# Modeling and Evaluating the Resilience of Critical Electrical Power Infrastructure to Extreme Weather Events

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***Abstract*—Electrical power systems have been traditionally designed to be reliable during normal conditions and abnormal but foreseeable contingencies. However, withstanding unexpected and less frequent severe situations still remains a significant challenge. As a critical infrastructure and in the face of climate change, power systems are more and more expected to be resilient to high-impact low-probability events determined by extreme weather phenomena. However, resilience is an emerging concept, and, as such, it has not yet been adequately explored in spite of its growing interest. On these bases, this paper provides a conceptual framework for gaining insights into the resilience of power systems, with focus on the impact of severe weather events. As quantifying the effect of weather requires a stochastic approach for capturing its random nature and impact on the different system components, a novel sequential Monte-Carlo-based time-series simulation model is introduced to assess power system resilience. The concept of fragility curves is used for applying weather- and time-dependent failure probabilities to system's components. The resilience of the critical power infrastructure is modeled and assessed within a context of system-of-systems that also include human response as a key dimension. This is illustrated using the IEEE 6-bus test system.**

***Index Terms*—Climate change, critical infrastructure (CI), power systems, reliability, resilience, resiliency, weather.**

## I. Introduction

ELECTRICAL power systems are among the critical infrastructures (CIs) of modern societies. CIs comprise the assets, services, and systems that support and enable the economic, business, and social activities [1]. Recent electrical wide-scale disturbances, such as [2]–[5], have evidenced the sometimes dramatic impact of a power disruption on other CIs, such as telecommunications and transportation.

As a CI, in fact, power systems must be reliable during normal conditions and in response to foreseeable contingencies. In this respect, power systems have been traditionally designed and operated driven by the key reliability aspects, i.e., security and adequacy [6]–[8], which are well-known and established concepts. However, its becoming more and more apparent how critical power infrastructure must also be resilient to high-impact low-probability (HILP) events. In this regard, resilience is an emerging concept that has not yet been adequately explored by the power engineering community. Hence, what constitutes power system resilience is still not very clear, which results in the lack of a universally accepted resilience definition and even a common understanding of the concept. On these premises, a conceptual framework is provided in this paper for modeling, quantifying, and bringing insights into power system resilience, with specific focus on extreme weather events.

In fact, extreme weather, as a HILP event, is considered among the major threats of the resilience of electrical networks. Therefore, the impact of severe weather on power systems resilience is used in this paper as a key application for realizing the proposed resilience framework. The influence of weather on power systems is evident worldwide. For instance, in the USA, the total annual economic impact from weather-related loss-of-supply events due to damage on the transmission and distribution networks ranges from \$20 to \$55 billion dollars [9]–[11]. In England and Wales, there are around ten loss-of-supply events per year due to events on the transmission network, of which around half are attributed to weather events [12]. Despite their low probability, severe weather events often have dramatic consequences because power systems are by definition system-of-systems, and by affecting the operation and reliability of some components (mainly the outdoor ones, e.g., towers and overhead lines), they may cause cascaded effects on the entire infrastructure.

However, quantifying and anticipating the impact of weather is a difficult task due to its high stochasticity. For this purpose, a novel time-series simulation model based on sequential Monte Carlo is introduced in this paper for assessing the impact of weather on power systems resilience and evaluating different measures for improving grid resilience within the discussed framework. The work described here focuses on the transmission network, because of the high impact of weather-related transmission permanent outages on the frequency, duration, and severity of customer disconnections. However, the proposed methodology is suitable for resilience studies in all power system areas, such as, for instance, distribution networks. The approach proposed to model weather-related outages relies on the concept of components' fragility curves, with specific and exemplificative applications to faults caused by wind to transmission lines and towers. In addition, the effect of human

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response in the context of the power system being a system-of-systems, which introduces a further (non-infrastructure related) systemic dimension to the problem, is also evaluated and modeled in the proposed resilience methodology.

This paper is organized as follows. Section II discusses and brings insights into the understanding of resilience when applied to power systems, conceptualizing the main features that a resilient power infrastructure should boast. Based on this, the influence of weather on electrical components and different measures for enhancing grid resilience to extreme weather is then provided in Section III. The methodology for assessing the impact of weather on power systems resilience within the proposed framework is introduced and elaborated in Section IV. Section V presents the illustrative case studies and the results obtained by applying the method to the IEEE 6-bus reliability test system. Section VI concludes this paper.

## II. Power Systems Resilience

The concept of reliability is well known, and numerous power system reliability studies have been developed in the last decades, such as [13]–[20]. However, as aforementioned, in order to preserve the system integrity under any conditions, the system design and operation must be not only reliability oriented, focusing on measures for known threats, but also resilience oriented, focusing on measures that can be taken due to the occurrence of HILP events, such as the extreme weather phenomena. In the light of climate change, this is increasingly important as their frequency, intensity, and duration are expected to increase [9]. Therefore, extreme weather events might no longer be of low probability in the future, but their impact will continue to be high if suitable actions are not taken to enhance the grid resilience. In this respect, preventive and corrective actions that can be applied to mitigate the weather effect are discussed in the next section.

