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Uncertainty Analysis of Dynamic Thermal Rating of Overhead Transmission Line

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Abstract

Dynamic thermal rating of the overhead transmission lines is affected by many uncertain factors. The ambient temperature, wind speed and wind direction are the main sources of uncertainty. Measurement uncertainty is an important parameter to evaluate the reliability of measurement results. This paper presents the uncertainty analysis based on Monte Carlo. On the basis of establishing the mathematical model and setting the probability density function of the input parameter value, the probability density function of the output value is determined by probability distribution random sampling. Through the calculation and analysis of the transient thermal balance equation and the steady- state thermal balance equation, the steady-state current carrying capacity, the transient current carrying capacity, the standard uncertainty and the probability distribution of the minimum and maximum values of the conductor under 95% confidence interval are obtained. The simulation results indicate that Monte Carlo method can decrease the computational complexity, speed up the calculation, and increase the validity and reliability of the uncertainty evaluation.

Keywords

Confidence Interval, Dynamic Thermal Rating, Monte Carlo Method, Transmission Line Carrying Capacity

1. Introduction

The concept of dynamic thermal rating (DTR) was proposed in 1970s, which is the conductor current of overhead transmission line based on the dynamic environmental measurement and its realization framework of the DTR system was given [1]. DTR is a technique that can dynamically improve the carrying capacity of transmission lines. The maximum current value of the transmission line is the static thermal capacity limit that is set up to prevent overheating when the line load increases. This limit is based on the worst climatic conditions to maintain the safe operation of transmission lines. In fact, the probability of the worst climatic conditions is very low [2]. The DTR calculates the maximum current value of conductors according to the real time environment and the conductor conditions. The DTR has a more accurate estimate of the current carrying capacity of the transmission line than the static thermal rating estimated under conservative conditions [3]. The DTR is usually higher than the static thermal

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rating, which means that the DTR can make better use of the capacity of the power system without overestimating the line capacity under extreme adverse conditions [4,5]. Building new lines takes a large number of investment and time. In the context of smart grid, we are seeking innovative solutions. The potential transmission capacity provided by DTR means that runtime of the equipment can be extended while minimizing or delaying network reinforcement [2-6]. DTR can not only improve transmission line utilization, but also can be used for real-time monitoring. The integration of DTR into power systems will improve penetration rates of renewable energy sources, decrease greenhouse gas emissions, reduce power generation costs and increase economic efficiency and social benefits [7]. However, the current research is in the stage of line condition monitoring system test and feasibility evaluation, and there are still many problems that need to be further studied in practical application [8].

The DTR of the overhead transmission system equipment is a way to maximize the current carrying capacity of the equipment and ensure normal and stable operation of the line. Because of the continuous change of climate factors, limited sampling points between line spans, and the inherent errors of measurement, there is a great deal of uncertainty in the evaluation of DTR. In order to more accurately estimate the line thermal rating, the uncertainty in the DTR calculation needs to be considered. Uncertainty is associated with the measurement results, which is used to characterize the dispersion of measurement results. Measurement uncertainty has been highly valued in various fields [9]. The traditional “Measurement Uncertainty Representation Guide” [10] only specifies the general assessment and presentation of the measurement results, and does not involve the question of how to evaluate the multi-channel measurement results and the dynamic uncertainty. From the theory of information and degree of freedom, the authors [11] proposed a weighted value according to the degrees of freedom and the method for uncertainty evaluation. This method makes full use of the measurement results of a variety of channels to obtain information, unifies the previous methods to deal with differences, and improves the reliability of the measurement results of the assessment, but the key of this method is to be good at analysis and evaluation of the degrees of freedom for information acquisition. Based on the Bayesian statistical dynamic uncertainty, the uncertainty of the Bayesian statistical inference principle is used for the case where there is a lot of a priori information and there are very few measurements. It is necessary to select different Bayesian model modeling [12]. Fuzzy evaluation can quantitatively deal with the various factors of impact analysis, so that the results of the analysis are more in line with the objective reality and more reasonable. But when there are many fuzzy factors to consider, each factor often has different levels, and the fuzzy factors that influence the parameter value can’t be quantified. The accuracy and effectiveness of the evaluation results can’t be guaranteed [13].

