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Chaotic eye-based fault forecasting method for wind power systems

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Her-Terng Yau ✉, *Meng Hui Wang*

Department of Electrical Engineering, National Chin-Yi University of Technology, 35, 215 Lane, Sec. 1, Chung Shan Road, Taiping, Taichung City, Taiwan

✉ *E-mail: pan1012@ms52.hinet.net*

Abstract: This study proposes a method for detecting possible faults in wind turbine systems in advance such that the operating state of the fan can be changed or appropriate maintenance steps taken. In the proposed method, a chaotic synchronisation detection method is used to transform the vibration signal into a chaos error distribution diagram. The centroid (chaotic eye) of this diagram is then taken as the characteristic for fault diagnosis purposes. Finally, a grey prediction model is used to predict the trajectory of the feature changes, and an extension theory pattern recognition technique is applied to diagnose the fault. Notably, the use of the chaotic eye as the fault diagnosis characteristic reduces the number of extracted features required, and therefore greatly reduces both the computation time and the hardware implementation cost. From the experimental results, it is shown that the fault diagnosis rate of the proposed method exceeds 98%. Moreover, it is shown that for oil leaks in the gear accelerator system, the proposed method achieves a detection accuracy of 90%, whereas the multilayer neural network method achieves a maximum accuracy of just 80%.

1 Introduction

The public has begun to pay attention to environmental protection with rising environmental awareness. The green energy is one of the solutions to reduce environmental pollution [1]. Wind power generation, photovoltaic power generation and fuel cell of regenerative energy are very popular research areas. The total installed capacity of global wind power has increased greatly with 6700 MW in 1966 to 237 669 MW in 2013 as shown in Fig. 1. The research and development of wind power have attracted great attention [2].

The fault occurrence probability of any power generation system increases after a long-term operation. The wind turbines are expensive [3, 4]. According to the data of Swedish wind power plants during 1997–2005, the easily breakable parts of wind power generators should be maintained more closely, and the average annual total hours of shutdown for repair and maintenance of wind power plants is considerable, thus affecting the benefit of wind power significantly [5].

Most existing fault diagnosis methods for wind turbines monitor the vibration or current signal, analyse the intercepted normal and fault signals, and apply some form of artificial intelligence algorithm to perform smart fault diagnosis. However, traditional wavelet analysis [6], neural network [7] and fuzzy theory [8] methods are impractical for real-time fault diagnosis. Although the wavelet analysis performs well in the analysis of vibration signal converted from time domain into frequency domain, besides wavelet decomposition for the intercepted signal, it shall find out the frequency band corresponding to the fault feature point according to Fourier transform, so as to find out the corresponding fault. Similarly, neural networks require a large number of training samples and involve a lengthy learning process. Finally, fuzzy theory methods cannot determine a robust set of fuzzy logic rules without a large volume of historical data, and consequently a large number of ends occur in the fault identification process.

It is important to design a system that can extract features of operating signals based on the system operation status, forecast the trend of features, forecast the fault state, send the analytical result to the control centre through wireless communication network [9, 10] in a short period of time for maintenance, adjusting the operating mode, preventing the wind power generator from accidents, ensuring the system a safe operation, increasing the management efficiency and reducing the operating and maintenance costs. As the wind electric power generation attracts more attention, an increasing number of fault detection systems has been used on wind electric power generation, with more functions, even troubleshooting of external problems. For example, the offshore wind power generation system can eliminate the vibration resulted from the seawater impact [11]. Although the recognition accuracy is high, the fault system is only applicable to distinguishing the state. The lifetime of wind turbine is shortened, when the machine is damaged because of faults. Therefore, this paper adopts grey prediction to prevent major faults, so as to prolong the lifetime of machine. The grey prediction method has been widely used for forecasting purposes in previous studies on wind turbine systems. Grey models can be used to predict wind speed and wind power [12–15]. It is also that the grey mode was improved to reduce the prediction error [16]. In the present paper, the grey prediction method is used to forecast the occurrence of faults. Most existing fault diagnosis systems for wind turbine power generation systems increase or decrease the number of sensors in accordance with the number of characteristics required by the diagnostic system to discern the faults. Thus, for diagnostic systems based on a large number of characteristics, the number of sensors increases and hence the hardware implementation cost also rises [17]. Recently, the concept of chaos synchronisation had successfully applied to fault diagnosis systems, such as photovoltaic systems [18], power quality systems [19] and gas insulated switchgear systems [20] and so on. Accordingly, in this paper, a chaotic synchronisation-based detector module is used to transform the main characteristic data of the system (i.e. the system vibration signal) into a chaos error distribution diagram, and the two centroid points (chaotic eyes) of this diagram are then taken as the fault detection characteristics. As a result, the fault diagnosis system can be implemented using just one sensor, and consequently the hardware cost is significantly reduced. Moreover, the grey prediction method requires very little information for forecasting purposes. By contrast, neural network methods require a large volume of historical data and a long learning time in order to ensure a reliable prediction result.

