Electric Power Systems Research 136 (2016) 352–361

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Multi-phase assessment and adaptation of power systems resilience to natural hazards

Sebastián Espinoza[a,b], Mathaios Panteli[b,*], Pierluigi Mancarella[b], Hugh Rudnick[a]

[a] Department of Electrical Engineering, Pontificia Universidad Católica de Chile, Avda. Vicuña Mackenna 4860, Santiago 7820436, Chile
[b] School of Electrical and Electronic Engineering, The University of Manchester, Oxford Road, Manchester M13 9PL, UK

ARTICLE INFO

Article history:
Received 25 August 2015
Received in revised form 1 March 2016
Accepted 13 March 2016
Available online 31 March 2016

Keywords:
Electric power systems
Floods
Fragility curves
Resilience
Resiliency
Windstorms

ABSTRACT

Extreme weather hazards, as high-impact low-probability events, have catastrophic consequences on critical infrastructures. As a direct impact of climate change, the frequency and severity of some of these events is expected to increase in the future, which highlights the necessity of evaluating their impact and investigating how can systems withstand a major disruption with limited degradation and recover rapidly. This paper first presents a multi-phase resilience assessment framework that can be used to analyze any natural threat that may have a severe single, multiple and/or continuous impact on critical infrastructures, such as electric power systems. Namely, these phases are (i) threat characterization, (ii) vulnerability assessment of the system's components, (iii) system's reaction and (iv) system's restoration. Second, multi-phase adaptation cases, i.e. making the system more robust, redundant and responsive are explained to discuss different strategies to enhance the resilience of the electricity network. To illustrate the above, this time-dependent framework is applied to assess the impact of potential future windstorms and floods on a reduced version of the Great Britain's power network. Finally, the adaptation cases are evaluated to conclude in what situations a stronger, bigger or smarter grid is preferred against the uncertain future.

1. Introduction

Natural disasters around the world, such as floods, ice and windstorms, hurricanes, tsunamis and earthquakes, have had a significant impact on countries' public security and economic prosperity [1]. Furthermore, it is expected that these events may occur more often and with greater severity, mainly because of global warming and climate change [2]. Therefore, it is a necessity to develop techniques for assessing the impact of natural disasters in a comprehensive and systematic way, which will enable the resilience enhancement to these catastrophic events.

Electric power systems, as critical infrastructure, are the backbone of modern societies. It is therefore crucial to design power systems that are resilient to potential high-impact low-probability events that may be driven by natural hazards and related to climate change. Within power systems, the concept *resilience* can be broadly defined as the ability of a power system to withstand the initial shock, rapidly recover from the disruptive event and apply adaptation measures for mitigating the impact of similar events in the future. A comprehensive resilience framework is presented in [3], where five key resilience elements are used to associate the short-term resilience of power systems to an event as well as their long-term resilience, namely: robustness/resistance, resourcefulness, redundancy, response and recovery, and adaptability. These key elements can be seen in the existing research for assessing the impact of earthquakes, hurricanes and windstorms on the electric power systems [4–7].

In [4], a joint effort of European universities analyzes the impact of earthquakes on various cities and different critical infrastructures, including the power system of Sicily. This study includes the use of fragility curves and an object-oriented programming to assess the pre- and post-disaster performance of the network. In [5], the impact of windstorms is analyzed using wind fragility curves, running DC optimal power flows on the IEEE-6 bus reliability test system and comparing different adaptation cases. The resilience of the electric system of Harris County, Texas, US, is evaluated in [6] by running four models: hurricane hazard model, components fragility model, power system response model and

* Corresponding author. Present address: Department of Electrical and Computer Engineering, University of Cyprus, 75 Kallipoleos Street, 1678 Nicosia, Cyprus. Tel.: +357 99459252.
E-mail addresses: sebaesp@puc.cl, sebastian.espinoza@manchester.ac.uk (S. Espinoza), mathaios.panteli@manchester.ac.uk (M. Panteli), p.mancarella@manchester.ac.uk (P. Mancarella), hrudnick@ing.puc.cl (H. Rudnick).

http://dx.doi.org/10.1016/j.epsr.2016.03.019
0378-7796/

restoration model. The results are classified in technical, organizational and social dimensions of resilience. In [7], micro-components of the transmission network under seismic stress are modeled to assess the resilience of the power system in Los Angeles, US. The vulnerability is also modeled with fragility curves and, as a result, risk curves are developed. Another notable effort towards practical use that has involved software developments is Hazus, from the Federal Emergency Management Agency [8]. Other governmental programmes, which share the concept of resilience with the present paper, include Ergo-EQ, from Mid-America Earthquake Center [9], Rt, from In Risk—a project funded by Natural Sciences and Engineering Research Council of Canada [10], and the Central American Probabilistic Risk Assessment (CAPRA), a platform developed by Central American Governments [11]. Even though the recent work on the topic has been a huge step towards understanding and measuring resilience, further research in this area remains a concerning issue given the consequences of these and other catastrophic threats to different systems around the world.

The novelty of this paper lies in the formalization of a multi-phase resilience assessment framework along with multi-phase strategic adaptation cases to enhance the resilience of critical infrastructures, with focus on electric power systems and weather hazards. In particular, the main phases of the proposed resilience assessment framework are: (i) *threat characterization*, (ii) *vulnerability of the system's components*, (iii) *system's reaction* and (iv) *system's restoration*, and the *enhancement* or *adaptation* strategies for the second, third and fourth phases are: (i) *normal case*, (ii) *robust case*, (iii) *redundant case* and (iv) *responsive case*, respectively [5,12].

In brief, given the magnitude and time profile of the weather-hazard, the concept of fragility curves is used, which provides the failure probabilities of the power system's components as a function of a weather parameter (e.g. wind speed) at any given time. By mapping the time-series weather profile to these fragility curves, the weather-dependent failure probabilities are obtained, which are then fed to a Sequential Monte Carlo-based simulation. This altogether allows the stochastic and spatiotemporal modeling of the natural hazards as they move across the system. In order to account for the uncertainty associated with the projected severity of weather events in the future, parametric studies and extreme value theory (which provides different intensities of weather events depending on the chosen return periods) are applied for analyzing a wide range of potential future scenarios. The multi-phase resilience assessment tool presented in this paper provides thus a systematic approach for evaluating the impact of extreme weather events as a direct impact of climate change, as well as investigating different ways for improving the resilience of power systems to such catastrophic events.

The organization of the paper is as follows: in Section 2, the influence of extreme weather and climate change on power systems is described. Then, in Section 3, the four-phase resilience assessment framework is outlined along with enhancement measures and the strategic adaptation cases. Thereafter, in Section 4, the resilience framework and adaptation cases are applied using a reduced version of the Great Britain's power system for assessing the impact of different scenarios of windstorms and floods on the test system. In Section 5, the simulation results are presented. Finally, Section 6 summarizes and concludes the paper.

2. Influence of extreme weather and climate change on electrical power systems

Many natural threats can include not just one single instantaneous impact, but multiple and even continuous impacts. For instance, the windstorms that affected China in 2005 produced more than 60 high voltage transmission towers to collapse, and the ice and snowstorms that devastated a large area in the south of the country lasted for hours [13]. Disasters can even last for days, like the hurricane Sandy in the US, where numerous substations, lines and transformers were damaged resulting in power outages across 16 states [1]. Most recently, two earthquakes hit Nepal in less than 20 days, producing devastating effects [14]. In a similar way, Chile was impacted in 2010 by an earthquake and tsunami followed by a severe replica within two weeks [15]. Therefore, it is imperative to develop a comprehensive analysis combining a suitable period of time and in a time-dependent way. So as to answer questions as: What hazard's intensity can the system withstand? How is the restoration going to be managed and in what time? What happens if a second impact occurs?

