Resilience of Power Systems to Ice Storms: Analysis and Quantification

Michael Abdelmalak, Jitendra Thapa, and Mohammed Benidris,
Department of Electrical and Biomedical Engineering, University of Nevada-Reno, Reno, NV 89557, USA
Emails: {mabdelmalak, jitendrathapa}@nevada.unr.edu and mbenidris@unr.edu

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***Abstract*—Major damage to power system components and prolonged power outages caused by severe ice storms call for developing approaches that assess the resilience of power systems against these storms. However, the diverse spatiotemporal characteristics of ice storms introduce high uncertainties related to system component failures, performance, and resilience level. This paper proposes a resilience assessment approach to evaluate the resilience of power systems under diverse ice storm characteristics. Spatiotemporal models are used in this paper to emulate the behavior of ice storms as they move across the system. Extensive statistical analyses are carried out to derive probability distribution functions for the parameters governing the behavior of ice storms in a given geographical region. A fragility model is used to determine the likelihood of a system component to fail as an ice storm moves across the system. Finally, a combinatorial enumeration-based approach is applied to quantify the resilience of power systems against ice storms. The proposed approach is tested by simulating ice storms in the 25000-bus synthetic power grid representing the Northeastern and Mideast regions of the United States. The results show that the proposed method is effective in assessing the resilience of power grids under diverse ice storm characteristics.**

***Index Terms*—Extreme weather events, ice storms, resilience evaluation, spatiotemporal characteristics.**

I. Introduction

The frequency, intensity, and duration of severe ice storms have increased dramatically in recent years. They have resulted in damages to major power system equipment, large blackouts, and loss of public trust in the electric power supply. For example, an extreme winter storm caused power outages to more than 400,000 customers for a few days in the Northeastern region of the United States in 2022 [1]. The severe impacts of ice storms have been exacerbated by the unpreparedness of power grids to resiliently respond to such events [2]. Therefore, developing resilience evaluation methods for power systems under diverse characteristics of ice storms is a necessary step toward enhancing grid resilience.

The impact of freezing ice storms on operational performance of power grids has gained significant interest in the last decade. In [3], a model based on geographically moving winds and freezing precipitation has been developed to assess the reliability of transmission networks during ice storms. In [4], a radial ice thickness model has been used to estimate the ice thickness using a modified Ramer precipitation-type algorithm and weather research and forecasting model. A probabilistic assessment model for weather induced loads on overhead transmission lines has been developed in [5]. In [6], a socioeconomic and ecological impact assessment approach has been conducted for the great Chinese 2008 ice storm. The study has provided a contingency plan based on utilization of interrelated advanced energy technologies. In [7], a reliability evaluation method to study the communication network of power systems during ice storms has been formulated. Although these methods highlight the importance of the impacts of ice storms on system operation, quantifying uncertainties of ice storms is a vital factor for long-term planning purposes.

Several studies have been conducted to address the impact of ice storms on power systems. In [8], a number of indices have been proposed to quantify the resilience at the system and component level during an ice storm. In [9], a cell partitioning algorithm has been used to determine transmission lines impacted by simulated ice storms based on predefined weather-related parameters. The amount of load curtailment and energy not served have been used to quantify impacts of ice storms on a resilience enhancement strategy adopting de-icing devices [10]. Although the aforementioned methods evaluated the impact of ice storms on the resilience operation of power systems, they have either used a specific actual event or a forecasted failure event. The role of geographically related spatiotemporal characteristics of ice storms is still underdeveloped. Also, most of these studies have been validated on relatively small-scale test systems. Therefore, an uncertainty quantification framework is required to assess the impact of different ice storms on large-scale power system resilience considering weather– and geographical–related parameters.

