Reliability evaluation of distribution network based on improved non sequential Monte Carlo method

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Abstract. In this paper the idea of stratification is utilized to form a homogeneous-stratified sampling method, which can increase the efficient of power system random fault state evaluation. Applying this method for reliability evaluation only generates a small number of independent random numbers, it decrease the amount of calculation and increase the efficient. The improved non sequential Monte Carlo method is then demonstrated and implemented in the reliability evaluation of RBTS-BUS5 system case, illustrating this algorithm can be used in reliability evaluation of distribution network.

Introductions

In order to obtain the reliability index of higher precision, it often requires a long calculation time. In order to reduce the simulation time and improve the convergence speed of Monte Carlo method, we can use the method of variance reduction. The usual methods of variance reduction are stratified sampling method，importance sampling method, the variable control method and dual variable method[1-4] and so on. However, there are some restrictive conditions of these methods in use.

In this paper ,we use scattered sampling technique to reduce the variance, different from other traditional sampling method where is sampling interval uniform segmentation, take each sampling interval mean value of experiment function as the new experimental function of the system in every sampling, so as to reduce the simulation variance, improve simulation accuracy. The method can greatly reduce the sampling number does not exist any constraints, and therefore have a very good adaptability.

The basic principle of non sequential Monte Carlo method

The non sequential Monte Carlo simulation method [5] is often referred to as the state sampling method. This method is based on the system state is a combination of all elements, and each state of the element is determined by sampling probability of components in the state. Each element is available to be simulated by a uniform distribution in the interval of [0, 1]. Assume that each element has two states of failure and work, and failure of components are independent each other.

Let s_i denote the state element i , Q_i on behalf of the failure probability, generating a uniform random number R_i in the interval of [0, 1] for the element i , make

$$S_i = \begin{cases} 0 & \text{(work\ state)} & \text{if } R_i > Q_i \\ 1 & \text{(failure\ state)} & \text{if } 0 \le R_i \le Q_i \end{cases} \tag{1}$$

The system state with N elements is represented by the vector s:

$$s = (s_1, \ldots, s_i, \ldots s_N)$$

When a system state is selected in the sample, namely carries on analyzing the system to determine whether it is a fault condition, if it is, then estimate risk index functions of the state. When the number of samples is large enough, the frequency of sampling system of S may be regarded as the probability of the unbiased estimation, i.e.

$$P(s) = \frac{m(s)}{M} \tag{2}$$

Where: M is the sampling number, $m(s)$ is the number of times of S appeared in the sampling system state.

Sampling principle of distributed sampling method and its implementation process [6]

The traditional sampling method is directly generated uniformly distributed random numbers in the interval of [0, l], and determine the system stochastic state by the random number. But scattered sampling algorithm divided interval [0, 1] into n sub intervals. And the lengths of sub intervals meet $1/n \ge \max\{f_1, f_2, \ldots f_m\}$, where, $f_1, f_2, \ldots f_m$ are the forced failure probability of system components. For a random number x_i, it can produce n state variables $(X_{i1}, X_{i2}, \ldots X_{ij}, \ldots X_{in})$ in the n intervals. In the j sub interval X_{ij} is determined according to the type 3

$$X_{ij} = \begin{cases} 0 & \frac{j-1}{n} \le x_i < \frac{j-1}{n} + f_i \\ 1 & x_i < \frac{j-1}{n} \text{ or } x_i \ge \frac{j-1}{n} + f_i \end{cases} \tag{3}$$

By the above formula indicates, when a random number vector X was generated, we can obtain n state vectors $X_{i1}, X_{i2}, \ldots X_{ij}, \ldots X_{in}$ through the use of scattered sampling technique, it greatly improve the efficiency in the use of random number. Take the arithmetic average value of experimental function $F(X_1), F(X_2), \ldots F(X_i), \ldots F(X_n)$ in each sub interval as a random function of vector X

$$F(X) = \frac{1}{n} \sum_{j=1}^{n} F(X_j) \tag{4}$$

In order to realize the scattered sampling algorithm, we can use the calculated risk index the loss of load probability LOLP and the expected power not supplied value EPNS to achieve, in the piecewise interval[j-1/n, j/n], The experimental function is defined as follows:

When computing LOLP, experimental function as follows:

$$F(X_j) = \begin{cases} 1 & load\ cutting\ system \\ 0 & No\ load\ cutting\ system \end{cases} \tag{5}$$

When computing EPNS, experimental function as follows:

$$F(X_j) = \begin{cases} \sum\limits_i P_i & load\ cutting\ system \\ 0 & No\ load\ cutting\ system \end{cases} \tag{6}$$

Among them, P_i is the value of load minus the total power outputting.

