Risk Analysis for Distribution Systems in the Northeast U.S. Under Wind Storms

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***Abstract*—With the growing trend of extreme weather events in the Northeast U.S., a region of dense vegetation, evaluating hazard effects of wind storms on power distribution systems becomes increasingly important for disaster preparedness and fast responses in utilities. In this paper, probabilistic wind storm models for the study region have been built by mining 160-year storm events recorded in the National Oceanic and Atmospheric Administration's Atlantic basin hurricane database (HURDAT). Further, wind storms are classified into six categories according to NOAA criteria and IEEE standard to facilitate the evaluation of distribution system responses under different levels of hazards. The impacts of wind storms in all categories are accurately evaluated through a Sequential Monte Carlo method enhanced by a temporal wind storm sampling strategy. Extensive studies for the selected typical distribution system indicate that our models and methods effectively reveal the hazardous effects of wind storms in the study region, leading to useful insights towards building better system hardening schemes.**

***Index Terms*—Critical facilities, distribution reliability, hardening planning, hazard, hurricane, wind storm.**

I. Introduction

FREQUENT wind storms have severely affected the Northeast U.S. in the past few years. For instance, tropical storm Irene hit the State of Connecticut (CT) on August 28, 2011, causing sustained interruptions of electric service up to 11 days for over 800 000 customers and a total damage of about $200 million in CT [1], [2]. On October 22, 2012, hurricane Sandy swept the Northeast U.S. causing at least $50 billion in damages to this area [3], [4]. More than 850 000 customers in all 149 cities and towns served by Connecticut Light & Power suffered prolonged outages. The power outages lasted for over a month in some area of New York City. Analyzing power distribution system risks under extreme weather, therefore, is of significance in identifying system weaknesses, designing system hardening schemes and thus enhancing disasters preparedness in the Northeast.

Impacts of extreme weather on power systems have previously been studied. In IEEE Standard 346, weather conditions are divided into three categories: normal, adverse, and major storm disaster [5]. The National Oceanic and Atmospheric Administration (NOAA) developed the Saffir-Simpson Hurricane Wind Scale (SSHWS) that classifies hurricanes into 5 levels based on hurricane's sustained wind speed [6]. A three-state weather model was presented in [7] to incorporate failures occurred under major adverse weather conditions, following an observation that reliability evaluation results obtained without considering weathers could be optimistic and misleading. Reference [8] presented a probabilistic hurricane simulation model established for assessing the Florida utility damage and risks under hurricanes. References [9] and [10] studied seasonal effects of wind and lighting on distribution system reliability, where time-varying failure rates based on partitioned weather severity levels were presented.

Actually, the effects of extreme weather on distribution systems are closely correlated to the region affected because of the specific elevation, terrain and vegetation in the particular region. The U.S. Northeast is a region with an appreciably high vegetation coverage rate. For instance, the forest cover rate of CT even reaches to 75% [11]. Thus power outages in the Northeast regional distribution systems are largely caused by blow-over or failures of trees and poles during wind storms. However, an appropriate model for this region that reveals the impacts of wind storms has not been established. Moreover, the wind speeds of storms impacting the Northeast area fall into particular ranges, for which existing wind storm classifications in the literatures may be unsuitable.

Main contributions of this paper include: 1) Probabilistic wind storm models including occurrence, intensity, and duration models are established by mining the HURDAT database from NOAA. These models capture the effects of wind storms on the Northeast region, and are used to generate accurate wind storm samples for system risk assessment. 2) Outage event records from Northeast Utilities are used to parameterize the weather-dependent component failure models. 3) An enhanced sequential Monte Carlo approach is developed to quantify system risks under six different categories based on a new storm classification criteria established for the Northeast

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TABLE I
DISTRIBUTION SYSTEM FAILURE STATISTICS

Cause	*The number of failures*	*Percentage*
Tree	3213	55.2%
Equipment	715	12.3%
Animal	500	8.6%
Unknown	576	9.9%
Others	817	14.0%
Total	5821	100%

region. The categorized risks in distribution systems provide more comprehensive characterization of wind storm hazards, which will facilitate utility companies and regulatory bodies to design response schemes against different categories of storms. CT is taken as a typical example for describing the process which is applicable for other regions in the Northeast. Responses of distribution systems to all six categories of wind storms are simulated using the Sequential Monte Carlo (SMC) method. Besides, the minimal path and zone partitioning approaches in [12] are adopted to accelerate the process of system state assessment.

The organization of this paper is as follows. Section II describes the wind storm modeling procedures for the Northeast regional systems. Section III discusses the parameterization of weather-dependent component models. Section IV is devoted to the reliability evaluation of distribution systems using an enhanced SMC method. Test cases and result analysis are summarized in Section V, followed by Section VI that concludes the paper.

II. WIND STORM MODELING FOR NORTHEAST REGIONAL SYSTEMS

The causes of distribution system failures based on Northeast Utilities' (NUs') outage records for eight selected towns during 2007–2011 [13] are shown in Table I.

From the table, it is clear that tree failures are responsible for the majority of system failures because trees are often in close proximity to overhead feeders, and the high wind during wind storms will result in widespread power outages in the Northeast region. It is therefore necessary to build accurate probabilistic models to quantify the effects of wind storms on system component failures. For any non-weather related damages (i.e., those due to aging or animals), their impacts have been statistically mapped into the component failure rates and repair times under normal weather conditions.

In this section, the HURDAT from NOAA will be used to establish the wind storm models suitable for the reliability evaluation of the U.S. Northeast distribution systems. The state of Connecticut is taken as an example to present the modeling procedures.

A. Data Source

HURDAT includes 1476 wind storms in the North Atlantic region during 1851–2011 with their detailed occurrence time, translational velocity (measurement of storm movement), Sustained Surface Wind Speed (SSWS, winds measured at a standard height of 10 m over a 1-min interval), central pressure, etc. First, two screening criteria are used for selecting the wind storms affecting CT.