In view of this, by comparing the advantages and disadvantages of other methods of uncertainty assessment, this paper determines uncertainty using the Monte Carlo (MCM). In order to ensure that the assessment of uncertainty is more reliable, we must carefully analyze the source of measurement uncertainty. Monte Carlo test can be used to replace the part of the real test, saving the design of the time and workload. So people can evaluate the uncertainty more reasonably. MCM principle is simple and easy to operate. When MCM is used to solve some problems, the impact of the conditions constrains imposed by the some problems is relatively small, so MCM has a wide range of applicability.

This paper is organized as follows: Section 2 discusses the calculation method of DTR based on transient thermal balance equation and steady-state thermal balance equation. In Section 3, we elaborates the Monte Carlo methods and procedures for assessing the uncertainty of transmission line current carrying capacity, including Monte Carlo input, Monte Carlo propagation, Monte Carlo output and report results. In Section

4, we introduce the climate model, wind speed model, wind direction model and ambient temperature model, respectively. The case analysis based on the Monte Carlo uncertainty evaluation model is showed in Section 5. Section 6 summarizes this paper.

2. Calculation Method of Dynamic Thermal Rating

2.1 Thermal Balance Equation

According to the principle of thermal balance, there are the following transient thermal balance equations:

$$I^2R(T_c)+Q_s=MC_p\frac{dT_c}{dt}+Q_r(T_c,T)+Q_c(T_c,T,V,\Phi) \tag{1}$$

where T_c is the transmission line conductor temperature. T represents ambient temperature. V is wind speed and Φ is wind direction. Q_s is the heat absorbed by the sunshine effect. Q_r is the radiation heat dissipation and Q_c is the conductor convection heat dissipation, respectively. The specific calculation method is showed in [14,15]. I is the current carrying value of the transmission line. R is the AC resistance of conductor per unit length (Ω/m) when conductor temperature is T_c. M is the mass of conductor per unit length (kg/m). C_p is the specific heat of a conductor material (J/kg·°C).

When the conductor temperature is no longer changed, the circuit is in a stable state. The differential term in the transient thermal balance equation is zero. So the static thermal balance equation is:

$$I^2R(T_c)+Q_s=Q_r(T_c,T)+Q_c(T_c,T,V,\Phi) \tag{2}$$

The equation can also be used to obtain maximum allowable ampacity:

$$I=\sqrt{\frac{Q_r(T_c,T)+Q_c(T_c,T,V,\Phi)-Q_s}{R\left(T_c\right)}} \tag{3}$$

Static thermal rating is the current carrying capacity obtained by the thermal balance equation in the stage of confined conductor temperature and worst climatic conditions. However, since the thermal balance equation can still be used for normal climatic conditions, the DTR can be determined by Eq. (3). On the other hand, other variables can be obtained by the thermal balance Eq. (2). For example, the conductor temperature in a real-time environment can be obtained by carrying capacity, ambient temperature and wind speed. It can also be used to calculate the risk of heat overload.

3. Monte Carlo Method and Procedure for Assessing the Uncertainty of Conductor Ampacity

3.1 Monte Carlo Method for Uncertainty Assessment

MCM is a numerical method that provides a numerical approximation of the output probability density function. MCM uses the random sampling method to obtain the random state of the system, through the occurrence frequency of the sample statistical simulation state to estimate its probability. MCM is widely used in the measurement of uncertainty assessment. The core of MCM is to get the standard deviation of the simulated sample, based on the distribution propagation. Since the flexibility of the method and the amount of computation independent of the system size, the MCM has a major impact on the uncertainty evaluation of the power system. The results show that the sampling times of the MCM are independent of the scale of the system under the given precision requirements. In addition, the computational efficiency can be improved by the algorithm improvement.

3.2 Monte Carlo Steps for Uncertainty Assessment

The main steps of assessment uncertainty include Monte Carlo input, Monte Carlo propagation, Monte Carlo output and reporting results.

3.2.1 MCM input

Step 1. Define the output value *Y*, which needs to be measured.

Step 2. Determine the input value $X_1,\cdots,X_N$ associated with *Y*.

Step 3. Establish the model between $X_1,\cdots,X_N$ and *Y*, namely $Y=f\left(X_1,\cdots,X_N\right)$.

Step 4. Use the available information to set the probability density function (PDF).

Step 5. Select the Monte Carlo test sample size, the general selected as *M*:

$M=\max(J,10^4), J=100/\left(1-p\right)$, *p* is the confidence interval. Usually *p* is 95%.

where output value *Y* in this paper represents the current carrying value I of the transmission line. Input value $X_1,\cdots,X_N$ (*N*=3) is the ambient temperature *T*, wind speed *V*, wind direction Φ, respectively. The model of $Y=f\left(X_1,\cdots,X_N\right)$ is thermal balance equations.

