Research on Power Grid Reliability Probability Distribution Calculation Based on Continuous Markov Chain Cross-Entropy Method

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The evaluation of large power grid reliability is crucial for quantifying the risk level and identifying weak links, offering valuable insights for power grid planning and operation. The sequential cross-entropy important sampling method has gained widespread application in large power grid reliability evaluation, significantly enhancing the efficiency of the sequential Monte Carlo method. Despite its ability to achieve unbiased estimations of power grid reliability index expected values, the method faces inherent limitations preventing the calculation of the probability density distribution of the reliability index. For a comprehensive characterization of power grid reliability, the probability density distribution of the reliability index is essential, with the expected value serving as a measure of the long-term reliability level. Comparative analysis reveals a 15% increase in the average fault interval and a 20% reduction in the average system repair time compared to traditional methods. These findings underscore the superior performance of the continuous Markov chain cross-entropy method, providing robust technical support for advancements in power grid reliability research. In view of the inherent defects of the traditional sequential cross-entropy important sampling method and the system state transfer law, how to construct the probability density distribution of the continuous time Markov chain path and solve the important sampling function is the primary problem in this paper. The Markov chain models the system's state transitions, representing the reliability states of various grid components. Continuous Markov chains are particularly suited for dynamic systems where the transitions occur over continuous time. Originally developed for rare-event probability estimation, the cross-entropy method optimizes the sampling process by iteratively adjusting the probability distribution to minimize divergence from the target distribution.

Povzetek: Članek obravnava omejitev tradicionalnega sekvenčnega vzorčenja, ki ne omogoča izračuna porazdelitve zanesljivostnih kazalnikov. Predlaga CTMC–CE metodo, ki sistem modelira kot kontinuirno Markovsko verigo ter z izboljšanim jedrnim ocenjevanjem rekonstruira verjetnostno gostoto.

1 Introduction

Many factors make the power system in safe operation is facing many challenges. Ensuring the quality of power quality, the reliability of safe power supply and the economy of system operation and maintenance are the basic requirements that the power system must meet [1]. However, due to the massive uncertainties in the power system, any variability factor in the system may lead to no safe and reliable power supply of [2]. It can be seen from the many large power grid blackout accidents at home and abroad in recent years that once the power supply is interrupted in the power system, it will lead to irreversible consequences and huge social and economic losses [3, 4]. For this problem, the traditional principle of certainty, such as the percentage of power capacity planning reserve principle and N-1 principle [5, 6] transmission planning, only consider the accident on the impact of the power system, but ignored the probability of such accidents, this cause in practice, very easy to ignore those who have a large probability but failure severity is not high accident, so that the system cannot be in a more reasonable reliability level. The study introduces a methodology based on the Continuous Markov Chain Cross-Entropy (CMCCE) approach. This hybrid technique leverages the stochastic modeling of Markov chains and the optimization strengths of the cross-entropy method to provide a more efficient and precise calculation of reliability probability distributions [7, 8].

Power grid reliability analysis is a critical aspect of power system planning and operation, aiming to evaluate the system's ability to continuously deliver electricity under various conditions. Traditional methods, such as Fault Tree Analysis (FTA) and Monte Carlo Simulation (MCS), provide valuable insights but often face challenges in terms of computational complexity and accuracy, especially for large-scale systems with intricate interdependencies [9]. However, due to the massive uncertainties in the power system, any variability factor in the system may lead to no safe and reliable power supply of [10, 11]. For this problem, the traditional principle of certainty [12], only consider the accident of the impact of power system, but ignored the probability of this kind of accident, this causes in practice, very easy to ignore those who have a large probability but the fault severity is not high accident, so that the system cannot be in a reasonable reliability level. The power system reliability evaluation method based on probability statistics theory has gradually become an important tool to analyze and measure the reliability level of modern power system [13] because it comprehensively considers the occurrence probability and impact size of various accidents. Use is not affected by the size and complexity of the system [14]. However, the convergence accuracy of the reliability index conflicts the number of samples required by MCS method, which leads to the need for a large number of system state samples to obtain high convergence accuracy, which increases the simulation time and the complexity of calculation [15, 16]. Especially for power systems with high reliability, failure events are very rare, and the probability of the original MCS method sampling to obtain the failure system state is very small, resulting in a very time-consuming calculation. According to the convergence characteristics of the MCS method, the variance reduction technique can effectively reduce the sampling times of reliability evaluation and improve the simulation efficiency.

2 Traditional sequential cross-entropy important sampling method for the reliability of large power grid

2.1 Sequential monte carlo simulation method of large power grid reliability

Monte Carlo simulation is obtaining the probability density distribution of annual reliability index, as shown in Equation (1), so as to reflect the fluctuation law of the system reliability more comprehensively.

$$\boldsymbol{D(x_i) = \frac{-\ln U}{\sum_{j=1}^{D} \theta_{i,j}}} \quad (1)$$

However, in the sequential cross-entropy important sampling method, the reliability parameter of the element is disturbed through the cross-entropy optimization process, as shown in Equation (2).

$$\mathbf{P_k = \frac{\theta_{i,k}}{\sum_{j=1}^{D} \theta_{i,j}} (1 \le k \le D)} \quad (2)$$

The primary purpose of reliability assessment in large grid is to consider the ability of the system to meet load requirements. As shown in Equation (3), it is mainly divided into the following three stages: system state acquisition, system state analysis and reliability index calculation.