2.1. Extreme weather events

A disruptive weather event can be classified into small, moderate, serious, major and extreme based on the number of customers disconnected, the duration and frequency [16]. Great Britain is significantly affected by weather-related electrical faults.

In [17], it is reported that only from April 2008 to March 2009, 211 faults occurred on the transmission network in England and Wales and further 44 in Scotland, of which 23 and 95%, respectively, were caused by weather. For example, several transmission substations and power stations are at high risk of flooding, while high winds can cause transmission lines and towers to collapse. The Climate Change act of 2008 required that the UK electricity industry reported on adaptation measures to deal with the effects of weather and the effect of climate change [18]. This motivates to analyze particularly windstorms and floods in this paper.

2.2. Climate Change and future hazard scenarios

In 1992, the United Nations Framework Convention on Climate Change (UNFCCC) was created with the objective to "stabilize greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interface with the climate system" [2]. To achieve this, the Intergovernmental Panel on Climate Change (IPCC) supports UNFCCC producing reports of the scientific, technical and socio-economic aspects of global warming.

According to the IPCC, climate change projections may vary from region to region, but generally it is likely that wet and dry extremes are going to become more severe [2]. In Great Britain, particularly for the variables studied here, reports indicate that while wind has a high uncertainty on how it will change [17], flood risk will escalate because of the potential increase of rainfall volume, intensity and frequency [19]. Unfortunately, existing studies disagree on the quantitative changes of rainfall volume, intensity and frequency [17].

3. Multi-phase resilience assessment and enhancement framework

Reliability aspects, related specifically to security and adequacy, have traditionally driven power system operation and planning. This has helped to build systems designed and operated to be reliable during normal conditions and abnormal but foreseeable contingencies. However, dealing with unexpected and less frequent severe situations still remains a challenge. In this section, the resilience and enhancement framework of Fig. 1 is proposed for evaluating the impact of natural disasters on the resilience of power systems and the effect of possible adaptation strategies.

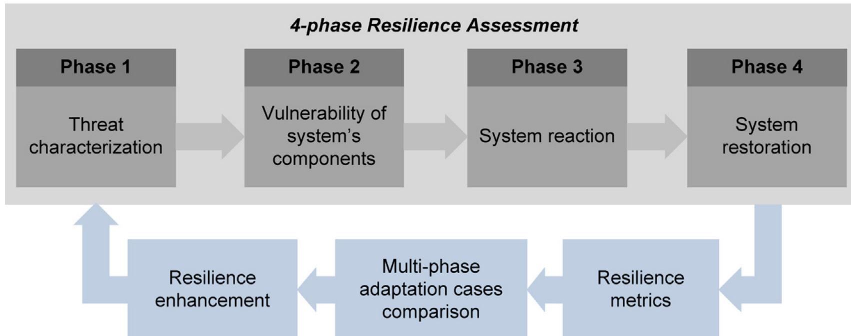

Fig. 1. The multi-phase resilience assessment and enhancement procedure.

3.1. The 4-phase resilience assessment framework

The proposed resilience assessment framework consists of four phases or stages: (i) threat characterization, (ii) vulnerability of system's components, (iii) system reaction or operation and (iv) system's restoration. Fig. 2 presents the model's flow chart that explains the simulation procedure for assessing the network's resilience following these four phases. As it can be seen in the flow chart, first the hazard scenarios are produced (phase one). Then a Sequential Monte Carlo Simulation (SMCS) is performed. After loading the electric power system and scenario hazard, each component is independently conditioned to a certain hazard's magnitude given by the scenario picked, thereafter, the damage states of the components are assigned using a probabilistic fragility curve (phase 2). Next, the system is deterministically operated running an AC or DC OPF (phase 3) and finally each component is restored following a recovery probabilistic distribution (phase 4). This is repeated sequentially for the defined time frame and all the scenarios produced in the first phase. The SMCS method applied is flexible, parallelizable and highly suitable to this problem given the great amount of random variables.

3.1.1. Phase 1: Threat characterization

The objective of this phase is to model the magnitude, probability of occurrence and spatiotemporal profile of a hazard. To do this, the causes, physical aspects and consequences of the threat must be understood. Two approaches can be taken, one is building deterministic scenarios, where a historic event is modeled, and the other is building probabilistic scenarios, where potential future scenarios are projected. For the deterministic modeling, depending on the natural hazard under investigation, different tools can be used. For extreme weather events, generally the weather database needed may be built by acquiring information through Climate Models (CMs) or by using real measurements with time and geographic

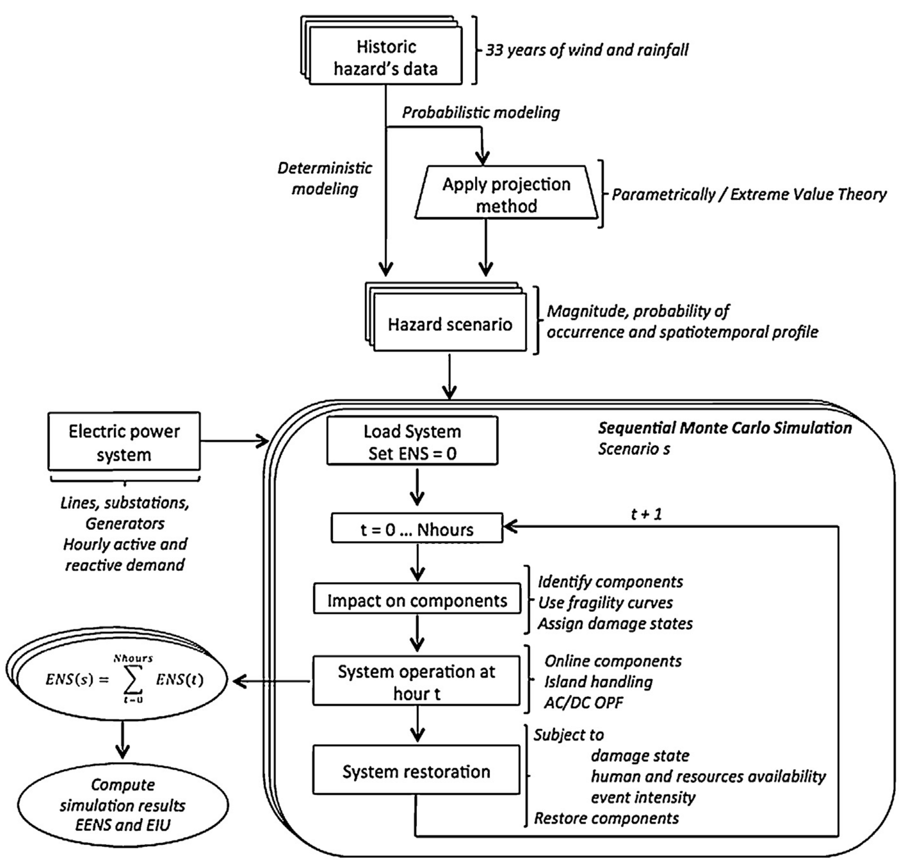

Fig. 2. The 4-phase resilience assessment model flow chart.

features from weather stations. CMs are models able to simulate the interactions of climate drivers including atmosphere, oceans, land surface and ice. In this research, CMs are used with the purpose to reproduce past threat scenarios with a certain geographic and time resolution.

