Investigating the Impacts of Climate Change and Natural Disasters on the Feasibility of Power System Resilience

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***Abstract*—Due to the increasing rate of high-impact low-frequency (HILF) events, power systems are more vulnerable against the destructive climate events compared to other infrastructures. From this point of view, the primary focus of this article is to investigate the vulnerability of power systems in the face of numerous types of natural disasters in terms of resilience metrics. To achieve this goal, a mesh-structured view of the power system at the transmission level is employed to model the action mechanism from different types of natural disasters on the power system. The Monte Carlo simulation method is further applied to evaluate the resilience metrics of the power system. From the perspective of resilience, the vulnerability of the system against different types of events is finally achieved in this paper. Simulation case studies on the IEEE 30-bus test system have demonstrated that the proposed modeling can not only facilitate in upgraded schemes, but also significantly decrease the amount of damages to the power system after natural extreme events.**

***Index Terms*—Climate change, extreme weather events, Monte Carlo simulation, microgrid, natural disaster, power system resilience.**

I. Introduction

Power systems resilience is a worldwide concept in measuring the ability of power systems to deal with severe natural disasters [1]. Specifically, due to the climate change caused by human intervention in nature, the increasing number of natural disasters has brought more attention to the importance of this concept [2]. In the context of power system resilience, events with a large number of outages are referred to as high-impact low-probability (HILP) events, such as, the superstorm Sandy (US) [3], hurricane Katrina (US) [4], the Texas freeze of February 2021 (US) [5], and the Fukushima earthquake (Japan) [6], in which millions of outages occurred in the power system. As a result, the impact of HILP events on power systems can cause millions of outages, extensively disrupting the system performances. For example, Hurricane Katrina caused almost three million outages [7]. The Texas freeze caused millions of outages at the peak, leading approximately 10 million people (only in Texas) living without electricity for several days [5]. The Hurricane Maria occurred in Puerto Rico resulted in the longest blackout in the history of the USA in September 2017, with as many as 1.5 million customers losing their electricity and even in some areas, the blackouts have been lasted for up to 120 days [8]. As a matter of fact, a high percentage of power system outage minutes in the US has been pointed out to be associated with climate disasters [9], during which the annual cost in the US that has been spent to tackle these events is approximately between $18-70 billion [8].

Although the phrase ”HILP event” is always used in conjunction with the resilience of the power system, limited papers have considered the behavior of HILP events in the power system as the fundamental of resilience impact assessment. Paper [10] depicted the behavior of different HILP events graphically. However, since the simulations on all the events were considered in the same way, assuming that the occurrence of the event which causes the outage of equipment near the event center is independent with the event's severity level, thus a comprehensive view of the impact over different HILP events on power system resilience is lacked and not provided in this paper. A probabilistic strategy for evaluating power system resilience based on the extreme weather storm that occurred in Iceland in December 2019 was presented in [11]. In this paper, climate-dependent component failure probabilities were defined through historical and forecasted wind-speed data for vulnerability determination. This assessment is only based on information from a specific event and is not generalized to other events and power systems under different climatic conditions. By using a mesh view, paper [12] has simulated the behavior of three types of HILP events on the power system and provided the resilience criteria. In this article, the areas close to the center of the event are considered to have many outages and the areas farther away are considered to be safer. The main focus on [12] was to evaluate the resilience of power system, and therefore calculations for different types of events will perform randomly with different intensities. In other words, compared with other events, this article does not specify towards which type of event the test system is more vulnerable, instead the primary goal is to assess the resilience against different events and find out that which event is more harmful for power system in terms of resilience.

Based on the above studies, it is necessary for power system operators and planners to have comprehensive mechanism to upgrade the power system schemes to improve the resilience. In other words, the investigations and the probability of HILP events need to be based on different regions. Therefore, the main purpose of this paper is to model the behavior of various events such as super storm, hurricane, earthquake, and severe freezing in the power system and evaluate the resilience criteria against each event. For this purpose, the mesh view of the power system is first achieved using image processing. The behavior of various weather-related events as well as earthquake is then modeled at the power system surface by using meteorological models. Subsequently, for each event, a large number of scenarios are generated (6000 scenarios in this paper) in which the location and intensity of the event are stochastically determined under each scenario. Since the topic is related to HILP events, all event intensities are considered to be high and different so that the results would be more realistic and generalized. In addition to that, under each scenario, the amount of damage is further evaluated based on the severity of the event and its behavioral model, the Monte Carlo simulation method is also used to calculate the resilience criteria. The resilience evaluations that consider various aspects of resilience such as Loss of load probability ($LOLP$), expected demand not supplied ($EDNS$), fragility index (FI), and restoration efficiency index (REI) are taken into account to properly interpret the needs of the power system to cope with each HILP event.