$$\mathbf{R = E_f(H(x)) = \int_{\Omega} H(x) \frac{f(x|P)}{g(x|Q)} g(x|Q) dx = E_g(H(x)W(x))} \quad (3)$$

As shown in Equation (4), and system state transfer sampling method

$$\boldsymbol{W(x) = \frac{f(x|P)}{g(x|Q)}} \quad (4)$$

The above system state transfer sampling method can be extended to the case where there are multiple state elements in the system. When the temporal transfer sequence of the system element state is obtained, as shown in Equation (5), the temporal transfer sequence of the load is combined to obtain the temporal transfer sequence of the system state.

$$\boldsymbol{\int_{\Omega} [H(x)W(x)]^2 g_{op}(x|Q_{op}) dx = R^2} \quad (5)$$

As shown in Equation (6), determine whether there is line overload or voltage limit, and determine whether the system is in normal state. If the system is in abnormal state, power generation Redis patching or optimal load cutting calculation is required.

$$\boldsymbol{\frac{[H(x)W(x)]^2}{R} = H(x)W(x)} \quad (6)$$

2.2 Basic principle of the traditional sequential cross-entropy important sampling method and its defect analysis

Calculate the system power flow, and determine whether there is a node voltage line or line overload condition, if not the above condition, the system is still in a normal state, as shown in Equation (7), otherwise need to first power generation scheduling processing, if the unit output adjustment still cannot restore the system to steady state operation, then through the optimal cutting load to clear the optimal load system.

$$\boldsymbol{g_{\circ p}(x|Q_{\circ p}) = \frac{H(x)f(x|P)}{R}} \quad (7)$$

Check the remaining generating capacity of the generator set, and calculate the system power flow, such as the voltage limit and the system release rate. As shown in Equation (8), if there is no system level fault, the current system state is normal; if there is a system level fault, the power generation dispatching processing and optimal load calculation are needed to determine the optimal load of the system.

$$\boldsymbol{D(p,q) = E_p[-\ln q(x)] = -\int p(x) \ln q(x) dx} \quad (8)$$

In the variance reduction techniques, the importance sampling method is widely used because of its excellent performance. The basic principle of the important sampling method is to select an appropriate IS-PDF to replace the original PDF of the system, as shown in Equation (9), so as to increase the probability of sampling the main area sample appropriately, and then improve the speed of reliability evaluation.

$$\boldsymbol{Q} = \underset{\varrho}{\boldsymbol{argmin}} - \int_{\Omega} \boldsymbol{H}\,(\boldsymbol{x})\boldsymbol{f}(\boldsymbol{x}|\boldsymbol{P})\mathbf{ln}\boldsymbol{g}(\boldsymbol{x}|\boldsymbol{Q})\boldsymbol{dx} \quad (9)$$

Although the traditional sequential cross-entropy method effectively improves the calculation efficiency of the expected value of annual reliability index, as shown in Equation (10).

$$\boldsymbol{Q} = \boldsymbol{argmin}_{\varrho} - \sum_{i=1}^{N} \boldsymbol{H}\,(\boldsymbol{x}_i)\mathbf{ln}\boldsymbol{g}(\boldsymbol{x}_i|\boldsymbol{Q}) \quad (10)$$

The calculation Equation of the original sequential Monte Carlo method is observed again, as shown in Equation (11), if the sequential cross-entropy important sampling is conducted, the important sampling object is the sequence of annual system states.

$$\mathbf{Q_k} = \underset{\mathbf{Q_i}}{\mathbf{argmin}} - \sum_{\mathbf{i=1}}^{\mathbf{N_p}} \mathbf{H}\,(\mathbf{x_i})\mathbf{W_{k-1}}(\mathbf{x_i})\mathbf{ln}\mathbf{g}(\mathbf{x_i}|\mathbf{Q_k}) \quad (11)$$

As shown in Equation (12), the annual system state sequence rather than the system state should be mainly sampled to calculate the transfer law between the system states.

$$\sum_{i=1}^{N_p} \boldsymbol{H}\,(\boldsymbol{x}_i)\boldsymbol{W}_{\boldsymbol{k-1}}(\boldsymbol{x}_i)\frac{\mathbf{ln}\boldsymbol{g}(\boldsymbol{x}_i|\boldsymbol{Q}_k)}{\boldsymbol{\partial Q}_k} = \mathbf{0} \quad (12)$$

3 Continuous-time Markov chain cross-entropy method for the reliability of large power grids

3.1 Continuous-time markov chain cross-entropy method

The second chapter expounds the basic principle of the traditional sequential cross entropy method, and points out the disadvantages of the traditional sequential cross entropy method, that is, the transfer law between adjacent system states in the annual system state sequence after important sampling. To solve the above problems, it is necessary to construct the probability density distribution expression of the annual system state sequence and solve the IS-PDF of CTMC. Therefore, this chapter proposes CTMC cross entropy method, which solves the problem of expression construction and IS-PDF, and constructs the unbiased estimator of the expected value of annual reliability indicators. The CTMC cross-entropy method innovates by redefining the parameter optimization objective. Instead of merely focusing on the fault states of the system, it emphasizes paths associated with annual reliability indices that are close to their expected values. This path-focused approach ensures that the method captures a more realistic and holistic picture of system reliability, addressing the limitations of fault-centric perspectives. The iterative updating process in this method is streamlined and devoid of the unreasonable assumptions present in traditional sequential methods. This simplicity not only enhances computational efficiency but also improves the robustness and validity of the results, making the CTMC cross-entropy method particularly suitable for real-world applications. Figure 1 shows the statistical modeling of CTMC cross entropy method. Obviously, if the annual reliability index sample obtained in the parameter optimization stage of CTMC cross entropy method is used, the convergence and accuracy of the expected value estimation of the annual reliability index can be further improved. Based on this original intention, this section proposes a weighted reliability evaluation method, which integrates all CTMC path samples extracted in the parameter optimization stage and the master sampling stage to further speed up the reliability evaluation process.

