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Uncertainty analysis of dynamic thermal rating based on environmental parameter estimation

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Abstract

Dynamic thermal rating (DTR) of transmission lines is related to wind speed, wind direction, ambient temperature, and so on. Among the environmental parameters, there is a difference between the obtained environmental parameters and the true value. Therefore, only the deterministic values of environmental parameters and DTR are not accurate enough. Considering the environmental parameters obtained with uncertainty, the uncertainty of environment parameters based on Monte Carlo Method (MCM) is studied in this paper. According to the heat balance equation of transmission lines, the uncertainty analysis of transmission line ampacity is realized based on CIGRE standard. The best estimation value, standard uncertainty, and confidence interval are obtained under a given confidence level of environmental parameters. The experimental results show that DTR can fully improve the transmission capacity of transmission lines, and MCM is an effective method to assess uncertainty of DTR.

Keywords: Transmission line, Dynamic thermal rating (DTR), Environmental parameters, Monte Carlo method (MCM), Uncertainty analysis

1 Introduction

Dynamic thermal rating (DTR) of transmission lines based on actual environmental parameters can greatly improve line capacity [1]. Without reconstructing the existing transmission lines, DTR can ease the contradiction between electricity consumption and power supply and improve line utilization with great economic benefits. DTR can be determined by line ampacity calculation model based on CIGRE standard [2–4]. The ambient environmental parameters of transmission lines are significant factors that affect the DTR, but the difference between the measured value and the true value cannot be ignored, and the uncertainty of DTR needs to be evaluated [5–8].

Guide to the expression of uncertainty in measurement (GUM) gives the basic method of assessing uncertainty [9, 10]. However, the method is limited by certain conditions: (1) the probability distribution of the input quantity is assumed to be symmetrical, approximately normal distribution or T distribution; (2) the probability distribution of the output is approximately normal or T distribution; (3) the measurement model is linear model or nonlinear model that can be reduced to linear model [7]. In 2008, the Joint Committee on Measurement Guidelines introduced a supplemental document. The Monte Carlo method (MCM) was used to assess measurement uncertainty [11–13]. According to the supplementary document, measurement uncertainty with the MCM is newly issued in China, which provides a method for assessing the uncertainty of measurement, thus broadening the application scope of uncertainty assessment.

In [14], the MATLAB method for evaluating random numbers in MCM was studied. The simulation of the relevant random variables was realized. It was concluded that MCM could overcome the shortcomings of GUM method in which it was difficult to evaluate the uncertainty of complex model. In [15, 16], the MCM evaluation uncertainty process was given, and the evaluation results of the GUM method were verified by MCM. The reliability of MCM uncertainty evaluation was proved. MCM can be applied to the situation where the GUM method is not

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applicable. To sum up, MCM is an effective method for uncertainty assessment. In this paper, MCM is used to evaluate the uncertainty of DTR of transmission lines.

This paper is organized as follows: Section 2 presents an extensive review of the uncertainty analysis of dynamic thermal rating. DTR of transmission lines based on CIGRE standard is introduced in detail in Section 3. In Section 4, we review the MCM and study the uncertainty of environmental parameters. In Section 5, after obtaining the uncertainty of the environmental parameters, we assess the uncertainty of DTR to ensure the reliability of the results. We conclude in Section 6.

2 Methods

The dynamic thermal rating is determined according to the real meteorological conditions of overhead lines according to wind speed, wind direction, and ambient temperature. The randomness of meteorological parameters and the existence of measurement errors all lead to uncertainty in the results of dynamic thermal rating. Therefore, it is not enough to give only a definite value of the current carrying capacity. It is necessary to give the uncertainty of the carrying capacity, and the result is more reliable. The dynamic thermal rating method based on CIGRE standard is studied. The Monte Carlo method is proposed to analyze and calculate the carrying capacity of the overhead transmission line.

3 DTR method based on CIGRE standard

This section briefly describes the CIGRE method of calculating DTR of overhead transmission lines. The steady state thermal balance equation of CIGRE standard is:

$$I^2 R_{\mathrm{ac}}(T_{\mathrm{c}}) + Q_{\mathrm{s}} = Q_{\mathrm{c}} + Q_{\mathrm{r}} \tag{1}$$

where the convection heat is Q_c, radiation heat is Q_r, sunshine heat absorption is Q_s, and the Joule heat is I^2R_{ac} generated by its own current, and T_c is the line conductor temperature. According to direct current (DC) resistance at 20 °C, to find the alternate current (AC) resistance at T_c is $R_{ac}(T_c) = k_j R_{dc}[1 + \alpha(T_c - 20)]$, k_j usually takes as 1.0123, R_{dc} is the DC resistance of the line, and α is the resistance temperature coefficient. The convection heat dissipation is shown in Eq. (2).

