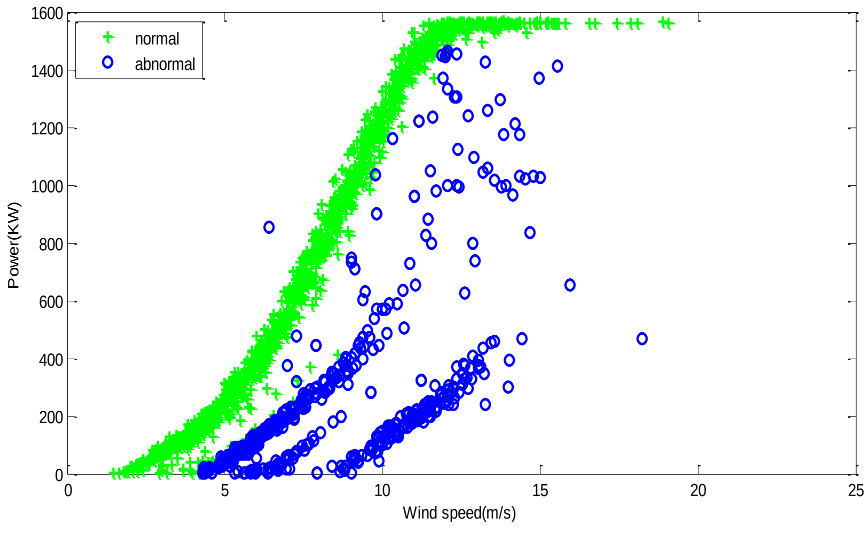


Figure 7. Processed Power Curve with AOIV Algorithm

Figure 7 shows the processed results of the same turbine with AOIV algorithm. The algorithm has added to the processing module of isolated points, which can avoid the impact of the data mining process; Meanwhile, variance analysis model is subtly used to realize the tracking and optimization of the threshold each wind-speed interval, and the generality of the algorithm is enhanced. The comparison is shown in table 2. ND is the amount of detected normal-data, LD is the amount of detected limited-power data. HD is the amount of detected halt-data. EDoN is the amount of error detection in ND. EDoL is the amount of error detection in LD. EDoH is the amount of error detection in HD.

Table 2. Contrastive Analysis Table

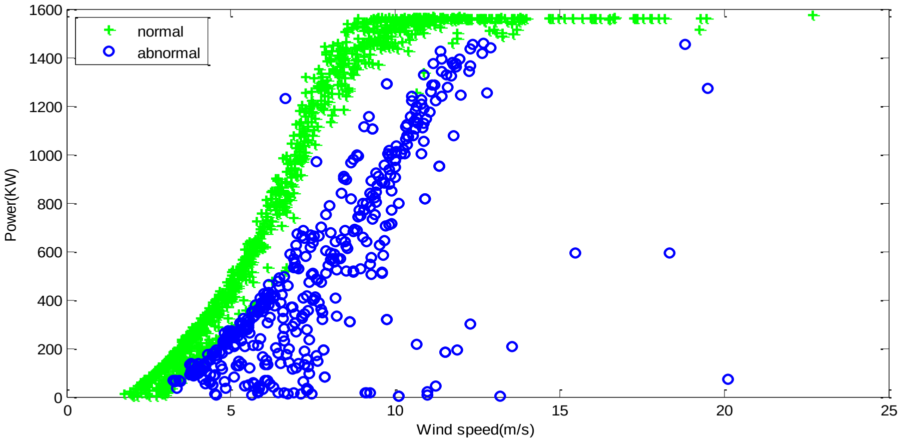
Parameter	Artificial	OIV(S=50)	OIV(S=85)	AOIV
ND	1341	1105	1282	1370
LD	426	662	485	397
HD	938	938	938	938
EDoN	0	32	196	30
EDoL	0	268	255	12
EDoH	0	0	0	0

Table 2 shows the data-mining results among the artificial statistics results, OIV algorithm and AOIV algorithm. Both of normal data and limit data have different degrees of error detection with OIV algorithm, and the variance threshold value is negatively correlated with the amount of the detected limit-data and positively correlated with the detected normal-data. After improving the algorithm, data processing results has a lower error rate. In fact, the impact of these error-detected data is very small and can be neglected. In addition, the method of detecting halt-data above three data-mining algorithm are same law in chapter 3.1 so that the amount of error detected halt-data is zero. In short, the AOIV algorithm based on power curve has more general and higher accuracy.

