Risk-Based Power System Resilience Assessment Considering the Impacts of Hurricanes

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***Abstract*—In this paper, a novel method is proposed to assess the power system resilience considering the impacts of hurricanes. Firstly, the transmission line outage model correlated to wind speed is developed. Then, Probability Load Flow (PLF) considering the random outage of lines and the variation of loads is designed, and Latin Hypercube Sampling (LHS) is used to improve the efficiency of Monte Carlo Simulation (MCS) in solving PLF. Moreover, risk indices, including line overloading, node voltage exceeding limit, load shedding and system collapse, are established to assess the resilience of power systems during hurricanes. The method is tested with a modified IEEE 14-bus system, and simulation results indicate the effectiveness of the proposed approach.**

Keywords—Hurricane, Latin Hypercube Sampling, probabilistic load flow, resilience assessment, transmission line outage

I. Introduction

In recent years, hurricanes and other extreme weather conditions have resulted in some serious power system blackouts, such as the 2008 south China blackout and the 2021 Texas winter blackout, which caused significant impacts and large economic losses. Resilience assessment of power systems can help improve the ability of power systems to withstand high-impact low-probability (HILP) events and rapidly restore services to critical loads after the unfavorable events [1]. Therefore, it has gained the attention of an increasing number of researchers.

The resilience of the power system is defined as having the ability to maintain and recover normal functions when confronted with severe accidents, extreme weather disasters or external attacks [2]. Resilience assessment of power systems can be divided into two categories: disaster withstanding capability assessment and post-disaster rapid recovery capability assessment. The former helps identify the weaknesses of the power system, while the latter is useful for designing an optimal recovery strategy. Risk indices are commonly used to quantify the disaster withstanding capability of the power system. In [3] actual historical datasets are used to quantitatively assess the resilience of the power system through risk indices. In [4] the resilience of the power system under severe weather threat is quantitatively assessed using risk indices such as Loss of Load Frequency (LOLF) and Loss of Load Expectancy (LOLE). The resilience triangle and the resilience trapezoid are used in existing studies in order to assess the rapid recovery capability of power systems after disasters [5]. Moreover, in [6] an improved resilience index RICD is proposed to quantify the post-disaster recovery capability of the power system considering the impacts of the typhoon weather. In [7], the resilience of the power system under ice disasters is quantitatively assessed by RICD.

The impacts of weather disasters on power systems are highly uncertain. However, little attention has been paid to uncertainties in such HILP events. In most of the existing literature it is simply assumed that all the components suffer from the same condition. This inaccurate assumption may lead to a too conservative or optimistic assessment result. Therefore, when the resilience assessment of the power system is carried out, it is necessary to apply uncertainty analysis methods and to consider both the consequences and the possibilities of contingencies during HILP events. Probabilistic load flow (PLF), as the most commonly used method for power system uncertainty analysis, is an efficient tool to analyze the characteristics of steady-state power systems with various uncertainties. Broadly speaking, there are three categories of methods in PLF evaluation: analytical methods [8], approximate methods [9] and Monte Carlo Simulation (MCS) [10]. Compared with other methods, MCS is flexible and robust in solving complex problems. However, Simple Random Sampling (SRS), which is a basic sampling technique, usually requires large sample sizes in order to obtain satisfactory results. Therefore, various improved sampling methods, such as Latin Hypercube Sampling (LHS) [11] and Quasi-Monte Carlo (QMC) [12], are proposed to improve the efficiency of MCS.

Project supported by the State Grid Shanghai Municipal Electric Power Company.

In this paper, a resilience assessment method for power systems considering the impacts of hurricanes is studied, which can quantify the disaster withstanding capability of power systems through risk indices. The relationship between the transmission line outage probability and the wind speed is established. Then, a PLF model considering the random fault of lines and the variation of loads is established, and LHS is used to solve the designed PLF problem. Moreover, risk indices, including line overloading, node voltage exceeding limit, load shedding and system collapse, are proposed to analyze the impacts of hurricanes on power systems. Finally, a modified IEEE 14-bus system is used to test the effectiveness of the method. The rest of the paper is organized as follows: in Section II the model exploring the impacts of hurricane on power system is developed, and the probabilistic load flow calculation method is established. In Section III the simulation results are given, followed by the conclusion in Section IV.