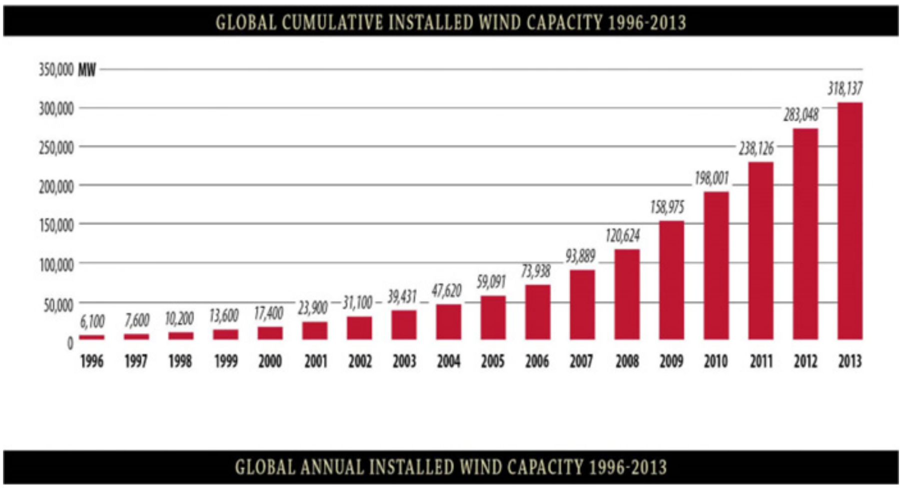

Fig. 1 *Total capacity of global wind power electric generating units during 1996–2013*

2 Design of experiment platform

The wind power experiment platform designed in the laboratory was used for this paper as shown in Fig. 2. The electric and mechanical signals of wind turbine were captured by sensors, transmitted through the Ethernet to the signal processing unit of remote monitoring computer [21–23]. The characteristic signal acquisition unit extracted applicable characteristics, and the signal data were stored in the database. The fault forecasting model was built using the data. The process of the fault diagnosis is shown in Fig. 3, including signal processing, feature extraction, characteristic trajectory forecast and fault diagnosis modules.

3 Model development

3.1 Chaotic synchronisation detection method

Meteorologist Norton Lorenz proposed the Chaos Theory in 1963 [24]. This theory is of research on unsteady behaviour of non-linear dynamic system. The chaotic synchronisation proposed in 1990 is a theory using a type of chaotic signal to control another type of chaotic signal and synchronising the two signals at last [25]. After that, many methods have been presented for the control and synchronisation of chaotic systems: see the papers [26–28] and the references therein. The two synchronous chaotic systems are called master system and slave system. When the initial values of master and slave systems are different, the operation trajectories of the two chaotic systems also differ. Thus, a controller has been affixed to the back end of slave system to track the master system. In this paper, the chaotic trajectory is used for detection of system signals. The master and slave chaotic systems are shown as (1) and (2).

Master

$$\begin{cases} \dot{x}_1 = F_1(x_1, x_2, x_3, \ldots, x_n) \\ \dot{x}_2 = F_2(x_1, x_2, x_3, \ldots, x_n) \\ \vdots \\ \dot{x}_n = F_n(x_1, x_2, x_3, \ldots, x_n) \end{cases} \tag{1}$$

Slave

$$\begin{cases} \dot{y}_1 = F_1(y_1, y_2, y_3, \ldots, y_n) + u_1 \\ \dot{y}_2 = F_2(y_1, y_2, y_3, \ldots, y_n) + u_2 \\ \vdots \\ y_n = F_n(y_1, y_2, y_3, \ldots, y_n) + u_n \end{cases} \tag{2}$$

