IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received September 5, 2021, accepted September 23, 2021, date of publication September 28, 2021, date of current version October 5, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3116086

Planning for a Resilient Home Electricity Supply System

EMON CHATTERJI[1], KATE ANDERSON[2], AND MORGAN D. BAZILIAN[3]

[1]Department of Electrical and Computer Engineering, University of Maryland, College Park, MD 20742, USA
[2]Modeling and Analysis Group, National Renewable Energy Laboratory, Golden, CO 80401, USA
[3]Colorado School of Mines, Golden, CO 80401, USA

Corresponding author: Emon Chatterji (emonchatterji@ieee.org)

ABSTRACT Resilience of power systems is already a key issue that is getting frequent attention all over the world. It is useful to analyze resilience issues not only for bulk supply, but at all levels including at a customer level. This is because distributed energy resources can play a prominent role in enhancing resilience. Although the literature on planning models, tools and data for bulk supply and distribution systems have expanded in recent years, customer-centric planning, e.g., for an individual household, is yet to receive adequate attention. Although solar PV and battery storage at a household level have been analyzed, how these resources can be optimally combined, together with grid supply, from a resilience perspective is the focus of this study. The study demonstrates how a conceptual framework can be developed to show the trade-off between system costs and resilience including its dimensions such as duration, depth and frequency of service outages. A planning model is developed that incorporates multiple facets of resilience and individual customer preferences. The model considers power system resilience explicitly as a constraint. The model is implemented for a household level case study in Miami, Florida. The results show there are complex trade-offs among different dimensions of resilience. The study demonstrates how combined resilience metrics can be formulated and evaluated using the proposed least-cost planning model at a household level to optimize grid supply together with solar, battery storage and diesel generators. The model allows a planner to directly embed a resilience standard to drive the optimal supply mix. These concepts and the modeling construct can also be applied at other levels of planning, including community level and bulk supply system planning.

INDEX TERMS Power system planning, resilience, optimization model, solar PV, battery storage.

NOMENCLATURE

A. INPUTS

t	Hours/sub-hours of the day.
d	All day types.
sun_d	Sunny/normal day types (day-types for which there are no storms).
$storm_d$	Days of the stormy day-type that face a risk of storm related outages.
y	Solar Profiles (1, …, y).
m	Months of the year.
s	Monte-Carlo samples that represent grid supply outage states due to storm.

The associate editor coordinating the review of this manuscript and approving it for publication was Payman Dehghanian.

B. INPUT PARAMETERS

$Weight_d$	Weight associated with each day-type.
$Demand_{y,m,d,t}$	Hourly/sub-hourly demand.
$PanelCost$	Annualized capital cost of roof-top solar.
$TaxDiscount$	Tax discount applicable for the state on roof-top panels.
$BatteryCost$	BESS cost.
$DGCost$	Annualized capital cost for a 10 kW diesel generator.
$GridCost$	Grid supply cost.
$BuyBackrate$	Feed-in tariff for solar power.
$HourlyDGCost$	Cost of running a diesel genset per kWh.
$LSPenalty$	Load shed penalty per kWh.
$EUELimit$	An upper limit on kWh of load shed.

DepthLimit	An upper limit on load shed depth.
FrequencyLimit	An upper limit on load shed frequency.