The new experimental function is:

$$F^*(X) = \sum_{j=1}^{k} \frac{F(X_j)}{n} \tag{7}$$

The expected value formula of $F^*_i(X)$ is:

$$E(F^*) = \sum_{i=1}^{N} \frac{F^*_i(X)}{N} \tag{8}$$

In the formula above, $F^*_i(X)$ is the system *ith* sampling experiment function.

The variance estimation formula of $F^*_i(X)$ is:

$$V(F^*) = \sum_{i=1}^{N} \frac{[F^*_i(X) - E(F^*)]^2}{N} \tag{9}$$

Application of distributed sampling method in the reliability evaluation of distribution network

Use the method above to evaluate the reliability for RBTS-BUS5 line of IEEE reliability testing system. RBTS-BUS 5 is a typical rural power distribution network as shown in Fig. 1. Table 1 and Table 2 separately listed the appropriate line data and user data. The rest data values were considered as: the value of line failure rate γ_L is $0.2/time \times (km \times a)^{-1}$, the value of repair time η_L is $1.5/h$ [7].
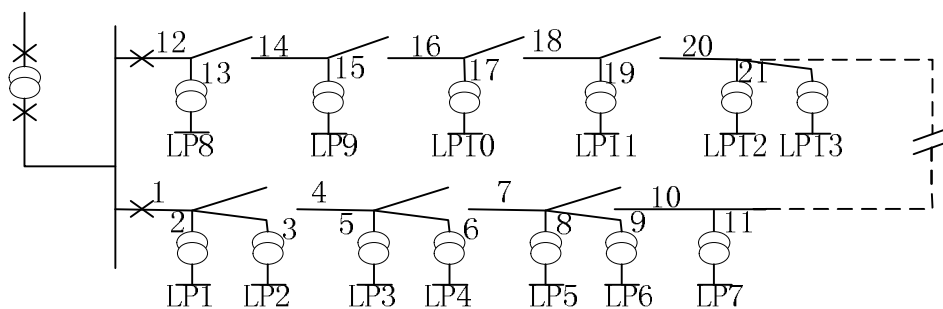

Fig.1 RBTS－BUS 5 The structure of ring network

Table 1 .The line data of RBTS-BUS5 ring network

Line number	Length (km)
1,6,9,13,14,18,21	0.5
4,7,8,12,15,16,19,22	0.7
2,3,5,10,11,17,20	0.8

Table 2 .The user data of RBTS-BUS5 ring network

Load point	Category	λ/time·α	r/h·time^{-1}	maximum load (*kW*)	average load (*kW*)	number of users
1,2,3,4	Resident	0.2360	1.5	740.0	0.4089	220
5,6,7	Agriculture	0.2165	1.6	752.5	0.4169	1
8,9,10,11	Resident	0.2588	1.4	1110.0	0.6247	1
12,13	Agriculture	0.2263	1.5	574.0	0.4089	195

The calculation flow chart of improved non sequential Monte Carlo method as shown in Fig. 2:
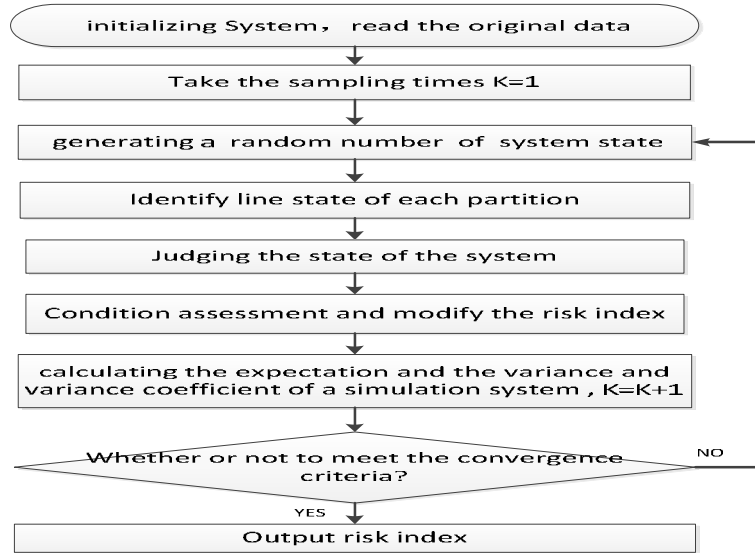

Fig.2 The calculation flow chart of improved non sequential Monte Carlo method

The theory based on the non-sequential Monte Carlo simulation algorithm of probability, scattered sampling method and analytical judgment were as follows. The risk assessment of power distribution system has been done by using improved and unimproved Monte Carlo method respectively. The calculated risk index were the loss of load probability LOLP and the expected power not supplied value EPNS. The convergence rate of EPNS is slower than rate of LOLP, so the variation coefficient of EPNS has been taken as convergence criterion in order to balance computational accuracy of both in these paper.The assessment results of RBTS-BUS5 ring network structure by two methods as shown in table 3

