INVITED PAPER

Modernizing Distribution System Restoration to Achieve Grid Resiliency Against Extreme Weather Events: An Integrated Solution

This paper aims to design a decision support tool for closed-loop distribution system restoration.

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ABSTRACT | Recent severe power outages caused by extreme weather hazards have highlighted the importance and urgency of improving the resilience of the electric power grid. As the distribution grids still remain vulnerable to natural disasters, the power industry has focused on methods of restoring distribution systems after disasters in an effective and quick manner. The current distribution system restoration practice for utilities is mainly based on predetermined priorities and tends to be inefficient and suboptimal, and the lack of situational awareness after the hazard significantly delays the restoration process. As a result, customers may experience an extended blackout, which causes large economic loss. On the other hand, the emerging advanced devices and technologies enabled through grid modernization efforts have the potential to improve the distribution system restoration strategy. However, utilizing these resources to aid the utilities in better distribution system restoration decision making in response to extreme weather events is a challenging task. Therefore, this paper proposes an integrated solution: a distribution system restoration decision support tool designed by leveraging resources developed for grid modernization. First, we review the current distribution restoration practice and discuss why it is inadequate in response to extreme weather events. Then, we describe how the grid modernization efforts could benefit distribution system restoration, and we propose an integrated solution in the form of a decision support tool to achieve the goal. The advantages of the solution include improving situational awareness of the system damage status and facilitating survivability for customers. The paper provides a comprehensive review of how the existing methodologies in the literature could be leveraged to achieve the key advantages. The benefits of the developed system restoration decision support tool include the optimal and efficient allocation of repair crews and resources, the expediting of the restoration process, and the reduction of outage durations for customers, in response to severe blackouts due to extreme weather hazards.

KEYWORDS | Automated feeder switch; distributed generator; distribution system restoration; extreme weather event; grid modernization; microgrid; resiliency; situational awareness; survivability

I. INTRODUCTION

Recent severe power outages caused by extreme weather hazards have highlighted the importance and urgency of improving the resilience of the electric power grid. People will never forget that Superstorm Sandy in 2012 left over 8 million customers without power across 15 states and

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Washington, DC on the east coast of the United States [1], [2], and Hurricane Irene in 2011 resulted in more than 6.5 million people loosing power [1]. A recent Congressional Research Service study estimates that the inflation-adjusted cost of weather-related outages in the United States is $25–70 billion annually [3]. Besides the United States, large-scale power outages caused by extreme weather events occurred in other countries over the last decade. For example, the most severe ice storm seen in the last couple of decades with large-scale power interruptions following the incident were reported in China during the ice storm of 2008. More than 200 million people were left without electricity, and the direct costs of the event were estimated to be more than $2.2 billion [4]. The Cyclone Dagmar of 2011 left about 570 000 customers (from a total of 3.2 million electricity customers) experiencing a power outage in Finland [5]. In January 2005, a severe storm swept across Northern Europe, from Ireland to Russia. More than 500 000 homes were left without power, with Denmark and Southern Sweden being hit particularly hard. Five nuclear power plants had to be shut down due to saltwater seeping into electricity distribution plants [6]. Recently, in September 2016, fierce storms and lightning strikes in Australia left the entire state of South Australia with 1.6 million people without power overnight [7].

Extreme weather is the number one cause of electric power outages in the United States [1]. According to the analysis by Hines *et al.* [8], among 933 events causing power outages from 1984 to 2006, as shown in Table 1, almost 44% were weather related. According to the database of grid disturbance events maintained by the U.S. Department of Energy (DOE) [9], around 78% of the reported 1333 electric grid disruptions from 1992 to 2011 were weather related [3]. Regarding Europe, natural disasters have become the primary threats for the continuity of electricity service. After the central European floods of 2002, 2010, and 2013, European winter storms and the heavy snow of 2012, and the northeast European hurricane of 2011, both the European Union and its member countries started questioning the security level of their electric power supply [10].

The number of outages caused by extreme weather is expected to rise as climate change increases the frequency and intensity of hurricanes, blizzards, floods, etc. [1], [11]. According to data provided by the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA) [12], as of July 2016, the United States has sustained 196 weather and climate disasters since 1980 where overall damages/costs reached or exceeded $1 billion with adjustment of consumer price index (CPI), as shown in Fig. 1. The 1980–2015 annual average is 5.2 events; the annual average for the most recent five years (2011–2015) is 10.8 events. In 2015, there were ten weather and climate disaster events with losses exceeding $1 billion each across the United States, as shown in Fig. 2. In 2016, there were eight weather and climate disaster events with losses exceeding $1 billion (as of July 2016), including two flooding events and six severe storm events.

The electric distribution grids still remain vulnerable to extreme weather events. Fig. 3 shows examples of distribution-line and substation damage caused by wind and flooding, respectively, during Superstorm Sandy [1], [13]. On the other hand, customers' expectations for the continuity of electricity services have increased with the evolution of modern society's reliance on electricity, which creates pressure on utilities to enhance the grid resiliency against extreme weather events. While system hardening and resilience investments

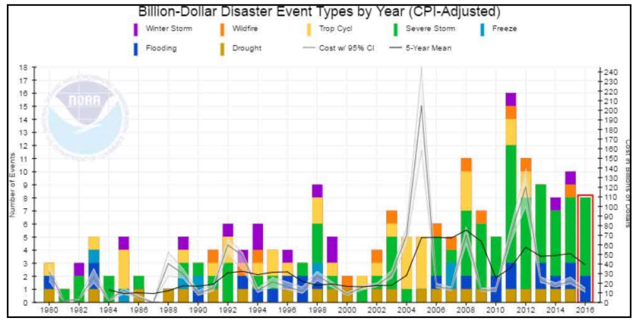

Fig. 1. ***Weather and climate disaster events with losses exceeding $1 billion in the United States, 1980–2016. (Source: NOAA's NCEI [12].)***

Table 1 Causes of Major Blackouts in the United States [8]

Cause	% of events	Mean size in MW	Mean size in customers
Earthquake	0.8	1,408	375,900
Tornado	2.8	367	115,439
Hurricane/tropical storm	4.2	1,309	782,695
Ice storm	5.0	1,152	343,448
Lightning	11.3	270	70,944
Wind/rain	14.8	793	185,199
Other cold weather	5.5	542	150,255
Fire	5.2	431	111,244
Intentional attack	1.6	340	24,572
Supply shortage	5.3	341	138,957
Other external cause	4.8	710	246,071
Equipment failure	29.7	379	57,140
Operator error	10.1	489	105,322
Voltage reduction	7.7	153	212,900
Volunteer reduction	5.9	190	134,543

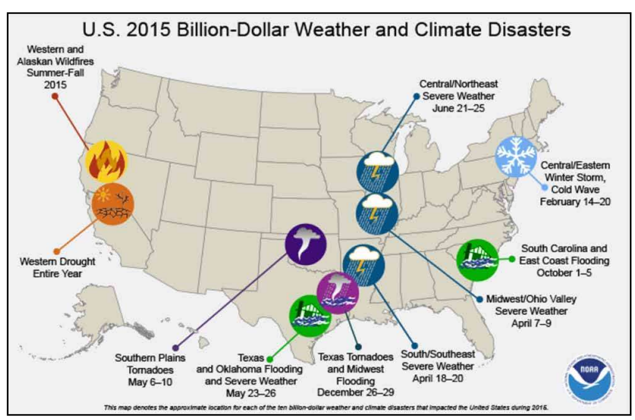

Fig. 2. ***The location of ten weather and climate disaster events with losses exceeding $1 billion across the United States in 2015. (Source: NOAA's NCEI [12].)***

(a) (b)

Fig. 3. ***Examples of vulnerability of distribution system to extreme weather events: (a) downed wires during Superstorm Sandy [1]; (b) substation flood in the Dumbo area of Brooklyn, NY, USA during Superstorm Sandy [13].***

(vegetation management, undergrounding, elevating substations, etc.) at the planning stage are very important, system restoration in response to the disastrous event is also indispensable to achieving resilient electric distribution systems.

Current distribution system restoration is based on predetermined priorities [14]; this approach is not adaptive with respect to the status of power grid damage under evolving weather events and available restoration capabilities and resources, and thus tends to be inefficient and suboptimal. In addition, lack of situational awareness of distribution grids after the disaster strikes poses great challenges to utilities' operators, and greatly delays the restoration process. As a result, customers may experience extended outages which cause large economic loss. These challenges come from the unique features of power outages caused by extreme weather events, such that the current restoration schemes that are designed for typical power outages may not be suitable. In this sense, it is imperative to improve the distribution system restoration strategies for utilities in response to disastrous events.

It has been observed that the grid modernization efforts in the power industry have the potential to enhance the grid resiliency. In the United States, grid modernization was initiated by the Department of Energy (DOE) under the American Recovery and Reinvestment Act of 2009 [15]. Under the largest program, the Smart Grid Investment Grant (SGIG), DOE, and the electricity industry have jointly invested \$8 billion in 99 cost-shared projects involving more than 200 participating electric utilities and other organizations. In the European Union, during the period from 2010 to 2020, cumulative investments in smart grid technologies will reach 56.6 billion [16]. The investments for grid modernization are also observed in other countries, including China, Japan, South Korea, Australia, and Brazil [16]. Among these efforts, distribution automation (DA) and advanced metering infrastructure (AMI) enable more observability and controllability of distribution systems, which can be leveraged to improve the restoration process, and these benefits have been shown through some pilot projects [17]. However, integrating these emerging technologies to provide the utility operators an improved restoration strategy is a challenging task.

To achieve this goal, this paper presents an integrated solution: a decision support tool that can assist utilities with distribution system restoration after extreme weather events. First, we provide an overview of the current distribution system restoration practices and discuss their limitations for restoring extreme-weather-related outages. Then, we describe the proposed integrated restoration decision support tool. With the integrated solution, two advantages can be achieved: 1) improving situational awareness of the system damage status; and 2) facilitating customers' survivability using local generation sources. The paper also gives a comprehensive review of how the existing studies in the literature could be leveraged to achieve these two objectives and pave the way for modernizing distribution system restoration practice in response to extreme weather events. The main contribution of this paper is to provide a framework for an integrated solution and potential methodologies, as well as discussion about some open problems on how we can exploit the benefits from grid modernization efforts to improve distribution system restoration under extreme weather events for utilities.

Note that although most of the studies are based on cases in the United States, including historical hazard data, statistical impacts of the extreme weather events on power grids, and grid modernization efforts, the methodologies discussed in the paper are for general cases and have the potential to tackle the challenges of distribution system restoration under extreme weather in other countries.

The remainder of the paper is organized as follows. Section II describes the current distribution system restoration practices and the corresponding limitations. Section III discusses how the grid modernization can be leveraged to improve distribution restoration and describes the proposed integrated solution in the form of a distribution system restoration decision support tool. Section IV reviews the existing methodologies for using weather information for damage assessment, and the multisource data fusion method to improve situational awareness. Section V reviews existing studies on how to utilize local distributed resources to enhance survivability for customers. We conclude our discussion in Section VI.