In contrast to reliability, the concept of resilience has had relatively little usage, and as a result, it is still not clear. Although there are several attempts to define power systems resilience, there is still no generally accepted definition. The UK Energy Research Center [21] uses the following resilience definition: "*Resilience is the capacity of an energy system to tolerate disturbance and to continue to deliver affordable energy services to consumers. A resilient energy system can speedily recover from shocks and can provide alternative means of satisfying energy service needs in the event of changed external circumstances.*" According to Overbye *et al.* [22], power grid resilience is defined as the ability to degrade gradually under increasing system stress and then to recover to its pre-disturbance secure state. It is also argued that the degree to which the system can cascade provides a measure of system resilience.

The National Infrastructure Advisory Council (NIAC), USA [23], provides a similar and more generic definition of resilience that is applicable to any CI, and it additionally considers the ability to absorb lessons by the disruptive events and adapt the operation and structure of a CI to prevent or mitigate the impact of similar events in the future. The main resilience features as provided by NIAC are robustness, resourcefulness, rapid recovery, and adaptability, as shown in

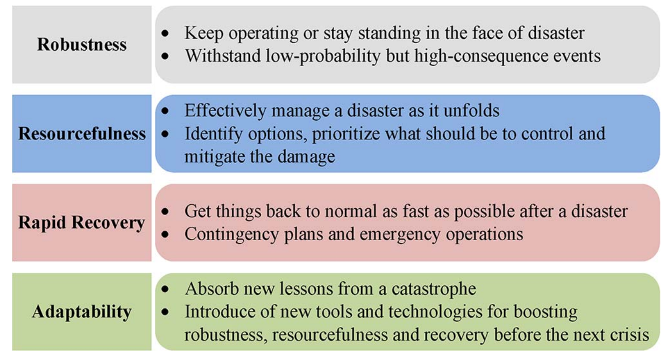


Fig. 1. Resilience main features by NIAC, USA [23].

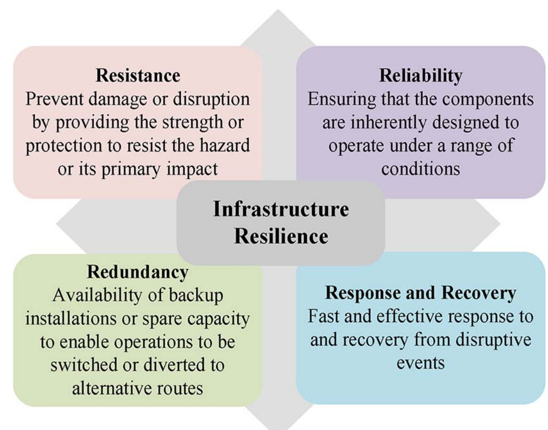


Fig. 2. Resilience main characteristics by Cabinet Office, U.K. [24].

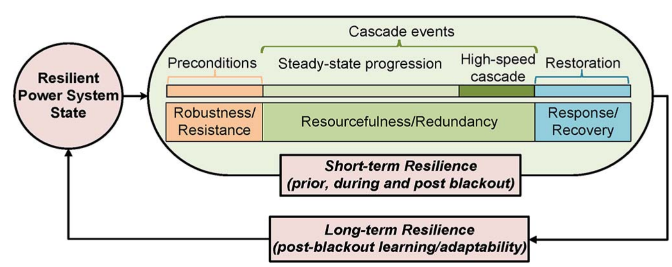


Fig. 3. Power systems' short- and long-term resilience.

Fig. 1. The Cabinet Office, U.K. [24], defines resilience of a CI as the ability to "*…anticipate, absorb, adapt to and/or rapidly recover from a disruptive event*". According to the Cabinet Office, the main characteristics of a resilient CI are resistance, reliability, redundancy, and response/recovery (see Fig. 2). Resilience is defined in [25] as the "*robustness and recovery characteristics of utility infrastructure and operations, which avoid or minimize interruptions of service during an extraordinary and hazardous event.*"

These resilience definitions show that resilience is a function of time, and, as such, it can be divided in *short-term* and *long-term* resilience. The short- and long-term resilience when applied in power systems is illustrated here using the blackout progress [26] shown in Fig. 3. The *short-term* resilience refers to the features that a resilient electrical network must have before (preconditions, such as load demand and weather conditions), during (cascade events), and after (restoration) an electrical event, i.e., robustness/resistance, resourcefulness/redundancy, and recovery, respectively. The effectiveness of

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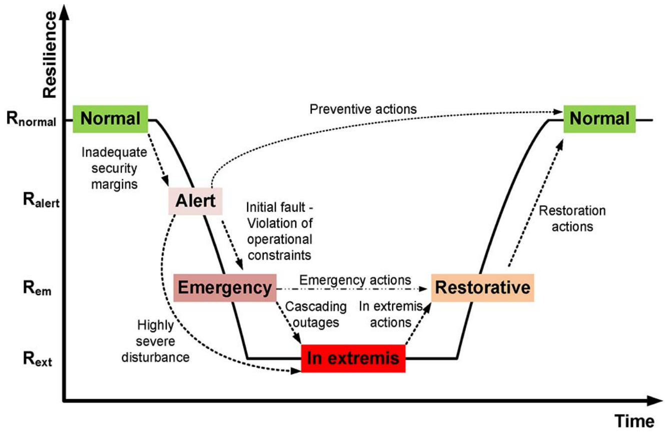


Fig. 4. Conceptual resilience curve.

the preventive and corrective actions heavily depends on the ability of the system operators to perceive and comprehend correctly the received information and data, detect the problem, set priorities, identify the available resources, and then apply the most appropriate measures for restoring the system to a resilient state. The *long-term* resilience refers to the adaptability of a CI to changing conditions and new threats. In power systems, adaptability is achieved through extensive risk and reliability studies, including potential future scenarios, to identify the main threats of power system stability. Measures are then applied when considered necessary for boosting grid resilience to both foreseeable and unexpected events.