Specifically, the innovative contributions of this paper are summarized and shown as follows:

- Characterize the modeling behavior of different destructive natural events in power systems.
- Analyze the resilience of power system against different natural disasters with different resilience criteria.
- Implement simulation case studies and provide solutions for future system planning and upgrading schemes.

II. Problem Formulation

A. Resilience framework

The resilience of power systems against HILP events is defined as the ability to withstand and fast recovery. Four important resilience criteria are considered to evaluate the power system in the face of a catastrophic event. From the technical aspect, the loss of load probability ($LOLP$) and expected demand not supplied ($EDNS$) are used in the paper. These parameters measure the quality of the power system during the event. Consumer satisfaction with the network that depends on the amount of fed loads, is also taken into account in these metrics. The proposed $LOLP$ and $EDNS$ metrics are given in (1), (2)-(3), respectively.

$$LOLP = \frac{1}{N_s}\sum_{s=1}^{N_s} \chi_s \times P_s \tag{1}$$

$$EDNS = \frac{1}{N_s}\sum_{s=1}^{N_s} \chi_s \times P_s \times \Omega_s \tag{2}$$

$$\chi_s = \begin{cases} 0 & if\ c_s - d_s \geq 0 \\ 1 & if\ c_s - d_s < 0 \end{cases} \tag{3}$$

where N_s is the number of scenarios and should be great enough, χ_s is a binary variable that indicates whether the load of the system exceeds the total generation capacity (equal to 1) or not (equal to 0), d_s is the total load of the system in scenario s, c_s is total generation capacity of the system in scenario s, P_s is the probability of event occurance in scenario s, s is the index of scenarios, and Ω_s it the amount of the load curtailment in scenario s, which is achieved by optimal power flow (OPF) calculation.

To evaluate the ability of the power system to withstand against HILP event, the FI criteria is employed and calculated based on the number of lines on outage during the event with the expression shown as follows:

$$\Upsilon = \frac{1}{N_s}\sum_{s=1}^{N_s} \int_0^{\infty} k_s f_s(k) dk \tag{4}$$

where k_s is the number of lines on outage in scenario s, f_s is the fragility function in scenario s, and Υ is the expected number of lines on outage.

It is evident to see that, the process of power system restoration after a catastrophic event also depends on the extent of damage to other human infrastructures, such as transportation, communication systems, cyber infrastructures, and material resources. Moreover, the type and severity level of the extreme event are also effective in this criteria. With the above, the proposed restoration index is then described in (5) and (6).

$$\Psi = \frac{1}{N_s}\sum_{s=1}^{N_s}\sum_{i=1}^{5} w_i \varepsilon_i P_s \times P_s^{char} \tag{5}$$

$$\sum_{i=1}^{5} w_i = 1 \tag{6}$$

where w_i is the weight coefficient, ε_i is the value of restoration factor on the i^{th} network, i is the index of grid restoration factors, P_s^{char} is the probability of event characteristics, and Ψ is the grid restoration metric. Due to the page limitations, detailed equations and proofs are omitted in this paper and please see paper [12] for more information.

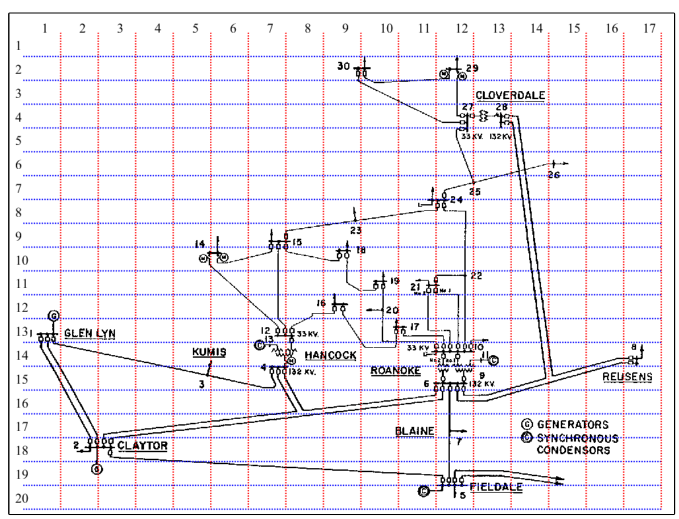

Fig. 1: Mesh view of a IEEE 30-bus test system.