$$Q_{\mathrm{c}} = \pi k_{\mathrm{cf}}(T_{\mathrm{c}} - T_{\mathrm{a}}) K_{\mathrm{angle}} N_{\mathrm{u}} \tag{2}$$

where $k_{cf} = 2.42 \times 10^{-2} + 3.6 \times 10^{-5} \times (T_c + T_a)$ is the ambient air thermal conductivity, T_a is the ambient temperature, and K_{angle} is coefficient of wind direction. Convection heat dissipation is also divided into two cases of high wind speed and low wind speed, where the Nusselt number is N_u and $N_u = B_1(R_e)^n$. R_e is the Reynolds number as shown in Eq. (3).

Table 1 Nusselt number parameters

Surface roughness	Reynolds range	B_1	n
Various surface	$(10^2, 2.65 \times 10^3)$	0.641	0.471
$R_f \le 0.05$	$(2.65 \times 10^3, 5 \times 10^4)$	0.178	0.633
$R_f > 0.05$	$(2.65 \times 10^3, 5 \times 10^4)$	0.048	0.800

$$R_{\mathrm{e}} = \frac{D\rho_0 \exp(-1.16 \times 10^{-4} H_{\mathrm{e}}) V_{\mathrm{w}}}{1.32 \times 10^{-5} + 4.75 \times 10^{-8}(T_{\mathrm{c}} - T_{\mathrm{a}})} \tag{3}$$

where D is the line diameter, ρ_0 is air density at the sea level, V_w is wind speed, H_e is the line altitude, B_1 and n is decided by R_e and the line surface roughness $R_f = d/[2(D - 2d)]$ (d is the outer diameter) as shown in Table 1. D is 27.63 mm and d is 3.07 mm for the transmission line of LGJ-400/50.

The CIGRE standard also takes into account the effects of wind direction on Q_c, the correction factor is $K_{angle} = A_1 + B_2 \sin(\phi)^{m1}$. When the angle between the wind and the line is $0^{\circ} \le \phi \le 24^{\circ}$, then $A_1 = 0.42$, $B_2 = 0.68$, $m_1 = 1.08$. When the angle is $24^{\circ} \le \phi \le 90^{\circ}$, then $A_1 = 0.42$, $B_2 = 0.58$, and $m_1 = 0.9$. When there is no wind, the number of Nusselt is determined by the value of G_r and the value of P_r, $N_u = A_2(G_r \times P_r)^{m_2}$. P_r and G_r are shown in Eqs. (4) and (5).

$$P_{\mathrm{r}} = 0.715 - 1.25 \times 10^{-4}(T_{\mathrm{c}} + T_{\mathrm{a}}) \tag{4}$$

$$G_{\mathrm{r}} = \frac{D^3 \rho_o^2 (T_{\mathrm{c}} - T_{\mathrm{a}}) g}{[(T_{\mathrm{c}} + T_{\mathrm{a}})/2 + 273]\mu_{\mathrm{f}}^2} \tag{5}$$

where $g = 9.8\ m/s^2$ and A_2, m_2 are determined by $G_r \times P_r$, which are shown in Table 2.

The radiation heat dissipation is shown in Eq. (6).

$$Q_{\mathrm{r}} = 0.0178 D\varepsilon \left[\left(\frac{T_{\mathrm{c}} + 273}{100} \right)^4 - \left(\frac{T_{\mathrm{a}} + 273}{100} \right)^4 \right] \tag{6}$$

where ε represents the radiation coefficient of transmission line, ranging from 0.23 to 0.91; ε is 0.23 for the new transmission lines; and ε is 0.91 for the long life lines. Radiation heat is decided by the line

Table 2 The value of parameters A_2 and m_2

$G_r \times P_r$	A_2	m_2
$(10^{-1}, 10^2]$	1.020	0.148
$(10^2, 10^4]$	0.850	0.188
$(10^4, 10^7]$	0.480	0.250
$(10^7, 10^{12}]$	0.125	0.333

diameter, conductor temperature, ambient temperature, and radiation cooling coefficient. The greater the radiation heat is, the more help to improve the transmission capacity of the line.