II. OVERVIEW OF CURRENT DISTRIBUTION SYSTEM RESTORATION PRACTICE AND CHALLENGES

A. Current Distribution System Restoration Practice

Distribution system restoration is one of the core functionalities in the distribution management system (DMS) of the utilities. After a power outage occurs as a result of a sustained fault, the outage management system (OMS) will receive the customers' trouble call to pinpoint the faulted area and dispatch crews to repair the fault. Before the repair is completed, the outage load will be restored by altering the topological structure of the distribution grid (i.e., via network reconfiguration by controlling the switch devices manually or automatically) to connect to another feeder and/or another lateral on the same feeder. After the faulted section is repaired, the network is reconfigured to the normal state. Fig. 4 illustrates

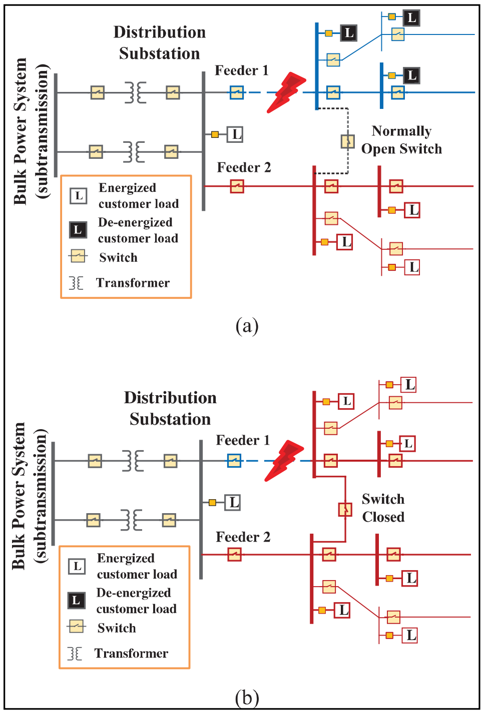

Fig. 4. ***Illustration of distribution service restoration by network reconfiguration: (a) the fault at Feeder 1 causes a power outage for downstream customers; (b) using network reconfiguration, the outage load is restored by Feeder 2.***

the restoration process using a simple two-feeder system. This scheme, which is called distribution service restoration, can reduce outage duration for customers and enhance the system reliability, and is an integral part of fault location, isolation, and service restoration (FLISR) in the modern DMS [18]. The methodologies of the distribution service restoration have been extensively studied in the literature; they include expert systems [19], [20], fuzzy logic [21], [22], multiagent systems [23], [24], heuristic search [25], and optimization [26]. These methods can effectively isolate the fault and restore as much load as possible after the general outage occurs in the distribution grid.

The utility's restoration activity in response to storms and other extreme weather events is generally guided by predetermined priorities. These provide a high-level guide to the order in which systems should be restored, based on importance and criticality. According to the survey by the Distribution System Testing Application and Research consortium, the restoration priorities are very similar across the utilities, and the general order is listed as follows [14][1]:

1) large transmission lines;
2) substations;
3) public safety calls;
4) main or three-phase backbone feeders;
5) emergency services and facilities critical to public health and safety;
6) single-phase lines serving large blocks of customers;
7) lines serving neighborhoods and multiple customers;
8) individual customers.

The time needed to restore a distribution system following a major event is highly dependent on a quick and accurate assessment of system damage [14]. Damage assessment scouts, also called field checkers or spotters, evaluate storm damage before line crews are dispatched. The role of a damage assessor is to patrol the feeders to identify trouble spots, evaluate the extent of the damage, and develop initial estimates of resources needed for restoration. The assessment generates critical information that helps to define the scope of the work, prioritize efforts, and assign resources. The typical damage assessment process is as follows [14][2]:

- scores of damage evaluators or damage assessment teams are sent out to survey all the feeders and taps;
- assessors record and tally the number of broken poles, spans of wire down, damaged transformers, etc., and the location of the damage;
- when teams return to the dispatch location (usually at the end of the day), the information is passed on to someone to prioritize the trouble and dispatch crews to perform the repairs.

Once the damage assessment is complete, coordinators in the control center have a fairly good idea of the size and extent of the damage and the resources required. Crews are then dispatched to repair damage and restore service on the basis of certain rules and guidance that consider various factors (e.g., ease of repair or access to the damaged area). Besides the utilities' own personnel, the U.S. electric industry has developed effective mutual assistance programs, in which utilities call in crews from across a region to help restore downed lines, poles, and transformers [28]. The mutual assistance framework has also been set up in Europe to speed up restoration after a major power disturbance by facilitating arrangements among the members for access to spare parts and workforces [27]. The host utility needs to provide logistical support in the form of lodging, food, and fuel; must have on hand the necessary spare materials and equipment; and must have the capability to efficiently dispatch crews to the affected areas [14].

[1]Note that the restoration priorities are from the survey regarding the cases for the United States. However, the predetermined priority-based restoration scheme is a general rule for power distribution grids in other countries as well. For example, as shown in [27], the recovery measures of the floods in 2014 in Southeastern Europe include the rehabilitation of damaged and destroyed power lines and equipment on a priority basis. In another example of severe icing in 2014 in Slovenia, the fault handling was carried out by working from high to low voltage [27], which is also based on a predetermined priority.

[2]Note that the damage assessment process is based on the survey regarding the cases for the United States. But it is a general practice for restoration after extreme weather in other countries. For example, during the severe icing event in 2014 in Slovenia, the loss of communications systems resulted in manual assessment of the situation after the disaster [27].

Successful restoration efforts also include effective communications, both internal and external. The internal communications are essential to manage and coordinate restoration activities, while the external communications are equally important to create public trust and reinforce the perception of a successful effort [14]; e.g., providing accurate estimated time of restoration (ETR) will alleviate the frustration of the customers experiencing the blackout.

B. Inadequacy of Current Restoration Practice for Extreme Weather Events

While the current distribution system restoration schemes work well for typical power outages, the story may change for extreme weather events. The challenges come from the unique features of power outages due to extreme weather events, as shown in Table 2 from our previous work [29]. These features are highly related to the characteristics of the extreme weather event. For example, a storm may topple trees at several locations that snap utility poles to cause multiple faults and cause a widespread outage, and these locations depend on the path of the storm. On the contrary, a typical outage is usually caused by one or a few random faults. Sometimes even bulk power systems suffer damage as a result of the disaster, which in turn causes outages that conventional restoration mechanisms may not be able to deal with in an effective manner. In addition, natural disasters may destroy other infrastructures which are interdependent with power grids (e.g., transportation network, communications network, gas pipelines) so that the restoration process will face even more difficulties. Conversely, a typical power outage usually does not suffer from these issues. These differences will result in the limitations of the current restoration practices in response to extreme weather events, as discussed below.

1) Degraded Customers' Survivability: The distribution system restoration strategies designed for typical outages may not be suitable for recovery from natural-disaster-induced outages. If the distribution system experiences a complete loss of electricity, or some isolated islands are formed as a result of the extreme weather event, customers may experience extended outages until the faulted areas are repaired and energized again. This process may take a week or longer, as actually happened during Superstorm Sandy. This scenario poses new challenges for utilities to achieve survivability for customers, which refers to the ability to maintain some basic level of electrical functionality to individual consumers or communities in the event of a complete loss of electrical service from the distribution system [28]. Actually, the concept of assisting customers with survivability features is relatively new to the electric industry. Historically, many customers such as hospitals, banks, and data centers have assumed responsibility for their own survivability, relying on backup generators and uninterruptible power supplies (UPS) [28]. However, owing to modern society's high dependence on electricity and the rapid evolution of customer expectations regarding electricity supply continuity (e.g., for communications and modern conveniences) after an extreme weather event, the utilities are facing pressure to achieve survivability for customers before the completion of repairs on faulted areas.

Table 2 Differences Between Typical Outages and Natural-Disaster-Induced Outages [29]

Typical Outages	Outages Due to Extreme Weather Events
• Single fault due to one component failure	• Multiple faults due to catastrophic damage
• No stochastic feature involved in general analysis	• Uncertainty & stochasticity with the process of natural disasters
• No spatio-temporal correlation for the fault; fault happens randomly	• Spatio-temporal correlation for the faults due to natural disasters
• Most power generation units are working and stay connected	• Power generation units may be out of service
• Transmission & distribution networks remain intact	• Transmission & distribution networks are damaged and incomplete
• Only involve power grids infrastructure	• Have interdependence with other infrastructures
• Quickly repair and restore	• Difficult to repair and restore, e.g., debris after the disaster

2) Lack of Situational Awareness: Lack of situational awareness after disastrous events is another challenge to distribution system operators, which largely delays the restoration process and causes large economic costs to customers. Unlike the transmission systems, most of the current distribution systems are "blind" in terms of monitoring and control capabilities beyond the distribution substation. Even with some observability enabled by AMI or DA, data after a natural disaster may be unavailable or questionable, since the devices as well as the underlying communications network may also be damaged. To pinpoint the faulted areas, the current OMS usually depends on customer trouble calls, which are slow and inaccurate, or even unavailable owing to damaged telecommunication systems. The existence of so-called "nested outages," i.e., an outage within an outage, which are more common in power outages due to extreme weather events, creates additional difficulties in identification of outage areas.

On the other hand, the damage status information is usually captured by field assessors, which is also a very slow process, and the crews cannot be dispatched until the damage information is collected and analyzed. Furthermore, as indicated in the white paper by GTM Research [30], the separation of the damage assessment system from the OMS during restoration results in data silos for the two processes, which impact the ability to achieve situational awareness in a timely manner. In this sense, utilities have little knowledge about what components/networks are damaged and how severely they are damaged after natural disasters, and thus it is difficult for utilities to schedule repair crews and restore the distribution system effectively and efficiently.

III. AN INTEGRATED SOLUTION FOR DISTRIBUTION SYSTEM RESTORATION

It has been observed that the progress of grid modernization efforts in recent years has provided the potential to improve distribution system resiliency. However, integrating these emerging technologies and devices during the restoration process is not an easy task for utilities. In this section, the grid modernization efforts toward grid resiliency are introduced. Then, an integrated solution to help utilities' decision making for distribution system restoration is described.

A. Grid Modernization Efforts Toward Grid Resiliency

The investments in grid modernization efforts have been conducted in many countries in the world. In the United States, as a result of the American Recovery and Reinvestment Act of 2009, the DOE, in collaboration with the power industry, launched the SGIG program [31]–[33], aiming at modernizing electric power grids through deployment of advanced devices and smart grid techniques. Fig. 5 shows the SGIG expenditures by categories of technologies and systems. In the European Union, the investments in smart grid technologies are from several funding agencies including the European Recovery Fund, the European Regional Development Fund, and the European Educational Research Association [16]. Fig. 6 shows the geographical distribution of investments and project categories of smart grid technologies in the European Union.