For probabilistic scenarios different projection methods can be used. The selected method has to be suitable to be applied to weather events and to be able to make an estimate of anticipated forces, possibly much greater than have ever been observed, using historical or model-generated data. For the case of data generated by CMs, parametric studies are useful, where the parameters are modified by a certain factor (usually taking in consideration real extreme measurements or expert knowledge). For the case of instrumentally measured data, one option is power law, which has modeled numerous natural phenomena, such as the Gutenberg-Richter number-size distribution of earthquake magnitude and other probabilistic predictions of data behavior [20]. A second option, which is later used in this study, is extreme value theory (EVT) [21], which is based on the distribution of the maximums (or minimums) by defining a return period T (e.g. 100-years) and estimating its return value $X(T)$ (e.g. 60 mm). This would mean that an event of $X(T)$ is estimated to happen every T years. EVT has two main approaches: Block Maxima Approach (BMA) and Peaks Over Threshold (POT). Both approaches, have the aim of estimating $X(T)$ for rare extreme events. In the case of BMA, this is done by a parametric modeling of maximums (or minimums) taken from large blocks of independent data. In the case of POT, this is done by a parametric modeling of independent exceedances above a large (or low) threshold. Both approaches then use the Generalized Extreme Value (GEV) distribution [22,23]. GEV has the flexibility of combining the three types of extreme distributions, namely Type I-Gumbel, Type II-Fréchet and Type III-Weibull. GEV's cumulative distribution function (CDF) is as follows.

$$F\left(x;\psi,\beta,\xi\right)=e^{-\left(1+\xi\left(x-\psi/\beta\right)\right)^{-1/\xi}},\quad \text{for}\quad 1+\frac{\xi\left(x-\psi\right)}{\beta}>0 \qquad (1)$$

In Eq. (1), ψ (location), β (scale) and ξ (shape) are the three main parameters of GEV. The particular cases of $\xi=0$, $\xi>0$ and $\xi<0$ are, respectively, equivalent to the distributions Type I, whose tails decrease exponentially; Type II, whose tails decrease as a polynomial and Type III, whose tails are finite. When the parameters are estimated to fit the dataset, a projection diagram can be drawn to visualize the return periods and return values [24].

3.1.2. Phase 2: Vulnerability of system's components

The aim of this phase is to determine the damage level of each component of the system. To do this, the following three steps are considered: (i) identify the vulnerable components, (ii) fragility modeling of components and (iii) assign damage states.

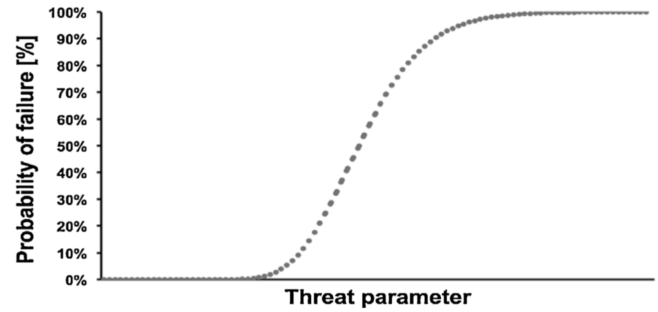

Fig. 3. Generic fragility curve: probability of failure (%) vs threat parameter.

In the first step, the components identified are those that are vulnerable-to-the-threat that could possibly have a high impact on the network resilience. Also, the type of component must be selected. In electric power systems, components can be classified in macro or micro [4]. For example, high/medium/low voltage substations/power plants, distribution circuits, transmission towers and lines can be classified as macro components. Circuit breakers, transformers, lightening arrester, switches and all those elements that describe the internal logic of macro components are micro components. The use of one or another depends on the objectives of the resilience study being undertaken.

The second step corresponds to modeling the fragility of the components to the natural threats. The concept of Fragility Curves has its origins as a structural reliability concept [25,26], and is a useful tool for a stand-alone analysis of each component. A fragility curve, as shown in Fig. 3, expresses the probability of failure of a component conditioned on the impact of the hazard. In practice, these failure probabilities are compared with a uniformly distributed random number $r\sim U(0,1)$. If the failure probability of the component is larger than r, then the component fails.

It is important to note that a "failure" of the component does not necessarily imply a complete collapse of the component (i.e. removal from service). For example, after a seismic movement a power plant that is composed by more than one generator might have just a portion of them out of service, meaning that the power plant will be able to work at a degraded maximum generation capacity. At the same time, other components such as transmission lines have a binary damage state; tripped or non-tripped. Thus, as a third step, the damage state of the components must be addressed. In order to do this, two approaches can be used as shown in Fig. 4, where (a) uses different fragility curves for different damage levels (as used by [8]) and (b) relates damage level to the zone of the fragility curve defined by percentiles (as used in this study).

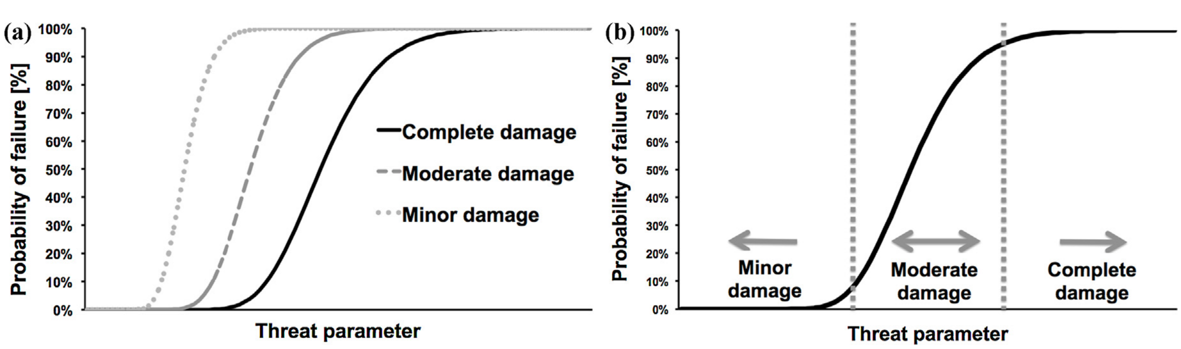

Fig. 4. (a) Different fragility curves to assign damage states. (b) Different zones in the fragility curve to assign damage states.

3.1.3. Phase 3: System reaction

The objective of the third phase is to evaluate the performance of the critical infrastructure when it is exposed to the extreme event. In electrical power systems, to do this, numerous evaluation tools have been developed over the last decades; such as the CASCADE model, which studies the cascading mechanism of a blackout [27]; the ORNL-PSERC-Alaska (OPA) model, which is based on a DC optimal power flow and it is built upon Self-Organized Criticality [27–29]; the Hidden Failure model, which is based on approximated DC power flow and standard linear programming optimization of generation redispatch to represent hidden failures of the protection system [30]; and the Manchester model, which is built upon AC power flow and used load shedding and a power flow solution to determine the power system operation [31–33].

