Research on the Minimum Path and Monte Carlo Algorithm for Reliability of Distribution Network

Xianfu Zhou, Member, IAENG, Feng Lu, Songsong Zheng, Yifeng Yang, Lei Xiang

Abstract—**With the characteristics of the multiple points and wide area in the complex load model, the failure probability is relatively high in the distribution network. So, the analysis technology of the distribution network fault occurrence is very important. The power supply reliability of the distribution network needs to be analyzed and evaluated. At present, the reliability evaluation has become a common work in the distribution system. It has become a basic index related to the power supply quality. The statistical data show that 80% of the power accidents are caused by the distribution network faults. Improving the reliability of the distribution network is of great significance to elevate the quality of power supply. It reduced the probability of the distribution network faults effectively. In this paper, from the load and system reliability in the distribution network by using the distributed power supply. Several main factors affecting the reliability of power supply are analyzed, such as failure rate, blackout duration, average annual blackout time to assess the reliability of the distribution network.**

Index Terms—**Fault rate, Distribution network, Minimum path method, Sequential Monte Carlo method**

I. INTRODUCTION

With the rapid progress in our country, the deepening environmental awareness and the increasing utilization of new energy sources, the research on the distributed generation (DG) technology has been accelerated significantly [1]. For the flexibility in the generation mode, environmental friendliness, moderate scale and the low voltage output, the distributed power is becoming an important choice for distribution grid access. It reshapes the operation mode of the distribution grid and has a profound impact on its reliability. It is worth noting that due to the diversity of DG modeling methods, its reliability assessment methods also show a diversified trend. At present, numerous scholars have proposed techniques applied to reliability assessment of distribution networks. Moreira proposed a scalable approach to large scale risk-averse distribution grid expansion planning [2]. Raymond presented the situational awareness of the road map to generate plant modernization and reliability [3]. Navidi suggested the coordinating distributed energy resources for reliability can significantly reduce future distribution grid upgrades and peak load [4]. Atrigna proposed a machine learning approach to fault prediction of power distribution grids under heatwaves [5]. Alvi offered the real-time control of a distribution linear state estimator at commonwealth [6]. Aquino enhanced the power grid resilience against ice storms [7]. Currie proposed the data privacy for the grid [8]. Moraski utilizes rail-based mobile energy storage systems to enhance the reliability of the power grid in environments with climate uncertainty [9]. Jozi F researched the evaluation of reliability in the deregulated radially distribution network with consideration of vehicle to grid [10]. Garip set the reliability analysis of the microgrids [11]. Baembitov supposed the state of risk prediction for management and mitigation of vegetation and weather caused outages in distribution networks [12]. Poudyal used the risk-based active distribution system planning for resilience against extreme weather events [13]. Zeng discussed the quantifying the capacity demand response in smart distribution system [14]. Shawon proposed a two-stage performance optimization-based microgrid formation in distribution networks with DG [15]. Baembitov researched the incorporating wind modeling into electric grid outage risk prediction and mitigation solution [16]. Khan used the optimal control and communication strategies in the multi-energy generation grid [17].

Manuscript received December 2, 2024; revised August 24, 2025.

This work was supported in part by the Science and Technology Project of State Grid Zhejiang Electric Power Co., Ltd (5211UZ240004).

Xianfu Zhou is the vice manager of the State Grid Huzhou Electric Power Supply Company, Huzhou, 313000, China. (phone: 086-187-2921-9213; e-mail: ttla02@163.com).

Feng Lu is a manager of the State Grid Zhejiang DeQing County Power Supply Company, DeQing, 313200, China. (e-mail: 10907083@qq.com).

Songsong Zheng is an engineer of the marketing department in the State Grid Huzhou Electric Power Supply Company, Huzhou, 313000, China. (e-mail: 5638176@qq.com).

Yifeng Yang is a vice manager of the State Grid Zhejiang Changxing County Power Supply Company, Changxing, 313100, China. (e-mail: 735634463@qq.com).

Lei Xiang is an engineer of the marketing department in the State Grid Huzhou Electric Power Supply Company, Huzhou, 313000, China. (e-mail: 582578036@qq.com).

II. DISTRIBUTION NETWORK MODEL WITH DG

The impact of DG on the reliability of distribution networks is mainly reflected in two aspects. One is the uncertainty output of DG and the other is DG cannot guarantee the continuous power supply for user needs. When a fault occurs in the distribution network, Moraski utilizes rail-based mobile energy storage systems to enhance the reliability of the power grid in environments with climate uncertainty. In the reliability assessment of the distribution networks, the DG models include the probability models and time series models. The basic principles of these two models are as follows:

A. Probability Model

This model calculates the probability by the different output of DG. The simplest probability model is the two-state model. Assuming that the probability of DG operating at rated power is P_1 and the probability of shutdown is P_2. It is sufficient to satisfy $P_1 + P_2 = 1$. When the probability model is used to construct the DG, the evaluation methods use analytical or sequential Monte Carlo simulation methods in common. When conducting reliability evaluation, the output size of the distributed power sources is first determined. Based on the DG output, determine the island area division and load supply situation, and calculate the reliability index.

B. Time Series Model

The time series model aims to obtain the output power amplitude of DG in chronological order. Usually, a typical variation curve is adopted for one hour. Therefore, 8,760 sampling points are needed for one year's data. When using time series models for distributed power sources, the reliability assessment method usually adopts the sequential Monte Carlo simulation method. During the simulation process, the output power of distributed generation can be determined. Based on the output power of the distributed power source, the islanding division and load power supply conditions can be determined, and then the reliability index can be calculated.

