Line loss prediction based on particle swarm optimization combined with extreme learning machine

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Abstract. As a key economic index to measure the planning and management level of power grid company, line loss is not only the main content of completing the construction and transformation task of power grid company, but also an important assessment standard for the operation level of power grid company. In order to improve the generalization ability and prediction accuracy of extreme learning machine (ELM), particle swarm optimization (PSO) algorithm is applied to extreme learning machine (ELM), and a line loss prediction method based on PSO combined with ELM is proposed. The particle swarm optimization algorithm is used to select the optimal hidden layer deviation and input weight matrix to calculate the output weight matrix, so as to improve the accuracy and stability of the extreme learning machine. Experimental results show that the proposed method can effectively improve the accuracy of line loss prediction.

Keywords: Extreme learning machine; particle swarm optimization; line loss prediction.

1. Introduction
With the steady development of China's economy, the continuous improvement of people's living standards and the aggravation of the global energy crisis, the economic requirements of power grid operation are constantly improved on the basis of traditional security and reliability requirements at the national level. Among them, line loss and line loss rate are very important comprehensive indicators. Large scale energy saving and loss reduction scheme is reflected in all aspects of the power grid, which plays a positive role in improving the economy of power grid operation and reducing energy waste. The value of line loss refers to the energy loss in the form of heat energy, which is the effective power consumed by resistance and conductance, and is the abbreviation of power loss of power grid. As an important index which can comprehensively reflect the comprehensive management level and operation level of regional electric power, the power grid company must rely on scientific and technological means to further strengthen the line loss management, so as to reduce the line loss rate and improve the comprehensive strength. It is one of the operation and management objectives of electric power enterprises to analyze and study the line loss with advanced technology, so as to minimize the loss of energy in transmission.

At present, there are many literatures for line loss prediction model. For example, Zhi min Lu [1] adopts policy technology to reduce power grid losses through load forecasting and dispatching
optimization based on a comprehensive database of grid structure parameters and operation parameters. Lin Hu, Gu Dong, Kang Lin [2] proposed a line loss rate prediction method based on gradient lifting decision tree, and verified the effectiveness of the method in anomaly detection and actual project management. Yasuoka J, Brittes, Schmidt [3] used different demand curves of neural network to predict the demand value of distribution substation and initial feeder level, and the prediction accuracy was improved. Liu [4] calculated the theoretical line loss of low-voltage distribution station area by the method of load electricity and established a mathematical model with the theoretical line loss of station area as variable. The results show that the method can not only calculate the theoretical line loss of low-voltage distribution station area, but also identify the unknown line loss. Li Yunbing, Xu Lanlan [5] improved the accuracy of the prediction results by establishing a line loss power prediction model based on gated cyclic neural network. An Xiaohua, Ouyang Sen and Feng Tianrui [6] established the line loss index system and carried out the correction calculation by using the optimization design method of fuzzy clustering ground state correction for theoretical line loss rate of medium voltage distribution network feeders. Jin Baohua, Zhang Mingxing and Wu huaitian [7] established a model by introducing the growth rate of line loss as a constraint, and built a line loss prediction model considering three factors of voltage, current and power. By combining the output data abnormal users and line loss abnormal users, they output a list of suspected electricity stealing users, and proposed an anti stealing prediction method based on power big data.

Extreme learning machine is a single hidden layer feedforward neural network proposed by Professor Huang guangbin of Nanyang Technology [8]. In recent years, extreme learning machine has attracted the attention of many experts and scholars at home and abroad for its superior performance and simple structure, and has been applied to the field of prediction. Yang Xin [9] carried out variational mode decomposition on the vibration signals of each typical fault to obtain the intrinsic mode functions of different scales, and improved the prediction performance by using the kernel extreme learning machine diagnosis model of multi feature extraction and kernel principal component analysis. Liu Dacheng [10] introduced kernel function into the extreme learning machine model to solve the energy-saving goal. In order to further enhance the generalization ability of ELM, more and more researchers improve the basic ELM algorithm. Yue Youjun [11] introduced crow search algorithm into kernel extreme learning machine model to carry out short-term load forecasting, reducing the impact of original non-stationary load series on the prediction results. Gao Caiyun [12] optimizes the extreme learning machine through genetic algorithm to predict the settlement and deformation of subway tunnel. The results show that compared with BP neural network, the prediction result of genetic algorithm extreme learning machine is more accurate. Han Du [13] used the elm model optimized by particle swarm optimization to predict the landslide displacement during rainy season. Through experiments, it was verified that the model has high accuracy and good generalization performance, and proved the feasibility of particle swarm optimization to improve the extreme learning machine.