This paper proposes an impact assessment framework of spatiotemporal uncertainties of ice storms on the resilience of transmission grids. It extends our work developed in [11] to validate the scalability of the proposed method on a realistic large-scale transmission system and to include comprehensive impact assessment from spatial and temporal perspectives. First, the propagation path of an ice storm is simulated using a geographical-based freezing ice storm model considering the variations of weather and geographical parameters governing its propagation. A fragility model is used to calculate the probability of failure of system components based on the level of ice thickness. The PDFs of the translational speed, central pressure difference, wind speed and direction, and ice accumulation rate determined through statistical analysis are integrated into a combinatorial enumeration approach to simulate ice storms with diverse spatiotemporal propagation behavior. For each simulated ice storm, the minimal amount of load curtailment and total energy not served considering generation and transmission operational constraints are calculated. The overall resilience level is computed using the occurrence probability of each generated ice storm and the corresponding total load curtailments. The proposed method is validated and its scalability is tested on the 25000-bus synthetic power grid of the Northeastern and Mideast region of the United States. The main contribution of this paper is to quantify resilience of large-scale power systems considering the stochastic spatiotemporal characteristics of ice storms.

The rest of the paper is laid out as follows. Section II provides a comprehensive description of the ice storm spatiotemporal model. Section III explains the resilience index quantification methodology. Section IV shows various test cases on the 25000-bus system. Section V summarizes the paper and provides concluding remarks.

II. Ice Storm Modeling

A. Spatiotemporal Model of an Ice Storm

The spatiotemporal characteristics of ice storms are governed by weather-related parameters and geographical-related parameters [11]. Weather-related parameters include, but are not limited to, wind speed, translational speed, and ice precipitation rate, whereas geographical-related parameters can be coordinates of the ice storm landing site. System components may fail as a result of increased ice accumulation and extended freezing temperature during an ice storm. To calculate the thickness of the ice on transmission lines, a freezing rain ice model in [12] is adopted, which can be expressed as follows,

$$\Delta H(t) = \Delta H_0 - 0.02\ [1+\sin(\phi-\delta)]t, \tag{1}$$

where $(H,\ H_o)$ are the central and original central pressure, δ is the angle between the translational direction of an ice storm and the due north (the anti-clockwise is negative), and ϕ is the angle between the due north and the coastline.

The maximum radius of an ice storm is calculated using the central pressure difference and the landing-site coordinates [13] as follows,

$$r_{max}(t) = e^{(2.63-5.086\times10^{-5}(\Delta H(t))^2} + 0.0395 y_c(t), \tag{2}$$

where r_{max} is the maximum radius of the ice storm.

The level of ice thickness will differ based on the relative position between the center of the ice storm and the component under study, which is calculated using (3).

$$R_{ice}(t) = (N_h/\rho_i\pi)\sqrt{(P_{ice}\rho_w)^2 + (3.6V_w(t)W)^2}, \tag{3}$$

$$W = 0.067P_{ice}^{0.846}, \tag{4}$$

where $R_{ice}(t)$ is the ice thickness at time t, N_h is the number of hours of freezing rain, $(\rho_i,\ \rho_w)$ are the density of ice and water, P_{ice} is the ice precipitation rate, $V_w(t)$ is the wind speed at time t, and W is the liquid water content of rain-filled air. Both P_{ice} and $V_w(t)$ vary based on the euclidean distance between the component under study and the ice storm center.

The coordinates (latitude and longitude) of ice storm center at time instant t can be calculated as follows,

$$x_c(t) = x_l + V_T\ t\ \sin(\delta), \tag{5}$$

$$y_c(t) = y_l + V_T\ t\ \cos(\delta). \tag{6}$$

where $(x_l,\ y_l)$ are the ice storm landing coordinates, V_T is the translational speed of an ice storm in m/sec.

Fig. 1 visualizes the movement of an ice storm crossing transmission lines and towers. System components that are near or at the center of the ice storm will get high levels of ice accumulations whereas ice accumulations on components lying outside the maximum impact radius will be very small and can be neglected.

