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Enhancing distribution system resilience against extreme weather events: Concept review, algorithm summary, and future vision☆

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ABSTRACT

Distribution system infrastructures are vulnerable to extreme weather events, such as hurricane, ice coating, flood, and wildfires. Resilience is a measure of the system's ability to prevent the damage during extreme events and to recover the system function after such events. With the economic development, it becomes increasingly important for power utilities to maintain critical loads always in service and to reduce the unserved energy of all loads. If many distribution system equipments are damaged, the utility companies dispatch static or mobile distributed energy resources, reconfigure the network topology in order to restore the islanded sections of the distribution system. In recent years, a large number of studies have been done on operation and planning strategies to enhance the distribution system resilience. This review paper introduces the background of resilient distribution system. Then, it makes a comprehensive summary of the resources for resilience enhancement, the mathematical model of operation and planning algorithms. In particular, the objective function, mathematical formulation, decision variables, and solution algorithm of each study are compared. Finally, the roadmap of resilient distribution system is extracted and the future research direction on this topic is proposed.

1. Introduction

Modern urban distribution systems (DSs) are able to maintain most of the loads in service under the challenge of average weather-related disturbances, such as continuous rain, snow, and strong wind. However, some low-probability extreme weather events can still cause large-scale power outages in DSs [1,2]. For example, in 2017, power outages due to hurricanes Harvey, Irma, and Maria caused a total economic loss of around $202 billion in the U.S. [3]. In February 2021, the ice storm in Texas, U.S led to large-scale generator outages and load shedding of up to 25GW (33% of total load). 4.5 million customers were left unserved during the most serious period (February 15th ~ 16th) [4]. Since such severe disturbances may cause physical damage to power system infrastructures, it usually takes more than one day to repair all damaged equipment.

The concept "power system resilience" is a criterion to assess the ability of a system to withstand and recover from significant power outages caused by natural disasters or deliberate attacks [5,6]. According to the report [7] by Electric Power Research Institute of the U.S., DS resilience is based on 3 elements (e.g., prevention, recovery, and survivability). The main distinguishing characteristic between reliability and resilience is, the former refers to high-probability, low-impact disturbances and the latter refers to low-probability, high-impact ones [8]. A conceptual resilience curve associated with an extreme event is adopted for illustration, as shown in Fig. 1. *R* refers to an index of the system function of energy supply. The system states involve pre-

Abbreviations: BESS, Battery energy storage system; CCG, Column-and-constraint generation; DER, Distributed energy resource; DS, Distribution system; DSO, Distribution system operator; KKT, Karush–Kuhn–Tucker; LP, Linear programming; MEG, Mobile emergency generator; MESS, Mobile energy storage system; MG, Microgrid; MILP, Mixed-integer linear programming; MINLP, Mixed-integer nonlinear programming; MISOCP, Mixed-integer second-order cone programming; MPS, Mobile power source; NLP, Nonlinear programming; OMS, Outage management strategy; PH, Progressive hedging; PV, Photovoltaic; RCS, Remote-controlled switch; SOCP, Second-order cone programming.

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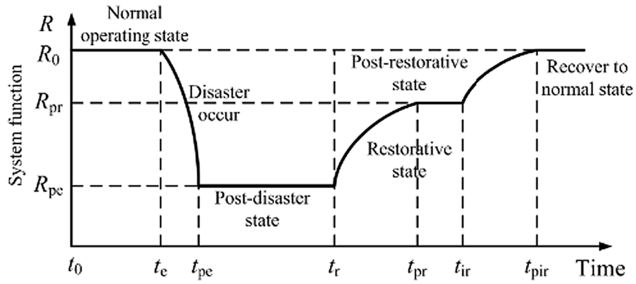

Fig. 1. A conceptual resilience curve associated with an event.

disturbance resilient state (t_0, t_e), disaster progress (t_e, t_{pe}), post-disaster degraded state (t_{pe}, t_r), restorative state (t_r, t_{pr}), post-restorative state (t_{pr}, t_{ir}) and infrastructure recovery (t_{ir}, t_{pir}). In particular, the extreme event strikes the DS at t_e, resulting in a prolonged outage as electric service to end-users is disrupted. The faulted components are identified in (t_{pe}, t_r) for DSO to make the restoration plan, which is implemented from t_r to enhance the system function to R_{pr} [9]. Based on the definition, resilience is measured by the outage duration or the cumulative unserved energy of load curtailment. The basic resilience metrics of a DS include Expected Outage Duration (EOD) and Expected Energy Not-Served (EENS), given by - [10,11].

$$EOD = \frac{\sum_{i=1}^{N_L} EOD_i \cdot P_i}{\sum_{i=1}^{N_L} P_i} \tag{1}$$

$$EENS = \sum_{i=1}^{N_L} EENS_i \tag{2}$$

where i and N_L are the index and total number of load bus, respectively; P_i is the daily peak load at bus i; EOD_i and $EENS_i$ are the expected outage duration and the expected energy not-served of load i, respectively.

$$EOD_i = \frac{\sum_{s=1}^{N_s} OD_{i,s}}{N_s} \tag{3}$$

$$EENS_i = \frac{1}{N_s} \sum_{s=1}^{N_s} \sum_{t=1}^{T} \Delta P_{i,t,s} \tag{4}$$

where $OD_{i,s}$ is the outage duration at bus i, scenario s; N_s is the number of stochastic scenarios; t and T are the index and total number of time step, respectively; $\Delta P_{i,t,s}$ is the load shedding at bus i, time t, scenario s. In fact, considering the importance of different load types, many researchers adopt the economic loss of unserved energy as a resilience metric, which can be regarded as the weighted EENS.

Strategies for enhancing DS resilience can be classified into the operating phase and planning phase. The operating phase indicates making the best use of existing resources (e.g., tie lines, DERs) to minimize the EENS or expected economic loss after the N-k faults. The planning phase, however, means an optimal allocation of new devices so that they can be used for post-disaster restoration. Generally, the outer loop is planning action with the budget constraint, while the inner loop is operation strategy under the newly-added devices. From the power planning and operation aspects, there are three major approaches to enhance resilience. The first is hardening distribution poles in critical lines so that they are less likely to be broken in extreme weather events [12–14]. This is a “preventive approach” according to the resilience definition. The second is to build more redundant tie lines. If part of a feeder is islanded due to faults, the DSO will close tie lines to pick up the islanded feeders while keeping the radial topology of the whole network [15–17]. This is called network reconfiguration [18,19]. The third is to increase the penetration of DERs, including diesel generators, PV systems, and BESSs [20]. If the DS suffers N-k fault, the DSO will form MGs to serve local loads with DERs. In recent few years, the MPSs attract much attention since they have better dispatch flexibility (in both spatial and temporal dimensions) than DERs [21,22]. For each approach, the utility company can enhance resilience by increasing the investment in DS infrastructures. Obviously, preparing for the low-probability extreme event with an unlimited budget is not economical. Therefore, the essence of resilience enhancement study is to make a trade-off between maximizing the critical load in service and minimizing the planning cost.

Several review papers on resilient DS have been published with different research interests. Ref. [23] reviewed the general framework of power system resilience against extreme weather, which includes the system fragility model, the infrastructure hardening, and system restoration methodologies. Ref. [18] discussed the current post-fault restoration practice and the benefit of grid modernization on DS restoration. However, the mathematical models for resilience enhancement were not fully summarized in [18,23]. A comprehensive review of resilience enhancement algorithms was given in [8]. Despite the detailed summary of optimization models, the evolution and future research direction of this topic was not discussed. Based on the above motivations, this review paper is focused on the methodologies of resilience-oriented DS operation and planning under extreme weather events. The existing works on resilient DS study are classified into short-term operation and long-term planning phases. Furthermore, the operation approach is further divided into two stages: pre-disaster resource allocation and post-disaster restoration (resource dispatch). The correlations between different types of studies are analyzed in detail. Based on a summary of the existing works, the paper analyzes the future research direction.