The short-term resilience of a power system changes during an electrical disturbance, depending on its ability to cope effectively and rapidly with the evolving system conditions or its ability to degrade gradually during an electrical disturbance. Fink and Carlsen [27] discuss the possible states of a power system based on the security margins, which are the normal, alert, emergency, *in extremis*, and restorative. The transitions between these states depend on the severity of the electrical events and on the effectiveness of the preventive and corrective control actions. A different degree of resilience corresponds to each of these power system states. The conceptual resilience curve in Fig. 4 is used here to show how these system states can be mapped to the concept of resilience and the importance of each resilience feature at each state.

During the normal state, the resilience of the system, i.e., $R_{\mathrm{normal}}$, is high as all the operational constraints are satisfied, and the security margins are adequate. Therefore, the *robustness/resistance* of the system is sufficient to cope with a sudden electrical outage. However, this reduces when the system enters the alert state, and the security margins may become inadequate $(R_{\mathrm{alert}})$. The system operators need to use the available assets and *resources* to quickly apply preventive control actions to restore the system to the normal state. If a disturbance occurs before such actions are implemented, the system enters the emergency or *in extremis* state depending on the severity of the disturbance. For instance, severe weather events can result in the simultaneous outage of several components, leading to the transition of the system from the alert state to the *in extremis* state. The system resilience, i.e., $R_{\mathrm{em}}$ and $R_{\mathrm{ext}}$, respectively, decreases further as it is less resistant to new outages. The *resourcefulness* and *redundancy* are key resilience features at this stage of a blackout for mitigating its consequences, applying the emergency or *in extremis* actions and enabling the effective and quick *response* and *recovery* of the system.

Following the disturbance, its causes and impact have to be evaluated and incorporated in the contingency and risk studies to provide *adaptability* to similar or new threats. The short-term resilience characteristics of the system would thus be enhanced for dealing with natural disasters in the future.

## III. Enhancing Grid Resilience to Adverse Weather

Electrical utilities more and more recognize the effect of extreme weather events on power system operation and resilience. For example, high temperatures, high winds, heavy snow and ice accumulation, lightning strikes, and floods can cause the failure of key components of the system, as discussed in [12] and [28]. A fault due to weather conditions can be temporary, which can be restored quickly by auto- or manual reclose, or permanent, which could take several hours or even days to restore depending on the equipment damage. Several defense plans are thus applied for enhancing the grid resilience to such events, which can be divided in *short-term* and *long-term* ones, as discussed in Section II.

The *short-term* measures refer to the preventive and corrective measures applied before, i.e., days or weeks, during and after the extreme weather event. Based on the weather forecast by the meteorogical office, the electrical utility should use the available assets as efficiently as possible to prepare for the forthcoming weather event. Actions that can be taken include reserve planning, generation redispatch, ensure black-start capabilities, coordination with neighboring networks, energy storage, and demand-side response. For example, National Grid PLC, U.K., planned for approximately 2.7 GW short-term operating reserves in 2013/2014 based on the peak average cold spell electricity demand of 56.3 GW. It also operates the network in an “N-3” secure state during bad weather conditions instead of an “N-2” secure state as it is the practice under normal weather conditions [29]. Following the weather event, the quick recovery is vitally important. Black-start capabilities, proper communication procedures, and restoration and emergency strategies enable the fast restoration of the damaged facilities and of the disconnected customers.

The *long-term* measures refer to the long-term adaptability planning for enhancing the network resilience to future adverse weather events and climate change. These measures include, but are not limited to, the following [9], [10], [30]–[34]:

1) risk assessment and management for evaluating and preparing for the risk introduced by such events;
2) accurate estimation of the weather location and severity;
3) improve emergency and preparedness plans;
4) tree trimming/vegetation management for clearing the transmission lines rights-of-way;
5) undergrounding the distribution and transmission lines;
6) upgrading components with more robust materials;
7) redundant transmission routes by building additional transmission facilities;

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8) re-routing transmission lines to areas less affected by the weather;
9) elevating substations and relocating facilities to areas less prone to flooding;
10) maintain backup towers and materials;
11) increase visualization and situation awareness through advanced monitoring and prediction tools.

The impact of long-term measures on the short-term resilience features during a weather event varies. For example, enhanced situation awareness could help operators manage the disaster as it unfolds using the available assets and resources, whereas topology and structural measures could improve the robustness/resistance of the system to the influence of severe weather. The illustrative case studies in Section V demonstrate the effect of some of these long-term measures on the resilience features of a power system.

## IV. Time-Series Resilience Analysis Methodology

A time-series simulation model for power system resilience studies is introduced in this section. The aim of this model is to provide an illustration of the theoretical resilience concepts discussed in Sections II and III. This is achieved by determining the impact of weather on the resilience of a power system and evaluating the effect of different measures for improving the key features of the grid resilience.

### A. Key Modeling Aspects

Modeling the influence of weather on the reliability of power systems is a complex task because of the stochastic nature of the weather and several modeling requirements, which are discussed in this section.

