IOP Conference Series: Materials Science and Engineering

PAPER • OPEN ACCESS

Method on condition assessment of pitch system based on fuzzy matter-element analysis

To cite this article: Shuangxi Zhao *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **592** 012092

Method on condition assessment of pitch system based on fuzzy matter-element analysis

Zhao Shuangxi[1], Zhang Lei[2], Hou Lijun[3], Xiao Cheng[2,4,a] and Zhu Xipan[2]

[1] REsource Electric Tianjin Ltd, Tianjin 300380, P. R. China
[2] School of Artificial Intelligence, Hebei University of Technology - Tianjin 300130, China
[3] RENergy Electric Tianjin Ltd, Tianjin 300380, P. R. China
[4] School of Electronics and Control Engineering, North China Institute of Aerospace Engineering, Langfang 065000, P. R. China

[a] E-mail: xiaocheng1130@163.com

Abstract. In order to improve the real-time reliability of wind turbine and solve the effect of artificial factors, fuzzy matter-element analysis is proposed. The pitch system, which has high failure rate, is researched in this paper. The condition assessment model of pitch system is built in two steps: (1) To avoid the subjective judgment of the parameter distribution, this thesis uses 3σ rule and quartile analysis method to get the boundary data sets. The ANFIS algorithm is used to train the data to reduce the extreme value, and results of multi-feature fault detection are obtained. (2) Results from fault detection are applied in condition assessment model based on fuzzy matter-element analysis to realize the unification of fuzzy value of detection result and grade assessment. The method is applied to test the actual operation state of wind turbine. The results show that it can obviously reflect the pitch system and has better assessment effects.

1. Introduction

In the wind turbine control system, the pitch system as a core component is one of the components with high failure rate. If the pitch system fails, it may cause serious consequences such as blade breakage, speeding, and collapse. In this paper, the pitch system is taken as the research object, and a method combining multi-feature fault detection and fuzzy matter element analysis and evaluation is proposed to evaluate the system reliability.

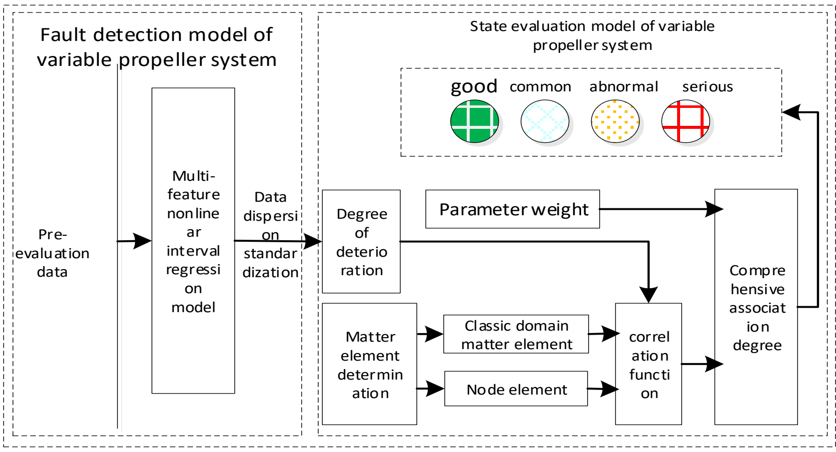

Figure 1. Condition assessment model of pitch system

2. Fault detection model of variable propeller system

Combining the mathematical model of the characteristic parameter mining of the variable propeller system based on the Relief method and the nonlinear state estimation of the variable paddle system fault identification [1]. The characteristic parameters closely related to the pitch system are selected as shown in Table 1.

Table 1. Parameter sets of pitch system

Wind speed	3#Pitch angle	3#Pitch drive current
Wind wheel speed	Generator speed	1#Pitch speed
1#Pitch angle	1#Pitch drive current	2#Pitch speed
2#Pitch angle	2#Pitch drive current	2#Pitch speed

The 3σ criterion [2] and the four fraction analysis [3] are all basic statistical theories.

1) Aafter pre-processing, the maximum value $V_{\max}$ and minimum value $V_{\min}$ of wind speed are obtained. The threshold of wind speed ε_V is selected and the components $[V_{\max}, V_{\min}]$ will be divided into N_V parts. According to the requirements of the literature [5], $\varepsilon_V = 0.5$.

$$N_V \approx \frac{V_{\max} - V_{\min}}{\varepsilon_V} \tag{1}$$

The training sample set 1 is used in the expression form $\{(x_{vk}, \bar{d}_{vk}), k = 1, 2, \ldots, N_V\}$. x_{vk} is taken as the center point value of each wind speed interval. $\bar{d}_{vk}$ is the average of all the output of each interval. The standard deviation is σ_{vk}.

