Research on Operation Reliability Evaluation of Power-generating Unit

Shuai Di¹,a
¹Thermal Control Technology Institute, Datang Northeast Electric Power Test & Research Institute Co., Ltd, Changchun 130000, China
aiddby0431@163.com

Abstract—Objective and reasonable evaluation is the basis of power-generating unit optimal operation, but evaluation method based on single weight can’t adapt to the high accuracy requirement of comprehensive evaluation. In order to achieve the accurate evaluation of power-generating unit operating reliability, this paper firstly calculates subjective weight and objective weight of target attribute by analytic hierarchy process method and entropy weight method. It calculates the associated weight of target attribute by grey relational degree method, and it obtains the linear combined weight by relaxation factor. Then, the power-generating unit operating reliability is evaluated by improved TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution), and the evaluation result is obtained. Finally, the relaxation factor is continuously evaluated from 0 to 1 to perform sensitivity analysis. This paper evaluates the operation reliability of nine wind turbines in a wind farm, and the evaluation result is closer to actual operation state of wind turbines. This method has high reliability and practical value, and it provides a new technical means for making a reasonable maintenance plan of wind turbines.

1. Introduction
In recent years, the wind power has developed rapidly. At the same time, many shortcomings and problems have been exposed, which directly lead to the low operation level and the low maintenance level of wind farms. They have a negative impact on the operation hours improvement and power generation efficiency. The operation state and deterioration trend of wind turbines are hidden in SCADA data. In order to realize the intelligent operation and maintenance of large wind farms, it is necessary to analyze SCADA data reasonably and obtain several indexes for evaluating wind turbine reliability. It can achieve the reasonable evaluation and wind turbine reliability ranking. Based on evaluation result, it can provide a basis for wind turbine maintenance and classify the maintenance priority of wind turbines in the same health state. It can realize the intelligent operation and maintenance of large wind farms and improve the economic benefits.

Through statistical analysis of power curve, wind energy utilization curve and power generation efficiency, the operating state and power generation performance of units are evaluated in literature [1-2]. Literature [3] evaluated the performance of different wind turbines types according to the reliability of actual power curve. Based on the correlation of SCADA data, literature [4] studies unit health status and proposes quantitative evaluation method. In literature [5-7], methods such as neural network, clustering, fuzzy, K-nearest neighbor method and principal component analysis are used to evaluate the power generation performance of units. In literature [8], Extreme Learning Machine was used to train the neural network model, and which was used to evaluate the working condition of the...
gear box. In Literature [9], Online Sequential Extreme Learning Machine was used to evaluate the state of transmission system. Literature [10-12] realize the abnormal identification of the whole wind turbine based on data-driven method.

Based on SCADA data of nine wind turbines, this paper obtains the combined weight by AHP, entropy weight method and grey correlation method. It uses improved TOPSIS method to comprehensively evaluate the wind turbines reliability, and it provides a basis for intelligent operation and maintenance.

2. Reliability Comprehensive Evaluation Index of Wind Turbine

The equipment reliability evaluation indexes are usually used to evaluate the operating state of power-generating unit. MTTR is the mean repair time of trouble shoot. TMTBR is the mean interval time of trouble shoot. FN is the failure number. MRTBF is the average running time without failure. Ai is the average availability.

MRTBF refers to the average working time between two adjacent failures in a certain period of time. Ai is the percentage between available hour number and available running time. MRTBF and Ai are the key indicators to evaluate equipment reliability, and they are the main basis to distinguish reliability of power-generating units. TMTBR is the average time between equipment failures. The larger these indicators are, the healthier the unit is, and they are called benefit indicators.

FN refers to the failure number of power-generating unit. MTTR refers to the average equipment failure time, which is the measure of reliability. The smaller these indicators are, the less healthy the unit is, and they are called cost indicators.

The traditional reliability evaluation method of wind turbine is setting a threshold value for a single evaluation index, and the turbines are divided into three grades: normal, sub-health and serious. The wind turbines which are in same health grade don't have a proper order, and the maintenance priority can’t be determined. Wind turbine operating conditions are complex, and they have gray scale to a certain degree. There are many indexes which affect the wind turbine reliability. In order to obtain accurate ranking results and make reasonable maintenance plan of wind turbine, it is necessary to carry out Multi-attribute comprehensive evaluation.

