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An Improved Hybrid Method for Power System Reliability Assessment

1st Liping QU, 2nd Tailu Gao
School of Electrical Engineering and Information,
Beihua University
Jilin, China
Email:*goudan1990@126.com*

3rd Jie Zhang, 4th Bin Liu, 5thWenchao Cui
School of Electrical Engineering and Information,
Beihua University
Jilin, China
Email:*gaotailu135102@163.com*

***Abstract*—In order to improve the sampling efficiency of the non-sequential Monte Carlo simulation method, an improved hybrid method combining the analytical method and the significant Latin hypercube sampling method is proposed based on the idea of state space partitioning. The method partitions the system state space based on the determination of the significant state subspace to avoid sampling the zero-fault state of the system. The reliability index of the significant state subspace is efficiently solved by the analytical method, and the remaining state subspace is sampled by the significant Latin hypercube sampling method. Finally, the correctness and efficiency of the proposed algorithm is verified by evaluating the reliability of the IEEE-RTS system.**

Keywords-reliability assessment; mixed methods; state space segmentation; importance sampling; Latin hypercube sampling

I. INTRODUCTION

With the rapid development of the national economy, the requirements for the power system are getting higher and higher. In recent years, large-scale power outages have occurred many times at home and abroad, causing huge economic losses and seriously affecting people's normal lives [1]. Therefore, in order to achieve the best comprehensive benefit of the power system, it is necessary to carry out a practical and effective reliability assessment of the power system. At present, the methods of power system reliability assessment are roughly divided into two types: analytical methods and Monte Carlo methods [2]-[3]. Monte Carlo method is to obtain the state of the entire system through random experiments, but because the calculation amount is not strongly correlated with the number of components, this method is especially suitable for reliability analysis of large-scale systems. The disadvantage of the Monte Carlo method is that it needs to obtain high-precision reliability indicators through long-term simulation calculations. Therefore, various variance reduction techniques need to be used to improve the convergence speed. Common variance reduction techniques include scattered sampling, adaptive sampling, and dual variable sampling [4]. Literature [5] proposes an adaptive importance sampling technique that can optimize the probability distribution of the system state space, but the construction of the initial value of the sampling density of this method is constrained by the nature of the system, so when the system reliability is high, this technique will make the sampling The efficiency is reduced. An adaptive stratified significant sampling algorithm was proposed in the literature [6], however, the sampling process is cumbersome and not possible to use on a large scale; the literature [7] divides the system state space into a non-faulty part and a faulty part of all orders and uses different evaluation methods for analysis according to the characteristics of each part. However, the influence of the importance of system components on the system state is not considered, so the reliability evaluation effect is not ideal.

In this paper, an improved hybrid method for power system reliability assessment is proposed in response to the problems of many sampling times, slow calculation speed, and low calculation accuracy of the Monte Carlo simulation method in assessing the reliability of power systems. The method first uses significant sampling to determine the significant state subspace, then divides the system state space, uses the high computational accuracy of the analytical method to effectively solve the reliability index of the significant state subspace, and adopts the significant Latin hypercube sampling method for the remaining state subspace. In order to achieve the purpose of improving the calculation speed and reducing the sampling variance.

II. IMPORTANT LATIN HYPERCUBE SAMPLING METHODS

Important Latin hypercube sampling, as the name implies, combines importance sampling with Latin hypercube sampling. The key to this method is to construct the optimal probability density distribution function using the importance sampling method and then to perform Latin hypercube sampling on the constructed function. The interval [0,1], etc. is divided into N non-overlapping sub-intervals according to the requirements of the Latin hypercube sampling method. When the system is sampled, the system states are extracted from the N subintervals until all the system states are used up, which maximizes the sampling coverage of the entire sampling interval and reduces the large number of fault-free states of the system. The possibility of re-extraction thus most truly reflects the actual probability distribution; at the same time, the Latin hypercube sampling method can also avoid data truncation and ensure the integrity of the sampling interval.

A. Non-sequential Monte Carlo Simulation

The non-sequential Monte Carlo method is used to analyze the reliability of power systems in the following three steps: (a) system state sampling; (b) state estimation; (c) reliability index statistics.