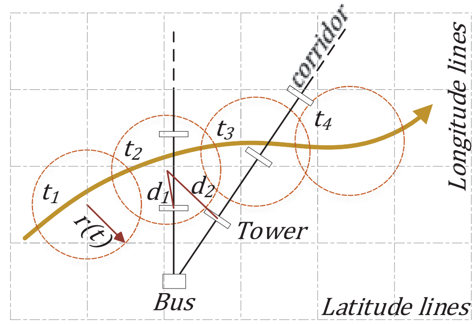

Fig. 1. The path of an ice storm across a few transmission lines

B. Ice Storm Fragility Model

The fragility model aims to map the impact of weather parameters into a probability of failure of each component through spatiotemporal analysis. In this work, an ice storm fragility model from [12] is integrated with the ice storm propagation model adopted from [14] to compute the failure probability of transmission corridors based on ice accumulation. An ice storm with a total duration of T is discretized into T_N time steps. At discrete time instants, the failure rate of each component is calculated based on the instantaneous ice thickness level. The impact of ice storms on transmission towers and line segments are also considered. Each transmission corridor is assumed to be split by M towers into N line segments. The instantaneous failure rates of the transmission towers and line segments can be calculated as follows,

$$\lambda_{i,m}(t_j) = \begin{cases} 0, & R_{i,m}(t_j) \le R_{to} \\ e^{\left[\frac{0.6931(R_{i,m}(t_j)-R_{to})}{4R_{to}}\right]} - 1, & R_{to} < R_{i,m}(t_j) \le 5R_{to} \\ 1, & R_{i,m}(t_j) > 5R_{to} \end{cases} \tag{7}$$

$$\lambda_{i,n}(t_j) = \exp\left\{11 \times \frac{R_{i,n}(t_j)}{R_{li}} - 18\right\}\Delta l, \tag{8}$$

where $(\lambda_{i,m},\ \lambda_{i,n})$ are the failure rate of the m^{th} tower and n^{th} line segment of the i^{th} corridor at time t_j, $(R_{i,m}(t_j),\ R_{i,n}(t_j))$ are the ice thickness on the m^{th} tower and n^{th} line segment at j^{th} time instant, $(R_{li},\ R_{to})$ is the ice thickness threshold design of line segment and transmission tower, and Δl is the line segment length.

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The corresponding probability of failure of the transmission towers and lines segments during the ice storm for a specific transmission corridor can be calculated as follows,

$$P_{i,m} = 1 - \exp\left\{ - \sum_{j=0}^{N_t-1} \lambda_{i,m}(t_j)/(1-\lambda_{i,m}(t_j))\Delta t \right\} \quad (9)$$

$$P_{i,n} = 1 - \exp\left\{ - \sum_{j=0}^{N_t-1} \lambda_{i,n}(t_j)\Delta t \right\}, \quad (10)$$

where ($P_{i,m}$, $P_{i,n}$) is the probability of failure of the m^{th} tower and n^{th} line segment of the i^{th} transmission corridor, and N_t is the number of discrete time instants.

The equivalent probability of failure of a specific transmission corridor is calculated as follows,

$$P_i = 1 - \prod_{1}^{M}(1 - P_{i,m}) \prod_{1}^{N}(1 - P_{i,n}), \quad (11)$$

where M and N are the number of transmission towers and line segments along a specific transmission corridor, and P_i is the probability of failure of the i^{th} corridor.

III. Resilience Quantification Framework

A. Resilience Index

Resilience metrics are usually defined to measure the ability of the power system to absorb, recover from, and adapt to high-impact-low-probability events [15]. The normalized area of performance degradation (Q) in the resilience triangle and the resilience trapezoidal curves has been widely used for resilience evaluation [2], [12]. To evaluate the system resilience, the amount of load supplied can be used as an indicator for the system performance during extreme events [16]. As most of the methods capture the resilience of the system for a particular event scenario, a modified resilience index can be used to evaluate the resilience of the transmission system against diverse events as follows,

$$R = \sum_{s \in S} P_s Q_s, \quad (12)$$

where R is a quantitative resilience index, P_s is the probability of occurrence of the s^{th} ice storm, Q_s is the degradation in system performance. In this paper, the value of Q_s is represented by the total amount of load curtailment during an ice storm. Though a conditional value at risk metric can be incorporated to account for the associated risk, the main scope of this work is to quantify the operational resilience from a steady-state system perspective.