1) Storms Passing Through Connecticut: The area of CT covers the range of its latitude ($40°58'$N–$42°03'$N) and longitude ($71°47'$W–$73°44'$W). By comparing the storm tracks with the area boundary, we can count the number of the storms passing through CT.

2) Storms Affecting Connecticut: Some storms did not pass through CT directly, while still impacting it. Utilities will typically record these storms; based on the records, the list of these storms can be obtained. Then, their detailed information such as wind speed is derived from HURDAT.

The two screening criteria will overlap with each other; after excluding the overlaps, all the storms used to build the wind storm model for CT are listed in Table X (see the Appendix). Wind storms are rare events; thus, each data point has its unique contribution to the statistical modeling. In order to increase the fitting accuracy, we choose to use all the data points and adopt the maximum likelihood method to ensure the accuracy of the models.

B. Wind Storm Occurrence Probability Model

Occurrence frequency model determines the number of wind storms and the intervals between successive wind storms during a specific period. Homogeneous Poisson (HP) is a commonly probabilistic function to model the wind storm occurrence [14]–[16], and the HP function can be described by

$$P\left[N(t)=k\right]=\frac{(\eta t)^k}{k!}e^{-\eta t},\quad k=0,1,2,\cdots. \tag{1}$$

In the period of $(0,t]$, $P[N(t)=k]$ is the probability that the number of wind storms is k, η refers to the average wind storm occurrence rate, and t is the time period considered.

Based on (1), the occurrence interval time T of wind storms is demonstrated to be exponentially distributed [16]:

$$f_T=\begin{cases}\eta e^{-\eta t}, & t>0\\ 0, & t\le 0.\end{cases} \tag{2}$$

Therefore, in Monte Carlo simulations, T can be simulated by the sequential sampling [17]:

$$T=-\frac{1}{\eta}\ln U \tag{3}$$

where U is a uniformly distributed random number between [0,1]. As shown in Table X, there are 32 storms that affected CT during 1851–2011 (161 years), thus $\eta=32/161=0.1987$ occurrence/year (occ./yr).

C. Wind Storm Intensity Model

The potential damage (quantified by weather-dependent component models introduced in Section III) of a wind storm is strongly related to the storm intensity, which is described by the SSWS of the storm. In this section, SSWS probability distribution is fitted using a maximum likelihood method based on the historical records shown in Table X [18], [19]. Fig. 1 illustrates the fitted curves based on Weibull, Normal and Lognormal distributions. The distribution fitting results indicate that Weibull distribution has a maximum likelihood (Weibull: 74.54%, Normal: 72.56%, Lognormal: 63.48%) and its distribution function is shown as follows:

$$f(x)=\frac{\beta}{\alpha^\beta}x^{\beta-1}e^{-\left(\frac{x}{\alpha}\right)^\beta}$$

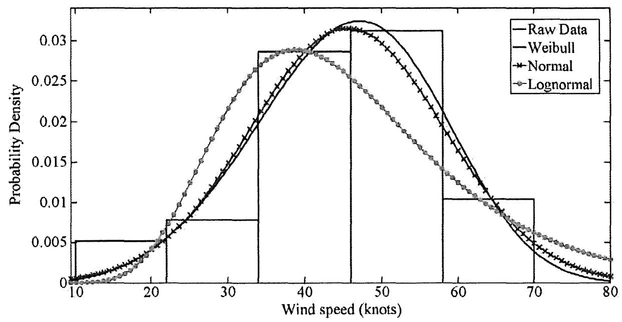

Fig. 1. Distribution fitting of the SSWS for wind storms.

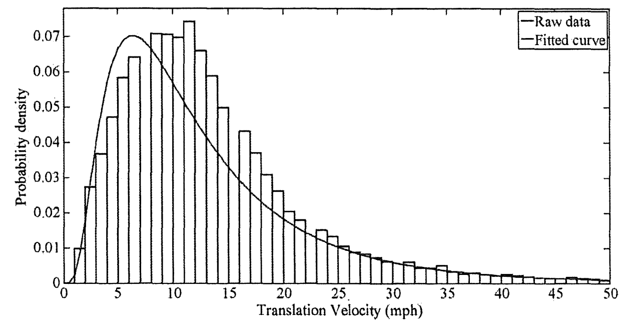

Fig. 2. Distribution fitting of the translation velocity for wind storms.

TABLE II
PROBABILITY DISTRIBUTION PARAMETERS OF THE SSWS

Parameter	*Estimate*	*Std. Err.*
α	50.12	2.16
β	4.29	0.61

TABLE III
WIND STORM CLASSIFICATION CRITERIA

Wind storm category	*Sustained surface wind speed(knots)*
Normal	<40
Major Storm	40-57
Tropical Storm	57-65
Cat.1 Hurricane	65-83
Cat.2 Hurricane	83-96
Cat.3 Hurricane	>96

where $\beta > 0$ is the shape parameter and $\alpha > 0$ is the scale parameter. Distribution fitting results of β and α are listed in Table II.

Then, the SSWS of wind storms can be sampled using the following formula [17]:

$$X = \alpha(-\ln U)^{\frac{1}{\beta}} \tag{4}$$

where U is a uniformly distributed random number between [0,1].

The category (cat.) of a wind storm is a significant factor considered by utility in the preparation for and response to the storm. As can be seen in Fig. 1, the wind speeds of wind storms in the Northeast region range from 10 knots to 80 knots. It has been predicted that the chance of having hurricanes with wind speeds higher than 80 knots is increasing in the Northeast U.S. in this century [22]. Therefore, wind storms are classified into six levels based on NOAA's SSHWS and the weather categories of IEEE Standard 346. The criteria for the classification are shown in Table III.