In this paper, particle swarm optimization algorithm is used to optimize the model of extreme learning machine to improve the generalization performance. Taking the power consumption data collected by the power consumption information acquisition system as the object, the line loss prediction model of power enterprises is constructed for the stable substation area, which provides an effective means for enterprises to improve the level of business efficiency and avoid the risk of business efficiency.

2. Basic Model

2.1. ELM

ELM is a single hidden layer feedforward neural network learning algorithm. The characteristic of extreme learning machine is that the weights of hidden layer and bias do not need to be changed after initialization, and the weights of output layer are directly obtained by generalized inverse, while the weights of traditional BP neural network need to be adjusted continuously by error feedback, which is shown in Figure 1.
The implementation process of ELM is as follows:

Take set \( \{ x_i, t_i \} \) \( _{i=1}^{N} \subset R^n \times R^m \). There are L neurons in the hidden layer whose excitation function is \( g(\cdot) \), which is a nonlinear function. In this paper, sigmoid is selected.

1. Random initialization weight threshold \( a_i, b_i, i = 1, L, a_i \). They are the input weight thresholds of the \( i \)-th hidden layer neuron.

2. Calculating the output matrix of hidden layer nodes

\[
H = \begin{bmatrix}
h(x_1) & g(a_1, b_1, x_1) & \cdots & g(a_L, b_L, x_1) \\
M & M & \cdots & M \\
h(x_n) & g(a_1, b_1, x_n) & \cdots & g(a_L, b_L, x_n)
\end{bmatrix}_{n \times L}
\]

3. The output weight \( \beta \) from hidden layer to output layer is calculated.

\[
\beta = H^+ \cdot T, \beta = \begin{bmatrix} \beta_1^T \\ M \\ \vdots \\ \beta_L^T \end{bmatrix}_{L \times m}, T = \begin{bmatrix} i_1^T \\ M \\ \vdots \\ i_n^T \end{bmatrix}_{n \times m}
\]

In which: \( H^+ \) is the left pseudo inverse matrix of the hidden layer output matrix \( H \); \( T \) is output, i.e. \( r = \frac{i_n}{j_n} = 1 \).

4. Calculate the output value. When the error \( \| O_j - T_j \| \) of \( O_j \) is less than or equal to constant \( \epsilon \), ELM finishes training.

\[
O_j = \sum_{i=1}^{L} \beta_i g( a_i, b_i, x_i), \| O_j - T_j \| \leq \epsilon, \; j = 1, L, n
\]

2.2. Particle swarm optimization

PSO simulates the migration and aggregation of birds, and the flight process of particles is regarded as the searching process of individuals. The steps of PSO algorithm are as follows: suppose \( N \) particles constitute a population, \( P = \{ p_1, p_2, \ldots, p_N \} \), Where \( p_i \) is the \( i \)-th particle. Firstly, \( N \) random solutions of \( O(x) \) are initialized, It is expressed as \( x_{i1}^{(0)}, x_{i2}^{(0)}, \ldots, x_{in}^{(0)} \in R^n \). Then the \( k \)-th iteration is carried
out. The position $x^k_i$ of each particle in n-dimensional space after the kth iteration is regarded as the new solution, and the fitness function $f(x)$ value is used to evaluate the quality of the solution. The smaller the value, the better the position and the better the $x^k_i$. The particle velocity $v^k_i$ and position $x^k_i$ are updated as follows

$$v^k_i = \omega \cdot v^{k-1}_i + c_1 \cdot r_1 \cdot (p^{best}_i - x^{k-1}_i) + c_2 \cdot r_2 \cdot (gbest^k - x^{k-1}_i)$$