*1) Analytical Simulations or MCS?:* The majority of the methods in the literature for evaluating the weather-associated impact on power systems reliability uses analytical techniques [35]–[42], with Markov approach being the dominant analytical technique. Analytical techniques are preferred for small-scale system configurations because of their simplicity and low computational burden, but the simulation techniques are more suitable when complex systems and operational conditions are modeled.

Therefore, the modeling of the weather influence on the operation and resilience of a large-scale power system would require a simulation approach in order to capture the stochastic behavior of the weather, both space- and time-wise. Monte Carlo simulations (MCS) is used in [15], [43], and [44]. A time-sequential model (TSDISREL99) was developed in [45] using time-varying failure and restoration rates for evaluating the impact of weather on the system reliability indices. MCS is also used in [46], where a probabilistic approach is described for estimating the occurrence of critical line temperatures under fluctuating power flows and meteorogical conditions.

*2) Dividing the Network in Weather Regions:* It is usually assumed that the system is exposed to the same weather conditions at any given time by modeling the weather event as a standstill event, which reduces the complexity of the modeling procedure because no regional weather aspects are considered. This is a valid assumption for distribution systems that cover a small geographical area, and they are usually exposed to the same weather at any given time.

However, it is not applicable in transmission system resilience studies, which cover a large geographical area, and the weather event moves across the transmission network sequentially with time. Billinton and Li [47] show that this assumption leads to the overestimation of the problem and to the estimation of pessimistic inadequacy indices. It is therefore more practical and realistic to divide the transmission network in weather regions. This would also help determine the resistance of each system region to extreme weather, which will guide the implementation of the appropriate resilience measures to the most affected areas. The weather can be assumed the same within each region, but it traverses and changes from region to region. Different criteria can be used for defining these weather regions, such as voltage levels [48] and meteorogical and geographical characteristics [47].

*3) Restoration Time During Extreme Weather Events:* The weather conditions significantly affect the restoration time of the damaged components, as it might be impossible or very difficult for the repair crews (RCs) to approach safely the areas affected by the weather event. The use of highly accurate restoration times is vitally important in both analytical and time-sequential resilience studies, as fast response and recovery are among the main resilience features.

Different approaches are used for modeling the repair time during extreme weather events. In [41], [48], and [49], it is assumed that no repair can take place during the bad weather period. A repair rate equal to the one during normal weather conditions is used in [50] based on the assumption that the electrical utility employs additional manpower and resources during bad weather situations. Billinton and Singh [37] assume a fixed but larger than the normal weather repair time during bad weather conditions. In another study by Wang and Billinton [45], weight factors are used to reflect the impact of weather, day, and time on the repair time, which require, however, a vast amount of historical and empirical repair data from each electrical utility. A repair rate divider is applied in [43] to show the increase in the repair time of a transmission line due to adverse weather, which considers the different weather conditions that a line may experience in different weather regions. Alternatively, empirical input can be obtained from electrical utilities for determining the restoration time.

*4) Independent and Common Cause Failures:* Adverse weather events, such as high winds, usually result in the outage of a single transmission line. However, if their intensity, e.g., extremely high winds, and/or duration is very high, it is possible that a transmission tower collapses, resulting in a multiple line failure. Power systems are traditionally designed to provide resistance against single outages ("N-1" security criterion), but not against multiple electrical outages ("N-k" security criterion) which may occur during adverse weather. The outage of more than one transmission circuits due to a single tower collapse is considered a common cause failure, which is evaluated in [49]–[51]. Common cause failures decrease the power system resilience, because they significantly reduce the resistance/robustness to new electrical failures, and they also

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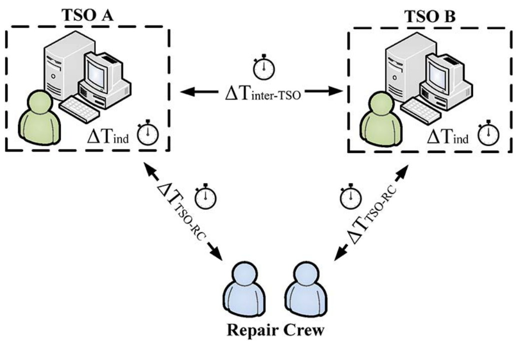


Fig. 5. Sources of delay in human reaction.

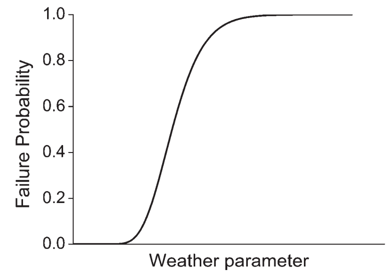


Fig. 6. Generic fragility curve.

limit the available assets for effectively managing the disaster as it unfolds (resourcefulness/redundancy).

*5) Impact of Human Response During Weather Emergencies:* Aforementioned, the effectiveness of the control measures to be applied depends on the ability of the operator to quickly detect the problem and decide on the most appropriate actions to be implemented. Therefore, the resourcefulness feature of resilience heavily relies on operators' reaction during weather emergencies. Panteli *et al.* [52] show that insufficient situation awareness and ineffective response by the operators has a high impact on the probability of cascading outages. Furthermore, a comprehensive model is suggested in [53] for incorporating the influence of operators' response time in the probabilistic reliability assessment of power systems. Hence, in addition to existing weather-related work where the effect of human response is usually neglected and within the concept of system-of-systems, situation awareness, decision-making, and information sharing between the system agents have be considered in the weather-related resilience studies.