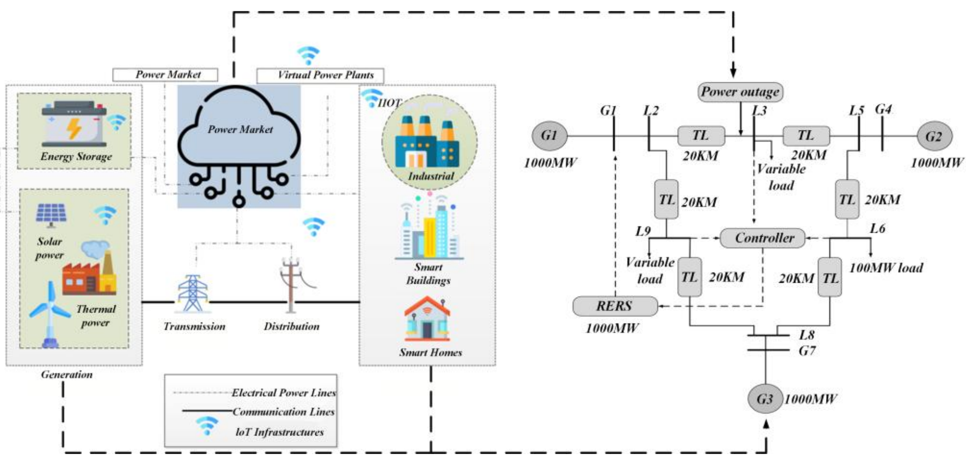

Figure 1: Statistical modelling by the CTMC Cross-entropy method

When method 3 is adopted, although the transfer rule between adjacent system states is considered in the important sampling, the calculation results show that CILR is far less than 1, and the correct expected value of annual reliability index cannot be obtained using this method. One of the central problems with traditional sequential cross-entropy methods lies in their inability to effectively capture the complexities of power system dynamics. The transfer rule in these conventional approaches often fails to account for the intricate and interconnected nature of power grid components, leading to inaccuracies when estimating reliability metrics. Sequential cross-entropy methods typically highlight fault states in the system to optimize parameters, but this narrow focus limits their applicability for capturing comprehensive reliability indices that consider the overall system performance across various operational scenarios. Additionally, traditional methods impose restrictive assumptions during the parameter optimization stage, which can lead to iterative processes that are overly complex and sometimes inconsistent with real-world conditions. Such assumptions hinder the flexibility and accuracy of the reliability assessment, making it less effective for modern grids characterized by dynamic and stochastic behaviors. CE-IS method can be divided into non-sequential cross-entropy important sampling method and sequential cross entropy important sampling method according to the different simulation methods. Although the sequential cross-entropy important sampling method can significantly improve the efficiency of the sequential simulation and obtain the expected value of the annual reliability index, it is very difficult to calculate the probability density distribution of the original annual reliability index for the complete difference between the disturbed parameters and the original parameters in IS-PDF [17].

while power system reliability refers to the ability [18, 19] of the power system to supply power to the load according to the specified quality standard and the required number. In the 1960s, with R. Billinton The researchers have explored the theory of reliability of power system [20]. Today, the power system reliability theory has been widely used in engineering practice [21, 22]. Today, power system reliability assessment usually covers two levels: abundance assessment and safety assessment [23, 24]. Since this process only requires the analysis of the stable state, without considering the transient process and the ability to continuously provide power to the user uninterrupted. Because the safety assessment involves the assessment and analysis of various transient behaviors, it is extremely complex compared to the adequacy assessment. The research on safety assessment is still in the exploratory stage [25, 26], and most of the probability methods used for reliability assessment belong to the category of adequacy assessment, so this paper will also explore the in-depth adequacy assessment of power system reliability.