When modeling the impact of extreme weather events, it is important to take into account the diverse impact of the weather fronts moving across the system, which is both spatial- and temporal-dependent. The resilience model used in this phase should thus be capable of capturing this spatiotemporal stochastic impact of the natural disasters on the resilience of power systems. It should also be capable of providing a component and area vulnerability index, which will enable the resilience enhancement of the most vulnerable components. Furthermore, following the disaster, it is very likely that the system will be divided in multiple islands, which should be incorporated in the impact assessment model.

3.1.4. Phase 4: System restoration

The response to the disaster and the restoration times following the disaster are strongly related to the following three aspects: (i) to the damage caused, (ii) to the amount of human and material resources available, and (iii) to the accessibility of the weather-affected area. The restoration process can only be undertaken under the condition that both repair teams and spare parts are available. The fast restoration and recovery of critical infrastructure is a crucial feature of resilience (as discussed in Section 1). Therefore, proper and effective emergency and restoration strategies should be in place to restore the system to its pre-disaster state as fast as possible.

3.2. Enhancement measures and strategic adaptation case studies

The probability of extreme weather events is relatively low, but their impact is so high that is vitally important to enhance the resilience of critical infrastructures. Particularly, for electric power systems, this can be achieved through a wide range of short- and long-term measures. Short-term measures are discussed in detail in [3,34]. Long-term measures can be grouped in strategic adaptation cases that improve specific phases of the resilience of the system. Namely, the cases are: (i) Normal, which is the basic network; (ii) Robust, which improves the resistance of the system; (iii) Redundant, which includes backup installations or spare capacity enabling the diversion of the power flows to alternative parts of the network; and (iv) responsive, which enables a faster response from the disruptive events. It can thus be seen that these adaptation case studies can improve, respectively, the 2nd, 3rd and 4th phases of the resilience framework.

4. Resilience assessment framework applied to windstorms and floods

4.1. The Great Britain simplified electric power system

The multi-phase resilience assessment framework is illustrated by assessing the impact of windstorms and floods on a reduced version of the GB's network, which is shown in Fig. 5(a). The grid consists of 29 nodes, 98 overhead transmission lines in double circuit configuration and one single circuit transmission line between nodes 2 and 3, and 65 generators (with 81.5GW of installed capacity) which are located at 24 nodes and include several technologies, such as wind, nuclear and CCGT. This simplified network is based on and has been validated against a solved AC Load Flow reference case that was provided by National Grid Electricity Transmission (NGET), the transmission system operator of Great Britain [35]. It includes the main transmission routes, relevant demand information and generation characteristics.

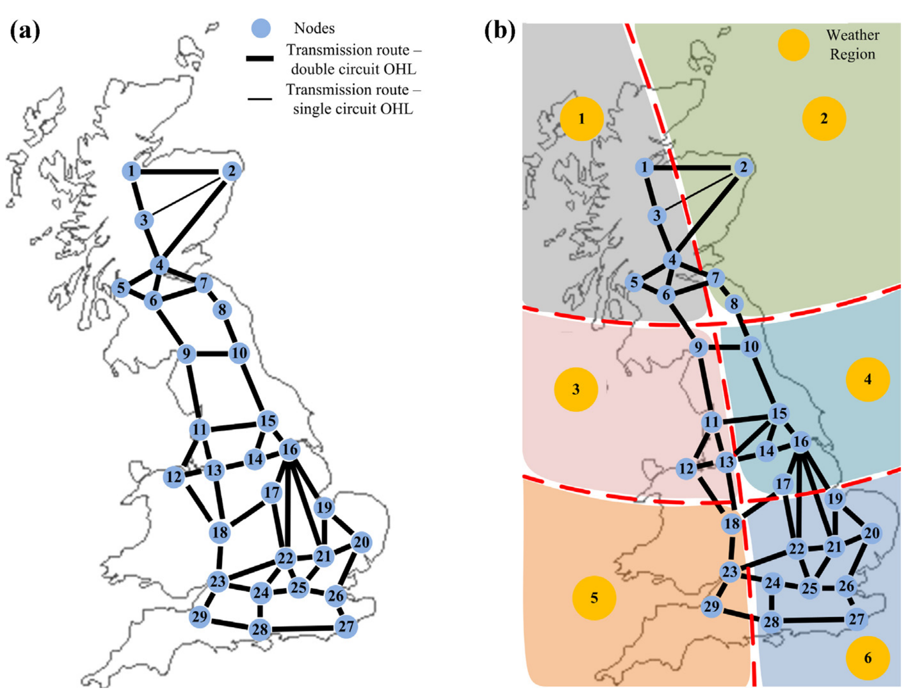

Fig. 5. (a) Great Britain's simplified system. (b) Weather regionalization of the system.

4.2. Multi-phase resilience assessment of Great Britain's electric power system

4.2.1. Phase 1: Windstorms and floods characterization

The resilience of the test network is evaluated against windstorms and floods, which constitute severe threats to the Great Britain's network. In order to account for the spatial feature of the weather events, the test network is arbitrarily divided into 6 weather regions, as shown in Fig. 5(b). Weather conditions are assumed to be homogeneous within each region, so all components in the same weather region are stressed by the same hazard's magnitude. Potential future scenarios were modeled as explained hereafter.

For the windstorms modeling, the main characteristic is the geographic mapping of the location and magnitude of wind speed. Therefore, hourly mean wind data for 33 years (1979–2011) was obtained using the Climate Model called MERRA re-analysis [36]. On the other hand, floods are more complex and affected by many factors, such as the capacity of drainage system, saturated ground, high river levels and accumulated rainfall. But in general, especially river and groundwater floods are strongly related to the last variable. For example, in [37] flood is linked directly to accumulated rainfall. The hourly rainfall data for the same years, i.e. 1979–2011, was obtained from more than 17,000 rain gauge stations all over Great Britain, which has been provided by MET Office, UK [38]. This analysis altogether provides the temporal characterization of the threats: 33 years of wind and rainfall profiles with hourly resolution.

In order to deal with the uncertainty associated with the future weather conditions as a direct impact of climate change, five scenarios have been developed for evaluating the impact of windstorms, floods and both hazards together.

Given that wind speed was taken from a Climate Model, where the focus is on average measurements (with a maximum average of approximately 20 m/s), one suitable approach to use in order to model extreme winds that can damage the transmission components is to parametrically scale up the wind profiles. Therefore, the winds profiles of the 6 weather regions have been scaled up using a multiplication factor in the range {1,3} in steps of 0.5, resulting in five windstorm scenarios (meaning that ×2 and ×3 would represent approximately wind speeds of 40 and 60 m/s, respectively). The wind profile is scaled up by the same factor in the whole network, so the impact affects the entire network instead of specific areas.

For floods, given that the rainfall data was taken from real measurements, five levels were also modeled by applying extreme value theory. Assuming the data is independent and identically distributed, the Block Maxima Approach (BMA) and the Generalized Extreme Value (GEV) distribution was used. Then the parameters of the GEV distribution were estimated to fit the dataset and a

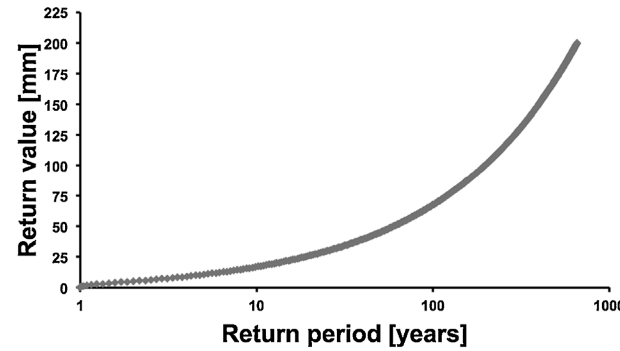

Fig. 6. Projection diagram for Region 4 (horizontal axis in logarithmic scale).