3.2.2 MCM propagation

Step 1. Extract *M* sample values x_{ir} from $f_{X_i}(x_i)$ of the input values X_i, $i=1,\cdots,N, r=1,\cdots,M$.

Step 2. Calculate the corresponding $y_r=f(x_{1r},x_{2r},\cdots,x_{Nr})$ for each sample vector $(x_{1r},x_{2r},\cdots,x_{Nr})$, $r=1,\cdots,M$.

where $f_{X_i}(x_i)$ (*i*=1, 2, 3) of this paper represents the probability density functions of ambient temperature, wind speed and wind direction, respectively. $y_r=f(x_{1r},x_{2r},\cdots,x_{Nr})$ represents the r^{th} Monte Carlo sampling model values of output value *Y*.

3.2.3 MCM output

The discrete representation *G* of the PDF of the output *Y* can be obtained as follows:

Step 1. The model values y_r obtained by MCM are sorted in a non-descending order and the sorted model values are denoted as $y_{(r)}, r=1,\cdots,M$.

Step 2. Perform a small numerical perturbation of all the repeated model values $y_{(r)}$, which makes the set of $y_{(r)}$ form a strictly increasing sequence.

Step 3. Set G to assemble $y_{(r)}$, $r = 1, \cdots, M$.

Step 4. The $y_{(r)}$ or y_r is plotted as a histogram at a suitable sub-interval interval to obtain a frequency distribution, which provides an approximation probability density function $g_Y(y_r)$ for Y. The resolution of the histogram depends on the selected sub-interval spacing, so it is generally not based on the histogram but according to G to carry out various calculations.

3.2.4 Report results

Step 1. The estimated value y and the standard uncertainty $u(y)$ of Y are calculated by G.

Step 2. Calculate the inclusion interval $[y_{low}, y_{high}]$ of Y for a given the confidence interval p.

$$\tilde{y} = \frac{1}{M}\sum_{r=1}^{M} y_r \tag{4}$$

$$u(\tilde{y}) = \sqrt{\frac{1}{M-1}\sum_{r=1}^{M}\left(y_r - \tilde{y}\right)^2} \tag{5}$$