3. Determine the Evaluation Model of Combination Weight

3.1 Technique for order preference by similarity to an ideal solution

Topsis method can evaluate and sort by calculating Euclidean distance between target attributes and ideal solutions. This method makes full use of original data information, and it solves the multi-objective decision problem of limited solutions. It has the advantages of real, intuitive and reliable. The decision matrix Y is \( m \times n \) data matrix. Each attribute is a column, and a data sample is a row. The decision matrix is processed by dimensionless data index, and the evaluation matrix Z is obtained.

Multiplying each attribute of evaluation matrix by corresponding weight to obtain the weighted normalized evaluation matrix X:

\[
X_{ij} = w_j \cdot z_{ij}
\]

The ideal solution is the set of each attribute optimal values, which is an imaginary optimal scheme. The negative ideal solution is the set of each attribute worst value, which is an imaginary worst solution.

For the benefit index, ideal solution is \( \max_i x_{ij} \), and negative ideal solution is \( \min_i x_{ij} \). For the cost index, ideal solution is \( \min_i x_{ij} \), and negative ideal solution is \( \max_i x_{ij} \).

Calculating relative proximity \( L_i \):

\[
L_i = \frac{d_i^+}{d_i^+ + d_i^-}
\]
In formula (2), $d^+_i$ and $d^-_i$ are the Euclidean distance. $Li$ is between 0 and 1, and it is the basis for evaluating ranking. The closer is to 1, the stronger the unit reliability is.

The calculation process amplifies $w_j$ influence on the evaluation result. The sum of $w_j^2$ is not equal to 1, and the evaluation result will also be affected. The standard Euclidean distance can effectively weaken the influence and obtain more accurate evaluation results.

$$d^+_i = \left( \sum_{j=1}^{n} w_j (z_y - z^+_i)^2 \right)^{\frac{1}{2}} \quad (3)$$

$$d^-_i = \left( \sum_{j=1}^{n} w_j (z_y - z^-_i)^2 \right)^{\frac{1}{2}} \quad (4)$$

It can be seen from Equations (3) and (4) that the weight is more reasonable.

### 3.2 Subjective and objective combination weight

The entropy weight method calculates objective weight by data difference information.

If the information entropy is larger, the information provided is smaller. The less it plays in comprehensive evaluation, the less its objective weight is.

The objective weight of each evaluation index is $\{\beta_j\}$. Entropy weight method relies too much on data samples and objective information, and the objective weight obtained can not be accurately and scientifically used for comprehensive evaluation.

Analytic hierarchy process calculates the subjective weight of object attributes by establishing comparison matrix. It can be used for qualitative and quantitative analysis of multi-attribute decision problems.

Subjective and objective weights are combined for scientific evaluation. $\{\alpha_j\}$ is Calculated by AHP method, and $\{\beta_j\}$ is calculated by entropy weight method.

According to the principle of minimum discrimination information, the combined weight of entropy AHP is:

$$\psi_j = \frac{\alpha_j \beta_j}{\sum_{j=1}^{n} \sqrt{\alpha_j \beta_j}} \quad (j=1, 2, \ldots, n) \quad (5)$$

### 3.3 Modification of grey weight

Wind turbine operating conditions are complex, and operation data in a certain degree have grayscale properties.

In order to build a more scientific reliability evaluation model, the grey relational weight is multiplied by a relaxation factor $d$ to adjust weight linearly.

Calculating correlation coefficient $P_r(k)$:

$$P_r(k) = \frac{\min_i \min_j [C^r_y - C^r_i] + \rho \max_i \max_j [C^v_y - C^v_i]}{[C^r_y - C^r_i] + \rho \max_i \max_j [C^v_y - C^v_i]} \quad (6)$$

In the formula, $\rho \in [0,1]$, and $\rho$ take 0.5 generally.

The grey weight of each evaluation index is $\{w_j\}$ ($j=1,2,\ldots,m$).

The linear combination weight is:

$$\phi_j = \frac{w_j + d\psi_j}{\sum_{j=m}^{n} w_j + d\psi_j} \quad (7)$$
In the formula, \( d \) is the relaxation factor, which changes from 0 to 1 and adapts to the established model in this paper. It can adjust the correction range of grey weight on entropy AHP weight.