Table 1
Threats analyzed with their correspondent key vulnerable components identified.

Threat	Vulnerable components	
Windstorms	Transmission lines	Transmission towers
Floods	Substations	Power plants

projection diagram was drawn for each region. An example of a projection diagram for Region 4 is shown in Fig. 6.

Thereafter, five return periods were chosen (i.e. 10-year, 33-year, 100-year, 150-year and 250-year), which provided five return values for peak rainfall within 1 h for every region. For example, for Region 4 the return values projected were: 17 mm, 32.9 mm, 59.7 mm, 74.1 mm and 97 mm, respectively, (which is reasonable taking into account that the highest hourly rainfall recorded by Met Office was 92 mm in 1901 [39]). Then, rainfall scale parameters are calculated with Eq. (2), where given a return period λ-year, the scale parameter, $\pi(\gamma, \rho, \lambda)$, for the year γ and region ρ is equal to the return value $T(\lambda\text{-year})$ [mm] divided by the peak rainfall value of year γ in the region ρ, $P(\gamma, \rho)$ [mm].

$$\pi(\gamma, \rho, \lambda) = \frac{T(\lambda - \text{year})}{P(\gamma, \rho)}, \quad \text{for} \quad \gamma \in [1979, \ldots, 2011] \tag{2}$$

4.2.2. Phase 2: Vulnerability of electrical components

Even though most frequent faults happen at a distribution level, less common but with a higher impact occur at a transmission and generation level. Because of this, and to be able to have a nation-wide perspective of resilience this research focuses on the generation and transmission level. The key vulnerable macro components shown in Table 1 were identified and modeled.

Subsequently, the vulnerability of each identified component is analyzed through fragility curves. Examples of lines and towers' wind fragility curves are presented in Fig. 7(a) [5]. Likewise, in Fig. 7(b), the flood fragility curves used are shown. Floods are

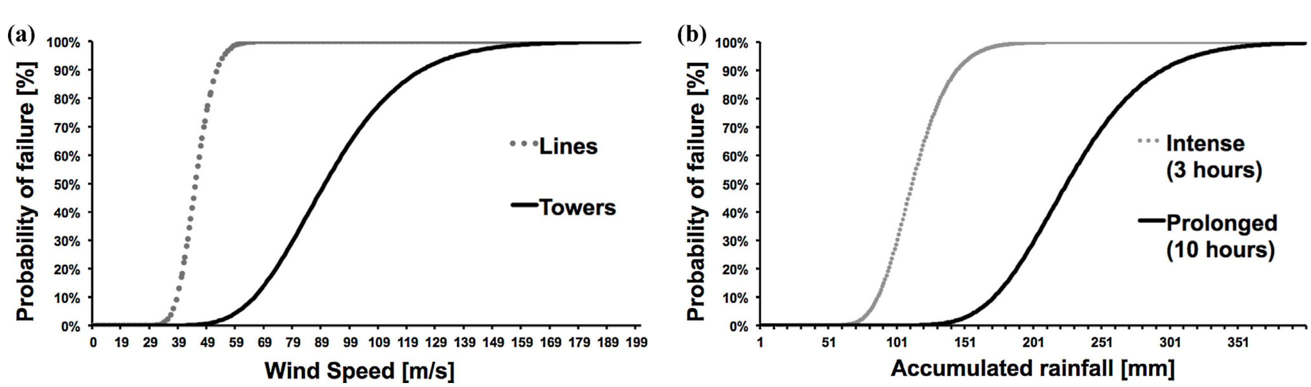

Fig. 7. (a) Lines and towers' wind fragility curves. (b) Floods by intense or prolonged rainfall fragility curves.

Table 2
Mean times to repair (hours) for different weather intensities.

Threat	Component	MTTR for different weather intensities [Wind speed (m/s)/accumulated rainfall (mm)]		
		Low	Moderate	High
Windstorms	Lines	$MTTR_{base}$	$MTTR_{base} \times$ rand {2,4}	$MTTR_{base} \times$ rand {5,7}
	Towers	$MTTR_{base}$	$MTTR_{base} \times$ rand {2,4}	$MTTR_{base} \times$ rand {5,7}
Floods	Power plants	$MTTR_{base}$	–	$MTTR_{base} \times 2$
	Substations	$MTTR_{base}$	–	$MTTR_{base} \times 2$

strongly related to the accumulated rainfall, which can be produced by an intense short event (<3 h) or a prolonged event (<10 h). These implicate that beginning with rainfalls of approximately 20 mm/h for at least 3 h, the risks of flooding exist [40]. Also, in order to take into account the particularities of power stations and substations, when a flood occurs a probabilistic assignation is done (i.e. 38% for power plants and 33% for substations) based on a report that classifies the floods risk of power plants and substations [41] (this means that 38% of the power plants flooded will actually fail). Therefore, in the case of floods, the component's risk profile and the floods fragility are jointly used. The accuracy of these curves can vary depending on the particularities of each component. Consequently the accuracy of the assessment can be improved in further works by improving the methods to generate the fragility curves.

As can be seen in Fig. 5(b), some transmission lines pass across multiple areas experiencing different weather conditions at each region. In the case of lines, the highest line failure probability among the regions is used for the whole line. In the case of towers, which are considered to be every 300 m across the lines, a percentage of the line's length in each region is assumed for estimating the number of towers in every region. The aggregated failure probability of all towers supporting a line is then used to estimate the line failure probability due to a tower collapse.

Finally, following the failure of a component, the damage state has to be assigned. The approach in this study is to establish the damage through zones in the fragility curve as shown in Fig. 4(b). For example, power plants have four possible damage states: minor, moderate, extensive and complete. These states are determined by the percentiles 0–25th, 25–50th, 50–75th and 75–100th of the fragility curve, where the maximum generation degrading is 25%, 50%, 75% and 100%, respectively. Lines, towers and substation's potential damage are modeled with two states: operative and non-operative.

4.2.3. Phase 3: Power system reaction

In order to capture the spatiotemporal impact of the wind and rainfall fronts moving across the transmission network, a Sequential Monte Carlo-based time-series simulation model has been developed. This enables the representation of the weather and electrical events in a chronological order as they happen in reality at different locations of the test system. An hourly simulation step is used to exemplify the simulation, which is considered sufficient for modeling weather events. However, any time resolution can be used if desired and provided that the relevant information is available, e.g. weather profile. Further, one winter week is used as simulation period, where extreme wind and rainfall events are expected considering that severe weather events do not usually last longer in Great Britain.

At every simulation step, the wind- and rainfall-affected failure probabilities of the electrical components obtained by the fragility curves are fed to the time-series simulation model as explained in the previous phases. Following this approach, the real-time weather-adjusted operation state of each electrical component is obtained. An AC Optimal Power Flow (OPF) is used for assessing the performance of the test network at every simulation step, which helps determine if load shedding is required for stabilizing the system. Finally, following a severe disturbance the model is also capable of detecting islanded nodes and operating them independently until they are reconnected following the restoration of the transmission lines, which is very important when studying high impact events that can result in the separation of the network in many disconnected islands. It has to be noted here that this does not refer to the studies related to the controlled islanding of power systems (like for example during disturbances, which is treated in [42,43]) for boosting their resilience to such events.

