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REVIEW

Electrical energy systems resilience: A comprehensive review on definitions, challenges, enhancements and future proceedings

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Abstract

Secure energy providing is a critical feature of sustainable societies, where this subject requires reliable operation of generation, transmission and distribution infrastructures. In order to achieve the mentioned goal, the influence of uncertainties should be analyzed using appropriate methods, criteria and tools. The high-impact low-probability (HILP) events are special uncertainties that can affect the safe operation and lead to irreparable damages. This paper presents a comprehensive review of resilience in electrical energy systems consisting of fundamental concepts and definitions, challenges, enhancements and future proceedings. In this regard, a resilience evaluation framework is designed first in which all the necessary actions for a resilience study are defined. In the next step, various HILP events are introduced and then the resilience concept is defined accurately and related curves are investigated. Afterwards, the resilience assessment indices and quantitative measures are described and their details and applications are precisely explained. As well, the resilience enhancement strategies are discussed from short-term and long-term perspectives and eventually, resilience-based objective functions and optimization approaches are classified in the last part. It is noteworthy that the main research gaps are also clarified according to the reviewed papers and further suggestions are expressed to cope with the declared problems.

1 | INTRODUCTION

1.1 | Motivation

In recent years, natural disasters lead to critical issues in electrical energy systems such as cascade power outages [1, 2]. The reported information by national and international centres shows the significant impact of the mentioned events on different infrastructures [3, 4]. According to Figure 1, the occurrence of natural disasters has increased from 1900 to 2021, where many of them took place after 2000 due to various reasons such as population growth and economic development. As exhibited in Figure 2, the Asian continent has the highest portion of natural disasters during the last 30 years and its contribution is also increased by 2021 from 39 % to 40 %. In order to have a better perception, the influence of natural disasters for 1991 to 2020 (average of past 30 years) is compared in Figure 3. As evident, the total number of natural disasters in 2021 is equal to 436 which is about 15.95 % higher than the average of past 30 years. Furthermore, the total deaths and affected people in 2021 are about 322.97 % and 87.85 % lower than the declared interval, while the economic losses increase by about 124.911 %. It is noteworthy that floods, storms and earthquakes have a great influence on system operation among all types of natural disasters. As a result, the resilience operation of all infrastructures against various natural disasters is of high importance and should be accurately evaluated to show the system robustness in critical conditions.

1.2 | Literature survey

Since traditional electrical energy systems are designed based on reliability criteria, the effect of high-impact low-probability (HILP) events has not been well considered. In this regard, recent studies have focused on the resilience concept to

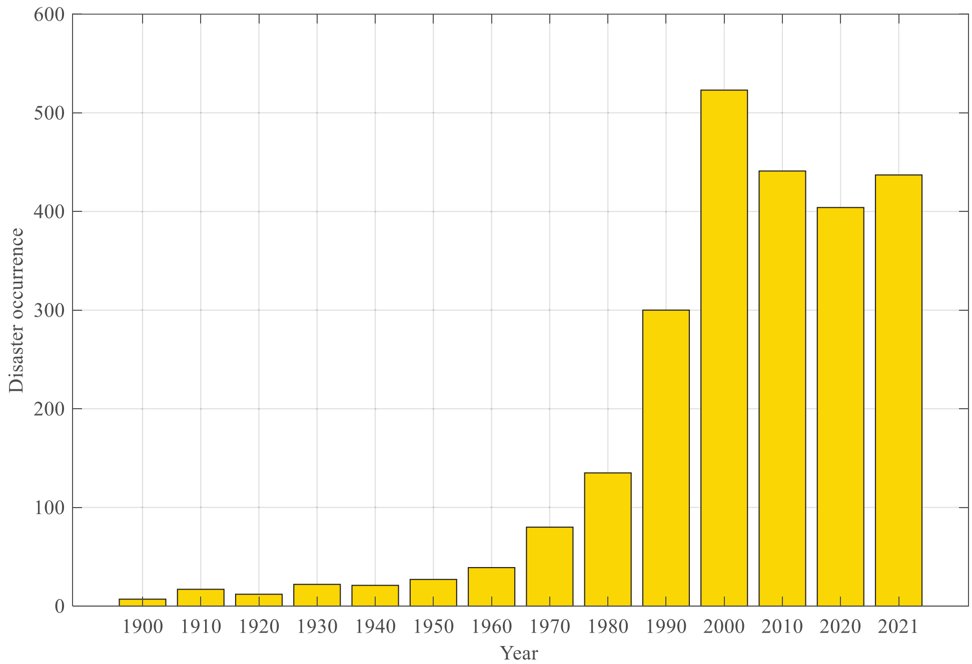

FIGURE 1 Trend of natural disasters occurrence around the world from 1900 to 2021.

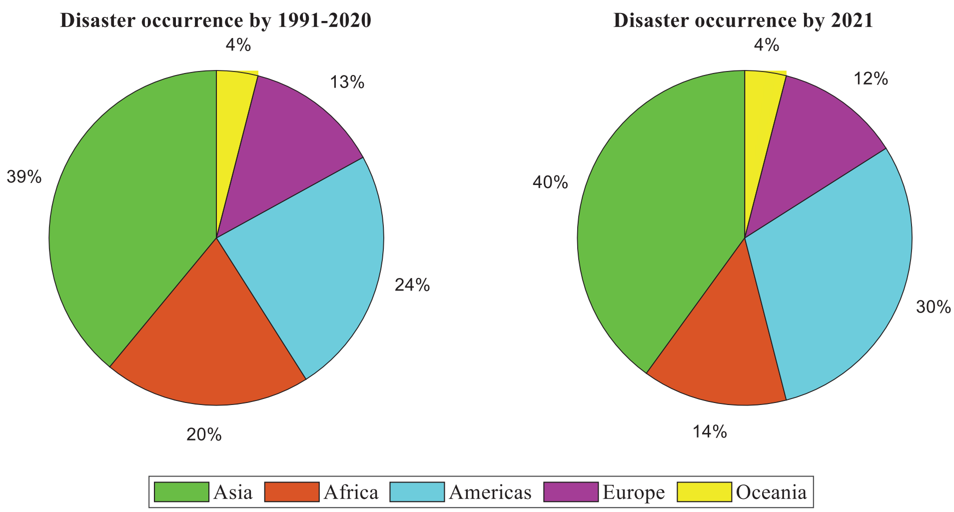

FIGURE 2 Comparison of natural disasters occurrence by region between 1991 to 2020 and 2021.

investigate the robustness of different infrastructures. Reference [5] explains the concepts and indicators of power system resilience and suggests hardening strategies and smart grid technologies to enhance resiliency. The microgrid formation is introduced as an applicable solution to improve the resilience of electrical energy systems [6, 7]. In a recent study, a review is presented on various strategies for preparing, hardening and enhancing proactive resilience with a focus on microgrid formation to improve power system resilience against natural disasters [8]. An overview is provided to define resiliency in distribution networks and classify and assess related criteria [9]. The role of electric vehicles (EVs) in grid resilience considering vehicle to grid (V2G) capability is evaluated, where the results approve that simultaneous management of electricity and transportation networks can improve the resilience operation [10]. References [11, 12] distinguish the differences between reliability and resiliency indices and review resilience researches in the planning and operation of distribution systems in the presence of distributed generations (DGs). The resilience concept, its measurement approaches and the difference between resilience and other indices such as reliability, risk and security are explained in [13]. The modelling and simulation of various energy infrastructures have been analyzed based on five resilience indicators for stakeholder, network development, system failure,

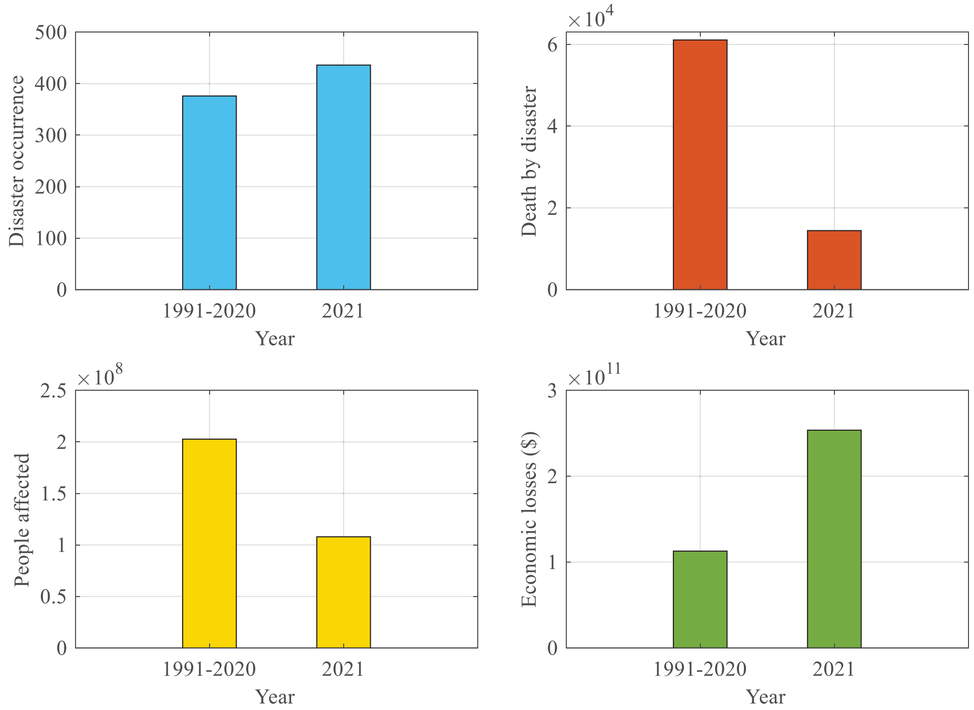

FIGURE 3 Influence of natural disasters for 1991 to 2020 (average of 30 years) and 2021.

interdependence operation and socio-economic issues [14]. Reference [15] categorizes the high-impact events and clarifies the technical definitions of power system resilience and linkages between resilience and other concepts such as security and reliability. The resilience enhancement challenges and opportunities within smart grids as well as resilience definition and quantification are presented in [16]. A comprehensive review is proposed to determine the definitions and measures of engineering systems resilience [17]. Reference [18] studies the methods and tools for predicting natural disasters related to power system disturbances, hardening, operation and restoration models. The key strategies in realizing power system resilience for the preparation stage and after the event proceedings are investigated in [19]. The fundamental challenges and approaches for quantifying resilience including modelling, data analytics and metrics are analyzed in [20]. Reference [21] presents a comprehensive review of current practices of power system resilience metrics, evaluation methods and future directions. The definitions, frameworks, quantitative assessment and enhancement methodologies for resilience in electrical energy systems are evaluated in [22]. The most widely methods and techniques in planning, operating and restoring power systems during HILP events are reviewed in [23]. The resilience assessment and quantification for energy systems and the relevant literature are classified according to four key functions consisting of resistance, restabilization, rebuilding and reconfiguration [24]. Reference [25] aims to investigate the optimal allocation and operation of energy storage units and microgrids to face regular extreme weather conditions. The main differences between the concept of resiliency, accessibility, durability, flexibility, hardening, maintainability, reliability, stability, survivability, sustainability and vulnerability are discussed in a complementary study to specify the goal of each index [26]. A conceptual framework is suggested to identify the key variables, factors and ideas in the resilience of power systems and define the relationship between each metric [27]. The methodologies to assess the impacts of climate changes including extreme events and uncertainties are also described in [28]. Since real-time operation needs online data analysis of measurement units, Reference [29] has focused on developing artificial intelligence techniques and their applications to improve resiliency and guarantee reliable and secure operation.