Following the models in [52] and [53], during the weather event, the transmission system operators (TSOs) need to become adequately aware of the situation, coordinate with other potentially affected TSOs, and also coordinate with the RC to restore the damaged system components. The following events can thus result in the delay of the restoration of damaged components and the actions implementation during a weather event (see Fig. 5):

1) delay in the development of individual situation awareness in the affected control centers $(\Delta T_{\text{ind}})$;
2) delay in the information sharing between the system agents, either between TSOs $(\Delta T_{\text{inter-TSO}})$ or between TSOs and the RC $(\Delta T_{\text{TSO}-\text{RC}})$.

Since one of the key characteristics of resilience is its relation to time, the delay in human response to electrical and weather events must be considered in the resilience studies.

### B. Description of Resilience Assessment Methodology

The proposed resilience analysis model uses sequential MCS. Sequential MCS models the behavior of the system as a sequence of random events that affect each other as the system progresses through time. It is based on the random generation of times to failure (TTF) and times to repair (TTR) using the failure and repair rates of the power system components. A detailed description of this method can be found in [54].

However, differently from more conventional sequential MCS methods, in this approach, instead of using constant and weather-independent failures rates of the components for randomly generating their TTF at every simulation trial, a weather-dependent failure probability is used based on the evolving weather conditions at every simulation step. The permanent failure probabilities of the transmission lines and towers at each simulation step are provided here through their fragility curves, which express their failure probability as a function of the weather parameter. A generic fragility curve is shown in Fig. 6. The shape of the curve varies depending on the relation between the weather parameter and the component failure probability. Empirical statistical data would help develop highly accurate fragility curves.

The profile of the weather parameter, e.g., hourly wind profile or lightning density, is then mapped to these curves to obtain the hourly failure probabilities of the components at every simulation step. In this way, no distinction is made between normal and bad weather conditions, as it is assumed in the majority of the existing techniques, enabling the more realistic modeling of the weather as a continuously fluctuating phenomenon. More specifically, at every time step, a number in the range [0,1] is randomly generated and compared with the failure probability obtained from the fragility curve at the relevant value of the weather parameter (for example, wind speed). If the randomly generated number is larger than the failure probability, it is considered that the component does not trip. If the randomly generated number is lower than the failure probability, then the specific component is tripped. The TTR are randomly sampled when a component outage occurs. This procedure ultimately gives the operating state of each component at every simulation step.

As further comments on the modeling aspects, it has to be noted that an hourly resolution is chosen here to exemplify the methodology and based on the fact that hourly studies are usually deemed adequate for the purposes of modeling weather impact. However, the proposed methodology is applicable to any desired, possibly higher, time resolution of the weather profile, also depending on the data availability. In addition, the model could be extended to capturing the effect of multiple weather parameters acting simultaneously (for instance, wind and rain). This would require a multidimensional fragility curve that maps the magnitude of the relevant weather parameters (e.g., wind speed and rain intensity) onto the components' failure probability. Studies in this regard are object of future work.

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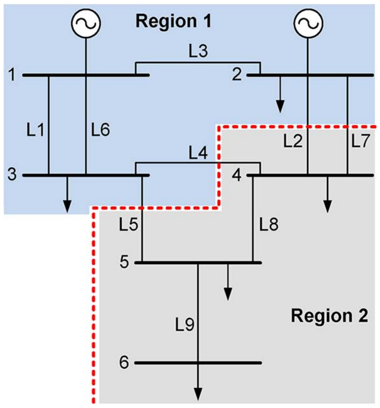


Fig. 7. Illustrative test system and weather regions.

A DC optimal power flow [55], [56] is used for assessing the system performance at every simulation step. For estimating the impact of weather on the frequency and duration of power interruptions, the loss of load frequency (LOLF) and loss of load expectation (LOLE) are used here as reliability indices [54]. The effect of different measures for enhancing grid resilience on these reliability indices is then evaluated, which will provide long-term adaptability and, as a result, will improve the short-term resilience features.

## V. Simulation Data, Case Studies, and Results

This section describes the test system, simulation data, and case studies used for illustrating the proposed resilience assessment methodology.

### A. Test System and Simulation Data

The IEEE 6-bus reliability test system [57] is used for illustrating the proposed methodology. Without loss of generality, the test system is arbitrarily divided in two weather regions, as shown in Fig. 7. As discussed in the previous section, the same weather is assumed within each region. Only the impact of wind on the permanent failure probability of the transmission lines and towers is considered here for illustrating the proposed resilience framework and assessment methodology. However, as aforementioned, any weather parameter or combination of weather parameters could in case be used if the relevant fragility curves are available. Three wind profiles with different density for each weather region are used here: normal, high, and extreme. These wind levels are used for illustrating the case studies, as discussed later. The normal probability distribution of the regional wind profiles is presented in Fig. 8. The hourly wind profiles can be obtained by sampling these probability distributions.

