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Research on Early Fault Diagnostic Method of Wind Turbines

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Abstract

Challenging environmental factors combined with high and turbulent winds make serious demands on wind turbines and result in significant component fault rates. In this paper, an early fault diagnostic research is conducted upon wind turbines. Firstly, the SCADA (Supervisory Control and Data Acquisition) system is used to analyze the units' long-hour operating data, preparing for the further modeling work. Then the MSET (Multivariate State Estimation Technique) is adopted to estimate the temperature of the gear box and to obtain a result of high accuracy; with the Moving Window Calculation (MWC), the residual value between the estimated value and the real value is studied to get the dynamic trend of its average value; according to this trend in training, we define the threshold region of the residual mean value. Considering a man-made deviation in the observation vectors, faults of the gear box are simulated and studied. When the residual mean value curve exceeds the setting thresholds, an alert will be given to remind the operators of hidden problems in the unit. Research shows that this early diagnostic method is quite effective in detecting the abnormal performance of wind turbines in a real-time manner.

Keywords: SCADA, Fault diagnostic, MWC, MSET

1. Introduction

Wind power, one of the green, safe and low-carbon energy, is so fast-developing in generating electricity that it has become the fourth major power source after coal, water and nuclear. It is also the only renewable power resource that owns over one hundred million kilowatt global installed capacity apart from water. The development of wind power brought about a series of problems at the same time, with the maintenance of wind turbines being the foremost. As the main components of a large-scale wind turbine are fixed at a height of over one hundred meters, special equipment like cranes are needed in the repairing of impellers, gear boxes and generators. When it comes to the units located at sea, other important factors like the boats' chartering and weather should also be considered. As to a wind plant of which the designed life-span is twenty years, the maintenance cost takes up 10-15% of the total income; while the ratio is 20-25% to the one on the sea.

Owing to the ignorance of wind turbines' features and the lack of management experience, the testing and repairing system of thermal plants are still widely used in the wind plants in our country. The maintenance of thermal power equipment mainly covers its status supervision and diagnosing methods (life-span of the metal, cavitations, scaling etc.); while the faults in a wind turbine are caused by mechanical stress and the aging of electronic parts for they are the major components of a wind turbine unit. In fact, a wind turbine approximates to electronic equipment running under poor condition, so it is rather rational to discuss the fault diagnosing methods and maintenance system combing its own electronic characteristics. The condition monitoring and fault diagnosing of wind turbines is a process to supervise, estimate and analyze the operating data of the major components (impellers, gear boxes, generators, transducers etc.), so as to detect faults promptly. Using related condition monitoring techniques, we can master the turbines' running state in a real-time way. Thus, serious damages to the equipment can be avoided in advance and the maintenance cost will be greatly reduced.

This paper proposes a state estimation of the gear box's temperature based on the SCADA data and the MSET. Then the MWC residual statistical method is adopted to analyze

the results and obtain its mean value curve. Whenever this curve exceeds the setting thresholds, a system alarm will occur.

2. Condition Monitoring and Fault Diagnosing of Wind Turbines

A wind turbine, a complex system, consists of several subsystems: tower, wind wheel, wheel hub, pitch system, gearing system, yaw, brake, generator, variable-frequency system, master control system, variable-voltage and grid-tied system. Each subsystem is made up of several parts. These subsystems cooperate with each other to conduct complicated operations. Besides, the dynamic characteristics of a wind turbine include both continuous and disperse parts. Being greatly influential by some external uncontrollable factors, such as the wind's speed, direction and altering frequency, the turbine is located in so complex a working condition that it performs differently accordingly.

The present fault diagnosing methods applied in wind turbines are listed as follows [1]: the diagnostic method based on statistical data, the one based on time sequence prediction, the one model controlling, the one based on vibration analysis, and the one adopting other testing techniques (sound transmitting [3], ultrasonic- electric capacity liquid level test [6]). Document [3] adopts the BP neural network to construct the model of gear box and generator, and uses the Multi-agent method to analyze the diagnostic results of different components in order to demonstrate the overall operating state of the unit. However, the modeling process upon neural network theory takes rather long a time for training, while training samples are always difficult to select. And the signals' acquisition speed can hardly meet the needs of the analysis of high-frequency vibration. Documents [4-6] summarize the various ways of condition monitoring for wind turbines in the recent years. Document [7-10] constructs the hardware experimental platform for gear box and generator. Though it analyzes the vibration signals using the wavelets analysis method, the model is quite different from the practical state. Document [11] diagnoses the faults based on an automatic analysis of the SCADA data. It does not correlate some key factors, such as vibration scope, temperature, power and start-stop records, giving rise to a relatively separation of study contents and diagnostic results.