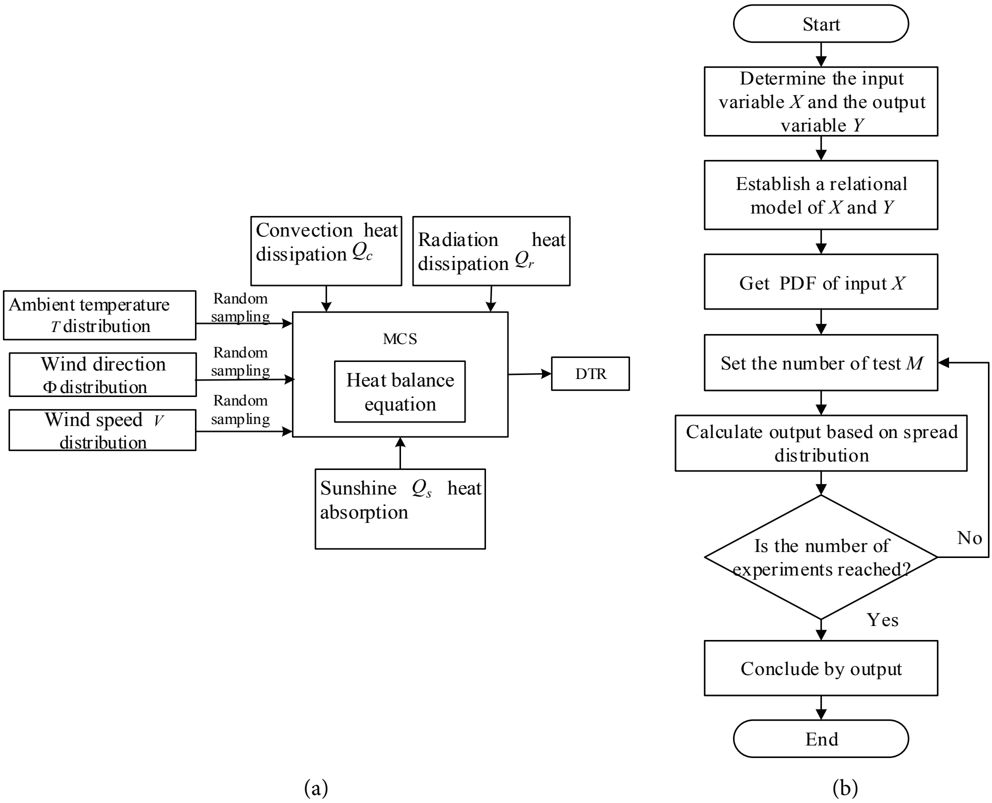

Fig. 1. (a) Monte Carlo simulation block diagram based on thermal balance equation and (b) Monte Carlo flow chart.

The average value $\tilde{y}$ and the standard deviation $u(\tilde{y})$ of the output values determined by the above formula are the estimated value y and the standard uncertainty $u(y)$ respectively of Y.

The discrete representation G of PDF determines the inclusion interval of Y. If pM is an integer, let $q = pM$. Otherwise, we take the integer part of $q = pM + 1/2$. Then $[y_{low}, y_{high}]$ is the p-inclusive interval of Y, where for any $r = 1, \cdots, M - q, y_{low} = y_{(r)}, y_{high} = y_{(r+q)}$. If $(M - q)/2$ is an integer, take $r = (M - q)/2$. Otherwise, r is equal to the integer part of $(M - q + 1)/2$, which can get the probability symmetry p-inclusive interval $[y_r, y_{r+q}]$. If the PDF is asymmetric, the shortest p-inclusive interval can be used to determine r^* , which makes $y_{(r*+q)} - y_{(r*)} \le y_{(r+q)} - y_{(r)}, r = 1, \cdots, M - q$ and we also obtain the shortest inclusive interval $[y_{(r*)}, y_{(r*+q)}]$. For symmetric PDF, the probabilistic symmetric p-inclusive interval and the shortest p-inclusive interval are the same.

The flow chart of Monte Carlo simulation (MCS) is shown in Fig. 1(a) by the above methods and steps of Monte Carlo assessment of uncertainty. In addition, Fig. 1(b) simply shows the flow chart of the implementation by MCM.

4. Climate Model

The sources of uncertainty in uncertainty assessment of the conductor current based on MCM are wind speed, wind direction and ambient temperature. To obtain the uncertainty of the conductor temperature, it is necessary to know the distribution of wind speed, wind direction and ambient temperature. The three quantities are independent of each other.

The wind speed model is generally studied using the Weibull distribution. The frequency histogram of the wind speed data shows that there is a peak at a low wind speed (0 m/s). That is, the wind speed frequency near 0 m/s is abnormally high, and the wind speed error distribution measured in real time is not consistent with the distribution of Weibull [16]. However, the analysis of wind speed statistics shows that the error distribution of wind speed is in accordance with the application conditions of the central limit theorem. So the wind speed error data conforms to the normal distribution.

The wind direction model generally adopts the first-order autoregressive Bayesian time series model. The VM distribution angle is in the range of $[0\pi, 2\pi]$, and the VM distribution is a good choice when dealing with angle-related cyclic data [17]. However, the statistical analysis of the wind direction combined with the sampling data of several days shows that the error distribution of the wind direction can also be considered as Gauss distribution.

The ambient temperature changes relatively slowly in time and space, and the temperature measured by the sensor is close to the true value. According to the central limit theorem, it can be assumed that the error distribution of ambient temperature obeys the normal distribution and the expected value of the error is zero.

5. Case Analysis

5.1 Gauss Distribution

The normal distribution is a very important probability distribution in the fields of mathematics, engineering and so on. It has a great influence on statistics [18]. If the random variable X obeys a normal distribution whose mathematical expectation is μ and the variance is σ^2. Among, σ is the standard deviation. The mathematical model is as follows:

$$f(X)=\frac{1}{\sigma\cdot\sqrt{2\pi}}\cdot\exp\left[-\frac{(X-\mu)^2}{2\cdot\sigma^2}\right] \tag{6}$$

The normal distribution is the distribution of successive random variables with two parameters μ and σ^2. μ determines the position of the normal distribution, and σ^2 determines the magnitude of the normal distribution. The parameter μ is the mean of the random variable that follows the normal distribution. The parameter σ^2 is the variance of the random variable. Therefore, the mathematical expectation of the random variable X obeying normal distribution is μ, and variance is σ^2. They can be denoted as $X \sim N(\mu,\sigma^2)$. The probability of random variable obeying normal distribution is about the μ symmetry. The closer the value to μ is, the greater the probability, and the maximum is reached at μ. The farther away from μ the value is, the smaller the probability. The value is 0 at the positive (negative) infinity. The smaller the standard deviation σ is, the more concentrated the distribution is near the μ. The larger the σ is, the more dispersed the distribution is.

