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On-line status assessment of wind turbines based on improved fuzzy comprehensive evaluation method

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Abstract. To satisfy the requirements of on-line status assessment of wind turbines, a fuzzy comprehensive evaluation method combined with normal cloud model based on SCADA data was proposed. Firstly, a concept was introduced, The Dynamic Inferior, which can take both the variation of assessment indices into the calculation process of inferior degree and the changing of the wind turbine operating condition into consideration. A Markov chain model was adapted to predict the variation of assessment indices. Then, a normal cloud model with the dynamic inferior degree as inputs was adopted to calculate the membership degree of different assessment indices to overcome the subjectivity of normal membership functions. Furthermore, a fuzzy comprehensive assessment method was developed to assess the status of wind turbines online. Finally, the method was tested on the historical SCADA data of wind turbines. The results showed that this method was capable of not only accurately assessing the status of wind turbines online, but could also warn of problems early, which can prevent the occurrence of serious complications.

Keywords: On-line status assessment, wind turbine, normal cloud model, dynamic inferior degree, fuzzy comprehensive evaluation method

1. Introduction

In recent years, scholars have studied the status assessment of wind turbines using different methods including neural networks, support vector machine, copula theory, bi-spectrum analysis, healthy status theory, and fuzzy comprehensive evaluation [4, 6, 8, 10–14]. Among these methods, the fuzzy comprehensive evaluation method is more suitable due to its ability to quantitatively evaluate the status of a complex system with multi-factors and multi-hierarchies based on the fuzzy linear transformation and membership degree. The inferior degree is used to describe deviations of assessment indices from a normal status. In the related literature, the computation of inferior degree only considers the current indices values but ignores the influence of variable parameter trends on the inferior degree [4, 12, 14]. In fact, the degradation of wind turbines is a process from quantitative changes to qualitative changes. Therefore, the status of a wind turbine depends not only on the current value, but also the change trend of assessment indices. What's more, the membership function is an important tool to translate the inferior degree into the membership degree. However, normal membership function is always highly subjective, which leads to the model overriding the fuzziness of the uncertainties and ignoring the randomness [13]. To overcome these shortcomings, Li Deyi proposed a normal cloud model that is capable of constructing the mapping between qualitative and quantitative, and can provide a new choice to map the inferior

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degree into the assessment level of wind turbine [1, 3]. Although a normal cloud model can overcome the shortage of traditional membership function, the deviation of membership degree caused by the variable parameter trend of assessment indices cannot be reflected dynamically through the cloud membership degree that is calculated with the traditional inferior degree [15]. Therefore, the dynamic inferior degree was selected as the input in a normal cloud model to solve the above problems. Finally, by combining the cloud model and the fuzzy comprehensive evaluation method, an on-line status assessment method for wind turbines was proposed in this paper.

2. On-line status assessment of wind turbine

2.1. Dynamic inferior degree and its calculation method

An equation for calculating dynamic inferior degree of partial small assessment indices is as follows:

$$g(x) = \left\{ \begin{array}{ll} 0, & x_p < x_{\min} \\ \frac{x_p - x_{\min}}{x_{\max} - x_{\min}}, & x_{\min} < x_p < x_{\max} \\ 1, & x_p > x_{\max} \end{array} \right\} \quad (1)$$

where $x_{\max}$ is the maximum value and $x_{\min}$ is the minimum value within the range of assessment indices, respectively; x_p is the predictive value, which is superposed by the current value and the value of parameters variable trend. Because the calculation of dynamic inferior degree synthetically considers the current value of assessment indices and variable parameter trend, the dynamic inferior degree can describe wind turbine operating conditions dynamically.

In Equation (1), the key to calculate the dynamic inferior degree is to predict the variable trend of parameter accurately. Considering the amount of measured data is large, both the prediction precision and the computation complexity should be taken into account. The state transfer matrix of Markov chain model can predict the state of the next moment based only on the state of the current moment, which has already been successfully used in data tendency forecasting [2, 7, 9]. Therefore, the Markov chain model was chosen to predict the variable parameter trend.

