Input data analysis for the thermal rating prediction of the overhead conductor

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Abstract. The thermal rating of the overhead conductor is closely related to meteorological factors such as wind speed, wind direction, ambient temperature and solar radiation. Therefore, both the historical thermal ratings and meteorological data are alternative input data to predict the thermal rating of the overhead conductor. It is important to select suitable input data to improve the prediction accuracy of the prediction results. Based on the collection of micro-meteorological data from overhead line monitoring system, this paper presents a method to determine the input data for the thermal rating prediction by analysing the autocorrelation of overhead thermal ratings and the cross-correlation between thermal rating and historical micrometeorological data. The results show that the proposed method can provide reference information for the selection of predictive input quantities and prediction time domain.

1. Introduction
The thermal rating of the overhead line is closely related to the meteorological environment [1]. At present, the static thermal rating (STR) [2] widely used in engineering is calculated under the assumption that relatively unfavourable meteorological conditions occur simultaneously (high ambient temperature, low wind speed, strong sunshine), which are clearly conservative [3]. With the continuous growth of power generation and load, the large-scale access of new energy power generation has made the grid load capacity challenge [4], and it has become one of the important factors that restrict the economic operation of power systems and the absorption of new energy [5][6]. Therefore, it is of great value to grasp the variation range and probability distribution law of the thermal rating of the overhead line to help the power system operators to predict the load capacity of the overhead line, and then to make operational control decisions. That is conducive to efficient use of equipment and energy saving and emission reduction [7][8].

However, since the thermal rating predictive inputs used in prediction method are mostly single, the accuracy of the prediction results is not high enough to meet the actual needs of the scheduling. In addition, through the analysis of the thermal rating of the overhead line, it can be known that for a given line model, environmental factors play a decisive role in the load capacity. Therefore, the prediction of the heat setting value of the transmission line is indispensable for environmental
conditions. At the same time, the thermal rating of the overhead line is calculated by the thermal equilibrium equation of the conductor around the meteorological environment and the line operation information of the overhead line collected by the DTR (dynamic thermal rating) system[9][10] at equal time intervals. Therefore, the thermal rating constitutes a random sequence of equal time intervals, as well which may have a certain time relationship.

In summary, based on the historical meteorological data and the thermal rating data collected by the DTR system, the input variables and the prediction time domain of the thermal rating prediction are analysed respectively. Finally, the quantile-based regression prediction method is used to verify the effectiveness of the proposed method.

2. Heat balance model for DTR

The DTR is mainly affected by four factors: wind speed and direction, ambient temperature, and solar radiation [11]. After constructed the model of weather deviation, the steady-state heat balance model for overhead lines showed as (1).

\[ q_i(T(t)) + q_s(t) = q_c(T(t)) + q_r(T(t)) \quad (1) \]

Where, \( t \) is the time (s) and \( T \) is the temperature of the wire (℃), \( q_i \) is the resistance heat of conductor per unit length considering the temperature effect of conductor resistance (w/m), mainly related to capacity and temperature. \( q_s \) is heat gain rate from sun (w/m), \( q_c \) is the convected heat loss rate per unit length (w/m), \( q_r \) is radiated heat loss rate per unit length (w/m).

Where, the specific formula of each element is as follows,

\[ q_i(T) = I^2 R(T) \quad (2) \]

\[ R(T) = \frac{R(T_{\text{high}}) - R(T_{\text{low}})}{T_{\text{high}} - T_{\text{low}}} \times (T - T_{\text{low}}) + R(T_{\text{low}}) \quad (3) \]

\[ q_s = \alpha Q_{se} \sin(\theta) A' \quad (4) \]

\[ q_{c1} = 1.01 + 0.0372 \left( \frac{D \rho f V_e}{u_f} \right)^{0.51} k_f \cos(\angle) (T - T_a) \quad (5) \]

\[ q_{c2} = 0.0119 \left( \frac{D \rho f V_e}{u_f} \right)^{0.6} k_f \cos(\angle) (T - T_a) \]

\[ q_{c3} = 0.0205 \rho_f^{0.5} \left( T - T_a \right)^{1.25} \]

\[ q_r(T) = 0.0178 D \rho f \left[ \left( \frac{T + 273}{100} \right)^4 - \left( \frac{T_a + 273}{100} \right)^4 \right] \quad (6) \]