According to the 3σ criterion

$$\begin{cases} y_{vk}^{+} = \bar{d}_{vk} + 3\sigma_{vk} \\ y_{vk}^{-} = \bar{d}_{vk} - 3\sigma_{vk} \end{cases} \tag{2}$$

Getting the upper and lower boundary data sets of the training sample set 1 $\{(x_{vk}, y_{vk}^{+})\}$ 、 $\{(x_{vk}, y_{vk}^{-})\}$.

2) After pre-treatment, the maximum value $\Omega_{\max}$ and minimum value $\Omega_{\min}$ of the rotor speed are obtained. Select the speed division threshold ε_Ω. Divide $[\Omega_{\max}, \Omega_{\min}]$ into N_Ω parts. Select $\varepsilon_\Omega = 0.3$.

$$N_\Omega \approx \frac{\Omega_{\max} - \Omega_{\min}}{\varepsilon_\Omega} \tag{3}$$

The training sample set 2 is used in the expression form $\{(x_{\omega m}, d_{\omega m}), m=1,2,\ldots,N_\Omega\}$. $x_{\omega m}$ is taken as the center point value of the speed interval of each wind wheel. $d_{\omega m}$ is the median value of all the output in each interval. The corresponding lower four bit value d_{Q1m}, Upper four division value d_{Q3m}, Four division distance $\Delta d_{IQRm} = d_{Q3m} - d_{Q1m}$.

According to the four division analysis method.

$$\begin{cases} y_{\omega m}^{+} = d_{Q3m} + 1.5\Delta d_{IQRm} \\ y_{\omega m}^{-} = d_{Q1m} - 1.5\Delta d_{IQRm} \end{cases} \tag{4}$$

The data set of the upper and lower boundary of the training sample set 2 is $\{(x_{\omega m}, y_{\omega m}^{+})\}$.

The fitting and generalization ability of ANFIS are stronger than that of ANN [4]. ANFIS method is used to fit training set 1, training set 2 and its upper and lower boundary data sets. The upper boundary function f^+, the lower boundary function f^- and the training set fitting function f are obtained.

The pre-evaluation data is input into the above regression model, and the output of the pitch system fault detection model is obtained by standardizing the data dispersion. According to the principle of the smaller and better the matter in the optimization principle of matter-element analysis, the fuzzy value of the single feature is obtained, and then normalized by the dispersion and mapped to [0,1]. Recorded as:

$$\mu(x[\mathrm{j}]) = \begin{cases} 1 & , y[j] \geq f^{+}(x[j]) \\ \dfrac{y[j] - f(x[j])}{f^{+}(x[j]) - f(x[j])}, & f^{+}(x[j]) > y[j] > f(x[j]) \\ \dfrac{f(x[j]) - y[j]}{f(x[j]) - f^{-}(x[j])}, & f^{-}(x[j]) < y[j] \leq f(x[j]) \\ 1 & , y[j] \leq f^{-}(x[j]) \end{cases} \tag{5}$$

In order to offset the influence of a small number of extreme points, the data amount of the unit time period is set to N_T, and the average fuzzy quantity value of the individual item features is $\bar{\mu}(x)$, and $\bar{\mu}(x)$ is used to indicate the membership value of each feature:

$$\bar{\mu}(x) = \frac{1}{N_T} \sum_{j=1}^{N_T} \mu(x[\mathrm{j}]) \tag{6}$$

In the formulas (5) and (6), $j = 1, 2, \cdots N_T$.

3. Pitch system state evaluation model

3.1. Theory modeling principle based on fuzzy matter element analysis

Matter-element analysis is a systematic research method proposed by Cai Wen. It has been in the process of improvement and improvement. It is widely used in system evaluation, predictive analysis, decision analysis and other solutions [5-6].

If the thing P is described by n features $C_1, C_2, \cdots, C_n$ and the corresponding fuzzy magnitude $\mu(x_1), \mu(x_2), \cdots, \mu(x_n)$. Then n is called a dimensional fuzzy matter element, which is recorded as:

$$\underset{\sim}{R}_n^{\mu} = [P, C, U] = \begin{bmatrix} P & C_1 & \mu(x_1) \\ & C_2 & \mu(x_2) \\ & \vdots & \vdots \\ & C_n & \mu(x_n) \end{bmatrix} \tag{7}$$

Among them: $\underset{\sim}{R}_n^{\mu}$ represents n dimensional fuzzy matter element; C_i represents the features of item i of the thing P; $\mu(x_i)$ represents the P value of item i, the corresponding value of C_i, the membership value of $x_i\left(i=1,2,\cdots,n\right)$. This value can be determined by the membership function. The membership function is determined according to the specific conditions. The fault detection model based on normal operation data is obtained.