Table 3 .The risk assessment results of RBTS-BUS5 by Uniform sampling method and scattered sampling method

Method	K	$LOLP$	V_{LOLP}	η_{LOLP}	$EPNS$	V_{EPNS}	η_{EPNS}
1	10000	0.12689	0.00560	0.58964	3.03904	35.91334	1.97193
2		0.13227	0.10963	2.50316	3.22738	258.10765	4.97794
1	20000	0.12701	0.00560	0.58893	3.04638	35.93139	1.96768
2		0.13355	0.11044	2.48828	3.26143	260.72031	4.95084
1	30000	0.12711	0.00560	0.58878	3.04751	35.96869	1.96797
2		0.13393	0.11074	2.48471	3.26884	261.45811	4.94661
1	40000	0.12721	0.00559	0.58749	3.04582	35.87051	1.96637
2		0.13396	0.11075	2.48437	3.28076	262.42012	4.93770
1	50000	0.12728	0.00559	0.58727	3.04915	35.94385	1.96623
2		0.13417	0.11099	2.48303	3.28780	262.83584	4.93102

Where, method 1 and 2 represent improved and unimproved Monte Carlo method respectively, K is the sampling times, V_{LOLP} and V_{EPNS} mean variances of test functions which correspond to the risk indicators LOLP and EPNS respectively, η_{LOLP} and η_{EPNS} are the variance coefficient of the corresponding LOLP and EPNS respectively.

Conclusions

The results of risk assessment in the above examples indicated that method 2 reduces the sampling variance to a certain extent and improve the convergence speed of the Monte Carlo method compared with method 1 for the same sampling number. For instance, the example analysis of RBTS-BUS5 revealed that the variances of test functions (V_{LOLP} and V_{EPNS}) calculated by method 1 are 0.00559 and 35.94385 respectively, the variances calculated by method 2 are about 0.11099 and 262.83584 respectively after 50000 times of sampling calculation. The ratio of the variance of Test functions calculated by method 1 and the variance by method 2 were about 5.04% and 13.68% respectively. In other words, method 1 has better convergence property compared with methods 2. This can also be verified by size relationship of variance coefficient of two methods. For example, the variances coefficient (η_{LOLP} and η_{EPNS}) calculated by method 1 are 0.58964 and 1.97193 respectively, the variances coefficient calculated by method 2 are about 2.50316 and 4.97794 respectively after 10000 sampling calculation. The ratio of the former and the latter were 23.55% and 39.61% respectively. What is more, the ratio was 23.65% and 39.87% after 50000 times of sampling calculation. Fig. 3 and Fig. 4 described the change law and contrast about V_{LOLP} and V_{EPNS} of the two methods.
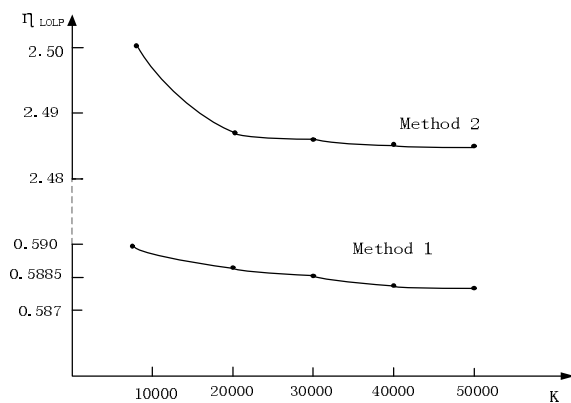

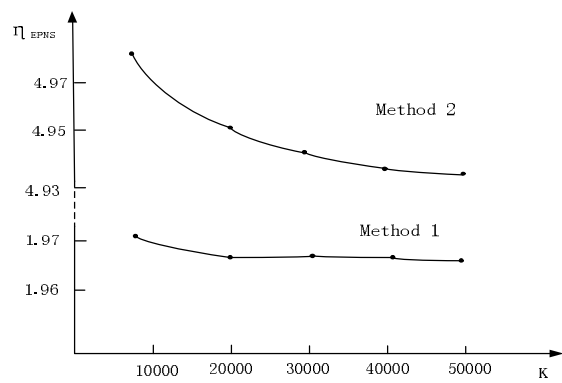Fig.3 the value of η_{LOLP} in different sampling times under the method of 1 and 2

Fig.4 the value of η_{EPNS} in different sampling times under the method of 1 and 2

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