Among them, the investments in electric distribution systems and advanced metering infrastructures provide the potential to enhance distribution system restoration in the following ways in response to extreme weather events.

1) Distribution Automation: The development of DA enables the deployment of field devices such that the visibility and controllability of the distribution system behind the substation is enhanced. One important field device is the remote fault indicator, which is a low-cost sensor that can detect electric signatures associated with faults, such as high currents or low/no voltage [34]. Fault analysis applications can utilize the data provided by fault indicators to achieve improved accuracy in locating and identifying faults and their causes. Fig. 7(a) shows a fault indicator designed and manufactured by Schweitzer Engineering Laboratories (SEL) [35], and Fig. 7(b) shows the deployment of fault indicators on overhead distribution lines.

Automated feeder switches are also emerging as a result of the development of DA. These switches can open and close a feeder section in response to control commands, which provide controllability of the distribution network

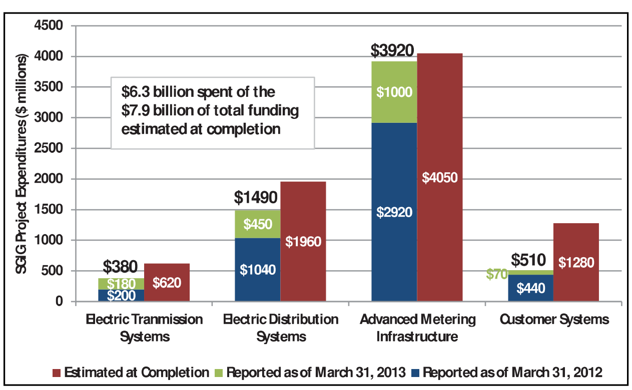

Fig. 5. ***The U.S. DOE Smart Grid Investment Grant program [32].***

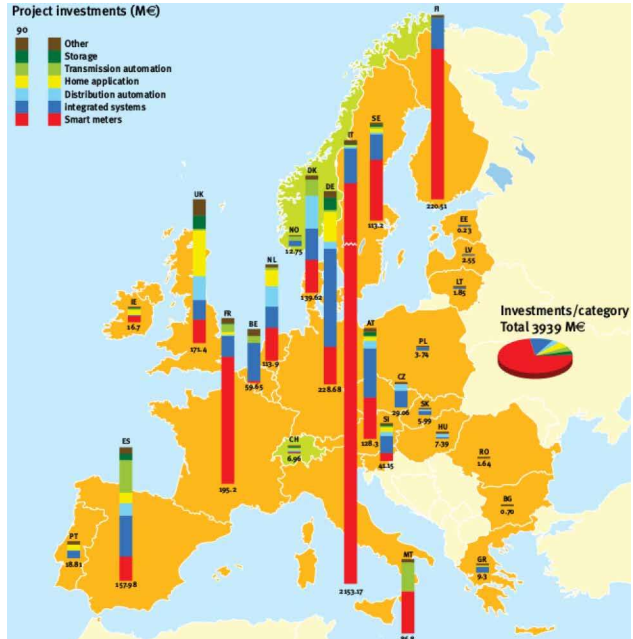

Fig. 6. ***Geographical distribution of investments and project categories of smart grid technologies in the European Union [16].***

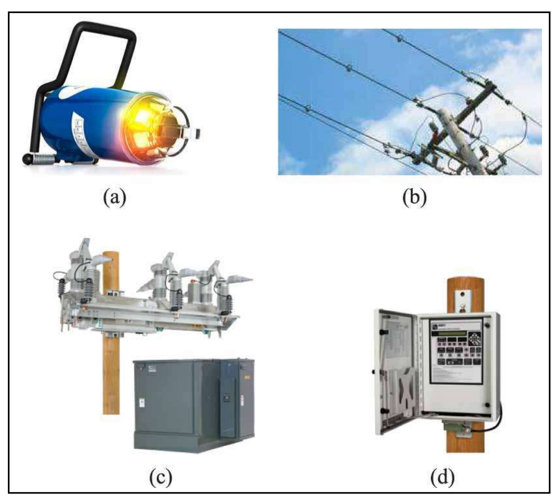

Fig. 7. ***Examples of field devices for distribution automation: (a) overhead fault indicator [35]; (b) deployment of overhead fault indicator; (c) automated feeder switch [36]; and (d) automatic switch control system [37].***

to isolate faults and reconfigure faulted segments of the distribution feeder to restore power. Fig. 7(c) shows the IntelliRupter PulseCloser Fault Interrupter designed and manufactured by S&C Electric Company [36], which integrates fault interruption, fault isolation, and circuit restoration in a single, easy-to-install package, and Fig. 7(d) shows the corresponding automatic switch control system [37]. For example, in the SGIG project implemented by the Electric Power Board (EPB) in Chattanooga, TN, USA, more than 1400 automated feeder switches have been installed with the corresponding communication and information management [17]. In a July 2012 derecho that affected half of EPB's customers, EPB's response was up to 17 h faster because of the automated feeder switches, which restored power to 40 000 customers instantly [17].

With the development of grid modernization, the increasing penetration of distributed generation technologies and microgrids provides localized power resources, which may provide huge benefits during restoration in response to extreme weather events. As recommended in the report by GridWise Alliance [2], these distributed energy resources (DERs) can be leveraged to serve critical loads when the utility grid is down after extreme weather events. The automated feeder switches and the associated control mechanism make it possible to utilize these DERs to ensure the survivability of the customers and reduce outage sizes and durations. The resilience benefits of the DERs was demonstrated by Sendai Microgrid (SM) in Japan during the 2011 great east Japan earthquake and tsunami. When the earthquake occurred, the Tohoku Electric Power Company stopped supplying power to the area surrounding SM, resulting in an almost three-day outage. Nevertheless, SM was able to continuously supply power to some small critical loads within the campus and provided full heat and power service for almost two and a half of the three blackout days [38].

2) Advanced Metering Infrastructure: The smart meters deployed in the AMI are equipped with outage notification capabilities that allow the devices to transmit a "last-gasp" alert when power to the meter is lost [34]. The information can be integrated into the OMS to provide additional way to pinpoint the outage area and help to assess the damage. Smart meters can also transmit "power on" notifications to operators when power is restored, or even allow utilities to "ping" meters in the affected areas to assess the outage boundary and verify the restoration progress, enabling field crews to be deployed more efficiently, thus reducing the restoration time. This benefit was shown in the SGIG project at PECO in Philadelphia, PA, USA, during Superstorm Sandy, where smart meter operations helped PECO avoid more than 6000 truck rolls as power restoration was confirmed by pinging meters without having to send repair crews [17].

B. An Integrated Distribution System Restoration Decision Support Tool

Although the new devices and technologies discussed in Section III-A could potentially help the utilities to improve the restoration process, it will be a challenge to determine how to best utilize these resources, especially during extreme weather events. A decision support tool that integrates these resources and technologies will be helpful for decision making by the utilities' operators during restoration. The tool leverages weather information/forecasts and system fragility assessment to improve utilities' situational awareness during restoration processes. Advanced optimization models with user-defined multiobjective metrics will be developed to schedule repair crews and restoration resources and reconfigure the distribution grids in real time. The tool is adaptive to system variations, as a feedback loop will be designed for decision updates. The structure of the proposed decision support tool includes four modules, as shown in Fig. 8.

- The data fusion module leverages the existing trouble call systems, weather information/forecasts, system fragility assessment models, and data from distribution field measurements to improve situational awareness and estimate and predict distribution system damage status after extreme weather events such as a hurricane, flooding, nor'easter, ice storm, or wildfire.
- The crew and resource dispatch module captures key attributes and constraints of repair crews and associated restoration resources, and integrates them into restoration models.
- The advanced control module utilizes the resources enabled by distribution automation, e.g., automated feeder switches and DERs, to reconfigure distribution grids and pick up loads.

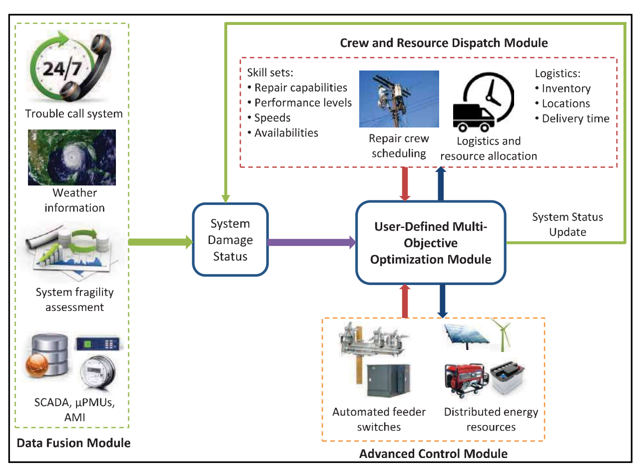

Fig. 8. ***The overall structure of the integrated distribution system restoration decision support tool.***

- The user-defined multiobjective optimization module exploits advanced optimization models to coordinate repair crew scheduling, resource allocation, distribution grid reconfiguration, and load pickup according to different metrics specified by users. The tool is adaptive to system variations, as a feedback loop of updated information will be integrated into the decision-making process.

The benefits of the proposed integrated distribution system restoration support tool include the optimal and efficient allocation of repair crews and resources, the expediting of the restoration process, and the reduction of outage time for customers in response to severe blackouts due to extreme weather hazards. Thus, the economic costs of power outages can be reduced. It will further benefit the whole electricity industry, including utility companies, customers, independent system operators/regional transmission organizations (ISOs/RTOs), regulatory agencies, and vendors. The anticipated benefits to various entities and stakeholders are summarized as follows.

- Utilities can use the tool to expedite the restoration process and utilize the distribution automation devices and technologies to reduce the outage durations and sizes during extreme weather events.
- Electricity customers will benefit from the reduced sizes and durations of power outages during extreme weather events.
- ISOs/RTOs will be able to use the methodology to coordinate transmission-level restoration processes with distribution-level utilities to improve the overall system restoration.
- Regulatory agencies will have a quantitative method to evaluate the resilience enhancement of the distribution system due to the development of advanced control and optimization technologies.
- Vendors may be able to use the tool to specify the requirements of certain devices that will be utilized in the restoration and enhance the development of outage management systems.

This integrated solution for distribution system restoration decision making has two key advantages compared to the existing solutions.

1) Improving situational awareness of system damage status. The data fusion module in the tool will integrate multiple sources of information, including weather information/forecasts, system fragility assessment, customers' trouble calls, smart meters, and distribution SCADA (protective relays, fault indicators, etc.) to better estimate the damage status after the extreme weather event. As a result, the process of restoration can be faster.
2) Facilitating survivability for customers in the event of a complete loss of electrical service from the utility grid. The advanced control module will integrate the new devices and technologies enabled by smart grids and distribution automation to reconfigure the distribution grid and pick up load in an optimal way. As a result, the DERs can be utilized to serve the critical loads after extreme weather events to reduce the customers' outage size and duration.