Where, \( I \) is conductor current (A), \( R(T) \) is AC resistance of conductor at temperature \( T_c \) (Ω), \( T_{\text{high}} \) is maximum conductor temperature for which ac resistance is specified, \( T_{\text{low}} \) is minimum conductor temperature for which ac resistance is specified, \( D \) is conductor diameter (mm), \( \varepsilon \) is emissivity (0.23 to 0.91), \( \alpha \) is solar absorptivity (0.23 to 0.91), \( k_f \) is thermal conductivity of air (W/(m·℃)), \( A \) is projected area of conductor per unit length (mm²/m), \( q_{c1}, q_{c2}, q_{c3} \) is convective heat loss rate per unit length (w/m). At any wind speed, the larger of the two calculated convection heat loss rates is used between \( q_{c1} \) and \( q_{c2} \) while \( q_{c3} \) is applied to zero wind speed. \( Q_{se} \) is total solar and sky radiated heat flux rate elevation corrected (W/m²), \( \rho_f \) is density of air (kg/m³), \( \mu_f \) is dynamic viscosity of air (Pa·s), \( \theta \) is effective angle of incidence of the sun’s rays (°), \( T_a \) is ambient air temperature (℃), \( V_e \) is speed of air stream at conductor (m/s), \( \angle \) is wind direction factor.
From (2) to (6), we can get the conclusion that the thermal rating of transmission line is mainly dependent on the ambient temperature \( (T_a) \), wind speed \( (V_w) \), wind direction \( (k_{angle}) \) and light intensity \( (Q_{se}) \) once the location and type of overhead lines are determined.

3. Data analysis

In this section, on the basis of collecting the 2018 year micro-meteorological data of a 220kV overhead conductor (LGJ 240/35), the cross-correlation of the thermal rating of the overhead conductor and the cross-correlation between the current carrying capacity and the historical micro-meteorology are analysed. Firstly, an autocorrelation function (ACF) test is performed on the thermal rating to extract which autocorrelation feature. Among them, the ACF calculation formula is as follows.

\[
\rho_{k+t}(a) = \frac{E[(e_{k+t} - b_{k+t}) (e_{k+t-a} - b_{k+t-a})]}{h_{k+t}}
\]

Where, \( e_{k+t} \) represent the thermal rating of the \( k+t \) period. The \( b_{k+t} \) and \( h_{k+t} \) are mean and variance of the thermal rating corresponding to the \( k+t \) period, respectively. \( e_{k+t-a} \) indicates the thermal rating that lags behind \( e_{k+t} \) \( a \) periods. \( \rho_{k+t}(a) \) indicates that the correlation coefficient value which lags \( a \) period of the \( k+t \) period thermal rating.

From this, the ACF values of the thermal rating of the overhead wire can be calculated at different lag times. Among them, the ACF values of the lag time within 3 hours are shown in Fig. 1. It can be seen from the figure that the ACF value of the thermal rating decreases slowly with the increase of the lag time, showing a typical ACF tailing feature. At the same time, the ACF value of the lag time within 2 hours is greater than 0.5, and the ACF value of the lag time within 1 hour is greater than 0.7, indicating that there is a strong autocorrelation between the thermal rating of each period within 1-2 hours. Therefore, it can be considered that when the thermal rating prediction model is established, the thermal rating within 1-2 hours of the backtracking history can be taken as part of the predicted input data.