The wind fragility curves of the transmission lines and towers used here are shown in Fig. 9 (the two case studies, i.e., normal and robust, will be discussed later). The tower fragility curve is the output of a working package of the Resilient Electricity Networks for Great Britain (RESNET) project [58], in which the authors are involved. The line failure probability is assumed to be linearly increasing for high wind speeds (> 20 m/s), whereas the line normal failure probability is used for low wind

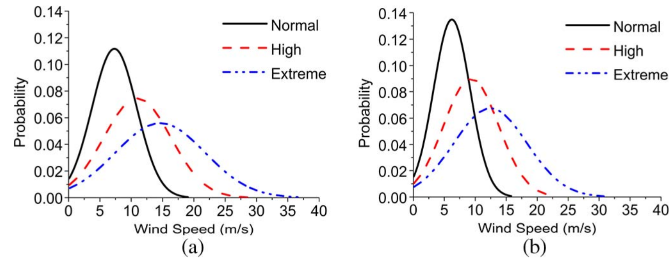


Fig. 8. Probability distribution of the regional wind profiles. (a) Region 1. (b) Region 2.

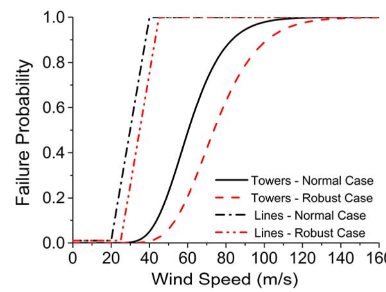


Fig. 9. Wind fragility curves of transmission lines and towers for the normal and robust networks.

TABLE I
PERCENTAGE OF LINES IN EACH WEATHER REGION

| Transmission Line | Line Percentage | |
|---|---|---|
| | Region 1 | Region 2 |
| L2 | 50 | 50 |
| L4 | 30 | 70 |
| L5 | 70 | 30 |
| L7 | 50 | 50 |

speeds (< 20 m/s), i.e., normal weather conditions, where the wind does not to have an impact on the line failure probability. It has to be noted that realistic line fragility curves are assumed here for illustration purposes. If empirical data for relating the line failure probability to the wind speed are available, then a more accurate line fragility curve can be used for real cases.

Using the weather regions in Fig. 7, four transmission lines (L2, L4, L5, and L7) are crossing two regions, experiencing different weather conditions at each region. Therefore, the impact of wind on their failure probability will be different in the two regions. At every simulation step, the highest wind speed of the two regions is detected and used for obtaining the failure probability of the transmission lines and towers using the wind fragility curves shown in Fig. 9. This results in the use of the highest line failure probability between the two regions. A percentage of the lines in each region is assumed for estimating the number of towers in every region (Table I), which are assumed to be every 300 m across the lines. The aggregated failure probability of each tower is then used to estimate the line failure probability due to a tower collapse. The hourly wind profile of each region is used for the lines within a single region for estimating the towers and lines failure probability at every simulation step. The line normal failure probability for low wind speeds is assumed to be 0.01.

In order to take into account the common cause failures due to a tower collapse, it is assumed that lines L1 and L6 and lines L2 and L7, respectively, are on the same transmission tower. It

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also has to be noticed that the illustrative case studies focus on permanent outages on the transmission lines and towers because of their significant impact on the frequency, duration, and number of customer disconnection. Therefore, the lines' average outage duration is considered 10 h [57], whereas it is assumed that the towers' average outage duration is five times larger, i.e., 50 h. The restoration time during high and extreme wind speed events is considered to be double the restoration time during normal wind speed events.

### B. Case Studies

In order to evaluate the impact of weather on the reliability indices and the importance of the key resilience features and resilience enhancement measures discussed in Sections II and III, the following case studies are developed.

1) *Normal network*: The reliability indices are estimated without and with considering the wind effect on the failure probability of the transmission lines and towers. The fragility curves shown in Fig. 9 are used.
2) *Robust network*: The line and tower fragility curves are modified to make the components more robust to higher winds. This can be achieved by using better and stronger materials for the transmission lines and towers, and it reflects the robustness feature of resilience. The fragility curves for the robust network are shown in Fig. 9.
3) *Redundant network*: Parallel identical lines are added to lines L3, L4, L5, L8, and L9 to make the transmission network fully redundant. This refers to the redundancy/resourcefulness feature of resilience.
4) *Response network*: It is assumed here that the restoration time during high and extreme wind speed events is equal to the restoration time during normal wind speeds. This refers to the response/recovery features of resilience.

For evaluating the impact of human response in the context of system-of-systems as aforementioned, a delay in their reaction following an electrical event is added. Based on historical power system blackouts, such as [2]–[5], this delay varies from minutes to several hours. Therefore, regarding the duration of the delay and considering that an hourly simulation step is used, an increasing delay for the three wind levels is inserted, i.e., 1, 3, and 5 h, respectively. This reflects the increasing difficulty of the operators to cope with the growing amount of alarms and data as the weather event becomes more adverse, resulting in a higher deterioration of the system state. It can be assumed here that the two weather regions in Fig. 7 represent the two independent TSOs shown in Fig. 5. This delay is inserted in each case study discussed above for evaluating the importance of operators' effective reaction under different system structures and topologies, i.e., robust and redundant networks, respectively, and operational procedures, i.e., response network.

The robust and redundant networks refer to the preventive structural and topology measures to improve grid resilience. The response network can also be considered a preventive measure, as the emergency procedures are enhanced prior to the weather event to enable the faster post-disturbance restoration. These resilience enhancement measures indicate the outcome of the adaptability studies following a weather event and are applicable to any power system. The delay in the operators' reaction affects the effectiveness of the corrective actions during and after the weather/electrical emergency.