In Section IV, we will discuss how different sources of information can be integrated to estimate the system damage status to improve the situational awareness for utilities. Several existing technical approaches will be described, and a data fusion framework will be proposed to integrate these sources of information. In Section V, we will describe how the DERs and automated feeder switches can be leveraged to reconfigure the grid and pick up local loads, which provide the potential to reduce customers' outage duration and facilitate survivability. Some case studies are provided to demonstrate the approaches, and some special technical considerations will be discussed.

IV. IMPROVING SITUATIONAL AWARENESS

As shown in Fig. 8, the data fusion module utilizes multiple sources of information to improve the situational awareness of the damage status. One important source is weather information, which can bring in useful knowledge for estimating the damage to the distribution grid due to natural disasters. The integration of weather information with the customers' trouble call information as well as the measurements from field devices has the potential to achieve more accurate system damage status. A probabilistic data fusion framework is proposed as one of the possible options to explore the integration of multiple sources of information to improve the situational awareness.

A. Leveraging Weather Information for Damage Assessment

To integrate the weather information into the distribution damage assessment, an important task is to understand how different weather metrics impact the distribution grid; several existing studies address this issue. In general, the methodologies can be divided into two categories: component-level damage assessment and system-level damage assessment.

1) Component-Level Damage Assessment: The component-level damage assessment method aims to estimate how the weather impacts each individual component of the distribution grid. It applies a probabilistic damage model, which uses damage/fragility curves to represent the probability of damage as a function of weather metrics such as wind speeds and flood water depth. For example, the fragility of a distribution line exposed to extreme winds is determined by the failure of at least one of its support structures, i.e., distribution poles. Based on the observations made by Quanta Technology [39], the failure probability of an existing distribution support structure can be approximated by an exponential function using historical data, as follows:

$$\lambda_p = a \cdot \exp(b \cdot w_s) \tag{1}$$

where λ_p is the pole failure rate, w_s is the sustained wind speed, and a and b are tuning parameters based on historical data. Using historical data from Florida Power & Light results in $a = 0.0001$ and $b = 0.0421$ [39]. Besides the empirical methods using historical data, other methods based on physical models are also available. For example, Winkler *et al.* [40] used wind force and maximum rated line perpendicular stress resistance to approximate the probability of line failure. The wind force on line k, $F_{\text{wind},k}$, is calculated with the standard American Society of Civil Engineers (ASCE) design equation using wind gust speed (w_s) and line cross-sectional area A_c

$$F_{\text{wind},k} = Q\, k_z\, I_{FW}\, G_{WRF}\, C_f A_c w_s^2 \tag{2}$$

where other parameters in (2) accounting for air density (Q), terrain correction (k_z), hazard importance (I_{FW}), wire strain (G_{WRF}), and drag coefficient (C_f) are defined by the ASCE Engineering Practice Report 113 [41]. Line damage probability is calculated as the ratio of the maximum perpendicular force that the line can endure ($F_{brk,k}$) and the line wind loading ($F_{\text{wind},k}$) for a distribution line k

$$\text{Pr}_{\text{wind},k} = \min\left(\gamma \frac{F_{wind,k}(w_s)}{F_{brk,k}}, 1.0\right) \tag{3}$$

where factor γ is used to scale the line fragility estimates to match recorded failure data. The distribution grid suffers from significant vulnerability to damage caused by flying debris, as the distribution lines are close to the ground and often in close proximity to trees. Tree windthrow probability therefore affects the fragility of the distribution lines significantly. The study in [40] also discussed the flying debris models and how they will affect the distribution line failure probability.

The damage probability for substations in terms of windstorms can be represented via log-normal fragility curves [40]. These curves generate the probability of damage for a given wind gust speed (ws) while taking into account the local terrain and structural characteristics of the substation under consideration. The general form of the fragility curves is shown as

$$\Pr(\text{damage} | w_s = x) = \int_x^{-\infty} \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left(\frac{-(\ln x - \mu)^2}{2\sigma^2}\right) dx \tag{4}$$

where parameters μ and σ represent the logarithmic mean and standard deviation of the fragility curve, which can be taken from the Federal Emergency Management Agency (FEMA) HAZUS Hurricane Model [42]. This method considers substations as a single unit instead of employing fragility curves for individual substation elements as approximation.

Flooding is a major concern for substations. Flooding becomes a problem for substations when the amount of water exceeds the capacity of the drainage network. Flooding can cause severe damage to substation equipment, and may lead to interruptions in service continuity and widespread outages. The approach of estimating the impacts of flooding on a distribution substation is based on the metric of water depth in flooding, which dictates whether a substation remains in operation. The expected loss of functionality for substations from inundation is determined on a site-specific basis as a function of the depth of flooding. The functionality thresholds and damage functions will be obtained from the FEMA HAZUS Flood Model for each type of substation [43]; example information for low-voltage substations is shown in Fig. 9.

The severe weather forecasts can be combined with geographic information system (GIS) data on electric distribution components to determine the projected weather conditions at a specific location. Using the damage curves, the potential damage and availability of these grid components would be determined specifically for a given weather threat, coupled with the forecasted weather conditions. The historical and forecasting weather data are available in *shapefile* format (a popular geospatial vector data format for GIS) from the National Weather Service (NWS) [44] and NOAA [45] for the following weather metrics:

- precipitation;
- temperature;
- depth of flood water;
- hurricane and storm surge.

Besides these publicly available weather data, advanced weather forecasting models, e.g., the Weather Research and Forecasting (WRF) Model [46], can also be utilized to obtain weather forecasting with finer granularity.

2) System-Level Damage Assessment: Unlike the component-level damage assessment methods that investigate

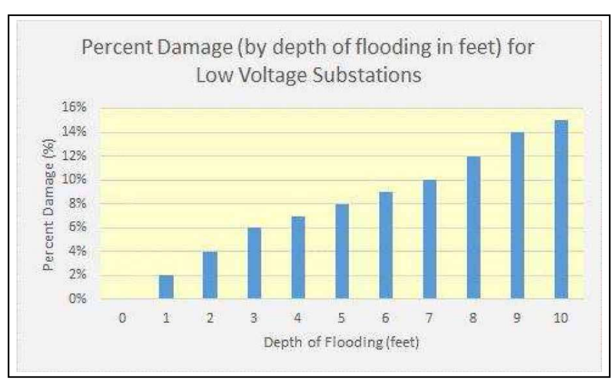

Fig. 9. ***Damage curve for substations in terms of flood water depth.***

the individual component failure risk, system-level damage assessment methods use characteristics of the overall system, the hazard, and the area to estimate the failure risk. Multivariate regression-based statistical models are usually applied for this type of approach. Guikema *et al.* [47] present several statistical models developed in previous work [48]–[51], as well as tree-based data mining models, for estimating the number of poles that will need to be replaced for an approaching hurricane.

The generalized linear model (GLM) is a generalization of a standard linear regression that allows regression analysis of count data. A GLM consists of three components: 1) a conditional distribution for the count events given the parameter(s) of the distribution; 2) a "link" equation relating the distribution parameter(s) to a function of the explanatory variables; and 3) an equation specifying the function of the explanatory variables to be used in the link function [47]. For example, a negative binomial GLM to model distribution system damage in grid cell i can be described as follows:

$$f_Y(y_i|\alpha,\lambda_i) \sim \frac{\Gamma(y_i+\alpha)}{\Gamma(y_i+1)\,\Gamma(\alpha^{-1})} \cdot \left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_i}\right)^{\alpha^{-1}} \cdot \left(\frac{\lambda_i}{\alpha^{-1}+\lambda_i}\right)^{y_i} \tag{5}$$

$$\log(\lambda_i) = \beta_0 + \sum_j \beta_j x_{ij} \tag{6}$$

where y_i denotes the number of damages (count data) in grid cell i, λ_i is the parameter of the negative binomial distribution, the vector $\mathbf{x}_i = [x_{i1}, x_{i2}, \ldots, x_{in}]'$ represents the explanatory variables of size n in grid cell i, the vector $\boldsymbol{\beta} = [\beta_0, \beta_1, \ldots, \beta_n]'$ is the regression parameters to be estimated, and α is the overdispersion parameter of the negative binomial distribution that is observed in power system performance data.

The generalized additive model (GAM) allows a nonlinear relation between the parameters of the conditional distribution and the covariates [47]. For example, the link function shown in (6) can be changed to represent a nonlinear smoothing function.

$$\log(\lambda_i) = \beta_0 + \sum_i s\,(x_{ij}). \tag{7}$$

The tree-based data mining methods represent the relationship between the response variable of interest (e.g., the number of damaged poles) and the explanatory variables through the use of recursive binary partitioning of the data set. For example, the classification and regression trees (CART) method used in [47] develops a single tree to capture the relationship between the response variable and the explanatory variables. In building the regression trees, the algorithm chooses the variable to split the data set and the value of that variable at which to split the data to maximize the decrease in the sum of squared errors (SSE) of the fitted values at that node. This process is continued until each end node reaches purity (SSE = 0) or until a minimum number of records are reached at a given node. Another tree-based method is Bayesian additive regression trees (BART). The BART model consists of a large number of small trees with each tree constrained by a prior to restrict each tree's contribution to the final model, making each individual tree a "weak learner." Fit and inference in BART are achieved through a Markov chain Monte Carlo algorithm [29], [52].

To evaluate the predictive accuracy, a holdout validation analysis is applied. The data set will be partitioned into training and validation sets (e.g., 80% of the data is the training set and 20% of the data is the validation set as a general rule). The mean absolute error (MAE) and mean squared error (MSE) are employed for the validation and comparison

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|, \tag{8}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2. \tag{9}$$

The comparison of accuracy of various statistical-based methods to predict the system damage is performed in reference [47], where MAE and MSE based on detailed pole-level damage data on the basis of 150 random holdout samples are shown. The results show that no statistical method can achieve 100% accuracy. Certain methods are superior to others in terms of MAE and MSE in these case studies, but we cannot derive a general conclusion on which method is the best since the result may be different for another geographic location with a different set of historical data.

The statistical models highly rely on the historical data available. For the damage assessment, the distribution system damage data set (e.g., pole replacement data) is the response variable. The explanatory data required for statistical models include power-system-related data and environmental data. The former consists of the topology of the grid, the number and availability of protective devices, the location and number of customers, etc. Environmental data may vary with the disaster scenario. Examples of such parameters and available sources of the data are listed as follows [29]:

- land and geometric characteristics of the area such as land use and land cover data, soil moisture levels, elevation characteristics, land slopes, and compound topographic index [53], [54];
- disaster variables such as hurricane duration and intensity, approaching angle, landfall position, and translation velocity [55];
- climate characteristics, such as standardized precipitation index (SPI) and annual and monthly precipitation [56].