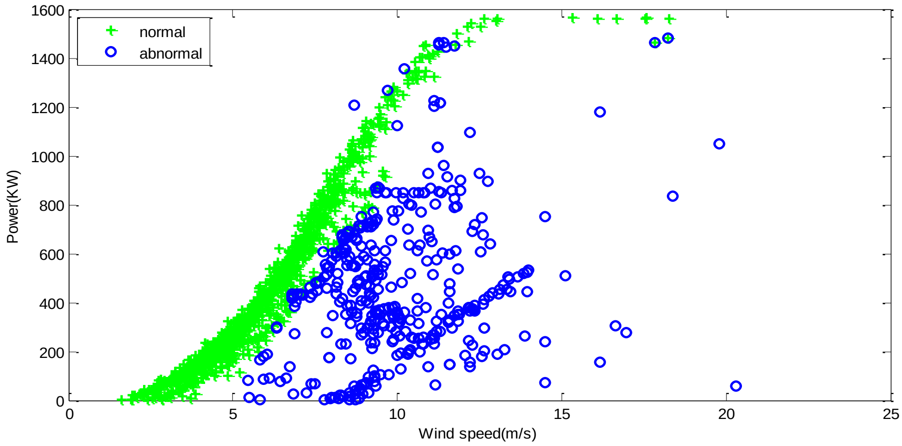
4.3. Performance Monitoring of Turbines

4.3.1. The Data-Mining with AOIV Algorithm

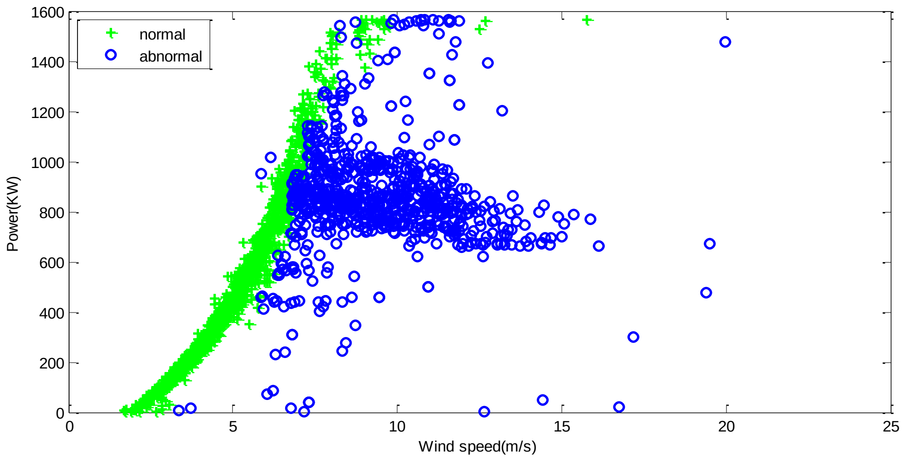
Taking into account the number of test turbines, here is only given some representative turbines selected from 33 turbines. As shown in figure 8, (a) is the power curve of turbine 15081504. (b) is the power curve of turbine 15081505. (c) is the power curve of turbine 15081506. (d) is the power curve of turbine 15081507.



