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Reliability Assessment of Power Generation System with Wind Farm

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Abstract

The reliability of power generation system with wind farm is evaluated based on Monte-Carlo simulation, and in the reliability assessment the randomness of wind speed and power load, failure rate of wind turbine generator(WTG) and conventional generator are take into account. Monte-Carlo simulation used in power generation system with wind power need large sample size and has low efficiency. So this paper proposes an improved Monte Carlo method (IMC) based on the combination of Latin Hypercube Sampling and Cholesky decomposition, this IMC method is effective to improve sample values coverage of random variables input spaces and the sampling efficiency. The calculation and analysis of improved IEEE-RTS 79 reliability test systems show that the proposed Assessment algorithm is effective.

Keywords*: Monte-Carlo simulation, reliability assessment, power generation system, Latin Hypercube Sampling; wind farm*

1. Introduction

Wind power is recognized as one of an ideal renewable energy power generation and large-scale development of wind power is benefit for energy development and environmental protection. However, due to the wind power output characteristics of randomness, intermittent and volatility, large-scale wind power integration will be seriously affect the grid voltage stability, system stability, and scheduling [1]. So it is an urgent need to assess power system reliability and security in the case of large-scale wind power integration.

Domestic and foreign scholars have made a preliminary study on the reliability of wind turbine. In paper [2], the reliability model of wind turbine is built considering the aspects of aging and failure of the unit, to establish the reliability using Markov process, but it ignores the drop-power operation state of wind turbine. In paper [3], Wind speed within the assessment period is divided into several periods, but this method is only applicable to long-term evaluation, it is difficult to be divided into several sections because of the randomness of the larger of a short period of time wind speed changes. In paper [4], wind speed of Weibull distribution is introduced to establish the reliability model of wind turbine, but this model does not take the failures and derating of wind turbine into account. Taking into account the stochastic nature of wind energy and wind power generating units forced outage to establish the reliability model of wind turbine, but it did not consider the derating state [5].

Monte Carlo method is often used for large-scale power system reliability analysis due to its simple principle and easy to implement [6], but in order to get higher accuracy often requires a large number of sampling samples and sampling time [7-9]. Literature [10-12] use separatist and Russian roulette method, importance sampling method and control variables method, respectively to reduce the sample variance and improve the sampling efficiency, but they all have not enough suitability.

In response to these above problems, the reliability model of the wind farm is established considering the randomness of the wind speed, the wind farm wake effects and the failure and derating state of the wind turbine. Considering the large sample size and low computational efficiency in the Monte Carlo method, the combination of Latin Hypercube sampling and Cholesky decomposition is proposed. This proposed method is effective in improving the sample values coverage of random variables input spaces and the sampling

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efficiency. The assessment procedures are created in MATLAB, and improved IEEE-RTS79 example calculation and analysis are carried out, the results verify the effective of the assessment method.

2. Reliability Model of Wind Farm

2.1. Wind Speed Model

A large number of wind speeds are measured, statistical results show that, the wind speed variation subject to the two-parameter Weibull distribution [13]. Use random variable V represents the size of the wind speed; its distribution function can be expressed as:

$$F(V) = P(v \le V) = 1 - \exp\left(-\left(\frac{V}{W_c} \right)^{W_k} \right) \tag{1}$$

Where W_k is shape parameter; W_c is the scale parameter whose value reflects the average wind speed of the wind farm; *V* stands for a given wind speed, the unit is m/s.
Make

$$U = F(V) = 1 - \exp\left(-\left(\frac{V}{W_c} \right)^{W_k} \right) \tag{2}$$

Where *U* is uniformly distributed random number in [0, 1].

According to equation (2) wind speed can be expressed as:

$$V = W_c(-\ln(U))^{1/W_k} \tag{3}$$

Due to the impact of the wake effects in large wind farms, the wind speed located in the downwind will be lower than on the wind direction, in this paper the Jensen models is employed to simulate the wake effects of the flat terrain[14], shown in Figure 1.

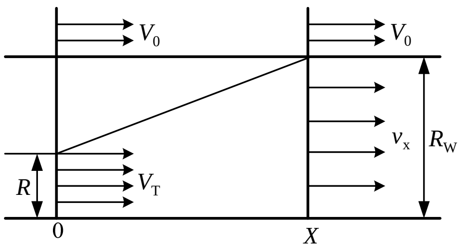

Figure 1. Jensen wake effect model

Where, R is the radius of turbine impeller, R_W is the radius of the wake, V_0 represents Average wind speed, V_T is wind speed of the blade, v_x is affected wind speed by the wake, X is the distance between the two turbines.