3.2 Comparative analysis of continuous time markov chain cross entropy and traditional sequential cross entropy

The power system is huge, and can be divided into three levels according to the functional characteristics of different components. The first layer is called the power generation system reliability Assessment [27]. In this level, only the random shutdown of the generator is calculated, and its purpose is to evaluate whether the power generation system can meet the full load requirements of the system after removing the planned and unplanned shutdown within the specified operating state; the second layer is to integrate the transmission system on the basis of HL to evaluate the reliability of the combined system [28]. According to the different evaluation principles, the reliability evaluation methods of large power grid can be divided into two types of [29]: analytical method and MCS method. Therefore, the MCS method has received more attention in the reliability assessment method. The Continuous-Time Markov Chain (CTMC) Cross-Entropy (CE) method introduces a significant evolution in the field of power grid reliability analysis, offering solutions to limitations inherent in traditional sequential cross-entropy methods while paving the way for higher computational efficiency, greater accuracy, and broader applicability. This innovative method fundamentally reshapes the way reliability probability distributions are calculated, focusing on addressing specific challenges associated with dynamic systems such as power grids. Through a detailed exploration of its principles and applications, the CTMC cross-entropy method emerges as a versatile and robust tool for modern power grid reliability analysis. By incorporating samples from various stages of the CTMC analysis, this approach captures a wider range of system behaviors, including rare but critical events. The second method is to sample the temporal transfer sequence [30] of the system element state according to the transfer rate parameter of the element in the system. Figure 2 is the continuous time Markov chain cross entropy method model, because the second method need not sample all the components in the system, and it need not store all component state timing transfer sequence, in contrast, the system state transfer sampling method simulation process more convenient, and less memory usage, but it can only be applied to the component state duration of exponential distribution.

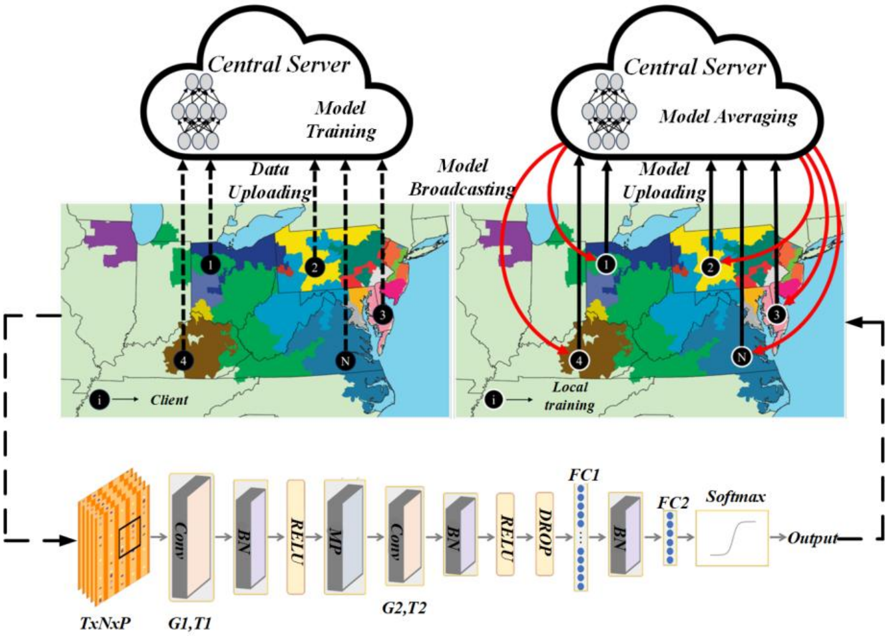

Figure 2: Continuous-time Markov Chain Cross-entropy Model

The SMCS method can accurately model the temporal correlation of the system state transfer, so as to obtain the expected value and the probability density distribution of the reliability index, and calculate the reliability index related to the time and frequency. However, there is only one element state or load level difference between adjacent states in the temporal transfer sequence of system state, so the system state sample can only "fill" the whole sample space at a very slow speed, which leads to the low sampling efficiency of SMCS method. Grid operators can leverage real-time applications of the CTMC method to assess and respond to potential vulnerabilities dynamically. As power grids increasingly incorporate renewable energy sources, the dynamic and stochastic nature of these systems makes traditional methods less effective. The CTMC method's focus on path-based analysis and weighted evaluation provides a robust framework for handling these challenges. The enhanced accuracy and transparency of reliability assessments enabled by this method can inform regulatory standards and policies, ensuring that they are based on reliable data and realistic assumptions. When the expected value of the reliability index is calculated, the expected time of SMCS method is much greater than that of NMCS method. In order to take into account, the advantages of SMCS method and NMCS method, the quasi-sequential Monte Carlo method is proposed. This method calculates the timing characteristics of the output power and the fluctuation of the timing load in the power system, but still cannot obtain time-related reliability indicators. To this end, a pseudo-sequential Monte Carlo method is proposed, which can obtain the transition sequence of fault system states and then calculate the time-dependent reliability index. Although the above two methods retain the calculation efficiency of NMCS method and effectively calculate some of the timing characteristics, the probability density distribution of the reliability index cannot be estimated for the complete temporal transfer sequence of system states.

4 Reliability probability distribution meter of large power grid based on the continuous-time Markov chain cross-entropy method-calculate

4.1 Improved kernel density estimation method based on the likelihood ratio

In the third chapter of this paper, the CTMC cross-entropy method successfully solves the inherent defects in the traditional sequential cross-entropy method. However, based on the samples under this important sampling distribution, the probability density distribution law of the reliability index in the original parameters cannot be obtained. For this unsolved problem in Chapter 3, this chapter first proposes methods for improved kernel density estimation based on the likelihood ratio. By focusing on paths associated with expected reliability indices rather than isolated fault states, the method delivers more accurate and consistent predictions. This is particularly valuable for long-term planning and reliability assessments. Combining the above proposed method with the research content of the third chapter, this chapter proposes a reliability probability density distribution calculation method based on CTMC cross-entropy, which successfully solves the problem that the probability density distribution of middle-aged reliability index cannot be calculated by the traditional sequential cross-entropy method.