Firstly, the state x of each component in the system is sampled. Let The event probability of the system state is

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P(X) and the state function is F(X),then the mathematical expectation and variance of the system reliability index are:

$$E(F(X))=\sum_{x\in\Omega}F(X)P(X) \tag{1}$$

$$V(F(X))=\sum_{x\in\Omega}(F(X)-E(F(X)))^{2}P(X) \tag{2}$$

Where: Ω represents the system state space. In the actual sampling, the values of E(F(X)),V(F(X)) are estimated according to equation (3), equation (4).

$$\widehat{E}(F(X))=\frac{1}{N}\sum_{i=1}^{N}F(X_i) \tag{3}$$

$$\widehat{V}(F(X))=\frac{1}{N}\sum_{i=1}^{N}(F(X_i)-\widehat{E}(F(X)))^2 \tag{4}$$

Where: $\widehat{E}(F(X))$ is the unbiased estimate of E(F(X)); $\widehat{V}(F(X))$ is the unbiased estimate of V(F(X)) ; N is the number of samples; and F(X_i) is the state function of the system for the ith sampling.

In reliability assessment, the convergence criterion is usually based on the coefficient of variance of the reliability indicator β, which is expressed by β

$$\beta=\frac{\sqrt{V(\widehat{E}(F(X))}}{\widehat{E}(F(X))}=\frac{\sqrt{V(F(X))/N}}{\widehat{E}(F(X))} \tag{5}$$

Rectifying equation (5) shows that the number of samples required for the non-sequential Monte Carlo simulation method is

$$N=\frac{V(F(X))}{\left(\beta\widehat{E}(F(X))\right)^2} \tag{6}$$

From the analysis of equation (6), it is clear that the only way to reduce the number of samples N while satisfying a certain sampling accuracy is to reduce the variance V(F(X)) of F(X).

B. Method of Importance Sampling

The significant sampling method is one of the most effective means of improving the Monte Carlo method. The main idea is to be able to modify the given probability distribution but also to leave the original sample expectation unchanged, in order to reduce the simulation time and shrink the variance.

First multiply the numerator and denominator in formula (1) by $P^*(X)$ respectively, so as to obtain the mathematical expectation of reliability index.

$$E(F(X))=\sum_{x\in\Omega}[F(X)P(X)/P^*(X)]P^*(X) \tag{7}$$

Let $F^*(X)=F(X)P(X)/P^*(X)$,then

$$E(F(X))=\sum_{x\in\Omega}F^*(X)P^*(X)=E(F^*(X)) \tag{8}$$

Where: $P^*(X)$ is the optimal probability distribution function and $F^*(X)$ is the state function of the system under this distribution function. Then the variance of the corresponding state function $F^*(X)$ is

$$V[F^*(X)]=\sum_{X\in\Omega}\frac{[F(X)P(X)]^2}{P^*(X)}-E^2(F(X)) \tag{9}$$

If $P^*(X)$ in equation (9) satisfies the conditions of $P^*(X)=F(X)P(X)/E(F(X))$, then

$$V[F^*(X)]=0 \tag{10}$$

The analysis of equation (10) shows that if $P^*(X)$ can be used instead of P(X) for sampling, then it is possible to reduce the sampling variance to 0. Therefore, the key to the important sampling method is to construct the optimal probability distribution function. Since $P^*(X)$ satisfying equation (10) is difficult to construct directly, it can be seen that $P^*(X)$ and P(X) satisfy a certain proportional relationship, so that $P^*(X)=mP(X)$, m is a proportional constant, thus transforming the construction problem of $P^*(X)$ into a problem of solving for m.

Define the optimal probability distribution function for the component *i* as

$$P^*(X_i=x_i)=\begin{cases}kf_i & \mathrm{x_i}=1\text{（element failure）}\\ 1-kf_i & \mathrm{x_i}=0\text{（element operation）}\end{cases} \tag{11}$$

Where: k is the optimal multiplier; fi is the forced outage rate of the ith element in the system; Xi is the state variable of the ith element. Since $P^*(X)=mP(X)$, then

$$F^*(X)=F(X)/m \tag{12}$$

where:

$$m=\prod_i[(1-x_i)k+x_i\frac{1-kf_i}{1-f_i}] \tag{13}$$

Extract the states of all components in the system, then use equation (13) to solve the m value, bring the obtained m value into equation (12) to solve the new state function value, and take the mean value of the obtained results after multiple sampling.