To monitor the condition of wind turbines, a dynamic model of its normal operation should be constructed, basing on which the early signs of abnormal acts are tested. Considering the random change of wind speed, the great turbulence of external surrounding factors (temperature), the great differences between different units, the close coupling relation among all the mechanical and electric components, it is difficult to apply traditional monitoring theories and methods in wind turbines.

The non-linear modeling is a method based on the operating data of the object. By analyzing and processing these data, the dynamic-characteristic model is constructed, which is the so-called data-driven modeling method. With plenty of operating data from the SCADA system, the turbines' condition can be monitored to discover early faults.

3. SCADA Data Analysis in Wind Farms

A large wind farm is always equipped with the SCADA system. Its basic function is to record the massive original data at a fixed time interval (generally 10s or 10 min) in the supervisory computers of central control room. These data mainly covers output energy, state and alarm information, fault information, transducer parameters and so forth. The quantity of the SCADA data is so big that the monthly records of a single unit is as many as hundreds MB. At present, the SCADA data in wind farms are merely used in monitoring the data, generating the report forms and recalling accidents after a fault occurs. Recorded in computers, the massive data are regularly copied to discs without being organized and analyzed, the reasons are as follows:

(1) The large number of SCADA data. For instance, the daily records of a single unit are over 10 MB when recording every 10s. For a large wind farm that consists of hundreds units, the huge quantity of data will impose higher standard on the SCADA system's efficiency.

(2) The features of wind turbines' operating. In wind-power generating, the source of energy is the natural wind, random and unpredictable. With the changes of wind, nearly all the data recorded by SCADA will change accordingly, such as the rotating speed of wheel, the vibration accelerated speed, the generating power, the temperature of gear boxed. These

random data bring great obstacles to the acquisition and further processing of information. Besides, measuring errors of transducers and other equipment make it even harder to correctly analyze the data.

(3) Effective theories and methods are needed to separate and extract the close relevance among parameters. Since the change of a single parameter is random and irregular, it is impossible to provide enough operating information only by observing each parameter in an isolated way.

(4) Wind turbines' characteristics are different from one to another. Even located in the same wind farm, two turbines of the same type may have totally different features, for they are fixed and installed in different positions. Take the vibration signals in the same transmitting chain-a unit's wide-range vibration may be acceptable according to operating experience, while a little vibration is likely to cause abnormalities to another unit of the same type. So it is difficult to conclude a common rule or equation to analyze the SCADA data, which makes it considerable work.

In fact, the wind turbines' operating state and their dynamic characteristics are shown in the massive SCADA information. This paper extracts the fault code and the related records from the processed SCADA data. By studying the relevance among SCADA data, it then constructs the inherent non-linear model with multiple variables under normal operating state.

When an abnormality occurs in the unit, the inner relevance among multiple variables will be broken. The non-linear multi-variable state estimated value will deviate from the measured value, which will increase the residual value. In order to monitor the unit's state, we must detect even the slightest abnormalities or changes promptly. Figure 1 shows the concrete flow.
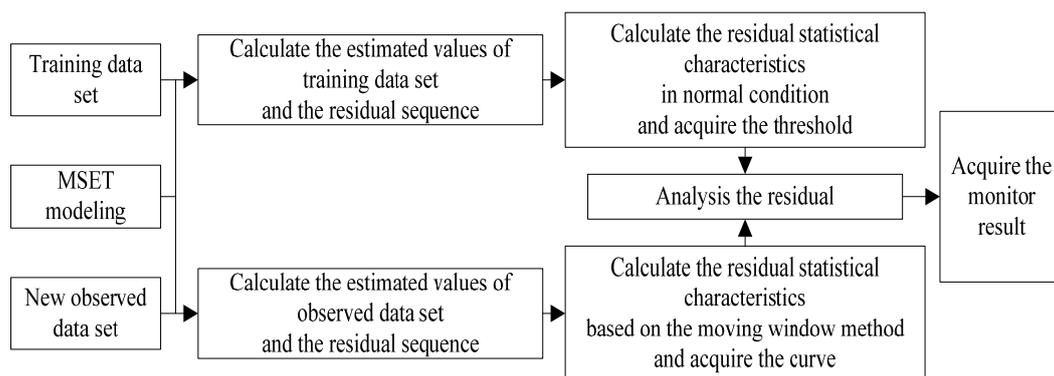
Figure 1. The fault diagnostic method based on the technique of statistical moving window

4. Basic Principle of Early Alert Method
4.1. MSET Model Construction

The MSET is a multi-variable state estimating technique first proposed by Singer [13]. It is now widely used in the nuclear power plant sensor calibration, electric product life-span prediction and software aging research [14-16]. The principle of MSET is as follows. It first studies the history data of normal working state; then it defines the relations among parameters; after that, an inherent nonlinear model with multiple correlated variables is constructed. This is how the state estimation works.