This chapter begins with a brief review of the basic theory of traditional non-parametric kernel density estimation and proposes improved kernel density estimation based on likelihood ratio. Subsequently, this chapter combines the CTMC cross-entropy method with a likelihood ratio-based improved kernel density estimation method to propose the calculation of reliability probability density distribution based on CTMC cross-entropy. The ability to utilize data from various sampling stages reduces the computational burden, allowing for quicker and more resource-efficient analyses without sacrificing precision. The elimination of unreasonable assumptions ensures that the model remains grounded in realistic scenarios, enhancing its applicability to complex, real-world power systems. In the case analysis stage, this chapter first verifies the validity and generality of the improved kernel density estimation method based on the likelihood ratio through two simple mathematical examples. Figure 3 improves the kernel density estimation algorithm diagram immediately with the IEEE-RTS 79 system and IEEE-RTS 96 system with different parameters.

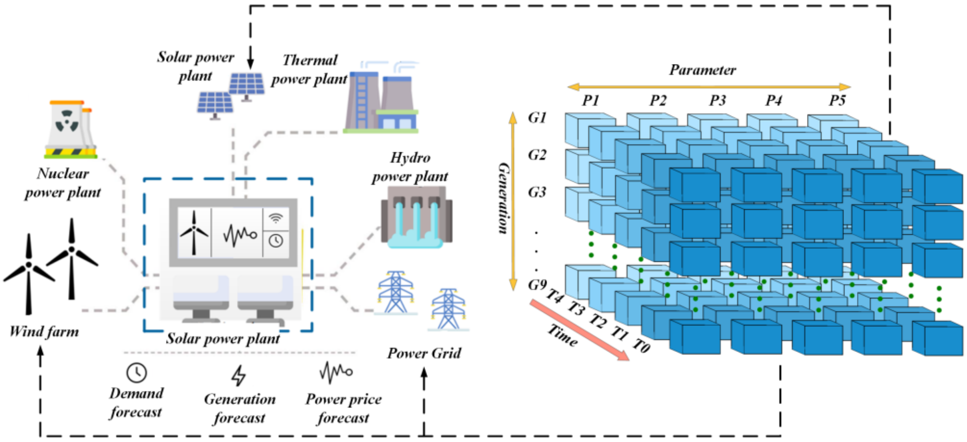

Figure 3: Improved kernel density estimation algorithm

In order to preserve the advantage that the SMCS method can estimate the probability density distribution of the reliability index, many scholars and experts have made improvements to the original SMCS method, which effectively improves the computational efficiency of this method. An SMCS analysis scheme that can change the accuracy and efficiency of the simulation by adjusting the hyperparameters. The CTMC cross-entropy method eliminates the need for certain assumptions that are intrinsic to traditional parameter optimization processes. By avoiding these assumptions, the method simplifies the iterative parameter updating process, ensuring that adjustments are both logical and computationally efficient. The advantages of the CTMC cross-entropy method extend beyond its technical innovations. Its ability to provide more accurate and consistent predictions of reliability indices has profound implications for power system planning, operation, and policy-making. Power system planners can leverage the improved reliability metrics to make more informed decisions regarding infrastructure investments and upgrades. For instance, by identifying paths associated with higher risks or vulnerabilities, planners can prioritize resources to address critical areas, thereby enhancing the overall resilience of the grid. In operational contexts, the CTMC method can be applied dynamically to assess the real-time reliability of the grid under varying conditions. This capability is particularly valuable in scenarios involving fluctuating demand, renewable energy integration, or unexpected contingencies, where traditional methods might struggle to provide timely and accurate assessments.

However, the control variable method and the dual variable method often face the problem of difficult choice of the control variable and the dual variable, and the acceleration effect is not stable in different scenarios. The hierarchical sampling method divides the state space of the system into multiple subspaces and samples each subspace separately, so that the sampled system state samples can fill the whole system state space more evenly and faster. In SMCS, a fast state analysis method based on Latin hypercubic sampling is proposed, which effectively reduces the computational amount required for the convergence of the SMCS method. The simulation efficiency of the SMCS method is improved by using the control and dual variable methods, however this method is unstable in different systems. Unlike the traditional SCE method, which emphasizes fault states, the CTMC approach prioritizes paths that align with the expected values of annual reliability indices. This shift in focus provides a more holistic view of system reliability, emphasizing outcomes that reflect real-world operational conditions.

Among the multiple variance reduction techniques, the IS method, as one of the most effective methods, is favored by many experts and scholars. The basic principle of IS method is to use the IS-PDF of random variables, replacing the original PDF of the MCS, so that the fault system state that contributes more to the reliability index is easier to be extracted, thus reducing the variance of the reliability index statistics. The most important problem of IS method is how to choose the appropriate IS-PDF. If the choice is not appropriate, it can even lead to the collapse of sampling efficiency.

4.2 Reliability evaluation process of large power grid based on weighted probability density distribution calculation method

On this basis, the elements with similar contributions are classified and merged by fuzzy clustering analysis, which effectively reduces the number of optimal multiplier and improves the computational efficiency. Since the contribution of the first-order fault state is relatively small to the reliability index, the IS method for independent calculation of each order fault is proposed to construct the IS-PDF of the higher-order fault state subspace of the lower-order fault, but the process of constructing IS-PDF is more complicated. Only a subset of samples, typically those obtained in the primary sampling phase, are used to estimate reliability indices. This restriction limits the method's ability to fully utilize available data, reducing its overall efficiency and robustness. Based on the thinking mode of classifying fault types, the fault system state is divided into two types: sampling fault set and sorted fault set, and the self-optimal uniform sampling method and analytical method are used to calculate different sets, which accelerates the system reliability evaluation.