Two given conditions must be specified when the Markov chain model is used to predict the variable parameter trend. The first one is the variation of the current moment. The second one is the state transfer matrix P. Using the SCADA data of wind turbines, the specific steps of prediction were as follow:

(1) The SCADA historical data series of each assessment index were obtained;
(2) Aimed at each series, the parameter variation series of assessment index was obtained after subtracting the value of the next moment from the value of the current moment;
(3) Each parameter variation series was divided into different states. And the mean and variance method was used to divide the status interval;
(4) The state transfer matrix P was built as follows:

$$P = [p_{ij}] \quad 1 \le i, j \le n \quad (2)$$

The element p_{ij} can be calculated as follows:

$$p_{ij} = m_{ij}/m_i \quad (3)$$

where m_{ij} is the number of state s_i transfer to state s_j; and m_i is the number of occurrences of state s_i.

(5) The status of s_i was determined based on the current parameter variation x_t. Then, the value of x_{t+1} was calculated by multiplying the median of the interval number and transition probability p_{ij} when s_i transferred into the possible status s_j in the next moment. The x_{t+1} was as follows:

$$x_{t+1} = \sum_{j=1}^{k} \frac{\varepsilon_{up}^{j} + \varepsilon_{down}^{j}}{2} \cdot p_{ij} \quad (4)$$

(6) The current value and the value of variable trend was superimposed to get the predictive value of the assessment index. The temperature of the driving end bearing of the generator was taken as an example, as shown in Table 1.

As shown in Table 1, the values of dynamic inferior degree and the traditional inferior degree were similar from T1 to T3 due to the continuous and slow changes. However, since T4, the generator drive end bearing temperature increased rapidly and the dynamic inferior degree was higher than that of the traditional inferior degree. Obviously, after synthetically considering the current value and its variable trend, the dynamic inferior degree was more effective in describing the abnormal status of the wind turbine.

Table 1
Values and inferior degree of bearing temperature

Moment	Current value (°C)	Predictive value (°C)	Traditional inferior degree	Dynamic inferior degree
T1	18.18	19.04	0.28	0.29
T2	18.93	20.72	0.29	0.31
T3	19.57	21.37	0.30	0.31
T4	28.81	38.91	0.39	0.49
T5	40.54	50.64	0.51	0.61
T6	53.28	63.38	0.63	0.73
T7	61.85	71.95	0.72	0.82

2.2. Normal cloud model

U was set as a quantitative domain represented by precise values and $X \subseteq U$. C was the qualitative concept of domain U. If $x \in X$ was a random occurrence of qualitative concept C and it satisfied the following two conditions in the meantime, then the distribution of x on domain U was called a normal cloud.

(1) $x \sim N(Ex, En'^2)$, where $En' \sim N(En, He^2)$;
(2) The membership degree of x to C is

$$r(x) = \exp(-(x - Ex)^2/(2En'^2)). \quad (5)$$

In Equation (5), the E_x is the point which best represents the qualitative concept. Entropy E_n synthetically measures the fuzzy degree and probability of qualitative concept and reflects its uncertainty. The excess entropy He reflects the cohesiveness of cloud drops in the data space and indirectly characterizes the cloud's discrete degree and thickness [15]. The assessment levels can be divided as $S = \left(S_1, S_2, S_3, S_4\right)$, which corresponds to four normal clouds $C_i = (C_1, C_2, C_3, C_4)$. The calculation method of the numerical characteristics are shown in Table 2.

In Table 2, a, b and c denote the limiting values of dynamic inferior degree intervals. According to the maintenance experiences, the corresponding intervals between dynamic inferior degree and assessment levels were set as S_1[0, 0.2), S_2[0.2, 0.5), S_3[0.5, 0.8) and S_4[0.8, 1.0], which meant a = 0.2, b = 0.5 and c = 0.8 in Table 2. q is generally regarded as a constant and can be adjusted based on fuzziness and randomness. In this paper, q was set as 0.005 after repeated testing.