B. Quantify Uncertainties

Combinatorial enumeration methods can be used to enumerate function values based on predefined PDFs. To simulate many potentially possible ice storms, the probabilistic ice storm model applies the combinatorial enumeration method. A PDF defining each geographical- and the weather-related parameter is divided into several equal portions. Ice storm scenarios are generated by selecting a random value for each parameter using the combinatorial enumeration method. In other words, the combinatorial enumeration method is used to enumerate through selection of specific segmented intervals. For instance, dividing the PDF of ice precipitation into C equal portions will result in a segmented interval of C_k. The wind speed probability for the s^{th} ice storm scenario can be obtained as follows,

$$P_r(P_{ice,s}) = \int_{P_{ice,s}-C_k/2}^{P_{ice,s}+C_k/2} f(P_{ice}) dP_{ice}, \quad (13)$$

The probability of each parameter is determined by following the aforementioned convention. Combining all those probabilities, the overall probability of occurrence of a specific ice storm scenario can be evaluated as follows,

$$P_s = \Big[P_r(H_{0,s}) P_r(P_{ice,s}) P_r(V_{T,s}) P_r(\delta_s) P_r(x_{l,s}, y_{l,s}) \Big]. \quad (14)$$

where P_r is the probability of a random variable.

For each simulated ice storm, a fragility model is used to evaluate the failure probability of each corridor. Load curtailment is calculated using DC optimal power flow model since the proposed method focuses on assessing resilience from a planning perspective giving less interest to transient and cascading failures. The proposed resilience assessment framework is illustrated in Algorithm 1.

IV. Implementation and Results

The proposed approach is applied on the 25000-bus synthetic system [17]. The ACTIVSg25k test case is a 25000-bus synthetic power system representing the Northeast and mid-Atlantic regions of the United States. Statistical analyses are conducted to determine proper PDFs governing ice storm parameters including central pressure difference, translational speed, wind speed and direction, ice precipitation rate, and landing location. Ice storm events from 1950 to 2020 are extracted from [18]. The best fitting PDF for these parameters are evaluated as described in Table I. Due to data scarcity, predefined PDFs are assigned to other parameters [19]. Also, the ice thickness threshold used in this paper is 15 mm [19]. The simulation is run for 10,000 ice storms generated using the predefined PDFs. To calculate the probability of occurrence of each simulated ice storm, the PDFs of key parameters are divided into 10 equal segments.

To visualize the impact of ice storm spatiotemporal characteristics, the sequential failure behavior is analyzed. Fig. 2 shows the frequency of failure of system components at hours 0, 6, 12, and 18. At the beginning of ice storms, very low impact frequency is observed compared to the end of ice storms. It is difficult to capture an exact directional behavior of ice storms in the area under study due to the lack of accurate information; however, we can conclude that the eastern side of the network will be more impacted compared to the western side. Some regions show almost the same impact regardless of the time perspective whether they were impacted at the beginning or the end of the storm.