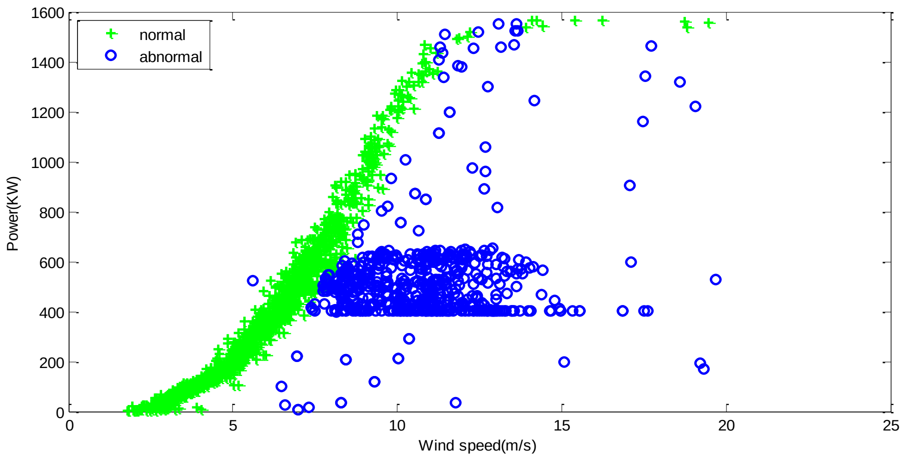
(a)



(b)



(c)



(d)

Figure 8. Processed Power Curve with AOIV Algorithm

From Figure 8 it can be seen that this approach can effectively detect the various power curve profile. Among them, the turbines 15081505 and 15081507 processing results are better; Turbine 15081504 has some abnormal points which are not detected in the low wind speed zone, this is likely due to be affected by air density, but the impact on the assessment and analysis of the power generation performance of turbines is very small; Turbine 15081505, 15081506 and 15081507 has been partially detected in the rated wind speed zone, which is due to the amount of data is too small to be mistaken for an isolated point, it can be neglected. According to the above, this approach algorithm has better versatility and accuracy.

4.3.2. The Analysis of Detected Faults

Through the analysis of data-mining results, it is easy to find that there are a large number of scattered points that represent the poor power generation performance. Certainly this method successfully identified the anomalies of turbines, which should be carried out relevant maintenance or technical innovation. If these abnormal profiles are analyzed deeply by the professional, the root cause of poor power generation performance of turbines will be found.

The patterns of irregular profiles in processed turbines can be briefly categorized to three main situations. Taking turbine 15081515,15081516 and 15081517 for example to describe the detailed analysis procedure in Figure 9 - 11.

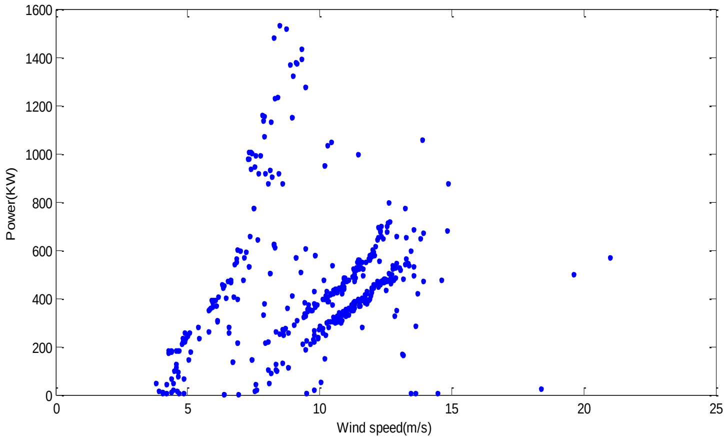


Figure 9. Abnormal Data

In Figure 9, the turbine 15081515 does not generate power normally so that power curves display abnormal curvatures. Actually, this is because of the pitch faults which usually seriously affect power generation performance of turbines.