II. Methodology

A. Impacts of Hurricanes on Power Systems

The fragility curve, which is a statistical tool representing the probability of exceeding a given damage state to the disaster intensity, has been widely used in the earthquake vulnerability analysis [13], hydraulic engineering [14] and other fields. It is proved to be an expeditious and effective vulnerability assessment instrument. Thus, in this study the fragility curve is adopted to express the probability of line outages to wind speeds.

In Fig. 1, the relationship between the transmission line outage probability and the wind speed is given, and it is essentially a cumulative distribution function (CDF) of a lognormal distribution [15]. As proposed in (1), p_i and w represent the line outage probability and the wind speed respectively, and the shape of the fragility curve depends on two parameters μ and σ, in this paper the values $\mu=3.8$ *and* $\sigma=0.22$ given in [15] are adopted for the test. However, for the practical application the two parameters must be carefully determined using history data analyze.

$$P_i = \frac{1}{2} + \frac{1}{2} erf\left(\frac{\ln(w) - \mu}{\sigma\sqrt{2}}\right) \tag{1}$$

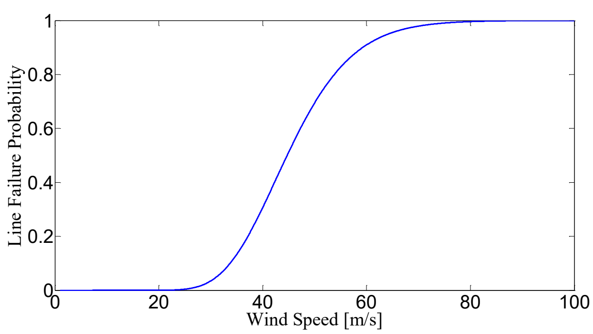

Fig. 1. Wind Fragility Curve

Moreover, the wind speed varies from area to area, and each transmission line can also spread across several areas. Thus, in this study the system is divided into several parts with different wind speeds, and the transmission line is a combination of several segments. The outage probability of each segment is determined by the wind speed at the midpoint of the segment. It can be easily understood that one transmission line will retreat from operation, if one or more segments fail due to the stark wind. Therefore, the outage probability of the transmission line can be expressed by

$$p_{lm} = 1 - \prod_{i=1}^{N} (1 - p_i) \tag{2}$$

where p_i indicates the outage probability of ith segment, and N is the total segment number of the transmission line from node l to node m. The outage probability of ith segment in line l-m is obtained by mapping the wind speed to the fragility curve. With (1) and (2) the outage probabilities of all transmission lines in the system can be calculated.

B. Probability Load Flow Calculation

The functions of PLF can be described by

$$Z = h(W) \tag{3}$$

where W are the input random variables, Z are the output random variables and $h(\cdot)$ represent the power flow equations. Given the probability distribution functions of W, the aim of PLF calculation is to obtain probability distributions as well as statistical indices of Z.

In this paper, MCS is used to solve PLF. Moreover, LHS is adopted to improve the sampling efficiency of MCS. The procedure of PLF calculation is given as follows:

1) The probability models of transmission line outages, the load demands as well as other uncertainties are given. There are m input random variables. The sample size N is determined.

2) The samples of each random variable are obtained by

$$x_{k,i} = F_k^{-1}\left[(i - 0.5)/N\right], i = 1, 2, ..., N \tag{4}$$

where F_k is the cumulative distribution function of the kth input variable, $x_{k,i}$ are the samples of the kth input variable.

3) The sample orders of input variables are permutated as follows. If the input random variables are independent with each other, Cholesky Decomposition (CD) [11] is adopted to arrange the orders of samples to diminish unwanted correlations. If there are correlated non-normal variables, Nataf transformation [16] can be used to induce desired correlations. Finally, the sample matrix with the dimension of $m\times N$ is obtained.

4) The state of the system is determined based on the ith column of the sample matrix (i = 1, 2, …, N). Then, isolated islands are detected. If there are generators in certain islands, the power flow calculation is performed. Otherwise, load shedding is considered. The results are stored.

5) Probability distributions and statistical indices of output random variables are calculated.