D. Wind Storm Duration Model

Storm duration model gives the duration of a wind storm for a specific region, and can be used to distinguish wind-storm related failures and non-weather related ones. However, the challenge is that, for a specific region such as CT or a town of CT, the storm information in the HURDAT is recorded every six hours, which is close to the wind storm durations. The coarse data resolution makes it challenging to estimate the storm duration. To resolve this challenge, a widely used engineering approach is adopted. Area affected by a storm is assumed to be a circle, and its radius can be calculated using an empirical model [21]. Base on the model, the size of hurricane for CT is about 76 miles (circle diameter), which means a wind storm can affect the whole state in a short period once it makes landfall on CT. Therefore, area affected by storms is omitted in duration calculation, and it is reasonable to assume that within the region, the translation velocity of wind storms is constant, and their translation direction is a straight line. These assumptions help obtain reasonably accurate estimations of storm durations based on limited data.

TABLE IV
PROBABILITY DISTRIBUTION PARAMETERS OF THE TRANSLATION VELOCITY

Parameter	*Estimate*	*Std. Err.*
m	2.34	0.0035
σ	0.70	0.0025

1) Translation Velocity Probability Model: Probability model of translation velocity is established by distribution fitting and the lognormal distribution is chosen to model the translation velocity [18], [19]. The function of the lognormal distribution is described by

$$f(c) = \frac{1}{c\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{\ln c - m}{\sigma}\right)^2}. \tag{5}$$

The maximum likelihood method is then used to determine the parameters σ and m by probability distribution fitting based on HURDAT. The fitted curve is illustrated in Fig. 2 and the resulting σ and m are presented in Table IV.

Based on the fitted probability distribution, translation velocities of wind storms can be calculated by [17]

$$c = e^{(m+\sigma Z)} \tag{6}$$

where Z is a random number following the standard normal distribution.

2) Wind Storm Duration Calculation: The shape of CT is an approximate rectangle and its width and length are 70 miles and 110 miles, respectively. If c is the translation velocity of a wind storm sampled by (6), then the shortest duration of the storm within CT will be $D_{min} = 70/c$ hours, and the longest duration will be $D_{\max} = \sqrt{70^2 + 110^2}/c$ hours. It is assumed that the duration is uniformly distributed between the shortest duration and the longest duration. Therefore, in the SMC process, the duration D can be generated by sampling a uniformly distributed number between $[D_{min}, D_{max}]$.

III. Parameterization of Weather-Dependent Component Models

Accurate weather-dependent component models are indispensable to quantify the reliability performance of distribution systems in the Northeast U.S. under various wind storms. In this section, weather-dependent failure rate model is described; failure proportions and annual expected durations of different weather conditions are determined to parameterize the model. Weather-dependent repair time model is also introduced. Its parameters are determined by the average restoration time statistics of customers in NU's actual distribution systems.

1) Component Failure Rate Model: In the Northeast U.S., failures are largely due to trees and poles falling down (see Table I) and their toppling are caused by the pressure of high wind. It is generally accepted that the pressure exerted on trees and poles is proportional to the square of wind speed [10], [25]–[27], which is the SSWS for wind storm. For instance, simultaneous measurements of wind speed and turning moment of a group of trees were used in [27] for analyzing the wind and tree interaction. A quadratic model was found to be the best fit to the data of turning moment and wind speed near the canopy top. Therefore, failure rates of components during wind storms are formulated to be proportional to the square of the wind speed:

$$\lambda_{wind}\left[\omega(t)\right] = \left[1 + \alpha\left(\frac{\omega^2(t)}{\omega_{crit}^2} - 1\right)\right]\lambda_{norm} \tag{7}$$

where $\omega(t)$ is the wind speed at time t; ω_{crit} is the critical wind speed that is determined based on Table III (the procedures can be found in the Appendix); λ_{norm} is the failure rate under normal weather conditions and it can be obtained from NUs' historical records statistics. Parameter α is the scaling factor to be determined; its derivation is based on [10] and is also summarized in the Appendix for easy reading. To parameterize α, failure proportion of each type of weather conditions, annual expected durations of wind storms and normal weather must be known and the determination processes are introduced as follows.

a) Failure proportion of wind storms and normal weather conditions: First, the failures are classified into two categories: occurring under normal weather and wind storms based on the Weather Type recorded in NU's data. Then, failure statistics are conducted by taking one of the feeders as an example. The statistics results are listed in Table V.

As can be seen in Table V, the proportion of failures that occurred under normal weather can be calculated by $F_n = 82/131.8 = 0.622$; Thus, the proportion of failures that occurred under wind storms is $F_{ws} = 1 - F_n = 0.378$.

b) Annual expected durations of wind storms and normal weather conditions: Based on the probability distribution fitting results shown in Table IV, the expected translation velocity of wind storms is $E(v) = 13.26$ mph. The expected duration of a single wind storm in CT is $E(D_{ws}) = 7.56$ hours, which is obtained using the approach introduced in Section II. The annual expected duration of wind storms can then be calculated by $D_{ws} = \eta E(D_{ws}) = 1.5$ hours, where η is the occurrence probability of wind storms in (3). Thus, the expected duration of normal weather conditions is $T_n = 8760 - D_{ws} = 8758.5$ hours. Failure proportion (F_{ws} and F_n) and annual expected durations (D_{ws} and T_n) of wind storms and normal weather conditions can then be used to determine the parameter α for the example feeder (see the Appendix).

TABLE V
Failure Statistics Results of the Example Feeder

Weather Conditions \ Years	*2007*	*2008*	*2009*	*2010*	*2011*	*Average*
Normal	80	84	69	112	65	82
Wind storm	24	56	24	37	108	49.8
Total	104	140	93	149	173	131.8

TABLE VI
Restoration Time Statistics of the Example Feeder

		2007	*2008*	*2009*	*2010*	*2011*	*Average*
OMC(hr)	Normal	15719	13703	7980	14849	8368	12124
	Major Storm	4818	40501	3594	17060	22592	17713
	Irene	-	-	-	-	352324	352324
NCA	Normal	7775	7793	4558	6030	3587	5949
	Major Storm	496	5917	610	2569	1045	2127
	Irene	-	-	-	-	3053	3053
RES(hr)	Normal	2	2	2	2	2	2
	Major Storm	10	7	6	7	22	10
	Irene	-	-	-	-	115	115

2) Component Repair Time Model: Component repair time varies directly with weather categories, locations and types of faulty feeders and can be expressed as follows:

$$r(cat., location, type).$$

It is challenging to find an analytic form of $r(\bullet)$. Therefore, an engineering approach is adopted. In order to determine component repair times, the average restoration time of customers for a specific failure is defined by

$$RES = \frac{OMC}{NCA} \tag{8}$$

where OMC is the outage minutes of customers, and NCA is the number of customers affected.