(4)

$$x^k_i = x^{k-1}_i + v^{k-1}_i$$

(5)

Where $W$ is the inertia weight; $c_1$ and $c_2$ are the acceleration factor; $r_1$ and $r_2$ are random numbers in the range of $[0,1]$; $p^{best}_i$ and $gbest^k$ are the optimal positions of particle extremum and particle swarm optimization in the first k iterations, respectively. And $gbest^k$ is the optimal solution of the optimization problem.

2.3. PSO combined with ELM

Aiming at the problem that the initial weights and thresholds generated randomly by ELM may appear invalid hidden layer nodes and lack of generalization ability, PSO is introduced to optimize the initial input weights and thresholds of ELM to overcome the disadvantages of random selection of initial input weights and thresholds of extreme learning machines. The specific implementation process is as follows:

Step 1: Data Preprocessing.
Step 2: Initialize Parameters.
Step 3: Calculate and evaluate the fitness value of each particle.
Step 4: Mark the current optimal position $pbest$ of individual particle and $gbest$ of particle swarm optimization.
Step 5: Adjust the speed and position of each particle.

![Figure 2](image_url). The framework of PSO combined with ELM
3. Experimental Results

3.1. Data Processing

The data items selected for the test include the power supply of the day, the power consumption of the day and the line loss rate of the substation area. The line loss data are from the real data collected from different areas. The collection date is from January 1, 2018 to July 14, 2020. Because the total amount of data of each station area is inconsistent after eliminating outliers, the line loss data of five stations are divided into training set and test set according to the ratio of 5:1.

In this paper, three indicators are used to evaluate the forecasting accuracy, namely root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) of expected value:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}
\]

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|
\]

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%
\]

3.2. Line loss prediction results

Compared with different cases and different models, the forecasting results are shown in Table 1.

| Case  | Model    | MAE    | MAPE   | RMSE   | $R^2$   | MSE    | Time / sec |
|-------|----------|--------|--------|--------|---------|--------|------------|
| Case1 | PSO-ELM  | 0.2069 | 0.055  | 0.2135 | 0.96592 | 0.029795| 15.453     |
| Case1 | ELM      | 1.005  | 0.2902 | 1.1571 | 0.85658 | 1.3389 | 0.158      |
| Case2 | PSO-ELM  | 0.0936 | 0.0293 | 0.1255 | 0.96097 | 0.015746| 15.800     |
| Case2 | ELM      | 1.2817 | 0.3844 | 1.3554 | 0.41958 | 1.8372 | 0.088      |
| Case3 | PSO-ELM  | 0.052  | 0.0068 | 0.0651 | 0.99715 | 0.0042408| 0.794      |
| Case3 | ELM      | 0.7464 | 0.0962 | 0.8399 | 0.67266 | 0.70546 | 0.093      |
| Case4 | PSO-ELM  | 0.0199 | 0.0107 | 0.0248 | 0.91169 | 0.00062 | 15.389     |
| Case4 | ELM      | 0.1895 | 0.1079 | 0.1936 | 0.88579 | 0.032007| 0.095      |
| Case5 | PSO-ELM  | 0.0029 | 0.00063| 0.0093 | 0.99929 | 8.5714E-5| 0.876      |
| Case5 | ELM      | 0.3825 | 0.0784 | 0.4224 | 0.7212 | 0.13298 | 0.097      |

As seen in Table 1, we can found that: (1) Comparing and analyzing the data of five stations, it can be seen that the prediction results of ELM prediction model are not very stable, which is greatly affected by the number of samples. The results show that the ELM model has some limitations, and it is easy to fall into the local optimum. Moreover, the prediction results are stochastic and the parameter setting is too subjective, which leads to poor prediction effect. (2) It can be seen that the MAE, MAPE and RMSE predicted by PSO-ELM algorithm are 0.2069, 0.055 and 0.2135 respectively, and the prediction accuracy can reach 96.592%, which are better than the index values predicted by ELM model. The results show that the MAE, MAPE and RMSE are 0.0199, 0.0107 and 0.0248, respectively, which are better than those predicted by ELM model. (3) In the experimental test, the line loss rate prediction based
on PSO-ELM basically takes about 15s or even less, which can meet the requirement of fast power line loss rate prediction.