1.3 | Contribution of paper

According to the literature survey, the resilience of power systems has been evaluated from different points of view. In order to have an accurate perspective, the main differences of this paper are compared with the reviewed references in Table 1. As seen, although many subjects have been previously investigated, a complementary research is required for analyzing the resilience concepts, indices, challenges, enhancements and future proceedings. As a result, this study proposes a comprehensive review of resiliency in electrical energy systems, where the key points and contributions can be summarized as follows:

- Proposing a resilience evaluation framework and roadmap including all the required actions for a resilience study.

TABLE 1 Comparison of reviewed papers based on their objectives in resilience of electrical energy systems.

Reference	Main subject: Resilience roadmap	Resilience concept	HILP events	Resilience curve	Resilience index	Resilience enhancement	Resilience optimization
[5]	✗	✓	✗	✗	✓	✓	✗
[6]	✗	✓	✗	✗	✓	✓	✗
[7]	✗	✓	✗	✓	✗	✓	✗
[8]	✗	✓	✗	✓	✗	✓	✓
[9]	✓	✓	✗	✓	✗	✓	✗
[10]	✗	✓	✗	✗	✓	✓	✗
[11]	✗	✓	✗	✓	✓	✓	✗
[12]	✗	✗	✓	✗	✓	✓	✗
[13]	✓	✓	✗	✗	✓	✓	✗
[14]	✗	✓	✗	✗	✓	✓	✗
[15]	✗	✓	✓	✓	✗	✓	✗
[16]	✗	✓	✗	✗	✓	✓	✗
[17]	✗	✓	✗	✗	✓	✓	✗
[18]	✗	✗	✓	✗	✗	✓	✗
[19]	✗	✗	✗	✓	✗	✓	✗
[20]	✗	✗	✓	✗	✓	✓	✗
[21]	✗	✓	✗	✗	✓	✓	✓
[22]	✓	✓	✗	✓	✓	✓	✗
[23]	✗	✓	✗	✗	✓	✓	✗
[24]	✗	✓	✗	✓	✓	✗	✗
[25]	✗	✗	✗	✗	✗	✓	✓
[26]	✗	✓	✗	✓	✓	✓	✗
[27]	✓	✓	✗	✗	✓	✗	✗
[28]	✗	✓	✓	✗	✗	✓	✗
[29]	✗	✗	✓	✗	✗	✓	✗
This paper	✓	✓	✓	✓	✓	✓	✓

- Introducing and classifying various HILP events in electrical energy systems using the latest researches.
- Investigating the resilience curves and their details based on before, during and after event proceedings.
- Categorizing resilience assessment indices and quantitative measures according to the applicable steps in resilience curves.
- Describing resilience enhancement strategies from short-term and long-term perspectives and reviewing resilience-oriented optimizations.
- Clarifying the main research gaps and suggesting appropriate solutions to cope with the declared problems.

2 | RESILIENCE ASSESSMENT FRAMEWORK AND ROADMAP

In order to achieve the resilience level of an electrical energy system, several proceedings should be considered. According to Figure 4, this paper suggests a roadmap in which the main steps to evaluate the resiliency are determined, as explained below

- In the first step, the type of event should be specified due to the variety of system responses to different conditions.
- In the second and third steps, a resilience metric is selected based on the previous descriptions such that it is capable of modelling the accurate operation under critical conditions and then, the damage level is calculated utilizing an appropriate index.
- In the fourth to sixth steps, the proceedings related to the before, during and after events are proposed to maintain the robustness of system against events, prevent unstable operation and reduce recovery time, respectively.
- In the final step, the resilience level is obtained according to the mentioned steps and the required analyses are performed to indicate the successfulness of the candidate method.

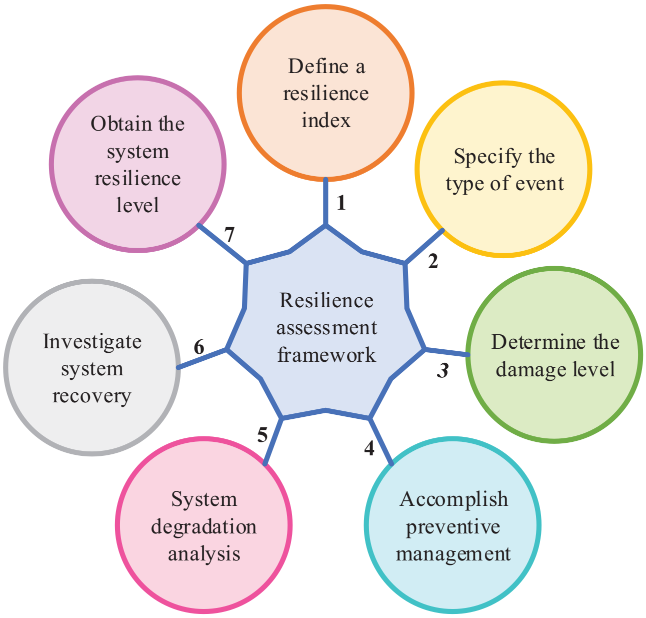

FIGURE 4 Resilience evaluation roadmap versus high-impact low-probability events.

It is noteworthy that the specifications and definitions of each step are presented precisely in a separate section.

3 | CLASSIFICATION AND DEFINITION OF HILP EVENTS

According to the occurrence probability of incidents and their influence on electrical energy systems, the HILP events can be divided into four categories including technical cascading failures, extreme natural disasters, space weather and cyber-physical attacks. In this regard, such events are presented and defined summarily in Figure 5 and their details are explained in the next subsections.

3.1 | Technical cascading failure

According to Figure 6, technical cascading failure analysis can be divided into two main groups consisting of planning and operation studies [30]. The operation studies are performed to increase the situational awareness of operators. They need to provide real-time solutions to reduce the spread of cascading failure. However, the planning studies provide a solution to expand the transmission infrastructure as a fundamental interaction for cascading failures. The largest power outage in history occurred in India due to a cascading failure caused by the update of the backup power line, where half of the population lived without electricity for 2 days [31].

Many methods have been used to model technical cascading failures. Reference [32] suggests a component-based algorithm to provide a traceable analytical model of load-dependent cascading failure that records some of the significant features of massive blackouts of electric power transmission systems. A topological-based model is presented to determine the risk of blackouts in which two topological methods are compared with a simple model of cascading outage for finding vulnerable sites [33]. The simulations approve that topological models, in some cases, lead to incorrect results regarding vulnerability. Another approach is the dynamic model which shows the dynamic behaviour of the power system and carefully considers the details during the cascading failure. It is noteworthy that the main disadvantage of such algorithms is the complex computational process. The existing dynamic simulation utilizes two prominent models including the Manchester [34] and ORNL-PSerc-Alaska (OPA) [35]. The first one is based on the AC power flow, instead, the second one consists of slow system dynamics.

3.2 | Extreme natural disasters and space weather

The reported information by international institutes approves that extreme natural disasters and space weather have significant influences on the social-economical aspects of different regions. In order to have a better perception, four main indices in natural disaster analysis including total occurrence, death, affected people and economic losses are compared in Figure 7 for the most involved countries from 1900 to 2021 [4]. As evident, the maximum total number of natural disasters is equal to 1098 which occurred in the USA and then, China and India with 982 and 751 have the second and third places, respectively. Nevertheless, China and India have the most affected people and death among all countries. In return, economical losses equal to 1.932 trillion dollars are imposed on the USA in the mentioned period. These results validate that many factors such as accurate predictions, preventive measures, advanced and robust infrastructures and correct training are required to decrease the percentage of victims.

Natural disasters such as floods, earthquakes, hurricanes, tornadoes etc. have notable effects on electrical energy systems. The results of such events can be attributed to the felling of trees on distribution lines in the storm or tornado and extensive harm to power plants and stations in the earthquake. Since the sun is the primary source of space weather, coronal mass ejections (CME) that mean the significant explosion of plasma structures and magnetic fields from the atmosphere of the sun along with sudden bursts of radiation or solar flares cause space weather effects. The electromagnetic fields in space weather create a strong current in the wires which disrupts power lines and extensive blackouts [36]. The enormous magnetic storm named the Carrington event in 1859 disrupted telegraphs around the world and set fires in some places [37].