where F_i ($i = 1, 2, \ldots, n$) is a non-linear function, (1) and (2) form the

Fig. 2 *Experiment platform for wind power generation system of this paper*

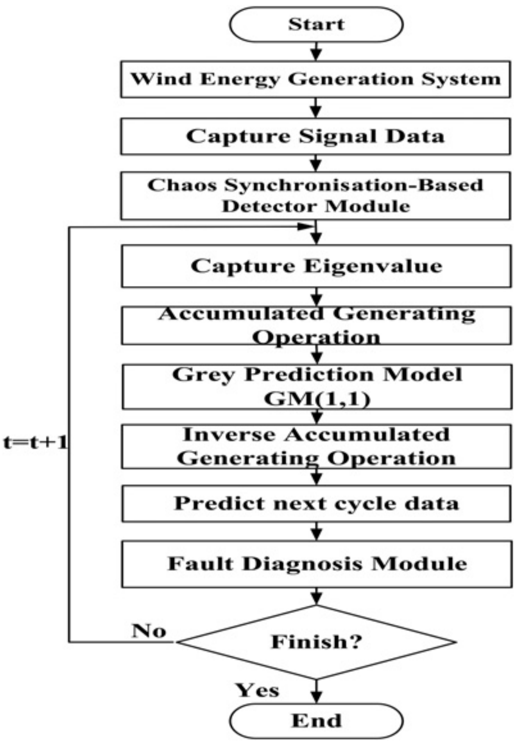

Fig. 3 *Overall program flowchart*

error state as (3). The dynamic error is as (4)

$$e_1 = y_1 - x_1,\ e_2 = y_2 - x_2,\ \ldots,\ e_n = y_n - x_n \tag{3}$$

$$\begin{cases} \dot{e}_1 = F_1(x_1, x_2, x_3, \ldots, x_n) - F_1(y_1, y_2, y_3, \ldots, y_n) + u_1 = G_1 \\ \dot{e}_2 = F_2(x_1, x_2, x_3, \ldots, x_n) - F_2(y_1, y_2, y_3, \ldots, y_n) + u_2 = G_2 \\ \vdots \\ \dot{e}_n = F_n(x_1, x_2, x_3, \ldots, x_n) - F_n(y_1, y_2, y_3, \ldots, y_n) + u_n = G_n \end{cases} \tag{4}$$

where G_i ($i = 1, 2, \ldots, n$) is a non-linear equation, and the dynamic error equation is of chaotic system. The kinematic trajectory of attractor of chaos phenomenon, which is used in this paper, is mostly used to study various system operation states, such as the behaviours of periodic, non-periodic and random signal time-domain states. Therefore this paper uses chaotic dynamic error equation to recognise the system state. The dynamic error should be multiple data; the data mode is expressed as (5)

$$\begin{cases} \dot{e}_1[j] = & \dot{y}_1[j] & -\dot{x}_1[j] \\ \dot{e}_2[j] = & \dot{y}_2[j+1] & -\dot{x}_2[j+1] \\ \vdots & \vdots & \vdots \\ \dot{e}_n[j] = & \dot{y}_n[j+n-1] & -\dot{x}_n[j+n-1] \end{cases}, \quad j = 1, 2, 3, \ldots, j - n \tag{5}$$

The controller equalises the trajectories of two chaotic systems simultaneously. This tracking state is chaotic synchronisation, as expressed by (6)

$$\lim_{t\to\infty} \|y_i(t) - x_i(t)\| = 0, \quad i = 1, 2, \ldots, n \tag{6}$$

Two Lorenz chaotic systems are taken as examples in this paper. One is the master system, and the other one is the slave system, expressed as (7) and (8). The dynamic error state equation is established and expressed in matrix form as (9)

$$\text{Master:} \begin{cases} \dot{x}_1 = \alpha(x_2 - x_1) \\ \dot{x}_2 = \beta x_1 - x_1 x_3 - x_2 \\ \dot{x}_3 = x_1 x_2 - \gamma x_3 \end{cases} \tag{7}$$

$$\text{Slave:} \begin{cases} \dot{y}_1 = \alpha(y_2 - y_1) + u_1 \\ \dot{y}_2 = \beta y_1 - y_1 y_3 - y_2 + u_2 \\ \dot{y}_3 = y_1 y_2 - \gamma y_3 + u_3 \end{cases} \tag{8}$$

$$\text{Error state:} \begin{cases} e_1 = y_1 - x_1 \\ e_2 = y_2 - x_2 \\ e_3 = y_3 - x_3 \end{cases} \tag{9}$$

$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \\ \dot{e}_3 \end{bmatrix} = \begin{bmatrix} -\alpha & \alpha & 0 \\ \beta & -1 & 0 \\ 0 & 0 & -\gamma \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} + \begin{bmatrix} 0 \\ -y_1 y_3 + x_1 x_3 \\ y_1 y_2 - x_1 x_2 \end{bmatrix} \tag{10}$$

According to [25], we let $u_i = 0$ and the suitable parameter's values are selected to guarantee the error dynamics system is attracted in a bounded region in (10).

