A method for grounding grid corrosion rate prediction

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Abstract. Involved in a variety of factors, prediction of grounding grid corrosion complex, and uncertainty in the acquisition process, we propose a combination of EAHP (extended AHP) and fuzzy nearness degree of effective grounding grid corrosion rate prediction model. EAHP is used to establish judgment matrix and calculate the weight of each factors corrosion of grounding grid; different sample classification properties have different corrosion rate of contribution, and combining the principle of close to predict corrosion rate. The application result shows, the model can better capture data variation, thus to improve the validity of the model to get higher prediction precision.

1 Introduction

Substation grounding grid is protective earthing of important facilities and used for working earthing, lightning protection, which is an important part to ensure that the person, equipment, systems, and the transformer substation safe operation. In recent years, with the development of power system capacity increased, the power grid caused many major electric power operation faults because of the corrosion. Therefore, solve the grounding grid corrosion problems have become the basic guarantee for safe operation of power system.

In order to solve the problems, EAHP (extension analytic hierarchy process) method and Fuzzy Closeness to corrosion rate prediction model are presented in this paper. Draw the extension with the analytic hierarchy process, through the establishment of a "flexible" judgment matrix to determine the effect of various evaluation corrosion rate factor weights; the reasoning process has the characteristics of small workload, simple method and the rigorous. Considering the different corrosion rate contribution is different, when it calculates fuzzy closeness between samples, using the weights obtained by extension, the corrosion rate of the membership function structure obtained by the method of regression calculation, close to more reasonable model, improve the model prediction accuracy.

2 Determining factor weights of grounding grid corrosion based on EAHP

2.1 Build extension judgment matrix

Building judgment matrix is the quantitative process. The quantitative process refers to the scale through certain system and converts all kinds of original data to the standardization of the direct comparison format. In this paper, using the method proposed by SAATY reciprocity 1-9 scaling as the standard quantitative method of extension interval analytic hierarchy process (ahp). Under a certain criterion, Experts compare two between the relative importance of each element that Belonging to the same level, and two build extension interval judgment matrix \( A = (a_{ij})_{nxn} \), \( i, j = 1, 2, ..., n \). It’s positive reciprocal judgment matrix, this, \( a_{ij} = [a_{ij}^-, a_{ij}^+] \) is an an extension interval number. \( a_{ij}^-, a_{ij}^+ \) are respective line \( i \), column \( j \) extension interval judgment matrix elements of upper and lower endpoints.
2.2 Calculate comprehensive extension to judge matrix and weight vector
Suppose \( a^i_j = (a_{ij}^+, a_{ij}^-) \) \((i, j = 1, 2, \ldots, n; t = 1, 2, \ldots, T)\) is the number of \( t \) in the extension interval which is given, according to:

\[
A^i_j = \frac{1}{T} (a_{ij}^+ + a_{ij}^- + \ldots + a_{ij}^t)
\]

The extension interval number judgment matrix \( A = [A^+, A^-] \), \( A^- \) is the interval matrix composed of upper endpoint, \( A^+ \) is the interval matrix composed of lower endpoint. The steps for acquiring the satisfying consistency condition of weight vectors, as follows:

1. To calculate the maximum eigenvalue of \( A \) and \( A^- \) is a component of the normalized feature vector;
2. Calculate the value of \( k \) and \( m \);
3. Judge the consistency of matrix. If \( 0 \leq k \leq 1 \leq m \), then suggests that the consistency of judgment matrix extension interval is better. If the consistency is too low, it should correct judgment matrix until meet the requirements;
4. Calculate the weight in formula (3);

\[
S = (S_i, S_j, \ldots, S_m)^T = [k^x, m^x]
\]

Here, \( S_{ak} \) is the layer \( k \), the factor \( n \) on \( S_{ak} \) level of a factor of extension interval right weight.

2.3 Determine hierarchical single layer order
Suppose \( S_i = [S_i^-, S_i^+] \), \( S_j = [S_j^-, S_j^+] \), if \( V(S_i \geq S_j) \geq 0 \) \((i \neq j)\) show the degree of possibility of \( S_i \geq S_j \), then

\[
P_i = 1, P_j = V(S_i \geq S_j) = \frac{2(S_i^+ - S_i^-)}{(S_j^+ - S_j^-) + (S_i^+ - S_i^-)}
\]

Here: \( i, j = 1, 2, \ldots, n \), \( i \neq j \), \( P_i \) is the single layer order of the factor \( i \) corresponds to the certain factor in the upper layer in the certain layer, \( P = (P_1, P_2, \ldots, P_n)^T \) is the normalized single layer order weight vector.