Extreme natural disasters and space weather can be modelled using historical data or predicting the occurrence of events. The historical data is obtained through climate models or real measurements provided by meteorological stations based on time and geographical features [38]. In some cases, historical data is limited due to the non-sequential occurrence of natural

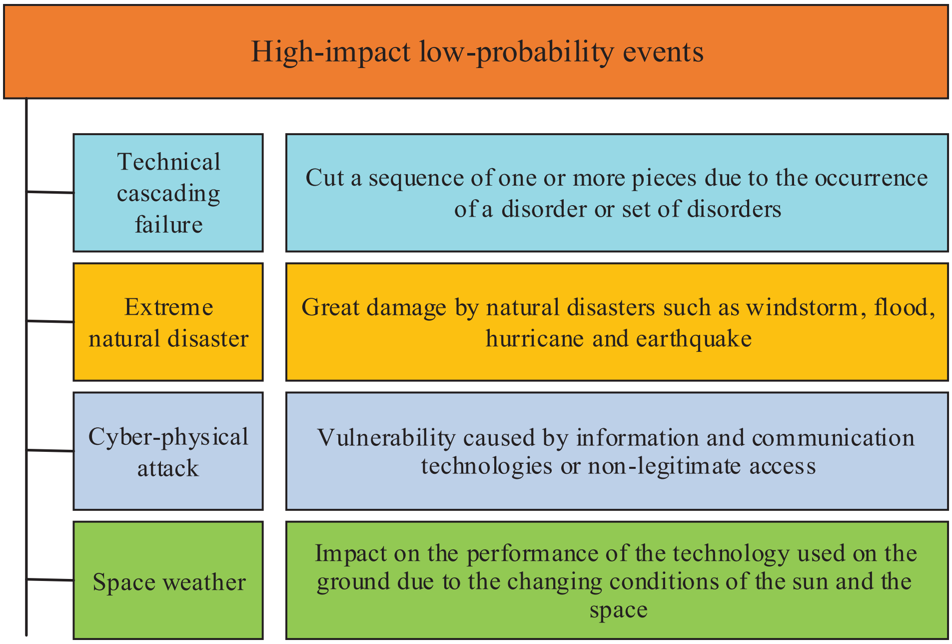

FIGURE 5 Classification of high-impact low-probability events in electrical energy systems.

events and hence, their modelling by historical data will be complex. Furthermore, some events do not always have a significant impact on the network, which means that many recorded data are not effective for evaluation. In this regard, two methods can be implemented to predict events. If the data is generated by climate models, parametric studies will be utilized, where the parameters are modified using real analysis or specialized knowledge. If the information is achieved by actual measurement, the power law is used to model many natural phenomena. In such approaches, the relative variations of one parameter lead to a proportional change in the other values. For instance, the Gutenberg–Richter (GR) law determines the number-size distribution of earthquake magnitude and other possible predictions [39]. Another procedure to predict events when the data is gathered from real measurements is the extreme value theory (EVT), which considers the probability of extreme events and ignores the previously observed low-impact events [40].

3.3 | Cyber-physical attacks

Due to the development of information and communication technologies (ICTs), cyber infrastructures are widely used in electrical energy systems [41]. The integration of such technologies with the measurement, protection, control and communication sections creates new features such as precise monitoring. In a cyber-physical electrical energy system, the received data is analysed by the control centre and appropriate decisions are made. Then, the required instructions are sent to the related equipment through the cyber infrastructures. Such systems can be a potential target for non-legitimate agents due to their connection vulnerability. As illustrated in Figures 8 to 10 [42], the total investment cost of electricity grids in the USA and China has the highest value among all countries around the world, where a huge amount of this cost is assigned to digital equipment. The results approve that the growth of digitalization since 2015 has significantly increased from 12% to 19%. In this regard, the penetration of smart meters and sensors has increased in the mentioned period such that the main portion of total investment cost in transmission and distribution networks is related to the development of smart meters, automation and management systems. Hence, it can be concluded that the structure of conventional grids has moved towards smartening. The reported information also exhibits that the number of cyber incidents with massive economic losses is increased in electrical energy systems, where seven cyber-attacks with losses of more than 1 billion dollars occurred in 2020.

The national institute of standards and technology (NIST) of USA has published a comprehensive guide and defined three objectives for smart cyber-physical systems including accessibility, integrity and confidentiality [43]. The availability and integrity are the most important aspect from the reliability point of view; however, confidentiality is critical in systems with high interactions such as multi-agent structures. The threats of smart grids can be divided into three categories based on the mentioned objectives [44]

- Threats with the aim of system access or denial of service (DoS) which is an attempt to delay, block or disrupt communications.
- Threats that are designed to damage system integrity and alter or disrupt the information exchange intentionally or illegally.
- Threats with privacy targets that try to gather unauthorized information from different sources.

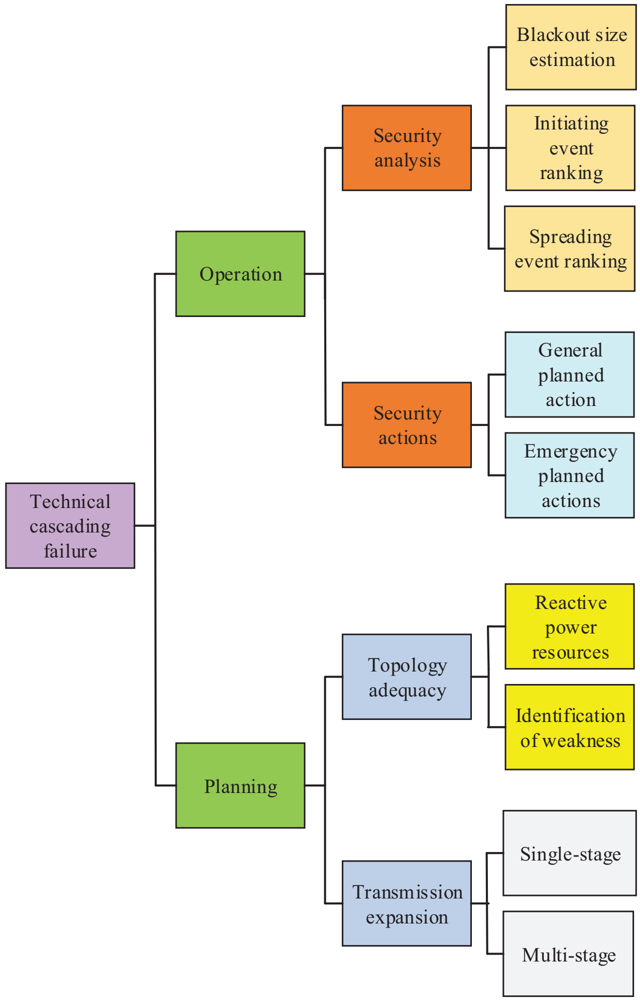

FIGURE 6 Classification of technical cascading failure studies in electrical energy systems.

In order to evaluate the impact of cyber-physical attacks, it is necessary to model the cyber-physical systems and then perform the required analyses. Thereupon, four approaches including graphical, mechanism, probabilistic and simulation are introduced and explained as follows [45]:

- **Graphical modelling**: This method directly obtains independent relationships between variables and quantitatively evaluates the system transfer state. The graph theory, complex network, finite state machine and Petri network are the main subsets of graphical modelling.
- **System mechanism**: The interactions between cyber-physical networks are analysed using system mechanism based on the combination of continuous/discrete events and static/dynamic behaviours. The analytic model, dynamic procedure, hybrid algorithm, variable structure and multi-agent system are the main subsets of system mechanism.
- **Probabilistic modelling**: Since cyber-physical networks have probabilistic performance under various events, uncertain approaches are for modelling their interactions. The stochastic and game theory models are the main subsets of probabilistic modelling.
- **Simulation modelling**: According to the discrete features of cyber systems and the continuous operation of electrical grids, an integrated system is designed to maintain the integrity and accuracy of the entire network.

The cyber-physical attacks also can be analysed using two main models. The first one is called complex network-based interdependent model and the second one is flocking-based hierarchical cyber-physical model. In recent years, complex networks have received a lot of attention. Initially, many studies have been conducted on the performance of isolated individual systems [46]. However, they are interconnected through complex interdependencies such as the relationship between fuel and power stations, energy and other variables [47]. The optimal performance of interdependent infrastructures is considered in a limited environment of resources [48]. The cyber-physical attacks are also examined according to the flocking opinion on the transient consistency problem [49]. In such a model, a degree of cyber technology is selected using physical connections based on the studied strategies and each agent consists of a dynamic node, a phasor measurement unit (PMU) and a local cyber controller.

4 | ELECTRICAL ENERGY SYSTEM RESILIENCE

The first explanation of resilience is defined in 1973 as 'measuring the stability of systems and their capability to attract changes and disruptions as well as maintaining similar relationships between government variables or populations' [50]. Reference [51] defines the engineering domain as 'the inherent capability of a system to regulate its performance in the event of disruption and unpredictable changes'. The system resilience terms have been developed by studying the resilience of critical infrastructures. The cabinet office of the UK defines resilience as the ability to forecast, attract, adapt and recover from a catastrophic event, where the main features are expressed in Figure 11 [52]. According to the national infrastructure advisory council (NIAC) of the USA, resilience is the capacity of a system to deal with adverse events by adapting through resistance or changing the structure of the system to achieve an acceptable level of performance. The resilience characteristics provided by NIAC are shown in Figure 12 [53]. Therefore, a resilient system has four main characteristics for confronting extreme events including prediction, absorption, recovery and adaptation which means the ability to prevent and minimize damage, rebuild components and learn from past events to improve the capabilities for future incidents, respectively.

5 | RESILIENCE ANALYSIS

The resilience of power systems is studied generally from two perspectives including component-level and system-level. At the

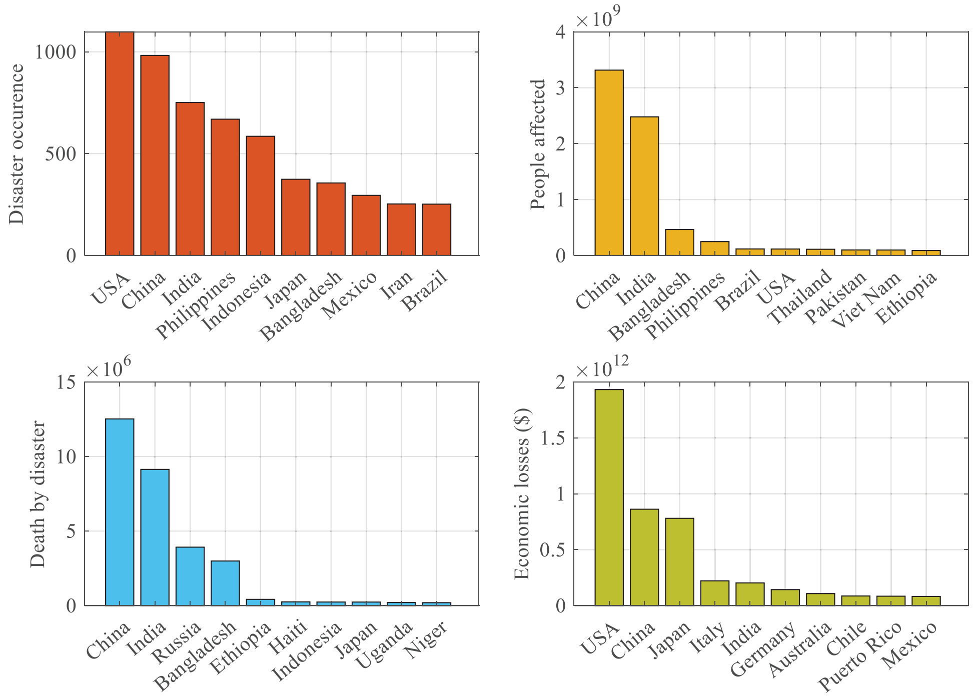

FIGURE 7 Top 10 affected countries by natural disasters around the world from 1900 to 2021.