3.2 *Forecast method*

The Grey Theory, proposed in 1982, uses a small volume of historical data for modelling, thus reducing the computing speed of database and prediction algorithm [29, 30]. This paper uses the historical operating data built by the monitoring system to predict the types and potential symptoms of system faults according to a small amount of operating information. This grey prediction method can provide information onto maintain or change the parts which are about to be damaged ahead of time, and to protect the system against heavier damage.

The Grey Theory has been used to define (11). It is the differential equation of grey GM (1,1) model

$$\frac{\mathrm{d}e_i}{\mathrm{d}t} + ae_i = b \tag{11}$$

where t is the independent variable of system; a and b are the undetermined parameters of grey model (a is the development coefficient and b is the grey control variable), e_i is the value of accumulated generating. This grey prediction modelling can be divided into parametric type and matrix type. The matrix form is used in this paper to build this model. The modelling procedure is expressed as the following equations.

Step 1: A set of sequence is captured using (11) in the initial forecast of the system as original sequence; when a cycle is finished, the system captures a set of sequence in the data again each time as new original sequence. Equation (12) is the original sequence ($e_i^{(0)}$) of forecast modelling

$$e_i^{(0)} = (e_i^{(0)}(1), e_i^{(0)}(2), \ldots, e_i^{(0)}(k)) \quad k = 1, 2, 3, \ldots, m; \quad m \in N \tag{12}$$

Step 2: The originally disorderly and irregular data are processed by accumulated generating operation to obtain a set of new and relatively regular sequence, the accumulated generating expression. Equation (13) shows the new sequence ($e_i^{(1)}$)

$$e_i^{(1)} = \left(\sum_{L=1}^{1} e_i^{(0)}(L), \sum_{L=1}^{2} e_i^{(0)}(L), \ldots, \sum_{L=1}^{n} e_i^{(0)}(L) \right) L \in N \tag{13}$$

Step 3: The average generation can adjust the weights of data, the weight α varies with the root loci; expressed as (14)

$$z^{(1)}(L) = \alpha * e_i^{(1)}(L) + (1-\alpha) * e_i^{(1)}(L-1)\ L > 1; \quad L \in N \tag{14}$$

Step 4: The undetermined coefficients a and b of GM (1,1) are worked out, the least square is used to determine the ranges of the two values, expressed as (15)

$$e_i^{(0)}(L) + az^{(1)}(L) = b\ L \in N \tag{15}$$

Equation (15) is converted into matrix equation (16), the parameters $\boldsymbol{H}$, $\boldsymbol{B}$ and $\hat{\boldsymbol{a}}$ are expressed as (17)–(19)

$$\boldsymbol{H} = B * \hat{a} \tag{16}$$

$$\boldsymbol{H} = \begin{bmatrix} e_i^{(0)}(2) \\ e_i^{(0)}(3) \\ e_i^{(0)}(4) \\ \vdots \\ e_i^{(0)}(L) \end{bmatrix} \tag{17}$$

$$\boldsymbol{B} = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ -z^{(1)}(4) & 1 \\ \vdots & \vdots \\ -z^{(1)}(L) & 1 \end{bmatrix} \tag{18}$$

$$\hat{\boldsymbol{a}} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^{\mathrm{T}}B)^{-1}B^{\mathrm{T}}H \tag{19}$$

The parameters a and b of (19) can be worked out by (20) and (21)

$$a = \frac{\sum_{L=2}^{n} z^{(1)}(L) * \sum_{L=2}^{n} e_i^{(0)}(L) - (n-1) * \sum_{L=2}^{n} z^{(1)}(L) e_i^{(0)}(L)}{(n-1) * \sum_{L=2}^{n} [z^{(1)}(L)]^2 - \left[\sum_{L=2}^{n} z^{(1)}(L)\right]^2} \tag{20}$$

$$b = \frac{\sum_{L=2}^{n} [z^{(1)}(L)]^2 * \sum_{L=2}^{n} e_i^{(0)}(L) - \sum_{L=2}^{n} z^{(1)}(L) * \sum_{L=2}^{n} z^{(1)}(L) e_i^{(0)}(L)}{(n-1) * \sum_{L=2}^{n} [z^{(1)}(L)]^2 - \left[\sum_{L=2}^{n} z^{(1)}(L)\right]^2} \tag{21}$$

Step 1: When parameters a and b are obtained, the prediction value of accumulated generating is shown as (22)

$$\hat{e}_i^{(1)}(L+1) = \left(e_i^{(0)}(1) - \frac{b}{a}\right)\mathrm{e}^{-aL} + \frac{b}{a}\ L \in N \tag{22}$$