As shown in Table VI, OMC, NCA and RES of the example feeder under each type of weather conditions are obtained based on NU's records. Based on Table VI, the RES of 2007–2011 under normal weather, major storm, and tropical storm Irene are 2, 10, and 115 hours, respectively. For the backbone feeder, it is reasonable to assume that individual component repairs are conducted in a fairly close time. Thus the mean repair time r of the backbone feeder will be close to the RES (with modification based on engineer's judgment). Further, repair times r under Category 1–Category 3 hurricanes are estimated based on NUs' response times under these weather conditions. The

TABLE VII
MEAN REPAIR TIMES UNDER DIFFERENT CATEGORY OF WEATHER CONDITIONS

Wind storm category	*Repair time(hours)*	
	Backbone	Lateral
Normal	2	3
Major storm	6	12
Tropical storm	120	336
Cat. 1 Hurricane	144	403
Cat. 2 Hurricane	173	484
Cat. 3 Hurricane	207	581

repair time ratios between backbone and lateral feeders are estimated from NU's statistics. Therefore, the values of r under all six categories of weather conditions are obtained as shown in Table VII.

When the weather-dependent failure rate and repair time models are determined, component failure rates and repair times are assumed to be exponentially distributed [20] and the time to failure (TTF) and time to repair (TTR) of components can be simulated using the Inverse Transform Method [17]. The TTF and TTR then will be used in reliability evaluation to reflect the impacts of wind storms.

It should be noted that, for a region outside of the Northeast, the risk assessment method in this paper is still applicable for evaluating hazards caused by wind storms. In this case, however, wind storm may no longer be the major contributing factor for system risks in such a region, and it is out of the study scope of this paper. In this paper, we take the State of Connecticut as a typical example to facilitate the discussion of the proposed risk assessment procedures, which are equally applicable for other regions in the Northeast. First, wind storm datasets for any region of interest are selected from NOAA databases by using the screening criteria presented in Section II-A. Then, wind storm models can be established using the method introduced in Sections II-B, C, and D. Further, weather-dependent models of system components for the specific region can be established based on the corresponding outage event records as described in this section. Therefore, following the procedures presented in this paper, one can perform a risk assessment for any feeder in any region vulnerable to wind storms.

IV. SEQUENTIAL MONTE CARLO SIMULATION

Due to its scalability, flexibility and accuracy, an enhanced Sequential Monte Carlo simulation method is adopted for assessment the reliability of the U.S. Northeast distribution systems under wind storms. The models of large real distribution systems including embedded generation and microgrid [12] and the impact assessments for multiple categories of wind storms are integrated into the SMC simulation method to facilitate the reliability evaluation considering various weather conditions.

A. Practical Aspects in Modeling Real-Life Distribution System

As seen in Fig. 3, the topology of an actual distribution system is complex and has numerous load points. The distribution system provides electricity for a CT town and contains more than 2000 devices including backbone lines (19 mi.), lateral lines (65 mi.), transformers (1306), and switchgears (390). For most real-life distribution system, the number of devices is huge, and therefore reasonable system scale reduction can help realize and accelerate the reliability evaluation.

Quite often, scale reduction is necessary for real-life projects because of input data limitation. Therefore, some assumptions may be required to conduct system simplification. For example, load points in the same backbone segment are assumed to have similar reliability performance if they are connected to the backbone directly, which means that they can be considered as one load in the reliability evaluation. Similarly, load points in the same lateral segment can also be considered as one load. After the simplifications, feeder segments are divided by switchgears; a single segment only contains one load point and its sub-segments. Therefore, the number of loads or equivalent load points decreases significantly.

B. Evaluating Reliability for Various Weather Conditions

In this paper, temporally varying wind storms are simulated using the SMC method. During the simulation, the wind storms are classified into six categories according to their SSWS. For each failure, the corresponding storm classification is recorded. Therefore, after the simulation, the effects of each category of wind storms can be obtained. The simulation framework is shown in Fig. 4 and the procedures are described as follows.

a) Generate an artificial wind storm through sequential sampling based on the occurrence probability model;
b) Obtain the duration of the wind storm based on the duration model;
c) Generate SSWS for the wind storm and classify it into a proper category based on Table III;
d) Generate TTF and TTR for components based on the weather-dependent component models;
e) For each component, determine whether its down-state period is during the wind storm; if yes, go to step f); if no, go to h);
f) Perform a state assessment process to determine the impacts of the wind storm based on the Minimal Path and Zone Partitioning Approach (MPZPA) [12].
g) According to the classification of the wind storm, update the reliability indices for this category of storms;
h) Go to step e) until all the components have been determined;
i) Go to step a) until the simulation time reaches a given maximum simulation time;
j) Calculate expected reliability indices and index probability distributions for each category of wind storms.