A certain physical process or operating data of a device can be represented by a matrix. This process or device consists of n variables and m states (m moments). The column vector is the operating data of all the related variables at a fixed moment and the row vector shows certain variable's value when the process or device is at State m. Let us suppose, the n related variables observed at Time i are referred to as the observation vector:

$$X(i) = [x_1(i), x_2(i), \cdots, x_n(i)]^T \tag{1}$$

Under normal operating state of the process or device, m historical observation vectors are collected to construct the memory matrix D, denoted as:

$$\boldsymbol{D} = [\boldsymbol{X}(1) \quad \boldsymbol{X}(2) \quad \cdots \quad \boldsymbol{X}(m)] = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(m) \\ x_2(1) & x_2(2) & \cdots & x_2(m) \\ \vdots & \vdots & & \vdots \\ x_n(1) & x_n(2) & \cdots & x_n(m) \end{bmatrix}_{n \times m}$$

(2)

Each observation vector in the memory matrix represents a normal operating state of the process or device. By selecting m historical observation vectors from an extended period of normal state properly, the subset space spanned by matrix D can be taken to represent the whole dynamic working condition of the process or device. Thus, the construction of memory matrix D is substantially a procedure of learning and memorizing the normal behaviors of the process or device.

During subsequence operation, the input to the MSET at each time step is a new observation vector Xobs and the output from the MSET is a prediction Xest for this input vector for the same moment in time. For each input vector Xobs, MSET will produce an m-dimensional weight vector W

$$\boldsymbol{W} = [w_1 \quad w_2 \quad \cdots \quad w_m]^{\mathrm{T}}$$

(3)

With

$$\boldsymbol{X}_{\mathrm{est}} = \boldsymbol{D} \cdot \boldsymbol{W} = w_1 \cdot \boldsymbol{X}(1) + w_2 \cdot \boldsymbol{X}(2) + \cdots + w_m \cdot \boldsymbol{X}(m)$$

(4)

Equation (4) means that the estimate of MSET is a linear combination of the m historical observation vectors in the memory matrix D. Then the weight vector is calculated and optimized. The residual between MSET estimate and the input is

$$\varepsilon = \boldsymbol{X}_{\mathrm{obs}} - \boldsymbol{X}_{\mathrm{est}}$$

(5)

The weight vector [17, 18] is constructed as follows:

$$W = (D^T \otimes D)^{-1} \cdot (D^T \otimes X_{\mathrm{obs}}) \quad {}_{(0 < \lambda < 1)}$$

(6)

$\otimes$ is a nonlinear operator used to replace the regular multiplying operator in matrix multiplication.

There are many optional nonlinear operators to choose from [19], with the Euclidean Norm (DIST), the City Block Distance (CITY) and the Linear Correlation Coefficient (LCC) being the foremost. In this paper, the nonlinear operator is chosen as the Euclidean distance between the two vectors

$$\otimes(\boldsymbol{X}, \boldsymbol{Y}) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

(7)

When two observation vectors are the same or similar, the distance between the vectors will be zero or near zero. When one vector is very different from the other, the distance between them will be great and the result of the nonlinear operator will be large. The weight vector in (6) reflects the similarities between the MSET input vector Xobs and the m historical observation vectors in the memory matrix D.

With (4) and (6), the final estimate of the MSET model for the process or device is

$$X_{\text{est}} = \boldsymbol{D} \cdot (\boldsymbol{D}^{\text{T}} \otimes \boldsymbol{D})^{-1} \cdot (\boldsymbol{D}^{\text{T}} \otimes X_{\text{obs}})$$

(8)

When the process or device works normally, the input observation vector of MSET is most likely to be located in the normal working space that is represented by the memory matrix D, in that it is similar to some historically measured vectors in the memory matrix. As a result, the estimate of MSET will have a high accuracy. When problems arise with the process or device, its dynamic characteristics will change, and the new observation vector will deviate from the normal working space. In this case, the linear combination of the historical vectors in the memory matrix will not provide an accurate estimate of the input and the residual will increase in magnitude.