The remaining parts of the paper are organized as follows. Section 2 reviews the impact of typical extreme weather events on DS infrastructure. Section 3 summarizes a wide variety of resources for post-disaster restoration. Section 2 and 3 discusses the problem background for the study on resilient DS, including the feature of extreme weather events and the DS resources for post-disaster restoration. Section 4 reviews the techniques for resilient DS operation, including pre-disaster allocation and post-disaster restoration. Section 5 reviews the long-term resilient DS planning. Section 6 presents the roadmap of resilience DS study and introduces the direction of future works. Finally, Section 7 concludes the paper.

2. Impact of extreme event on distribution system

Generally, the major components of a DS include a substation transformer, overhead line (or underground cable), service transformer, DERs, and measurement/protection relay devices. Among them, the overhead line, consists of distribution poles and conductor wires, is quite vulnerable to extreme weather [24]. For example, the strong wind or flood may tear down the distribution poles. The cryogenic, frozen rain and snow disaster may cause the overhead line and transformers covered by thick ice. Therefore, this section presents a summary of the impact of extreme weather on the DS and serves as the basis for system resilience enhancement strategies.

2.1. Hurricane or typhoon

2.1.1. Characteristics of hurricane

According to meteorological records, a hurricane usually originates in the ocean and moves towards a continent. After making landfall, the hurricane intensity rapidly decays as it moves further inland due to the finite heat capacity of the soil surface [25,26]. Therefore, DSs in coastal areas suffer the most severe damage in a hurricane event. The radial wind speed distribution of a hurricane is shown in Fig. 2 [27]. The wind is the strongest at the eyewall (at a distance of 22 km). The moving speed of a hurricane eye ranges between 20 and 30 km/hour. Consequently, it takes about two hours for the hurricane eye to sweep over a DS. In consideration of safety, repair crews do not work on the faulted lines until the hurricane eye moves away.

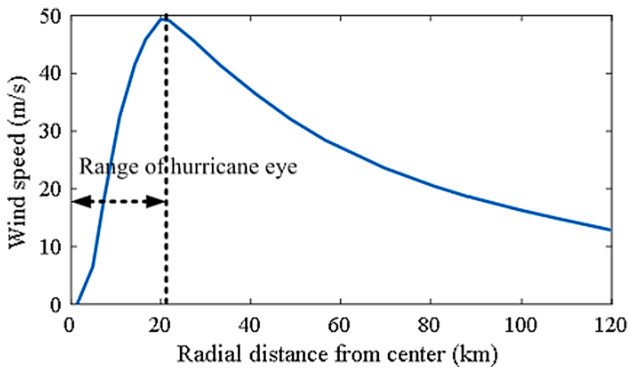

Fig. 2. Radial wind speed profile of a hurricane eye: An example.

2.1.2. Fragility models of overhead lines

Under a hurricane or typhoon, the distribution lines are usually damaged in two ways: 1) the broken trees fall onto power lines, and 2) strong wind directly blows down the poles [12]. Generally, the lines are randomly tripped by the strong wind. The probability of a line fault is affected by many factors, including the line length, wind speed, and the material and foundation of a distribution pole. It is difficult to accurately quantify the fault probability of each distribution line because it requires a large amount of historical data. Ref. [28] provides an approximate fragility model of distribution line under hurricanes. Based on the record of 12,000 distribution line faults caused by strong wind (from 2003 to 2010), this study fits the probability curve of the line fault with regard to wind speed, given by (5)

$$p_{ij}^{fau} = \alpha l_{ij}(v_w)^{\beta} \tag{5}$$

where p_{ij}^{fau} is the probability of line (i,j) being faulted, l_{ij} is the length of line (i,j), v_w is the wind speed, constants are estimated as $\alpha = 2 \times 10^{-17}/$ km and $\beta = 9.91$. For a numerical example, if $l_{ij} = 0.4$ km and $v_w = 38$ km/s, then $p_{ij}^{fau} = 3.6$ %.

2.2. Cryogenic, frozen rain and snow disaster

In winter, the cryogenic, frozen rain and snow disaster usually occurs in those moist areas whose temperature is slightly above 0℃. In comparison with the extreme cold weather condition, the frozen rain or mixed rain and snow may cause thick ice coating in transmission conductors, which may cause are two main impacts [29]:

- The conductor is broken due to a heavy ice load. Generally, it takes much longer time and effort to repair a damaged transmission conductor than distribution one because transmission conductors are usually located in rural or even mountain areas.
- Although the conductor is not physically damaged, it is tripped because the insulator covered with ice is broken down and faulted.

Although DSs are less vulnerable to ice coating, they are likely to be islanded if many transmission lines are faulted. For example, in early 2008, nine provinces in South China suffered the severe cryogenic, frozen rain, and snow disaster, which caused large-area power outages in both transmission systems and distribution systems [30]. When the transmission lines are being repaired by the crew, the DS needs to operate in an islanded mode for the restoration of critical loads.

2.3. Flood

During the raining season, the continuous strong precipitation or dam break can cause severe flood in the city. In some cases, the strong precipitation also comes with hurricane. The impacts of flood on urban DS are as follows:

- The flood damages distribution poles and cause the line fault [31]. Compared with hurricane-induced line faults, it takes longer time for the repair crews to repair the damaged lines because the road is usually inundated.
- The substation transformer can be tripped due to flooding. As a result, the whole DS loses power supply from the upstream system. The flood also causes communications failure between substations and/or operation centers, water damage to protection relay and control, equipment (e.g., control house) [32]. As a result, the whole distribution is de-energized and loses power supply.

2.4. Wildfire

During summer, DSs in forested and high-temperature regions are prone to wildfires. A few works also consider the resilient DS operation against wildfire. The impacts of wildfire on DS are two-fold [33,34]:

- The fire directly damages the DS components. For example, some wood distribution poles are burnt down. As a result, this damage causes an N-k fault in the DS that is similar to the effect of a hurricane. In this case, many post-hurricane restoration strategy applies to the post-wildfire one.
- The fire causes no physical damage to DS components (e.g., the distribution pole is concrete) but a decrease of the thermal rating of the lines due to the higher conductor temperature. IEEE Std. 738 [35] proposes a dynamic line rating model to evaluate the impact of the wildfire on the overhead conductor's temperature, considering the ohmic loss, solar radiation, heat convection, and heat radiation. The distribution line is tripped if its temperature violates the limit.

2.5. Summary

Overall, the low-probability high-impact extreme events have some common impact on the DS infrastructure: 1) Each kind of event is likely to cause physical damages to DS infrastructure or cause the DS to be disconnected from the upstream system; 2) Since the post-fault repair takes a long time, the DS usually needs to supply part of local loads by DERs. Earthquake is another disaster that causes DS outages. However, the probability is much lower than hurricanes [36]. In recent years, most of the researches on resilient DS consider hurricane events as the application scenario because it is more common than other extreme weather events.

3. Resources for distribution system Post-Disaster restoration

The DS automation and distributed, mobile devices are the basis to improve the resilience against extreme weather events [20,21,26]. As shown in Fig. 3, the post-disaster restoration involves the participation of a wide variety of resources, including communication devices, switches, static energy resources (e.g., DER), and mobile resources (e.g., repair trucks and MPSs).