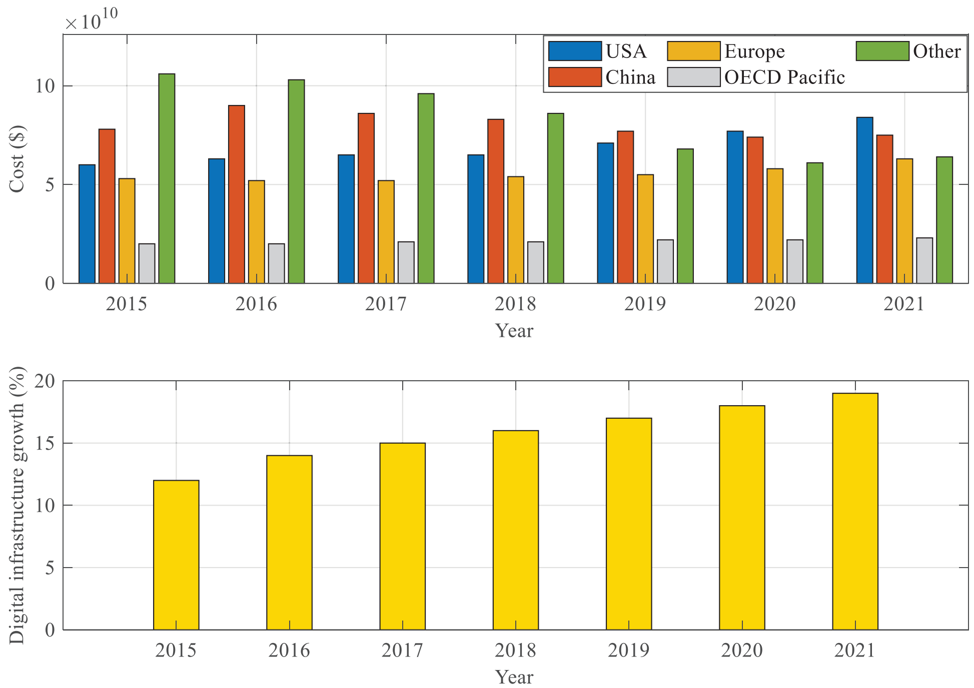

FIGURE 8 Global investment in electricity grids and the growth of digital infrastructure from 2015 to 2021.

system-level, the resilience is measured widely in the operation time. In contrast, the resilience measurement is done before and after the event at the component-level utilizing separate indices. The indicators before and after the incident are used to identify system weaknesses and optimal restoration strategies, respectively [54].

5.1 | Differences of resilience triangle and trapezoid

A resilient system has different features such as reducing the probability and consequences of failure (in terms of losses and negative economic and social effects) and decreasing recovery

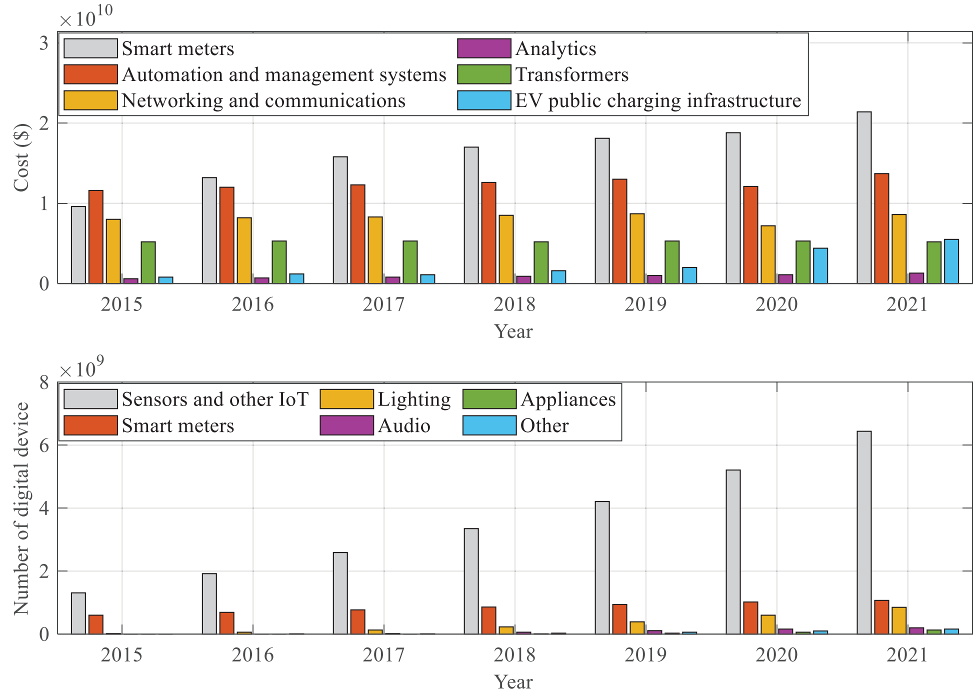

FIGURE 9 Investment of digital devices in transmission and distribution infrastructures from 2015 to 2021.

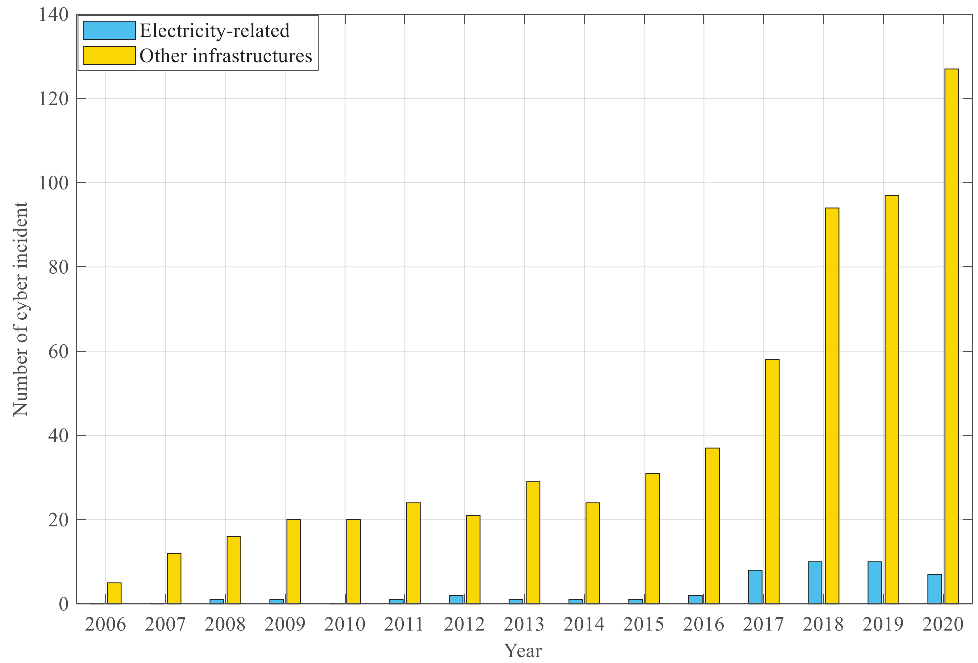

FIGURE 10 Cyber incidents around the world with losses of more than 1 billion dollars from 2006 to 2020.

time. The resilience measurement which has the mentioned key features is named the 'resilience triangle' and depicted in Figure 13 [55]. Such a concept is presented for the first time to evaluate the resilience of a social network against earthquakes. The system resilience is obtained with performance degradation integral over time after the disruption using the resilience triangle. However, it is not possible to measure the functionality of destruction time before recovery. Reference [56] has expanded the 'resilience triangle' and provided a 'resilience trapezoid' consisting of different phases to analyse the power system collision during the events. Figure 14 shows a resilience trapezoid in which the time sequence of different stages in the face of an event is specified. The resilience triangle is used for a specific threat, where the assessment is performed in a

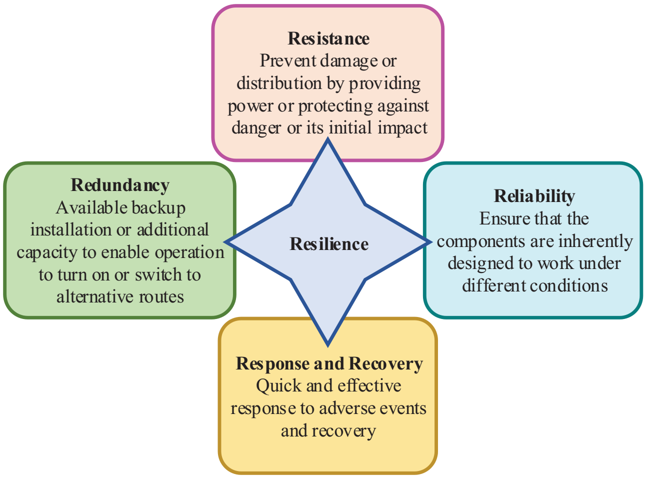

FIGURE 11 The components of a resilient infrastructure presented by the cabinet office of the UK.

single-phase without corrective actions and post-disruption degradation phase. In return, the resilience trapezoid has a multi-phase dynamic evaluation, corrective actions during the event, post-event destruction state and its duration and it can be executed for any threat [57].