### 3.4 Evaluation model based on grey entropy AHP combined weight

This paper uses TOPSIS method to evaluate the reliability of wind turbines. It replaces the Euclidean distance with standard Euclidean distance. It replaces the individual weights with linear weights. The evaluation process is shown in Figure 1.

4. **Application Cases**

**4.1 Application of grey entropy AHP combined weight evaluation model**

In this paper, reliability comprehensive evaluation and ranking of nine wind turbines in a wind farm are carried out. Now they are setting as No.1 to No.9.

It conducts dimensionless processing on SCADA data of nine wind turbines and obtains the normalized decision matrix, as shown in Table 1.

| No. | MRTBF | \( A_i \) | \( T_{MTBR} \) | MTTR | FN  |
|-----|-------|--------|-------------|-----|-----|
| 1   | 1.00  | 0.99   | 1.00        | 0.00| 1.00|
| 2   | 0.47  | 0.85   | 0.54        | 0.34| 0.97|
| 9   | 0.02  | 0.75   | 0.02        | 0.91| 0.28|

Objective weight can be obtained by entropy weight method: \( \beta = (0.351, 0.068, 0.359, 0.095, 0.127) \).

Subjective weight can be obtained by AHP method: \( \alpha = (0.386, 0.386, 0.092, 0.092, 0.043) \).

After calculation, \( CI=0.024, RI=1.12, CR=0.0213 \), and \( CR<0.1 \). It passes the consistency test.

Combined weight is obtained: \( \phi = (0.419, 0.184, 0.207, 0.107, 0.084) \).

Grey correlation weight is obtained: \( w = (0.162, 0.325, 0.167, 0.179, 0.167) \).

Taking the linear correction factor \( d \) as 1. Grey entropy AHP linear weight is obtained: \( \phi = (0.290, 0.254, 0.187, 0.143, 0.125) \).
The standard Euclidean distance \( D^+ \) between each scheme and ideal solution is calculated by TOPSIS method. The standard Euclidean distance \( D^- \) between each scheme and negative ideal solution is also calculated by TOPSIS method. The relative proximity \( L_i \) is obtained.

\[
D^+ = (0.378, 0.483, 0.665, 0.747, 0.373, 0.412, 0.656, 0.926, 0.737).
\]

\[
D^- = (0.922, 0.662, 0.644, 0.546, 0.737, 0.713, 0.631, 0.339, 0.522).
\]

\[
L_i = (0.709, 0.604, 0.492, 0.422, 0.663, 0.633, 0.489, 0.268, 0.414).
\]

In a comprehensive order from largest to smallest: No.1 > No.5 > No.6 > No.2 > No.3 > No.7 > No.4 > No.9 > No.8.

### 4.2 Comparison of different assessment models

The following are the ranking results of different evaluation models:

- The comprehensive order of entropy weight method is: No.1 > No.5 > No.2 > No.6 > No.7 > No.3 > No.4 > No.9 > No.8.
- The comprehensive order of AHP method is: No.5 > No.1 > No.6 > No.2 > No.7 > No.3 > No.4 > No.9 > No.8.
- The comprehensive order of grey correlation method is: No.5 > No.6 > No.1 > No.2 > No.3 > No.7 > No.4 > No.9 > No.8.
- The comprehensive order of entropy AHP method is: No.1 > No.5 > No.6 > No.2 > No.3 > No.7 > No.4 > No.9 > No.8.
- The comprehensive ordering of grey entropy AHP method is: No.1 > No.5 > No.6 > No.2 > No.3 > No.7 > No.4 > No.9 > No.8.

### 4.2.1 Comparison of single threshold assessment model

It sets thresholds for a single evaluation index to conduct comprehensive evaluation, and the reliability of each wind turbine is shown in Table 2. The sorting result accords with actual situation. Four healthy wind turbines are lined up in front. Three sub-health wind turbines are lined up in the middle. Two serious wind turbines are lined up in the behind. It proves the validity and correctness of five sorting results.

| number | healthy state | health | sub-health | serious |
|--------|---------------|--------|------------|---------|
| No.1   | No.2          | No.5   | No.6       | No.3    |
| No.4   | No.9          | No.8   |            |         |

Compared with the above results, it is not accurate to use a single weight to calculate. The ranking results of entropy AHP weight and grey entropy AHP linear weight are excellent, and the ranking results are exactly the same. The sorting results of No. 1 and No. 5 wind turbine are the same as entropy weight method. The sorting results of No. 6 and No. 2 wind turbine are the same as AHP method. The sorting results of No. 3 and No. 7 wind turbine are the same as grey correlation method. The sorting results of No.4, No.9 and No.8 wind turbine are the same as AHP, entropy weight and grey correlation method.