In particular, the MPZPA in step f) is a technique to accelerate state assessment in reliability evaluation of the distribution system. In this technique, the concept of "minimal path" in graph theory is introduced to indicate the connectivity between a source and a load. If any component in the minimal path is taken away, the connectivity is lost. Thus by means of the minimal path, the connectivity between sources and loads can be determined efficiently. Furthermore, in most instances, a fault will exert the same influence on the load points between the same two switches

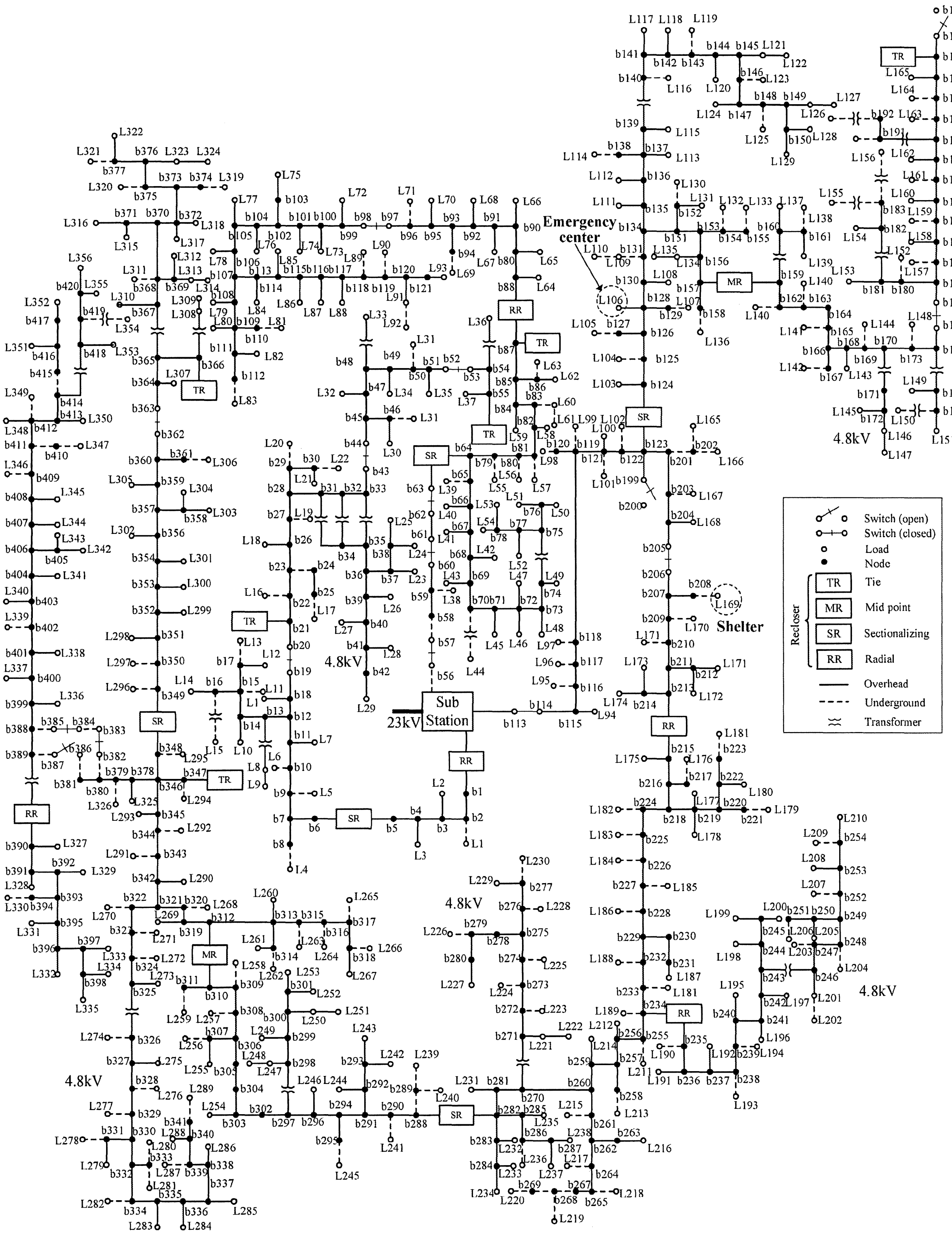

Fig. 3. One-line diagram of the test feeder.

or in the same sub-feeder. Therefore, these load points and the corresponding components can be partitioned into a zone to simplify the minimal path and accelerate simulation efficiency. The technical details of MPZPA can be found in [12].

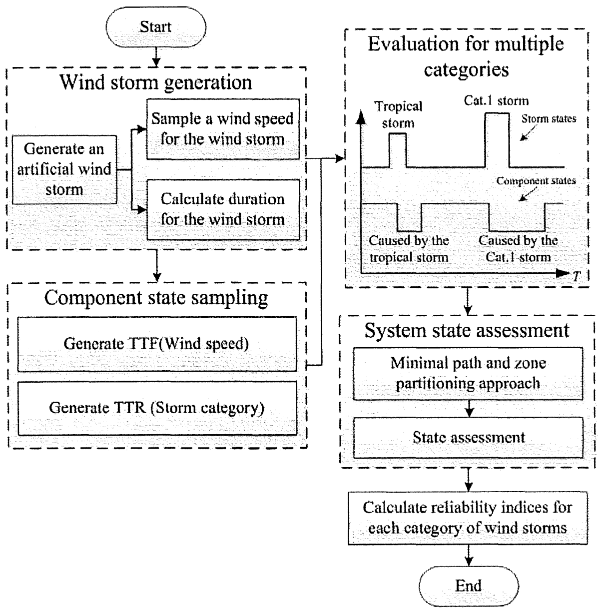

Fig. 4. Framework of the reliability evaluation.

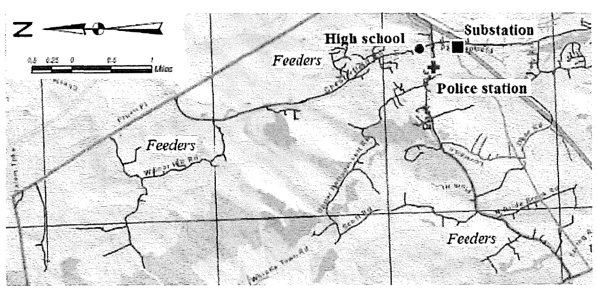

Fig. 5. Geographic diagram of the test system.

V. Case Studies

In this section, models and methods are established based on an actual distribution system in the Northeast U.S. The input data are briefly introduced, and reliability evaluation results are then presented and discussed.