The heat absorption in the CIGRE standard takes into account the absorption of direct sunlight, the absorption of albedo sunshine and the absorption of solar heat dissipation, as shown in Eq. (7).

$$Q_s = \alpha_s D\left[I_D\left(\sin\theta + \frac{\pi}{2}F\sin H_c\right) + (\pi/2)I_d(1+F)\right] \tag{7}$$

where $I_D = 1280\sin H_s/(\sin H_s + 0.314)$ is the absorption of direct sunlight heat. F is albedo growing with H_c. I_d is sun heat dissipation. In sunny weather conditions, it is the 10% of I_D. The DTR under actual environmental

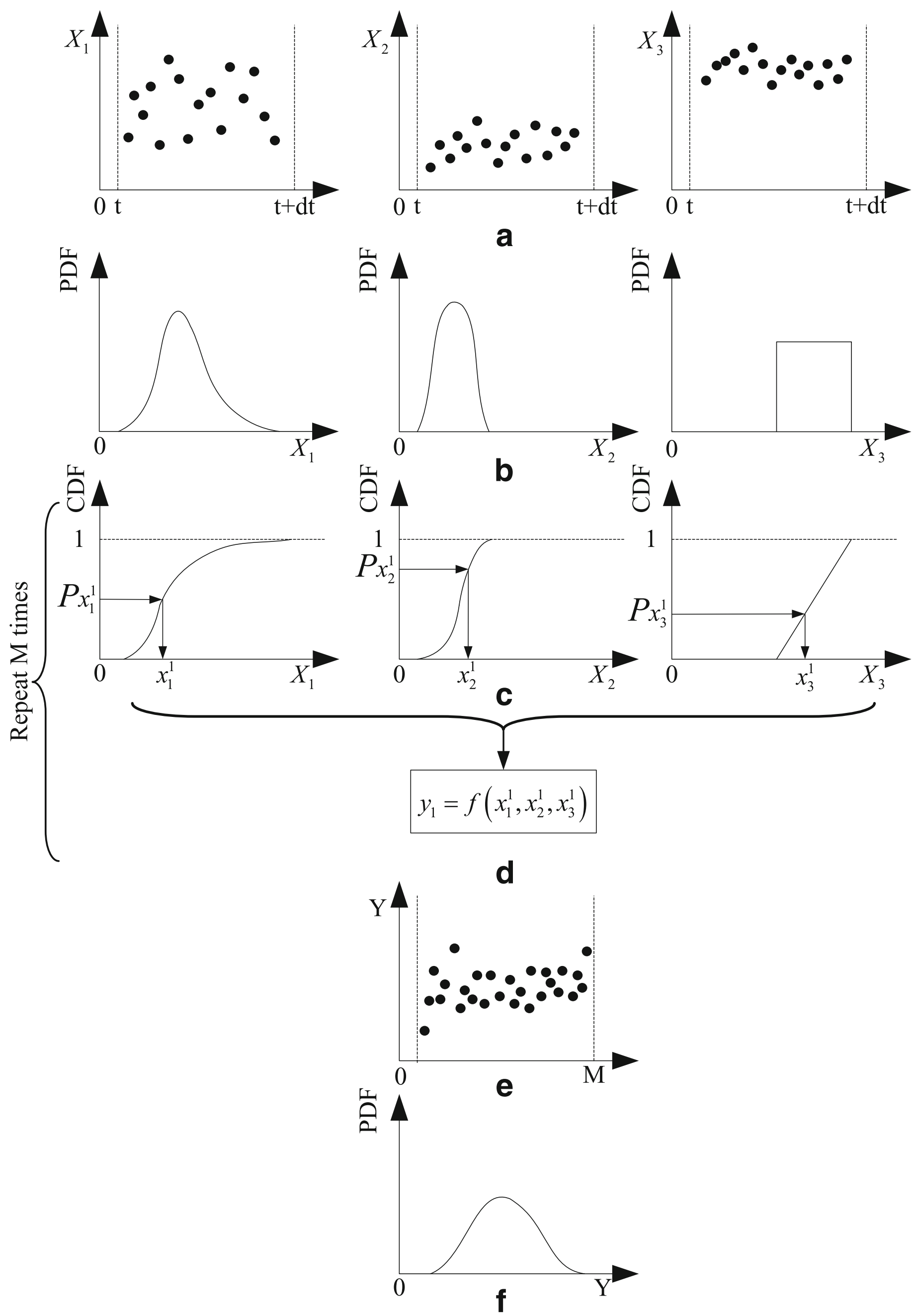

Fig. 1 Probability distribution transmission of input quantity: **a** input variables X_1, X_2, and X_3. **b** PDF of X_1, X_2, and X_3. **c** CDF of X_1, X_2, and X_3. **d** Mathematical model between input and output. **e** Discrete output variable Y. **f** PDF of output variable Y

