The non-excavation corrosion prediction model of grounding grid based on particle swarm optimization extreme learning machine

Wenbin Li¹,²,*, Yong Wang¹,², Yanting Feng¹,², Qing Wang¹,², Xuexia Xu¹,², Guowei Li¹,², Guozhen Dong¹,², Shangqian Jing¹,², Ersong Chen¹,², Xiaoliang Fan³, and Jianmin Liu³

¹State Grid Hebei Electric Power Research Institute, Shijiazhuang 050021, PR China
²State Grid Hebei Energy Technology Service Co., Ltd, Shijiazhuang 050021, PR China
³School of Energy, Power and Mechanical Engineering, North China Electric Power University, Baoding 071003, PR China

*Corresponding author: 2182224001@ncepu.edu.cn

Abstract. The grounding grid is an indispensable part in the electrical system. Nevertheless, the grounding grid materials are susceptible. Considering the small sample size and strong nonlinear feature of the grounding grid corrosion, we introduced a non-excavation corrosion prediction model based on particle swarm optimization extreme learning machine. This model utilized the extreme learning machine to fast deal with the nonlinear relationship, and utilized the particle swarm optimization to search global optimal solution. Compared with generalized regression neural network and BP neural network, the prediction results of this model are more accurate. Thus, this model might have bright future in improving the accuracy of corrosion prediction of grounding grids.

1. Introduction
With the development of power system towards higher voltage and larger capacity, there is an improving demand on the safety and reliability of system operation [1, 2]. The grounding grid is a device that must be installed in the power grid to ensure the safety of human beings and equipment. Right now, galvanized steel and carbon steel are widely used as grounding grid conductors [3]. With the deterioration of ecological environment and the improvement of line voltage level in China, the corrosion degree of grounding grid material surface is continuously intensified and even fracture occurs, which seriously affects the safe operation of power grid. Although the traditional method which detects the corrosion state of grounding grid by excavation is accurate, it needs to stop the system for inspection which wastes time [4]. Thus, it is necessary to systematically study the corrosion status of grounding grid, establish stable and reliable corrosion prediction model, and accurately predict grounding grid accidents without excavation, which could significantly improve the reliability of power grid operation. Based on the existing corrosion data of grounding grid, it is a potential solution to build the model through intelligent algorithm and then predict the grounding grid's corrosion. In reference [5], a corrosion prediction model with corrosion influencing factors as input parameters was established by
using BP neural network. The reference [6] first utilized the analytic hierarchy process to scientifically weight the corrosion factors, and then utilized the fuzzy theory to establish the prediction model. The reference [7] established a combined neural network and mechanistic approach for the prediction of corrosion rate. The reference [8] predicted corrosion behaviour of Alloy 22 using neural network as a data mining tool.

Because the corrosion is a long-term and gradual process, the dynamic monitoring of the grounding grid of the actual power station is usually carried out in months. Thus the number of corrosion data samples is usually less than 100, which is a typical small sample situation. In the case of too few samples, directly using neural network or other fitting methods will easily lead to the problem of over fitting. The analysis of over fitting has great uncertainty due to the small number of samples. Furthermore, it is not good to fit the corrosion rate directly according to these parameters with great difference in physical dimensions, although the corrosion rate is related to various indexes in soil. In particular, corrosion is a long-term, complex, time-integrated, nonlinear electrochemical process, and relevant environmental parameters are also relatively important parameters found in the exploration and research. Thus the trends in corrosion rates inferred from these parameters are naturally comparative and correlated, and the samples also have value beyond mere fitting.

This model utilized the extreme learning machine to fast deal with the nonlinear relationship, and utilized the particle swarm optimization to search global optimal solution. Compared with generalized regression neural network and BP neural network, the prediction results of this model are more accurate. Thus, this model might have bright future in improving the accuracy of corrosion prediction of grounding grids.

2. The predictin model

2.1. The fundamentals of extreme learning machine
The extreme learning machine (ELM) is a single hidden layer feedforward neural network learning algorithm. Compared with the traditional neural network, the parameters of the hidden layer neurons are randomly generated. Furthermore, no recursive adjustment is made during the training process of ELM, and the unique optimal solution can be obtained. As shown in Figure 1, this method has the advantages of fast learning speed, high accuracy, simple parameter adjustment and good generalization ability [9].

![Figure 1. Network structure diagram of the extreme learning machine.](image)