In this paper, the initial value of the optimal multiplier k is set to 1.1. In the literature [8] the formula for the optimal multiplier k is given.n_1 is the number of components that are out of service during the sampling process and n_0 is the number of components that are in the normal state during the sampling process for a given power system. Let $\beta_0=n_1/(n_1+n_0)$, then the optimal multiplier k can be calculated by the following equation.

$$k=\frac{-(B+\sqrt{B^2-AC})}{A} \tag{14}$$

Of which.

$$\begin{cases}A=\beta_0\overline{f_i}-(1-\beta_0)\overline{f_i}(1-\overline{f_i})\\ B=-\beta_0\overline{f_i}\\ C=\beta_0\\ \overline{f_i}=\frac{1}{n}\sum_{i=1}^{n}f_i\end{cases} \tag{15}$$

Where $\overline{f_i}$ is the average value of the forced outage rate of all components in the system .

III. IMPROVED MIXING METHOD

A. The basic principles of the improved mixing method

The main idea of the hybrid method is that because the analytical method has an accurate model and a clear physical concept, the analytical method should be fully utilized where the analytical method can be used, and the Monte Carlo simulation method should be used when the solution scale exceeds the analytical method's ability to solve. For the analytical method, when the system scale is large, it is difficult to guarantee the calculation time; for the Monte Carlo method, reducing the sampling times can improve the simulation speed, but the calculation accuracy is difficult to meet [9]. because power system reliability assessment has both strict calculation time requirements and control of calculation accuracy. In addition, for some important components of the system, although the failure probability of the components is low, the degree of influence on the system reliability assessment results is extremely large, which must be considered.

In view of the above problems, an improved hybrid method is proposed in this paper, which is different from the conventional hybrid method in that the analytical method and the Monte Carlo method are alternately used, in which the analytical method is only used to efficiently calculate the reliability index of the important state subspace, and the remaining state subspace is sampled by the important Latin hypercube sampling method. The principle of the proposed improved hybrid method is shown in Figure 1.

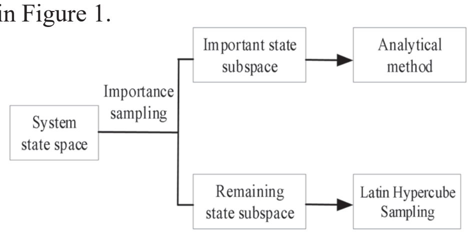

Figure 1. Schematic diagram of the improved hybrid method

B. Determination of Important State Subspace and Reliability Index Calculation

Assuming the offset degree vector $\theta = [\theta_1, \theta_2, \cdots, \theta_n]$ for the component forced outage rate, the offset factor θ_i for the ith component forced outage rate is

$$\theta_i = v_i / u_i \tag{16}$$

Where: v_i is the modified forced outage rate for element *i* and u_i is the original forced outage rate for element *i*. The larger the value of θ_i, the greater the influence of component *i* on the system reliability index. Therefore, the R components with a larger offset factor of the component forced outage rate are noted as important components, and the set of important components Z is determined by the solution method of important components.

A state of order s(s≤R) of a system is defined as an important state of order s of the system if all the states whose state components take the value 1 are in the set of important components, and all important system states form an important state subspace of the system Ω_Z[10]. The method of determining the important state subspace is as follows:

1) Solve for the corrected forced outage rate of each component in the system with the optimal probability distribution function of the system using significant sampling.

2) Solve for the degree of offset in the forced outage rate of each element, determine the set of important elements of the system Z, and finally determine the highest order of important states of the system H (H≤R).

3) Based on the depth-first search traversal method, all fault states in the system not greater than R order are traversed. Then, the important states whose order does not exceed H in the system are screened out, totaling N_Z, and the important state subspace of the system is composed of the above states. The calculation flow of the reliability index of the important state subspace is shown in Figure 2.

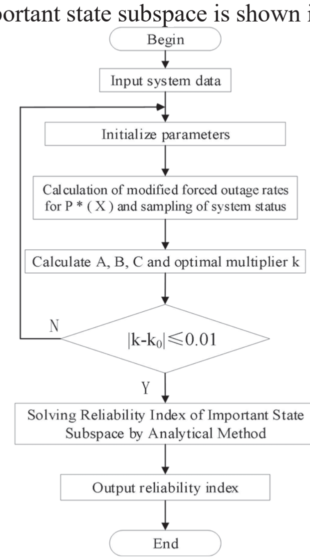

Figure 2. The calculation process of the reliability index of the important state subspace

C. Determination of Residual State Subspace and Calculation of Reliability Index

The remaining state subspace 2 is sampled using significant Latin hypercube sampling. Taking the calculation of the reliability index LOLP (Loss-of-load probability) as an example, the calculation of this index is completed in two stages: Stage I: Solve the corrected forced outage rate of each element in the system and the optimal probability distribution function of the system through important sampling. Stage II: Latin hypercube sampling is performed on the optimal probability distribution function of the system, and the reliability index LOLP is counted and calculated.