Note that statistical models in the literature are based on the stationarity assumption (i.e., power system components stay unchanged over the time horizon). However, there will be upgrading of the system components over time, especially due to the grid modernization efforts. One method to tackle this issue is to include the power system component change information in explanatory variables in statistical models, so that the inference results can capture the effects of system change over time.

The system-level assessment method can also be utilized by utilities to achieve efficient and effective emergency response planning in advance of an approaching disaster. The assessment can be used to inform the public about the estimation of the scale of the outage and duration of the restoration, which is also an important task for utilities before and during restoration.

B. Other Sources of Information for Damage Assessment

The system damage status can be estimated utilizing other sources besides the weather information, including the traditional customer trouble calls, data from fault-indicating devices enabled by DA for feeder information, and smart meter data enabled via AMI on the customers' end. Each source of these data will provide information on system outage, fault, and damage from different temporal and spatial dimensions; thus, integrating them can achieve improved situational awareness of the system status after extreme weather events.

1) Customer Trouble Calls: Traditionally, distribution grids have little observability and controllability beyond the substations. When a power outage occurs, utilities rely on trouble calls from customers to pinpoint the outage area. The OMS will match the phone number from each call to the specific customer locations, so that the distribution transformer and protective devices on the corresponding feeder can be identified. When sufficient trouble calls are collected, the OMS predicts the tripped protective devices and faulted line sections. Through call center automation techniques, including interactive voice response (IVR) and automated callbacks [30], the collection of the trouble calls could be expedited. Laverty and Schulz [57] proposed a topology-based algorithm that associates trouble calls with each other to provide more accurate information about outages during heat storms. However, the accuracy of the method based on trouble calls relies on the availability of trouble calls from customers, which is an issue during natural disasters, since they could also impact the telecommunication systems.

2) Data From Fault-Indicating Devices: The data from fault-indicating devices could capture the electric signatures associated with faults and the control center could get the data through the distribution SCADA. The fault-indicating devices generally include circuit breakers (CBs), feeder terminal units (FTUs), fault indicators (FIs), etc. There are some existing studies on how to utilize information on the tripped relay and circuit breakers to identify the most probable faulted section of the distribution grid, e.g., the methods in [58] and [59] based on expert systems, and the method in [60] based on overcurrent direction and network structure. Recent work [61] proposed an automatic and fast faulted line section identification based on the data from fault indicators, which have been widely installed in distribution systems because of their lower cost. The information can be further leveraged to estimate the fault location once the faulted line section is identified, as discussed in, e.g., [62]–[64], and references therein. In addition, the continuous measurements from field devices can be exploited to identify the faulted segment. For example, the method in [65] uses current magnitude to identify multiple faulted segments and further uses voltage sag to reduce the candidate faulted segments. However, in the event of disasters, the data from these field devices may become unavailable owing to damage to the devices or the underlying communication system (i.e., SCADA), so that fault identification by these methods, based on incomplete data, may provide ambiguous results. In addition, these methods rely on the electric signature at the time of the fault, so further damage to the outage/faulted area cannot be identified or located.

3) Data From Smart Meters in AMI: With the development of AMI, smart meters are capable of outage notifications via underlying two-way communications systems. These notifications provide useful information to pinpoint the outage and damage from the customers' end. Many studies appear in the literature on identifying power outages using smart meters. Chen *et al.* [66] proposed a fuzzy-petri-nets-based method to detect outage events using AMI data. Liu and Schulz [67] designed a knowledge-based system to locate distribution system outages utilizing wireless automated meter reading systems. Sridharan and Schulz [68] proposed probabilistic and fuzzy model-based filter algorithms to process outage data from automated metering system. Smart meters could also help with identifying the fault location using their voltage measurements [69], and during the restoration process, smart meters could provide verification and confirmation of the restoration [70]. However, like the distribution SCADA system, the underlying communication network for AMI is vulnerable to natural disasters, leading to the availability issue for the smart meter data.

4) Data From μPMU: The microphasor measurement units (μPMU), a new synchrophasor measurement device designed for distribution systems and funded by DOE Advanced Research Project Agency—Energy (ARPA—E) [71], could provide more accurate and finer-granularity measurements to monitor the distribution grid status. Fig. 10 shows the μPMU developed by the Power Standards Lab (PSL). A scoping study by Lawrence Berkeley National Laboratory [72] shows the effectiveness of μPMUs for distribution system restoration. With deployment of more μPMUs in distribution systems, the situational awareness could be further improved.

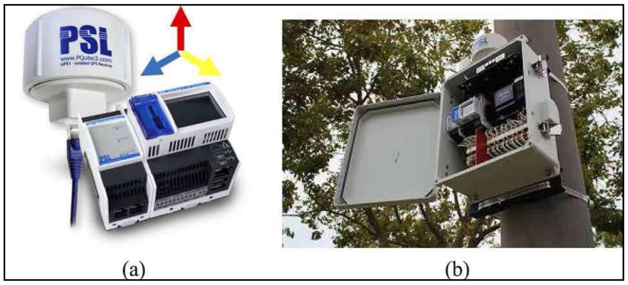

Fig. 10. *μ PMU by the Power Standards Lab [73]: (a) PQube 3; (b) outdoor pole mount with the wireless 4G modem.*

5) Data From Social Media: In addition to these field devices, with customers actively engaged in social media such as Facebook and Twitter, the ever-growing digital media network can be considered as social sensors to identify the location and extent of an outage without adding new measurement and communication instruments [74]. The usefulness of social media in outage detection has been recognized by the power industry [75]. Sun *et al.* [74] propose a probabilistic framework for the detection and location of power outages by using the abundant amount of data collected from Twitter, which can be utilized as an additional source of information to improve utilities' situational awareness.

C. Multisource Data Fusion Schemes

As discussed before, each source of data could provide useful information for estimating the system damage status from different perspectives; however, due to features of natural disasters, these data may be incomplete. Therefore, a data fusion method that combines the input data from various sources, including weather, measurements from field devices, customers' trouble calls, smart meters, and even social media, to estimate and predict the distribution grid status is desired. There are several studies in the literature that combine some of these sources for outage and fault identification. Sun *et al.* [76] utilized fault-indicating devices to identify faulted line sections in medium-voltage feeders and trouble call systems to locate faulted areas for low-voltage distribution systems, and the interaction between these two schemes is discussed. Liu and Schulz [77] proposed a knowledge-based system to locate distribution system outages using comprehensive data from customer trouble calls, a wireless automated meter reading system, and distribution SCADA. Jiang *et al.* [78] proposed a multihypothesis method for identification of the faulted section on a feeder or lateral using data from smart meters and protective devices.

1) Data Fusion Framework: In the proposed distribution system restoration decision support tool introduced in Section III-B, the data fusion module aims to design a multisource data fusion scheme to improve the situational awareness of system damage status. It consists of five major elements, as shown in Fig. 11. These are: 1) fragility assessment that correlates various weather conditions with the impacts on functionalities of individual grid components; 2) a feeder-level situational assessment model that determines or infers the states of grid components based on field measurements; 3) a customer-level outage assessment model based on customers' trouble calls and smart meter data in OMS to identify outage areas; 4) an automated interface that a) synthesizes the outcomes of the fragility curves and the situational assessment model to determine the state of major components in the grid and b) updates the component models in the grid according to the component states to represent their operation conditions; and 5) a grid analysis model that contains models of grid components including generation and load as well as geological information of the equipment and topology of the grid such that the grid status can be determined from the component states. In the data fusion module, an inferring scheme will be developed to synthesize the available measurements for situational assessment. To build the analytical grid model, a GIS-based distribution power flow model is preferred to provide connectivity and determine the feasibility of power flow.

2) Data Fusion Methodologies: To apply a data fusion method, the damage estimation from each source of information should be unified into a generic probabilistic model. For the fragility curve-based methods that assess the impact of extreme weather to distribution grid in the component level, the probabilistic model is directly given by the fragility curve that estimates the damage probability given the weather metrics. If the parameters of the physical model of the component are available, the probability of the damage given the weather metrics can be obtained according to the physical model, for example, the probability of failure is represented by (2) and (3).

For the statistical regression-based methods which estimate the damage count in a given area, we aim to convert the system-level statistical information to component-level damage probability. Assume that the damage count Y_i in a given area is described by Poisson distribution, that is, $Y_i \sim \text{Poisson}(\lambda_i)$ for type i component with failure rate $\lambda_i = \mathbb{E}\{Y_i\}$, where Y_i is the response variable representing

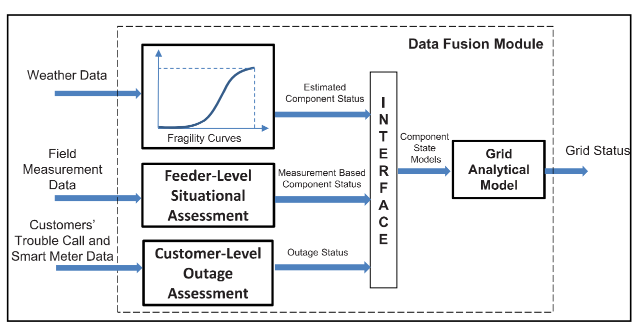

Fig. 11. *Multisource data fusion module.*

the historical data regarding damage count. In the GLM method, we apply the logarithmic link function

$$\log(\lambda_i) = \beta_0 + \sum_{p\in\mathcal{P}} \beta_p X_p \tag{10}$$

where Xp is the explanatory variable describing the value of pth weather metric of all weather metrics (by set $\mathcal{P}$). Using historical weather data, the coefficient β_p can be estimated using regression methods. With the model, the failure rate in a given area can be estimated using the weather information/forecasts. The component-level failure probability can then be computed using the exponential distribution. Note that for each type of component in the given area, the failure probability of each component is the same, because the failure rate describes the damage properties of this area from the statistical perspective.

The fault section identification algorithms using measurement data from fault-indicating devices (described in Section IV-B2) can yield a unique faulted line section by assuming each line section is equipped with a fault-indicating device. However, due to the damage sustained from the natural disaster, some devices may also be damaged, or in the case that not all line sections are equipped with a fault-indicating device, the algorithm will result in multiple faulted line section candidates. We can convert this ambiguity into a probabilistic model to allocate a probability to each instance of line section damage, so that a generic probabilistic damage assessment model from fault-indicating devices can be derived. For the fault section identification using smart meters and other sources of information, the similar approach can be applied to model the multiple identification results into a generic probabilistic damage assessment model.