III. Reliability analysis methods for distribution networks

A. Analytical Method

At first, the failure mode impact analysis method is used. Through the search of the reliability data of each component in the system, the failure mode consequences table is established. According to the specified reliability criteria, all states of the system are tested and analyzed. So, it could find out each failure mode and consequences impact on the system and obtain the reliability index of the load point. This method is suitable for the simple radial networks.

Another one is the analysis method based on the minimum path. This method calculates the minimum paths of each load point respectively and, in combination with the actual network conditions, analyzes the impact of component failures on the reliability of load points on non-minimum paths. Subsequently, for each load point, it is only necessary to calculate the components and nodes on its minimum path to obtain the reliability index corresponding to that load point. Because of the influence of branch line protection, isolation switches, segmented circuit breakers and the influence of planned maintenance, the algorithm can handle the situation of whether there is a backup power source and a backup transformer.

The last way is the network equivalence. Using an equivalent component to replace a part of the distribution network, and equating the reliability of that part of the network to this component. Considering the impact of this component's reliability on the upper and lower feed lines, the complex structure of the distribution network was simplified into a simple radial main feeder system gradually.

B. Simulation Method

In this section, we choose the Monte Carlo as our simulation method. When evaluating the reliability of the power supply, the system's state is obtained through random sampling, and the estimated value of reliability indicators is obtained by combining the statistical methods. The reliability index solved by analytical method is an exact value, but the simulation results are not completely accurate. The accuracy of the results is closely related to the sample number. Monte Carlo method can be further divided into sequential and non-sequential simulation methods.

In this article, within the MATLAB environment, we mainly use the probability model of DG+ minimum path method and the time series model of DG+ sequential Monte Carlo simulation method to evaluate and simulate the reliability of the distribution network.

IV. Implementation plan

A. Implementation of Probabilistic Model and Minimal Path Method

1) Modeling the probability of DG output power

Using the DG as a generator with several capacity states, assuming four states of full generation, two decreasing operations, and full outage. The output fluctuation of DG is characterized by the transfer probability between states, and the state probability of each capacity is obtained by Markov state transition method. The system changes state independently. Here, S_i represents the output power level ($s_1>s_2>s_3>s_4$). a_{ij} is the state transition probability of the output power transferring from S_i to S_j. The established generator multi-capacity state model is shown in Fig. 1:

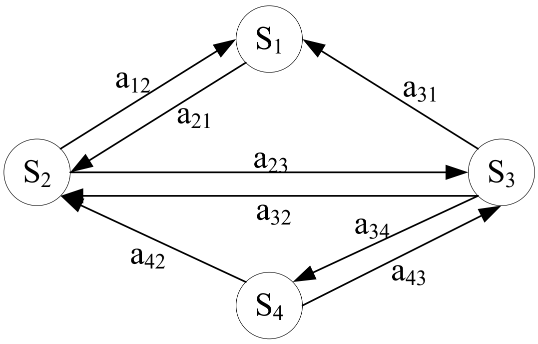

Fig.1. The multi-capacity state model of the generator

According to the state space, the state transition rate matrix of the system can be obtained:

$$A' = \begin{bmatrix} -a_{12} & a_{12} & 0 & 0 \\ a_{21} & -(a_{21}+a_{23}) & a_{23} & 0 \\ a_{31} & a_{32} & -(a_{31}+a_{31}+a_{34}) & a_{34} \\ 0 & a_{42} & a_{43} & (a_{42}+a_{43}) \end{bmatrix} \tag{1}$$

Here, A' represents the Markov state transition probability of DG. For the finite state and traversing of the whole Markov system, its distribution probability is a stationary distribution after entering the steady state. Let the instantaneous state probability $P_i(t)$ limit P_i of each output level of DG constitute the equilibrium probability vector of each output level:

$$\begin{aligned} P_s &= \lim_{t\to\infty}\left[P_1(t), P_2(t), P_3(t)......\right] \\ &= \left[P_1, P_2, P_3......\right] \end{aligned} \tag{2}$$

$$P_s A' = P \tag{3}$$

The equilibrium probability vector P_S satisfies the linear equation:

$$P_1+P_2+P_3+P_4=1$$
$$\left[P_1,P_2,P_3,P_4\right]A=0 \tag{4}$$

The corresponding probability for the power level of DG is P_1, P_2, P_3, P_4.

2) Calculate the shortest path from load to the power node

To find the shortest path from load k to the main power node, the algorithm such as Dijkstra algorithm, Bellman Ford algorithm, Floyd algorithm and SPFA algorithm were used to determine the components in the path.

3) Determining the effect of component failure on load k

Based on the presence or absence of backup power sources, segmented devices and fuse protection, the system determines the impact of component failures on load and whether the components are on the minimum path of the load.