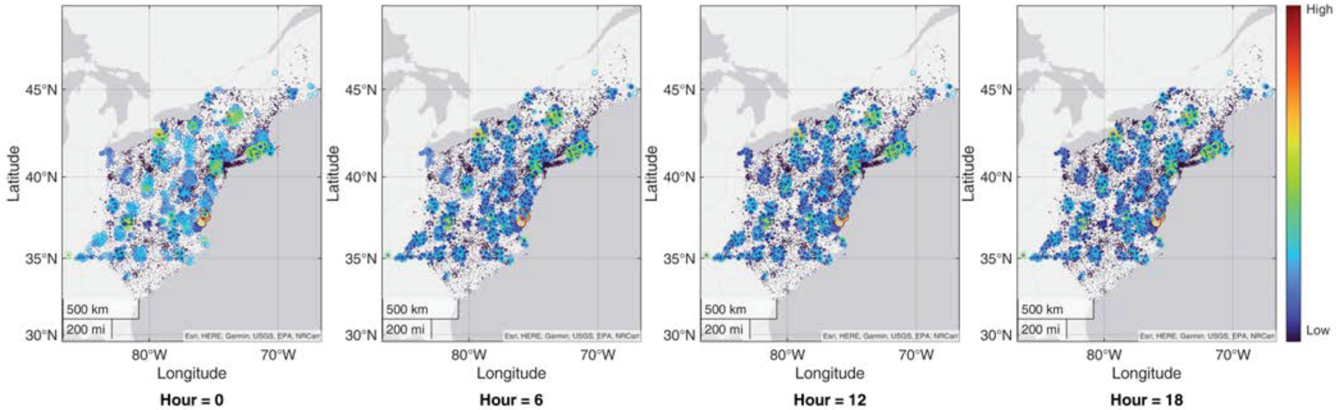

Fig. 2. Sequential impact frequency of ice storms on the 25000 bus system

Algorithm 1: Power System Resilience Assessment Considering Ice Storm Uncertainties

Input: Number of ice storms (S) and PDFs of weather-related and geographical-related parameters

Split the PDFs into C equal portions

for $s \leftarrow 1$ **to** S **do**

  Generate a random number for storm and location parameters; Compute the probability of each parameter based on the provided PDFs; Calculate the occurrence probability (P_s) of the s^{th} ice storm using (14); Create the propagation path of the s^{th} ice storm using the generated random values

  for $t \leftarrow 1$ **to** T **do**

    for $i \leftarrow 1$ **to** I **do**

      for $m \leftarrow 1$ **to** M **do**

        Calculate the thickness of ice on transmission towers; Compute the failure rate of each transmission tower; Calculate the probability of failure

      for $n \leftarrow 1$ **to** N **do**

        Determine the thickness of ice on transmission line segments; Compute the failure rate of each transmission line segment; Evaluate the probability of failure

      Evaluate the probability of failure of the i^{th} corridor using (11)

    Remove the failed corridors from the system topology and calculate the minimal load curtailment using DC optimal power flow

  Evaluate Q_s by summing the amount of load curtailment for the whole ice storm

Compute the system resilience index R using (12)

Output: System resilience index

TABLE I
PDFs REPRESENTING GEOGRAPHICAL AND WEATHER PARAMETERS

Key parameter	PDF	Parameters
Translational speed	Uniform	$a = 0$, $b = 15$ m/sec
Latitude (y)	Uniform	$a = 34°$N, $b = 45°$N
Longitude (x)	Uniform	$a = 90°$W, $b = 70°$W
Ice precipitation	Lognormal	$\mu = 9.3$ cm/hour, $\sigma = 20.78$
Wind speed	Lognormal	$\mu = 2.7$ m/sec, $\sigma = 0.5185$
Wind direction	Binormal	$\mu_1 = -73.3$, $\mu_2 = -7.2$ $\sigma = 22.6$, $\sigma = 70.35$, $\alpha = 0.5$
Difference in pressure	Uniform	$a = 1.5$, $b = 3$

The amount of load curtailment at each instant is calculated for all ice storms. Fig. 3 (a) shows the histogram of average load curtailment among all scenarios. Out of all scenarios, almost 70% of the simulated ice storms have caused less than 50 MW of total load curtailment. Overall, there are 6255 scenarios with zero load curtailment implying that the system will withstand an ice storm with a probability of almost 63%. Fig.3 (b) provides a deeper histogram on scenarios exhibiting load curtailment. Most of the scenarios have a very small amount of load curtailment emphasizing the overall high resilience level of the system under study. Also, only 28 scenarios have shown average load curtailment exceeding 300 MW, representing only 12.7% of the system nominal load. The highest average load curtailment is 527.1 MW amongst all scenarios exhibiting load curtailment. These figures provide an overall statistical profile of the negative impact of ice storms on system operational performance.