Table 2
Calculation method of numerical characteristics

S_i	C_i	Ex_i	En_i	He_i
S_1	C_1	$Ex_1 = 0$	$En_1 = (Ex_2\text{-}Ex_1)/3$	q
S_2	C_2	$Ex_2 = (a+b)/2$	$En_2 = (Ex_2\text{-}Ex_1)/3$	q
S_3	C_3	$Ex_3 = (b+c)/2$	$En_3 = (Ex_3\text{-}Ex_2)/3$	q
S_4	C_4	$Ex_4 = 1.0$	$En_4 = (Ex_4\text{-}Ex_3)/3$	q

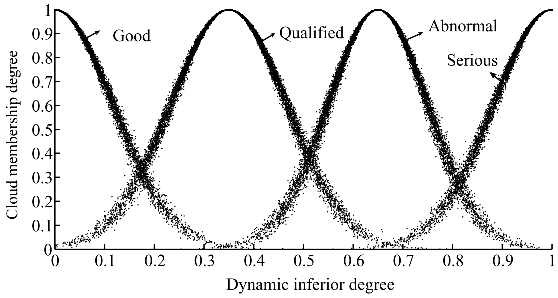

Fig. 1. Normal cloud model curve of each assessment level.

According to the numerical characteristics shown in Table 2, four normal cloud models of assessment levels were generated, as shown in Fig. 1.

After taking the dynamic inferior degree g of assessment indices into the normal cloud model, the cloud membership degree r_i' of each assessment level was obtained. Its equation was as follows:

$$r_i' = \exp\left(-\frac{(g - Ex_i)^2}{2En_i'^2}\right) \quad (6)$$

Although the cloud membership degree obtained had minute random variations, it tended to be stable. As such, the average r_i of ten calculation results of cloud membership degree was taken in this paper. Its equation was as follows:

$$r_i = \sum_{k=1}^{10} r_{ik}'/10 \quad (7)$$

2.3. On-line status assessment method

By combining the normal cloud model with the fuzzy comprehensive evaluation method, a novel on-line status assessment method for wind turbines was proposed. The specific flow chart is shown in Fig. 2.

The assessment system was divided into three layers. Firstly, the assessment object layer was established, which included the on-line operating conditions of the wind turbines. Then, the subsystems were established, including a generator system (U_{11}, drive end bearing temperature; U_{12}, non-drive end bearing temperature; U_{13}, winding temperature; U_{14}, cooling air temperature; U_{15}, generator speed), gear box system (U_{21}, input shaft temperature; U_{22}, output

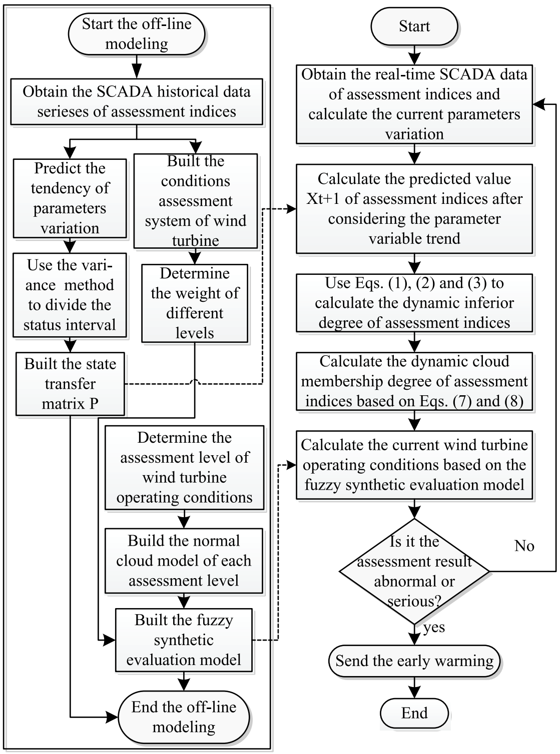

Fig. 2. On-line status assessment flow chart of wind turbine.

shaft temperature; U_{23}, oil temperature; U_{24}, spindle temperature), control system(U_{31}, control room temperature; U_{32}, cabinet temperature; U_{33}, tower bottom temperature), environmental factors (U_{41}, wind speed; U_{42}, average wind speed; U_{43}, environment temperature), and grid-connected factors (U_{51}, voltage of phase A; U_{52}, current of phase A; U_{53}, active power; U_{54}, power factor; U_{55}, frequency). Finally, each subsystem was divided into multiple assessment indices based on the SCADA monitoring items.