The layout of such resources in DS is illustrated in Fig. 4. In this example, there are three lines being faulted in an emergency condition. The tie lines are closed via RCSs so that part of the islanded load can be served by the adjacent feeder [18]. Furthermore, the DS operator may also open some SSs and split the whole distribution system into several self-supplied MGs. The new network topology is maintained for several hours or over one day until the broken lines are successfully repaired. This is called "network reconfiguration" [19,20,37]. The radial structure should be kept in each MG. If an area of the DS cannot be connected by any tie lines, the decision maker can dispatch MPSs to Bus 2 and to form a networked MG [38] (e.g., shown in blue dashed circle in Fig. 4). Note: Bus #1 ~ 4 represent the buses where the MPS can integrate. The main technical challenge of MG formation is to maintain the stable voltage

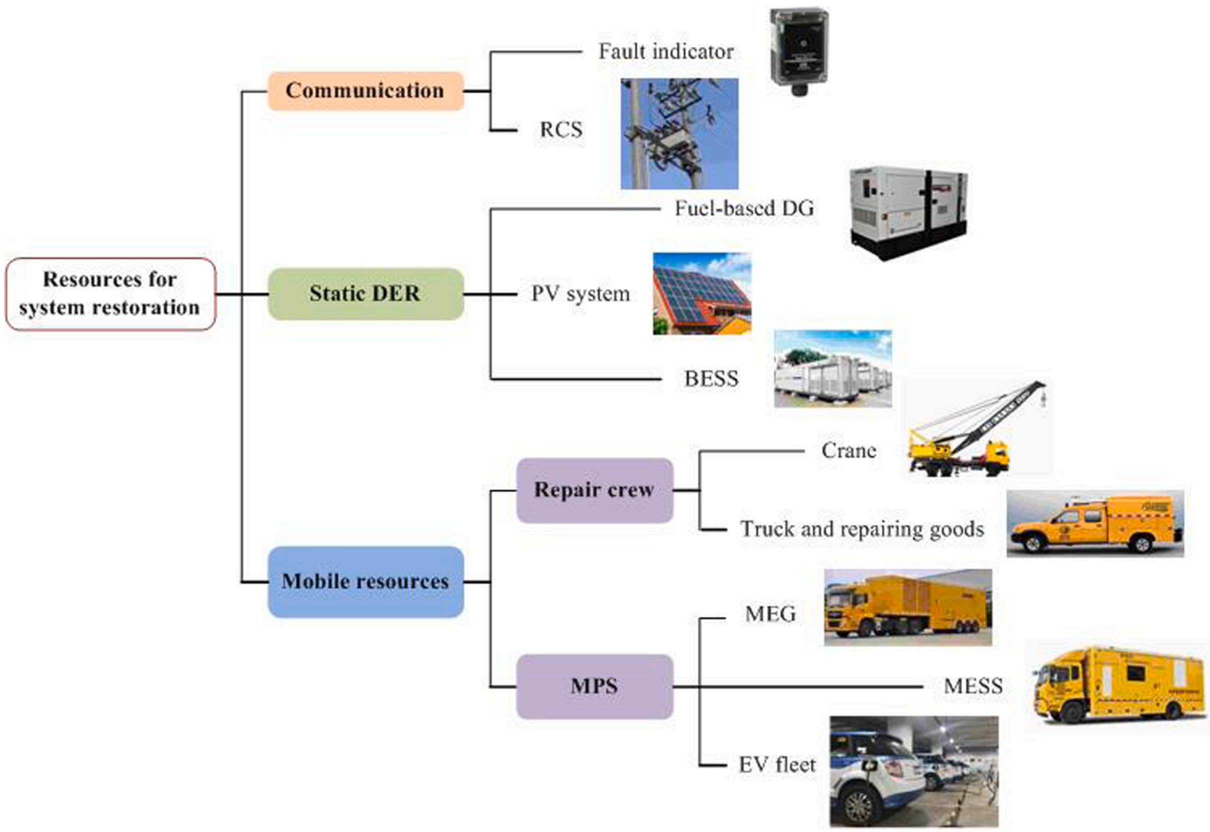

Fig. 3. Classification of distribution system resources.

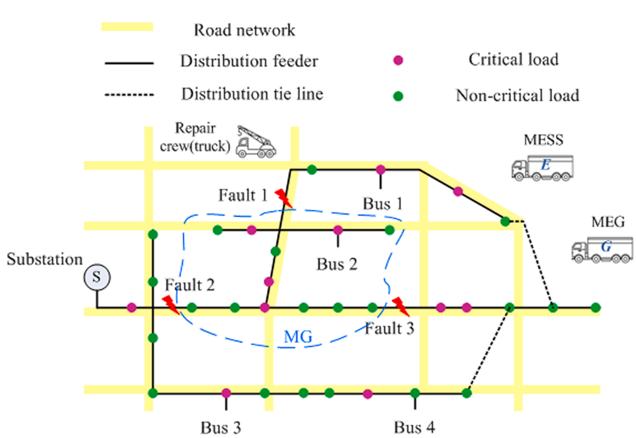

Fig. 4. Distribution system with the layout of resources related to post-disaster restoration.

and frequency within each MG in order to prevent the unexpected action of protection relay devices [39]. Ref. [40] proposes an inverter control strategy to regulate the voltage and frequency after MG formation. Therefore, it ensures the technical feasibility of MG formation. The detailed function of each resource is discussed in this section.

3.1. Fault indicators and Remote-controlled switches

The DS operation relies on the DS communication devices. The DSO locates the fault through fault indicators and controls the line switching state through the RCS [41]. A common distribution system consists of several feeders. The RCS is classified into normally-closed sectionalizing switches (SSs) and normally-open tie switches (TSs) (as shown in the dashed line of Fig. 4). The whole system is built in radial topology because protection devices are designed based on this topology [42].

3.2. Repair crews

Generally, an emergency repair crew includes a truck that is loaded with repairing goods (e.g., distribution poles, conductors, insulators, and transformers) for replacing the damaged ones, a crane that can lift the distribution pole, and several electric technicians. After a severe natural disaster, the repair crews travel from the depot to the fault locations to repair the damaged lines. However, the number of faulted lines is usually larger than the number of repair crews. Hence, it is necessary to determine the optimal sequence of line repairs that can lead to the largest amount of load to be restored [43,44].

3.3. Distributed energy resources

In urban DSs, DERs usually refer to geographically static, small-scale energy resources that include fuel-based DG, photovoltaic (PV) systems, and battery energy storage systems (BESSs). Generally, PV systems are non-dispatchable DERs, while fuel-based DGs and BESSs are dispatchable DERs [20,45].

- *Fuel-based DG*: It is also called micro-turbine generator, including diesel generator or natural gas generator [20]. Compared with renewable energy sources, fuel-based DGs have the advantage of stable power output. When the system is islanded, the generator can be quickly started to serve the local load. The disadvantage is that the generator is quite noisy when it is in operation [46].
- *Rooftop PV system*: The rooftop PV systems are integrated to the DS. We can assume that the PV systems always operate at the maximal power point. The PV operating cost is zero. However, during extreme weather (e.g., hurricane), the solar irradiance might fluctuate.

Hence, the distributed PV systems cannot ensure stable power output for post-fault restoration [45,46].
- *BESS*: The advantage is flexible sizing, stable power output, and safe operation. However, if discharged at the rated power, a battery can only sustain for a maximum of 4 h due to its energy capacity. Therefore, BESSs should operate together with PV systems in order to mitigate their power output fluctuation and provide stable power output [45,46].

3.4. Mobile power sources

Static DERs can be dispatched in temporal dimension but lacks the flexibility of spatial dispatch. In some disaster scenarios, a DS with low DER penetration is seriously damaged and requires a large generation capacity, while another DS with high DER penetration is not seriously damaged. MPSs solve this paradox because of their travel capability. The decision maker is able to dispatch the MPSs from a large area to those communities with the most serious line damages. MPSs are classified into three types.

- *MEG*: Indicating truck-mounted diesel generators with standard interfaces that allow for islanding operation [21].
- *MESS*: Indicating truck-mounted battery energy storage systems with standard interfaces that allow for islanding operation [47]. The MESSs transportability can efficiently transfer energy among different DSs at appropriate times and locations to facilitate critical loads service restoration [38].
- *EV fleet*: Indicating the personal electric vehicle and electric public buses [48,49]. They are connected to the DS node through a charging station [50]. Besides, a large number of idle EVs in the charging station have great potential in providing restoration power supply. However, due to their small capacity and large number, the transportation is much less convenient than MESS. Therefore, it is more feasible to consider the EV fleet as a static DER for post-disaster restoration.

4. Resilient distribution system operation

4.1. Stage-based classification and general framework

Resilient DS operation indicates minimizing the economic loss (or weighted sum) of unserved load during the system restoration period by making the best use of the existing DS resources. The operation strategies for resilience enhancement is called the outage management strategy (OMS) in literature [51,52]. Generally, the operation can be divided into two stages: pre-disaster resource allocation and post-disaster restoration. Hence, the research works on the resilient DS operation can be classified into three types:

- Type I refers to the pre-disaster allocation of mobile resources, such as repair crews or MPSs [49,53,54] so that the resources can be dispatched within a small area after the disaster.
- Type II refers to the post-disaster restoration by network reconfiguration and DER/MPS dispatch [19,20,37].