A point x on the real domain, a finite interval $X_0=<b,c>$ (symbol $<>$ only represents the endpoint of the interval, regardless of the open and closed property). The distance between the definition point X and the finite real interval X_0 is $\rho\left(x,X_0\right)$.

$$\rho\left(x,X_0\right)=\left|x-\frac{b+c}{2}\right|-\frac{c-b}{2} \tag{8}$$

Set the interval $X_0=<b,c>$, $X=<a,d>$, $X_0\subset X$ and have no common endpoints; Then x is about the interval X_0, and the location of X is:

$$K\left(x\right)=\frac{\rho\left(x,X_0\right)}{D\left(x,X_0,X\right)} \tag{9}$$

Where: a and b become the classical domain and the limitation domain, respectively.

Determine the classical domain matter $\underset{\sim}{R}_{mn}^{X_0}$, which is recorded as:

$$\underset{\sim}{R}_{mn}^{X_0}=[P_m,C,X_{0m}]=\begin{bmatrix} P_m & C_1 & \left\langle b_{m1},c_{m1}\right\rangle \\ & C_2 & \left\langle b_{m2},c_{m2}\right\rangle \\ & \vdots & \vdots \\ & C_n & \left\langle b_{mn},c_{mn}\right\rangle \end{bmatrix} \tag{10}$$

For pitch systems, where: P_m is the $m\left(m=1,2,3,4\right)$ grade of the pitch system state. It is indicated that the operation of the pitch system is "good", "general", "abnormal" and "serious". $\left\langle b_{mi},c_{mi}\right\rangle$ is the range of values for the classic domain of P_m on C_i. Its value is based on specific characteristics. The classical domain elements identified in the paper are shown in Table 2.

Table 2. Classical field matter-element range

Characteristic Parameters	Level 1	Level 2	Level 3	Level 4
Pitch angle 1	<0,0.20>	<0.20,0.50>	<0.50,0.80>	<0.80,1.0>
Generator speed	<0,0.15>	<0.15,0.35>	<0.35,0.60>	<0.60,1.0>
Motor drive current 1	<0,0.20>	<0.20,0.35>	<0.35,0.50>	<0.50,1.0>
Pitch speed 1	<0,0.05>	<0.05,0.15>	<0.15,0.25>	<0.25,1.0>

The membership function is a real-valued function with a range of [0, 1]. $\left\langle a_{pi},d_{pi}\right\rangle$ is the range of values of P_p for C_i. The value in the paper is $\left\langle 0,1\right\rangle$. Determine the region object $\underset{\sim}{R}_{pn}^{X}$, which is recorded as:

$$\underset{\sim}{R}_{pn}^{X}=[P_p,C,X_p]=\begin{bmatrix} P_p & C_1 & \left\langle a_{p1},d_{p1}\right\rangle \\ & C_2 & \left\langle a_{p2},d_{p2}\right\rangle \\ & \vdots & \vdots \\ & C_n & \left\langle a_{pn},d_{pn}\right\rangle \end{bmatrix} \tag{11}$$

If $\underset{\sim}{R}_{n}^{W}$ is used to indicate the repeating compound, and the weight of the i-th feature of the thing P is represented by w_i, then:

$$\underset{\sim}{R}_n^W = [P, C, W] = \begin{bmatrix} P & C_1 & w_1 \\ & C_2 & w_2 \\ & \vdots & \vdots \\ & C_n & w_n \end{bmatrix} \tag{12}$$

ξ_i is used to represent the membership value of the feature of the i-th item, which is $\xi_i = \mu(x_i), (i = 1, 2, \cdots, n)$. $X_{0m}^{(i)}$ is used for $\langle b_{mi}, c_{mi} \rangle$ and $X_p^{(i)}$ for $\langle a_{pi}, d_{pi} \rangle$. Then according to equations (9) and (10), the value of the correlation function for level m can be expressed as:

$$K_m(\xi_i) = \begin{cases} -\dfrac{\rho\left(\xi_i, X_{0m}^{(i)}\right)}{\left|b_{mi} - c_{mi}\right|} & , \xi_i \in X_{0m}^{(i)} \\ \dfrac{\rho\left(\xi_i, X_{0m}^{(i)}\right)}{\rho\left(\xi_i, X_p^{(i)}\right) - \rho\left(\xi_i, X_{0m}^{(i)}\right)} & , \xi_i \notin X_{0m}^{(i)} \end{cases} \tag{13}$$