D. Calculation methods for system state space reliability indicators

The system state space is divided into the important state subspace and the remaining state subspace. The calculation of the reliability index should be obtained by adding the reliability index $E_Z[F(X)]$of the important state subspace and the reliability index $\widehat{E}_Y[F(X)]$ of the remaining state subspace. Therefore, the calculation formula of the system state space reliability index $\widehat{E}[F(X)]$ is:

$$\widehat{E}[F(X)] = \widehat{E}_Y[F(X)] + E_Z[F(X)] \tag{17}$$

When solving the coefficient of variance of the reliability index of the system state space, because the system state in the important state subspace is determined and no sampling is required, the coefficient of variance of the reliability index of the system state space is only determined by the remaining state subspace.

IV. CASE ANALYSIS

In this paper, we do not look at the case of faults between components, but only at the case of independent faults of components. The IEEE-RTS system is used as an example to illustrate the feasibility of the method proposed in this paper. The system contains 32 generators and 38 lines, with a total installed capacity of 3405MW and a maximum annual load of 2850 MW[11].

The procedures in this paper were written in Matlab's matpower toolbox and used an optimal DC current model with the objective of minimizing load dumping for load dumping. The method proposed in this paper (Method III) was used to evaluate the reliability of the generation and transmission part of the IEEE-RTS system. LOLP and EPNS (Expected Power not supplied) are chosen as reliability indicators, and the coefficient of variance of EPNS is chosen as the convergence criterion βEPNS. The computational results obtained are also compared with the significant Latin hypercube sampling method (Method II for short) and the conventional LHS method (Method I for short). In order to avoid chance and reduce simulation errors, the arithmetic mean of three assessments was taken for the same variance coefficient reliability assessment results.

A. Reliability Evaluation of the IEEE-RTS System

Table 1 shows the LOLP, EPNS, and the number of sampling times obtained by using the three different algorithms under different calculation precisions, as well as the percentage r_N of the times used by other methods and the times used by method I.

Tab. 1: Comparison of Reliability Evaluation Results of the Three Methods at the same accuracy

β_{EPNS}	Methods	LOLP	EPNS/MW	Sampling frequency	r_N/%
	I	0.0792	22.9538	2816	100
0.10	II	0.0802	24.1883	1859	66.0
	III	0.1012	28.3542	1701	60.4
	I	0.0774	25.4509	3759	100
0.08	II	0.0744	22.2917	3731	99.3
	III	0.0956	27.3524	3307	87.9
	I	0.0735	23.1684	6573	100
0.06	II	0.0810	23.5312	5588	85.0
	III	0.0923	28.5021	4930	75.1
	I	0.0749	22.8848	15027	100
0.04	II	0.0769	23.1914	12105	80.6
	III	0.0895	29.4352	10219	68.0
	I	0.0762	22.9280	56356	100
0.02	II	0.0788	24.0518	47477	84.2
	III	0.1012	31.5683	39450	70.1
	I	0.0754	23.0834	226407	100
0.01	II	0.0765	23.2586	188032	83.1
	III	0.1053	33.2083	147170	65.0

As can be seen from Table 1, the sampling efficiency of Method III is significantly improved compared to Methods I and II for the same computational accuracy (variance coefficient β_{EPNS}). When the variance coefficient β is less than or equal to 0.06, the calculation volume of Method II is reduced by about 15-20% on the basis of Method I. The proposed Method III can further reduce the computational effort by about 10-15% on the basis of Method II. The results show that the proposed method can give full play to the dual advantages of the analytical method and the important Latin hypercube sampling method. Using the idea of state space partitioning, it can speed up the reliability evaluation and improve the computational efficiency on the basis of Method I and Method II, which verify the efficiency of the improved algorithm equations.

V. CONCLUSION

In this paper, the influence of system state importance on the reliability evaluation of power systems is fully considered. Combining the advantages of the analytical method and the important Latin hypercube sampling method, an improved hybrid method in power system reliability estimation is proposed. Through the analysis of the IEEE-RTS system, the following conclusions are obtained:

(1) The proposed method first divides the system state space by determining the important state subspace. It not only avoids sampling the zero-fault state of the system but also gives full play to the advantages of the high accuracy of the analytical method.

(2) The residual state subspace is sampled using the important Latin hypercube sampling method, which to a certain extent avoids a large number of repeated extractions of the normal state of the system, effectively reduces the sampling variance, and improves the sampling efficiency.

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