4) Determining the conditions for island formation

With the location of fault, the position of the load, the switch action and the output power of the DG, it determines the conditions for island formation. Here, assuming no DG, a fault in component m will cause load k to fail. So, it is necessary to judge whether an island can be formed by DG to restore power to load k. The probability of island formation should be calculated with the probability of each output of DG. When conducting island partitioning, the principle of breadth is generally adopted. By satisfying the connectivity constraints and power balance constraints, which is illustrated in Fig. 2:

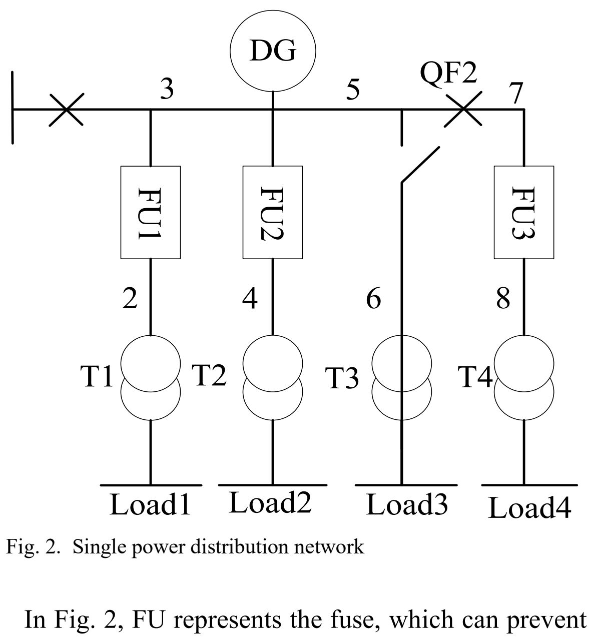

Fig. 2. Single power distribution network

In Fig. 2, FU represents the fuse, which can prevent the circuit from short-circuit faults. It protects the normal operation of the distribution system. QF is the circuit breaker that is the air switch. According to the needs of the double-circle graphic representation when power transformers, it is the electrical equipment. In addition, the single-power distribution system has four loads and one DG (distributed power supply). The four states of DG are [S_1, S_2, S_3, S_4] = [0, 100, 200, 300] KW, respectively. The occurrence probability is 0.25, and the load on branches1-4 is 100KW. If a fault occurs at line 3 and circuit breaker QF1 opens, as long as the DG output meets a certain requirement, an island can be formed to restore power supply to loads 2-4. When the status is S_2, S_3, S_4, the power supply to load 2 can be restored. Then the probability of load 2 being restored by DG in the event of a fault in line 3 is 0.75. When the status is S_3 or S_4, the power supply to load 3 can be restored, which means that the probability being restored by DG in the event of a fault in line 3 is 0.5. When the state is S_4, the power supply to load 4 can be restored, which means that the probability of load 4 being restored by DG in the event of a fault in line 3 is 0.25. The different output of DG leading to different island divisions. In addition, the location of the fault can also affect the formation of islands. Assuming a fault occurs at line 5 and circuit breaker QF1 opens, no matter what state the DG output is in, at most the power supply to load 2 can be restored. Because the fault in line 5 prevents DG from forming a power supply circuit with load 3 and load 4, which cannot meet the connectivity constraints of island formation. So, this step needs to judge the probability of restoring power supply to load k in different circumstances.

5) Cumulative load reliability indicator

Reliability metrics such as average annual failure rate, average annual downtime, and average annual lost load are calculated for cumulative loads based on the above.

6) Iteration termination judgment

If the reliability metrics of all the loads are counted, proceed to the next step, otherwise make k=k+1 then return to step 2).

7) Statistical reliability indicators

Statistical system reliability metrics are based on the reliability metrics of all load nodes. When the minimum path algorithm is used, the first step is to find the shortest path between each load and the power source, which is the minimum path of the load. For this load, the components of the entire distribution network can be divided into components on the minimum path and the non-minimum paths, respectively. The components on the smallest path will have an impact on the load when they fail. With the location and protection configuration of the non-minimum path components, it is possible to determine whether they have an impact on the load. Finally, the reliability indicators of each load be calculated and the overall indicators of the power distribution system can be further derived.

B. Time Series Model and Implementation Steps

1) Modeling the timing of DG output power

At first, a temporal model for DG output power is established. The status and output power level of wind turbine units are mainly influenced by the characteristics of wind speed variation; it can be expressed as:

$$P_t=\begin{cases}0 & V_t\le V_{ci}\\ \left(A+BV_t+CV_t^2\right) & V_{ci}\le V_t\le V_\gamma\\ P_\gamma & V\le V_\gamma\le V_{co}\end{cases} \tag{5}$$

V_{ci} is the cutting value of the wind speed, the V_{co} is the cutting out of the wind speed. V_t is the rated wind speed and P_t is the rated output power. Although wind speed shows significant randomness and volatility, its statistical characteristics still follow certain laws. Wind speed follows the Weibull distribution the probability density function is:

$$f\left(v\right)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}e^{-\left(\frac{v}{c}\right)^{k}} \tag{6}$$

Here, k is the shape parameter and C is the scale parameter. By simulating the light intensity data within a specific time period, a probability distribution model can be constructed. This light intensity usually follows a Beta distribution, and its probability density function expression is as follows:

$$f\left(r\right)=\frac{\Gamma\left(\alpha+\beta\right)}{\Gamma(\alpha)\Gamma(\beta)}\times\left(\frac{r}{r_m}\right)^{\alpha-1}\times\left(1-\frac{r}{r_m}\right)^{\beta-1} \tag{7}$$

Among them, α and β are the shape parameters of the Beta distribution. R and r are the actual light intensity and its maximum value within that period. The output power of photovoltaic panels is positively correlated with the light intensity. The functional relationship is:

$$P=A\times r\times n \tag{8}$$

A is the area of the photovoltaic panel and n is the conversion efficiency.

2) Initializing simulation parameters

Read the reliability parameters of the device and initialize the simulation years.