Given the probabilistic model of damage estimation using different sources, the objective of data fusion is to combine the probabilistic information. We assume that M information sources are available and the observations from the mth source are arranged in the vector $\mathbf{x}^{(m)}$. Data fusion aims to compute the global posterior probability $p(\mathbf{y}|\mathbf{x}^{(1)},\mathbf{x}^{(2)},\ldots,\mathbf{x}^{(M)})$, given the information contributed by each source, where $\mathbf{y}$ indicates the event of damage to a component. Generally, each source of information can contribute two conditional probabilities: a local posterior probability $p(\mathbf{y}|\mathbf{x}^{(m)})$ and a likelihood function $p(\mathbf{x}^{(m)}|\mathbf{y})$. In this problem, however, the local posterior probability $p(\mathbf{y}|\mathbf{x}^{(m)})$ is what each source of information can contribute, which is actually the result of the probabilistic model of damage assessment for each source, while it is intractable to obtain the likelihood function because the relation between the damage and the observations is through complicated algorithms (e.g., statistical regression or certain fault section identification algorithms), and we cannot obtain the reverse of these algorithms to compute the likelihood function.

With the local posterior probability $p(\mathbf{y}|\mathbf{x}^{(m)})$ of the damage from each source of information computed, probabilistic data fusion models can be exploited to combine local posterior probabilities. For example, the linear pool model [79], as shown in Fig. 12, applies linear combinations of local posterior probabilities

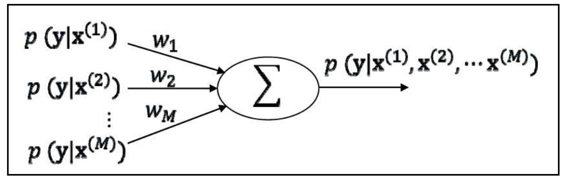

Fig. 12. ***Linear pool data fusion model.***

$$p(\mathbf{y}|\mathbf{x}^{(1)},\mathbf{x}^{(2)},\ldots,\mathbf{x}^{(M)}) \propto \sum_{m=1}^{M} w_m \cdot p(\mathbf{y}|\mathbf{x}^{(m)}). \tag{11}$$

The weight w_m reflects the significance attached to the mth information source. It can be used to model the reliability or trustworthiness of an information source if such parameters are available, and we can use equal weights if such information is not available.

The independent pool model [80] applies the product of local posterior probabilities

$$p(\mathbf{y}|\mathbf{x}^{(1)},\mathbf{x}^{(2)},\ldots,\mathbf{x}^{(M)}) \propto \prod_{m=1}^{M} p(\mathbf{y}|\mathbf{x}^{(m)}) \tag{12}$$

which is illustrated in Fig. 13.

We can see that both models have flexibility regarding the number of sources M, i.e., it can tackle any number of sources. This feature is very useful as the data fusion framework can be easily applied for different electric utilities with diverse sources of information. The proposed probabilistic data fusion framework provides an optional solution so that multiple sources of information can be complementary to each other to improve the accuracy of damage assessment. Note that there are still several technical challenges in obtaining situational awareness accurately using the existing approaches and the proposed data fusion framework in practice, such as model uncertainty as a result of the extreme weather, limited amount of historical data, nonstationarity feature of the problem, data quality issues of measurements, etc., which are still open problems in this research area.

V. FACILITATING SURVIVABILITY

As shown in Table 2, the lack of power availability during outages due to extreme weather events poses challenges for conventional restoration strategies, which are based on

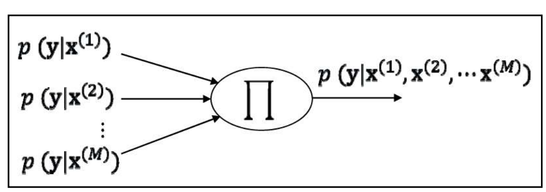

Fig. 13. ***Independent pool data fusion model.***

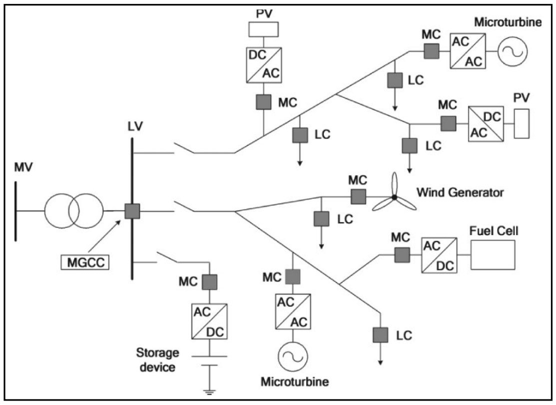

Fig. 14. ***Microgrid architecture comprising microsources, storage devices, loads, and control devices [82].***

the assumption that most utility power sources are working and stay connected. In this case, DERs could provide valuable resources to facilitate survivability of customers. However, the challenge is how to manage these local power resources to serve the critical loads in an effective and efficient manner [81]. Microgrids, which are small-scale power systems typically on the medium- or low-voltage distribution feeder that include distributed load and generation together with storage and protection devices, provide an applicable solution. Fig. 14 shows a typical microgrid architecture that consists of different types of components [82].

A. Using Microgrids for Grid Resiliency

A key advantage of microgrids in terms of resiliency is that microgrids add active network components (i.e., DERs), which provide operational flexibility and reduce conventional power vulnerabilities caused by centralized generation and control architecture and long distances between power sources and loads [83]. Microgrids provide an effective solution to managing these distributed resources so that utilizing them for system restoration after extreme weather events is possible. Furthermore, the uneven damage distribution of the disaster on the distribution grid increases the resilience when applying microgrids for load restoration, as the chances of all microgrids being damaged are very low [83]. The value of microgrids for enhancing customers' survivability and grid resilience has been recognized in several recent studies in the literature [84]–[87]. They are being adopted by some state governments and industries, and the technical, regulatory, and financial barriers to implementation are being studied, e.g., [81], [88], and [89].

Existing methods of using microgrids to enhance distribution restoration can be categorized as two types, according to the conditions of the microgrids: 1) microgrids with fixed boundary; and 2) dynamic formation of microgrids, which will be discussed below.

B. Utilizing Microgrids With Fixed Boundary

This type of method is based on already-installed microgrids, whose boundaries are fixed. In this case, a microgrid can act in the island mode to serve its own critical loads by utilizing local generation and storage facilities even when the utility grid is unavailable. This operation mode requires special control for the frequency and voltage, since no support comes from the utility grid. The power electronics inverters in this case act as voltage source to control the frequency and voltage [82]. Moreira *et al.* [90] recommend the following sequence of actions for a microgrid central controller to perform service restoration: 1) sectionalize the microgrid around each microsource (MS) with black-start (BS) capability; 2) build the low-voltage (LV) network utilizing storage devices; 3) synchronize small islands energized by the MSs; 4) connect the controllable loads to the LV network; 5) connect noncontrollable MSs or MSs without BS capability; 6) connect other loads; 7) change the control mode of MS inverters; and 8) synchronize the microgrid with the medium-voltage network. In [91], Resende *et al.* further propose a novel distribution system architecture that allows the coordination among multiple microgrids for service restoration, and the corresponding sequence of actions is defined.

In addition to the critical loads within its boundary, a microgrid can also be utilized to pick up critical loads outside its boundary using its available surplus power. In this case, the microgrids act as virtual feeders to pick up critical loads, and this scheme is especially useful for areas where no other suitable restoration path or source is available [29]. To pick up the external loads, feasible paths should be formed to connect the microgrid to the load; the automated feeder switches could help to expedite this process. Li *et al.* [92] proposed a spanning tree search algorithm to find the feasible path using automated feeder switches to maximize the restored load and minimize the number of switching operations without violations of operational constraints. Xu *et al.* [93] further extended the work to propose an optimal placement strategy for automated feeder switches to enhance the resiliency. Mohagheghi and Yang [94] proposed a mathematical model to utilize microgrids to alleviate the outage in the absence of a suitable restoration path/source. Besides picking up external loads, microgrids could also have the potential to provide ancillary services such as blackstart to the bulk power system restoration. For example, Castillo [95] developed a stochastic mixed-integer linear program (MILP) to assess the impact of coordinating microgrids as a blackstart resource to the regional grid or RTO after a natural disaster.

C. Dynamic Formation of Microgrids

This type of method does not require existing microgrids; instead, the microgrids can be formed dynamically by controlling the automated feeder switches. Because of the greater flexibility this scheme could provide compared to the methods based on fixed-boundary microgrids, it will be adaptable to the different outage and damage scenarios of natural disasters. However, this scheme also poses challenges for controlling and coordinating these smart switches without violating the operational constraints.

1) MILP Formulation of Microgrid Formation: In our previous work [96], a microgrid formation mechanism to restore critical loads in the absence of a utility grid is proposed. We consider a radial power distribution system consisting of N nodes denoted by the set of nodes $\mathcal{N}:=\{1,\ldots,N\}$, and L power lines represented by the set of edges $\mathcal{L}:=\{(i,j) \subseteq \mathcal{N}\times\mathcal{N}\}$. Let $c_{ij}\in\{0,1\}$ denote the binary decision variables indicating whether the switch associated with line (i,j) is open ($c_{ij}=0$) or closed ($c_{ij}=1$), and let $s_i\in 0,1$ denote the binary decision variables representing whether the switch connecting the load and node i is open ($s_i=0$) or closed ($s_i=1$). By controlling these switches, K self-adequate microgrids can be formed to maximize the total prioritized loads to be restored. The microgrid formation problem is modeled as an MILP problem. To model node clustering constraints that specify which microgrid a node belongs to, we define auxiliary binary decision variables $v_{ik}\in\{0,1\}$ indicating whether node $i\in\mathcal{N}$ belongs to microgrid $k\in\mathcal{K}$ ($v_{ik}=1$ if node i belongs to microgrid k, and $v_{ik}=0$ if otherwise), and the node clustering constraints can be expressed as

$$\sum_{k\in\mathcal{K}} v_{ik} = 1,\ \forall i\in\mathcal{N} \tag{13}$$

to represent that if the load at node $i\in\mathcal{N}$ can be energized by microgrids, this node can only belong to one of the K microgrids.

For node i at which the DG k is installed (i.e., $i=k$), node i will belong to microgrid k, which can be written as the following equality constraints:

$$v_{ik} = 1,\ i=k,\ \forall i\in\mathcal{N},\ k\in\mathcal{K}. \tag{14}$$

The radial topological features are captured in the microgrid connectivity constraints. Specifically, for a radial distribution network, each microgrid is a subtree network with the root node being the node where the DG is installed. In that sense, one node can belong to microgrid k only if its parent node (for this microgrid) belongs to microgrid k, which can be expressed as

$$v_{ik} \le v_{jk},\ \forall k\in\mathcal{K},\ \forall i\in\mathcal{N}\backslash\{k\},\ j=\theta_k(i) \tag{15}$$

where $\theta_k(i)$ denotes the parent node of node i regarding microgrid k.