In the above formula, it is obtained by the formula (8):

$$\rho\left(\xi_i, X_{0m}^{(i)}\right) = \left|\xi_i - \frac{b_{mi} + c_{mi}}{2}\right| - \frac{c_{mi} - b_{mi}}{2} \tag{14}$$

$$\rho\left(\xi_i, X_p^{(i)}\right) = \left|\xi_i - \frac{a_{pi} + d_{pi}}{2}\right| - \frac{d_{pi} - a_{pi}}{2} \tag{15}$$

w_i is the weight of the i-th feature of the thing P. The weighted average of the correlation function values of each feature with respect to the level m is the comprehensive degree of association of each level m, namely:

$$D(P_m) = \sum_{i=1}^{n} w_i K_m(\xi_i) \Big/ \sum_{i=1}^{n} w_i \tag{16}$$

Determine $D^* = \max\{D(P_m) \mid m = 1, 2, 3, 4\}$, that is, determine that thing P should belong to level m.

3.2. Pre-assessment data verification

A period of data before and after the fault is taken is selected as a test sample, a total of 3169. The multi-feature nonlinear interval regression model was input, and the output results are shown in Fig. 2.

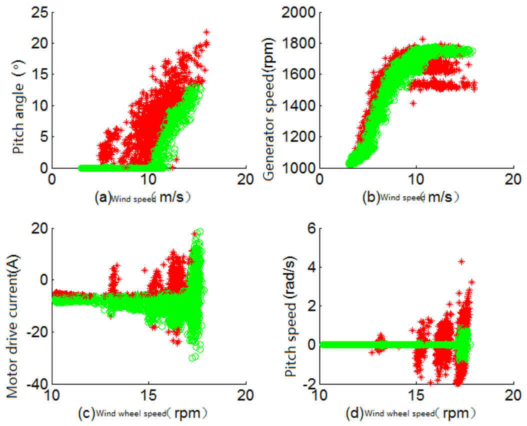

Figure 2. Output results of Multi-feature nonlinear interval regression model

Select $N_T = 352$, about 1 hour data collection. After calculation, the subordinate values of each characteristic of the test sample are shown in Table 3.

Table 3. Membership value of each characteristic of pitch system

Time number	Pitch angle (1、2、3)	Generator speed	Pitch drive current	Pitch speed (1、2、3)

			(1、2、3)	
1	0.0960	0.5530	0.3450	0.0028
3	0.7505	0.3479	0.1052	0.1335
5	0.8886	0.5606	0.4419	0.3352
7	0.5385	0.6071	0.3331	0.1818
9	0.1540	0.4894	0.4426	0.0227

According to the engineering design and maintenance records, combined with the statistical data of the failure rate, the parameter correlation ratio results are [94,95,95,92,92,91,89,15,16,15] to determine the relative weight of each parameter. The relative weights of the parameters i and j are a_{ij}, and the relative weights of the parameters j and i are $a_{ji}=1/a_{ij}$, and finally a judgment matrix $A=\left(a_{ij}\right)_{n\times m}$ of the pairwise comparison is formed, namely:

$$A=\begin{bmatrix} 1.0000 & 0.9894 & 0.9894 & 1.0220 & 1.0220 & 1.0109 & 1.0568 & 6.6429 & 6.2000 & 6.6429 \\ 1.0108 & 1.0000 & 1.0000 & 1.0330 & 1.0330 & 1.0217 & 1.0682 & 6.7143 & 6.2667 & 6.7143 \\ 1.0108 & 1.0000 & 1.0000 & 1.0330 & 1.0330 & 1.0217 & 1.0682 & 6.7143 & 6.2667 & 6.7143 \\ 0.9785 & 0.9681 & 0.9681 & 1.0000 & 1.0000 & 0.9891 & 1.0341 & 6.5000 & 6.0667 & 6.5000 \\ 0.9785 & 0.9681 & 0.9681 & 1.0000 & 1.0000 & 0.9891 & 1.0341 & 6.5000 & 6.0667 & 6.5000 \\ 0.9892 & 0.9787 & 0.9787 & 1.0110 & 1.0110 & 1.0000 & 1.0455 & 6.5714 & 6.1333 & 6.5714 \\ 0.9462 & 0.9362 & 0.9362 & 0.9670 & 0.9670 & 0.9565 & 1.0000 & 6.2857 & 5.8667 & 6.2857 \\ 0.1505 & 0.1489 & 0.1489 & 0.1538 & 0.1538 & 0.1522 & 0.1591 & 1.0000 & 0.9333 & 1.0000 \\ 0.1613 & 0.1596 & 0.1596 & 0.1648 & 0.1648 & 0.1630 & 0.1705 & 1.0714 & 1.0000 & 1.0714 \\ 0.1505 & 0.1489 & 0.1489 & 0.1538 & 0.1538 & 0.1522 & 0.1591 & 1.0000 & 0.9333 & 1.0000 \end{bmatrix}$$