4.2. Moving Window Residual Statistical Method
The biggest advantage of the Moving Window Residual Statistical (MWRS) method lies in that it enables distribution of residual to be shown continuously, basing on which whether a variable value is normal or not is judged. Under the same accuracy level, the MWRS method can provide the earliest sign of developing faults. Through this method, the paper eliminates unknown factors and random disturbances (such as transducers' measuring errors) of an operating wind turbine and promotes its reliability as well. By a proper selection of the window's width, the successive residual statistical characteristics are monitored promptly, which improves the stability of the device and deduces the chances that error alarms happen. When an abnormality occurs to the unit, these dynamic models can detect even the slightest changes of parameters, so as to diagnose the faults at a early stage.

If, during a certain period of time, the residual sequence of the gear box's temperature from the MSET model is:

$$\boldsymbol{\varepsilon}_{\text{GT}} = [\varepsilon_1 \quad \varepsilon_2 \quad \cdots \quad \varepsilon_N \quad \cdots]$$

(9)

A time window with width N is adopted to calculate the moving average or mean value and standard deviation for the N successive residuals in the window

$$\overline{X}_i = \frac{1}{N} \sum_{i=1}^{N} \varepsilon_i$$

(10)

Then assume that the residual average fault threshold is E_Y, the maximum of residual average of MSET model under normal condition is E_V, so the fault threshold of gear box EY is:

$$E_Y = \pm k_1 E_V$$

(11)

In this equation, k1 can be chosen based on operating experience.

When the residual of MSET model exceeds a set threshold, an alert will be given to remind the operator of the potential threatens to the gear box's safe operating.

5. Model Construction of Gear Box's Temperature Based on SCADA Data
5.1. Selection of Variables
All of the operating data of wind turbines are recorded in the SCADA system. It is a computer-based system which is aimed to realize the automatic scheduling and planning of working process. By supervising and controlling the devices' state, the SCADA achieves the functions of data acquisition, device controlling, parameter measuring and regulating, and information alerting.

In this paper, the wind turbine is manufactured by Vestas and its concrete parameters are: rated power 0.9MW, cut-in wind speed 3mps, cut-out wind speed 25 mps, rated wind speed 15 mps, over-voltage protection setting value 1.2p.u, low –voltage protection setting value 0.85p.u.. The SCADA records 126 operating parameters and state information every 10 min:

the former includes time tag, active power, reactive power, bearing temperature and oil temperature in gear boxes, cabin temperature, external temperature, fault codes, hydraulic-pressure oil temperature, three stator voltage and current, rotated speed of generator and so on; while the latter consists of start and halt of unit, overheating of generator, pitch system fault, generator fault, frequency-convertor fault, hydraulic-pressure system fault, gear box fault and so on.

Following a review recorded by SCADA, the parameters related to the bearing temperature of a gear box are chosen to construct its observation vector Xobs of MSET.

(1) Active power (P): P is closely related to the bearing temperature of a gear box. When P increases, the load of a gear box will aggrandizes which leads to an increase in the gear box. P is influenced by wind speed, rotated speed of gear box, yaw angle.

(2) Wind speed (u): The variable speed turbines are studied in this paper, which pursue the best usage of wind power by achieving the optimal tip speed ratio. The higher the wind speed is, the faster the gear box rotates, and the higher its temperature will be.

(3) Rotated speed of gear box (U): The gear box has the function to accelerate or decelerate the speed. As U is closely related to turbines' P, a higher U is always accompanied with a bigger P.

(4) Yaw angle (A): The directions of natural winds are changeable and unpredictable. In order to enhance wind power's efficiency, a function as a significant parameter to adjust turbines' direction to meet the wind, this has a profound influence on system's safety and efficiency.

(5) Bearing temperature of gear box (Tgear): Operating under severe working condition and heavy loads for long hours, the bearings of gear boxes are likely to suffer faults and damages. The frequent damages arise mainly from noises, temperature, vibrations, lubrication problems and other bad states.

(6) Oil temperature of gear boxes (Toil): With a temperature sensor in the gear box, the Toil must be higher than 0   (it varies according to the requirements of lubrication oil), and then heated to over 10   to operate. In normal working states, the oil pump continuously ejects oil into gears and bearings. When Toil is higher than 60°C, the oil cooling system starts to function and the heated oil is transmitted to an external exchanger to be cooled by natural wind or water. When Toil is below 45 , the oil cooling loop is cut, and the cooling process stops. The over-heated Toil is always caused by the long hours of full-loaded operating.

(7) Cabin temperature (Tcabin): Tcabin is also a factor that influences the gear box temperature. When Tcabin is too low, the mechanical components can hardly operate properly; while too high a Tcabin will shorten the electric components' life span.