According to Figure 1, the affected wind speed by wake effects can be calculated as:

$$v_x = V_0 \left(1 - \left(1 - (1 - C_T)^{1/2}\right)\left(\frac{R}{R + kX} \right)^2 \right) \tag{4}$$

where, k and C_T the stand for flow declined coefficient of wake and thrust coefficient of wind turbine, respectively.

2.2. Wind Energy Conversion Model

After a large number of studies, there is a specific relationship between the output power of the wind turbine and wind speed curve, called a wind turbine power curve A typical wind turbine power curve [15] is shown as:

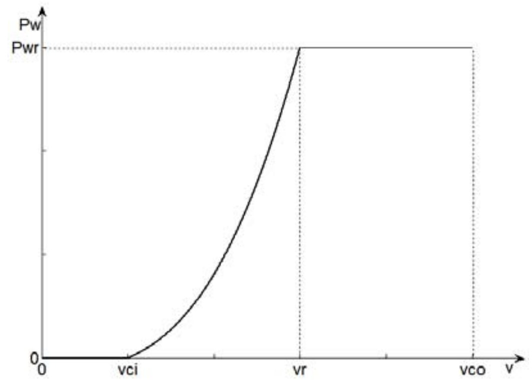

Figure 2. Wind turbine power curve

where, v_{ci} is cut-in wind speed, v_{co} is cut-out wind speed, v_r is rated wind speed, P_{WR} is the active power under the rated wind speed, v is the wind speed value of the wind farm
According to the aerodynamics, the wind turbine electric power is proportional to the third power of wind speed; its output power can be expressed as:

$$P_W(v_x) = \begin{cases} 0 & (v_x < v_{\mathrm{ci}}) \cup (v_x > v_{\mathrm{co}}) \\ \dfrac{P_{\mathrm{WR}}}{v_{\mathrm{r}}^3 - v_{\mathrm{ci}}^3}\left(v_x^3 - v_{\mathrm{ci}}^3\right) & (v_{\mathrm{ci}} \le v_x \le v_{\mathrm{r}}) \\ P_{\mathrm{WR}} & (v_{\mathrm{r}} < v_x \le v_{\mathrm{co}}) \end{cases} \tag{5}$$

Where, P_W is he active power.

2.3. Fault Model of Wind Turbine

Wind turbine three-state fault model including operation, derating and outage status is shown as:

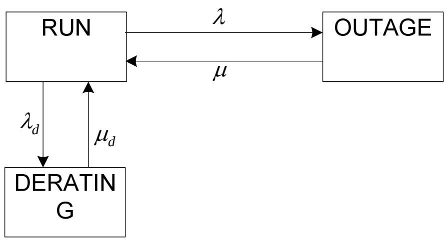

Figure 3. Wind turbine multi-state fault model

where λ and λ_d are outage and derating rate, respectively; μ and μ_d are repair rate, respectively.
Generally, wind turbine outages and derating state are random event, the Markov method is applied to state space diagram shown in Figure 2, the results are shown as:

$$
P_{\text{fo}} = \frac{\mu_d \lambda}{\lambda_d \mu + \lambda \mu_d + \mu_d \mu}
$$
$$
P_{\text{do}} = \frac{\lambda_d \mu}{\lambda_d \mu + \lambda \mu_d + \mu_d \mu} \tag{6}
$$

where P_{fo} and P_{do} are the probability of outage and derating state, respectively.

According to the law of large numbers, wind turbine status can be expressed as:

$$
\text{S} = \begin{cases} 0\ (\text{RUN}) & P_{\text{do}} + P_{\text{fo}} < U \le 1 \\ 1\ (\text{OUTAGE}) & P_{\text{do}} < U \le P_{\text{do}} + P_{\text{fo}} \\ 2\ (\text{DERATING}) & 0 \le U \le P_{\text{do}} \end{cases} \tag{7}
$$

where S represents the operational status of the wind turbine, P_{fo} is the outage probability of the wind turbine; P_{do} is the probability of derating state; U is uniformly distributed random number in [0, 1].

2.4. Wind Farm Output Model

According to equation (5) and (7), the output power of the wind turbine is:

$$
P_{\text{G}i} = \begin{cases} P_W(v_x) & P_{\text{do}} + P_{\text{fo}} < U \le 1 \\ 0 & P_{\text{do}} < U \le P_{\text{do}} + P_{\text{fo}} \\ \alpha \cdot P_W(v_x) & 0 \le U \le P_{\text{do}} \end{cases} \tag{8}
$$

where $P_{\text{G}i}$ is the output of i wind turbine, $P_W(v_x)$ is absorbed energy of the wind turbine under wind speed v_x, α is derating factor.