C. Risk Assessment Indices

Risk assessment is a quantitative estimation method to determine the risk related to a potential hazard, which has been widely used in power system to provide information about the actual operating situation. When the risk exceeds a specific threshold, the operator must take proper measures to prevent the system getting into emergency situation. As expressed in (5) the risk assessment requires two components, i.e. the severity function $S(E_i)$ and the corresponding probability $p(E_i)$.

$$R=\sum_{i=1}^{N}S\left(E_i\right)*p\left(E_i\right) \tag{5}$$

where E_i indicates the ith contingency state, and N represents the total number of possible contingencies.

In this paper the risk indices designed as follows.

a) Risk Index of Voltage Exceeding Limit

Severity function is used to quantify the impacts of bus voltage limit violation. In this study the acceptable bus voltage magnitude range is from 0.95 p.u. to 1.05 p.u., then the severity function is expressed as

$$\mathrm{S}_{v,j}=\begin{cases}-10V_j+9.5 & V_j\le 0.95p.u.\\ 0 & 0.95p.u.\le V_j\le 1.05p.u.\\ 10V_j-10.5 & V_j\ge 1.05p.u.\end{cases} \tag{6}$$

Where V_j represents voltage magnitude of the jth bus. Then the bus voltage exceeding limit index of the entire system can be calculated by:

$$\begin{aligned}R_{v,j}&=\int_{-\infty}^{+\infty}p_{v,j}\left(V_j\right)S_{v,j}\left(V_j\right)dV_j\\ R_{v,all}&=\sum R_{v,j}\end{aligned} \tag{7}$$

$p_{v,j}$ is the voltage probability density function of jth bus.

b) Risk Index of Line Overloading

In this study the maximum acceptable active power flow on the transmission line is defined as the value under the rated condition. And the severity function is given in (8).

$$S_{l,k}=\begin{cases}0 & \left|P_k/P_{k0}\right|\le 0.9\\ 10P_k/P_{k0}-9 & \left|P_k/P_{k0}\right|\ge 0.9\end{cases} \tag{8}$$

Where P_k is defined as the active power on the kth transmission line, and P_{k0} is the rated active power of that line. And the transmission line overloading risk index of the whole system is expressed by:

$$\begin{aligned}R_{l,k}&=\int_{-\infty}^{+\infty}p_{l,k}\left(P_k\right)S_{l,k}\left(P_k\right)dP_k\\ R_{l,all}&=\sum R_{l,k}\end{aligned} \tag{9}$$

Similarly $p_{l,k}$ is the active power probability density function of kth transmission line.

c) Risk Indices of Load Shedding and System Collapse

Considering the impacts of hurricanes several transmission lines may fail at the same time, which can result in the separation of the entire system into several islands. If certain island contains generators, the loads within this island can still be satisfied to some extent, otherwise the whole island will suffer from blackout. Therefore, the amount of load curtailment and the frequency of system collapse are also defined as another two assessment indices.

III. Case Study

A. Simulation Data

In this section, the proposed method is applied to a modified IEEE 14-bus test system [17], as illustrated in Fig. 2. The power system is divided into four parts with various wind speeds. The wind speeds in the four areas are 25 m/s, 30 m/s, 32 m/s and 35 m/s respectively. The transmission line outage probability can then be calculated using the algorithm given in Section II. For each transmission line, the outage probability of each segment is firstly determined, and the line outage probability is then obtained, as is given in Table I.

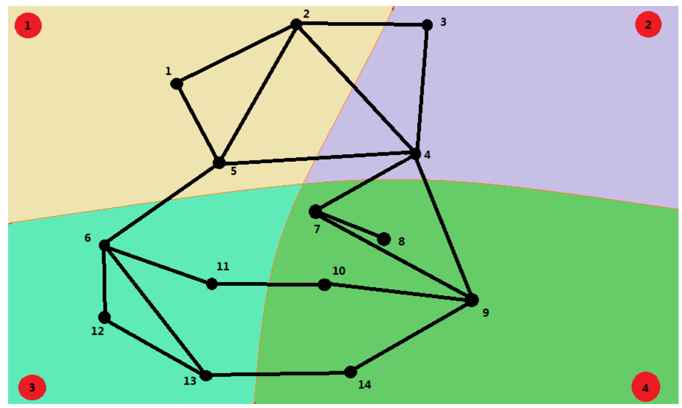

Fig. 2. The modified IEEE 14-bus test system

TABLE I. Outage Probability of Each Line

Line	Outage probability	Line	Outage probability
1-2	0.0082	6-11	0.1245
1-5	0.0041	6-12	0.0643
2-3	0.0429	6-13	0.1808
2-4	0.0763	7-8	0.1331
2-5	0.0123	7-9	0.3484
3-4	0.0687	9-10	0.2484
4-5	0.1086	9-14	0.2484
4-7	0.1633	10-11	0.1888
4-9	0.4374	12-13	0.1245
5-6	0.1281	13-14	0.2968