(8) External temperature (Tc): Because the local temperature that the wind turbine experiences changes greatly in the short term (from day to night for example) and in the longer term (weeks to month) due to passing weather systems and seasons it must be taken explicitly into account. Thus, different Tc will produce different gear box temperature.

5.2. SCADA Data Record Analysis

As wind turbines are greatly influenced by external factors (temperature, wind speed etc.), this paper probes into the SCADA data of Jan.2011 of a certain wind turbine. Figure 2 shows the 721 10-minute data from 17:20:00 22nd Jan. 2011 to 17:20:00 27th Jan. 2011.

Tables 1-6 list the SCADA operating records of which the power is less than 0 during this period. In these charts, every fault code is corresponding to a fault reason. The 0 fault code represents no fault. As to the state of the wind turbine, 0 refers to shut-down and 1 means normal operating.

In Table 1, the high-wind fault code is alerted when the wind speed is 23.7 mps and 19.7 mps. But under neither condition does the wind speed reach the cut-in wind speed. The reason lies in that the wind speed is 24.1 mps at 5:20:00 23rd Jan. 2011and reaches 25 mps during 5:20:0 to 5:30:00, which makes the turbine cut out. Because of the self protection and system delay, a 144 fault code is alerted at 5:30:00 and 5:40:00 23rd Jan. 2011.
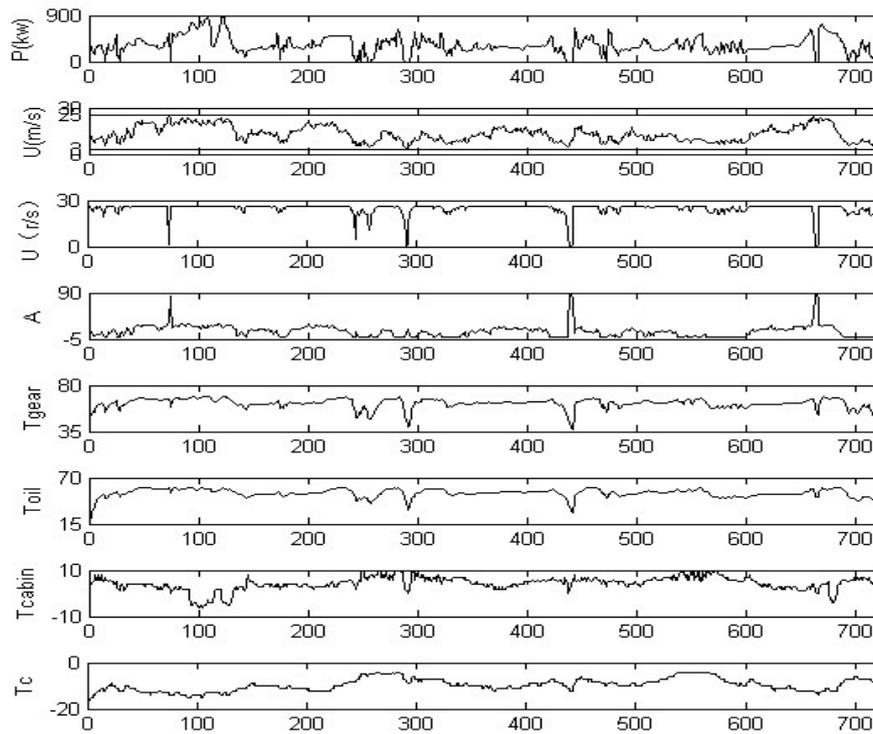
Figure 2. Historical curve from 17:20:00 22 th Jan to 17:20:00 27 th Jan

Table 1. Node specific offline parameter SCADA data records 1

Num	Data	Time	Wind speed	Active power	Fault code	Fault reason
1	2011/01/23	5:20:00	24.1		0	
2	2011/01/23	5:30:00	23.7	11.8	144	Over wind speed
3	2011/01/23	5:40:00	19.7	148.7	144	Over wind speed

Table 2. SCADA data records 2

Num	Data	Time	Wind speed	Active power	Fault code
1	2011/01/24	9:40:00	5.9	-19.7	0
2	2011/01/24	9:50:00	7.9	-22	0

Table 3. SCADA data records 3

Num	Data	Time	Wind speed	Active power	Fault code
1	2011/01/24	11:40:00	5.4	-7.6	0
2	2011/01/24	11:50:00	5.1	-16	0
3	2011/01/24	12:00:00	4.5	-15.1	0