TABLE II
SIMULATION RESULTS

| Case Study | Reliability Indices | | | | | |
|---|---|---|---|---|---|---|
| | LOLF (occs./week) | | | LOLE (hrs/week) | | |
| | Normal | High | Extreme | Normal | High | Extreme |
| Normal | 0.039 | 0.041 | 0.131 | 0.4 | 0.44 | 0.73 |
| | 0.042 | 0.048 | 0.16 | 0.41 | 0.47 | 0.83 |
| Resilience Enhancement Measures | | | | | | |
| Robust | 0.026 | 0.028 | 0.04 | 0.35 | 0.38 | 0.43 |
| | 0.037 | 0.039 | 0.052 | 0.39 | 0.42 | 0.55 |
| Redundant | 0.032 | 0.035 | 0.042 | 0.37 | 0.4 | 0.44 |
| | 0.035 | 0.037 | 0.049 | 0.38 | 0.41 | 0.52 |
| Response | 0.026 | 0.038 | 0.13 | 0.3 | 0.34 | 0.65 |
| | 0.036 | 0.042 | 0.14 | 0.34 | 0.38 | 0.71 |

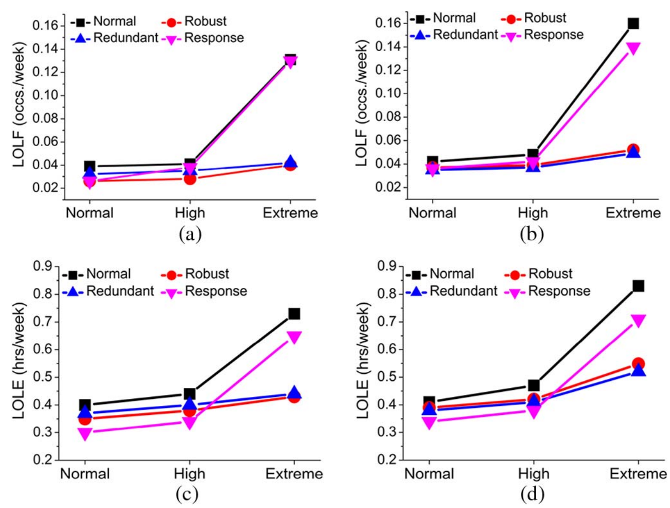


Fig. 10. Graphical presentation of simulation results. (a) No delay LOLF. (b) Delay LOLF. (c) No delay LOLE. (d) Delay LOLE.

Each case study is illustrated for the three wind levels in Fig. 8. This provides an indication of the grid resilience to different wind profiles, which represent increasing stress levels imposed to the transmission network. An hourly simulation step and the hourly load profile provided in [57] are used. As mentioned above, the use of hourly resolution is, in general, deemed adequate for modeling different wind phenomena, ranging from moderate wind events to severe storms and hurricanes (see, for instance, [43] and [45] for similar studies). A simulation window of one week is considered in the studies. A winter week is used, where the peak demand of the test system is observed and high winds are usually expected. The considered reliability metrics LOLE and LOLF indicate the average number of hours that some customers are disconnected due to events on the transmission network and the number of occurrences of such disconnections per week, respectively.

### C. Simulation Results

Table II and Fig. 10 show the LOLF and LOLE for the case studies and the wind levels considered here. In each case study, the first row in Table II shows the system indices without delay,

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and the second row shows the system indices with delay. The LOLF and LOLE without considering the impact of wind and delay is 0.026 occurrence/week and 0.29 h/week.

When the effect of wind on the failure probability of the electrical components is taken into account, it can be seen that these indices increase as the components become less resistant (i.e., higher failure probability) to the fluctuating weather conditions, and therefore, the entire system becomes less resilient. In addition, LOLF and LOLE increase as the wind density increases from normal to extreme. Particularly, the system indices significantly increase in the extreme wind scenario for the normal and response networks. In contrast, the robust and redundant networks are less sensitive to the change in the wind speed, as a smaller increase in LOLF and LOLE is observed with the increase in the wind level. This shows that the structural and topology improvements make these networks more resilient to weather-related outages.

Comparing the robust and redundant networks with the normal network, it can be seen that LOLF and LOLE are lower for all the wind levels. Therefore, the higher resistance and resourcefulness, respectively, result in lower frequency and duration of power interruptions. Additionally, the difference in LOLF between the robust and redundant networks is the lowest in the extreme wind scenario (when the delay is not considered), which shows that for extreme wind events, the robust and redundant networks have the same impact on system resilience. This is because the frequency of component outages is high, even for the robust network. It has to be noted, however, that for normal wind levels, the robust network leads to equal LOLF with the scenario when the wind effect is not considered (0.026 occurrence/week).

The response network leads to a decrease in LOLF for normal and high wind levels, as a fast reaction to the weather-related outages reduces the probability of outage propagation. However, LOLF is almost equal to the LOLF of the normal network for the extreme wind level. This is because of the higher frequency of the component outages under the extreme wind phenomena.

Regarding LOLE, a comparable duration of customer interruption is observed for the robust and redundant networks. The response network has the lowest LOLE under normal and high wind speeds, but it significantly increases for the extreme wind scenario due the higher outage probability of the components. However, it is still lower than the LOLE of the normal network.