3) Determine faulty equipment and time of failure

In this step, the transmission terminal function (TTF) of each equipment needs to be calculated. Subsequently, the occurrence time of the fault event and the identification of the faulty equipment are determined with the preset rules. It is usually assumed that the device with the minimum TTF value is the component that failed with the simulation.

4) Determining the affected load

Based on the location of the faulty component at each load, the action status of the switch and the output size of the DG, the system determines the load that caused the shutdown. The formation of islands needs to be considered in this step and the basis for division is the same as above.

5) Iteration termination judgment

Combined the simulation time and the TTF, the duration of the fault to determine whether the simulation threshold has been reached. If the judgment is true, the simulation process will terminate and jump to 6) for the result output. Otherwise, return to 3).

6) Reliability statistics

Statistics on the reliability metrics of each load node and the average system reliability metrics.

If the above result is right, the system should statistic the reliability. This method summarizes the reliability index of each load node and the average reliability of the system. In the implementation of the Sequential Monte Carlo method, the first step is to establish a clear sampling order, and then take the sample points one by one according to this order and calculate their corresponding function values. After several iterations, the method is able to continuously optimize the estimation of the integral value until a predetermined accuracy.

When using sequential sampling, the simulation time depends on the device TTF. When sampling a fault, the faulty device is determined based on set rules. The component with the minimum TTF among all current devices is usually identified as the failed element in the failure event. It is also possible to consider the first n devices with the smallest TTF as faults (nth order faults). When calculating load reliability, the failure rate is the number of simulated outages (normal operating hours), and the mean failure duration is the total simulated outage time (number of outages).

C. Time series model and implementation steps of non-sequential Monte Carlo method

At first, assuming there are two states, faulty and normal operation in each component in the distribution system. The states of each component are independent of each other. Secondly, using s_i denotes the state of component a, the failure rate of this component is λ_i and the average repair time is γ_i. Finally, if E_i in the range of $[0,\gamma_i]$, a random number E_i distributed between [0,1] is generated for this component. It means that the component is faulty. Otherwise, the component can be considered in the normal operating state. Components remain the normal state time is recorded as the normal operating time TTF. The component failure time is recorded as the repair time TTR and the section switching time is the switching time TTS. So, it can be approximated that the component failure repair time to obey the exponential distribution then to find the TTF, TTR and TTS.

The specific steps of the solution with the following steps: At the beginning, determine the state of each component in the system. Then using the fault components to determine the affected load and outage time. So, the time to complete a system state sampling process, repeated many times will be able to get the load outage frequency and outage duration, and then further to obtain the reliability of the system index.

V. TEST RESULTS

A. The system topology and the branch node

Since the IEEE RBTS BUS6 F4 is a three-phase AC circuit system, based on different models for the reliability assessment of distribution networks, this paper uses it as an example to illustrate the application of analytical and Monte Carlo methods. The topology is shown in Fig. 3. Here, the boxes represent the loads in the system and the circles are the nodes. So, the system contains 23 loads and 54 nodes. The connecting lines between the nodes represent the branch circuits. Forks represent fuses, besides that from this figure we can see that this system contains 2 DG.

B. Simulation results with the sequential Monte Carlo

Based on the timing model and sequential Monte Carlo, the simulation results of the annual average number of outages are shown in Fig. 4.

In Fig. 4, the blue columns represent the case with DG and the red is the case without DG. We can conclude that the average number of outages per year is generally lower in the case of DG than in the case of no DG, which basically indicates that the security of the distribution network is higher and the quality of power supply is better in the case of DG. With the same method, the average outage time simulation result is shown in Fig. 5.