Table 4. SCADA data records 4

Num	Data	Time	Wind speed	Active power	Fault code
1	2011/01/24	17:20:00	4.9	-20.5	0
2	2011/01/24	17:30:00	3.6	-22	0
3	2011/01/24	17:40:00	3.9	-21.2	0
4	2011/01/24	17:50:00	6.9	-21.4	0
5	2011/01/24	18:00:00	6	-3.6	0

From Tables 2-4, we can see that faults codes are 0. It infers that the three shut-downs are caused by manned reasons instead of faults and that is the so-called manned shut-down. Generally speaking, the reason of a manned shut-down is the power grid imposes a limit on the generating amount of wind farms, which stops the normal operating of the turbines. In Table 4, both the wind speeds at 17:30:00 and 17:40:00 24th Jan. 2011 are lower than the cut-in speed and the turbines are not generating.

In Table 5, the first two shut-downs are caused by manned operations and the rest are because that the automatic yawing makes the active power less than 0. Chart 6's fault code 144 is because that the wind speed at 7:30:00 27th Jan. 2011 reaches 24.1 mps, which approximates the cut-out speed and triggers the fault code at the next time due to the system delay.

Table 6 shows that four shut-downs occur from 17:20:00 22nd Jan. 2011 to 17:20:00 27th 2011. All of them are manned shut-downs. In the mean time, there are no gear box faults and repairing records in Jan. and after Jan.

Table 5. SCADA data records 5

Num	Data	Time	Wind speed	Active power	Fault code	Fault reason
1	2011/01/25	17:50:00	5.4	-19.4	0	
2	2011/01/25	18:10:00	4.4	-16.5	0	
3	2011/01/25	18:20:00	5.9	-22	275	Automation yaw
4	2011/01/25	18:30:00	9.3	-21.4	275	Automation yaw
5	2011/01/25	18:40:00	8.6	-21.2	275	Automation yaw
6	2011/01/25	18:50:00	8.9	-3.4	275	Automation yaw

Table 6. SCADA data records 6

Num	Data	Time	Wind speed	Active power	Fault code	Fault reason
1	2011/01/27	7:40:00	22.7	-21.1	144	Over wind speed
2	2011/01/27	7:50:00	21.7	-20.9	144	Over wind speed
3	2011/01/27	8:00:00	22.5	-21.1	144	Over wind speed
4	2011/01/27	8:10:00	20.3	-3	144	Over wind speed

To build the MSET model, operating data of normal state are selected and a process matrix is constructed. We abandon the data of which the power is less than 0, assume the data of which the wind speed is lower than 3 mps is 3mps and the data of which the wind speed is higher than 25 mps is 25 mps. Other data are all from the normal operating information and referred to as the process memory matrix D. The ultimate process memory matrix D consists of 685 observation vectors. After constructing the D, we can predict the new input observation vector of MSET temperature model using Equation 8.

5.3. Construction And Checking of The Model

669 historical operating data from 17:20:00 22nd Jan. 2011 to 17:20:00 27th Jan. 2011 confirm the correctness of the MSET model. During this period, the maximum and minimum values of gear box bearings' temperature are 70℃ and 50℃ respectively.

In this paper, the first 500 data are chosen to construct the matrix D, and the bearing temperature column of the rest 199 data is chosen to be the input Xobs. The first picture of Figure 3 is the observed value and estimate curve through simulation test, and the second picture shows the residuals between observed value and estimate value.

Using the moving window statistical method to further analyze the residuals above, we conclude its characteristics curve as Figure 4. We assume the window width N=20 and calculate the threshold Ev's value. The maximum absolute residual value is 0.493 (k1=3, $E_Y = \pm 1.479$).

5.4. Simulation Test of Early Diagnostic Alert

After the construction and correctness checking of MSET model, we add the temperature offset to imitate the situation when a gear box fault leads to its temperature increase. Starting from Point 51, a step temperature offset of 0.25 is added to the 199 data.