A. Data Preparation

The distribution system consists of two feeders, as illustrated in Fig. 5. Its one-line diagram is shown in Fig. 3. The system supplies 356 load points and 3804 customers. The total load is 14.35 MW. The reliability parameters are listed in Table VII in Section III and Table XI in Appendix C. The parameter α of the weather-dependent failure rate model is estimated to be 4175.6. The repair times under different weather conditions are shown in Table VII. The Monte Carlo run will repeat until the coefficient of variation of expected energy not supplied (EENS) [17] reaches below 0.003. The simulation was conducted on a PC with i7-2600 processor, and the CPU time is 5 min.

There are two critical facilities in the test system (see Fig. 5), one is the high school and another is the police station. Under extreme weather conditions, they are used as a Shelter and an Emergency Center, respectively. Analyses and discusses are focused on the results of these critical facilities and the system.

TABLE VIII
EXPECTED RELIABILITY INDICES AT THE CRITICAL LOAD POINTS

Weather conditions \ Reliability Indices	*Shelter*			*Emergency Center*		
	λ(occ./yr)	r(hr/failure)	U(hr/yr)	λ(occ./yr)	r(hr/failure)	U(hr/yr)
Normal	2.7224	2.16	5.89	3.2299	1.83	5.9
Major storm	0.0793	9.03	0.72	0.0924	7.76	0.72
Tropical storm	0.0265	369.74	9.81	0.0308	318.74	9.81
Cat.1 Hurricane	0.0743	458.65	34.09	0.0862	393.47	33.92
Cat. 2 Hurricane	0.043	554.27	23.81	0.0498	477.04	23.75
Cat.3 Hurricane	0.0265	663.77	17.58	0.0306	574.86	17.6

TABLE IX
EXPECTED SYSTEM RELIABILITY INDICES

Weather conditions \ Reliability indices	*SAIFI (int./syst. cust./yr)*	*SAIDI (hr/syst. cust./yr)*	*CAIDI (hr/affected cust./yr)*	*ASAI*	*EENS (MWh)*
Normal	3.3525	6.63	1.98	0.999243	94.94
Major storm	0.0869	0.75	8.58	0.999915	10.67
Tropical storm	0.0285	10.03	352.31	0.998855	143.55
Cat.1 Hurricane	0.0798	34.73	435.16	0.996036	496.99
Cat.2 Hurricane	0.0461	24.39	528.54	0.997216	348.76
Cat.3 Hurricane	0.0282	17.89	634.20	0.997958	256.02

B. Expected Reliability Indices

After the reliability evaluation, we calculate the outage rate (λ), outage duration (r) and annual outage time (U) for the load points; system reliability indices SAIFI, SAIDI, CAIDI, ASAI, and EENS are also derived [17]. Both expected values and probability distributions of these indices can be obtained by the SMC simulation and the expected values are listed in Tables VIII, IX. Results in the both tables are classified under different categories of wind storms.

As shown in Tables VIII and IX, λ and SAIFI under abnormal weather are much smaller than that under normal weather, because these two frequency-related indices reflect the occurrence frequency of wind storms as well as the outage frequency.

According to Table VIII, the outage rate and duration of the Shelter under major storm are 0.0793 occ./yr and 9.03 hr/failure, respectively, whereas those are 2.7224 occ./yr and 2.16 hr/failure under normal weather. In other words, the outage frequency under major storm is less than 3% of that under normal weather, but the outage duration under major storm is only about 4.5 times of that under normal weather. This is why the indices U, SAIDI, ASAI, and EENS (Reflect both the frequency and the duration of outages) under major storms are even smaller than those under normal weather.

As listed in Tables VIII and IX, λ and SAIFI under tropical storms are smaller than those under major storms and Cat. 1–2 hurricanes, because the damage of tropical storms is not as significant as Cat. 1–2 hurricanes and their occurrence frequency is less than that of major storms. For Cat. 3 hurricanes, though they have severe damage on power system, their occurrence frequency is very low. Therefore, λ and SAIFI under Cat. 3 hurricanes are less than those of Cat. 1–2 hurricanes. Similarly, U, SAIDI, EENS, and ASAI have the worst performance under Cat. 1 hurricanes, because Cat. 1 hurricanes have significant hazards as well as high frequency.

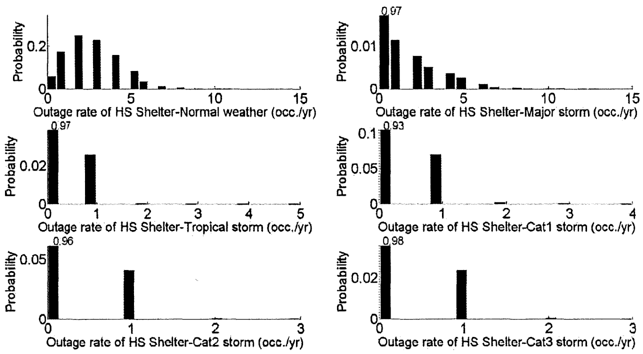

Fig. 6. Outage rate distributions of the shelter.

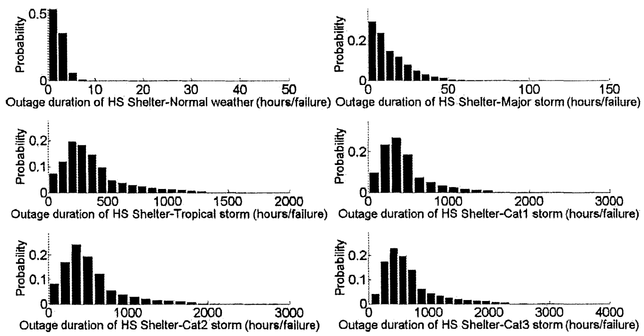

Fig. 7. Outage duration distributions of the shelter.