A very important property of the normal distribution is that the distribution of the sum of a large number of independent random variables tends to be normal distribution under certain conditions, which is called the central limit theorem. The central significance of central limit theorem is that, according to the conclusion of this theorem, other probability distributions can be approximated by normal distribution.

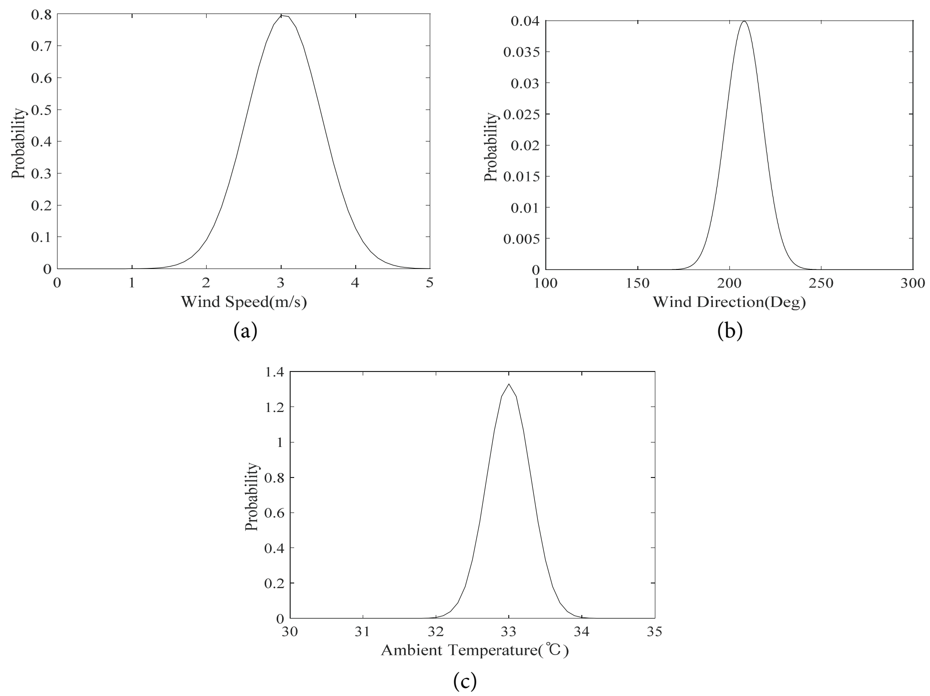

Fig. 2. Probability density function distribution curves of wind speed (a), wind direction (b), and ambient temperature (c).

According to the monitoring of wind speed, wind direction and ambient temperature at 12:00 on August 12, 2016, the normal distribution of wind speed, wind direction and ambient temperature is obtained by reference to the typical variance value [19]. The distribution of wind speed, wind direction and ambient temperature respectively is as follows.

From the probability density distribution curves of wind speed, wind direction and environmental temperature in Fig. 2, we can know that the climate at this time is almost the worst of the year.

5.2 Monte Carlo Simulation Results

Firstly, Monte Carlo is used to carry out discrete sampling through MCMs and steps. Then steady-state current carrying capacity, transient current carrying capacity, uncertainty and 95% confidence interval are obtained based on the steady state thermal balance equation and transient thermal balance equation. The steady-state current is the current carrying value of the overhead transmission line when the conductor temperature is 70°C, and the rated current carrying value of the transmission line is 500 A. The size of the uncertainty indicates the size of the measurement data error. The greater the uncertainty is, the greater the risk of transmission line capacity increasing will be.

From the above analysis, the average value of the steady-state current carrying capacity is 889.06 A, and the shortest inclusion interval is [721.9, 1055.9] under the 95% confidence interval. The probability distribution of the steady-state current carrying capacity is displayed in Fig. 3. As shown in Fig. 3, most of the current carrying value exceeds the rated current carrying value of the conductors, mainly in the 95% confidence interval. The current carrying capacity is increased by 44.38% to 111.18% compared to the rated current carrying value. The maximum current carrying value reaches 1200 A, and the maximum frequency appears when the current is 900 A. The probability is 0.037.