Step 2: The value of grey prediction is obtained by IAGO; expressed as (23)

$$\begin{cases} \hat{e}_i^{(0)}(k) = \hat{e}_i^{(1)}(k), & k = 1 \\ \hat{e}_i^{(0)}(k+1) = \hat{e}_i^{(1)}(k+1) - \hat{e}_i^{(1)}(k), & k > 1 \end{cases} \tag{23}$$

3.3 Extension theory

This paper used the extension theory to deduce an algorithm for fault forecasting. The extension theory was proposed by Tsai (1983), who studied the law and methods for solving contradictory problems quantitatively and qualitatively [31]. The matter-element model and extension set were used to quantify things. The correlativity was used for planning, so that the information of things can be extracted easily. The matter-element theory and extension set are two main cores of the extension theory. The matter-element theory concerns the matter-element extensibility and matter-element transformation properties. The extension set aims at the probability of things change. The matter-element transformation transforms matter and quantity for solving problems and contradictions [18]. The extension set uses extension model and fuzzy mathematics to handle contradictory and incompatible problems. The range of fuzzy set is extended from $\langle 0,\ 1\rangle$ to $\langle -\infty,\ \infty\rangle$. Fig. 4 is the schematic diagram of fuzzy set and extension set.

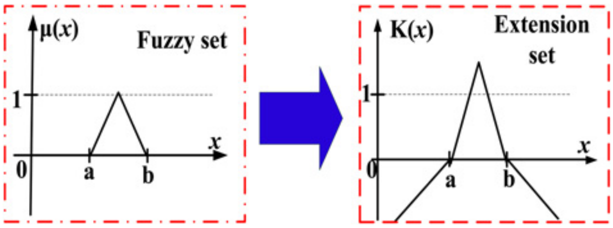

Fig. 4 *Schematic diagram of fuzzy set and extension set*

The extension theory refers to various persons, affairs and objects in daily life 'thing', and expresses them as 'thing name'. Various things have differently described patterns and types, and the participators corresponding to thing occurrence are called 'thing characteristics'. The thing characteristics have corresponding 'characteristic quantity values'. Therefore, in order to elaborate the matter-element of a thing, there should be three elements, including thing name N (Name), thing characteristic C (Characteristic) and characteristic quantity value V (Value). Equation (24) is the mathematical expression of matter-element, the specific evaluation procedure of extension theory is described below

$$R = (N,\ C,\ V) \tag{24}$$

Step 1: The ranges of extension classical domain and joint domain are expressed as (25) and (26)

$$R_k = (N_k,\ C_i,\ E_{ki}) = \begin{bmatrix} N_k & c_1 & \langle a_{k1},\ b_{k1}\rangle \\ & c_2 & \langle a_{k2},\ b_{k2}\rangle \\ & \vdots & \vdots \\ & c_n & \langle a_{kn},\ b_{kn}\rangle \end{bmatrix} \tag{25}$$

$$k = 1,\ 2,\ \ldots,\ m$$

$$R_P = (N_p,\ C_i,\ e_{pi}) = \begin{bmatrix} N_p & c_1 & \langle a_{p1},\ b_{p1}\rangle \\ & c_2 & \langle a_{p2},\ b_{p2}\rangle \\ & \vdots & \vdots \\ & c_n & \langle a_{pn},\ b_{pn}\rangle \end{bmatrix} \tag{26}$$

Step 2: Import the matter-element to be tested, expressed as (27)

$$R_t = (q,\ C_i,\ e_{ti}) = \begin{bmatrix} q & c_1 & e_{t1} \\ & c_2 & e_{t2} \\ & \vdots & \vdots \\ & c_n & e_{tn} \end{bmatrix} \tag{27}$$

Step 3: The weight coefficient of each characteristic is stipulated according to the importance, expressed as (28)

$$\sum_{i=1}^{n} w_i = 1 \tag{28}$$

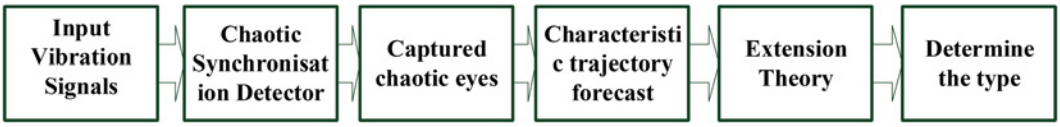

Fig. 5 *Experimental flow of the fault forecasting for wind power systems*

Step 4: The value of correlation grade between the data to be tested and various level sets is calculated as (29)