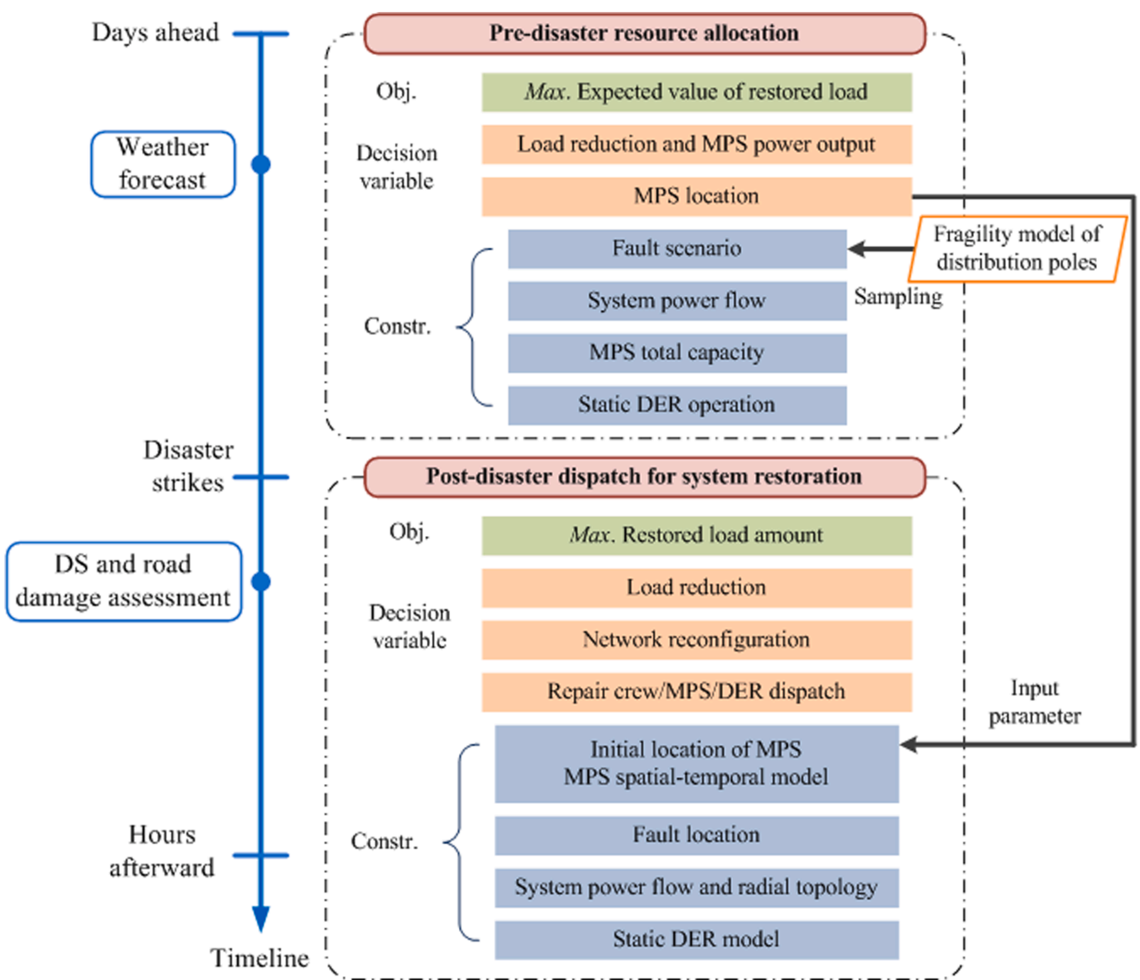

Fig. 5. Framework of resilient distribution system operation.

- Type III combines the pre-disaster allocation and post-disaster restoration methods [21,43].

Based on a wide variety of existing research works, we summarize the objective function, decision variables, constraints, and coupling mechanism of the OMS in a general framework, as shown in Fig. 5. The framework is further explained in the following aspects:

4.1.1. Optimization stage/level

Extreme weather may cause N-k faults in the DS. Before the disaster strikes, the mobile resources are assigned to critical spots. Due to the uncertainty of fault location, the problem can be modeled as a two-stage stochastic optimization [60] or three-level robust optimization [21]. After the extreme weather, the DS repair and restoration are started according to the DS damage assessment. The decision variable of the first stage serves as the input parameter of the second stage [43,44,50].

4.1.2. Objective function

The objective is to minimize load shedding cost or to maximize the (weighted) restored load. The two forms are equivalent. Besides, since load curtailment cost is generally higher than the generation cost, the objective of minimizing (generation cost + load shedding cost) is effectively equivalent to minimizing load shedding cost [17,54].

4.1.3. Decision variables

The post-disaster restoration may include those time-varying decision variables: the load curtailment (or restored load), the power output of dispatchable DER, location and power output of MPS, and the state variable of repair crews. Besides, the network reconfiguration introduces a set of binary variables (state of RCS).

4.1.4. Constraints

In each stage, the constraints can be classified into three parts: 1) system power flow, 2) DER/MPS/repair crew operation, 3) system operating condition, such as fault location, load profile, solar profile. In Type III study, the decision variables of mobile resources in the first stage serve as the constraint for the second stage, as shown in Fig. 5. In particular, the spatial–temporal characteristic of MPS dispatch introduces a large number of binary variables. The details can be found in Appendix A. Besides, most of constraints are commonly used by other literatures (load reduction, radial topology, and linearized DistFlow) and are omitted here for simplicity.

4.1.5. Scenario generation and reduction

The pre-disaster resource allocation involves deciding the upcoming stochastic faults. Based on the fragility model of devices, the decision-makers generate sufficient random scenarios by using Monte Carlo simulation [12,55]. In order to reduce the computation workload, the scenarios are reduced by K-means clustering algorithm [56,57].

4.1.6. An example of OMS result

The optimization result of an OMS is illustrated by numerical examples. In this paper, we consider two types of fault condition. Fig. 6 (a) shows an N-4 fault scenario where the substation is in normal operating condition. Before the faulted lines are repaired, the decision maker solves post-disaster restoration strategy for an optimal reconfiguration and DER scheduling. A large number of load buses (Bus 5 ~ 13, 26 ~ 30) are connected with adjacent tie lines and served by the upstream system. Other load buses (Bus 14 ~ 18, 31 ~ 33) that cannot be connected to the substation are formed into a self-supplied MG. Fig. 6 (b) shows an N-3 fault scenario where the substation is faulted. The DS is split into several MGs. Due the limited capacity of DERs, the decision maker schedules the DER according to the weight of different load in order to minimize the load shedding cost [20].

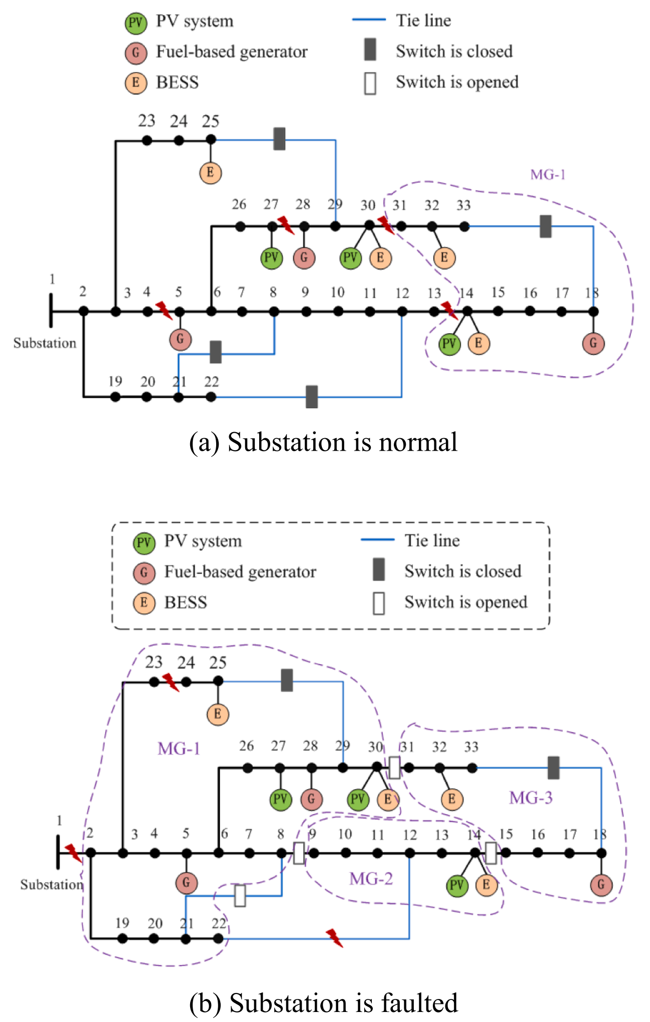

Fig. 6. Example of distribution network reconfiguration.