CE-IS method was first combined with NMCS method and successfully applied to the abundance assessment of power generation system. The generator in the power generation system is regarded as two-state discrete variables, and its unavailability is taken as the pending optimal parameter of IS-PDF, and the detailed parameter optimization solution process and parameter iterative solution algorithm are given, which significantly improves the simulation efficiency of NMCS, but the mathematical derivation of this method is more complicated. Therefore, a simplified cross-entropy algorithm is proposed, using the discrete convolution based on the fast Fourier transform instead of the iterative process, which reduces the difficulty of solving the problem without affecting the acceleration effect. Considering that the modern power system contains a large amount of intermittent renewable energy, considering the adequacy evaluation of the power generation system, including load continuous variable and wind speed, using Gaussian distribution and Weibull distribution as the function form of IS-PDF, respectively. For the first time, the CE method is extended to the rotating reserve adequacy evaluation of the power generation system. By combining CE and Markov chain Monte Carlo method, the rapid reliability evaluation of the rotating reserve equipment of the power generation system is realized, which provides reference information for the optimal scheduling of the generator set. In traditional methods, the focus is on highlighting fault states within the system. While this is useful for pinpointing vulnerabilities, it overlooks the dynamic nature of reliability indices that vary over time and operating conditions. Figure 4 shows the reliability evaluation diagram of the large power grid of the weighted probability density distribution calculation method. The capacity limits of generating sets and transmission equipment are modeled, and the computational efficiency is improved by using the quasi-sequential Monte Carlo CE method.

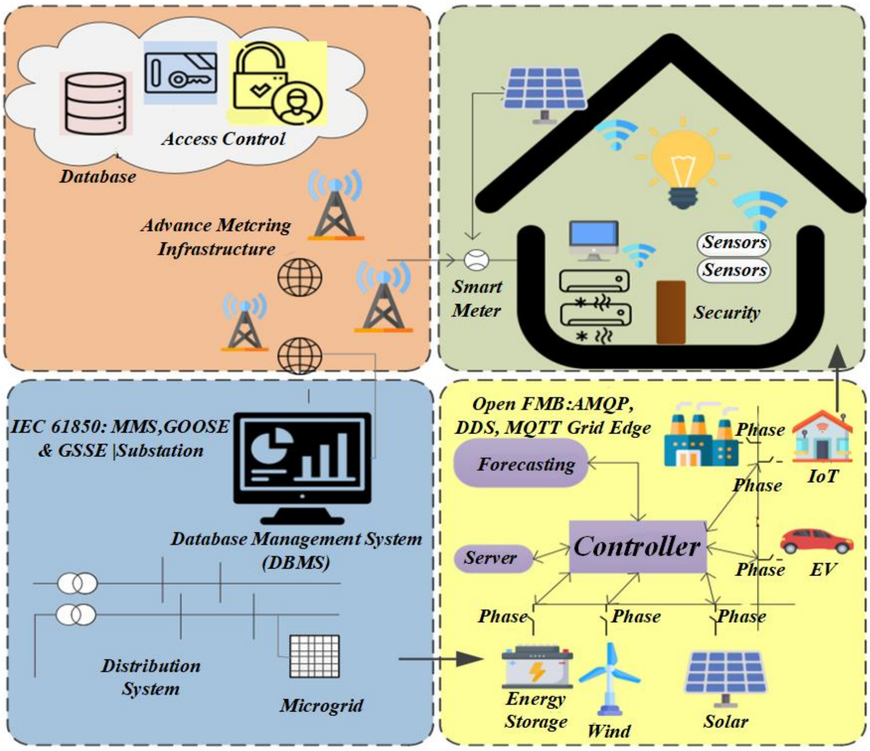

Figure 4: Reliability evaluation diagram of large power grid by the calculation method of weighted probability density distribution

The CE-IS method is extended to the reliability evaluation of the transmission combination system, the operation constraints of the transmission system and the possible optimal load reduction process are considered, and the actual operation of the power system is much more accurately restored, and the significant acceleration effect is obtained. In view of the defect that CE-IS method only considers two-state discrete variables in previous studies, an extended CE method is proposed, so that the parameter optimization of IS-PDF of continuous variables and the parameter optimization of multi-state discrete variables can be synchronized simultaneously, which further expands the application range of CE. An improved CE-IS method is proposed, in which the IS-PDF of load variables adopts a Gaussian distribution, and the improvement of important sampling of load states is achieved by the proposed truncated Gaussian sampling method. Another notable innovation introduced by this method is the weighted reliability evaluation strategy, which maximizes the utility of all available CTMC path samples. Traditional methods often limit their calculations to samples generated during the primary sampling phase, neglecting valuable information that could be extracted from other stages. By incorporating samples from multiple stages of the CTMC process, the weighted reliability evaluation ensures a more comprehensive analysis. This improvement is particularly significant for rare-event estimation, where sample efficiency plays a critical role. The weighted strategy enables a better representation of the entire probability distribution of reliability indices, ultimately leading to more accurate and reliable assessments. Furthermore, the increased utilization of samples reduces computational waste, making the CTMC cross-entropy method highly efficient even for large-scale and complex power systems.