B. Mesh view of power system

A mesh view of the IEEE 30-bus test system is shown in Fig. 1. In this figure, it is assumed that the surface of the power system can be divided into 20×17 = 340 equal cells. Each cell has two components (i.e., row and column) and are used to locate the event and equipment. When an event occurs in a cell, the central areas and margins of the event are extracted accordingly to the corresponding type of the event. For example, if an event happens in cell (12, 7) (12^{th} row, 7^{th} column), the lines between buses 14 and 12, and buses 15 to 12 are then tripped out (see Fig. 1).

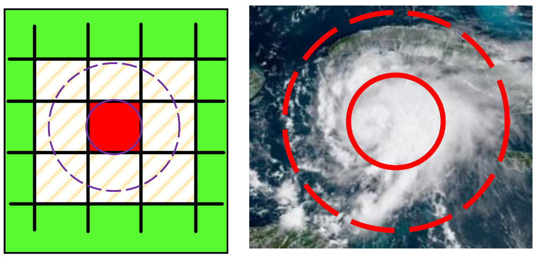

Fig. 2: Model of storm operation on mesh view of the power system.

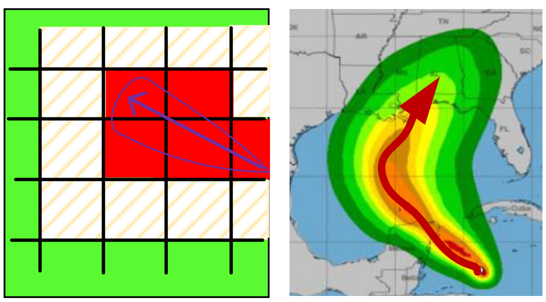

Fig. 3: Model of Hurricane operation on mesh view of the power system.

III. Extreme Event Modeling in Power Systems

A. Supperstorm

Storms typically occur in one area and are accompanied with heavy rainfall. According to the geographical maps of the storm, the corresponding model on the mesh view of the power system is shown in Fig. 2.

As shown in Fig. 2, the center of the storm shown in red indicates the tremendously high probability of equipment outage in this area. In other words, any equipment located in this cell is almost 100% likely to go out of circuit. Hashed areas are the frontier of the event where equipment is less likely to break down. The green areas are the safe areas of the power system where the probability of equipment outage is very low. Therefore, the stochastic parameters related to the storm represent the probability of the occurrence, the location on the mesh view cells of the power system, and the storm intensity [12].

B. Hurricane

As shown in Fig. 3, the main difference between hurricane and storm is that the hurricane is accompanied with strong wind. Therefore, the stochastic model includes the parameters of probability of occurrence, location, direction of motion, and the hurricane intensity [13].

C. Earthquake

An earthquake is a natural event that occurs in the deep of the earth. Strong shocks of the earthquake can cause serious damage to human infrastructure, especially when it comes to the power system. According to the existing models for earthquake behavior, the model is shown on the mesh view of the power system in the form of concentric ellipses, the higher the distance from the center, the lower its intensity is. The model from earthquakes in this paper is shown in Fig. 4. Similarly, the stochastic parameters of the earthquake are the probability of its occurrence, location and severity level [13].

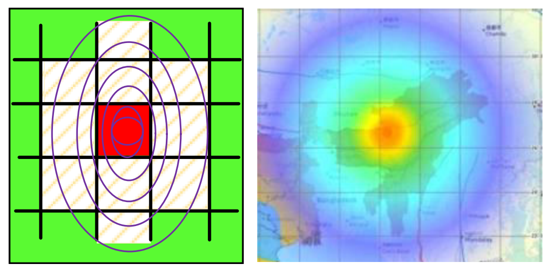

Fig. 4: Model of earthquake operation on mesh view of power system.

D. Ice-freezing

Base on the geographical maps, it is assumed in this paper that the ice freezing is occurred in an area of the power system (that may contain some cells) with no border areas. Therefore, it is only the center of the event that experiences the emergency condition while the other parts remain to be safe. The proposed model for ice-freezing behavior on the mesh view of the power system is shown in Fig. 5.

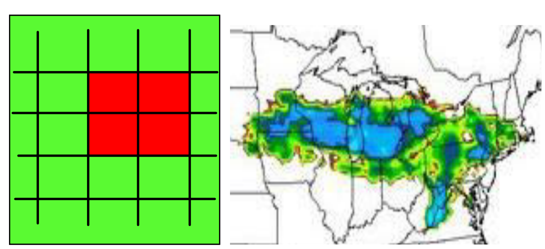

Fig. 5: Model of ice-freezing operation on mesh view of the power system.