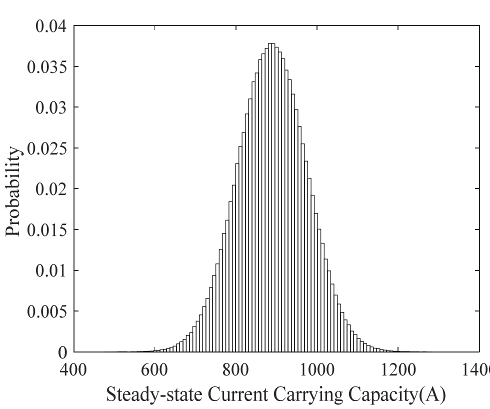

Fig. 3. Steady-state current value of transmission line.

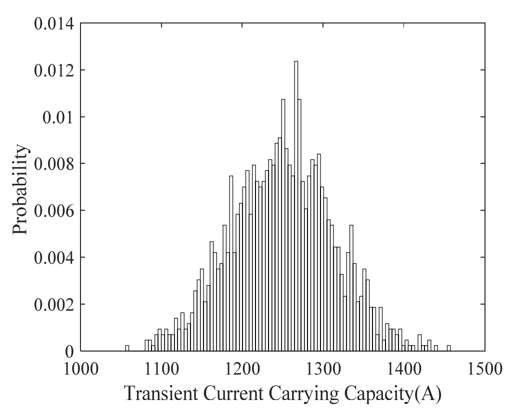

Fig. 4. Transient current value of transmission line.

Similarly, the mean value of transient current carrying value is 1249.7 A, and the shortest inclusion interval is [1125.0, 1371.7] under the 95% confidence interval based on the transient current value definition and transient thermal balance equation. Compared with the rated rated current carrying value, transient current carrying capacity is increased from 125% to 174.34%. The probability distribution of transient current value is displayed in Fig. 4. On the basis of the rated current carrying capacity and steady-state current carrying capacity, there is more room for transient current carrying capacity. This also reflects the potential of transient current carrying capacity of transmission lines and provides guidance for short-term overload operation of transmission lines.

In the conventional design, the line time constant is generally not more than 30 minutes, and the 170 sets of observation data are taken from 12:00 on August 12m 2006 to 14:00 on August 19, 2016. The measurement is carried out every one hour interval. The probability distribution and the cumulative probability density distribution of the steady-state current carrying capacity mean value are obtained. The minimum and maximum steady-state current carrying values with the cumulative probability density distribution under the 95% confidence interval are also obtained.

The PDF of a random variable is a function of the probability density of each point in the sample space. Cumulative probability distribution function (CDF) is used to describe the probability that a random variable is less than or equal to a certain value. It can completely describe the probability distribution of a real random variable.

Histogram distribution of the current value is obtained by the normal distribution of meteorological parameters. The frequency distribution can be regarded as the probability distribution under certain conditions. Then, when the probability is accumulated, a CDF curve of the current carrying capacity is obtained. The cumulative probability distribution curve can not only directly reflect the distribution of the carrying capacity, but also find the most reliable distribution range of the carrying capacity through the cumulative probability curve. Practical experience shows that the true distribution range is exactly at that point where the cumulative probability curve changes most steeply and the slope is the largest.

It can be seen from the probability distributions in Figs. 5 and 6 that in most cases, the steady-state current average value of the conductor exceeds the rated current carrying value of 500 A. The cumulative probability distribution curve of the steady-state current average value is shown in Fig. 5(b). It can be seen that the probability of below the rated current carrying value of 500A is less than 0.1. However, the probability that the minimum current value of the conductor under the 95% confidence interval is lower than the rated current carrying capacity is larger, as shown in Fig. 6(a), with a probability of 0.3.