4.2.4. Phase 4: Power system restoration

As explained in Section 3, three aspects can be taken into consideration for the components restoration. In this study, for simplicity reasons, the restoration curves are only related to the difficulties of the repair crews to enter the affected areas. The component restoration curves are defined by exponentially distributed curves with mean parameters as shown in Table 2. A Mean Time To Repair (MTTR) of 10 and 50 h is assumed for lines and towers, respectively, and 10 and 20 h for power plants and substations, respectively (referred to as $MTTR_{base}$). The weather intensity is classified here as follows: for windstorms, it can be Low (less than 20 m/s), Moderate (between 20 m/s and 40 m/s) or High (more than 40 m/s), while for floods it can be Low (less than 138 mm for intense accumulated rainfall or 280 mm for prolonged accumulated rainfall) or High (more than 138 mm for intense accumulated rainfall or 280 mm for prolonged accumulated rainfall). As weather intensity increases, the repair crews need more time to enter the affected area and restore the damaged components, which is modeled here as a random increase in $MTTR_{base}$ as can be seen in Table 2.

4.3. Multi-phase strategic adaptation cases

In this study, the adaptation strategic case studies discussed in Section 3.2 are applied to the critical transmission route shown in Fig. 8 from North to South Great Britain, where the largest demand nodes are located. Following extensive resilience studies (mainly focusing on the maximum power flows on the transmission lines), this corridor was identified as one of the critical transmission routes for preserving the resilience of the entire power system, i.e. minimizing the amount and duration of load shedding in case of severe weather and electrical events.

Particularly, for the normal case, the basic network was used with no resilience enhancement. For the robust case, the fragility curves of the components (see Fig. 7) in the critical path were shifted to the right a 15% of the 50th percentile of the curve. For the redundant case, identical parallel lines have been added to the critical transmission path. Finally, for the responsive case, the mean times to repair of the components in the critical path were supposed unaffected by the severity of the weather.

5. Results and discussion

5.1. Resilience metrics

Depending on the aim of the resilience study, the performance of electric power systems can be measured using numerous different

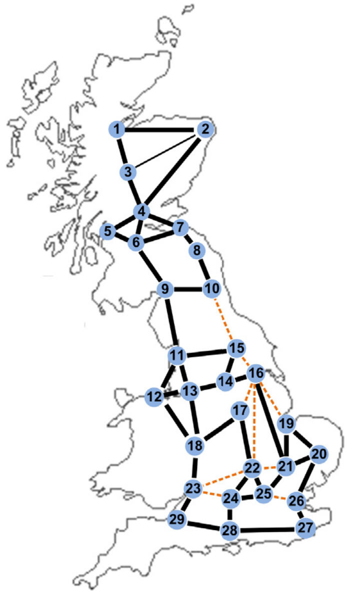

Fig. 8. Dotted lines show the critical transmission corridor for which the adaptation case studies are applied.

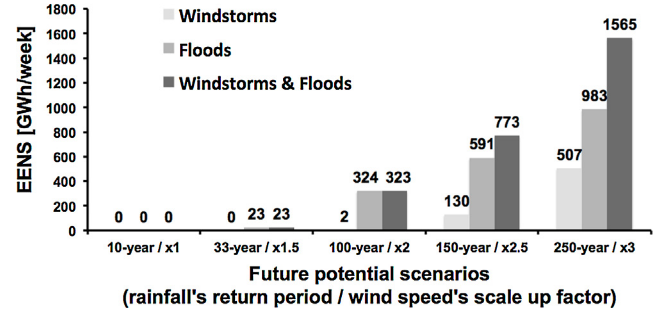

Fig. 9. EENS [GW h/week] of different hazards in potential future scenarios.

metrics. Two measurements that are able to describe the impact of the extreme event are the Expected Energy Not Supplied (EENS) and the Energy Index of Unreliability (EIU) [44,45]. The first, shown in Eq. (3), indicates how much service (energy) was not provided during the studied time period as an absolute number (MW h or GW h). The second, shown in Eq. (4), is directly related to EENS, which is normalized using the total energy demand in the studied time frame (%). In the following equations, E_k is the energy not supplied with a probability p_k and E represents the energy demand in the whole study period.

$$\text{EENS}\,[\text{GW h}] = \sum E_k * p_k \tag{3}$$

$$\text{EIU}\,[\%] = \frac{\text{EENS}}{E} * 100\% \tag{4}$$

Although EENS and EIU are commonly used as reliability indices, they are also suitable among the well-known reliability indices to describe key features of the resilience concept, which is discussed in Section 1. This is because calculating EENS and EIU along the process and within the time frame of the four phases proposed in the resilience assessment procedure enables the analysis of the resilience degradation and recovery during an event, as well as the comparison of system's resilience performance in different scenarios and stress by different hazards.

Still, EENS and EIU are not able to capture other potentially important resilience features, such as how fast the performance decreases or how slow the performance recovers, the downtime (i.e. the duration of the reduced system performance), the number of customers not served, etc. Further, EENS and EIU lack an economic dimension; therefore additional research on resilience metrics is fundamental and is object of on-going work by the authors.

5.2. Simulation results

The impact of windstorms and floods is first modeled independently, and then the combined impact of these threats is evaluated. In Fig. 9, the comparison between these single and multi-hazards is represented using EENS for different intensities of the weather hazards. Where the impact increases with the intensity of the event and the combination of hazards is much more severe than the single threats. The impact of floods is greater than the windstorms mainly because the substations affected by floods are more important to the network than other components.

Then, the EENS results for the strategic adaptation cases in the different future scenarios are illustrated in Fig. 10(a) and (b), for windstorms and floods, respectively. It can be seen that the best adaptation case for both hazards is robustness, followed by responsiveness and finally redundancy, where for floods this last strategic case has almost no improvement. This can be explained by the different components each hazard has impact on, where windstorms affect lines and towers, and floods affect power plants and substations. When the nodes of a network (substations) are impacted, alternative paths are also affected; hence redundancy of lines and towers enhances resilience significantly only for windstorms.

In Fig. 11, the improvement of the strategic cases compared to the normal case of the three most severe scenarios can be seen through the percentage of decrease of EENS. As the intensity of the event increases, the improvement produced by the robust and redundancy adaptation cases decrease; but in the case of floods, as the intensity of the event increases, the improvement produced by the responsiveness strategy increases. Hence, in this case, for

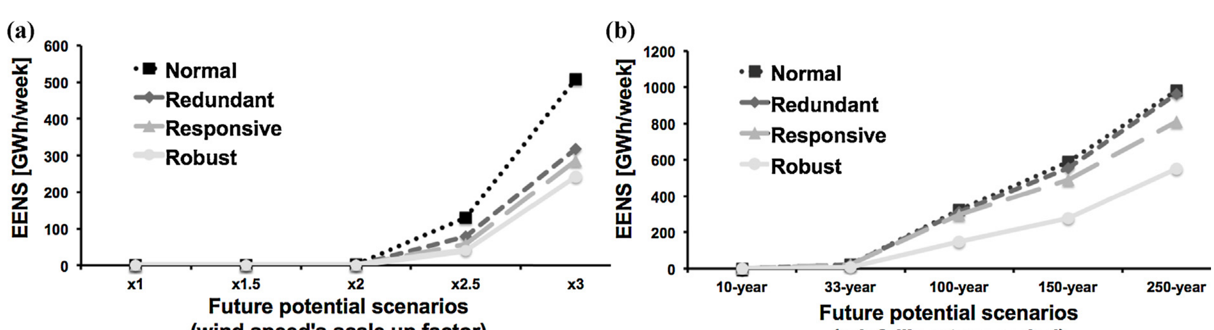

Fig. 10. (a) Windstorms adaptation cases results. (b) Floods adaptation cases results.