B. Probabilistic Load Flow Analysis

In this section, PLF is solved for the IEEE 14-bus system. The outage probability of each line is given in Table I, and the load active and reactive power are modelled as normal distributed variables with the coefficient of variation equal to 15%. The result obtained by SRS with the sample size of 50000 is regarded as the benchmark, and the results obtained by LHS and SRS with smaller sample sizes are analyzed. In Table II and III, the errors of statistical indices of voltage magnitudes and angles are given. With the same sample size, the errors of LHS are smaller than those of SRS. In other words, LHS is more efficient than SRS in solving PLF calculation.

In Fig. 3 and Fig. 4, the sample size of LHS and SRS is defined as 1000, and the probability densities of power flow through lines are given. In accordance with the results in Table II and Table III, the probability densities obtained by LHS are more consistent with the benchmark. It should be noted that, since the system is significantly affected by the hurricane, it is likely that transmission line outage will occur in the operation. Therefore, it is possible that the load flow through lines can be zero, as is shown in Fig. 3 and Fig. 4.

TABLE II. ERRORS OF STATISTICAL INDICES OF VOLTAGE MAGNITUDES

Sample size	**Error of mean (%)**		**Error of standard deviation (%)**	
	LHS	*SRS*	*LHS*	*SRS*
500	0.03	0.05	6.41	7.12
1000	0.02	0.03	4.66	4.83
2000	0.01	0.02	2.97	3.53

TABLE III. ERRORS OF STATISTICAL INDICES OF VOLTAGE ANGLES

Sample size	**Error of mean (%)**		**Error of standard deviation (%)**	
	LHS	*SRS*	*LHS*	*SRS*
500	0.63	1.25	5.78	8.35
1000	0.54	0.91	4.55	6.62
2000	0.36	0.65	3.36	4.07

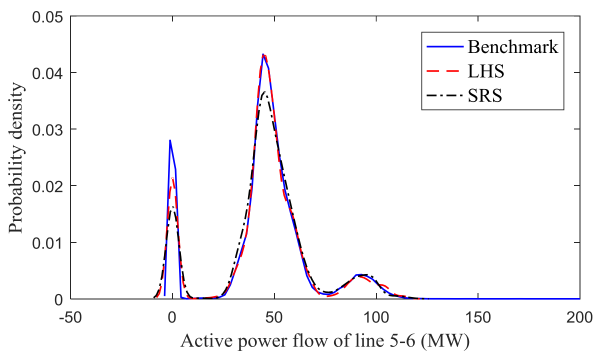

Fig. 3. Probability densities of active power flow through lines obtained by LHS and SRS with the sample size of 1000.

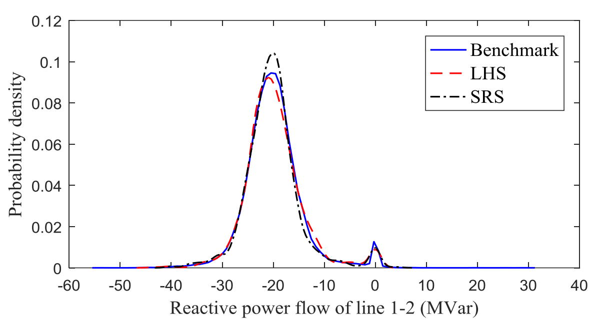

Fig. 4. Probability densities of reactive power flow through lines obtained by LHS and SRS with the sample size of 1000.