The active output of the wind farm can be expressed as:

$$
P_{\text{F}} = \sum_{i=1}^{m} P_{\text{G}i} \tag{9}
$$

where, m represents the number of the WTG.

3. Latin Hypercube Sampling Method

Latin Hypercube sampling is a stratified sampling method which could effectively reflect the overall distribution of the random variables using sampled values. Its main purpose is to ensure that all sampling areas can be covered by sampled points. The procedure of LHS method can be divided into two main steps: sampling and permutation.

3.1. Sampling

Assuming the probability cumulative function of X_k is represented as:

$$
Y_{\text{k}} = F_{\text{k}}(X_{\text{k}}) \tag{10}
$$

For a sample size N, the range of Y_k is divided into non-overlapping intervals of equivalent length. One sampling value is chosen from each interval by choosing the midpoint or selected randomly. In this study, the midpoint value is adopted and the range of Y_k is set to [0 1], the nth sample of X_{kn} can be determined by:

$$
X_{kn} = F_k^{-1}\left(\frac{n-0.5}{N}\right) \tag{11}
$$

where N is the number of maximum samples.

The sample values of X_{kn} is then assembled in a row of the sampling matrix **X**, once all the input random variables are sampled, a primary sampling matrix can be obtained.

3.2. Permutation

The purpose of permutation is to eliminate or lower the correlation between the sampled values of the random variables. The original ordering matrix **L** is generated by random permutating 1, …, *N* in every row. Generally, the correlation coefficient is employed to assess the degree of correlation for ordering matrix L, shown as:

$$\rho_{\mathrm{rms}} = \frac{\sqrt{\sum_{i=1}^{K}\sum_{j=1}^{K}\rho_{ij}^2 - K}}{\sqrt{N(N-1)}} \tag{12}$$

wher ρ_{ij} is the correlation between *i* and *j* row of **L**, which can be obtained by:

$$\rho_{ij} = \frac{\sum_{k=1}^{K}\left[\left(L_{ik}-\overline{L_i}\right)\cdot\left(L_{jk}-\overline{L_j}\right)\right]}{\sqrt{\sum_{k=1}^{K}\left(L_{ik}-\overline{L_i}\right)^2\cdot\sum_{k=1}^{K}\left(L_{jk}-\overline{L_j}\right)^2}} \tag{13}$$

All elements ρ_{ij} calculated by equation (13) could form K×K order correlation matrix defined to be $\boldsymbol{\rho}_{\mathbf{L}}$ which is positive definite and symmetric. $\boldsymbol{\rho}_{\mathbf{L}}$ can be decomposed by the Cholesky decomposition into two the product of two lower triangular matrices, shown as:

$$\boldsymbol{\rho}_{\mathbf{L}} = \mathbf{D}\mathbf{D}^{\mathrm{T}} \tag{14}$$

where **D** is a lower triangular matrix.

Then a K×N matrix can be constructed by the equation (15) whose correlation matrix is an identity matrix, in other words, its correlation coefficient is equal to 0.

$$\mathbf{G} = \mathbf{D}^{-1}\mathbf{L} \tag{15}$$

However, different from **L**, the data in matrix are not necessarily integer or positive and cannot be directly used to indicate ranks in the sampling matrix. So the rows of **L** are updated to be the ranks of the data in the corresponding row of **G**. It is proved that the correlation of **L** updated by **G** is less than the original one [16]; repeat this process until the **L**'s correlation coefficient is less than a predetermined value.

4. Reliability Assessment for Power Generation System With Wind Farm

The power generation system reliability refers to the measure of the ability to meet the electricity and electrical energy needs of the power system for the uniform generators connected to grid.

Process block diagram of reliability assessment for power generation system with wind farm based on Latin hypercube sampling Monte Carlo methods are shown as Figure 4.

According to Figure 4, the basic steps of the reliability assessment of the generation system with wind turbine are shown as:

1) Enter the raw data of the power system and wind farm: generating capacity load levels; wind turbine outage and derating rate; wind speed distribution parameters; maximum sampling frequency and minimum coefficient of variation;
2) Calculate the number of input random variables K and determine the sample sizes N, then Generate K×N order Latin hypercube sampling matrix whose correlation will be reduced utilizing Cholesky decomposition method;

3) Determine the system state using n columns sampling value of the Latin hypercube sampling matrix, when power shortage occur, calculate the loss of load and cumulative reliability index;
4) ）if Sampling times exceed the maximum sampling time, then the sampling end, otherwise, n = n +1 go to step 2.
5) Calculate the reliability index.