IV. Simulation Results

The IEEE 30-bus test system is evaluated in simulation case studies, in which the corresponding mesh view is shown

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in Fig. 1. Stochastic scenarios are first generated in the pre-simulation stage. To generate the scenarios, uncertain parameters are determined with random values under each parameter being generated using the normal distribution function. This process is shown in Fig. 6.
To evaluate the resilience of the test system in the face of natural disasters, for each type of event, 6000 scenarios are generated based on its random parameters. The Monte Carlo simulation is further used to calculate the resilience criteria. The implementation process of the proposed method under each scenario can be found in Fig. 7.

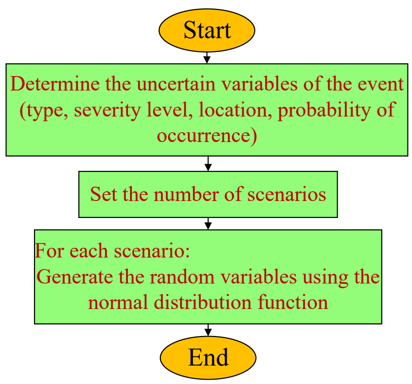

Fig. 6: The proposed scenario generation method.

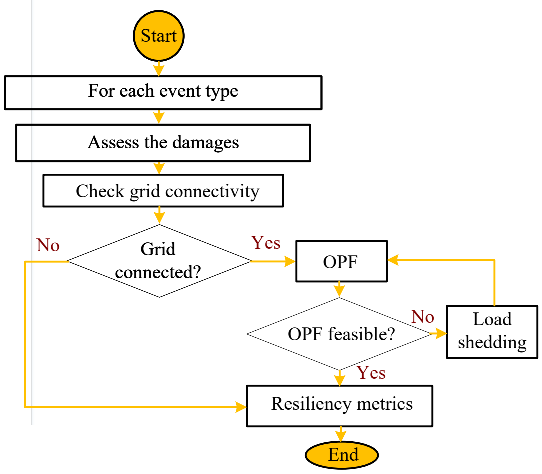

Fig. 7: The flowchart of the proposed method under each scenario.

Detailed simulation results for different events are shown in Figs. 8-11. It should be noted that in these simulations the intensity of all events is considered to be extremely severe. In Fig. 8, it is evident to see that from the $LOLP$ standard point of view, the tested power system is weaker against hurricanes compared to other event types and is more resistant to earthquakes. This is due to the Hurricanes are usually accompanied with strong wind, thus the power system is more vulnerable when it comes to transmission lines.

The criterion $EDNS$ following with the $LOLP$ standard against hurricanes is higher than other types of events. As shown in Fig. 9, although the values of $EDNS$ metric for all types of event are approximately the same, it is expected to lose more loads in the event of a Hurricane compared with other event types. This is because the dependence of the power system on transmission lines are very vulnerable to speedy wind. By increasing the penetration of the distributed energy resources (DERs) in the power systems, since the energy hubs are located closer to the load centers, therefore the dependence on transmission lines is reduced. That is why networked-microgrids are considered as the high potential solutions to enhance the resilience of modern power systems.

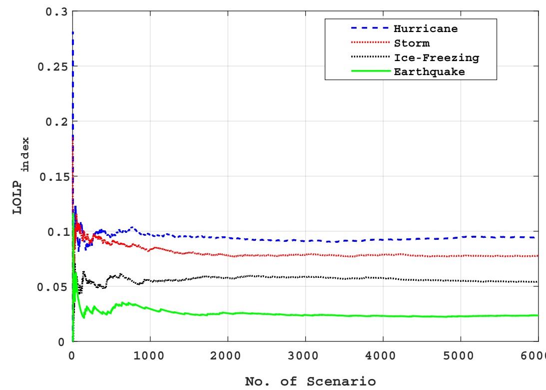

Fig. 8: The LOLP metric convergence during simulations.

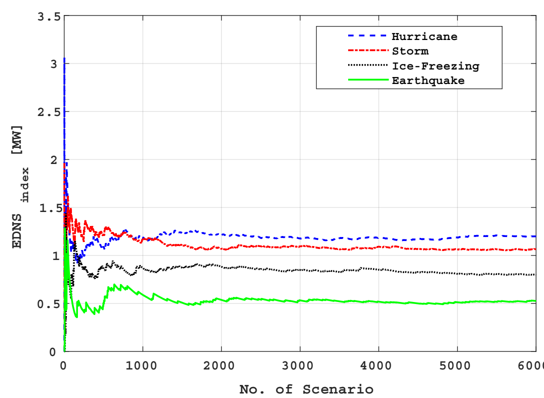

Fig. 9: The EDNS metric convergence during simulations.