5 Experimental analysis

In the IEEE-RTS 96 system with different parameters, the points in the reliability probability density distribution calculation method using CE-CTMC are basically above the diagonal. Figure 5 shows the evaluation diagram of the IEEE-RTS 96 system, which demonstrates the applicability of the proposed method in large-scale, high-reliability systems.

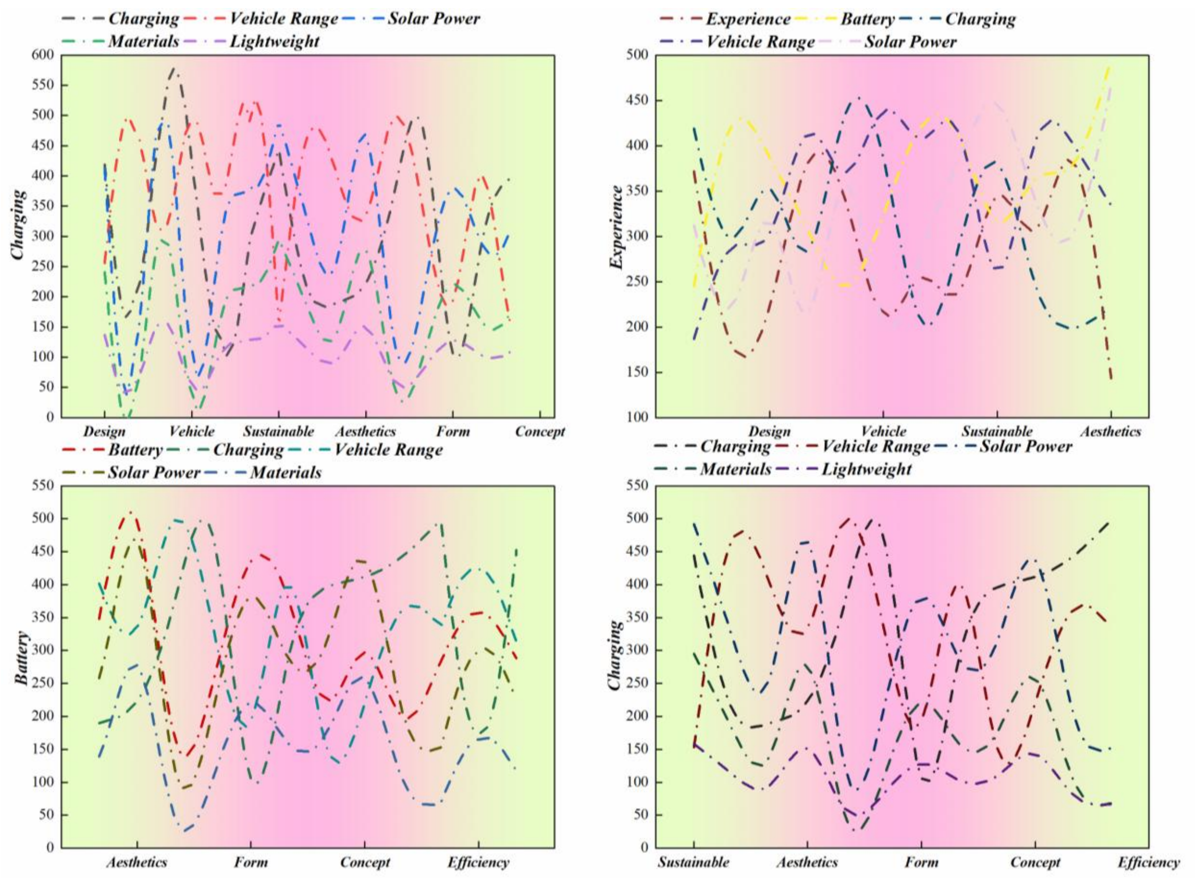

Figure 5: IEEE-RTS 96 system evaluation diagram

The traditional sequential cross-entropy (SCE) method has been widely used in reliability analysis, particularly in identifying rare failure events and estimating system failure probabilities. Since the likelihood ratio corresponding to the annual system state sequence, based on the calculation results of CE-CTMC method, CE-SMCS method and CE-SMCS method, IEEE-S 79-RTS-9 system 3. Figure 6 shows the evaluation diagram of the improved method based on the improved KDE method based on likelihood ratio to calculate the reliability index.