It shows that the combination weight and linear combination weight are more reasonable and practical. It reflects subjective factors, objective factors, and gray factors. It can represent the true state of wind turbines.

### 4.2.2 Comparison of combined algorithm evaluation models

The ranking results of entropy AHP weight and grey entropy AHP linear combination weight are consistent. This shows that the grey weight has little influence on reliability comprehensive ranking of wind turbines. The relaxation factor is introduced to adjust grey weight, and the sensitivity analysis results are shown in Fig. 5. With the increase of relaxation factor, the distance of each relative closeness degree is obvious and uniform. This paper takes the relaxation factor as 1 to establish evaluation model.
The grey entropy AHP combined weight evaluation model can effectively divide the maintenance priority. No.8 and No.9 wind turbine are in serious condition, but it can be seen from Figure 5 that No.8 is obviously more serious than No.9.

The No.8 wind turbine needs priority maintenance to adjust fan state and eliminate hidden trouble. No.1 is in much better state than No.2, No.5 and No.6. No.3, No.4 and No.7 have little difference in operating state. This method can effectively divide the maintenance priority. The higher the priority is, the sooner maintenance is required.

5. Conclusion
In this paper, the subjective weight and objective weight are calculated by AHP method and entropy weight method. The grey weight is calculated by grey correlation method, and linear combination weight is obtained. The linear combination weight is applied to the improved TOPSIS method, and the improved method can comprehensively evaluate the wind turbine reliability. The result shows that this method has higher accuracy.

When it comes to indicators that can’t be defined by specific thermodynamic model in the follow-up study, it should complement information with expert knowledge and experience, and it shouldn’t seek absolute objectification results. The comprehensive evaluation model and weight determination method presented in this paper can provide useful comparison and reference for similar problems.

References
[1] KUSIAK A, ANDRE W, ANOOP V. Monitoring wind farms with performance curves [J]. IEEE Transactions on Sustainable Energy, 2013, 4(1): 192-199.
[2] DAI Shuoming. Analysis of power generation performance evaluation methods for wind turbines [J]. Technological Development of Enterprise, 2016, 35(9): 95-96.
[3] LAPIRA E, BRISSET D, ARDAKANI H D, et al. Wind turbine performance assessment using multi-regime modeling approach [J]. Renewable Energy, 2012(45): 86-95.
[4] YANG Wenxian, COURT R, JIANG Jiesheng. Wind turbine condition monitoring by the approach of SCADA data analysis [J]. Renewable Energy, 2013, 53: 365-376
[5] LI S, WUNSCH D C, HAIR E O’, et al.Comparative analysis of regression and artificial neural network models for wind turbine power curve estimation [J]. Journal of Solar Energy Engineering, 2001, 123 (4): 327-331.
[6] USTUNTAS T, SAHIN A D. Wind turbine power curve estimation based on cluster center fuzzy logic modeling [J]. Journal of Wind Engineering and Industrial Aerodynamics, 2008, 96(5): 611-620.

[7] JIA Xiaodong, JIN Chao, MATT B, et al. Wind turbine performance degradation assessment based on a novel similarity metric for machine performance curves [J]. Renewable Energy, 2016, 99: 1191-1201

[8] Qian P, Ma X, Cross P. Integrated data-driven model-based approach to condition monitoring of the wind turbine gearbox[J]. IET Renewable Power Generation, 2017, 11(9): 1177-1185.

[9] Qian P, Ma X, Zhang D. Estimating Health Condition of the Wind Turbine Drivetrain System[J]. Energies, 2017, 10(10).

[10] Yang H, Huang M., Lai C, et al. An approach combining data mining and control charts-based model for fault detection in wind turbines[J]. Renewable Energy, 2018, 115: 808-816.

[11] Sun P, Li J, Wang C, et al. Condition assessment for wind turbines with doubly fed induction generators based on SCADA data[J]. Journal of Electrical Engineering & Technology, 2017, 12(2): 689-700.

[12] Sun P, Li J, Wang C, et al. A generalized model for wind turbine anomaly identification based on SCADA data[J]. Applied Energy, 2016, 168: 550-567.