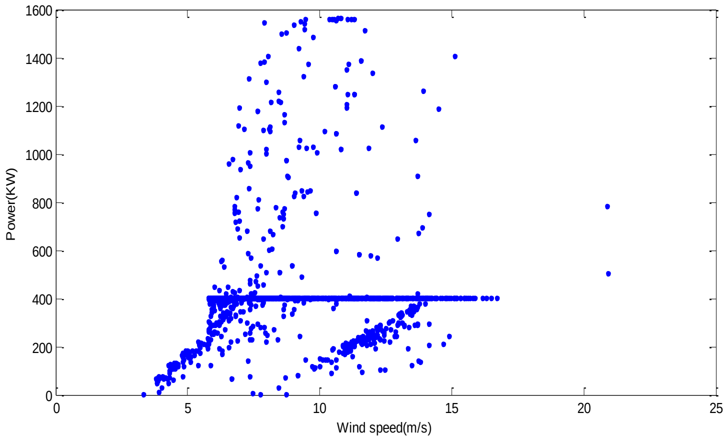


Figure 10. Abnormal Data

The power curve of turbine 15081516 in figure 10 is abnormal apparently. There are two faults in this turbine. One is the pitch faults and another is the human factors which schematically reduce the power generation for making full use of electricity in different regions.

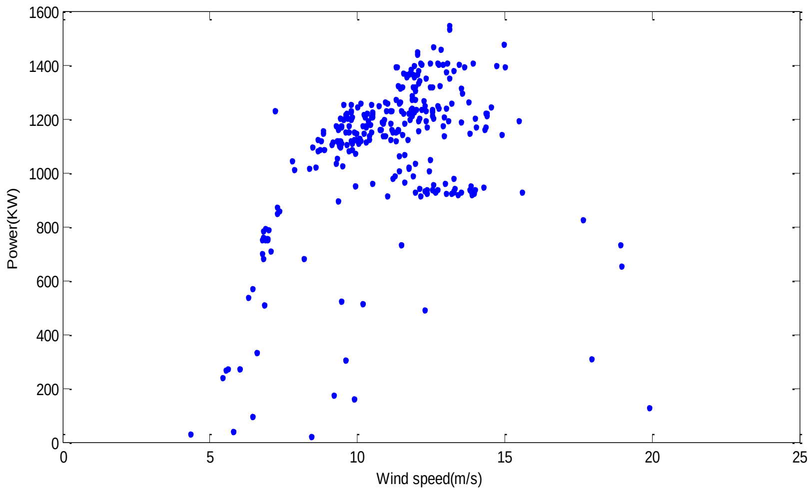


Figure 11. Abnormal Data

In Figure 11, the abnormal scattered points is usually due to the high temperature caused by cooling system failures in the gearbox, and it is difficult to produce a ideal power curve with adjusting control system. For such a situation, it is necessary to maintain the cooling system of the wind turbine.

In short, the power generation performance could be monitored with the AOIV algorithm.

5. Conclusion

In this paper, we proposed a data-mining method to identify impaired power generation performance by analyzing the curvature and shape of the wind power curve. The outlier detection based-on distance were applied to eliminate the impact of isolated points in the power curve analysis, while the variance analysis model realize the self-adaptive threshold to enhance the accuracy rating of data-mining. Compared to other methods, this way could more accurately and fleetly detect the anomalies of turbines just by analyzing power curve without complex sample training. It can also process the real time data for online monitoring and identify the weakened performance of generating unit.

Some industrial studies were conducted to prove the effectiveness and accuracy of the algorithm. We have mined the power curve of 33 sets of wind turbines, and the great data results are obtained. The future research will investigate an intelligent method to identify the fault type and the root cause with poor performance of turbines. In addition, the relationship between wind power and multiple parameters will be considered in the data mining.

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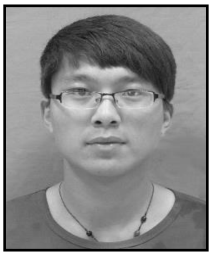

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