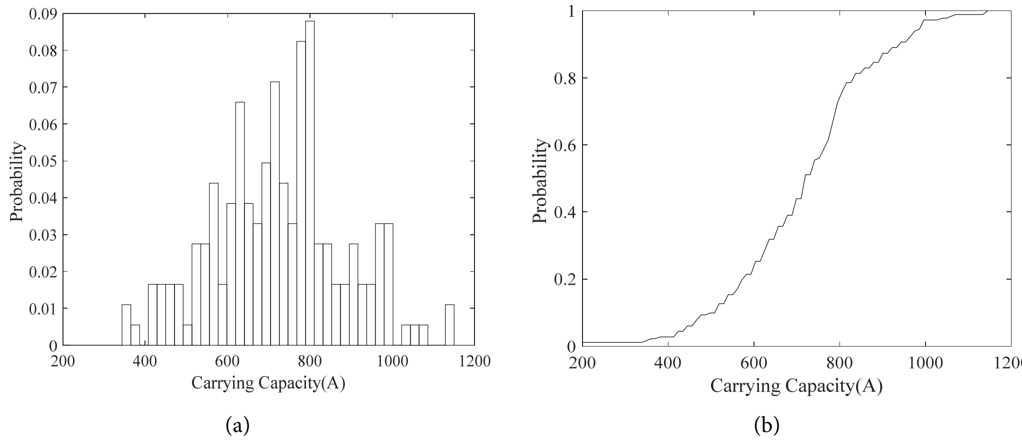

Fig. 5. Steady-state current carrying capacity average value: (a) PDF and (b) CDF.

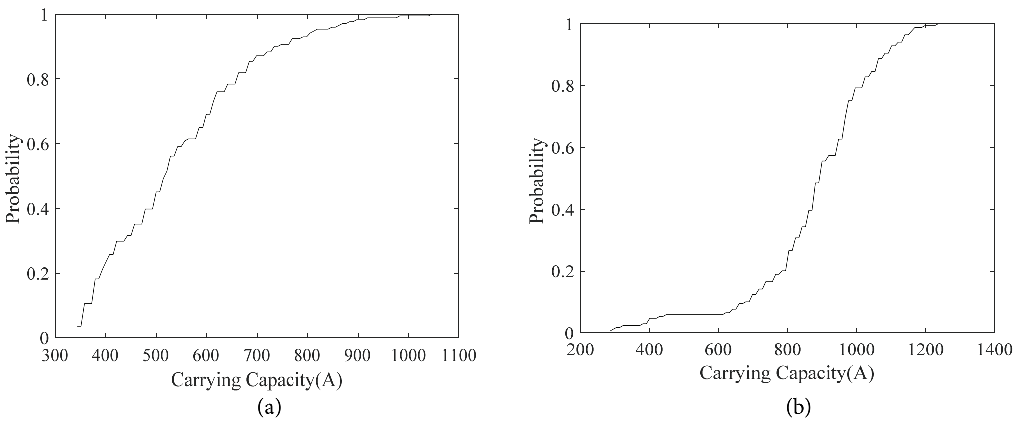

Fig. 6. CDF of conductor current carrying capacity minimum value (a) and maximum value (b) under 95% confidence interval.

The cumulative probability distribution curve of the maximum current value of the conductor under the 95% confidence interval in Fig. 6(b) shows that the probability of current carrying value below the rated current carrying value is only 0.05. Through the above analysis, it can be concluded that only the rated carrying value is not reliable enough. Dynamic current carrying capacity can better reflect the actual carrying capacity of the transmission line, and can better provide operational risk information for dispatchers. It is a very economical and effective measure to improve the transmission capacity of the existing line at the highest allowable temperature of conductor to determine the dynamic current value of transmission line based on dynamic meteorological conditions.

6. Conclusion

The climate models of environmental temperature, wind speed and wind direction are established by MCM. The MCM is used to the calculation of transmission line current value by combining the DTR. Based on the MCM and the detailed steps of the uncertainty assessment model, the steady-state current value, transient current value, steady-state current average value, the minimum and maximum value probability distribution histogram of line current value under 95% confidence interval are obtained, as well as the cumulative probability distribution curve of the steady-state current average value and the minimum and maximum value of the conductor current carrying capacity under the 95% confidence interval, respectively. Sampling the sources of uncertainty through Monte Carlo reduces time complexity and workload, which makes people evaluate the uncertainty more accurately. The calculation results show that the DTR can reflect the current carrying capacity of the overhead transmission line well. Through the evaluation method of this paper, it can give the operator risk operation information of the line. According to the model calculation, the temperature distribution of the transmission line under different current carrying situation can also be obtained, and the risk of the line operation under different conditions is also analyzed. In future work, we are devoted to the study of the prediction technology of overhead ampacity based on the uncertainty evaluation of the overhead transmission line current value, and combine the load forecasting technology to carry out the intelligent load dispatching better.

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