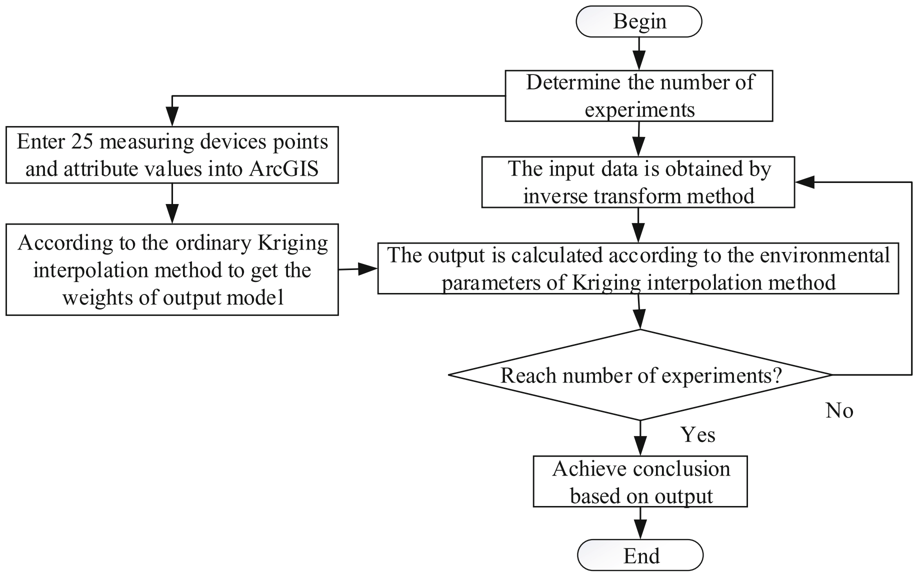

Fig. 2 Calculation procedure for uncertainty of environmental parameters

parameters is taken into account when the steady state equilibrium is deduced from Eq. (1), and the ampacity is calculated in Eq. (8).

$$I = \sqrt{\frac{Q_s - Q_c - Q_r}{R_{ac}(T_c)}} \tag{8}$$

4 Monte Carlo method

The MCM is known as a random simulation method or a statistical testing method. It is based on the stochastic sampling. By means of random sampling, the random number in the corresponding distribution of the random variables is repeatedly selected. The stochastic number satisfying the particular distribution is obtained as the input data. The discrete value of the output is calculated by solving model. Then, the best estimated value, the standard uncertainty, and the corresponding inclusion interval under a given confidence level are acquired from the statistical results of the output value. MCM is an effective

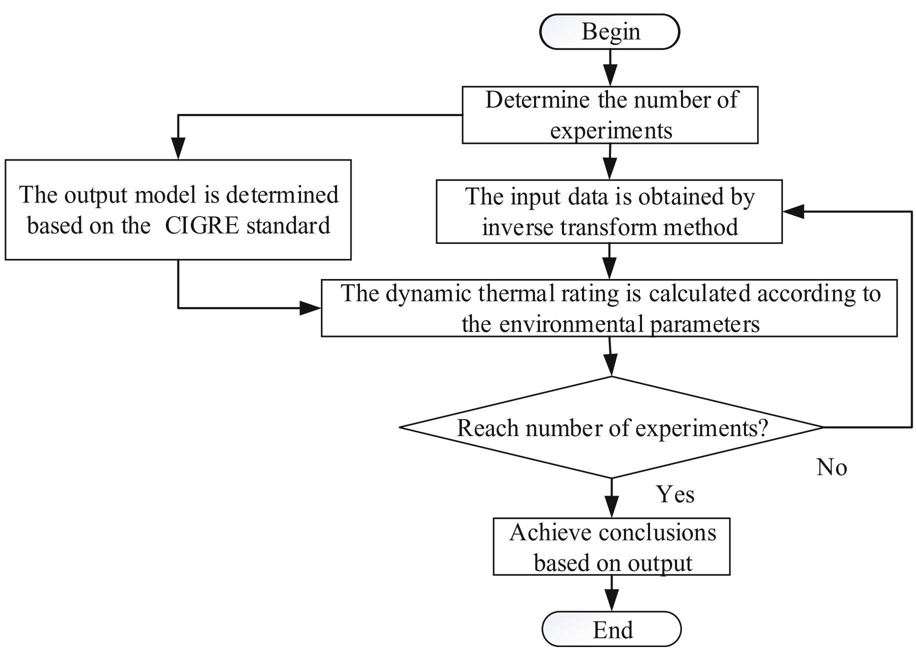

Fig. 3 Calculation procedure for uncertainty of DTR

solution for some complex models which are difficult to calculate for an analytic solution.

4.1 Process of MCM to solve the uncertainty problems

Solving uncertainty problems with MCM usually involves three steps: The first step is model building. By analyzing the problem, the mathematical model between the output and the input is determined, and the number of experiments to be carried out by MCM is given.

The second step is probability distribution and transfer. By the probability density function of the input quantity, the random number is obtained from the inverse transformation method. The output quantity is obtained by substituting the random number as the input quantity into the mathematical model. Repeat this step and stop when the experiment number is reached.