2.4 Determine hierarchical general order
Get \( P^k = (P^k_1, P^k_2, \ldots, P^k_h) \), here, \( k \) is the layer \( k \); \( h \) is the factor \( h \), when \( h = 1, 2, \ldots, n_{k-1} \), obtain the \( n_k \times n_{k-1} \) order matrix:

\[
P^k = (P^k_1, P^k_2, \ldots, P^k_h)
\]

If the \( k \) - 1 layer to the total target of sorting weight vector is \( W^{k-1} = (W_{1}^{k-1}, W_{2}^{k-1}, \ldots, W_{n_{k-1}}^{k-1})^T \), then the \( k \) layer on the synthesis of all the elements to the total target sorting is obtained as formula (6).

\[
W^k = (W_1^k, W_2^k, \ldots, W_h^k)^T = P^k W^{k-1}
\]

In addition, generally there are: \( W^k = P^k W^{k-1} \ldots P^2 W^1 \), which \( W^1 \) is the single layer order vector. Generally, \( W^k = P^k W^{k-1} \ldots P^2 W^1 \), here, \( W^1 \) is actually single sorting vector.

3 Predicting grounding grid corrosion rate using Fuzzy comprehensive method

3.1 To determine the corrosion of typical sample
There are \( n \) variable factors affecting the corrosion rate, denoted by: \( P_i = V(P_i \geq P_j) = 5.6014 \) . A random sample of \( z \) samples, \( P = (0.5195, 0.3878, 0.0927) \), \( A \), \( z \) is the number of samples, so The
corresponding $z$ grounding grids $n$ soil physical and chemical characteristics of the sample matrix $X$ made of corrosion characteristics.

3.2 To determine the fuzzy membership function

To determine the degree of membership is the core of the fuzzy prediction. In general, to determine the size of the basic principles of membership is based on the relative importance of samples are located in the class, or where the class of contribution. Therefore, the correlation coefficient is close relation between measured variable degrees of quantity. On the degree of linear correlation between two variables called single phase correlation coefficient of measurement. Usually expressed as a $r$ sample correlation coefficient.

$$r_{ij} = \frac{\sum_{i=1}^{n}(x_{ij} - \bar{x}_i)(y_{ij} - \bar{y}_j)}{\sqrt{\sum_{i=1}^{n}(x_{ij} - \bar{x}_i)^2} \sqrt{\sum_{j=1}^{n}(y_{ij} - \bar{y}_j)^2}}$$

(7)

Here, $r_{ij}$ is the correlation coefficient of the $i$-th and the $j$-th characteristic factor; $z$ is the number of samples; $\bar{x}_i$ is the average of the $i$-th characteristic factors. For sample matrix $X$, according to formula (7) to obtain related relationship of $z$ characterized factors and corrosion rate. We select the improved sigmoid function to obtain a sample membership. The form of have the small, follow as:

$$u(x,a,b) = \begin{cases} 1 & x \leq a \\ \frac{1}{1 + e^{-k(x-a)/(b-a)}} & a < x < b \\ 0 & x \geq b \end{cases}$$

(8)

Where, $x$ : input sample characteristic parameters; $a$ : the current input minimum characteristic parameters; $b$ : the current input maximum characteristic parameters; $k$ : the predefined parameter, value of [1,10].

We choose the partial small as the membership function. Let $a=0$, $b=8$, $k=9$. Finally, according formula (8), obtain the data $s_i$ on $[0,1]$. Additional, membership matrix $S$ follow as.

$$S = [T_1, T_2, \ldots, T_n] = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1z} \\ s_{21} & s_{22} & \cdots & s_{2z} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & \cdots & s_{nz} \end{bmatrix}$$

According to fuzzy mathematics theory, the grounding grids experimental data of each different region as the theory of domain, depicting the fuzzy set close to was measured with degree. Different indicator $x$ is inconsistent with the size of the corrosion rate of $y$, it shows that the influence of corrosion of grounding grids there are differences in the contribution of various indicators on corrosion rate.

$$\phi(T, T') = \frac{1}{2}[(T \otimes T') + (I - T \Theta T')]$$

(9)