Assume that there are N different samples \((x_i, y_i)\), where \(x_i = [x_{i1}, x_{i2}, ..., x_{in}] \in R^n\), \(y_i = [y_{i1}, y_{i2}, ..., y_{ik}] \in R^k\). Thus, the output expression of a feedforward neural network with l hidden layer nodes and G (x) excitation function is
where $i$ is the input weight connecting the input layer to the $j$-th hidden layer node, $\beta_j$ is the output weight connecting the $j$th hidden layer node to the output node, and $b_j$ is the deviation value of the $j$th hidden layer node. By transforming equation (1) into matrix form, we can get

$$Y = HB$$

where $H$ is the output matrix of hidden layer. In the extreme learning machine algorithm, the input weight and hidden layer can be given randomly and there is no need to adjust during the training process. The hidden layer matrix $H$ is a definite matrix before training. The training of feedforward neural network is actually transformed into a problem of solving the least square solution $\hat{\beta}$ of the output weight matrix. The output weight matrix $\hat{\beta}$ can be expressed as

$$\hat{\beta} = H^+ Y$$

where $H^+$ is the generalized inverse of a matrix $H$. According to the equation (1-3), the output weight matrix is determined by the deviation between the input weight matrix and the hidden layer. Because ELM randomly gives the initial input weight matrix and the hidden layer bias, some input weight matrix and the hidden layer bias may be 0, leading to part of the hidden layer node is invalid. Therefore, the precision and time of extreme learning machine training will be affected by randomness in some practical applications.

2.2. Particle swarm optimization

For the initial weight and threshold randomly generated by ELM in the previous section, invalid hidden layer nodes may appear and the generalization ability is insufficient. Thus, particle swarm optimization (PSO) is introduced to optimize the initial input weight and threshold of ELM, which could overcome the disadvantage of random selection of initial input weight and threshold value of extreme learning machine, and avoid blindly training artificial neural network [10].

PSO was inspired by the way how birds find food. This algorithm treats the possible solution to each optimization problem as a bird in the search space and calls it a particle. Each particle has its own speed and position to determine the direction and distance of their flight. The Fitness value of all particles is calculated according to fitness function. Furthermore, each particle has a memory function, which can remember the best location to search for and follow the current optimal particle in the solution space. At each iteration, the particle can update itself by tracking the individual best and the global best as follows.

$$V_{id}^{i+1} = \omega V_{id}^{i} + c_1 r_1 (P_{id}^g - X_{id}^{i}) + c_2 r_2 (P_{id}^b - X_{id}^{i})$$
$$X_{id}^{i+1} = X_{id}^{i} + V_{id}^{i+1}$$

In the equation (4) and (5), $X_1, X_2, \ldots, X_n$ not only represents the position of the $i$th particle in the $D$-dimensional search space, but also represents a potential solution of the problem. Furthermore, $k$ is the number of hidden layer nodes, $\omega$ is the inertia weight. $P = (p_1, p_2, \ldots, p_D)^T$ is the global best position of the swarm. The learning factors are denoted as $c_1$ and $c_2$. The terms $r_1$ and $r_2$ are randomly given in the range $U(0,1)$.
2.3. The PSO-ELM prediction model

The PSO-ELM prediction model is an effective algorithm for parameter optimization of ELM by using PSO. The specific training steps are as follows:

Step 1: Initialize particle swarm and set PSO related parameters. The individual (particle) in the population is composed of the input weight and the hidden layer threshold. Where the particle length is \( L = k(q+1) \), \( k \) is the number of nodes in the hidden layer, \( q \) is the number of neurons in the input layer.

Step 2: Put the corresponding random input weight and threshold of each particle into the ELM training algorithm in equations (1-3), and get the predicted value of the output weight matrix. The root mean square error (RMS) of each particle in the initial population was calculated as the particle fitness, and the current particle fitness was compared with the individual optimal fitness. The individual extreme best was updated according to the larger fitness value, and the global extreme best was updated simultaneously.

Step 3: In the iteration process, the particle velocity and position are updated according to Equations (4) and (5). When the maximum number of iterations or the best fitness is reached, the optimization iteration process is stopped.

Step 4: The optimal input weight and hidden layer threshold obtained by the above steps are substituted into Equation (3) to calculate the output weight matrix and obtain the predicted result.

3. Results and discussion

In this paper, the observation data from 25 substations are selected as samples [11]. The corrosion of grounding grids in soil is affected by a variety of factors. In this research, five representative soil physical and chemical properties are selected as influencing factors, including water content, resistivity, porosity, \( \text{SO}_4^{2-} \) content and \( \text{Cl}^- \) content. In order to show the superiority of the proposed method, generalized regression neural network (GRNN) and BP neural network were used to train, fit and predict the samples. We further applied the above three models to predict the test samples, and the relevant test results are shown in Table 1.

| Number | Actual value | PSO-ELM | GRNN | BP |
|--------|--------------|---------|------|----|
| 1      | 6.63         | 6.74    | 7.36 | 6.05|
| 2      | 3.48         | 3.67    | 4.01 | 4.26|
| 3      | 7.42         | 7.46    | 7.06 | 6.95|
| 4      | 6.53         | 6.45    | 6.03 | 5.75|
| 5      | 6.90         | 6.65    | 7.02 | 7.86|
| 6      | 8.33         | 8.50    | 8.64 | 8.12|
| 7      | 6.51         | 5.90    | 7.02 | 7.26|
| 8      | 6.79         | 7.01    | 6.10 | 7.05|
| 9      | 5.83         | 6.32    | 5.14 | 5.64|
| 10     | 10.12        | 10.06   | 10.75| 11.31|
| 11     | 9.59         | 9.98    | 9.21 | 8.95|
| 12     | 7.99         | 8.36    | 7.90 | 7.01|