3. Results and analysis

3.1. Data analysis

The SCADA data of wind turbines were chosen, as shown in Table 3. The current data series were obtained from the SCADA data, and the predicted data series were the predicted value.

In Table 3, the change trend of the generator driving end bearing temperature (U_{11}) increased significantly from moment T3 to moment T4, which gave the appearance of deterioration. And in the following moments, the deterioration also appeared in the generator winding temperature (U_{13}) and the gearbox input shaft temperature (U_{21}). This showed that there was something wrong with the wind turbine since moment T4 and the monitors should heighten their vigilance to discover the problems.

3.2. Status assessment of wind turbines

Moment T4 was taken as an example, and the processes of status assessment were performed, as listed below.

(1) Determination of weights, the analytic hierarchy process was firstly used to determine the fixed weight, and then the variable weight theory was used to calculate the varied weight based on the fixed weight.
(2) Calculation of dynamic inferior degree, Aiming at the predicted data series, the dynamic inferior degree g_I of each subsystem was calculated.
(3) Calculation of dynamic cloud membership degree matrix, the dynamic cloud membership degree matrix of assessment indices in each subsystem was calculated.
(4) Status assessment of wind turbine. The assessment results of each subsystem were calculated based on the dynamic cloud membership degree matrix R_i and varied weight B of assessment indices, and then the synthesized cloud membership degree matrix R was obtained.

Finally, the assessment result vector of the wind turbine were $V = A * R = \left[0.24\ 0.70\ 0.05\ 0 \right]$. However, considering the complexity of the wind turbine structure and the "short board" effect in the failure mechanism of fuzzy comprehensive evaluation, the deterioration of bottom parameters should be paid careful attention to provide advance warning of a wind turbine's potential failures in a timely manner. In this case, the strategy of selecting the lowest level with a non-zero value was used to directly consider the membership degree of the bottom parameters.

Taking moment T4 as an example, although the membership degree of "good" and "qualified" was both bigger than the membership degree of "abnormal," the level of "abnormal" was the lowest. As such, the final assessment result of the wind turbine operating condition was abnormal in T4 based on the proposed strategy, which was the same as the

Table 3
Data of assessment indices

Assessment indices	T1		T2		T4		T5		T6		T7	
	Current value	Predicted value	Current value	Predicted value	Current value	Predicted value	Current value	Predicted value	Current value	Predicted value	Current value	Predicted value
U_{11}(°C)	18.18	19.04	18.93	20.72	28.81	38.91	40.54	50.64	53.28	63.38	61.85	71.95
U_{12}(°C)	21.69	21.98	22.06	22.14	23.14	23.22	23.46	23.54	24.02	24.10	24.27	24.35
U_{13}(°C)	34.00	34.68	34.88	35.01	38.46	43.24	42.53	53.54	53.55	64.56	64.63	75.64
U_{14}(°C)	19.25	19.83	20.11	20.05	23.15	23.72	23.93	23.87	24.03	23.97	24.16	24.10
U_{15}(r/min)	1304.7	1281.2	1281.1	1265.6	1221.3	1205.8	1200.6	1185.1	1185.7	1170.2	1165.3	1149.8
U_{21}(°C)	24.79	24.33	24.64	24.23	26.08	31.51	30.23	45.91	46.01	61.69	62.53	78.21
U_{22}(°C)	22.97	23.03	22.81	22.93	23.24	23.36	23.41	23.53	23.55	23.67	23.71	23.83
U_{23}(°C)	39.69	41.12	40.44	42.23	41.86	41.67	42.56	44.35	43.85	52.02	50.79	58.96
U_{24}(°C)	14.28	14.03	14.01	12.76	13.59	12.68	13.16	13.15	13.2	13.24	13.31	13.35
U_{31}(°C)	9.85	9.95	9.93	10.02	10.63	10.72	10.79	10.88	10.85	10.94	10.96	11.05
U_{32}(°C)	24.48	24.51	24.53	24.56	24.77	24.8	24.86	24.89	24.93	24.96	25.13	26.17
U_{33}(°C)	28.43	28.61	28.67	28.86	28.8	28.99	29.05	29.24	29.31	29.50	29.55	29.74
U_{41}(m/s)	13.65	13.94	14.01	14.38	14.56	14.93	15.07	15.35	15.27	15.64	15.53	15.90
U_{42}(m/s)	10.37	13.27	13.17	13.45	13.88	14.2	14.13	14.45	14.39	14.71	14.64	14.96
U_{43}(°C)	10.91	11.30	11.44	11.72	12.61	12.93	13.07	13.39	13.36	13.68	13.76	14.08
U_{51}(V)	392.37	392.14	391.83	391.78	391.53	391.48	391.20	391.15	390.93	390.88	388.54	388.49
U_{52}(A)	570.20	568.89	515.40	515.32	436.6	436.52	396.73	396.65	396.50	396.42	378.40	378.32
U_{53}(kW)	1512.0	1511.4	1421.6	1421.0	1563.6	1557.1	1228.4	1210.8	1031.9	1014.3	729.9	712.3
U_{54}	1	0.99	1	0.99	1	0.99	1	0.99	1	0.99	1.00	0.99
U_{55}(Hz)	50.03	50.02	50.04	50.03	50.04	50.03	50.03	50.02	50.03	50.02	50.02	50.01