In formula(9), $\phi$ is the closeness between the $i$-th samples and the measured samples, $T_i$ :is the $i$-th training sample set, $T' :$is the measured samples,

$$T_i \otimes T' = \vee_{s_j \in S} [w_j \times (x_j \land x'_j)], T_i \Theta T' = \wedge_{s_j \in S} [w_j \times (x_j \lor x'_j)]$$

(10)

Taking into account in building a model of grounding grid corrosion rate prediction, if the original training set sites excessive, closeness $\phi$ obtained large difference, the use of a relatively low closeness
site information will have a negative impact on the model accuracy. Therefore, the closeness \( \varphi_i > \varepsilon \) were selected as “excellent” new training sample set, \( \varepsilon \) is the threshold, value of [0,1]. Supposing, there are \( p \) filtered sample sets, \( \varphi_i \) is the closeness of \( k \)-th \( (k = 1, \ldots, p) \) site, \( v_k \) is corrosion rate, when distribute weight, normalize \( \varphi_i \), the measured corrosion rate contribution of the \( k \)-th site is:

\[
\lambda_k = \frac{\varphi_i}{\sum_{k=1}^{p} \varphi_k}
\]

Then the corrosion rate of the site is obtained, as shown as:

\[
u = \sum_{k=1}^{p} \lambda_k \times v_k
\]

4. Application examples

4.1 Confirm factor weights of grounding grid corrosion

The evaluation factors set \( A = \{B_1, B_2, \ldots, B_n\} \) is divided into several mutually disjoint sets according to the different attributes by the given factors \( A \), there into every first level evaluation index \( B_i \) corresponds to \( k \) second level evaluation index \( B_{ij} \) \((i = 1, 2, \ldots, n; j = 1, 2, \ldots, k) \), As shown in Table 1.

| Table 1 The evaluation factor system of corrosion rate |
|-------------------------------------------------------|
| \( B_{11} \) Ca\(^{2+} \) | \( B_{12} \) Mg\(^{2+} \) | \( B_{13} \) K\(^+ \) / Na\(^+ \) |
| \( B_{14} \) SO\(_4^{2-} \) | \( B_{15} \) Cl\(^- \) | \( B_{16} \) HCO\(_3^- \) |
| \( B_{17} \) CO\(_3^{2-} \) | \( B_{18} \) Saltness | \( B_{19} \) PH |
| \( B_{20} \) Organic content | \( B_{21} \) Height | \( B_{22} \) Northern latitude |
| \( B_{23} \) East longitude | \( B_{24} \) Mean annual precipitation | \( B_{25} \) Mean annual temperature |
| \( B_{26} \) Mean lowest temperature |

According to 1–9 scaling principle, we can construct extension interval number judgment matrix of criterion layer by the evaluation 2 experts. They show the different matrix in the different expert team in Table 2.

| Table 2 Extension judging matrix of rule layer to target layer |
|--------------------------------------------------------------|
| Object Layer | \( B_i \) | \( B_j \) | \( B_k \) |
| Expert 1      | \( B_1 \) | \textless 1,1\textgreater | \textless 0.556, 0.833\textgreater | \textless 0.769, 0.833\textgreater |
|               | \( B_2 \) | \textless 1,2, 1.8\textgreater | \textless 1,1\textgreater | \textless 0.435, 0.667\textgreater |
|               | \( B_3 \) | \textless 1,2, 1.3\textgreater | \textless 1,5, 2.3\textgreater | \textless 1,1\textgreater |
| Expert 2      | \( B_1 \) | \textless 1,1\textgreater | \textless 0.8, 1\textgreater | \textless 0.833, 1.25\textgreater |
\[
B_2 <0.8,1.25> <1,1> <0.64,0.667>
\]
\[
B_3 <0.8,1> <1.5,1.56> <1,1>
\]

In Table 2, we can get the corresponding extension interval judgment matrix:
\[
A^+ = \begin{bmatrix}
1 & 1 & 1 \\
0.678 & 1 & 1.5 \\
0.801 & 0.538 & 1 \\
\end{bmatrix},
A^- = \begin{bmatrix}
1 & 1.15 & 1.25 \\
0.917 & 1 & 1.98 \\
1.042 & 0.667 & 1 \\
\end{bmatrix}
\]

The corresponding feature vector of the eigenvalue of maximum of \( A^- \) is \( 0.618, 0.63, 0.46 \) and the feature vector of \( A^+ \) is \( 0.594, 0.654, 0.4 \). By formula (3),
\[
1 \quad S = (0.5928, 0.6161)
\]
\[
2 \quad S = (0.6051, 0.6781)
\]
\[
3 \quad S = (0.4498, 0.4859)
\]

By formula (4):
\[
1 \quad P_V = 5.6014
\]
\[
2 \quad P_V = 4.1818
\]
After normalization, we get the index of each factor weight in the same way, using formula (5), (6) can calculate the other indexes. The results are shown in Table 3.

