Prediction of overhead transmission line ampacity based on extreme learning machine

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Abstract. Caused by the fluctuation of weather conditions, the transmission line ampacity varies with time. For power system operators, the accurate forecast results of overhead transmission lines ampacity are very important and helpful in making planning and control decisions. To assist the system operators in making better use of the transfer capability of transmission lines, it is urgent to improve the ampacity forecast results. In this paper, a novel method based on the extreme learning machine (ELM) is proposed to predict the ampacity. Taking the historical weather and ampacity data as the input data, an ELM-based method can predict the ampacity rapidly and accurately. Numerical simulations based on the recorded actual weather data around a transmission line validate the efficiency of the ELM-based ampacity forecast method.

1. Introduction

At present, with the continuous increase in power consumption and the fast growth of renewable energy power generation, the power transmission capacity of the existing power transmission system is bearing huge burdens [1]. To alleviate the tension of transmission capacity, building new overhead transmission lines may be feasible, but it causes other problems, such as consuming too much time and capital. Therefore, it is necessary for system operators to fully exploit the transmission capacity of the existing power transmission system to ease the stress of the power transmission system.

The static thermal rating (STR) of a transmission line is calculated under given conservative weather conditions [2], [3]. Since the assumed weather conditions are not common, the utilization of STR fails to make full use of the transfer capacity of transmission lines. To calculate the real-time ampacity, the dynamic thermal rating (DTR) was proposed in 1978. The ampacity calculated based on DTR technology is usually higher than STR [4]. Therefore, DTR technology is very effective in fully utilizing the transmission capacity of the existing transmission system and delaying network reinforcements [5].

Based on DTR technology, the real-time weather data around overhead transmission lines can be recorded, which can be used for the studies on the ampacity forecast methods. [6] and [7] predicted the four weather factors around the transmission lines firstly. Then the ampacity is predicted based on the predicted weather data. In [8], a statistical method is proposed to predict the ampacity on the basis of the numerical weather forecast (NWP).
In this paper, an ELM-based method is proposed to improve the ampacity forecast results. The proposed method takes historical weather and ampacity data as input data and can provide accurate ampacity forecast results in a fast speed.

This paper is organized as follows. Section 2 describes the calculation method of the steady-state ampacity. Section 3 proposes the ELM-based ampacity forecast method. Section 4 analyses the forecast results of the proposed method. The conclusions are drawn in section 5.

2. Ampacity calculation method

According to the steady-state thermal model established in [9], the line rating of an overhead conductor can be expressed by:

\[
I_{\text{max}} = \left( \frac{q_s + q_c - q_r}{R(T_{\text{max}})} \right)^{1/2},
\]

where \(T_{\text{max}}\) is the maximum value of the permissible temperature (70°C in this paper); \(R(T_{\text{max}})\) denotes the resistance when its temperature is \(T_{\text{max}}\); The calculation formulas of the heat gain from sun (\(q_s\)), the convection heat loss of an overhead conductor (\(q_c\)) and the radiated heat loss of an overhead conductor (\(q_r\)) are defined in [9].

Using (1), the actual 6-day actual ampacity with a 15-minute time step were calculated based on recorded historical data of the four weather factors. The calculation results are shown in figure 1.

As shown in figure 1, the actual ampacity varies greatly among time periods. In addition, the actual ampacity are all higher than the STR. Therefore, it is necessary to exploit the actual transfer capacity of transmission lines in the practical operation.

3. Ampacity forecast method

In this section, extreme learning machine (ELM) is utilized for the forecast of the ampacity of a transmission line. The ELM-based ampacity forecast method is introduced in subsection 3.1.

3.1. The ELM-based ampacity forecast method

According to [10], ELM can be considered as a single hidden layer feed-forward neural network. Different from conventional neural network methods that involve many iterations, the ELM can randomly initialize the input weight parameters and biases, and then identify the output weight parameters directly through a matrix computation. Therefore, the ELM is a fast-computational method. The ELM with \(k\) hidden nodes is defined as:


\[
f \left( x_j; w, b, B \right) = \sum_{i=1}^{k} B_i g \left( w_i \cdot x_j + b_i \right), \quad j = 1, \ldots, N, \quad (2)
\]

where \( B_i \) is the output weight parameter connecting the \( i \)th hidden node and the output node; \( g(\cdot) \) is the activation function; \( w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T \) is the weight vector connecting the \( i \)th hidden node and the input nodes; \( x_j \) is the input vector; \( b_i \) is the threshold of the \( i \)th hidden node; \( N \) is the sample size.

The ELM with \( k \) hidden nodes can estimate the output of \( N \) samples with zero error, which indicates that:

\[
\sum_{i=1}^{k} B_i g \left( w_i \cdot x_j + b_i \right) = y_j, \quad (3)
\]

where \( y_j \) is the actual output value. The above \( N \) equations can also be expressed as:

\[
HB = Y, \quad (4)
\]

where \( H \) is the hidden-layer output matrix defined in (5); \( B \) is the output weights matrix defined in (6); \( Y \) is the matrix of actual outputs defined in (10).

\[
H = \begin{bmatrix}
g \left( w_1 \cdot x_1 + b_1 \right) & \cdots & g \left( w_k \cdot x_1 + b_k \right) \\
\vdots & \ddots & \vdots \\
g \left( w_1 \cdot x_N + b_1 \right) & \cdots & g \left( w_k \cdot x_N + b_k \right)
\end{bmatrix}_{N \times k}, \quad (5)
\]

\[
B = [B_1, \ B_2, \ \cdots, \ B_k]^T, \quad (6)
\]

\[
Y = [y_1, \ y_2, \ \cdots, \ y_N]^T. \quad (7)
\]

Assumed that the input weight parameters and the hidden-layer biases are stochastically initialized and fixed, the optimal output weights matrix can be obtained by:

\[
\hat{B} = H^+ Y, \quad (8)
\]

where \( H^+ \) denotes the Moore–Penrose generalized inverse of matrix \( H \); \( H^+ \) can be obtained using the singular value decomposition (SVD) method. Since matrix computation in (8) is not complex, the training speed of the ELM is very fast.

After obtaining the parameters in the ELM model, taking the historical weather and ampacity data as input in (2), the ampacity at the predictive time period can be forecasted.

4. Case study

In this section, the weather data were recorded around a transmission line from October 1st, 2019 to November 2nd, 2018 (33 days) with a 15-minute time step. We utilized 30-day data as train data for the estimation of the parameters in ELM. Then the remaining 3-day data were taken as test data to examine the predictive performance of the proposed ELM-based method.

4.1. Forecast results of the ampacity

To verify the effectiveness of the ELM-based method, the ampacity forecasts were conducted for every 15 minutes. The number of hidden nodes of ELM is 30, and the training time is 0.0736 seconds. The ampacity forecast results are shown in figure 2.
Figure 2. Actual ampacity, STR, forecast results.

As seen in figure 2, the forecast results are close to the actual values, and are all higher than the STR (about 426A). The mean absolute percentage error of the forecast results is 8.39%. Therefore, the forecasted ampacity can help operators in making better utilization of the transfer capacity of overhead transmission lines.

5. Conclusion
In this paper, an ELM-based method was proposed for the forecasts of transmission line ampacity. The ELM-based method utilizes a nonlinear model, and can provide determined ampacity forecasts with smaller errors.

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