$$k_k(e_i) = \begin{bmatrix} \dfrac{-\rho(e_i,\, X_{ki})}{|X_{ki}|}, & e_i \in E_{ki} \\ \dfrac{\rho(e_i,\, X_{ki})}{\rho(e_i,\, X_{pi}) - \rho(e_i,\, X_{ki})}, & e_i \notin E_{ki} \end{bmatrix} \tag{29}$$

where the distance between characteristic e_i and each classical domain R_k is defined as (30), the distance between characteristic e_i and joint domain R_P is defined as (31)

$$\rho(e_i,\, E_{ki}) = \left| e_i - \frac{a_{ki} + b_{ki}}{2} \right| - \frac{b_{ki} - a_{ki}}{2} \tag{30}$$

$$\rho(e_i,\, E_{pi}) = \left| e_i - \frac{a_{pi} + b_{pi}}{2} \right| - \frac{b_{pi} - a_{pi}}{2} \tag{31}$$

Step 5: Calculate the correlation grade between input matter-element and various classes

$$\beta_k(q) = \sum_{i=1}^{n} w_i k_k(x_i), \quad k = 1,\, 2,\, \ldots,\, m \tag{32}$$

Step 6: correlation grade normalisation: The relative value of correlation grade of various level sets is calculated, the normalised equation of (33) is used to make the correlation grade values of various level sets in $\langle 1,\, -1 \rangle$

$$\beta_k'(q) = \frac{2\beta_k(q) - \beta_k(q)_{\min} - \beta_k(q)_{\max}}{\beta_k(q)_{\max} - \beta_k(q)_{\min}} \tag{33}$$

Step 7: Determine the type of evaluated matter-element. If $\beta_r'(q)$ equals to 1, the undetermined matter-element is of No. r type, the correlation of other types is measured by correlation grade.

4 Results and discussion

This paper used Lorenz chaotic as master and slave systems. The parameters in the chaos system are selected as $\alpha = 10$, $\beta = 28$ and $\gamma = 8/3$. The GM(1,1) mode of Grey Theory was used to predict the error dynamic states. By capturing the errors e_i from the master system x_i and the slave system y_i. In this paper of the wind power system, the amount of vibration was captured to enter the slave system, thereby the amount of errors were captured between master and slave system as the characteristic of system. Seven types of faults were diagnosed in the operation of wind power generation system. Fig. 5 shows the flow of the fault forecasting for wind power systems on this experimental. The fault types included are normal, one blade damaged, two blades damaged, 30% of oil spills in gear accelerator, 50% of oil spills in gear accelerator, 70% of oil spills in gear accelerator and 90% of oil spills in gear accelerator. This paper used sensors to capture the gear case vibration value, generator vibration value and gear case oil temperature of wind turbine. The values of the three primary characteristics were stored in the database. When the three primary characteristics were formed into chaos error distribution diagram by chaotic synchronisation-based detector module, the centroid (chaotic eye) was used as characteristic. The distribution diagram formed of a primary characteristic had two centroids (chaotic eyes), and the values of X-axis and Y-axis of the centroids were recorded. Thus, there were 12 sub-characteristics. The centroid (chaotic eye) of chaos error distribution diagram was forecast using Grey Theory; and then the extension diagnostic method was used to diagnose the present fault point situation and the forecast fault point situation of the power generation system. This paper used the LabVIEW to design the man–machine interface.

This paper used sensors to capture the data in different conditions, and stored them in the database, where 10 000 data in the database were used as modelling data. The classical domain and joint domain of the extension matter-element model were set using the modelling data. In addition, 5000 data were used for test. To detect subtle change in the system, this paper imported the original data into the chaotic synchronisation-based detector module to form chaos error distribution diagram. However, as there were many error distribution points in the diagram, this paper used the centroid (chaotic eye) of diagram as the characteristic of fault diagnosis to set the characteristics range effectively and reduce the quantity of extracted features. Fig. 6 shows the signal waveform of gear case vibration. The chaotic synchronisation-based detector module read 1000 data each time, and different fault conditions form different chaotic distribution diagrams. Fig. 7 is the chaotic distribution diagram of gear case vibration value at different oil levels of gear accelerator. Fig. 7*a* shows the normal state, Fig. 7*b* shows 50% of oil spills in gear accelerator and Fig. 7*c* shows 90% of oil spills in gear accelerator. The red triangles represent the centroids (chaotic eyes) of X-axis positive field and negative field. Fig. 8 is the chaotic distribution diagram of generator vibration value in blade fault state and in normal state. Fig. 8*a* shows the normal state and Fig. 8*b* shows blade failed.