When the delay in operators' reaction is included [see Table II, second row, and Fig. 10(b) and (d)], the lack of a fast response to the electrical events results in a higher probability of cascading outages and, thus, in a higher LOLF and LOLE for all the case studies. The LOLF of the redundant network becomes slightly smaller than the LOLF of the robust network. This shows that the resourcefulness provided by the redundancy leads to higher resilience when the operators do not react rapidly following the electrical incident. In addition, when the delay is considered, the response network leads to lower LOLF (0.14 occurrence/week) than the normal network (0.16 occurrence/week) in the extreme wind scenario. LOLE remains the lowest for the response network in the normal and high wind speed levels, but it increases in the extreme wind scenario.

### *D. Discussion*

The simulation results show that the test system can cope quite effectively with the normal and high wind levels, but the frequency and duration of customer interruption significantly increases for the extreme wind level. This reflects the actual behavior of power systems exposed to fluctuating weather conditions, i.e., to be robust ("adequate") to foreseeable normal and abnormal weather conditions as expected in a well-designed and operated system, but to be vulnerable (not "resilient") to unforeseeable extreme weather conditions. For example, LOLF in the extreme wind scenario is more than three times larger than the LOLF in the normal wind scenario for the normal network (0.131 and 0.039 occurrence/week, respectively). Although the probability of extreme wind events is low, as shown in Fig. 8, the simulation results show that their impact may be so high that resilience enhancement measures might have to be applied, such as increasing the components' robustness and adding redundant transmission routes. This would ultimately have to be supported by cost–benefit analysis considerations that also take account of possible dramatic consequences of HILP events.

As concluded from Table II and Fig. 10, developing and maintaining sufficient situation awareness that results in a fast and effective reaction is critical during weather emergencies. It is therefore important to support the human decision-making with advanced visualization and information systems, which further highlights the system-of-systems features of the resilience framework discussed here. The simulation results show that the redundant network is the least sensitive to the delayed reaction by the operators, as the lowest increase in LOLF is observed. In addition, comparing the normal and response networks can be seen that having in place effective preparedness plans mitigates the impact of delayed reaction by the operators, which is an inevitable phenomenon due to the human nature of the operators.

## VI. Conclusion

Power systems are traditionally reliable during normal conditions and foreseeable contingencies, but may not be adequately resilient to HILP events, such as severe weather phenomena and natural hazards. In contrast to reliability, the concept of resilience in power systems and its main threats is still not entirely clear, particularly in terms of modeling aspects and quantitative analyses. This paper has provided a general overview of the resilience definitions that are applicable to any CI and then discussed how the key resilience features can be matched to the fundamental characteristics of a power system. The proposed resilience conceptual framework provides the basis for understanding power system resilience and developing resilience-oriented studies.

Severe weather, as a HILP event, has a significant impact on the grid resilience, as it affects the reliability of the outdoor system components. A review of the main aspects to consider when assessing the impact of weather on the resilience of a power system is provided in this paper, such as the effect of weather on the repair rate of the components. A novel time-series resilience analysis model is developed using sequential MCS, which is capable of capturing the stochastic behavior

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and impact of wind events. In order to reflect the impact of wind on the permanent outage probability of the transmission towers and lines, fragility curves are used that express the outage probability as a function of the wind speed. The proposed methodology is flexible as any weather parameter can be modeled if its fragility curve is available. In addition, the development of multidimensional fragility curves expressing the correlated effect of multiple weather parameters, e.g., wind speed and rain intensity, will be considered in future studies, as this would be a more realistic representation of the components' failure probability. As mentioned in this paper, this can be easily accommodated in the proposed sequential MCS-based methodology, provided that such fragility curves are available.

The simulation results show that weather has a significant impact on the frequency and duration of customer disconnection and that the impact may be highly nonlinear with the severity of the weather event. This is particularly important as it is expected that power systems might become more subject to extreme weather in the future due to climate change. Therefore, measures have to be taken to enhance the grid resilience to adverse weather events. The case studies developed in this paper show that improving the short-term resilience features, i.e., making the transmission towers and lines more robust, adding redundancy, and improving the responsiveness and preparedness to a weather emergency, help enhance the grid resilience. It is also shown that operators' situation awareness and reaction during a weather emergency affect the grid resilience. Additional smart solutions, such as demand response, energy storage, and system integrity protection schemes, will be evaluated in future studies for further boosting the resilience of power systems to extreme weather events. The cost and benefit of implementing these smart solutions will then be compared with alternative system reinforcement options to decide on the most suitable and cost-effective measures for improving grid resilience.

The proposed resilience framework and assessment methodology, whereby the system-of-systems dimension of the problem fully emerges, are applicable to any power system. Their application to real contexts can help electrical utilities and system operators recognize the degree to which their system is vulnerable to extreme weather. This, in turn, can support the implementation of appropriate resilience measures for mitigating the influence of climate change and severe weather and eventually inform regulators and policy makers about suitable directions to improve the resilience of critical power infrastructure. The application of the proposed approach to real power systems can also help validate its accuracy. This can be done by comparing the simulation output with recorded data showing the statistical impact of weather on LOLF and LOLE in similar conditions as the simulated ones. Work in this direction is being carried out on a model of the Great Britain transmission network and will be object for future publication.

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