Solving the eigenvector of the judgment matrix $A_{10\times10}$ uses the following equation:

$$A\eta=\lambda_{\max}\eta \tag{17}$$

Where: $\lambda_{\max}$ is the largest eigenvalue, η is the corresponding feature vector. The feature vector is normalized to obtain a weight vector W .After the above calculation, various features are obtained (pitch angle 1, pitch angle 2, pitch angle 3, pitch drive current 1, pitch drive current 2, pitch drive current 3, generator speed, pitch speed 1, Pitch speed 2, pitch speed 3. The corresponding weights are [0.1357 0.1368 0.1368 0.1923 0.1923 0.14090 0.1092 0.1142 0.1152 0.1142].

Evaluation of the state of the pitch system, t=1, The comprehensive relevance of each level is $\left[D(P_1),D(P_2),D(P_3),D(P_4)\right]_{t=1}=\left[0.0011,-0.0193,\text{-}0.0200,\text{-}0.0202\right]$. According to the principle of maximum degree of comprehensive relevance, get $D^*=D\left(P_1\right)$. At this point the pitch system is generally in a "good" state. From the actual monitoring data, all the indicators are running in the normal state, which is consistent with the calculation results of the evaluation method in this paper. Similarly, the state of the pitch system can be obtained at other times, as shown in Table 4.

Table 4. The changing process of pitch system

Time number	Comprehensive relevance of each level				Evaluation result
	$D(P_1)$	$D(P_2)$	$D(P_3)$	$D(P_4)$	
$t=2$	-0.0034	0.0025	-0.0119	-0.0153	general
$t=4$	-0.0093	-0.0069	-0.0032	0.0015	serious
$t=6$	-0.0086	-0.0030	0.0065	-0.0056	abnormal
$t=8$	0.0000	-0.0069	-0.0138	-0.0165	good

4. Conclusion

The existing state evaluation focuses on the study of the whole wind turbine, and it is difficult to characterize the actual operating state of its subsystems, so it is necessary to evaluate the operation status of the subsystems. Therefore, this paper chooses the pitch control system with high failure rate as the research object. Considering the interaction between the multiple characteristics of the variable propeller

IOP Conf. Series: Materials Science and Engineering **592** (2019) 012092 doi:10.1088/1757-899X/592/1/012092

system and selecting the closely related parameters, the fault detection model is set up, and the fault identification can be carried out by the actual analysis and verification. The average degradation degree of each of the above features is substituted into the fuzzy matter-element analysis model introduced in this paper. The actual data is verified. The results are not only accurate than the traditional binary decision-making evaluation results, but also consistent with the performance of on-site maintenance. The superiority of this method in evaluating the state of the pitch system, and the method of fuzzy matter element evaluation theory are practical and feasible, which can be used for on-site reference.

Acknowledgments
This research is supported by the China Postdoctoral Science Foundation (2017M611172) and Hebei Key R&D Program Project under grant No.18214316D.

Reference

[1] Yin S, Yu Z Y, Meng K F. Fault identification of pitch control system of wind turbine based on nonlinear state estimation[J]. Proceedings of the CSEE,2014,S1:160-165.
[2] Shen X J, Fu X J, Zhou C C, et al. Characteristics of outliers in wind speed-power operation data of wind turbines and its cleaning method[J]. Transactions of China Electrotechnical Society, 2018,33(14):3353-3361.
[3] Zhao Y G, Ye L, Zhu Q W. Characteristics and Processing Method of Abnormal Data Clusters Caused by Wind Curtailments in wind Farms[J]. Automation of Electric Power Systems,2014,21:39-46.
[4] Zhou Q, Xiong T T, Wang M B, et al. Diagnosis and early warning of wind turbine faults based on cluster analysis theory and modified ANFIS[J]. Energies, 2017, 10(7):898-915.
[5] Cross P, Ma X. Model-based and fuzzy logic approaches to condition monitoring of operational wind turbines[J]. International Journal of Automation and Computing, 2015, 12 (1) :25-34.
[6] Liu H X, Yuan Y M, et al. Normal cloud model for condition evaluation of wind turbines based on fusion theory[J]. Acta Energiae Solaris Sinica,2018,39(10):2891-2900.