4.2. Type I: Pre-Disaster operation

The pre-disaster operation means taking actions when the disaster is forecast to strike the target area in one or two days. The first problem is to allocate mobile flexible resources can help utilities to achieve faster and more efficient post-event power restoration. Due to the uncertainty of the fault location, researchers usually formulate the problem as a stochastic programming to minimize the operating cost by allocating MPSs [49] or repair crews [54,58,59]. In [49,53], the authors release the power flow constraint and figure out the optimal restoration path via heuristic searching. Then, the optimization results under different paths are verified by the power flow constraint. This searching-verifying solution method requires a lower computation workload than directly solving the NLP. However, the method cannot guarantee to find the global optimal solution. The latest work in [60] proposed a comprehensive pre-allocation strategy of MPS and repair crew based on the DS fragility model with the consideration of three-phase DS model. Furthermore, the DS pre-disaster operation methods is also applicable to the transmission system, in which the unit-commitment constraints of large-scale generators should be considered [54,61].

The representative works on pre-disaster allocation algorithms are summarized in Table 1. The stochastic optimizations are formulated as multi-stage or multi-level programming, which is usually an NP-hard problem due to high dimensions and many binary variables. Hence, the solution of such problems is obtained by iterative algorithms, such as benders decomposition, column-and-constraint generation (CCG), and

Table 1
Summary of Pre-disaster allocation algorithm.

Ref.	Year	The objective of the highest level (stage)	Formulation	Decision variable [1]	Solution method
[49]	2017	*Max.* (Expected benefit of serving critical load – cost of MPS allocation)	Stochastic NLP	MPS location, network reconfiguration	Heuristic search & power flow verification
[54]	2015	*Min.* (Cost of generator allocation + Expected cost of load loss & generator operation)	Two-stage stochastic MILP	Location and quantity of repair crews	Benders decomposition
[58]	2020	*Min.* (Cost of load shedding + cost of DER operation – revenue of selling energy to customers)	Bi-level robust MILP	DG operation	Proposed block coordinate descent and line search techniques
[59]	2021	*Min.* Expected cost of (buying energy from main grid + DG operation + load shedding) [2]	Two-stage stochastic MICP	DG operation	
[60]	2021	*Min.* Expected cost of (MPS operation + RCS action + load shedding)	Two-stage stochastic MILP	Location of MPSs and repair crews	PH

[1] Since the decision variables “restored load” or “load curtailment” appear in all OMS strategies, the load variables are omitted in this table.
[2] In this paper, “DG” represents fuel-based DG for simplicity.

progressive hedging (PH).

4.3. Type II: Post-Disaster restoration

The study on post-disaster restoration aims to find an optimal DER scheduling, repair crew dispatch, or network reconfiguration under the deterministic fault scenarios. If the power supply from the upstream system is available after the disaster, the decision maker conducts network reconfiguration to maintain the whole network in radial topology [17] or to split the DS into several MGs which are supplied by DERs [20,37]. In recent years, many types of research have been done on post-disaster DS restoration with different focuses. In [20], the on-outage part of the system is split into self-supplied MGs to minimize the affected customers. In [62], the authors propose a two-stage restoration strategy, in which the first stage optimizes the reconfiguration topology and the second stage schedules the critical load to be restored. By assuming the DS can be supplied by the upstream system, Ref. [17] keeps the whole DS as a radial structure in the restoration period. The radial constraint is modeled as nonlinear equations and the problem is solved by a heuristic-searching-based method. In comparison with the static network reconfiguration, the hourly reconfiguration approach with optimal DER scheduling can achieve better utilization of DERs [63]. However, the hourly switching actions can degrade the life of RCSs. Ref. [38] proposes a restoration scheme of temporal-spatial MESS dispatch and MG formation to minimize the total cost of load shedding, DG operation, and MESS transit. The MESS can effectively transfer the energy from among MGs within the DS, especially when the peak load hours of MGs are different. The spanning tree [38,64] and fictitious network (also named as single commodity flow) [19,22] are two approaches to model the radial structure constraints as a set of linear equations.

Despite the well-defined models, the above restoration strategies are only focused on DER scheduling and network reconfiguration, while ignores the optimal repair crew dispatch that enables more efficient restoration. Therefore, it is necessary to develop a mathematically rigorous strategy to optimally coordinate repair sequence, network reconfiguration, and DERs to minimize the operating cost during the restoration period [43,44]. The study in [65] proposes a two-stage stochastic optimization considering the uncertainty of repair time and load profile. The first stage finds the optimal sequence of repair crews, and the second stage completes service restoration using reconfiguration and DERs. The authors in [44] propose a tri-stage repair and restoration strategy to handle the uncertainty of load profile and repair time. In particular, the study considers an unbalanced DS model and a more detailed crew model (e.g., line repair crew and tree removal crew) for the restoration.

Above all, the representative works on the Type II problem is summarized in Table 2.

4.4. Type III: Pre- and Post-Disaster restoration

Several recent literatures consider the coordination between pre-disaster allocation and post-disaster dispatch [21,22,43,50,70], as shown in Fig. 5. The whole problem can be formulated as a two-stage restoration strategy. The first stage clusters and allocate the repair resources in order to facilitate an efficient post-disaster repair and restoration, while the second stage co-optimizes the repair crews, network reconfiguration (MG formation), and DER dispatch based on the deterministic load demand [43]. The study in [50] proposes a two-stage robust optimization of MPS pre-positioning and scheduling considering the uncertainty of component damages. The first stage is formulated as a tri-level robust optimization to determine the optimal MPS pre-position for rapid restoration. Then, the second stage is a dynamic dispatch of the location and output power of MPS in order to maximize the operating cost. Ref. [22] proposes a rolling restoration strategy to minimize the total operating cost by coordinating MESSs, MGs in multiple DSs. In particular, the strategy considers subsequent damage and repairs to both the transportation systems and the DSs during the restoration process. The representative studies of Type III are summarized in Table 3.

5. Resilience-oriented distribution system long-term planning

Power system long-term planning refers to installing equipment according to the forecast future operating condition [72]. Traditionally, the optimal DS planning was to make optimal siting and sizing decisions of DG and BESS to minimize the long-term operating cost, reduce power loss, or enhance voltage profile [73,74]. Those approaches were focused on the normal operating condition. In recent 5–6 years, researchers proposed the resilience-oriented DS planning (RDSP), which includes hardening lines or installing DGs to minimize the load shedding amount under N-k fault conditions. Overall, since the planning problem involves the modeling of uncertain factors (e.g., fault location, load profile), the

Table 2
Summary of Post-disaster restoration algorithm.