**Table 3** Corrosion rate of weights to criteria layer

| criterion layer | \( A \) | \( B_1 \) | \( B_2 \) | \( B_3 \) | each factor weight \( W \) |
|-----------------|--------|--------|--------|--------|-----------------|
| 11              | 0.0540 | 0.3878 | 0.0927 | 0.0281 |
| 12              | 0.0479 | 0.0281 |
| 13              | 0.0561 | 0.0292 |
| 14              | 0.1367 | 0.0710 |
| 15              | 0.2003 | 0.1040 |
| 16              | 0.0462 | 0.0240 |
| 17              | 0.0389 | 0.0202 |
| 18              | 0.2668 | 0.1386 |
| 19              | 0.1075 | 0.0588 |
| 110             | 0.0456 | 0.0237 |
| 21              | 0.3282 | 0.1273 |
| 22              | 0.5094 | 0.1975 |
| 23              | 0.1624 | 0.0630 |
| 31              | 0.5294 | 0.0491 |
| 32              | 0.3088 | 0.0286 |
| 33              | 0.1618 | 0.0150 |

In this, we use the information of 60 sites in Shaanxi Province substation to verify the algorithm, the information was followed as Table 4.

It verifies the prediction model through Fuzzy Closeness, we selected six sites as test set, and they are: Xiecun, Dingjun, Moziqiao, Wuhou, Qianyang, Shenmu, Zhenyuan, Qindu. According to the positive and negative correlation coefficient, we select the semi-Gauss distribution of membership function and obtain the corresponding fuzzy relation matrix.

Determining threshold \( \varepsilon = 0.8 \), screened to meet the conditions of the “excellent” training set for subsequent prediction model to provide reliable data sources.
According to the corrosion factors of membership degree calculation, we calculate the intimacy between grounding grid corrosion training samples and testing samples. According to the corrosion factors of membership degree calculation, we calculate the intimacy between grounding grid corrosion training samples and testing samples. The method according to the forecast model ignores the corrosion rate and corrosion prediction is derived nearly weight factors, the result is shown in Table 5.

| Measured site | Actual rate | Predict rate | Relative error |
|---------------|-------------|--------------|----------------|
| Xiecun        | 0.1783      | 0.181238     | 1.65%          |
| Dingjun       | 0.1452      | 0.175058     | 20.56%         |
| Moziqiao      | 0.1892      | 0.174191     | 7.93%          |
| Wuhou         | 0.2009      | 0.168713     | 16.02%         |
| Qianyang      | 0.1221      | 0.16984      | 39.10%         |
| Shenmu        | 0.1596      | 0.158151     | 0.91%          |
| Zhenyuan      | 0.1756      | 0.174366     | 0.70%          |
| Qindu         | 0.2341      | 0.196727     | 15.96%         |

5. Conclusion
In this paper, we used two-stage structure which combines the Extension Analytic Hierarchy Process and Closeness Fuzzy to build a model to predict the grounding grid corrosion rate for compensating the deficiencies of the conventional method and improving the prediction accuracy.

References
[1] Wang Guiping, Jia Yazhou. “Evaluation Method and Application of CNC Machine Tool’s Green Degree Based on Fuzzy-EAHP”. Journal of Mechanical Engineering, 2010,40(3):141-147.
[2] Du Jingyi, Du Bowei, Han Juan. “A Novel Analyzing Method to Predict Grounding Grid Corrosion Rate”. Mathematics in Practice and Theory, 2015,45(19):123-130.
[3] Du Qin Jia, Yang Jianfeng, Xue Bin, et al. Image Registration and mosaic Based on Vector Similarity Matching Principle [J]. Microelectronics & Computer, 2013, 30(6): 22-25.

[4] Du Zhang Yingjiao, Luo Xianjue, Niu Tao, et al. New model of corrosion diagnosis for grounding grids based on constrained total least squares algorithm [J]. Journal of Xi’an Jiaotong University, 2010, 10(44): 110-115.

[5] Qin Jia, Yang Jianfeng, Xue Bin, et al. Image Registration and mosaic Based on Vector Similarity Matching Principle [J]. Microelectronics & Computer, 2013, 30(6):22-25.