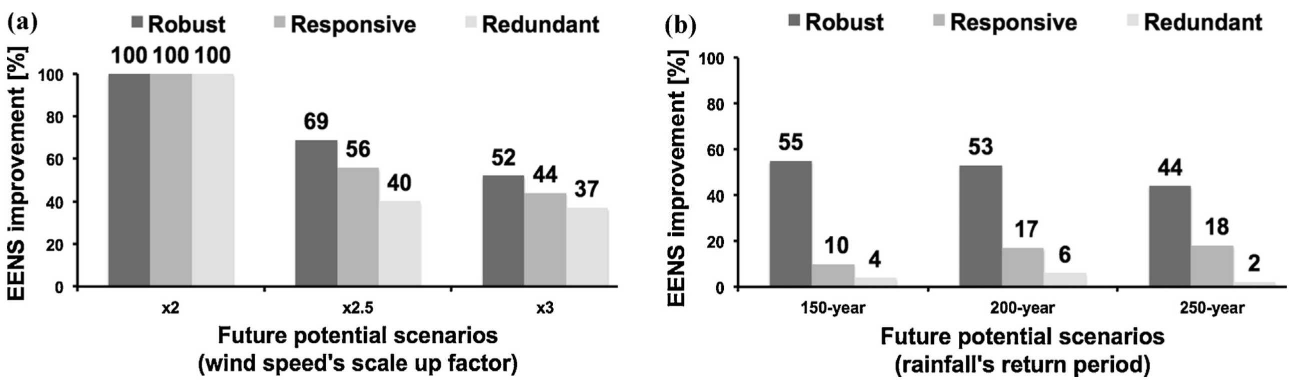

Fig. 11. (a) Windstorm adaptation results improvements for the three most hazardous events. (b) Floods adaptation results improvements for the three most hazardous events.

Table 3
EIU results.

Comparison of hazards in different scenarios			
Scenarios	Windstorms (%)	Floods (%)	Windstorms & floods (%)
10-year/×1	0.00	0.00	0.00
33-year/×1.5	0.00	0.32	0.32
100-year/×2	0.03	4.50	4.49
150-year/×2.5	1.81	8.22	10.75
250-year/×3	7.05	13.67	21.76

more severe events having a better response plan becomes more important.

Finally, in Table 3, the EIU results are presented. Here *E*, or total week-demand, is equal to 7193 GW h. It can be seen that the EIU results are relatively low except for the very extreme cases. This can be mainly due to the high reliability of the test network. However, this low impact when expressed through EENS or EIU can be very high in terms of financial losses, therefore a socio-economic analysis should be performed to correctly assess the resilience of the system and decide between different enhancement measures.

6. Conclusions

Resilience of electric power systems has emerged as a new concept after the recent catastrophic events around the world. It can be expected that resilience will be as important as reliability was in the past. However, the differences between these two concepts have to be considered, particularly that while reliability provides protection against foreseeable low-impact high-probability events, resilience provides protection against high-impact low-probability events, is a time-dependent process and far more complex, as the knowledge of many different fields and thus multidisciplinary work is required. Currently, different research teams are working on defining the concept and developing tools to describe, measure and enhance resilience. As a contribution to the topic, this paper presents a formalization of the resilience process and enhancement measures in a multi-phase approach.

The proposed resilience framework consists of four phases. These are (i) threat characterization, where the hazard's magnitude, probability of occurrence, spatiotemporal profile and future scenarios are defined; (ii) vulnerability assessment of the system's components, where the identification of the vulnerable components, the application of fragility curves and the assignation of damage states is done; (iii) system's reaction, where the performance of the system through sequential Monte Carlo Simulations and Optimal Power Flows is carried out, and (iv) system's restoration, where the component's recovery is related to the damage caused, human and material resources availability and the accessibility to the affected area. Finally, the whole process is measured in a time-dependent way with the Expected Energy Not Supplied index and the possibility to compare with different systems through the Energy Index of Unreliability.

The strategic adaptation cases presented are: normal, which is based on a reduced version of the current national grid; robust, which is a more resistant network; redundant, which is a version with more alternative paths; and responsive, which has faster recovery parameters.

These case studies have been illustrated by assessing the impact of floods and windstorms on a reduced version of the Great Britain's electric power system. The results show that normal weather events do not represent a threat of major disruption, but when one models a flood event that may happen every 33 years or a windstorm where the normal wind speed is doubled, then the risk of blackouts becomes significantly higher. Regarding the effectiveness of the adaptation cases, for both windstorms and floods the best strategy is to improve the resistance of components, then to count with better restoration procedures and as a third option to invest in redundancy, whereas the last one implicates almost no improvement for floods.

It is important to note that performing the resilience analysis of the test system required several data that were not completely available at the time of the present research. Therefore, assumptions had to be made in order to run the model as it was stated in each phase. Thus, it is expected that the use of more reliable and accurate data from power companies would improve the accuracy of the simulation results.

Future research might be focused on improving each of the resilience phases, through the better understanding of the physical features of different hazards, developing more accurate fragility curves and a better modeling of the complex process of restoration. Also, the challenge is to assess all kind of threats that may impact real systems around the world, along with including people's behavior and the interdependencies with other key sectors. Also in order to evaluate the contribution of each component or area to the resilience of the system, their criticality needs to be estimated and ranked. This will provide further insights on the most critical parts of the system, supporting the targeted resilience enhancement efforts. Finally, work must be done related to the socio-economic impact and management of natural disasters, as well as consider the economic cost of the adaptation measures described and investigated in this paper, which is a critical dimension in the decision-making on the efforts for boosting the resilience of a power system. Therefore, a cost-benefit analysis needs to accompany this analysis in order to weight the benefits of each adaptation measure over its contribution to the resilience enhancement.

The aim of the comprehensive and systematic analysis exposed in this study is to help governments and disaster management related institutions to be better prepared for the uncertain future driven by natural disasters and climate change.

Acknowledgments

This work was supported by the Resilient Electricity Networks for Great Britain (RESNET) project, which is funded by the Engineering and Physical Sciences Research Council (EPSRC), UK (grant no. EP/I035781/1). Also thanks to CONICYT, Chile, for funding under Fondecyt 1141082 project.