The third step is statistical calculation. The best estimate value, the standard uncertainty, and the corresponding inclusion interval at the given confidence level are presented from statistical analysis of all the discrete outputs obtained by the model.

Suppose that the confidence interval corresponding to the output confidence level of 100p% is finally required. The number of MCM repeated calculations is M times, and M satisfies Eq. (9).

$$M \geq \frac{1}{10p} 10^4 \tag{9}$$

The distribution characteristics of the input quantity are transmitted through the corresponding transfer model, and the distribution characteristic of the output quantity can be obtained. It is assumed that the three inputs are independent. Figure 1a represents the value (X_1, X_2, X_3) of the corresponding input in time dt. Figure 1b is the probability density function (PDF) corresponding to the three input quantities. Figure 1c is the cumulative density function (CDF) calculated from the PDF integral. The random input variables are obtained by M times inverse calculation. Figure 1d shows that the input variables obtained by the inverse calculation are substituted into the mathematical model to calculate

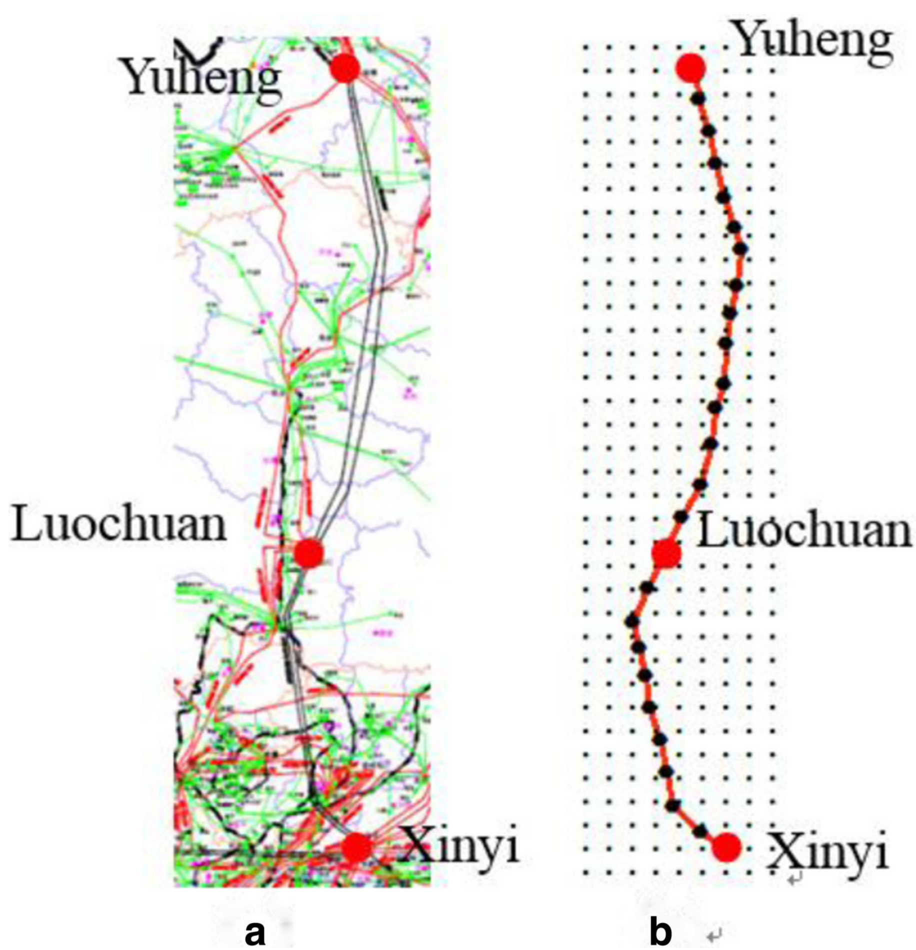

Fig. 4 The geographical location of the studied line: **a** geographic wiring diagram and **b** meteorological data network

output variables. Figure 1e shows discrete output variables, and Fig. 1f is the corresponding PDF according to the discrete output variables. The optimal estimate value, the standard uncertainty and the inclusion interval under the given confidence level are obtained.

From Fig. 1, we can see that X_1 obeys the lognormal distribution, X_2 obeys the normal (Gaussian) distribution, and X_3 obeys the uniform distribution. The distribution function is sampled for M times, and the sampled data as input variables is taken into the mathematical model to obtain discrete output variables, then the mean of output variables, the standard deviation, and the confidence level can be got.

4.2 MCM for analyzing environmental parameters and DTR uncertainty

The flow chart for solving the uncertainty of environmental parameters and DTR is shown in Figs. 2 and 3, respectively.