Figure 5 is the estimate simulation result of MSET model with temperature offsets added in. The first picture is the comparison of observed value and estimate value and the second is its residual curve. From the second picture's curve, we can see that the errors at the first 50 points are very small, while it increases gradually from the 51st point, and the deviations are mainly the temperature offsets.
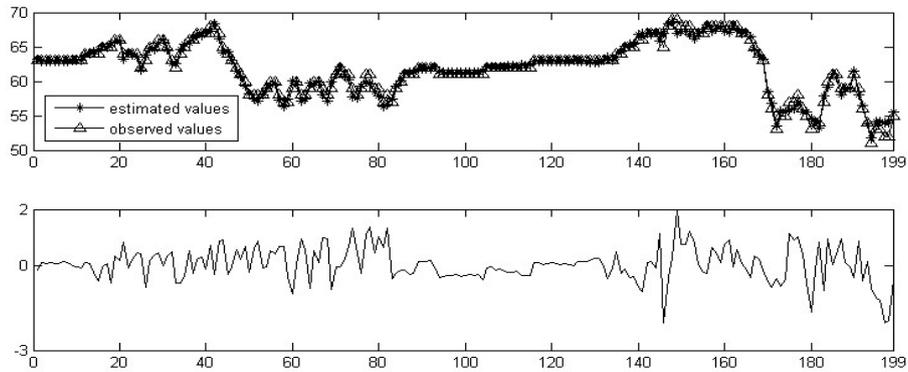

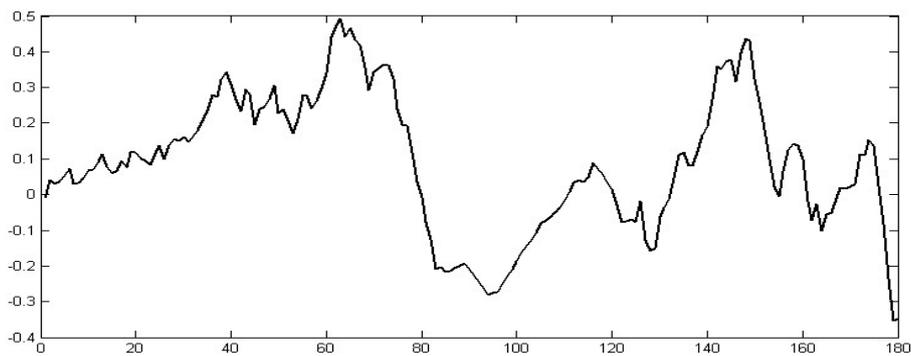Figure 3. Curves of observed value and estimate value and residual

Figure 4. Residual's moving window statistical characteristics
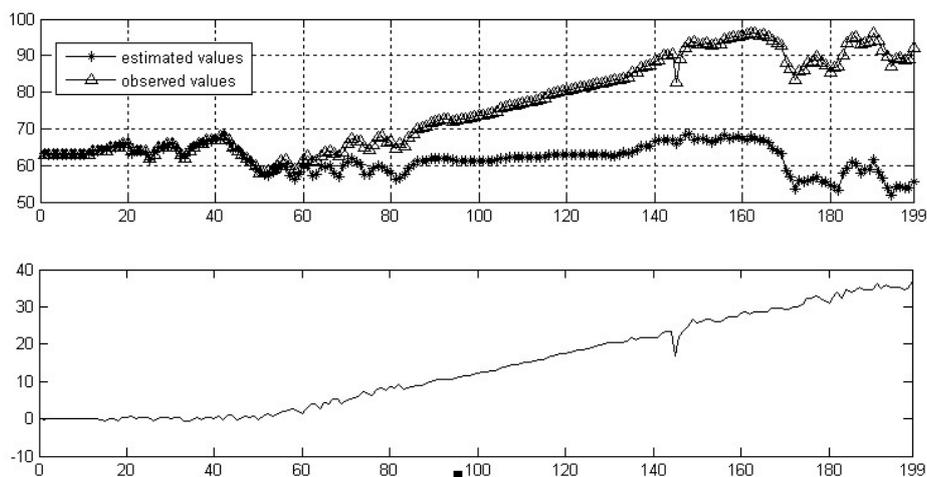
Figure 5. Estimate results with temperature added

Then the residuals after temperature offsets are taken into account and a simulation test is conducted based on the moving window statistical method. We assume the window width N=10, and its characteristics curve is shown in Figure 6.
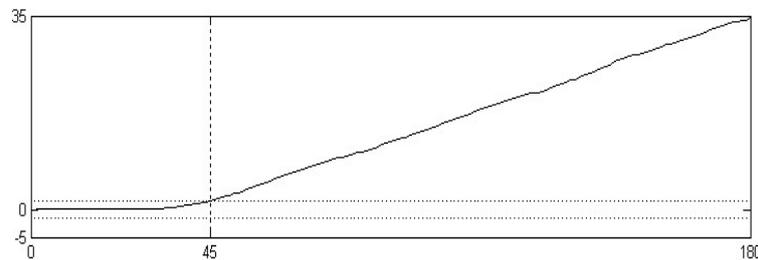

Figure 6. Residual moving window statistical characteristics curve after temperature offset