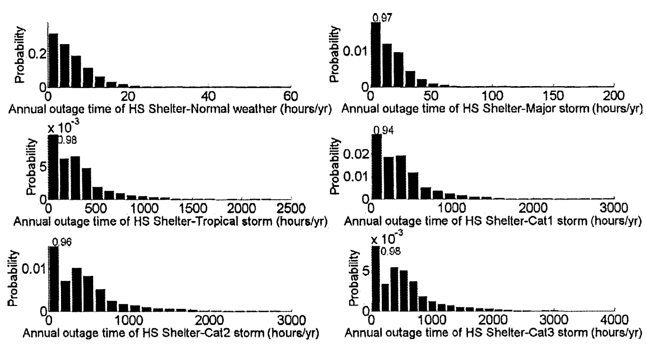

Fig. 8. Annual outage time distributions of the shelter.

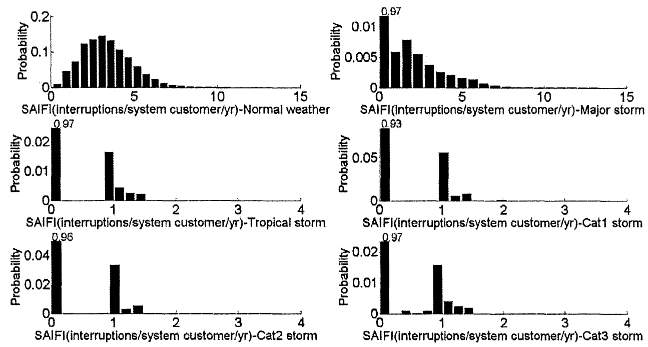

Fig. 9. SAIFI distributions.

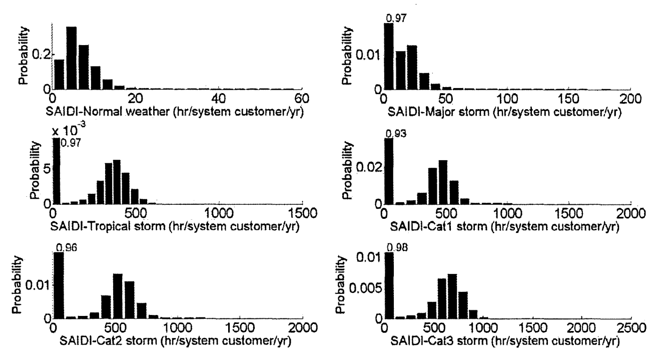

Fig. 10. SAIDI distributions.

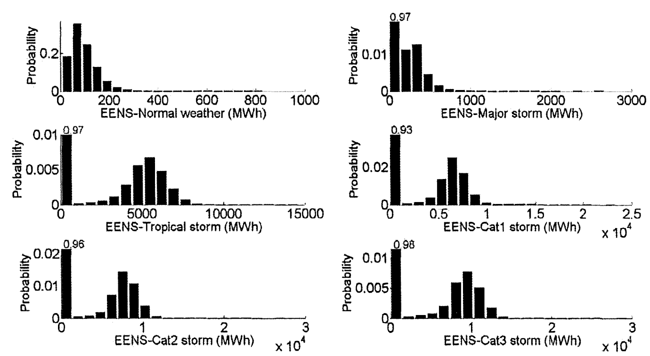

Fig. 11. EENS distributions.

It can also be seen from Tables VIII and IX that the indices r and CAIDI increase obviously with the increase of the wind storm intensity. For instance, r under Cat. 3 hurricanes is almost 300 times of that under normal weather.

As discussed above, it is clear that wind storms (except for major storms) have significant impacts on the load point and system reliability performances. The expected reliability indices vary under different weather conditions and, thus, wind storm classification and reliability evaluation for each category of storms can describe the impacts more comprehensively.

C. Probability Distributions of Reliability Indices

As shown in Figs. 6–11, index distributions of the critical facilities and the system are also provided for further analyses and discussions.

1) Critical Facility Index Distributions: As illustrated by Figs. 6–8, the effects of wind storms increase with their intensity increasing, though their frequencies become low. For instance, the distribution extreme value of index λ under normal weather is 15 occ./yr, and that under Cat. 3 hurricanes is 3 occ./yr, whereas the distribution extreme values of indices r and U increase significantly with the storm severity increasing.

As can be seen in Fig. 8, index distributions can reveal rare events that have significant impacts on reliability. For instance, extreme value of index U under Cat. 3 hurricanes is close to 4000 hr/yr, but its probability is just millionth.

2) System Index Distributions: Figs. 9, 10 shows that under severe storms, the outages may only happen once but last for a long time. For instance, SAIFI under tropical storms and Cat. 1–3 hurricanes are more likely to be 1 interruptions/system customer/yr, while the index SAIDI under these storms are likely to be more than 400 hr/system customer/yr. Here the outage frequencies under severe storms are found to be quite close (Cat. 1: 0.0798 occ./yr; Cat. 2: 0.0461 occ./yr; Cat. 3: 0.0282 occ./yr). These results are consistent with the field reliability statistics by NU (Cat. 1: 0.05–0.1 occ./yr; Cat. 2: 0.025–0.05 occ./yr; Cat. 3: 0.014–0.025 occ./yr), which validates the correctness of our simulation algorithm.

Due to the specific damage degrees and the specific response strategies of the utility, for each category of storms, distribution systems usually have a particular restoration time and the restoration time under severer weather conditions last longer. As can be seen in Fig. 10, SAIDI aggregates around 400 under tropical storms, about 500 under Cat. 1–2 hurricanes, and the value becomes about 650 under Cat. 3 hurricanes. Similar to SAIDI, indices EENS also aggregate around specific values and the values increase with the storm intensity increasing (see Fig. 11). These results indicate that our method can accurately capture the failure bunching effect during disastrous situations. By SMC simulation considering wind storm classifications, the phenomena above can be revealed and quantified accurately.

As shown in Fig. 11, EENS of the system under Cat. 1–2 hurricanes could be more than 5000 MWh and even reach 10 000 MWh under Cat. 3, though the probabilities are very low (e.g. the probability of reaching 10 000 MWh EENS is 0.0075 under Cat. 3). Therefore, system hardening schemes, such as tree-trimming schedules, microgrids, undergrounding cables, and distributed generators should be designed to improve the system reliability performance under extreme weather conditions [23], [24]. The quantitative reliability results can be used to evaluate benefits and costs under different categories of wind storms for existing distribution systems and system hardening options such as undergrounding cables, microgrids, and emergency generators. Moreover, indirect costs due to weather disasters such as reputational and regulatory costs could be significant and should be quantified along with other unreliability costs.