The location and attribute values of the points with known environment parameter are put into the geographic statistical analysis model in ArcGIS software. The estimating environmental parameter value of a point is obtained by Kriging interpolation. Experiments are repeated by MCM. After reaching the number of experiments, we count the discrete output of each experiment to get the best estimate, the standard uncertainty, and the corresponding interval endpoint with the confidence level of $100p\%$.

In Fig. 3, the input data include wind speed, wind direction, and ambient temperature. The above input parameters are brought into the CIGRE standard heat balance equation, and the dynamic thermal rating of overhead lines can be obtained. As can be seen from Figs. 2 and 3, obtaining input data based on the inverse transform method is an important step in the MCM. If the distribution function $F(x)$ of random variable X is continuous and $r = F(x)$ is set, then r is a uniform random variable on the interval (0, 1). Therefore, the sampled value $x = F^{-1}(r)$ of the random variable X obeys the corresponding distribution function. $F(x)$ can be obtained by extracting the random

Table 3 Longitude, latitude and environmental parameters of 25 known points

Points	Longitude (E)	Latitude (N)	Temperature (°C)	Wind speed (m/s)	Wind direction (°)
1	109.676	37.989	22.31258	1.71582	156.3338
2	109.686	37.884	22.67912	2.14189	149.2344
3	109.729	37.744	23.01952	2.33556	143.2542
4	109.758	37.609	23.21038	2.26855	138.0481
5	109.792	37.470	23.42952	2.04048	131.4788
6	109.835	37.340	23.60655	1.84029	127.6865
7	109.864	37.244	23.64497	1.68302	125.5642
8	109.844	37.095	23.60006	1.58664	125.6270
9	109.820	36.970	23.35387	1.59052	124.9162
10	109.801	36.845	22.94237	1.58255	126.9266
11	109.792	36.671	22.68975	1.67703	136.2848
12	109.758	36.570	22.96728	1.94498	143.1490
13	109.739	36.416	23.63994	2.66577	155.6990
14	109.695	36.243	23.97541	3.58796	166.6059
15	109.614	36.113	23.72943	3.75889	174.8989
16	109.469	35.806	22.48813	1.522706	190.5641
17	109.404	35.666	21.78378	0.61640	193.0289
18	109.424	35.551	22.06700	0.53014	229.0574
19	109.457	35.435	22.58040	0.86832	257.9343
20	109.472	35.300	23.21345	1.47723	269.2503
21	109.515	35.166	23.27094	1.95238	284.4721
22	109.544	35.021	22.47640	2.07477	298.0574
23	109.577	34.882	20.53267	1.54755	299.1291
24	109.688	34.771	18.89304	1.05216	268.7144
25	109.823	34.685	19.47246	1.30290	239.6672

number of evenly distributed over the interval (0,1). If the random number which obeys normal distribution $X \sim N(\mu, \sigma^2)$ is X_i, and r_i is the random number representing standard normal distribution, the equation is shown in Eq. (10).

$$\frac{x_i - \mu}{\sigma} \sim N(0, 1) \tag{10}$$

Thus, Eq. (11) can be obtained.

$$x_i = \mu + \sigma r_i \tag{11}$$

5 Case study

5.1 MCM for analyzing the uncertainty of environmental parameters

The ambient temperature changes slowly in space and time. According to the central limit theorem, the error between the true value and the measured value obeys the normal distribution. As shown in Fig. 4, the MCM is used to analyze the uncertainty of environmental parameters at the location of Luochuan (109.537°E, 35.946°N). In order to combine with the actual line, this paper chooses a 750-kV transmission line from Yuheng, Luochuan to Xinyi according to the geographical wiring diagram of Shaanxi power grid. The transmission line length is 386.7 km. In this paper, we select the latitude range of 109.2°–110.0° E and the latitude range of 34.6°–38.1° N. The range of longitude span is 80 km and the latitude span is 350 km, as we can see in Fig. 4a. The environmental parameter data is from the China meteorological data network. We can get the area of a total of 9 × 36 = 324 measurement points and the corresponding environmental parameters, as shown in Fig. 4b. In the calculation process, the typical variance values of the temperature, wind speed, and wind direction of each known measurement points are 0.3, 0.5, and 1.0 [17], and the random number corresponding to the normal distribution is acquired by the inverse method. The latitude and longitude and environmental parameters of the 25 known points on the transmission line are given in Table 3.