References

[1] P. Southwell, Disaster Recovery within a Cigre Strategic Framework: Network Resilience, Trends and Areas of Future Work, Cigré, Paris, 2014 Aug.
[2] R.K. Pachauri, L.A. Meyer (Eds.), Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, IPCC, Geneva, 2014.
[3] M. Panteli, P. Mancarella, The grid: stronger, bigger, smarter?: Presenting a conceptual framework of power system resilience, IEEE Power Energy Mag. 13 (May/June) (2015) 58–66.
[4] K. Pitilakis, H. Crowley, A. Kaynia (Eds.), SYNER-G: Systemic Seismic Vulnerability and Risk Assessment of Complex Urban, Utility, Lifeline Systems and Critical Facilities, Springer, Dordrecht, 2014.
[5] M. Panteli, P. Mancarella, Modeling and evaluating the resilience of critical electrical power infrastructure to extreme weather events, IEEE Syst. J. pp (2015) 1–10.
[6] M. Ouyang, L. Dueñas-Osorio, Multi-dimensional hurricane resilience assessment of electric power systems, Struct. Saf. 48 (2014) 15–24.
[7] M. Shinozuka, et al., Seismic performance of electric transmission network under component failures, Earthquake Eng. Struct. Dyn. 36 (2007) 227–244.
[8] Federal Emergency Management Agency, Hazus—MH MR5: Technical Manual, Federal Emergency Management Agency, Washington, DC, 2015.
[9] Mid-America Earthquake Center, ERGO - Multi-hazard, Assessment, Response, and Planning, Available: http://ergo.ncsa.illinois.edu/ (accessed: May 2015) [Online].
[10] M. Mahsuli, T. Haukaas, Computer program for multimodel reliability and optimization analysis, J. Comput. Civ. Eng. 27 (2013) 87–98.
[11] Central American Governments, Central American Probabilistic Risk Assessment (CAPRA), Available: http://www.ecapra.org/ (accessed: May 2015) [Online].
[12] C. Pickering, S. Dunn, S. Wilkinson, Securing community resilience by modern infrastructure design, in: Fourth ECCOMAS Thematic Conference on Computational Methods in Structural Dynamics and Earthquake Engineering (COMPDYN), Kos Island, Greece, 2013, pp. 1–9.
[13] Q. Xie, R. Zhu, Earth, wind, and ice, IEEE Power Energy Mag. 9 (2011) 28–36.
[14] United States Geological Survey, April-May 2015 Nepal Earthquakes, 2015, Available: ⟨http://earthquake.usgs.gov/earthquakes/eqarchives/poster/2015/NepalSummary.pdf⟩ (accessed May 2015) [Online].
[15] United States Geological Survey, M8.8 Maule, Chile, Earthquake of February 2010, 2010, Available: ⟨http://earthquake.usgs.gov/earthquakes/eqarchives/poster/2010/20100227.pdf⟩ (accessed May 2015) [Online].
[16] W. Associates, Conneticut October 2011 Snowstorm Power Restoration Report, W. Associates, Connecticut, 2011.
[17] L. McColl, et al., Assessing the potential impact of climate change on the UK's electricity network, Clim. Change 115 (2012) 821–835.
[18] United Kingdom Parliament, Climate Change Act 2008, United Kingdom Parliament, 2008 Nov.
[19] E. Evans, et al., An update of the foresight future flooding 2004 qualitative risk analysis, in: The Pitt Review, 2008 June.
[20] S. Burroughs, S. Tebbens, Upper-truncated power laws in natural systems, Pure Appl. Geophys. 158 (4) (2001) 741–757.
[21] S. Coles, An Introduction to Statistical Model of Extreme Values, Springer, Bristol, 2001.
[22] A. Jenkinson, The frequency distribution of the annual maxima (or minima) values of meteorological elements, Q. J. R. Meteorolog. Soc. 81 (1955) 158–171.
[23] J. Hosking, J. Wallis, E. Wood, Estimation of the generalized extreme value distribution by the method of probability weighted moments, Technometrics 27 (1985) 251–261.
[24] E. Gumbel, Statistics of Extremes, Columbia University Press, New York, NY, 1958.
[25] Joint Committe of Structural Safety (JCOSS), General Principles on Reliability for Structural Design, Joint Committe of Structural Safety (JCOSS), Copenhagen, 1981.
[26] F. Casciati, L. Faravelli, Fragility Analysis of Complex Structural Systems, Research Studies Press, Taunton, MA, 1991.
[27] I. Dobson, A. Carreras, D. Newman, A probabilistic loading-dependent model of cascading failure and possible implications for blackouts, in: Proceedings Hawaii International Conference on System Sciences (HICSS), Hawaii, 2003.
[28] B.A. Carreras, et al., Critical points and transitions in an electric power transmission model for cascading failure blackouts, Chaos 12 (2002) 985–994.
[29] I. Dobson, A. Carreras, D. Newman, An initial model for complex dynamics in electric power system blackouts, in: Proceedings Hawaii International Conference on System Sciences (HICSS), Hawaii, 2001.
[30] J. Chen, J. Thorp, I. Dobson, Cascading dynamics and mitigation assessment in power system disturbances via a hidden failure model, Int. J. Electr. Power Energy Syst. 27 (2005) 318–326.
[31] M. Rios, et al., Value of security: modeling time-dependent phenomena and weather conditions, IEEE Trans. Power Syst. 17 (Aug.) (2002) 543–548.
[32] D. Kirschen, et al., Computing the value of security, IEEE Proc. Gener., Transm. Distrib. 150 (Nov.) (2003) 673.
[33] D. Kirschen, et al., A probabilistic indicator of system stress, IEEE Trans. Power Syst. 19 (Aug.) (2004) 1650–1657.
[34] M. Panteli, P. Mancarella, Influence of extreme weather and climate change on the resilience of power systems: impacts and possible mitigation strategies, Electr. Power Syst. Res. 127 (2015) 259–270.
[35] M. Belivanis, K. Bell, in: University of Strathclyde (Ed.), Representative Great Britain Model: Notes, University of Strathclyde, 2011.
[36] NASA, Merra Re-analysis, 2015, Available: ⟨http://catalogue.ceda.ac.uk/uuid/bbd6916225e7475514e17fdbf11141c1⟩ (accessed May 2015) [Online].
[37] P. Guhathakurta, O. Sreejith, P. Menon, Impact of climate change on extreme rainfall events and flood risk in India, J. Earth Syst. Sci. 120 (2011) 359–373.
[38] Met Office U.K., Hourly Rainfall Data, Part of the Met Office Integrated Data Archive System (MIDAS), 2006, Available: ⟨http://gmao.gsfc.nasa.gov/merra/⟩ (accessed April 2015) [Online].
[39] Met Office U.K., Climate Extremes. Weather Highest Records, 2015, Available: ⟨http://www.metoffice.gov.uk/public/weather/climate-extremes/#?tab=climateExtremes⟩ (accessed April 2015) [Online].
[40] D. Houston, et al., Pluvial Flooding in Urban Areas: The Invisible Hazard, Joseph Rowntree Foundation, York, 2011.
[41] D. Hames, et al., Infrastructure Assets, Planning Indicators, HR Wallingford, 2014.
[42] J. Quiros-Tortos, R. Sanchez-Garcia, J. Brodzki, J. Bialek, V. Terzija, Constrained spectral clustering-based methodology for intentional controlled islanding of large-scale power systems, IET Gener. Transm. Distrib. 9 (9) (2015) 31–42.
[43] D. Trakas, E. Voumvoulakis, N. Hatziargyriou, Decentralized control of power system zones based on probabilistic constrained load flow, in: 2014 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), 2014.
[44] R. Billinton, W. Li, Reliability Assesment of Electric Power Systems Using Monte Carlo Methods, Plenum Press, New York, NY, 1994.
[45] R. Allan, R. Billinton, Probabilistic assessment of power systems, Proc. IEEE 88 (Feb.) (2000) 140–162.