Fig. 4 provides analysis on the hourly load behavior, which shows the total, maximum, average, and standard deviation of hourly load curtailments. Due to the sequential failure behavior of system components, the amount of load curtailment increases as an ice storm evolves through the system. The maximum amount of load curtailment for all scenarios is 330 MW at the beginning of the simulation and 660 MW at the end of simulation. This implies that severe negative impacts of ice storms increase with the increase in the duration of ice storms. It also highlights the importance of corrective and proactive resilience enhancement strategies to reduce the severity of such events. Although the average hourly load curtailment is relatively low (the highest value is 15 MW),

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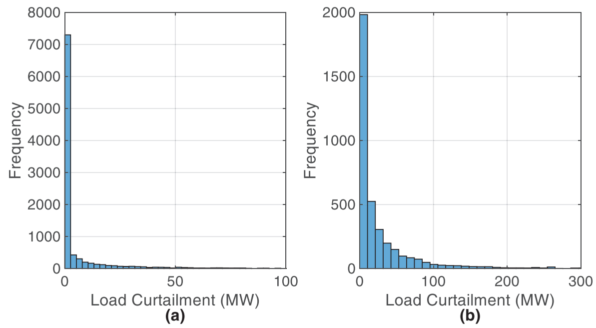

Fig. 3. Histogram of the average load curtailment for (a) all scenarios and (b) scenario with load curtailments

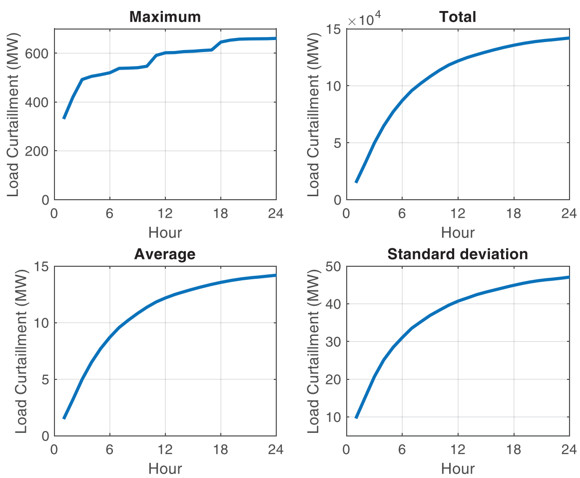

Fig. 4. Hourly load curtailment statistics of the 25000 bus system

the hourly load curtailment variance is high (the highest value is 48 MW). Therefore, the stochastic behavior of ice storms has been realized in the high variation of load curtailment.

The resilience metric for the 25000-bus synthetic power system is 2.43—i.e., the average amount of load curtailment for the system under study at the current status. It reveals the robustness of the system against ice storms. The lowest value can be zero which implies that the system is fully resilient against ice storms; whereas, the highest possible value is the total system nominal load, which means complete blackout.

V. Conclusion

This paper has proposed a resilience assessment methodology to quantify the spatiotemporal uncertainties of ice storms on the resilience of electric transmission systems. An ice storm propagation model is used to simulate diverse ice storms using calculated PDFs governing ice storm behavior. A fragility model is used to calculate the status of each system component based on ice thickness at sequential time instants. The proposed algorithm was demonstrated on the 25000-bus synthetic system representing the Northeastern region of the USA. The total amount of load curtailment along with the probability of occurrence is used to calculate a resilience metric. The results showed the effectiveness of the proposed method to quantify the impact of ice storms. The proposed algorithm provides a benchmark resilience metric to evaluate diverse resilience enhancement strategies. Considering the role of protection system and addressing transient stability and cascading failure behavior would be valuable for future research.

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