This paper used grey prediction to predict the centroid (chaotic eye) of chaotic distribution diagram. The next cycle centroid was predicted according to the root locus of change in the centroid of chaotic distribution diagram, so as to predict the situation of next cycle. This paper used 5000 testing data in the database for prediction. The case of 90% of oil spills was predicted according to the data of normal, 30% of oil spills, 50% of oil spills and 70% of oil spills, so as to prove the feasibility and accuracy of grey

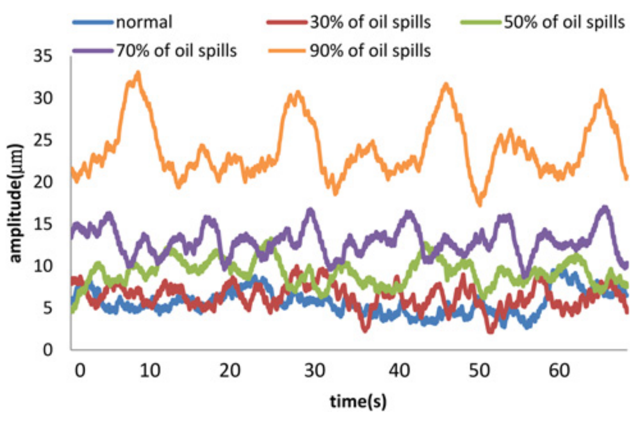

Fig. 6 *Measured vibration signal of oil spill in gear case*

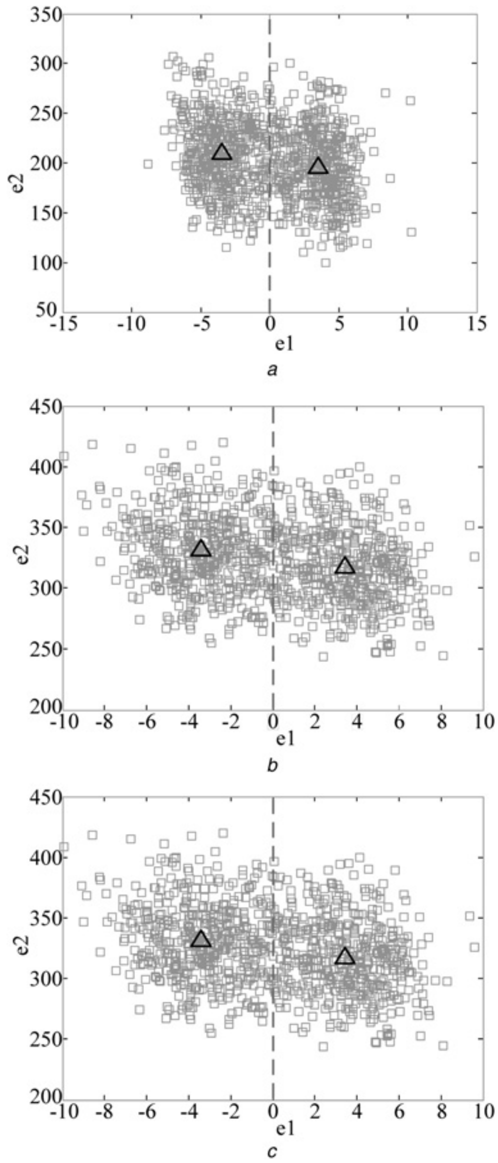

Fig. 7 *Chaotic distribution diagram in different blade fault conditions*

a Normal state
b 50% of oil spills in gear accelerator
c 90% of oil spills in gear accelerator

prediction. Fig. 9 is the curve diagram of real centroid fault trajectory and forecast trajectory. As seen, the method proposed in this paper can predict the trend of fault occurrence effectively and accurately for prevention.

In the test of fault diagnosis and forecasting, the chaotic distribution diagram formed 10 000 data of various characteristics (gear case vibration value, generator vibration value, gear case oil temperature etc.) in the database. The classical domain and joint domain in each condition were set, and the extra 5000 data in the database were used for test. The results proved that the accuracy rate of extension theory is as high as 98.8%. In the present paper, the fault diagnosis accuracy of the proposed system was compared with that of a multilayer feed-forward neural network [32]. Tables 1 and 2 show the accuracy rates of the various fault diagnosis methods and its forecasting methods. It is seen that the multilayer neural network scheme achieves a maximum accuracy rate of 80%. However, the proposed scheme has a maximum accuracy of 90%. We also try to obtain the optimised parameters by trial and error for obtaining better accuracy. Tables 1 and 2 show that the multilayer neural network with the (12-10-7) configuration yields the highest accuracy of the various neural network schemes.