In addition, the microgrid branch-node constraints specify the relation between nodes and lines in a microgrid. If both nodes i and j belong to microgrid k, i.e., $v_{ik}=v_{jk}=1$, then the line connecting nodes i and j should also belong to microgrid k. Together with (14), we can further derive that if the children node of (i,j) (regarding microgrid k) belongs to this microgrid, then line (i,j) belongs to microgrid k. If line (i,j) belongs to any one of the microgrids in $\mathcal{K}$, the switch on this line (if it exists) should be in the closed state. Thus, the branch-node constraints to specify switch state on line (i,j) in terms of node clustering variables v_{ik} can be expressed as

$$c_{ij} = \sum_{k\in\mathcal{K}} v_{hk},\ h=\zeta_k(i,j),\ (i,j)\in\mathcal{L} \tag{16}$$

where $h=\zeta_k(i,j)$ denotes the children node of line (i,j) regarding microgrid k.

Additional microgrid load pickup constraints specify the condition on whether the load at node i can be energized by microgrid $k\in\mathcal{K}$, which can be represented by satisfying the following two conditions simultaneously: 1) node i belongs to microgrid k, i.e., $v_{ik}=1$; and 2) the switch associated with the load is closed so that the load is connected to node i, i.e., $s_i=1$. These two conditions formulated as $v_{ik}\cdot s_i=1$, which is a quadratic constraint. To address the nonlinearity issue, we define auxiliary binary decision variables $\gamma_{ik}\in\{0,1\}$ as $\gamma_{ik}=v_{ik}\cdot s_i, \forall i\in\mathcal{N}, k\in\mathcal{K}$, and the quadratic equality constraints can be converted to the following three linear inequality constraints:

$$\gamma_{ik} \le v_{ik},\ \forall i\in\mathcal{N},\ k\in\mathcal{K} \tag{17}$$

$$\gamma_{ik} \le s_i,\ \forall i\in\mathcal{N},\ k\in\mathcal{K} \tag{18}$$

$$\gamma_{ik} \ge v_{ik}+s_i-1,\ \forall i\in\mathcal{N},\ k\in\mathcal{K}. \tag{19}$$

Besides these logical constraints discussed above, other operational constraints are modeled, including voltage range constraints at each node, and real and reactive power output range constraints for DGs. The objective function aims to maximize the total priority weighted load picked up, where the weights indicate the importance and priority of the loads for restoration. The detailed formulation can be found in our previous work in [96].

With this scheme, DGs can be utilized to serve critical load locally to facilitate the customers' survivability after extreme weather events. Fig. 15 illustrates the formation of three microgrids based on the IEEE 37-node test system [96]. Our work in [97] proposed a self-healing strategy by sectionalization of the distribution system into microgrids, with the consideration of the uncertainty of renewable generation.

2) Multi-Time-Step Sequential Restoration: A feasible service restoration plan should include a sequence of control actions (e.g., switching, DG dispatching) that the system operator can follow to restore the affected customers step by step. However, the previous work focuses on how to generate a "snapshot" of the optimal reconfiguration of the grid (e.g., the microgrid formation scheme in [96]). The snapshot configuration must be verified by switching order management (SOM) in the control center. If some constraints happen to be violated, the solution should be updated and verified by SOM again. This iterative process

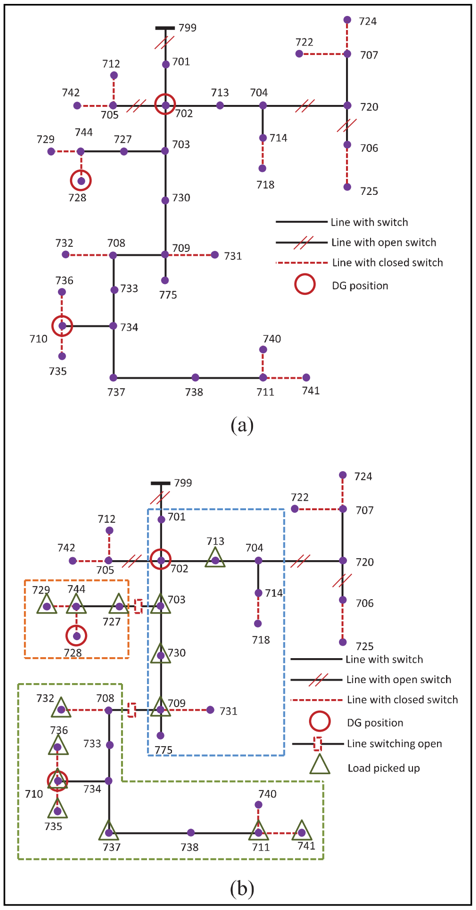

Fig. 15. ***A case study of dynamic microgrid formation based on the IEEE 37-node test system [96]: (a) the original IEEE 37-node test system with three DGs; and (b) three microgrids are formed energized by these DGs.***

will continue until a feasible solution is found. There are some existing studies on how to find an optimal and feasible switching sequence for the traditional restoration scheme described in Section II-A, such as the generic algorithm [98] and dynamic programming [99]. However, for dynamic formation of microgrids, the operation of DGs and the switching action should be carefully coordinated; i.e., during the restoration process, it is important to ensure secure and safe operation when performing the switching actions and ramping the DGs up and down. Pham *et al.* [100] divided the problem into two steps: 1) optimal switching operation sequence searching by branch and bound algorithm; and 2) validating the switching sequence by simulation.

Our work in [101] proposes an innovative multi-time-step distribution restoration scheme to coordinate switching action and DG dispatching in an integrated manner. An MILP model, which can be solved efficiently, is formulated to maximize the energized loads while satisfying various operational constraints. To satisfy network topological constraints, we can derive several logical constraints governing the binary decision variables, for example, a switchable line can only be energized when both end nodes are energized; a switchable load can only be restored when the node it connects to is energized; a node can be energized when a black start DG connects to it, or an energized line connects to it; and a non-black-start DG can only be started when it connects to an energized node. In addition, the sequential constraints should be satisfied, that is, each line should be energized only when at least one of its ends is energized at a previous interval. Other constraints include the power flow model, transformer and line capacity constraints, DG power output constraints, voltage range constraints, ramp rate limit constraints, frequency response rate constraints, etc., which can be found in [101] in detail.

To illustrate the sequential restoration results, we test the algorithm on the modified IEEE 13 node test feeder. The single line diagram of the test feeder is shown in Fig. 16. The system is assumed to be completely de-energized due to an extreme-weather-related event. Two lines and one load are assumed to be damaged and cannot participate in the restoration. There are three DGs connected to nodes 650, 646, and 680. Two case studies are considered: in case 1, only DG1 connected to the substation node is used for service restoration; in case 2, three DGs will participate in the restoration. Table 3 summarizes the restoration sequence for loads and lines at each step. Fig. 17 illustrates the step-by-step restoration sequence energized by three DGs (case 2).

Table 3 Restoration Sequence for Loads and Lines in Cases 1 and 2

Step No.	Load restored		Line closed	
	Case 1	Case 2	Case 1	Case 2
1				
2	L632	L632	1	1
3	L645	L645	2,4	2,4,6
4	L692	L634, L646	5,13	3,5,12,13
5	L634	L692	3	10,11,14
6		L675		15
7	L646	L671	6	
8		L611		

3) Mobile Generator Dispatch With Microgrid Formation: In addition to the static DGs, a mobile generator, which is a

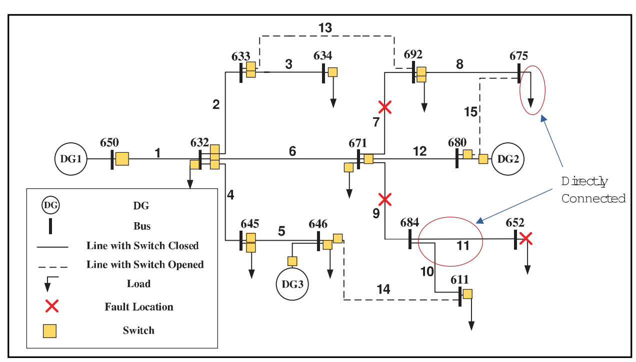

Fig. 16. ***Single line diagram of modified IEEE 13 node test feeder with three DGs.***

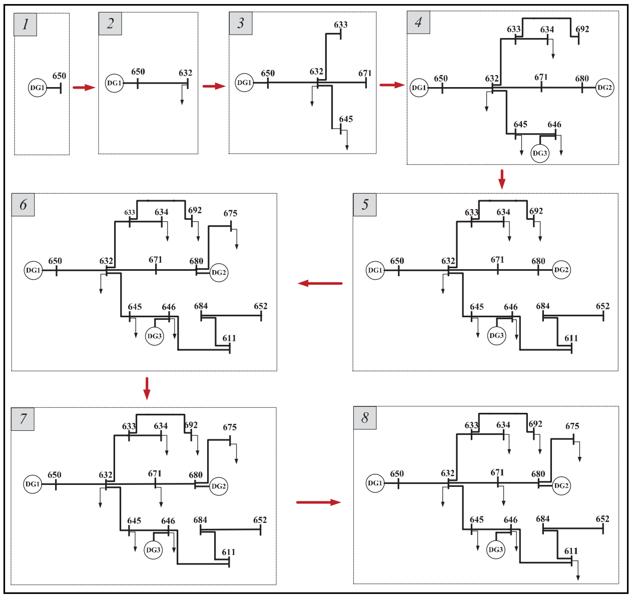

Fig. 17. *Illustration of step-by-step restoration sequence for case 2.*

truck-mounted generator with the merits of mobility and large capacity (up to several MW), could be quickly connected to provide replacement power to critical or isolated loads, thus providing more flexibility to facilitate customers' survivability. As suggested in the GridWise report [2], electric utilities should increase the use of mobile generators to provide temporary power during extreme weather events. However, currently they are not well utilized. For example, before Superstorm Sandy struck, 400 industrial-size truck-mounted emergency response generators were prepared by the FEMA, but only a fraction of them were providing power even three days after Sandy made landfall [102]. Our work in [103] integrates the dispatch of mobile generators into the microgrid formation by proposing a two-stage dispatch framework:

- in the first stage (i.e., prior to a natural disaster), prepositioning is conducted to placing utilities' mobile generators across their staging locations to ensure the earliest possible response after the natural disaster strikes;
- in the second stage (i.e., after the natural disaster strikes), real-time allocation is optimized to send mobile generators from staging locations to allocated locations. Upon arrival, they are connected to the grid and form microgrids to pick up critical loads.

With the proposed two-stage framework, the mobile generators can be better utilized to serve critical loads after extreme weather events.