C. Risk Assessment Results

In order to explore impacts of different wind speeds on the result of power system resilience assessment, the following three cases are designed:

a) Case 1: The entire power system suffers from the same lowest wind speed 25 m/s;

b) Case 2: The system is divided into four parts, and the wind speeds are 25 m/s, 30 m/s, 32 m/s, 35 m/s respectively;

c) Case 3: The entire power system suffers from the same highest wind speed 35 m/s;

As shown in Fig. 5, the overloading probability of line 1-5 in case 1 is 0.01, whereas raises to 0.04 in case 2. The overloading risk index of the system also increases from 1.73 in case 1 to 1.99 in case 2, which means that the proposed method can provide an objective assessment result. In Fig. 5, the overloading probability of line 1-5 in case 3 is 0.17, and the risk index of the entire system is 7.93. Since wind speeds in case 3 are the highest, the operating risk is also the largest among the three cases. Fig. 6 illustrates the cumulative distribution functions of the voltage magnitude of bus 8. It can be observed that the probability of voltage exceeding limit is 0.82 in case 1, and increases to 0.84 and 0.87 in case 2 and 3 respectively. Moreover, the voltage exceeding limit risk indices of the entire system are 3.49, 9.30, and 13.42 for the three cases.

Thus, it can be concluded that wind speeds during hurricanes significantly affect the probabilities of transmission line outage as well as the operating risks of power systems.

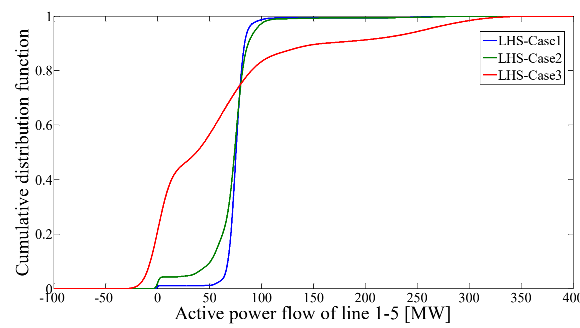

Fig. 5. Cumulative distributions of active power flow through line 1-5

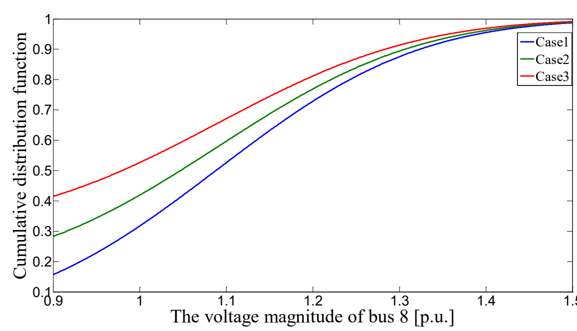

Fig. 6. Cumulative distributions of the voltage magnitude of bus 8

Eventually, the probabilities of load shedding and system collapse are also analyzed. In Table IV, the means and standard deviations of the load shedding and the frequencies of system collapse are given. In case 1 the wind speed is respectively low which leads to a small transmission line outage probability, thus the amount of load curtailment is also small. On the contrary, case 3 is the most serious situation because of the starkest wind.

In case 2, since the wind speed distribution is relatively reasonable, the results of load shedding and system collapse are between those in case 1 and case 3.

TABLE IV. MEAN AND STANDARD DEVIATION OF LOAD SHEDDING AND THE FREQUENCY OF SYSTEM BREAKDOWN

	Case 1	**Case 2**	**Case 3**
Mean of load shedding (MW)	0.04	13.62	32.42
Standard deviation of load shedding (MW)	2.95	49.26	72.74
Frequency of system collapse (%)	0.01	3.22	8.21

IV. CONCLUSION

In this paper, the risk-based resilience assessment of power systems during hurricanes is studied. Firstly, the transmission line outage probability model correlated to the hurricane wind speed is developed. Then, the operation model of power systems considering uncertainties is given, and LHS is used to solve the designed stochastic problem. Moreover, risk indices, including line overloading, node voltage exceeding limit, load shedding and system collapse, are established to analyze the impacts of hurricanes on power systems. The proposed method is tested with the IEEE 14-bus system. Simulation results indicate LHS is more efficient compared with SRS in PLF calculation. Hurricanes significantly affect the operating risk indices and should be properly modelled in order to accurately capture the states of power system.

In the future, we will test our algorithm in an actual system, and extend the resilience assessment framework to other natural disasters.

ACKNOWLEDGMENT

We are greatly thanks to the support of the State Grid Shanghai Municipal Electric Power Company.

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