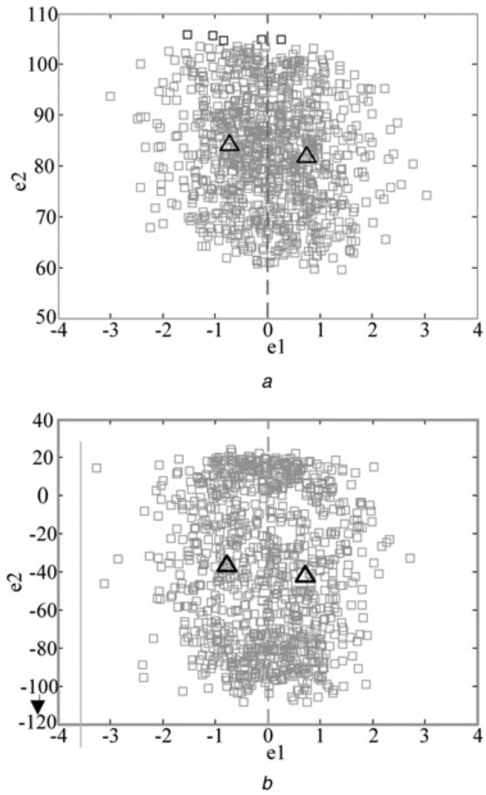

Fig. 8 *Chaotic distribution diagram in different blade fault conditions*

a normal state
b blade failed

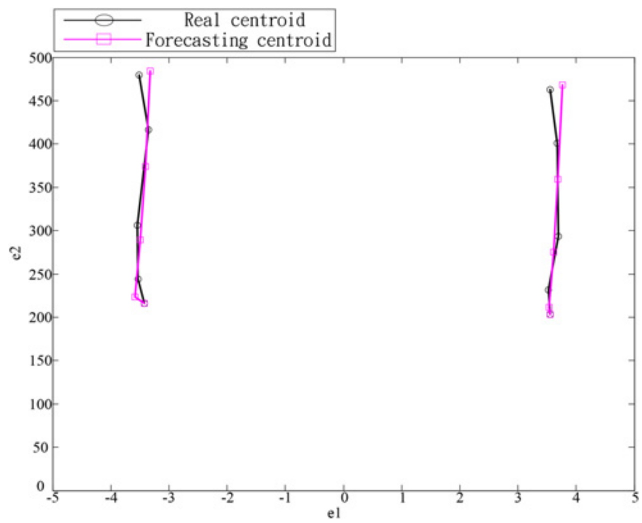

Fig. 9 *Trajectories of forecasting and real centroids*

Table 1 Accuracy rates of various fault diagnosis methods

Testing method	Learning times	Learning accuracy rate, %	Test accuracy rate, %
method proposed in this paper	n/a	n/a	98.8
K-means clustering method	n/a	76.91	61.35
multilayer neural network I (12-9-7)	1000	83.28	77.81
multilayer neural network II (12-10-7)	1000	84.53	79.72
multilayer neural network III (12-11-7)	1000	82.43	75.22

Table 2 Accuracy rates of various fault forecasting methods

Method	Fault forecasting accuracy rate, %
method proposed in this paper	90.4
K-means	67
multilayer neural network (12-9-7)	81
multilayer neural network (12-10-7)	82
multilayer neural network (12-11-7)	79

5 Conclusions

This paper has proposed a fault diagnosis method for wind turbine systems based on chaos theory, the Grey prediction method and an extension theory pattern recognition technique. In the proposed method, a chaotic synchronisation-based detector module is used to transform the system vibration signal into a chaos error distribution diagram. Notably, the chaos error distribution diagram is constructed using the signal obtained from just one sensor. Consequently, both the computation time and the hardware implementation cost are significantly reduced. Having identified a potential fault in the system state, Grey theory is used to predict the actual occurrence of this fault in the future. Finally, extension theory is applied to determine the specific nature of the fault. Importantly, the proposed method enables potential faults to be identified in advance such that appropriate steps can be taken to ensure the continued safe operation of the system. The experimental results show that the proposed method achieves a successful fault diagnosis rate of more than 98%, and therefore outperforms the traditional *K*-means and multilayer neural network methods with recognition rates of 61.35 and 79.72%, respectively. Furthermore, in detecting oil leaks in the gear accelerator system (one of the most common faults in practical wind turbine systems), the proposed scheme achieves an accuracy rate of 90%, whereas the multilayer neural network scheme has an accuracy rate of just 80%.

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