Table 4 The weight of ordinary Kriging method

Points	Longitude (E)	Latitude (N)	Weight of temperature	Weight of wind speed	Weight of wind direction
1	109.676	37.989	0.006944	0.008530	− 0.001115
2	109.686	37.884	− 0.00294	− 0.001504	0.0008418
3	109.729	37.744	0.002148	− 0.001837	0.0000016
4	109.758	37.609	0.002923	− 0.001088	0.0003786
5	109.792	37.470	0.007261	− 0.0004456	0.0006067
6	109.835	37.340	− 0.00124	− 0.0003863	0.0001889
7	109.864	37.244	0.006372	0.01251	− 0.001392
8	109.844	37.095	0.001841	0.04135	− 0.000122
9	109.820	36.970	− 0.01450	− 0.04352	0.0003414
10	109.801	36.845	0.03040	− 0.01894	0.0009870
11	109.792	36.671	− 0.01211	− 0.0005961	− 0.001447
12	109.758	36.570	− 0.05701	0.003447	0.002044
13	109.739	36.416	0.1986	0.0003571	− 0.000862
14	109.695	36.243	− 0.4985	− 0.0006602	− 0.001380
15	109.614	36.113	0.8586	0.5111	0.5072
16	109.469	35.806	0.7825	0.4983	0.4942
17	109.404	35.666	− 0.4213	− 0.002698	− 0.000438
18	109.424	35.551	0.07082	− 0.002142	− 0.002012
19	109.457	35.435	0.06238	0.004119	0.002807
20	109.472	35.300	− 0.02833	− 0.001016	− 0.000671
21	109.515	35.166	− 0.00514	0.002383	0.001088
22	109.544	35.021	0.01500	− 0.02644	− 0.000957
23	109.577	34.882	− 0.00392	− 0.01687	− 0.001596
24	109.688	34.771	− 0.00001	0.03288	− 0.000289
25	109.823	34.685	0.005737	0.003186	0.0007310

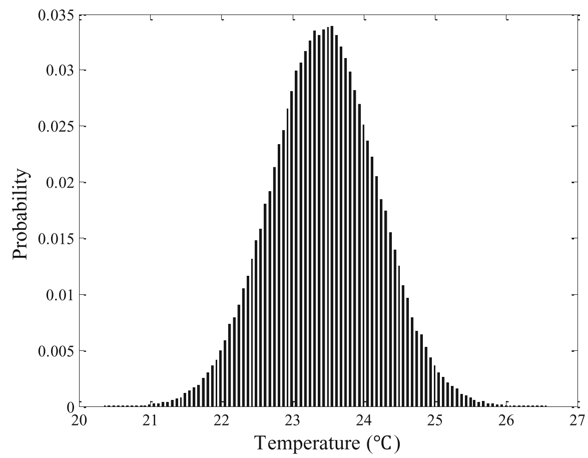

Fig. 5 Ambient temperature distribution histogram

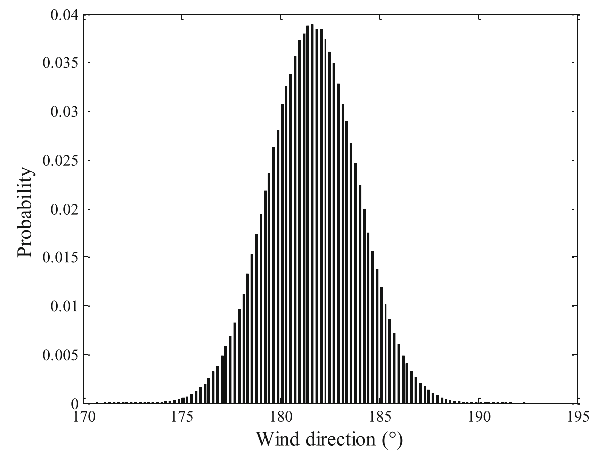

Fig. 7 Wind direction distribution histogram

The corresponding weights for the 25 points to get Luochuan parameters by the ordinary Kriging interpolation method are shown in Table 4. The uncertainty of environmental parameters at Luochuan is analyzed by the Monte Carlo method. The histograms of the temperature, wind speed, and wind direction distributions obtained by the MCM are shown in Figs. 5, 6, and 7.

The best estimate value, standard uncertainty, and the shortest confidence interval of 95% (sampling number M is 200000) are shown in Table 5.

As can be seen from Table 5, the best estimate value of the MCM is in the shortest inclusion interval with a confidence level of 95%. The standard uncertainty of wind speed is the minimum and the wind direction is the maximum. Among them, the standard uncertainty of wind direction is the largest. And the range of included intervals with the corresponding confidence level of 95% is also the largest.

5.2 Results and discussions

From Table 5, we can see that the temperature, wind speed, and wind direction of Luochuan at 8 a.m. on September 17, 2016, are subject to the following distribution.

$$\begin{cases} T_{\mathrm{a}} \sim Norm\left(23.4471, 0.5488^2\right) \\ V_{\mathrm{w}} \sim Norm\left(2.6358, 0.5072^2\right) \\ \phi_{\mathrm{w}} \sim Norm\left(181.6417, 2.2416^2\right) \end{cases} \tag{12}$$

Combined with CIGRE standard, we get the distribution diagram of dynamic thermal rating when the line maximum allowed temperature is 70 °C, as shown in Fig. 8.