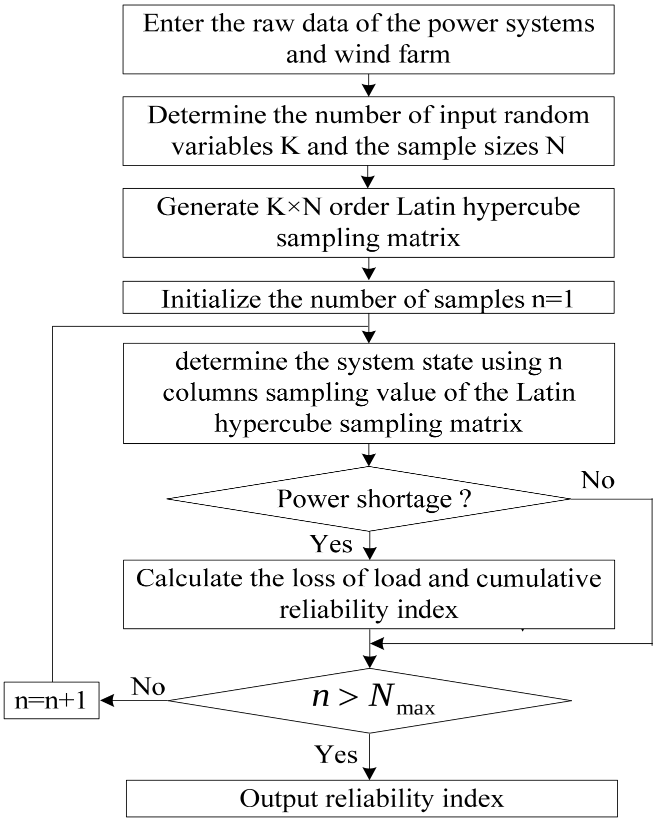

Figure 4. Process block diagram of reliability assessment

5. Simulation Results

5.1. Simulation Example Description

Computational analysis are carried out using the improved RTS79 test system [17] which contains 32 coal-fired generators with total installed capacity of 3405MW with the basic annual load peak for 2850MW and one wind farm with installed capacity of 500MW. The parameters thermal generators are shown in Table 1; and the wind turbine parameters are shown in Table 2.

Table 1. Parameters of thermal generators

Capacity /(MW)	Unit number	Outage probability	MTTF /(hours)	MTTR /(hours)
12	5	0.02	2940	60
20	4	0.10	450	50
50	6	0.01	1980	20
76	4	0.02	1960	40
100	3	0.04	1200	50
155	4	0.04	960	40
197	3	0.05	950	50
400	2	0.12	1100	150

Table 2. Parameters of wind farm and load flow

Capacity /(MW)	Unit number	λ_f / (Occ/ye)	μ_f / (Occ/ye)	λ_d /(Occ/ye)	μ_d /(Occ/ye)	Derating factor
5	100	7.96	58.4	5.84	43.8	0.6

Wc /(m/s)	Wk /(pu)	Vci /(m/s)	Vco /(m/s)	Vr /(m/s)	Eload /(MW)	Vload /(MW)
8.5	2	3	25	10	2250	150

5.2. Method Validation

There are total 134 input random variables (100 wind turbine units, 32 conventional generator units, 1 load and 1 wind speed) in this test system. The load and wind speed distributions are normal and Weibull, respectively, the wind and conventional generator running state distributions are binomial.

The values of correlation coefficient of the ordering matrixes generated by random sampling and Latin hypercube sampling method, respectively of different sample sizes is shown in Table 3, it is obvious that the Latin hypercube sampling has a smaller value compared with random sampling.

Table 3. The correlation coefficient of the sample matrix

Sample sizes	200	400	600	800	1000
Random sampling	0.0475	0.0170	0.0091	0.0059	0.0043
Latin hypercube sampling	0.0100	0.0026	0.0011	0.0007	0.0004

In order to compare the convergence rate of random sampling and Latin hypercube sampling methods, the reliability index EPNS (Expected Power Not Supplied) calculated according to equation (16) is adopted, and the sample sizes of two method are all set to 50000, respectively, the simulation results are shown in Figure 5.

$$\mathrm{EPNS} = \sum_{i \in S} F_i \cdot P_i \tag{16}$$

where P_i represents the probability of the system in the state I, F_i is the load power cuts in the state I, **S** represents all the system states for power shortage.