VI. Conclusion

In this paper, wind storm probability models have been built based on historical data selected from HURDAT. Then, NUs' real-life system outage records have been explored to parameterize the weather-dependent component models. Further, this paper has introduced a distribution evaluation method by combining Sequential Monte Carlo simulation with the wind storm classification. Finally, the reliability evaluation considering wind storms under different levels has been conducted on an actual distribution system in the Northeast U.S.

Below are the main conclusions drawn from the results: 1) wind storms have significant effects on distribution system reliability and it is indispensable to involve extreme weather in the reliability evaluation; 2) reliability evaluation considering wind storm classifications provides the change trend of the reliability indices and reveals some severe but rare events; 3) the reliability evaluation is conducted on a real-life system and it focuses on the critical load points. Our risk assessment approach can be applied to the development of optimized system hardening or reinforcement strategies against extreme weathers. Recently, our approach has been adopted by Northeast Utilities in evaluating various system hardening options for selective CT towns under different weather conditions. Hardening schemes such as different types of microgrids, undergrounding cable system and emergency generators were evaluated and ranked. The final results have been summarized into a technical report providing extensive risk analysis results and suggestions on hardening scheme optimization for eight selected towns in CT.

TABLE X
WIND STORMS IMPACTED CONNECTICUT DURING 1851–2011

Storm id	Sustained surface wind speed(knots)	Date	Storm id	Sustained surface wind speed(knots)	Date
42	49	9/14/1858	738	67.8	9/9/1944
65	50	9/27/1861	837	57	8/25/1954
80	40	9/16/1863	848	35	8/7/1955
121	49	9/7/1869	897	45	7/28/1960
149	40	10/22/1872	899	57	8/29/1960
222	40	9/21/1882	1004	45	8/20/1971
274	40	8/14/1888	1014	49.2	6/14/1972
316	49	8/15/1893	1050	60	8/6/1976
318	55	8/15/1893	1137	57	9/16/1985
329	49	10/1/1894	1138	30	9/21/1985
347	45	9/20/1897	1157	20	8/21/1988
377	30	10/10/1900	1193	57	8/16/1991
481	35	7/31/1915	1216	15	8/14/1994
487	50	5/13/1916	1294	25	9/14/2000
645	45	9/5/1934	1421	45	8/28/2008
688	67.8	9/10/1938	1466	60	8/21/2011

Appendix

A. Wind Storms Impact Connecticut During 1851–2011

Based on the criteria presented in Section II, the wind storms that affected CT during 1851–2011 are selected from HURDAT and listed in Table X.

B. Parameterization Procedures of the Component Failure Rate Model

In this paper, parameterization procedures as follows are conducted on NU's real-life distribution system [10].

Component weather-dependent failure rate is assumed as

$$\lambda\left[\omega(t)\right] = \lambda_{ws}\left[\omega(t)\right] + \lambda_{n}\left[\omega(t)\right] \tag{9}$$

where $\lambda_{ws}[\omega(t)]$ is the failure rate during the wind storms, $\lambda_n[\omega(t)]$ is the failure rate under normal weather conditions. The two different failure rates are defined as

$$\lambda_{ws}\left[\omega(t)\right] = \begin{cases} \lambda_{wind}\left[\omega(t)\right], & if\ \omega(t) > \omega_{crit} \\ 0, & otherwise \end{cases} \tag{10}$$

$$\lambda_{n}\left[\omega(t)\right] = \begin{cases} \lambda_{normal}, & if\ \omega(t) \leq \omega_{crit} \\ 0, & otherwise. \end{cases} \tag{11}$$

Then, the expected value of failure rate can be described as

$$E\left\{\lambda\left[\omega(t)\right]\right\} = \frac{D_{ws}}{T_{tot}} E\left\{\lambda_{wind}\left[\omega(t)\right]\right\} + \frac{T_n}{T_{tot}} \lambda_{norm} \tag{12}$$

where D_{ws} and T_n denote the annual expected durations of the wind storms and normal weather conditions, respectively. The duration of one year is denoted as T_{tot}, which is 8760 hours.

To derive the expected failure rate in (7) the proportion of failures occurring during each type of weather condition F_{ws} and F_n must be known

$$\frac{D_{ws}}{T_{tot}} E\left\{\lambda_{wind}\left[\omega(t)\right]\right\} = F_{ws} E\left\{\lambda\left[\omega(t)\right]\right\} \tag{13}$$

$$\frac{T_n}{T_{tot}} \lambda_{norm} = F_n E\left\{\lambda\left[\omega(t)\right]\right\} \tag{14}$$

where λ_{norm}, F_{ws} and F_n are determined based on NU's historical statistics. Thus, the value of $E\{\lambda_{wind}[\omega(t)]\}$ can be calculated using (13) and (14).

Based on (7) and (12) the average value of the failure rate during the wind storms is shown as follows:

$$E\{\lambda_{wind}\left[\omega(t)\right]\}=\left[1+\alpha\left(\frac{E\left[\omega^2(t)|\omega\geq\omega_{crit}\right]}{\omega_{crit}^2}-1\right)\right]\lambda_{norm} \tag{15}$$

where $E[\omega^2(t)|\omega \geq \omega_{crit}]$ can be calculated based on Table X by defining $\omega_{crit} = 40$ knots. Therefore, the parameter α is obtained, and component weather-dependent failure rate model is determined.

C. Line Parameters of the Test System

TABLE XI
LINE PARAMETERS OF THE TEST SYSTEM

Equipment	Failure rate(occ./yr/mile)		Length(miles)
	Under normal weather	Under wind storms	
Backbone	0.23	Depend on equation (8)	18.88
Lateral	0.49		64.82

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