Table 6 gives the best estimates of the dynamic thermal ratings obtained from the MCM as well as the standard uncertainty and the minimum inclusion interval with a confidence level of 95%. According to the CIGRE standard based on the environmental

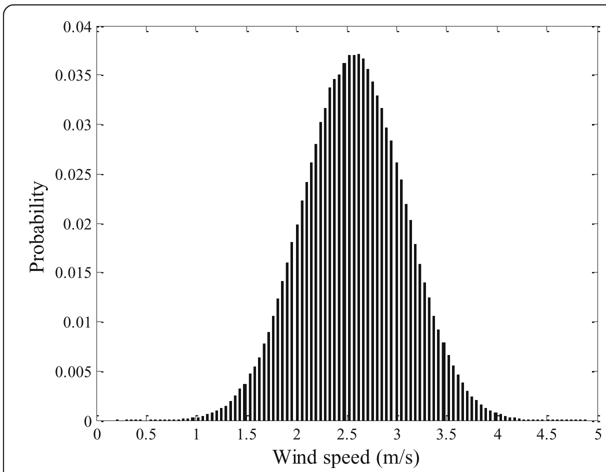

Fig. 6 Wind speed distribution histogram

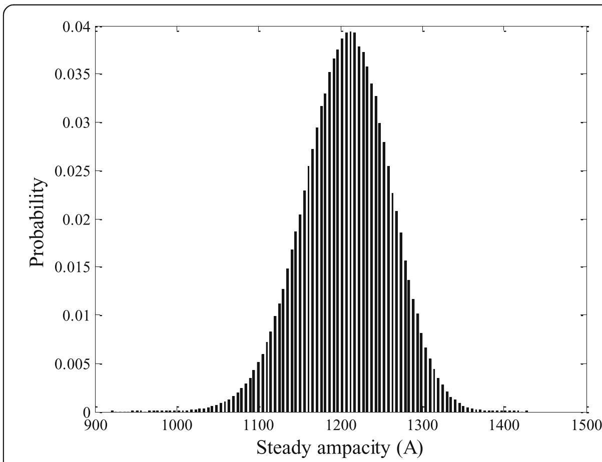

Fig. 8 CIGRE standard DTR distribution

Table 6 MCM for solving DTR uncertainty

Calculation standard	Best estimate value(A)	Standard uncertainty (A)	The shortest inclusion interval with the confidence level of 95% (A)
CIGRE	1178.5	44.7	[1087.3,1262.7]

parameters, the best estimation values of the dynamic thermal values obtained by the MCM are 1178.5 A, which is in the minimum inclusion interval with a confidence interval of 95%. When the line maximum temperature is 70 °C, static thermal rating of LGJ-400/50 transmission line is 592 A. According to CIGRE standard, the dynamic value of the line can be increased by 83.7–113.3% with the 95% confidence level. It can be seen that the dynamic thermal rating can greatly improve the transmission capacity.

6 Conclusions

In order to verify the reliability of the DTR of transmission lines, the DTR model based on CIGRE standard is given. The DTR uncertainty is evaluated by MCM method. The application scope and concrete process of the MCM are studied. According to the measurement data of environmental parameters, the estimation uncertainty of ambient temperature, wind speed, and wind direction at 8 a.m. on September 17, 2016, in Luochuan is given. Through Monte Carlo analysis and simulation, the optimal estimation of DTR, the standard uncertainty, and the inclusion interval under the given confidence level are gained. The uncertainty of DTR can be effectively analyzed by MCM method, and the calculation of the line transfer capability is more accurate. Comparing with the static thermal rating obtained by conservative environmental parameters, we find that the DTR technique can increase the line transmission capacity on the basis of the existing transmission lines and improve the efficiency of transmission lines. Future work should study the benefits of dynamic thermal rating.

Table 5 MCM to analyze the output of environmental parameter uncertainty

Environmental parameter	Best estimate value	Standard uncertainty	The shortest confidence interval with the confidence level of 95%
Temperature (°C)	23.4471	0.5488	[21.99,24.90]
Wind speed (m/s)	2.6358	0.5072	[1.64,3.63]
Wind direction (°)	181.6417	2.2416	[117.24,186.03]

Abbreviations

CIGRE: International Council on Large Electric Systems; DTR: Dynamic thermal rating; GUM: Uncertainty in measurement; MCM: Monte Carlo method

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Authors' contributions

YW is the main writer of this paper. She proposed the main idea. WT introduced the MCM algorithm. RW completed the simulation and analyzed the results. ZY gave some important suggestions for the DTR calculation. All authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing interests.

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