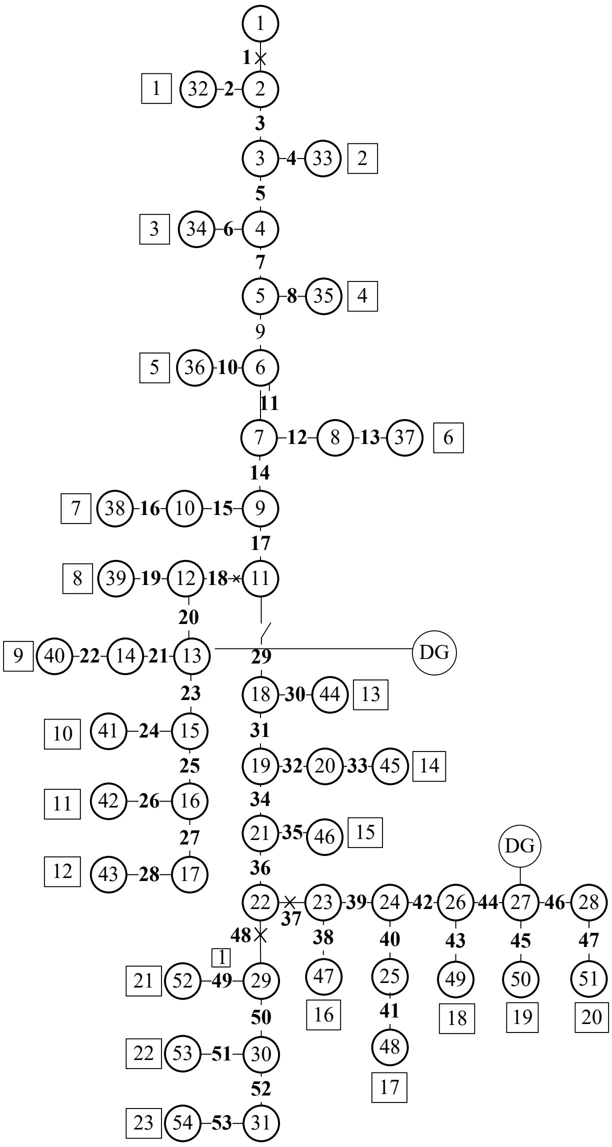

Fig. 3. IEEE RBTS BUS6 F4 Node and branch numbering mode

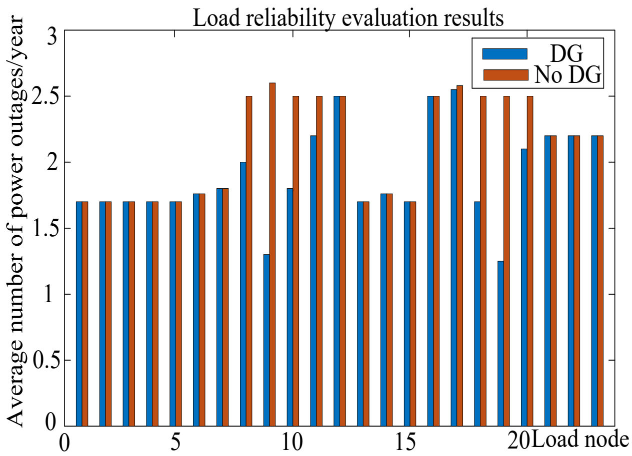

Fig. 4. The annual average number of power outages

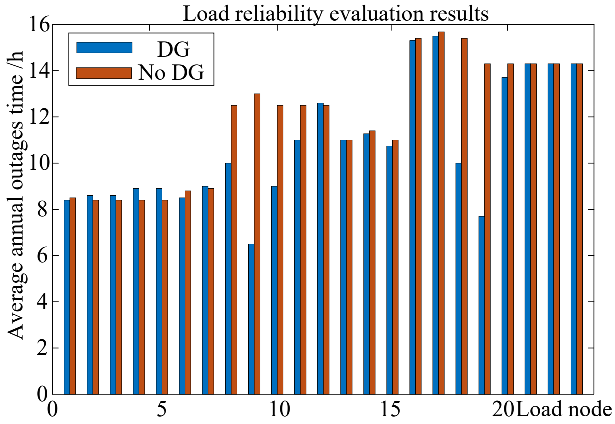

Fig. 5. The average annual outage time

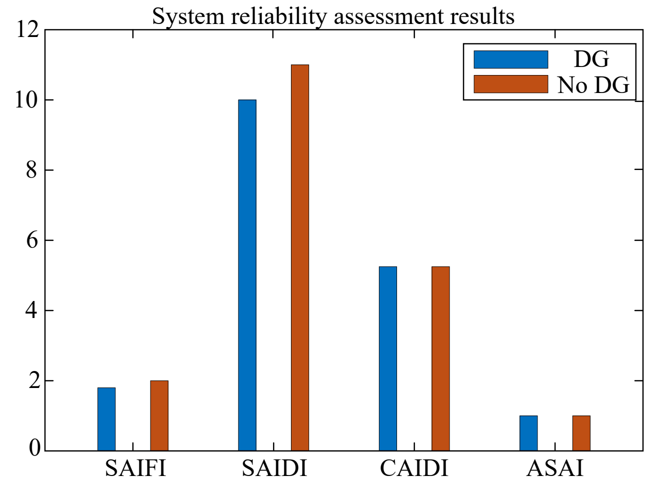

Fig. 6. The system reliability evaluation results

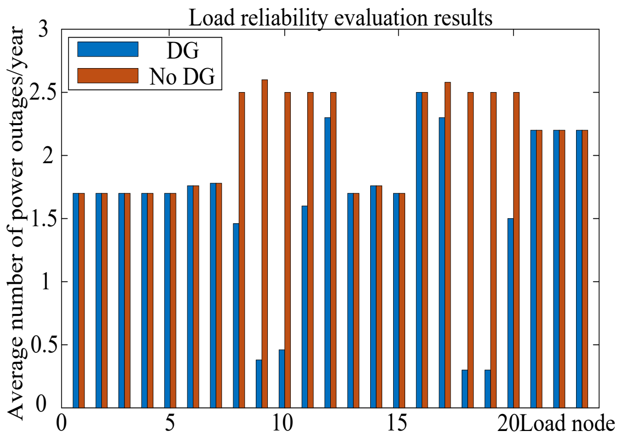

Fig 7. The annual average number of power outages under DG condition

It can be seen that the annual average outage time is generally lower in the case of containing DG than in the case of not containing DG. The inclusion of DG has a positive impact on the reliability of the distribution network, and can play a role in reducing the duration of faults.

The simulation results of system reliability evaluation are shown in Fig. 6. The values of SAIFI and SAIDI are lower in the case of DG than in the case of no DG, it indicates the distribution network with DG is more stable and its reliability is higher. The values of CAIDI (Average Household Outage Duration) and ASAI are the same in both scenarios, indicating that the impact of faults on users in distribution grids containing DG is the same as in distribution grids that do not contain DG.

The result of the annual average number of outages based on probability model and minimum path method is shown in Fig. 7. It can be observed the average annual number of outages is basically lower when DG is included than when it is not included, and the same conclusion as in Fig. 4 can be obtained.