D. Special Considerations

1) Distribution Power Flow Model: One important operation constraint is to make sure the voltage at each node is within certain ranges; thus the power flow model is

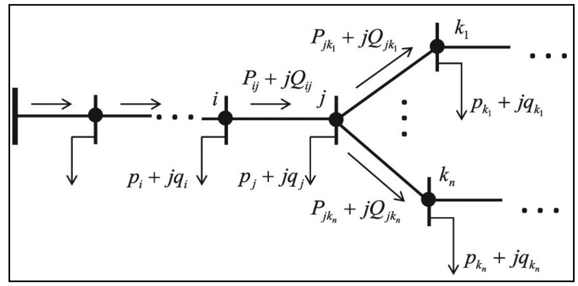

Fig. 18. *DistFlow model for a radial distribution grid.*

necessary in the optimization formulation. The iteratively based distribution power flow model (e.g., forward and backward sweep method in [104]) cannot be directly integrated into the optimization models. Instead, the DistFlow model proposed by Baran and Wu [105], [106] provides a viable solution for a radial distribution grid. For the radial distribution grid shown in Fig. 18, the DistFlow model can be represented by

$$P_{ij} - \sum_{k\in\mathcal{N}_j} P_{jk} = p_j + r_{ij}\frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \tag{20}$$

$$Q_{ij} - \sum_{k\in\mathcal{N}_j} Q_{jk} = q_j + x_{ij}\frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \tag{21}$$

$$V_i^2 - V_j^2 = 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) - (r_{ij}^2 + x_{ij}^2)\frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \tag{22}$$

where P_{ij} and Q_{ij} represent the real and reactive power flow from node i to j, V_j is the voltage at node j, and r_{ij} and x_{ij} denote the resistance and reactance of line (i, j), respectively. DistFlow can be further linearized by omitting the loss term (quadratic term) and approximating the voltage term, e.g., [96], [105], and [107], to make the computation more efficient. While the DistFlow model is for a balanced system, further studies [108]–[110] extended it to a three-phase unbalanced system by a linearization approximation, or convex relaxation which can be solved efficiently by the semidefinite programming (SDP) technique.

2) Cold Load Pickup Issue: Cold load pickup (CLPU) is a practical issue when restoring loads. CLPU refers to the observation that when a load is being restored after an extended outage, a much higher demand than the pre-outage level will result because a large concentration of thermostatically controlled loads (such as air conditioners, heaters, and refrigerators) will start at the same time, as illustrated in Fig. 19. A study by the IEEE PES Power System Relay Committee [111] discussed various aspects of CLPU issues. Schneider *et al.* [112] described several methods to quantify the CLPU profile.

This special load profile caused by the loss of demand diversity should be integrated into the restoration control sequence. In [113], Kumar *et al.* integrated the CLPU constraints into restoration using the generic algorithm. Our previous work [101] applied a typical delayed exponential

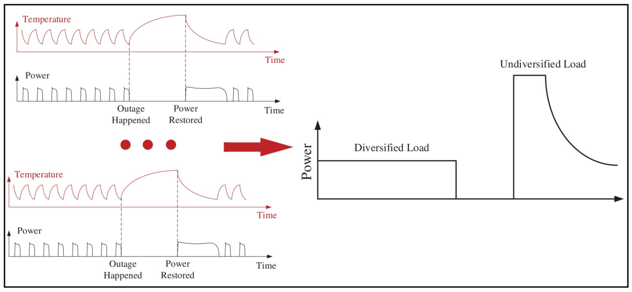

Fig. 19. ***Illustration of the CLPU issue.***

CLPU curve and used linearization to integrate it into the MILP formulation. Fig. 20 shows a typical delayed exponential CLPU curve. The outage occurs at t_0, and the load is restored at t_1. Due to the loss of diversity, the undiversified loading factor at t_1 is S_U. Then, the load starts to gain diversity at t_2 and decreases exponentially. The post-outage diversified loading factor is S_D, which is normally equal to the pre-outage loading level. It should be noted that the restoration time (i.e., t_1) for each load is not predetermined. Given a CLPU curve, we can calculate the load demand at each sampling time. In this work, we assume that the CLPU curve is equally sampled, and the sampling interval is Δt, which is the interval used for the restoration. Assuming total N samples are collected from the CLPU curve of load l, denote $L_l(k)$ as the load demand at the kth sample, and $\Delta L_l(k)$ as the load difference between two consecutive samples. $\Delta L_l(k)$ can be active power $\Delta P_l(k)$, reactive power $\Delta Q_l(k)$, or apparent power $\Delta S_l(k)$. Then, $\Delta L_l(k)$ can be calculated as

$$\Delta L_l(k) = \begin{cases} 0, & k = 1 \\ L_l(k) - L_l(k-1), & 1 \le k \le N \end{cases} \tag{23}$$

where $L_l(k)$ can be calculated using the exponential decay rate in Fig. 20. Then, the CLPU load (i.e., $P^L_{l,t}$ and $Q^L_{l,t}$ for active and reactive power) can be calculated in an accumulative manner, which could be formulated as

$$P^L_{l,t} = P^L_l\left(S^U x^L_{l,t} - \sum_{k=1}^{t} \Delta P_l(k) x^L_{l,t-k+1}\right) \tag{24}$$

$$Q^L_{l,t} = Q^L_l\left(S^U x^L_{l,t} - \sum_{k=1}^{t} \Delta Q_l(k) x^L_{l,t-k+1}\right) \tag{25}$$

where $x^L_{l,t}$ is the binary decision variable indicating whether the load l is energized at time step t in the MILP formulation of the sequential restoration model in [101]. P^L_l and Q^L_l are pre-outage active and reactive power of load l, respectively. With (23) and (24), the time sequence of load demand considering CLPU can be integrated in the multi-time-step sequential restoration optimization as discussed in Section V-C2.

3) Distributed Information Collection: Collecting information on grid status, e.g., load information and switch states, is a prerequisite for conducting restoration using

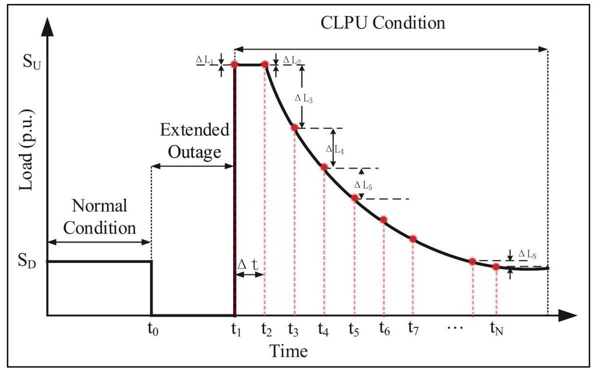

Fig. 20. ***The load demand under CLPU conditions.***

microgrids. However, the communication infrastructure may also be damaged during extreme weather events, posing challenges for restoration. An alternative communication solution is needed in this case. While satellite communication will usually not be impacted by extreme weather events, its cost is an issue, especially for device-level communications. Another possible solution is to utilize a peer-to-peer *ad hoc*-type communication network, which does not rely on infrastructure [114]. In previous work [96], we designed a distributed information collection scheme using only local communications, which can be achieved by this peer-to-peer communication architecture. The proposed method employs the average consensus algorithm discussed in [115] to achieve global information discovery by iterative local information update, as shown in (26)

$$\mathbf{z}_i^{k+1} = \mathbf{z}_i^k + \sum_{j\in\mathcal{R}_i} \varepsilon_{ij} \cdot (\mathbf{z}_j^k - \mathbf{z}_i^k) \tag{26}$$

where $\mathbf{z}_i^k$ represents the information vector at node i at step k, $\mathcal{R}_i$ represents the set of direct neighboring nodes of node i, and ε_{ij} is the step size, which is related to the graph characteristics of the network. With proper design of $\mathbf{z}_i^k$ regarding the actual status of the devices, the global information can eventually be obtained at each node using this simple linear iteration, with convergence guaranteed. The details of the distributed information collection scheme can be found in [96].

VI. CONCLUSION AND DISCUSSION

The increasing frequency and severity of extreme weather events, the vulnerability of distribution grids to natural disasters, and the higher expectations of customers regarding electricity service continuity during disasters are the main motivating forces for utilities to improve their restoration strategies in response to extreme weather events. This paper describes the current distribution system restoration practices and discusses their inadequacy for power outages during extreme weather events. To leverage the grid modernization development initiated by DOE, this paper presents an integrated solution based on a decision support tool that could assist utilities with decision making for distribution system restoration in response to extreme weather events. The solution features two advantages: 1) improving situational awareness of system damage status; and 2) facilitating survivability of customers. Many existing methodologies in the literature can be utilized to achieve these two advantages, and this paper provides a detailed review of these studies.

There still exist many challenges, from both regulatory and technical perspectives, for modernizing distribution system restoration to cope with extreme weather events. Here we give a brief discussion based on our observations.

A. Regulatory Challenges

Although DGs could have the potential to enhance supply continuity and customers' survivability during the outages after disasters, current interconnection standards (primarily the IEEE Standard 1547 [116]) require customer-owned DGs to be disconnected during disturbances, to guarantee the safety of utility crews and the power quality of the grids. These requirements were developed when the penetration of distributed resources was low; now, however, with the ever-increasing penetration of distributed resources, these requirements in the standard will underutilize these local resources during restoration due to extreme weather events. In this sense, there is a need to adjust the standard to accommodate scenarios in which the benefits of the local resources can be leveraged during restoration in response to extreme weather events.

Investments in grid modernization technologies could provide the potential to enhance grid resiliency and improve system restoration; however, current efforts are still heavily dependent on government investment, as the resilience and reliability benefits of these investments are not reflected in the electricity tariff. In addition, there is no scheme to compensate for the DG owners for providing service during blackouts resulting from extreme weather events. In this sense, government policy makers and electric utilities should consider the societal benefits when performing cost-benefit analyses of grid modernization investments. Appropriate changes in policy and regulatory environments are needed to facilitate vital investments and upgrades in grid modernization technologies [2]. Proper rate structures and incentives should be designed to encourage DGs and grid modernization investments.

B. Technical Challenges

The damage caused by extreme weather events will affect not only electric power systems, but also other infrastructure, such as communications networks, natural gas pipelines, transportation networks, etc. The interdependence between these infrastructures and electric power systems will have significant impacts on the utilities' restoration process. For example, damage to the transportation network may result in delayed repair-crew dispatch; the operations of certain DGs (e.g., internal combustion engine generators or microturbines) heavily rely on the availability of fuel; and situational awareness and damage assessment will be highly degraded if the underlying communications networks experience failures. Analysis and quantification of this interdependence and how it can be integrated into the distribution system restoration process is challenging and needs further R&D efforts.

Utilizing DERs to enhance supply continuity during restoration changes the way traditional distribution systems operate. For example, frequency and voltage need to be regulated by these local resources rather than from bulk power systems, so the coordination and control schemes need to be carefully designed. The lower inertia compared to the bulk power system will pose challenges for control schemes to guarantee system stability and dynamic performance. In addition, the protective devices and the corresponding control logic need substantial modifications to avoid serious problems as result of power injection from DERs. Tackling these challenges in a cost-effective way is not an easy task and requires R&D efforts with interdisciplinary expertise, including power systems operation and control, power system protection, power electronics, communications, operation research, etc. ■

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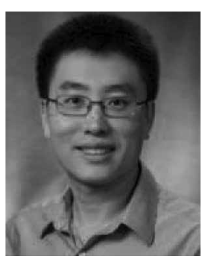

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