Ref.	Year	The objective of the highest level (stage)	Formulation	Decision variable	Solution method
[20]	2015	*Min.* (Voltage deviation + power exchange among MGs + cost of load shedding)	MINLP	DER dispatch, MG formation	
[37]	2016	*Max.* Weighted sum of restored loads	MILP	DER dispatch, MG formation	
[19]	2017	*Max.* Weighted sum of restored loads	MISOCP	DER dispatch, MG formation	
[52]	2018	*Min.* Cost of (DER operation + load shedding)	Two-stage MILP	DER dispatch, MG formation	
[62]	2019	*Max.* Weighted sum of restored loads	Two-stage MISDP (in 2nd stage)	DER dispatch, MG formation	Model simplification
[66]	2019	*Min.* cost of (Energy imported from upstream grid + load shedding)	SOCP	BESS, no network reconfiguration	
[17]	2021	*Min.* Cost of (DG operation + load shedding)	LP [1]	DER dispatch, network reconfiguration [2]	Heuristic search
[67]	2021	*Min.* Cost of (DG operation + load shedding)	MILP	DER dispatch, network reconfiguration	
[65]	2018	*Max.* Restored load	Two-stage stochastic MILP	Routing repair crew, DER scheduling, MG formation	PH
[44]	2020	*Min.* Cost of (load shedding + RCS operation)	Tri-stage MILP	Routing repair crew, DER dispatch, MG formation	Proposed re-optimization method
[38]	2019	*Min.* Cost of (Load shedding + DG operation + MESS transportation + MESS maintenance)	MILP	DER dispatch, MESS dispatch, MG formation	
[68]	2020	*Max.* Weighted sum of restored loads	MILP	Repair crew dispatch, MPS dispatch, MG formation based on soft-open-point	Auxiliary induce function based algorithm
[69]	2020	*Min.* Weighted sum of restored load	MILP	Maintenance crew & repair crew dispatch	

[1] In this study, the nonlinear constraints are temporarily released and solved by a heuristic search. Therefore, the remaining constraints are linear.
[2] In this table, network reconfiguration means keeping the whole network connected and served by the upstream grid.

Table 3
Summary of pre- and post-disaster restoration algorithm.

Ref.	Year	The objective of the highest level (stage)	Formulation	Decision variable	Solution method
[43]	2018	1st stage: *Min.* Total travel distance of repair crews 2nd stage: *Min.* Weighted sum of restored loads	Two-stage MILP	1st stage: Repair crew allocation 2nd stage: DER dispatch and MG formation	
[21]	2018	1st stage: *Min.* Expected duration of unserved load 2nd stage: Duration of unserved load in a deterministic scenario	Two-stage stochastic MILP	1st stage: MEG allocation and MG formation 2nd stage: MEG real-time dispatch	Scenario Decompo-sition
[70]	2019	*Min.* Cost of (MESS planning + DG operation + load shedding)	Two-stage stochastic MILP	MESS allocation	PH
[50]	2019	1st stage: *Max.* Weighted sum of survived loads 2nd stage: *Max.* (Weighted sum of restored load – MESS transportation – battery degradation)	Two-stage robust MILP	MPS allocation, MG formation, MPS dispatch	CCG
[22]	2020	*Min.* Cost of (Load shedding + DER operation + MESS transportation + MESS maintenance)	Two-stage stochastic MILP	1st stage: MESS allocation, network reconfiguration 2nd stage: DER and MESS dispatch	Rolling optimization
[71]	2020	*Min.* Cost of (MEG investment + load shedding)	Three-stage stochastic MILP	1st stage: number of MEG 2nd stage: location of MEG 3rd stage: MEG dispatch, MG formation	PH

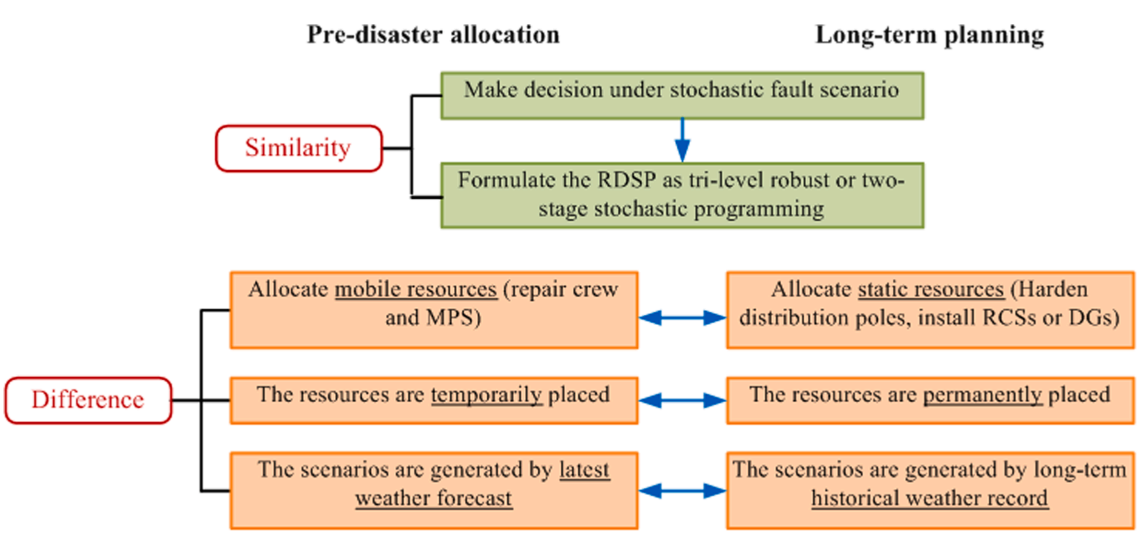

Fig. 7. Comparison between pre-disaster allocation and long-term planning problems.

RDSP is formulated as tri-level robust optimization or two-stage stochastic optimization. Note that RDSP and pre-disaster resource allocation have some similarities in the mathematical modeling. The major difference is: the former one is a permanent improvement of the DS, while the latter one is a temporary modification of the DS. The two approaches are compared in Fig. 7.

5.1. Tri-level robust optimization

The RDSP can be modeled as a "defender-attacker-defender (DAD)" tri-level robust optimization [75–78]. In the first level, the system planner (acting as a defender) determines the optimal locations for line hardening, DG, or BESS installation with the specified budget limit. In the second level, a natural disaster (attacker) maximizes the load shedding amount under the specified number of line faults. In other words, the worst-case scenario of N-k faults is selected. While in the third level, the system operator (defender) minimizes the load shedding through a post-disaster restoration strategy. The mathematical formulation of tri-level model is introduced in Appendix B.

The tri-level model cannot be directly solved by commercial solvers. It is converted into an equivalent bi-level model through KKT conditions then solved by iterative methods, such as CCG [76] or greedy search algorithms [77]. For example, the authors in [76] model the RDSP as a DAD model. They specify the budget limit, which includes the maximal number of lines to be hardened and the maximal number of DGs to be installed, respectively. The hardened lines are assumed not to be damaged in the disaster. Then, the third level is an optimal restoration strategy that considers the DG scheduling and MG formation. A sensitivity study quantifies the impact of budget limit on the load shedding loss so that the decision-maker can make a trade-off between the planning cost and the expected load shedding loss. The result of IEEE 33-bus system indicates that with the same budget limit and same scenario, the optimal DG placement achieves around 40% lower load shedding than the random DG placement [76].

The optimization models of representative works are listed in Table 4. Overall, although the tri-level robust programming requires lower computation than two-stage stochastic programming, the optimization result is too conservative as the worst-case scenario usually occurs with a very small probability.

5.2. Two-stage stochastic optimization

Two-stage stochastic programming is an effective approach to RSDP. The advantage is that it considers the overall impact of stochastic fault scenarios on the planning decision [12]. The mathematical formulation of two-stage model is introduced in Appendix C. Similar to tri-level model, the first stage (master stage) makes the decision of line hardening, RCS placement, or DG siting and sizing. The objective is to minimize the planning cost and the expected operating cost of a number of N-K fault scenarios. The stochastic scenarios are generated by sequential Monte Carlo simulation, considering the random faulted lines, load profiles, and solar irradiance profiles (if the model includes PV systems). The number of scenarios can be reduced by K-means clustering method [12,56,55]. While in each scenario of the second stage (slave stage), the operator minimizes the economic loss or load shedding. This approach fully considers the impact of all possible scenarios instead of the worst-case scenario. Since the dimension of two-stage stochastic programming is quite large, we usually decompose the whole problem into stage-based or scenario-based methods to solve it iteratively [57,79].

The representative works on RDSP are summarized in Table 5. The studies in [12,80] only consider the DG sitting and usually assume the same size for all DGs. In some N-k fault scenarios, however, the DGs with identical sizes might be insufficient at some buses and surplus at other buses although they are optimally placed. The study in [55] extended the model by considering both optimal DG siting and sizing in the RDSP. Therefore, the model can be solved for a global optimal DG allocation with the specified budget constraint. In the numerical result of IEEE 33-bus and 123-bus system, the optimal DG siting and sizing can achieve about a 10% lower load reduction result than optimal DG siting only.