Similarly, the paper uses the cross-correlation function (CCF) to analyze the cross-correlation between the thermal rating and the four elements of micrometeorology under different retrospective durations. To calculate the CCF value of the thermal rating and the wind speed under different retrospective durations during a certain period of time, the calculation formula is as follows:

\[
\rho_{i,j} = \frac{\sum_{i=1}^{R} (e_{\pi,i} - b_{i}) \cdot (V_{\pi,j} - \bar{V}_j)}{\sqrt{\sum_{i=1}^{R} (e_{\pi,i} - b_{i}) \cdot \sum_{\pi=1}^{R} (V_{\pi,j} - \bar{V}_j)}}
\]

Figure 1. Change of the autocorrelation function values

In this figure, the ACF values of the thermal rating of the overhead wire can be calculated at different lag times. Among them, the ACF values of the lag time within 3 hours are shown in Fig. 1. It can be seen from the figure that the ACF value of the thermal rating decreases slowly with the increase of the lag time, showing a typical ACF tailing feature. At the same time, the ACF value of the lag time within 2 hours is greater than 0.5, and the ACF value of the lag time within 1 hour is greater than 0.7, indicating that there is a strong autocorrelation between the thermal rating of each period within 1-2 hours. Therefore, it can be considered that when the thermal rating prediction model is established, the thermal rating within 1-2 hours of the backtracking history can be taken as part of the predicted input data.
Where, the subscripts \( i \) and \( j \) are used to identify the thermal rating and the wind speed sequence respectively. \( n \) is the number of samples, and the range is \( 1 \sim N \). the \( \rho_{i,j} \) is the correlation coefficient between the thermal rating sequence \( i \) and the wind speed sequence \( j \), and the value range is \([-1, 1]\]. 

\( e_{n,i} \) and \( V_{n,j} \) are the \( n \)th sample of the thermal rating sequence \( i \) and the wind speed sequence \( j \), respectively. \( b_i \) and \( \bar{V}_j \) are the mean of the thermal rating sequence \( i \) and the wind speed sequence \( j \), respectively.

It can be seen from the above that the CCF value of the thermal rating and the ambient temperature, the solar intensity and the wind direction at different traceback times can also be calculated from this. As shown in Figure 2, the Pearson correlation coefficient (PCC) of the four elements of micrometeorology with different thermal rating and different traceback time indicates that there is a strong cross-correlation between the each other within 1-2 hours of history. Strong cross-correlation, so micro-meteorological historical data should also be used as part of the predictive input when establishing the thermal rating prediction model.

![Figure 2. Pearson correlation coefficient between the thermal rating and historical micro-meteorology](image)

4. Simulation

From the analysis in the previous section, when the overhead line erection location and the conductor type are determined, the thermal rating mainly depends on the four meteorological elements of ambient temperature, wind speed, wind direction and solar intensity. At the same time, there is a certain relationship in the short-term thermal rating time series distribution. Therefore, this paper combines historical thermal rating information, meteorological information and the two as input variables (defined as input variables 1, 2, 3 in turn), and then based on the quantile regression technique [12] to predict the change of future thermal rating, and then the optimal input variables are selected by comparing the accuracy of the prediction results corresponding to different input variables. Among them, the input variables include the historical information of the first 4 moments of each sequence. The predicted result of the 0.5 quantile comparison with the actual value is as follows:
Figure 3. Comparison of actual thermal rating and 0.5 quantile of prediction results for different input variables

It can be seen from Fig. 3 that the prediction result (red solid line) is higher in accuracy when the historical thermal rating and micro-meteorology are used as input variables, and the fitting effect is the best. Therefore, this paper chooses historical thermal rating and micro-meteorology as the input variables of the prediction model to realize the prediction of the future thermal rating.

5. Conclusion
This paper analyses the predicted input of thermal rating based on the historical data of the thermal rating and micro-meteorological. The results show that when the historical micro-meteorological and thermal ratings are used as prediction inputs, the prediction results have the highest accuracy. However, it should be pointed out that the conclusions of this paper are based on the test data set, and are not general conclusions. Therefore, the analysis results of different overhead conductors may be different, but which does not affect the construction of the prediction method. For other overhead lines, the prediction input and prediction time domain can also be adjusted according to the specific situation by this method.

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