The simulation result of average annual outage time with the probability model and minimum path method is shown in Fig. 8. At some nodes, the average annual outage time with DG is significantly lower than that without DG, while at other nodes, there is almost no difference between the two values, and from the above observations we can draw the following conclusions that the stability of the distribution network system with DG is better in some areas.

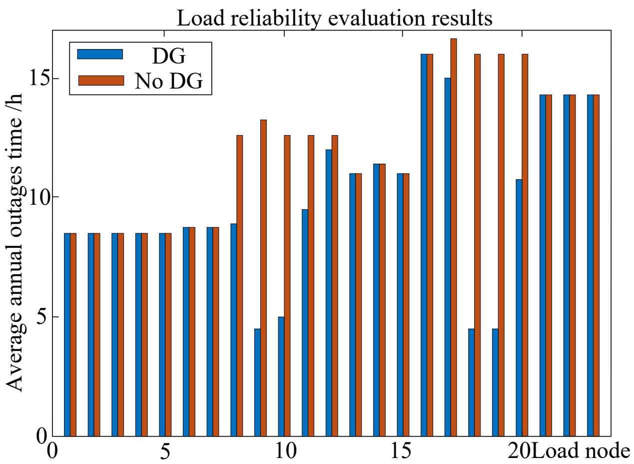

Fig. 8. The simulation results of average annual outage time

The system reliability evaluation with the probability model and minimum path method is shown in Fig. 9. The values of SAIFI and SAIDI are lower in the case of DG than in the case of no DG, which indicates that the distribution network with DG is more stable and its reliability is higher.

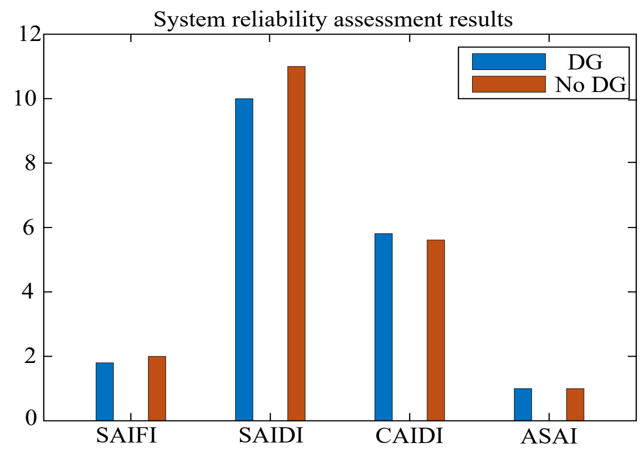

Fig. 9. The simulation results of system reliability evaluation

The opposite is true for CAIDI, which indicates that a fault in the distribution grid containing DG negatively affects this metric. ASAI has the same value in both scenarios, which indicates that a fault in the distribution grid containing DG affects this metric in the same way as in the distribution grid not containing DG.

According to Fig. 4 to Fig. 6. the average annual outage times and average annual outage time calculated by the sequential Monte Carlo method under the time series model with DG are lower than those without DG, and the system reliability evaluation results are more accurate. According to Fig. 7 to Fig. 9, it can be concluded that under the probabilistic model, the average annual outage times and average annual outage time calculated by the minimum-path method are lower when DG is included than when DG is not included, and the system reliability evaluation results are also better.

C. Simulation results of the non-sequential Monte Carlo

The simulation results of the non-sequential Monte Carlo on average annual number of outages are shown in Fig. 10. It can be observed the annual average outage time of the system load within the interval of two values basically, with the range of 1.7 and 2.5.

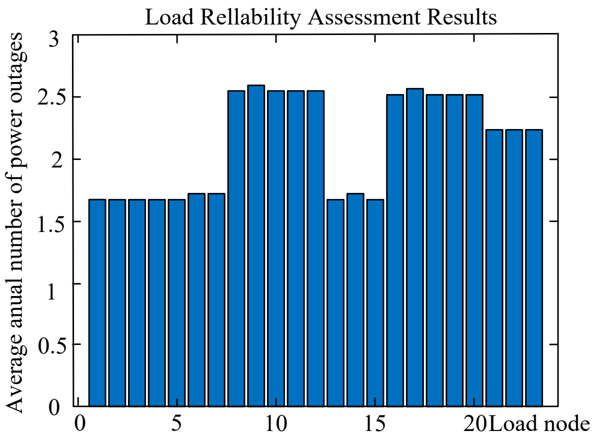

Fig.10. The annual average number of power outages

Similarly, the simulation results of the annual average outage time are shown in Fig. 11. With the application of the non-sequential Monte Carlo method, the annual average number of outages of the system load varies between four values, with an overall trend of steady change.

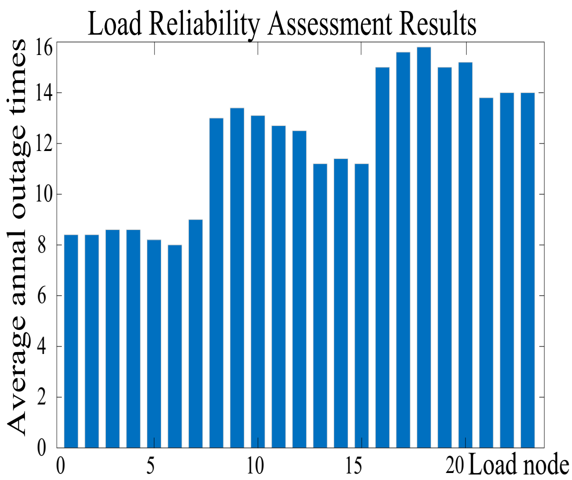

Fig. 11. The simulation results of average annual outage time

With the non-sequential Monte Carlo method, the results of the indicators in the distribution network are shown in Fig. 12.