The power system fragility criterion in this paper is calculated based on the number of transmission line outages due to a HILP event. Therefore, it is reasonable if the damages due to the hurricane are more severe than the other events. It can be concluded from Fig. 10 that transmission lines are much more vulnerable to ice freezing than earthquakes. This is due to the freeze occurs over a wider area and thus severely affects transmission lines. In addition to that, the necessary reinforcements for the earthquake are considered to design and locate the bases of transmission lines.

The recovery criterion (Ψ), is one of the most important criteria for assessing the resilience of power systems in the face of catastrophic events. The difficulty extent of recovering the power system after a disaster is calculated by considering the damage to other human infrastructures following the extreme event. Depending on the type of event, the difficulty of recovering the power system is shown in Fig. 11. The results

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of this figure have proved that hurricane is the most dangerous type of destructive event to damage power systems.

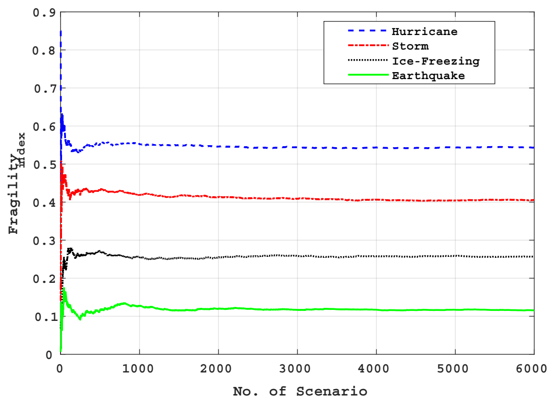

Fig. 10: The fragility metric convergence during simulations.

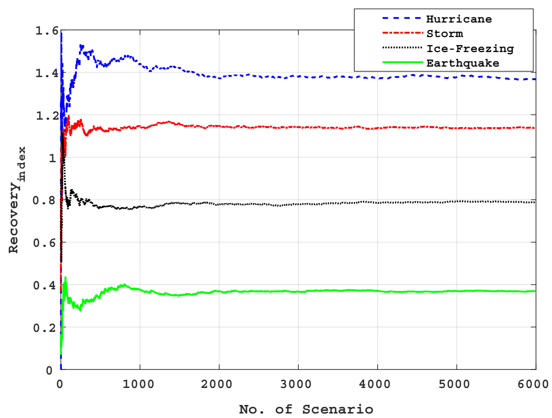

Fig. 11: The recovery metric convergence during simulations.

The calculated criteria for the resilience of the power system against various types of events are Subsequently shown in Table I. According to the information presented in Tab. 1, it can be concluded that power systems are much more vulnerable to hurricanes and are less exposed to earthquakes.

TABLE I: Resilience metrics of IEEE 30-bus test system against different HILP events.

Parameter	Hurricane	Storm	Ice-freezing	Earthquake
LOLP	0.0941	0.0775	0.0541	0.0235
EDNS	1.1967	1.0631	0.7978	0.5254
Fragility	0.5436	0.4055	0.2565	0.1156
Recovery	1.3658	1.1381	0.7867	0.3689

V. Conclusions

The primary goal of this paper is to evaluate the resilience of power systems in the face of climate change and natural disasters such as hurricanes, storms, ice freezing, and earthquakes. For this purpose, four quantitative criteria including (i) the loss of load probability ($LOLP$); (ii) expected demand not supplied ($EDNS$); (iii) the fragility of lines in the face of the HILP event (Υ); and finally (iv) the difficulty of system recovery (Ψ) are studied to assess the resilience of power systems. Power system mesh view and Monte-Carlo simulation method under 6000 scenarios are utilized to evaluate the power system's capability to deal with destructive natural disasters. Simulation results on the IEEE 30-bus test system have quantitatively shown that power systems are vulnerable to climate change and natural disasters due to their inherent characteristics. In addition, hurricanes with strong wind cause more damages to the power system, while the system is able to withstand earthquakes better than other events.

Since the transmission lines are considered as the most vulnerable equipment to disasters, one of the critical points presented in this paper is the dependence of the power system on transmission lines (at both transmission and distribution levels) for power transfer at the system level. The use of microgrids and the installation of energy hubs that are close to the load centers can significantly improve the resilience by reducing dependence to transmission lines. With that being said, our future work is to consider the impact of networked-microgrid modelings to achieve realistic and generalized solutions to deal with climate change and destructive natural disasters.

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