In Figure 6, after added with manned offsets and processed by moving window statistical method, the residual curve of bearing temperature increases constantly, and overtops its up threshold at Point 45, which triggers the early fault alert. The distance between this point and the first point at which manned offset is added (Point 51) is 45+20-51=14(20 refers to the window width). Thus, at the 65th (51+14=65) point, we can detect the abnormal acts of gear box's bearing temperature. As to Point 65, we can also calculate the deviation between original state and manned-offsetting state according to temperature offset steps and bearing temperature, that is 14*0.25=3.5 .
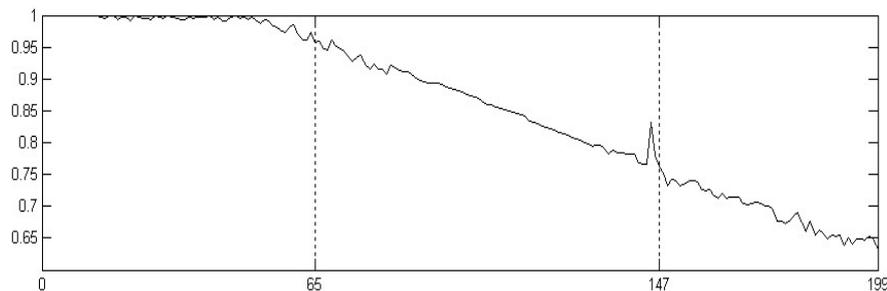

Figure 7. Similarity curve with temperature offset

Figure 7 shows the bearing temperature's similarity curve after manned offsets have been added in. We can tell that the similarity at Point 65 is 0.96, and the similarity at Point 147 is 0.76. A small similarity stands for an abnormal act of turbines' operation. In Figure 8, considering the manned offsets, the whole temperature curve are divided into three parts----normal operating state, device early warning state and alerting state. When the gear box is working normally and its temperature residual does not exceed the mean threshold, the turbine is in the normal operating state. When the residual exceeds the threshold, it will be in the early warning state. When device's temperature overtops the maximum value set by its manufacturer, an alert will occur (The normal operating temperature of this type of wind turbine: $T_{gear} \leq 91$). In Figure 7, at Point 147, the bearing temperature reaches 92.25 , which exceeds the maximum operating value and triggers the system alert. If the turbine moves on without taking necessary measures, the gear box will be damaged and the unit will not function properly and regularly.
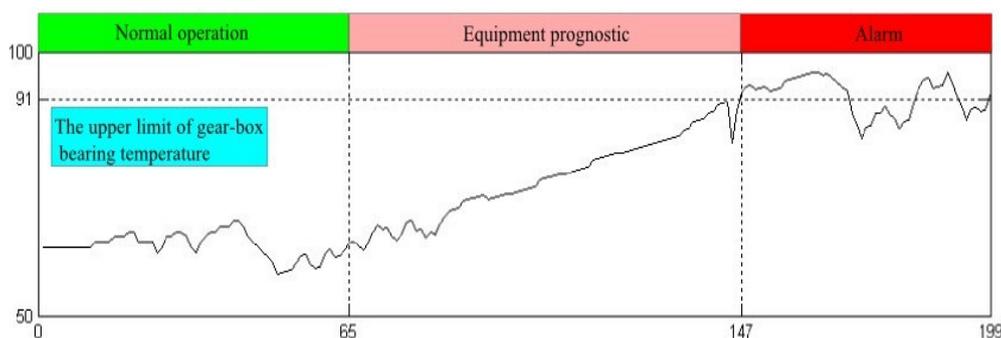
Figure 8. The prognostic system

6. Conclusion

Being simple in modeling algorithm and clear in physical meaning, the Nonlinear Multivariate State Estimate Technique (NMSET) is very appropriate for a complex and random process. By adopting the NMSET and selecting the proper variables related to the gear box temperature, this paper constructs a process memory matrix and a MSET model based on SCADA data. Compared with the neural network algorithm, this non-parameter construction method has clearer physical meanings and saves the training time. When a fault occurs to gear boxes and its temperature deviates from the normal value, the residual distribution of its MSET model will change accordingly. We can easily judge the current state of gear boxes just by calculating the trends of residual mean values and standard deviation and then comparing them with the setting thresholds. The effectiveness and correctness of this method is then confirmed by simulation tests and fault analysis. Finally, the Moving Window Statistical Characteristics technique can eliminate uncertainties and random disturbances (such as the sensor's measuring error) so as to improve the reliability of monitoring and early fault diagnosing.

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