5.2 | Resilience curves

The resilience curve is used to accurately analyse the response to a disturbance, as exhibited in Figure 15. The system performance on the vertical axis is a function of the time on the horizontal axis following an event. The operational resilience refers to features that help the system maintain its performance and resist a disaster. The infrastructure resilience refers to the physical capability of a system to minimize a portion that has been affected, collapsed or completely inactive [57]. At the time axis, resilience assessment begins at t_0, the event occurs at t_m and destruction starts at t_p. The progress of damage continues until t_D and then, the system enters the post-destruction state until t_{DD}. Afterwards, the restoration will be done until t_R and the post-restoration state starts and continues until t_{ir} and finally, the infrastructure recovery continues until t_{pir}. The time process of responding to an event is also divided into three phases including before, during and after the event intervals.

5.2.1 | Before event proceedings

As illustrated in Figure 15, such a phase is considered between t_0 and t_P. The resilience analysis of the power system starts from t_0 and the event occurs at t_m. This interval is divided into two parts, where $[t_0, t_m]$ is the preparation and management time for events like tornadoes or earthquakes and it takes from zero seconds to a few hours. The next time interval is $[t_m, t_P]$ that has several features such as robustness and resistance. It should be noted that the severity of the damage from t_m to t_P depends on the type and intensity of the event and resilience does not decrease rapidly. In interval $[t_0, t_P]$, the operators can identify potential damage to reduce the impact of events.

The main purpose of this step is to determine the level of damage for each component. In other words, the condition of the components is checked, which is in service or out of service. There are three steps to do that [58]: (a) identifying the vulnerable components, (b) obtaining the fragility model and (c) specifying the damage level. In the first stage, vulnerable components that have significant impacts on system resilience are identified. In the second stage, the fragility curve of vulnerable components and the probability of components failure against the event must be obtained. The quantitative expression of components vulnerability due to the severity of the event parameter leads to producing a normalized curve called the fragility curve. In practice, the component failure probability is determined based on the random number $r \sim U(0,1)$. If the probability is higher than r, the component will fail [39]. It should be noted that the component failure does not necessarily mean its complete destruction. In the third stage, five failure levels are defined for the fragility curve including non-damage, slight damage, moderate damage, extensive damage and totally damage. The fragility curves as statistical tools are used in different references to show the possibility of affected conditions when an event occurs [59].

The fragility curves of the distribution lines for the four levels of failure in an earthquake are illustrated in Figure 16, where the damage probability is a function of the peak ground acceleration (PGA). It is noteworthy that each fragility curve is characterized by a mean value and a standard deviation of the log-normal distribution. The fragility function for the level of damage ds is defined by (1) [60].

$$P\left[ds|S_d\right] = \phi\left[\frac{1}{\beta_{ds}}\ln\left(\frac{S_d}{\overline{S}_{d,ds}}\right)\right] \tag{1}$$

The event index, average value, standard deviation of the natural logarithm distribution of each level of failure and normal distribution function of cumulative function are modelled by S_d, $\overline{S}_{d,ds}$, β_{ds} and ϕ, respectively. After specifying the vulnerable components, preventive proceedings should be considered. The preventive management means controlling events to anticipate and prepare for future problems. According to Figure 15, preventive management is performed at $[t_0, t_m]$.

5.2.2 | During event proceedings

This phase includes $[t_P, t_D]$ interval in which the system performance decreases from P_0 to P_D. Following an event, effective management is done and the options and priorities are identified for controlling and reducing the damage. Hence, this part has the feature of 'resourcefulness'. The 'redundancy' feature also will be noticeable if the backup or additional capacity that enables performance or alternative routes is considered.

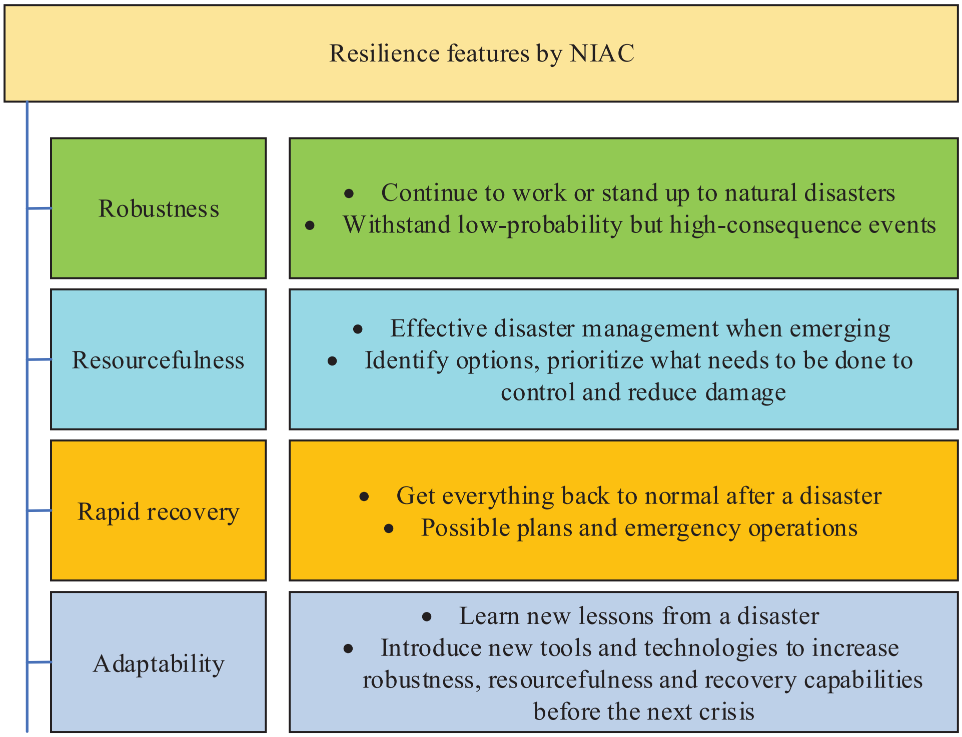

FIGURE 12 The specified features of a resilient system proposed by the NIAC of the USA. NIAC, National Infrastructure Advisory Council.

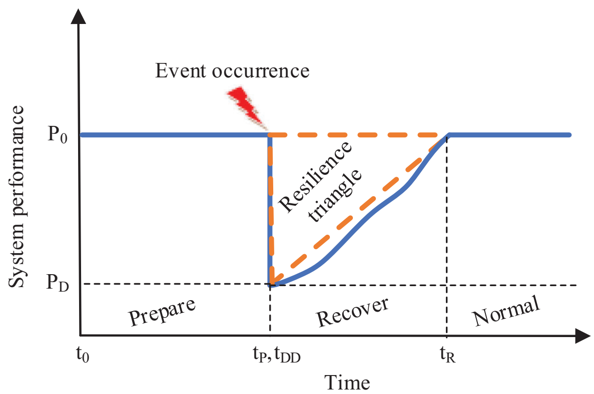

FIGURE 13 Electrical energy system performance following a HILP event. HILP, high-impact low-probability.

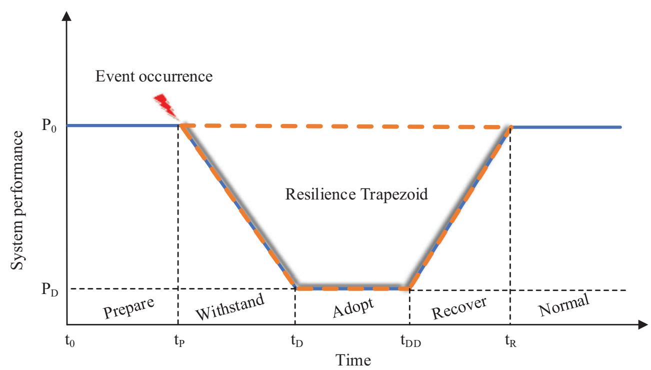

FIGURE 14 Electrical energy system performance following a HILP event in adapted mode. HILP, high-impact low-probability.

Another feature of this part is 'adaptability' and it can be concluded that improving the control mechanism in this area can enhance resilience.

At this step, the network performance is transferred from a normal state to a damaged state. The degradation state begins when a severe event occurs. Such a state indicates the effectiveness of the extreme event and if the restoration measures are not performed instantly after or during the event, the performance of the network remains in the degradation state. Initially, the model before the incident uses a system single-line diagram, load specifications, priorities and available generation resources. Then, the component fragility curve is obtained according to extreme natural disasters and space weather events.

The modelling techniques of fragility curve are divided into two types including analytical and simulation. Analytical methods are implemented in small systems, while simulation techniques are utilized for complex systems [61].

In most studies, analytical techniques have been used to assess the impact of climate on grid operation. In this regard, the Markov method models the power system degradation by creating consecutive chains and according to the network performance time dependence following a severe event [62]. Another way to perform analytical calculations is scenario-based methods. If N is the number of vulnerable components, then the number of 2^N scenarios can be defined for the predicted damage and the optimal power flow (OPF) is applied to determine the state of the system according to different

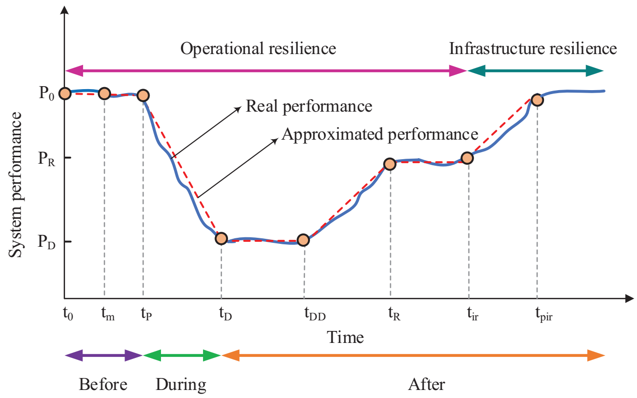

FIGURE 15 The resilience analysis curve in different phases following a HILP event. HILP, high-impact low-probability.

scenarios. The most common simulation approach is the Monte Carlo simulation (MCS). The choice of the state has been solved by the MCS as the biggest problem for numerical methods. In other words, MCS solves this problem by randomly sampling the states for a fixed number of simulations or until some convergence criteria are met. Moreover, if the system complexity is high, the probabilistic problem is divided into several deterministic problems using the MCS [63].