In Fig. 12, the four resilience indicators of the distribution system have corresponding values, with the largest value for SAIDI and the smallest for ASAI. Because SAIDI reflects the extent of the impact of each outage on the customer, while ASAI reflects the power supply capacity of the entire power system, which also reflects the weak power supply capacity of this power system intuitively. SAIFI is the average number of outages suffered by each customer. It can be calculated by the ratio of the total number of customer outages to the number of customers. CAIDI stands for the average duration of outages suffered by customers. It is an important indicator of the reliability of the power supply in the distribution network. It indicates the average duration of each outage suffered by a customer during one year.

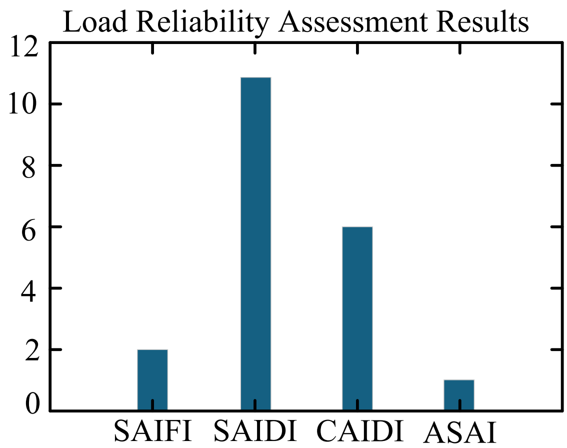

Fig. 12. The simulation results of average annual outage time

The simulation results of the error analysis in the average annual numbers are shown in Fig. 13.

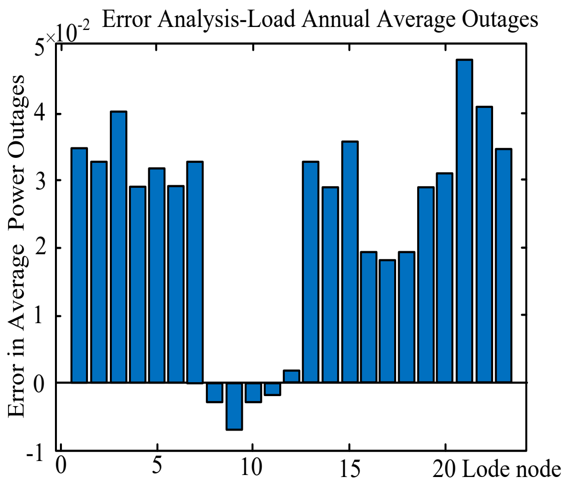

Fig. 13. Error analysis of the average annual number of power outages

It reflects the results of the error analysis of the annual flat outage time. There are positive and negative values occurring in the results. The mainly reason have three aspects. One is the positive error. The outage time is overestimated, due to the recording errors or sensor failures possibly. The other is the negative error. The outage time is underestimated, for the omission or equipment not recorded correctly. The third reason is the model simplification and assumptions. If the model is too conservative and the assumptions are stringent, resulting in overestimation of outage time. If the model is optimistic resulting in underestimation of outage time.

Comparing Fig. 4 and Fig. 10, the results of the annual average outage time obtained with the non-sequential Monte Carlo method remain two values roughly. Although the variation of the data with the sequential Monte Carlo method presents several different values, it can be concluded that the former is smoother in the reliability assessment of the distribution network. Comparing Fig. 5 and Fig. 11, it can conclude that the results of the annual average number of outages obtained by the non-sequential Monte Carlo method are smoother.

VI. Conclusion

In this paper, we used two methods to solve the different assessment needs and provide the valuable results, respectively.

At first, the probabilistic model-based least-path method assesses the reliability of the distribution network effectively. With simplifying the computational complexity, this method can teach the weakest point in the system directly. It provides an important reference for the optimal design of the distribution networks. Especially in the complex distribution system, the minimum path method is the powerful support for the assessment work by high computational efficiency. And then, we adopt the sequential Monte Carlo method based on the timing model. This method considered the timing characteristics of the equipment failures by simulating the operating state of the distribution network at different points. The advantage of the sequential Monte Carlo method can deal with the complex timing relationships and uncertainty factors, which provides a more detailed and comprehensive perspective for the reliability analysis of the distribution networks.

In summary, both of the two methods play an important role in distribution network reliability analysis. The former provides an important reference for the preliminary assessment and optimal design of distribution networks with its concise and efficient calculation and intuitive presentation of results, while the latter provides a more in-depth and comprehensive perspective for the reliability analysis of distribution networks with its comprehensive and detailed time-series simulation capability. In the future reliability assessment of distribution networks, we can choose the appropriate assessment method according to the actual needs or use the two methods in combination to obtain more accurate and comprehensive assessment results.