Table 4
Summary of RDSP with tri-level approach.

Ref.	Year	The objective of the highest level (stage)	Planning decision variables	Solution algorithm
[75]	2014	*Min.* Load shedding cost	Line hardening	Implicit enumeration
[76]	2016	*Min.* Load shedding cost	Line hardening, DG siting	CCG
[77]	2019	*Min.* Cost of (planning + load shedding + vehicles' travel time)	Line hardening, DG siting, mobile BES siting	Greedy search
[78]	2019	*Min.* Cost of (planning + yearly net operation)	Line hardening, DG & BESS siting and sizing	CCG

6. Discussion for future work

The review of a large number of existing literatures suggests that enhancing DS resilience against extreme weather events requires the cooperative dispatch of multiple resources. Furthermore, the long-term planning, pre-disaster resource allocation, and post-disaster dispatch are three periods for resilience improvement.

6.1. Roadmap of distribution system resilience

The evolution of DS resilience enhancement undergoes multiple stages, as summarized in Fig. 8. In each dashed-line block, the upper block represents the technical approach and the lower block represents the mathematical formulation. Before 2015, the term "resilience" was rarely used in literature, which is focused on utilizing reconfiguration to keep the network in radial structure and being served by the upstream

Table 5
Summary of RDSP with a two-stage approach.

Ref.	Year	The objective of the highest level (stage)	Planning decision variables	Methods for generating stochastic scenarios	Solution algorithm
[12]	2018	*Min.* (Planning cost + expected operating cost of selected scenarios)	Line hardening, DG siting	Generated by Monte Carlo simulation (MCS)	PH
[80]	2019	*Min.* (Planning cost + expected operating cost of selected scenarios)	Line hardening, DG siting	Generated by MCS	Dual decomposition
[81]	2019	*Min.* Loss of load expectation	RCS siting	Generated in a deterministic way	Scenario decomposition algorithm
[55]	2021	*Min.* (Planning cost + expected operating cost of selected scenarios)	DG siting and sizing	Generated by MCS, reduced by K-means clustering	PH

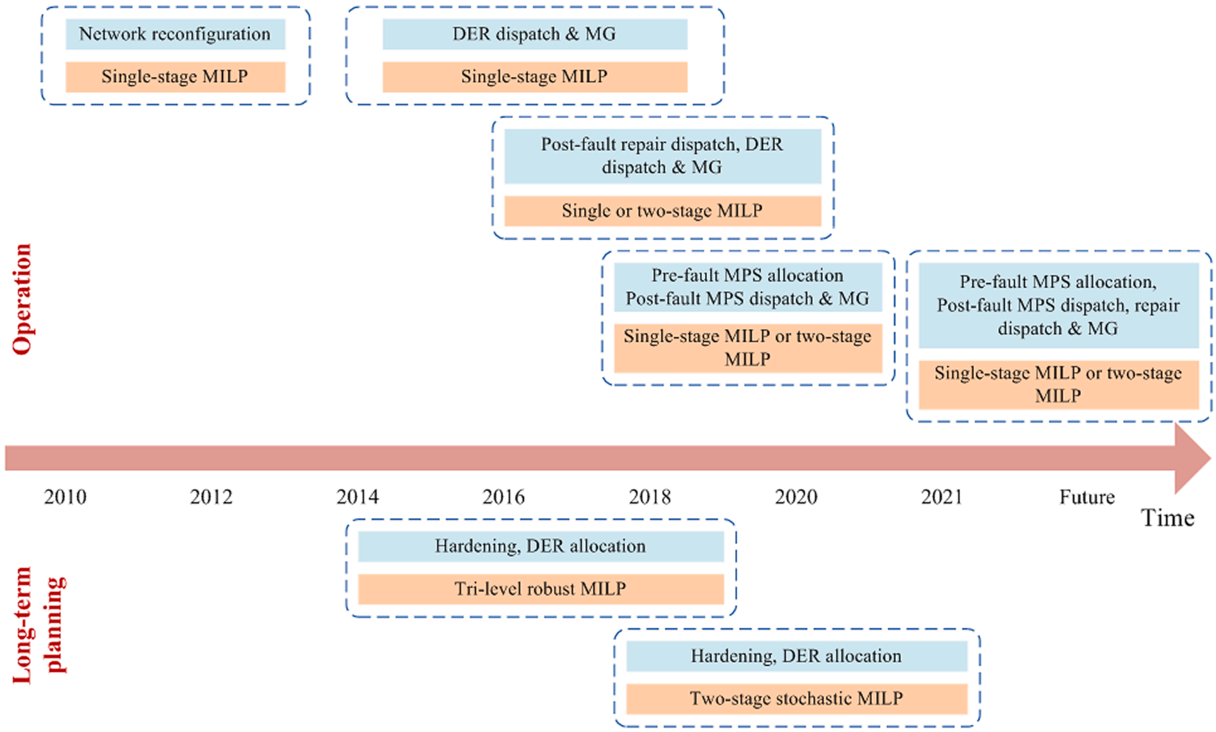

Fig. 8. Evolution of researches on enhancing DS resilience.

system. From 2015 to 2020, a variety of studies are focused on dispatch static DERs to form self-supplied MG to serve critical loads. Meanwhile, the RDSP is fully studied, including the optimal placement of RCS, line hardening, and DG allocation. Furthermore, since 2018, the rapid development of electrochemical storage facilitates the study on the spatial–temporal dispatch of MPSs for post-disaster restoration. However, the cooperative dispatch of repair crew and MPSs has not been fully studied. The future research on resilient DS operation and planning is analyzed in detail in Section 6.2.

6.2. Extension of operation and planning modeling

6.2.1. Pre-disaster resource allocation

The pre-disaster resource allocation is mainly determined by two factors: the spatial distribution of the infrastructure damage and critical loads. The infrastructure damage (e.g., fault location) is highly uncertain. Therefore, the pre-disaster resource allocation is a stochastic optimization, which relies on the damage forecast of the disaster. The decision-maker can concentrate the resources from a large area to a small area where the disaster is the most serious. Therefore, the MPS dispatch optimizes the utilization of resources for resilience enhancement. However, the existing work on pre-disaster resource allocation is focused on a single DS [21,50,38]. They cannot satisfy the requirement of allocating resources over an urban-level system that consists of decades of DSs. The future work should establish a comprehensive fragility model to estimate the infrastructure damage in a large area based on the geographical information, weather forecast, and infrastructure characteristics. Based on this forecast spatial distribution of the damage, the decision-maker can pre-allocate the MPSs and repair crews so that the post-disaster repair and restoration is more efficient.

6.2.2. Post-disaster resource dispatch

As discussed in Section 4.3 and 4.4, the latest methods of post-disaster restoration are focused on either dispatching the repair crew or MPSs. However, very few studies consider the coordination between repair crews and MPSs. In fact, the spatial–temporal dispatch of these two resources are coupled and occur simultaneously during the restoration period. Therefore, it is quite essential to study the cooperative dispatch of multiple mobile resources (e.g., repair crew, MPS) for post-fault restoration. With the progress of line repair, the decision-maker may change the network reconfiguration by RCS and the location of MPSs in order to serve a larger amount of critical loads under severe N-k fault scenarios. Based on this framework, the post-disaster dispatch strategy should solve for the repair sequence of faulted lines, the spatial status of MPSs (e.g., traveling, stop and being integrated), the power output of MPSs, and the real-time MG formation.