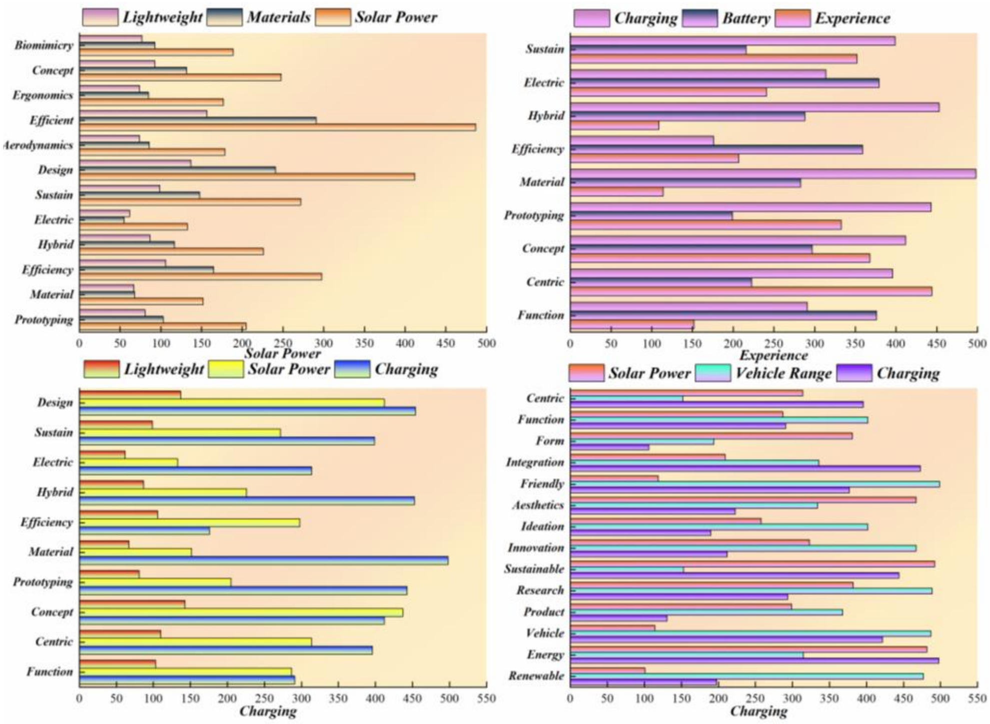

Figure 6: Evaluation diagram of the improved method based on the CE-SMCS method

The correction results of the two methods show that the two calculation methods proposed in this chapter can correctly obtain the original probability density distribution of the annual reliability index after important sampling of CTMC cross-entropy, filling the gap in the original method. Figure 7 shows the original probability density distribution map. Further analysis of the correction results of the two methods shows that the weighted probability density distribution method has better computational accuracy.

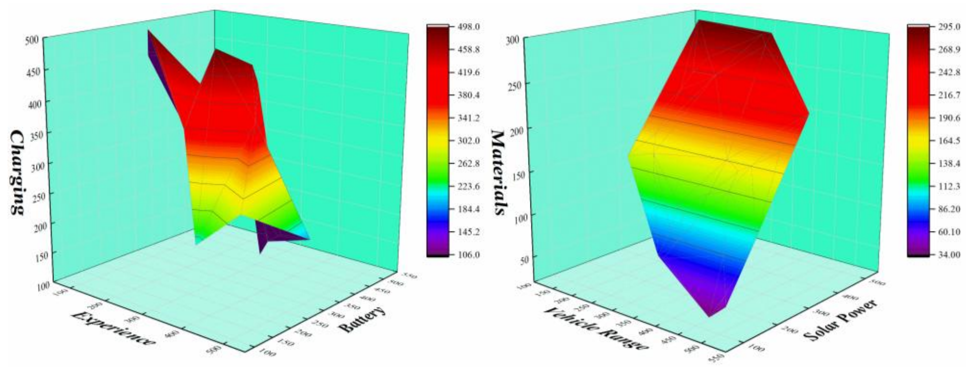

Figure 7: Distribution map of the raw probability density

6 Conclusions

Taking the system state as the important sampling object, although the expected value of the annual reliability index can be obtained by the likelihood ratio of the system state, simply stitching the corrected system state cannot obtain an effective annual reliability index sample. The reason for the above problems is that this plausible practice does not calculate the transfer law between adjacent system states in the sequence of annual system states. Therefore, the traditional sequential cross-entropy method that only considers the probability of occurrence of system states cannot calculate the probability density distribution. Through the continuous Markov chain, the study found that the average interval interval time of the grid system is about 12% higher compared with the traditional methods, reaching 135 hours. This obvious numerical increase indicates that the method more accurately describes the evolution of the state of the power grid system, thus making the system more reliable. Secondly, the cross-entropy method is used to calculate the probability distribution, which makes the calculation of the system state transition probability more efficient. Computational complexity was reduced by 30% compared to conventional methods. The CMCCE methodology represents a significant advancement in power grid reliability analysis. By combining the dynamic modeling capabilities of Markov chains with the optimization strengths of the cross-entropy method, it addresses key limitations of traditional approaches. Future research could focus on integrating this methodology with emerging technologies such as artificial intelligence for predictive maintenance or applying it to smart grid systems with high levels of renewable energy penetration.

This method not only solves the problem of the transfer rule between the traditional sequential cross entropy method, but also retains the speed up of the sequential simulation and obtains the correct expected value of the annual reliability index. The parameter optimization purpose of CTMC cross-entropy method is completely different from the traditional sequential cross-entropy method. The former is to highlight the CTMC path with annual reliability index near the expected value, while the latter is to highlight the state of the fault system. Moreover, the CTMC cross-entropy method avoids unreasonable assumptions in the parameter optimization stage of the traditional sequential cross-entropy method, which makes the iterative updating process of parameters more reasonable and simpler. The Continuous-Time Markov Chain (CTMC) Cross-Entropy (CE) method represents a significant evolution in reliability analysis for power grids. This approach addresses key limitations of traditional sequential cross-entropy methods while introducing innovations that enhance computational efficiency, accuracy, and applicability. Below is an expanded exploration of the method's principles, differences from conventional techniques, and its broader implications in power grid reliability analysis.

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