In order to make a more intuitive and thorough comparison on the error of the three prediction model, this research utilized the average relative error \( \sigma_{MAPE} \), the relative error of standard deviation \( \sigma_{MAPE} \), and mean square error (MSE) \( e_{MSE} \) to evaluate. The relevant calculation formulas are shown as:

\[
e_{MAPE} = \frac{1}{S} \sum_{i=1}^{S} \left| \frac{y_i - \hat{y}_i}{\hat{y}_i} \right|
\]
Based on the prediction results of the three models in Table 1, we further evaluated the results of cl-ML model, generalized regression neural network (GRNN) and BP neural network respectively through formula (6-8), as shown in Table 2.

| Model       | $\sigma_{\text{MAPE}}$ | $\sigma_{\text{MAPE}}$ | $\epsilon_{\text{MSE}}$ |
|-------------|-------------------------|-------------------------|-------------------------|
| PSO-ELM     | 0.0374                  | 0.0611                  | 0.0917                  |
| GRNN        | 0.0793                  | 0.1117                  | 0.3064                  |
| BP          | 0.0959                  | 0.1309                  | 0.5160                  |

By analyzing the indicators in Table 2, it can be found that the $\sigma_{\text{MAPE}}$ of PSO-ELM prediction model is much smaller than that of generalized regression neural network and BP neural network. This indicates that the relative error volatility of the prediction results of PSO-ELM model is small, that is, the PSO-ELM model has good adaptability and stability. Simultaneously, the $\sigma_{\text{MAPE}}$ and $\epsilon_{\text{MSE}}$ from the PSO-ELM model are also far less than the generalized regression neural network and BP neural network, indicating that the PSO-ELM model are closer to real values and shows more excellent accuracy.

4. Conclusion
In order to solve the problem of small sample and strong nonlinearity of grounding grid corrosion, this paper proposed a non-excavation corrosion prediction model based on particle swarm optimization extreme learning machine. This model utilized the extreme learning machine to fast deal with the nonlinear relationship, and utilized the particle swarm optimization to search global optimal solution. The test results show that the results of the three key indicators (mean relative error, standard deviation of relative error, mean square error) of the model proposed in this paper are far less than the commonly used generalized regression neural network and BP neural network. By combining ELM and PSO algorithm, the model in this paper can predict the corrosion of the grounding grid with high accuracy without excavation, which is of great significance to the optimization maintenance strategy of substation and the reduction of operation risk.

Acknowledgments
This work was supported by State Grid Hebei Electric Power Research Institute (kj2019-063: the no-dig corrosion detection technology of the ground grid).

References
[1] Z. Fu, X. Wang, Q. Wang, X. Xu, N. Fu, S. Qin, Advances and challenges of corrosion and topology detection of grounding grid. Appl. Sci. 9 (2019) 2290.
[2] M. Dong, Z. Shi, X. Li, G. Shao, F. Yang, D. Yao, K. Zhang, A diagnosis of grounding grid corrosion defects based on branch voltage disturbance. IEEE Access, 8 (2020) 36749-36756.
[3] J. Zhao, N. Durham, K. Abdel-Hadi, C. A. McKenzie, D. J. Thomson, Acoustic guided wave techniques for detecting corrosion damage of electrical grounding rods. Mesurement 147 (2019) 106858.
[4] Z. Zhang, D. Mei, Y. Dan, J., Zou, G. Liu, C. Gao, Novel method for diagnosing corrosion of grounding electrodes in soil. Electr. Po. Syst. Res. 178 (2020) 106049.
[5] Y. Guo. Study on the corrosion prediction of Q235 steel in Hainan substation based on neural
network. Beijing: North China Electric Power University, 2016.

[6] J. Du, J. Han, S. Kou. Prediction of corrosion rate of grounding network based on fuzzy extension level analysis, Comput. Appl. Softw. 31 (2014) 170-173.

[7] N. Birbilis, M. K. Cavanaugh, A. D. Sudholz, S. M. Zhu, M. A. Easton, M. A. Gibson, A combined neural network and mechanistic approach for the prediction of corrosion rate and yield strength of magnesium-rare earth alloys. Corros. Sci. 53 (2011) 168-176.

[8] M. Kamrunnahar, M. Urquidi-Macdonald, Prediction of corrosion behaviour of Alloy 22 using neural network as a data mining tool, Corros. Sci. 53 (2011) 961-967.

[9] W. Cai, J. Yang, Y. Yu, Y. Song, T. Zhou, J. Qin, PSO-ELM: A hybrid learning model for short-term traffic flow forecasting, IEEE Access 8 (2020) 6505-6514.

[10] M. R. Kalloop, D. Kumar, P. Samui, A. R. Gabr, J. W. Hu, X. Jin, B. Roy, Particle swarm optimization algorithm-extreme learning machine (PSO-ELM) model for predicting resilient modulus of stabilized aggregate bases, Appl. Sci. 9 (2019) 3221.

[11] C. Chen. Research on corrosion rate prediction method of grounding grid. Chongqing: Chongqing University, 2019.