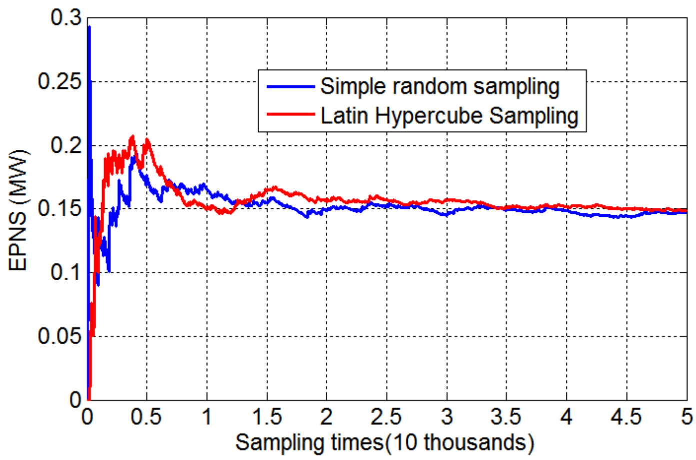

Figure 5. Reliability index EPNS of different sample times

Figure 5 is the convergence process of reliability index EPNS, from which we can see that the Latin hypercube sampling method has a faster convergence rate compared to random sampling method.

In order to verify the Latin hypercube sampling method with a higher sampling efficiency compared to random sampling method, set the calculation accuracy to 0.02 and 0.04 for the two methods, respectively. The required sampling times for the same accuracy are shown in Table 4.

Table 4. Sampling times in the same calculation accuracy

Sample methods	Reliability index	Calculation accuracy	Sampling sizes
Random sampling	EPNS	0.04	15220
		0.02	42535
Latin Hypercube Sampling	EPNS	0.04	8531
		0.02	21563

As can be seen from Table 4, for the same accuracy, the Latin hypercube sampling requires less sampling times compared to random sampling, in other words, the former has a higher sampling efficiency than the latter.

5.3. Sensitivity analysis of model parameters

System reliability index of different derating factor are shown as Figure 6. System reliability index EPNS of different scale parameters are shown as Figure 7.

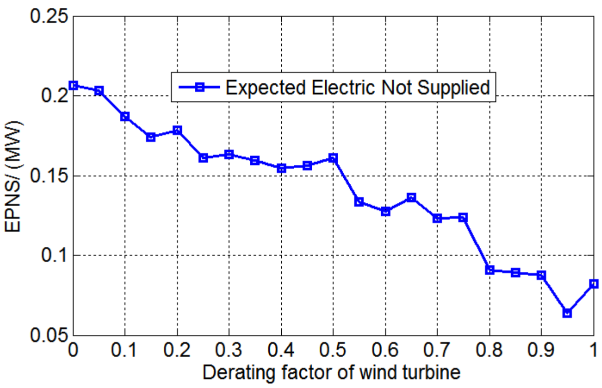

Figure 6. Reliability index EPNS of different derating factor of wind turbine

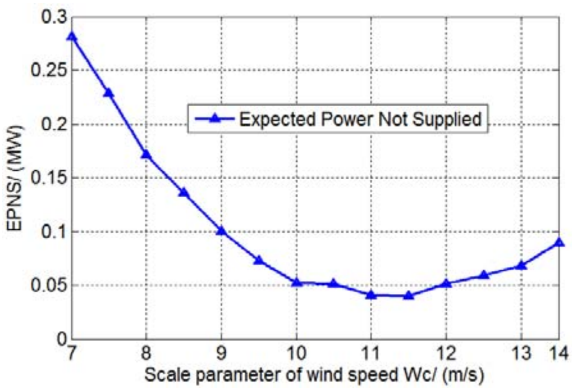

Figure 7. Reliability index EPNS of different scale parameter of wind speed

In the figure 6 shown above, the derating factor of 0 indicates that the derating state equivalent to the outage state, as 1 equivalent to running state, It can be seen that the derating of the wind turbine have a certain impact on system reliability index EPNS, so in actual assessment the appropriate derating factor should be selected.

From the figure 7 we can see that with the increase of the scale parameter, the reliability EPNS of the system is first increased, and then reduced.

6. Conclusion

This paper utilizes the Latin hypercube sampling combined with Cholesky decomposition method into Monte Carlo simulation for solving the large sample size and low efficiency problems. And apply it to power system reliability assessment aspects. The test examples have illustrated that Latin hypercube sampling method has a faster convergence rate and can achieve a better sampling efficiency than random sampling method.

Derating state as one of the wind turbine state has some influence on the reliability of the system, so it should be considered in the reliability modeling of wind turbine. The scale parameter of the wind farm speed has a greater influence on the reliability of the system, and its recognition accuracy has a direct impact on the reliability assessment results of the system.

Acknowledgments

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