5.2.3 | After event proceedings

This phase begins at t_D and continues until t_{pir} and it can be divided into four sub-intervals. The first interval is a post-event degraded state and it consists of features such as resourcefulness, redundancy and adaptability. The second interval is a system restorative state, where network loads are restored as much as feasible and the performance increases from P_D to P_R. It should be noted that P_R may be the same or lower than the performance before the event (i.e. P_0). Since this section gives a quick and effective response to a severe event, it has 'response' and 'recovery' features. The third interval is the post-restoration state with 'robustness' and 'resistance' features and P_R performance. In the fourth interval, a system infrastructure recovery is checked, the damaged parts of the infrastructure are repaired and the performance reaches P_0. After t_{pir}, the system is fully recovered and adapted and operates continuously until the next severe event. This section distinguishes resilience studies from reliability, identifies the system weaknesses and utilizes resilience improvement strategies. Moreover, adaptability should be included in resilience studies because it demonstrates the capability of the system to endure similar incidents or severe incidents in the future. This stage shows the duration of a severe event that the network returns from the damaged state to the pre-event state. The system resilience depends more on the recovery process that begins from t_{DD} and ends when the network performance reaches its pre-event state. At this point, the entire network function or just a specific part of it may be restored. It should be noted that depending on the network recovery resources, the recovery factor and recovery time change. The recovery resources include repair crews, temporary power supplies, etc. Furthermore, the infrastructure recovery process by the repair team may take more time after the event [64].

6 | RESILIENCE ASSESSMENT INDEX

Resilience indicators assess functionality and can be used to specify appropriate enhancement strategies. Although there is still no specific standard for measuring network resilience, all features including prediction, absorption, recovery and adaptation must be considered to determine the resilience. Since system performance changes over time, there must be a time-dependent resilience criterion to consider various aspects such as economic activity level and the critical facilities availability, operation security, power quality and many more [55, 65].

As exhibited in Figure 15, if the system performance is indicated by $P(t)$, the general form of the resilience assessment criterion can be modelled by (2) [54].

$$R = \frac{\int_{t_0}^{t_{pir}} P(t)dt}{\int_{t_0}^{t_{pir}} P_0 dt} = \frac{\int_{t_0}^{t_{pir}} P(t)dt}{P_0(t_{pir} - t_0)} \tag{2}$$

where R is the resilience index and represents the system resistance to the events and it can be separately calculated for each phase. In order to analyse the resilience triangle, the resilience criterion in (3) also can be considered. This criterion shows the performance losses after the incident and the duration required to reach an appropriate level of performance.

$$R = \frac{\int_{t_o}^{t_R} P_0(t) - P(t)dt}{\int_{t_o}^{t_R} P_0 dt} = \frac{\int_{t_o}^{t_R} P_0(t) - P(t)dt}{P_0(t_R - t_0)} \tag{3}$$

According to the resilience triangle, if the recovery time or the rate of performance degradation is reduced, resilience will increase. As a result, resiliency can be defined between 0 and 1, where based on the mentioned indices, the bigger values in (2) and lower values in (3) show higher resiliency, respectively.

In addition to the general form in (2), some other indicators have been proposed in the literature to measure resilience. A set of criteria for obtaining resilience is defined along with the ability to achieve performance in different phases of the resilience trapezoid [56]. Therefore, the collection of indices is described to exhibit the speed and size of the network destruction performance, the amount of time for destruction and the restoration velocity. Reference [66] introduces a time-dependent criterion as the ratio of recovery to losses. This ratio indicates that if the recovery is equal to the losses, the system will be entirely resilient. Furthermore, the most important aspects of resilience including reliability, vulnerability and recoverability

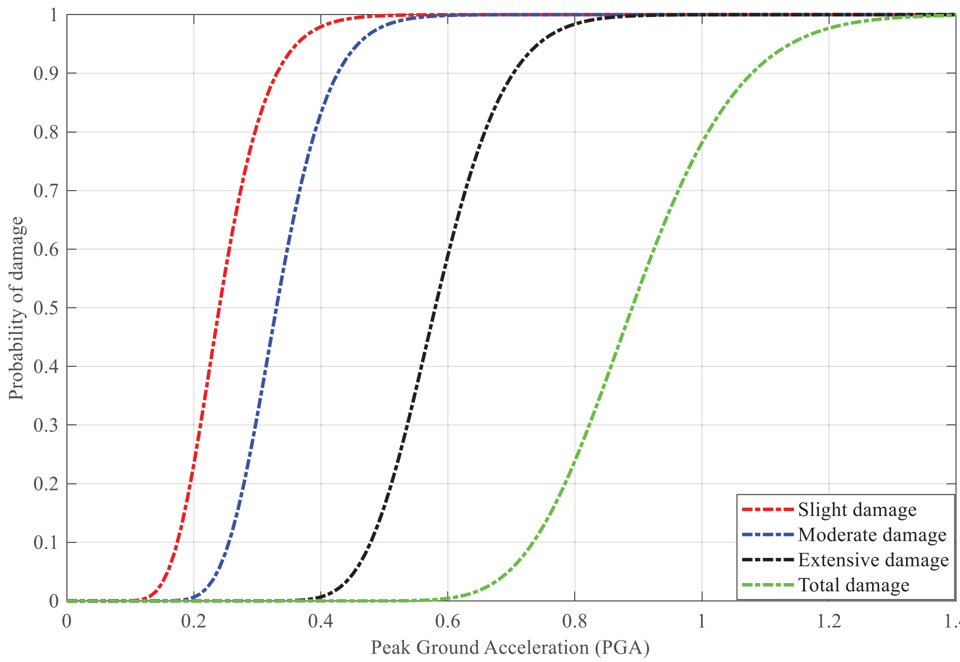

FIGURE 16 Fragility curves of power distribution lines in an earthquake.

are considered. In this regard, the resilience index is formulated by (4) according to the resilience curve.

$$R(t) = \frac{P(t) - P(t_D)}{P(t_0) - P(t_D)} \tag{4}$$

where the grid performances under normal and damaged conditions are stated by $P(t_0)$ and $P(t_D)$, respectively. A stochastic resilience criterion is defined in which the influences of exhaustion on the system are considered and the resilience index is examined from both robustness and resourcefulness aspects (5) to (7) [67].

$$R = \frac{T_i + F\Delta T_f + G\Delta T_r}{T_i + \Delta T_f + \Delta T_r} \tag{5}$$

$$\Delta T_f = T_f - T_i \tag{6}$$

$$\Delta T_r = T_r - T_f \tag{7}$$

where the event occurrence time, failure time, recovery time, duration of failure, duration of recovery, failure profile to specify robustness and redundancy, recovery profile to determine recoverability are indicated by T_i, T_f, T_r, ΔT_f, ΔT_r, F and G, respectively. It should be noted that for any failure event (f) and system performance (Q), the corresponding failure profile and recovery profile can be calculated by (8) and (9), respectively.

$$F = \frac{\int_{t_i}^{t_f} f dt}{\int_{t_i}^{t_f} Q dt} \tag{8}$$

$$G = \frac{\int_{t_f}^{t_r} r dt}{\int_{t_f}^{t_r} Q dt} \tag{9}$$

The resilience index is also presented considering the restoration time and system modes by (10) [68].

$$R = S_p \frac{F_r}{F_o} \frac{F_d}{F_o} \tag{10}$$

where the parameters F_o, F_d and F_r are the network performance under normal, defective and recovered conditions, respectively. As well, S_p indicates the restoration rapidity that is modelled by (11).

$$S_p = \begin{cases} (t_\delta / t_r^*) \exp\left[-a\,(t_r - t_r^*)\right] & t_r \geq t_r^* \\ (t_\delta / t_r^*) & \text{otherwise} \end{cases} \tag{11}$$

where the parameters a, t_δ, t_r and t_r* are decay controlling, slack time, time to final recovery (new balance state) and time to complete primary recovery actions, respectively.

7 | RESILIENCE ENHANCEMENT METHODS

Figure 17 is designed to show the general overview of the resilience enhancement process and its characteristics in each phase of the event occurrence [69]. Generally, resilience enhancement strategies are divided into operation-based (short-term) and planning-based (long-term) approaches. The short-term perspective extends optimization-based strategies and

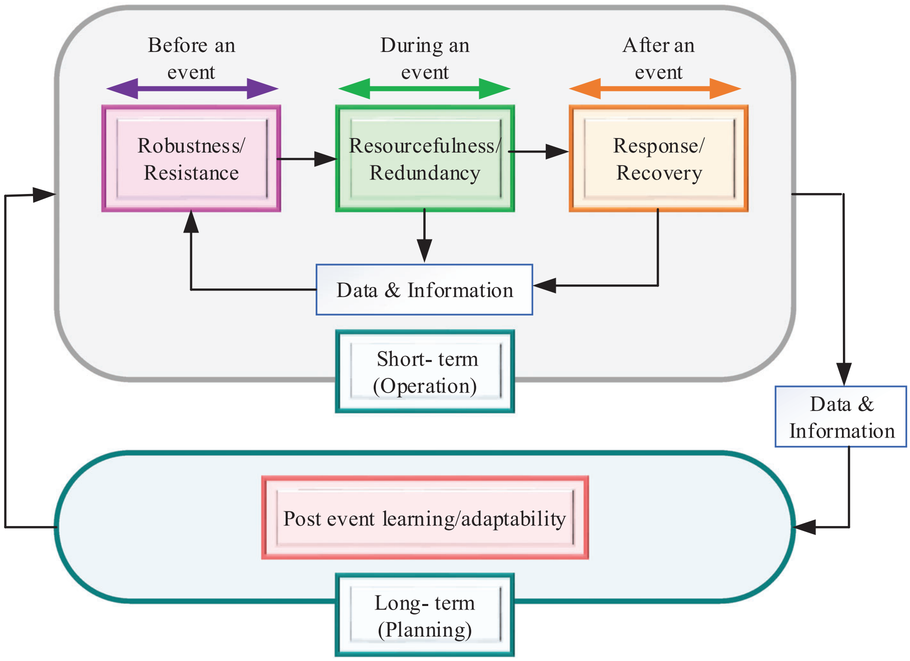

FIGURE 17 Short-term and long-term perspectives of system resilience enhancement methods.

involves intelligent and adaptive approaches against events. The long-term perspective focuses on organizing network development programs to tighten transmission and distribution systems versus severe incidents.