Table 4
Condition assessment results of continuous time

Method/Assessment results		Conditions assessment in moment T_i						
		T1	T2	T3	T4	T5	T6	T7
Method based on dynamic inferior degree	Assessment vector	(0.25, 0.75, 0, 0)	(0.25, 0.75, 0, 0)	(0.24, 0.76, 0, 0)	(0.24, 0.70, 0.05, 0)	(0.23, 0.50, 0.24, 0.01)	(0.23, 0.31, 0.33, 0.03)	(0.23, 0.31, 0.33, 0.03)
	Assessment result	Qualified	Qualified	Qualified	Abnormal	Serious	Serious	Serious
Method based on traditional inferior degree	Assessment vector	(0.26, 0.74, 0, 0)	(0.25, 0.75, 0, 0)	(0.25, 0.75, 0, 0)	(0.25, 0.75, 0, 0)	(0.24, 0.67, 0.08, 0)	(0.23, 0.48, 0.26, 0)	(0.23, 0.32, 0.34, 0.02)
	Assessment result	Qualified	Qualified	Qualified	Qualified	Qualified	Qualified	Abnormal

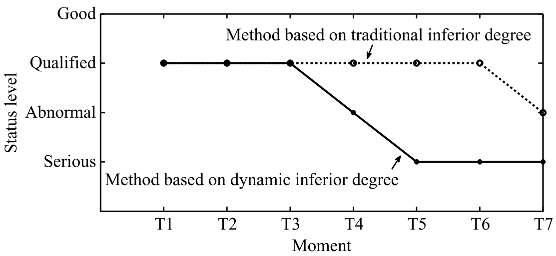

Fig. 3. Tendency chart of conditions assessment results.

actual condition. This means that monitors should take appropriate measures to prevent further deterioration of the wind turbine.

3.3. Comparative analysis of assessment results

In order to verify the validity of the condition assessment method based on dynamic inferior degree proposed in this paper, it was compared to the method based on traditional inferior degree. The condition assessment results are shown in Table 4, and the tendency chart of conditions assessment results is shown in Fig. 3.

As shown in Fig. 3, according to the proposed method, the status level of the wind turbine in T4 was “abnormal”, and then it became “serious” in T5. However, the status level obtained by the traditional method in T6 was still “qualified”, and the warning signal of abnormal status did not appear until T7. This means that the proposed method can accurately reflect the on-line status of wind turbine in time, so it can perform an early warning to the potential failure of wind turbine.

4. Conclusion

An on-line status assessment method for wind turbines was proposed in this paper. Firstly, the concept of dynamic inferior degree was proposed. By taken both the current values and the variable trend of the assessment indices into consideration, the dynamic inferior degree can reflect dynamic changes of the assessment indices. Then, by selecting the dynamic inferior degree as input, a normal cloud model was built to calculate the dynamic cloud membership degree. Finally, the proposed method is applied to the status evaluation of a wind turbine using the SCADA data. Compared to the status assessment results based on the traditional inferior degree, the assessment result of the proposed method is more accurate, which is capable of alarming early defects of wind turbine and preventing the occurrence of accidents.

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