From the above analysis, PSO-ELM algorithm has higher prediction accuracy, better fitting and faster prediction speed than ELM algorithm, so it is suitable for line loss rate prediction in station area.

4. Conclusion

In order to solve the problem that ELM generates input weights and thresholds randomly, which results in redundancy of network structure and affects its generalization ability and stability, PSO is proposed to optimize it. The initial weights and threshold parameters of the ELM are used as the space position of particles in PSO algorithm for global search. The global extremum searched by PSO corresponds to the optimal input weights and threshold parameters in the extreme learning machine. Combined with the optimization method, PSO-ELM model is established to predict the line loss of five stations with different quantities. The comparison between PSO-ELM model and ELM experimental results shows that PSO-ELM algorithm has higher prediction accuracy, better fitting and faster prediction speed than ELM algorithm, which is suitable for line loss rate prediction in station area.

References

[1] Zhi-Min Lu. Research on Lean Power Line Loss Management System of Power Supply Information & Communication Technology. Research Systems, 2014(1): 88-92.
[2] Lin Hu, Gu Dong, Kang Lin. Line loss rate prediction of low voltage substation area based on gradient lifting decision tree. Information technology, 2020, 44(08): 108-113 + 120.
[3] J. Yasuoka, J.L.P. Brittes, H.P. Schmidt, et al. Artificial neural network-based distribution substation and feeder load forecast. Forecasting, 2001, 5: 20-26.
[4] Liu tinglei, Wang Shao, Zhang Zhi, Zhu Jiangfeng. Niula method for calculating theoretical line loss in low voltage distribution station area by using load capacity. Power system protection and control, 2015, 43(19): 143-148.
[5] Li Yunbing, Xu Lanlan, Wang Xiaojun, Zhang Xiaoling. Line loss prediction method based on gated cyclic neural network. Power equipment management, 2020(02): 132-134.
[6] An Xiaohua, Ouyang Sen, Feng Tianrui, et al. Optimization design method and application of theoretical line loss rate benchmark value of medium voltage feeder. Power grid technology, 2016, 40(1): 199-203.
[7] Jin Baohua, Zhang Mingxing, Wu huaiqiang, et al. An anti stealing prediction method based on power big data. Journal of light industry, 2020, 35(4): 81-87.
[8] Chen Yuan, Chen Xiaoyun. Self coding feature representation of manifold extreme learning machine. Computer engineering and applications, 2020, 56(17): 150-155.
[9] Yang Xin, Yu Zuodong, Zhang Zhiyuan, Bing HanKun, Shen Henan, Wang Jixian. Turbine rotor fault diagnosis based on multi feature extraction and kernel extreme learning machine. Steam turbine technology, 2020, 62(02): 137-142.
[10] Liu Dacheng, Li Shaobo, Wei Hongjing. Prediction method of workshop energy saving target based on extreme learning machine. Journal of Guizhou University (NATURAL SCIENCE EDITION), 2020, 37(04): 52-58.
[11] Yue Youjun, Liu yinghan, Zhao Hui, Wang Hongjun. Short term load interval forecasting based on pole symmetric mode decomposition decentralized entropy and improved crow search algorithm kernel extreme learning machine. Science, technology and engineering, 2020, 20(22): 9036-9042.
[12] Gao Caiyun, Cui Ximin, Gao Ning. Entropy weight genetic algorithm and extreme learning machine for subway tunnel settlement prediction. Surveying and Mapping Science, 2016, 41(2): 71-75.
[13] Han Du, Danqing Song, Zhuo Chen, et al. Prediction model oriented for landslide displacement with step-like curve by applying ensemble empirical mode decomposition and the PSO-ELM method. 2020, 270-276.