7.1 | Operation-based methods

In operation-based methods, appropriate and immediate measures can be taken to reduce harmful effects in the network by collecting information about the event through forecasting tools. This concept is composed of various subjects such as microgrids and small-scale resources, mobile power sources, network reconfiguration, load restoration, repair crews and spare parts management, grid condition monitoring and situation awareness and mobile DC de-icing devices (MDIDs). It is noteworthy that to have a better comparison, the key points in each reference for resilience enhancement from the short-term point of view are summarized in Table 2.

7.1.1 | Microgrids and small-scale resources

The concept of microgrid can be considered an effective solution for resilience improvement because of their capability in island operation and maintaining the influence of renewable resources [70–72]. During the event occurrence, the affected zone is separated from the original network and several connected microgrids are created. The critical loads of one microgrid can be supported by another microgrid that does not have sufficient resources. Therefore, microgrids can be used as a local or communication source to improve system resilience [73]. The system resilience enhances by forming dynamic microgrids or networked microgrids [74–77]. Furthermore, the concept of multi-energy systems (MESs) in which different infrastructures are interconnected is utilized in recent studies to improve resiliency due to their capability to convert various types of carriers [78]. Reference [79] proposes a non-cooperative game-theory framework to investigate the strategic behaviour of distributed microgrids using the Nash equilibrium concept. In addition, other subjects such as demand side management (DSM), application of EVs and parking lots as flexible sources and network reconfiguration methods (NRMs) are usually considered the extra options to improve the efficiency of the main strategy. It should be noted that the influence of uncertain parameters is also modelled in many studies by scenario-based approaches, robust optimization and learning-based algorithms to decrease the risk of decisions.

7.1.2 | Mobile power sources

Mobile power sources have been used in many cases to enhance the electrical energy system resilience [80]. These sources include mobile emergency generators (MEGs), truck-mounted mobile energy storage systems (TMESSs) and EVs. Such units can be utilized to supply critical loads during emergency conditions or recover them after an event [81]. In industrialized countries, power and transportation systems undergo various changes where their coordination can enhance the resilience of the power system. The potential role of EVs as contributors to the grid and electricity market for resiliency services, as well as their capability to manage the network stress, is less well known. The annual energy outlook forecasts that the penetration of EVs in the United States will grow from less than 2% to 15% in 2040 [111]. The integration of EVs can be effective to provide

TABLE 2 Key points in each reference for resilience enhancement from the short-term point of view.

Ref	Subject DSM	DG	EV	MES	NRM	Uncertainty	Methodology	Enhancement
[70]	✓	✓	✗	✗	✓	✗	Proactive scheduling	Microgrid formation or small-scale resources
[71]	✗	✗	✗	✗	✓	✗	Analytical hierarchical process and percolation theory	
[72]	✓	✓	✓	✗	✗	✓	Survivable mathematical framework	
[73]	✗	✗	✗	✗	✗	✗	Optimal active/reactive power flow	
[74]	✗	✓	✗	✗	✗	✗	Distributed multi-agent coordination	
[75]	✗	✓	✗	✗	✓	✗	Resilient and privacy-preserving energy management	
[76]	✓	✓	✗	✗	✓	✗	Graph theory	
[77]	✗	✓	✗	✗	✗	✗	Non-cooperative game-theory	
[78]	✗	✓	✗	✓	✗	✓	Stochastic multi-stage scheduling	
[79]	✓	✓	✗	✗	✗	✓	Data-driven approach	
[80]	✗	✓	✗	✗	✗	✓	Two-stage dispatch framework	Mobile power sources
[81]	✗	✓	✗	✗	✓	✓	Two-stage restoration scheme	
[82]	✗	✓	✓	✓	✗	✓	Stochastic scheduling	
[83]	✓	✓	✓	✓	✗	✓	Distributed robust strategy	
[84]	✗	✓	✗	✗	✓	✗	Resilience framework	
[85]	✗	✓	✓	✗	✗	✓	Two-stage stochastic program	
[86]	✗	✓	✓	✗	✗	✓	Multi-agent deep reinforcement learning	
[87]	✗	✓	✗	✗	✓	✗	Deep neural network	
[88]	✓	✓	✓	✓	✓	✓	Fragility curves based model	
[89]	✗	✓	✓	✗	✗	✗	Multi-agent reinforcement learning	
[90]	✗	✓	✗	✗	✗	✓	Three-stage stochastic program	
[91]	✗	✗	✗	✗	✓	✓	Bi-level optimization	Network reconfiguration
[92]	✗	✓	✗	✗	✓	✗	Tri-level optimal hardening plan	
[93]	✓	✓	✓	✗	✓	✗	Optimal coordinated allocation	
[94]	✗	✗	✗	✗	✓	✗	Graph theory and Choquet integral	
[95]	✗	✗	✗	✗	✓	✗	Unified two-stage model	
[96]	✗	✓	✗	✗	✗	✓	Two-stage heuristic model	Load restoration
[97]	✗	✓	✗	✗	✗	✗	Maximum coverage problem	
[98]	✗	✗	✗	✗	✓	✗	Bi-level programming	
[99]	✗	✓	✗	✗	✓	✗	Multi-stage method	
[100]	✗	✓	✗	✓	✗	✗	Minimum diameter spanning tree	
[101]	✗	✓	✗	✗	✓	✗	Resilient restoration approach	
[102]	✗	✓	✗	✗	✓	✗	Co-optimization model	Repair crews and spare parts management
[103]	✗	✓	✗	✗	✓	✓	Two-stage stochastic program	
[104]	✗	✓	✗	✗	✗	✗	Spare parts management algorithm	
[105]	✗	✗	✗	✗	✗	✓	Machine learning-based algorithm	Grid condition monitoring and situation awareness
[106]	✗	✗	✗	✗	✗	✗	Quantum transient stability assessment	
[107]	✗	✗	✗	✗	✗	✓	Multi-level hierarchy framework	
[108]	✗	✗	✗	✗	✗	✗	Data-driven approach	
[109]	✗	✗	✗	✗	✗	✗	Multi-state model	
[110]	✗	✓	✗	✗	✗	✓	Two-stage robust optimization	Mobile DC de-icing devices

network service requirements such as demand response, valley filling, reserve management, emergency back-up, capacity firming, voltage control and frequency regulation. In this regard, references [82, 83, 85, 86, 88, 89] have utilized EVs or parking lots as mobile sources, while the allocation of other MEGs is specified by [84, 87, 90] to improve system resilience.

7.1.3 | Network reconfiguration

In several studies, network reconfiguration has been implemented by different approaches such as graph theory to improve system resilience [92–95]. For instance, Reference [91] presents a bi-level model for the distribution system reconfiguration to improve resilience against an event and minimize the load interruption cost. Therefore, a method is implemented to estimate the amount of damage incurred to the system. Then, in the first stage, network reconfiguring is performed by considering the damage estimation before the event. In the second stage, a new post-event reconfiguring has been applied to recover the loads.

7.1.4 | Load restoration

Fast and efficient restoration is an essential step to improve system resilience. Load restoration has been investigated in various studies using heuristic models, multi-stage and multi-level optimizations [96–99]. Reference [100] has focused on load restoration in an MES utilizing DGs and based on minimum diameter spanning tree problem. The advanced feeder restoration method to restore critical loads using DG sources is investigated recently [101]. In this study, the amount of critical loads is maximized using and the repair time is improved by the optimal placement of DGs. An optimal DG islanding strategy is used by considering reconfiguration after multiple faults and the load restoration flowchart is proposed based on smart grid technologies.

7.1.5 | Repair crews and spare parts management

The repair crew and spare part are a vital subject for managing the disruption of distribution systems after an event. Reference [102] proposes a resilient plan for disaster recovery logistics to restore the distribution system by the repair crew and mobile power sources. A new method is introduced to optimize the performance of the distribution system and repair crew routing for outage restoration after severe weather events [103]. The failure of components may cause other faults associated with it, considering the design of system. Therefore, it is essential to use spare parts to maintain proper system performance and minimize the impact of breakdowns. Reference [104] has focused on the limited number of spare parts due to technical and economic constraints. This study uses an optimization algorithm to purchase a sufficient number of spare parts and minimize wind farm costs.

7.1.6 | Grid condition monitoring and situation awareness

The system restoration process after the event can be done quickly if the real-time and actual information is accessible. Reference [105] utilizes grid monitoring to estimate the damage caused by the event and improves situational awareness based on machine learning. A hybrid framework composed of quantum computing, data science and machine learning is designed for the stability assessment of power systems [106]. Reference [107] presents a multi-level hierarchy framework to evaluate the situational awareness in active distribution networks and [108] uses a data-driven approach to rapidly predict forced outages in power systems. In a recent study, various factors that cause the formation of situation awareness in the central control are investigated and a multi-mode approach based on Markov modelling is presented to achieve the effects of insufficient situation awareness on the probability of power outage [109].

7.1.7 | Mobile DC de-icing devices

Reference [110] suggests a method to enhance the power system resilience in the transmission system against ice storms. In this regard, a cooperation is considered between the power grid scheduling program with the pre-determination and MDIDs routing. Hence, ice thickness in transmission lines is obtained in a two-step optimization method where in the first step, the pre-determined MDIDs and unit commitment in a day-ahead planning are coordinated, and then, the operation is specified according to the real-time ice thickness.

7.2 | Planning-based methods

Planning-based methods are hardening solutions that increase infrastructure resilience, reduce the physical effects of severe events and prevent the failure of large parts of the power grid. This approach can be investigated from various aspects including optimal location and sizing of sources, vegetation management, underground transmission lines, upgrading components and structures and elevating substations. It is noteworthy that to have a better comparison, the key points in each reference for resilience enhancement from the long-term point of view are summarized in Table 3.