6.2.3. Cooperative restoration of urban electricity-water–gas system

The final purpose of enhancing DS resilience is to maintain the normal regulation of the society after extreme weather events. On the one hand, besides the electricity supply, the water and natural gas supply are also indispensable to customers (e.g., hospital, university, residential community). On the other hand, the operation of water and gas distribution network depends on the power distribution network. A simple example of electricity-water–gas integrated system is shown in Fig. 9, the loss of water pump and gas compressor led to much less water and gas to be delivered to the customers [82]. However, very few literatures considered the combination of electricity, water, and natural

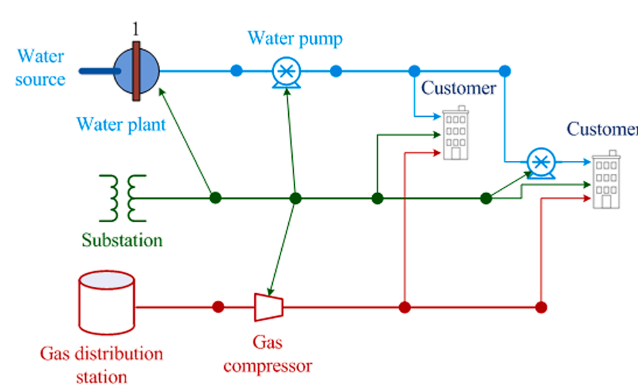

Fig. 9. Structure of the electricity-water–gas integrated system.

gas demands when determining service restoration strategies. Therefore, the existing methods on DS resilience enhancement cannot ensure optimal allocation of limited generation power capacity to satisfy demand of end-users [82–83]. The future work should be focused on studying the coupling mechanism of the urban infrastructure network and developing a service restoration method for electricity distribution systems aiming at providing electricity, water, and natural gas to critical customers.

6.3. Extension of solution algorithm

The cooperative, multi-time-step dispatch of multiple mobile resources introduces a large number of binary variables, especially when solving a large system. It can be quite difficult to directly solve such a high-dimension MILP. Decomposing the problem into several subproblems will be interesting in future works.

Furthermore, since the two-stage stochastic programming involves many scenarios, it is difficult to directly solve. Reinforcement learning is an alternative approach to solve DS optimization problems [84]. The decision maker in the first stage serves as the agent. The stochastic input (e.g., fault location, load profile), planning decision, and objective function value can be regarded as the state, action, and reward, respectively.

7. Conclusion

The modern urban DS is supposed to provide customers with stable power supply. In recent years, promoting DS resilience against low-probability-high-impact weather events draws higher attention. The mathematical essence of DS resilience is to minimize the customers' economic loss caused by extreme weather event with the limited DS resources. This paper makes a comprehensive summary of the impact of extreme weather events on DS, the resources for post-disaster restoration, the resilience-oriented operation, and planning algorithms. Based on the classification and review, the paper introduces the future research direction. The contribution can be summarized as follows.

- According to the timeline with regard to extreme weather event, the paper classifies resilience-enhancing methods into pre-disaster resource allocation, post-disaster restoration, and long-term resilience-oriented planning according to the control stage. Then, the paper utilizes tables to compare the objective function, mathematical formulation, decision variable, and solution algorithm of each study, which make it convenient to observe the evolution of resilience-enhancing methods.
- Nowadays, the rapid development of MPS, such as MEG and MESS, provides the post-fault restoration with more flexible resources. Based on a comprehensive analysis of the existing methods, this paper introduces the future research directions, including the cooperative dispatch of mobile resources for DS restoration and the data-based algorithms for resilience-oriented planning problems. Furthermore, since the customers' basic demand includes electricity, water and nature gas, a resilient DS should support the function of urban water/gas distribution system considering the interdependency among different urban infrastructure networks.

CRediT authorship contribution statement

Qingxin Shi: Conceptualization, Methodology, Formal analysis, Writing – original draft, Funding acquisition. **Wenxia Liu:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Bo Zeng:** Conceptualization, Writing – review & editing. **Hongxun Hui:** Conceptualization. **Fangxing Li:** Conceptualization.

Declaration of Competing Interest

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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None.

Appendix

A. Constraint of MPS

The MPS operation constraints describes the spatial state (traveling or integrating to a bus) and temporal state (power output) of an equipment. Taking the MEG as example:

$$\sum_{i\in\Omega_M}\beta_{m,i,t}\leqslant 1,\quad \forall m\in M \tag{6}$$

$$\sum_{m\in M}\beta_{m,i,t}\leqslant Cap_i,\quad \forall i\in\Omega_M \tag{7}$$

$$\gamma_{m,t}=1-\sum_{i\in\Omega_M}\beta_{m,i,t},\quad \forall m\in M \tag{8}$$

$$\beta_{m,i,t}+\beta_{m,j,t+1}\leqslant 1,\quad \forall m\in M,\ \forall i,\ j\in\Omega_M \tag{9}$$

$$0\leqslant P_{k,t}^{MEG}\leqslant\left(\sum_{i\in\Omega_M}\beta_{m,i,t}\right)\overline{P}_k^{MEG},\quad \forall k\in\Omega_{MEG} \tag{10}$$

where $\beta_{m,i,t}$ is a binary variable (1 if MEG m is connected to bus i at t, 0 otherwise), $\gamma_{m,t}$ is a binary variable (1 if MEG m is traveling at t, 0 otherwise), M is the set of MEG, Ω_M is the set of candidate bus for MEG integration, Cap_i is the allowed number of MPSs connected to the MG at bus i. $P_{k,t}^{MEG}$ is utput power of MEG k at t. Constraint (6) restricts each MEG to be connected to at most one bus in each time period. Constraint (7) limits the number of MEGs connected to each bus due to the capacity of the service transformer. Note that connected to the DS and traveling on the road network are mutually exclusive and collectively exhaustive states of a MEG, as given by (8) [50]. That is, we only need constraint (9) to ensure that the transportation of MPSs among different nodes satisfies the necessary travel time (1 time step). Constraint (10) indicates that the MEG k can inject power to the grid only if it is connected to bus *i*.

B. Tri-level robust optimization

The tri-level robust optimization is a DAD problem, whose general form is given by (11) [76].

$$\min_{\mathbf{h}\in\mathbf{Y}} \max_{\mathbf{u}\in\mathbf{U}} \min_{\mathbf{z}\in\mathbf{F}(\mathbf{h},\mathbf{u})} \quad \boldsymbol{c}^T\boldsymbol{x} \tag{11}$$

where **Y** is the feasibility set for DS planning decisions consisting of budget constraints for hardening or DG placement, **U** is the uncertainty set of a natural disaster that occurs after the implementation of a planning design. The disaster will cause a worst-case attack with the objective of maximizing the damage through a max–min bi-level game. Finally, after the natural disaster is realized and observed, the DS immediately responds to the disruption with feasible power flow decisions as defined by $\mathbf{F}(\mathbf{h}, \mathbf{u})$ to minimize the load shedding.

C. Two-stage stochastic optimization

In order to elaborate the proposed algorithms and facilitate the solution discussion, we use a compact notation to express the proposed two-stage model [79]. The first stage is

$$\min \quad \boldsymbol{c}^T\boldsymbol{x} + \sum_{s\in S} p(s) f(\boldsymbol{x}, s) \tag{12}$$

$$\text{s.t.} \quad \mathbf{Ax} \leqslant \mathbf{b} \tag{13}$$

where $\boldsymbol{x} \in \mathbb{Z}_+^{p_1} \times \mathbb{R}^{n_1 - p_1}$ represents the mixed-integer decision variables. In the second stage, $f(\boldsymbol{x}, s)$ denotes the OMS problem for each scenario s:

$$f(\boldsymbol{x}, s) = \min.\ \boldsymbol{g}^T\boldsymbol{y} \tag{14}$$

$$\boldsymbol{Wy} \leqslant \boldsymbol{r}(s) - \boldsymbol{T}(s)\boldsymbol{x} \tag{15}$$

Here, $\boldsymbol{y} \in \mathbb{Z}_+^{p_2} \times \mathbb{R}^{n_2 - p_2}$, $\boldsymbol{c} \in \mathbb{R}^{n_1}$, $\boldsymbol{A} \in \mathbb{R}^{m_1 \times n_1}$, $\boldsymbol{b} \in \mathbb{R}^{m_1}$, $\boldsymbol{g} \in \mathbb{R}^{n_2}$, $\boldsymbol{W} \in \mathbb{R}^{m_1 \times n_2}$,$\boldsymbol{g} \in \mathbb{R}^{n_2}$ comprise the parameter of the SMIP.

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