References

[1] G. G. Chen, S. T. Li, H. Y. Long, X. J. Zeng, P. Kang and J. M. Zhang, "A Hybrid Algorithm Introducing Cross Mutation and Non-linear Learning Factor for Optimal Allocation of DGs and Minimizing Annual Network Loss in the Distribution Network," IAENG International Journal of Applied Mathematics, vol. 51, no. 3, pp569-586, 2021

[2] A. Moreira, M. Helen, A. Valenzuela, J. H. Eto, J. Ortega and C. Botero. "A Scalable Approach to Large Scale Risk-averse Distribution Grid Expansion Planning," IEEE Transactions on Power Systems, vol. 39, no.1, pp2115-2128, 2024

[3] J. Raymond and D. Komljenovic. "Situational Awareness: A Road Map to Generation Plant Modernization and Reliability," IEEE Power & Energy Magazine, vol. 22, no. 3, pp29-41, 2024

[4] T. Navidi, A. El Gamal and R. Rajagopal. "Coordinating Distributed

Energy Resources for Reliability Can Significantly Reduce Future Distribution Grid Upgrades and Peak Load," Joule, vol. 7, no.8, pp1769-1792, 2023
[5] M. Atrigna, A. Buonann, R. Carli, G. Cavone, P. Scarabaggio, M. Valenti, G. Graditi and M. Dotoli. "A Machine Learning Approach to Fault Prediction of Power Distribution Grids under Heatwaves," IEEE Power & Energy Magazine, vol. 59, no. 4, pp4835-4845, 2023
[6] A. Alvi, T. Alford and M. Vaiman. "Pioneering Real-time Control: The Deployment of a Distribution Linear State Estimator at Common Wealth Edison," IEEE Power & Energy Magazine, vol. 22, no. 2, pp77-77, 2024
[7] J. Aquino, J. C. Prado, H. Nazaripouya and A. Z. Bertoletti. "Enhancing Power Grid Resilience Against Ice Storms: State-of-the-art, Challenges, Needs, and Opportunities," IEEE Access, vol. 11, no. 1, pp60792-60806, 2023
[8] R. Currie, S. Peisert, A. Scaglione and N. Ravi. "Data privacy for the Grid: Toward a Data Privacy Standard for Inverter-based and Distributed Energy Resources," IEEE Power & Energy Magazine, vol. 21, no. 5, pp48-57, 2023
[9] J. W. Moraski, N. D. Popovich and A. A. Phadke. "Leveraging Rail-based Mobile Energy Storage to Increase Grid Reliability in the Face of Climate Uncertainty," Nature Energy, vol. 8, no. 7, pp736-746, 2023
[10] F. Jozi, K. Mazlumi and S. H. Hosseini. "Evaluation of the Reliability of the Deregulated Radially Distribution Network with Consideration of Vehicle to Grid," Scientia Iranica, vol. 30, no. 5, pp1687-1702, 2023
[11] S. Garip, M. Bilgen, N. Altin, S. Ozdemir and I. Sefa. "Reliability Analysis of Microgrids: Evaluation of Centralized and Decentralized Control Approaches," Electric Power Components and Systems, vol. 51, no. 19, pp2319-2338, 2023
[12] R. Baembitov and M. Kezunovic. "State of Risk Prediction for Management and Mitigation of Vegetation and Weather Caused Outages in Distribution Networks," IEEE Access, vol. 11, no. 1, pp113864-113875, 2023
[13] A. Poudyal, S. Poudel and A. Dubey. "Risk-based Active Distribution System Planning for Resilience Against Extreme Weather Events," Transactions on Sustainable Energy, vol. 14, no. 2, pp1178-1192, 2023
[14] B. Zeng, C. H. Zhang, P. D. Hu, F. L. Yang, W. K. Li and H. W. Mu. "Quantifying the Capacity Credit of IDC-based Demand Response in Smart Distribution Systems," IET Generation Transmission & Distribution, vol. 17, no. 12, pp2757-2772, 2023
[15] S. M. R. H. Shawon and X. D. Liang. "A Two-stage Performance Optimization-based Microgrid Formation in Distribution Networks with Distributed Generations," IEEE Transactions on Industry Application, vol. 59, no. 5, pp5539-5549, 2023
[16] R. Baembitov, M. Kezunovic, K. A. Brewster and Z. Obradovic. "Incorporating Wind Modeling into Electric Grid Outage Risk Prediction and Mitigation Solution," IEEE Access, vol. 11, no. 1, pp4373-4380, 2023
[17] M. W. Khan, G. J. Li, K. Y. Wang, M. Numan, L. Y. Xiong and M. A. Khan. "Optimal Control and Communication Strategies in Multi-energy Generation Grid," IEEE Communications Surveys and Tutorials, vol. 25, no. 4, pp2599-2653, 2023

Xianfu Zhou received his master's degree in electrical engineering from Zhejiang University in 2003. As the technical backbone of Zhejiang Power Grid, his research interests include the power line carrier communication, grid communication and the load analysis based on the high-voltage grids. (ttla02@163.com).

Feng Lu received his Ph.D. electrical engineering from Zhejiang University in 2003. As the general manager of the company, He is committed to the research and exploration of new power equipment such as grid optimization, clean energy, and hydrogen storage.

Songsong Zheng received the bachelor's degree in the electronic information engineering from Zhejiang University of Technology in 2006. He is mainly responsible for the research and exploration of power marketing, renewable energy structure design, and new energy storage technologies.

Yifeng Yang received the bachelor's degree in electrical engineering and automation from Nanjing Institute of Technology in 2011. In the same year, he entered the Zhejiang branch of the State Grid. He is mainly responsible for the implementation of technologies such as the design of the top-level structure of the high-voltage power grid and the instantaneous load forecasting of the high-voltage grid.

Lei Xiang obtained his master's degree in automation from North China Electric Power University in 2012 and entered the State Grid Zhejiang Branch in the same year. His research interests include the design of smart meters and the management of smart power stations.