7.2.1 | Optimal location and sizing of sources

In previous years, the expansion of electrical energy systems has been performed based on various criteria such as reliability; however, due to many reasons such as increasing the number HILP events and using renewable resources as the main power sources, additional proceedings should be considered to improve the resilience operation. In this regard, recent studies have focused on new subjects to achieve the mentioned goal. A two-stage stochastic mixed-integer programming is

TABLE 3 Key points in each reference for resilience enhancement from the long-term point of view.

	Subject						
Ref	DSM	DG	EV	MES	Uncertainty	Methodology	Enhancement
[112]	✗	✓	✗	✗	✓	Two-stage stochastic program	Allocation of components
[113]	✓	✓	✗	✓	✗	Resilience-oriented planning	
[114]	✓	✓	✗	✓	✓	Two-stage stochastic program	
[115]	✗	✓	✗	✓	✗	Resilience-oriented planning	
[116]	✗	✓	✗	✗	✓	Three-stage hybrid framework	
[117]	✗	✓	✗	✓	✓	Resilient-constrained two-stage expansion planning	
[118]	✗	✗	✗	✗	✗	Analytic hierarchy process	
[119]	✗	✗	✗	✗	✗	Data-model hybrid driven approach	
[120]	✗	✓	✗	✗	✓	Three-level data driven model	
[121]	✗	✗	✗	✗	✗	Deep transfer learning approach	
[122]	✗	✓	✓	✗	✓	Robust two-stage tri-level	
[123]	✗	✓	✗	✗	✓	Reconfiguration optimization	
[124]	✗	✗	✓	✗	✗	Genetic algorithm	
[125]	✗	✗	✗	✗	✗	Statistical study and machine learning	Vegetation management
[126]	✗	✗	✗	✗	✗	Maintenance scheduling algorithm	
[127]	✗	✗	✗	✗	✓	Probabilistic method	
[128]	✗	✗	✗	✗	✗	Estimation-based approach	Undergrounding lines
[129]	✗	✗	✗	✗	✓	Risk-aware optimization	
[130]	✗	✗	✗	✗	✓	Two-stage stochastic program	Upgrading components
[131]	✗	✓	✗	✗	✓	Tri-level optimization	
[132]	✗	✗	✗	✗	✓	Age-dependent fragility models	
[133]	✗	✓	✗	✗	✓	Two-stage stochastic method	Elevating substations
[134]	✗	✗	✗	✗	✗	Alternative approaches	

DG, distributed generation; DSM, demand side management; EV, electric vehicles; MES, multi-energy systems.

proposed to determine the optimal size of different renewable energy sources considering economic benefits and resilient performance [112]. The proposed method models the interaction between sizing in the planning stage and the hourly distribution in the operational stage for both grid-connected and islanded modes concerning random grid disturbances, load and renewable generation. References [113, 114, 115, 117] optimize the allocation of DGs in MESs using stochastic and robust algorithms besides considering the influence of flexible loads to improve grid resilience. The location and sizing of components in electrical energy systems are also determined by various approaches such as data-driven models [116, 120, 123]. The influence of EVs and parking lots is analysed in [122, 124] and eventually, References [118, 119, 121] present modification strategies or transmission line expansion to enhance resiliency versus extreme events.

7.2.2 | Vegetation management

The vegetation management standards are applied along transmission and distribution lines to minimize damage from trees during storms and maintain system reliability. The effects of a vegetation management standard on the trimming or removal of trees in the vicinity of overhead lines are discussed in [125–127].

7.2.3 | Underground transmission lines

Underground transmission and distribution lines make poles and lines less prone to severe events. However, converting overhead lines to underground lines costs too much. Hence, comprehensive analytical framework for estimating the social costs and benefits of undergrounding lines to improve the power system reliability is presented [128–130].

7.2.4 | Upgrading components and structures

The system resilience will improve if the conventional components and structures are upgraded with new technologies. References [131, 132] have tried to investigate the impact of interconnections between various grids, new tools and their high investment costs on the resilience.

TABLE 4 Classification of resilience-oriented objective functions.

Type of function	Objective function	References
Single-objective	Max of critical load restoration	[64, 96, 101, 135–138]
	Min of total restoration time	[96, 98, 163, 164]
	Min of load-shedding (load interruption)	[98, 147, 165, 166]
	Max of energy served/Min of energy not served	[96, 167, 168]
Multi-objective	Resilience, operation cost, power loss, etc.	[79, 130, 133, 143, 160, 169–177]

TABLE 5 Classification of resilience-oriented optimization methods.

Optimization	Classification of each method	References
Deterministic	Linear programming (LP)	[141]
	Mixed-integer linear programming (MILP)	[72, 101, 102, 105, 135, 144–146, 168, 178]
	Mixed-integer second-order cone programming (MISOCP)	[110, 149, 150]
	Mixed-integer non-linear programming (MILNP)	[98]
Stochastic	Stochastic mixed-integer non-linear programming	[151, 166]
	Stochastic mixed-integer linear programming	[80, 130, 133, 143, 160]
	Heuristic methods	[151]

7.2.5 | Elevating substations

Substations can be severely damaged during floods. In order to prevent damage to substations, raising them is one of the most practical ways. Fixed barriers will be installed if floods frequently occur at substations, and temporary restrictions can be installed if floods are predicted [132–134].

8 | OBJECTIVE FUNCTIONS AND OPTIMIZATION METHODS

As mentioned in the previous sections, resilience is examined in three phases including before, during and after the event. In the first phase, operating costs are minimized by available resources. In the second phase, the total weight of survival loads during the event is maximized and in the last phase, the total weight of restored loads is maximized while the ancillary costs are minimized.

As presented in Table 4, resilience-based objective functions can be considered the max of critical load restoration, min of total restoration time, min of load-shedding (load interruption) and the max of energy served/min of energy not served. Reference [135] attempts to maximize the restored loads by the optimal formation of dynamic microgrids and management of various technologies. The load restoration maximization is also considered the objective function in many studies [64, 96, 101, 136]. A two-stage programming is presented to evaluate the resilience by considering the cost of resource allocation and critical loads restoration before and after the hurricane [112]. The critical loads restoration and minimization of the switching operations based on the tree span search is investigated recently [137]. A new process is presented for critical load restoration using DGs in which the problem is solved by the shortest path due to the accessibility of DGs and the optimal restoration pattern [138]. The objective function is to maximize the reliability of the restoration program to reduce the possibility of post-restoration failures in the aftermath of a disaster. A multi-objective optimization is used to achieve the capacity determination of DG resources and other contract programs concerning post-event energy resilience [139]. The objective function includes economic and environmental costs and the ratio of power deficiency after the occurrence of an event. Reference [140] proposes a multi-objective problem including minimizing the operation cost, maximizing the load support time with PV and battery energy storage systems, maximizing the support for the non-black-start unit and minimizing the expected supplied energy.

According to Table 5, many optimization methods are proposed to evaluate and improve resilience that they can be divided into deterministic and stochastic approaches. The deterministic methods such as linear programming (LP) [141], mixed-integer linear programming (MILP) [72, 76, 101, 135, 136, 142–147], mixed-integer second-order cone programming (MISOCP) [41, 110, 148, 149], mixed-integer non-linear programming (MILNP) [98], stochastic methods such as stochastic MILNP [150], stochastic MILP [80, 130] and heuristic methods such as particle swarm optimization and genetic algorithm [151]. The mentioned optimization problems are complex and need to be simplified. Therefore, algorithms such as column and constraints generation (C&CG) [152–154], nested C&CG [155, 156], scenario-based decomposition [157, 158], Bender's decomposition [159], progressive hedging algorithm [160], greedy search algorithm [161], dual decomposition algorithm [162] can be used. These algorithms can be run in software such as GAMS and MATLAB.

9 | CONCLUSIONS, CHALLENGES AND FUTURE DIRECTIONS

According to the recent blackouts around the world, the impact of HILP events on electrical energy systems becomes a critical subject. In this paper, a comprehensive study has been conducted including the main proceedings for analyzing the system resilience, various HILP events, resilience concept and resiliency curves, resiliency assessment indices, enhancement methods, objective functions and optimization approaches.

According to the reviewed references, there are still many challenges that need to be considered and discussed in the future. The challenges for further investigations are summarized as follows:

- Different studies have given definitions of resilience and addressed the characteristics of resilient power systems. There is general agreement on the characteristics of resilience including absorptivity, adaptability and recoverability. However, a specific standard or universally accepted definition does not exist for resilience.
- In addition to the lack of a standard definition, there is no standard indicator for assessing resilience and the resilience indicators mentioned only express the network absorption and restoration capacity. At the same time, indices are needed that also describe the predictive and adaptive capacity. The following factors must be considered to achieve the real nature of power systems. The characteristics and performance of the system; quantitative and qualitative analysis; deterministic and probabilistic aspects.
- There is low accuracy in weather-related forecasting methods and historical data of a single area is used for an event. Moreover, it is assumed that the data used are entirely reliable, while calibration, communication and other errors and uncertainties must be considered. Because of the lack of enough historical data and some ambiguities, cyber-attack simulation methods have to be developed, which is a big challenge.
- In order to accurately model failure in assessing the resilience of power systems, more researches should be done. In most cases, fragility curves are used to model failure. However, these curves do not include the side effects of events. Therefore, more studies are needed in this field.
- The study of modelling for the mentioned resilience improvement strategies is not enough yet, which can be extended.
- Preventive operational strategies are not emphasized in resilience improvement methods. In fact, implementing these strategies will help to reduce damage and serve more loads during the event.
- Cost-related issues have not been investigated adequately. In this regard, the transaction between the cost of electricity and emergency resources can help to provide resilience improvement methods.
- By reviewing various events, it should be ensured that the improvement strategy for one event does not affect the network capability associated with another event.
- The power supply of critical loads in isolated areas where power sources are not available has been neglected for modelling and suggesting resilience improvement techniques. However, some critical loads must be supplied through mobile energy sources.
- Electric sources are associated with other sources such as water, gas and communications. The study of resilience improvement methods in such systems is in the early stages due to the difficulty of dependent system issues.

AUTHOR CONTRIBUTION

Fariba Amini: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Project Administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review &; editing; **Saeid Ghassemzadeh**: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Project Administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review &; editing; **Naghi Rostami**: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Project Administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **Vahid Sohrabi Tabar**: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Project Administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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DATA AVAILABILITY STATEMENT

Data available on request due to privacy/ethical restrictions.

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