C. DECISION VARIABLES

SolarInstalled	Number of kW roof-top solar PV to be installed.
BatterykWh	Number of BESS kWh to be installed.
DGSelected	Binary variable to decide on installation of a 10 kW diesel generator.
$Grid_{y,m,sun,t}$	Supply from grid to meet household demand.
$Grid^{*}_{y,m,d,t,s}$	Supply of energy from the grid in kWh in sample s.
$Solar_{y,m,d,t}$	Available solar energy in kWh.
$Solar^{*}_{y,m,d,t}$	Available solar energy in kWh in sample s.
$SolarInHouse_{y,m,d,t}$	Solar energy in kW being used in the household.
$SolarInHouse^{*}_{y,m,d,t,s}$	Solar energy in kW being used in the household in sample s.
$SolarExport_{y,m,d,t}$	Solar energy in kWh being sold to the grid.
$SolarExport^{*}_{y,m,d,t,s}$	Solar energy in kWh being sold to the grid in sample s.
$SolarReject_{y,m,d,t}$	Solar energy in kWh being rejected (incurs a penalty).
$BatteryIn_{y,m,d,t}$	Energy in kWh entering the battery from solar panels.
$BatteryIn^{*}_{y,m,d,t,s}$	Energy in kWh entering the battery from solar panels in sample s.
$GridCharge_{y,m,d,t}$	Energy in kWh entering the battery from the grid.
$GridCharge^{*}_{y,m,d,t,s}$	Energy in kWh entering the battery from grid in sample s.
$BatteryOut_{y,m,d,t}$	Energy in kWh entering the household from the battery.
$BatteryOut^{*}_{y,m,d,t,s}$	Energy in kWh entering the household from the battery in sample s.
$BatteryLevel_{y,m,d,t}$	Energy in kWh stored in the battery (household BESS).
$BatteryLevel^{*}_{y,m,d,t,s}$	Energy in kWh stored in the battery in sample s (household BESS).
$DieselSupply_{y,m,storm,t,s}$	Energy in kWh entering the household from the diesel generator.
$BatteryIn_{y,m,d,t}$	Energy in kWh entering the battery from solar panels.
$LoadShed_{y,m,storm,t,s}$	Load shed for each outage sample during storm daytype.
$LoadShedEvent_{y,m,storm,t,s}$	A binary variable which is '1' only if there is an active power outage.
EUE	Expected unserved energy in kWh.
Depth	The fraction of load being shed.
Frequency	Total number hours of load shed.

I. INTRODUCTION

Resilience of power systems has emerged as an important planning criterion especially over the past two decades as major cyclones, floods, wildfires etc. have frequently affected electricity supply in many countries throughout the world including the USA. As Ton and Wang [1] discussed in 2015, resilience is becoming as important as affordability, reliability, flexibility and efficiency in power systems planning. There has been significant research and development in this area including actual extreme events that provide real-world case studies on the importance of resilience. Chandramowli and Felder [2] have demonstrated that the impact of climate change on electricity demand may lead to a reasonably significant increase in peaking capacity for the states of New York and New Jersey. Van Vliet *et al.* [3] show that cooling water scarcity could limit the availability of supply for predominantly thermal systems in the US and Europe. Hurricanes Irma and Maria caused great devastation to Puerto Rico where all 1.5 million customers of the Puerto Rico Electric Power Authority lost power. About 95 percent of customers had their service restored after about 6 months, but the remaining 5 percent—representing some 250,000 people—had to wait nearly a year [4].

A. AN OVERVIEW OF THE LITERATURE

There is a growing literature on the topic and an excellent and reasonably recent summary of it is provided by Mohamed *et al.* [5]. This section provides an overview by way of some of key works in the areas of power system resilience, differentiating between a (generation, transmission or distribution) system level analysis vis-à-vis distributed micro-grid level analysis. The discussion below first introduces an overview of the general literature on power system resilience. This is followed by a discussion on the growing recognition in the literature on how small-scale energy sources including microgrids and distributed energy resources can enhance resilience. Microgrids have received attention as an option to provide electricity access in developing countries [4], [5], improve reliability where the grid already exists, and to enhance resilience of the system. These are also receiving increasing attention in more developed countries to augment distribution networks rather than hardening the entire infrastructure. Distributed energy resources like roof-top solar and small-scale battery storage that may form part of microgrids as well, are also excellent resources. These may not only to provide cleaner and cheaper power in some cases, but also add to the resilience of the system [4].

The climate change research community has highlighted the risk that power systems face due to heat waves that reduce availability of cooling water for thermal plants [3], [6], hydroelectric plants [7], wind [8] and solar PV generators [9]. A World Bank study [10] demonstrates how some of these risks including flooding risks in Bangladesh can be integrated into a power system planning model to develop a more resilient mix of generation resources. The impact of extreme events that are increasingly becoming more frequent and more severe due to climate change may have serious implications for transmission [11], [12] and distribution [13], [14]. Kezunovic *et al.* [11] foreshadowed many of the problems around transmission line conductor sag, transformer outages, etc. that are being experienced today in California due to heat waves. High wind speed and ice loading also pose great challenges elsewhere in the world that are discussed in [12]. Willis and Loa [13] provide an excellent summary of the resilience issues encountered in a distribution system and how these are measured using an extensive set of approaches that have been published in the literature between 1997 and 2014.

Power system planning methods need enhancement to address resilience issues. The development of concepts, techniques and case studies in recent years have tried to address this by extending the standard least-cost planning methodology to address different complementary measures. For instance, as noted before Chandramowli and Felder [2] extended a least-cost planning model to analyze demand impacts arising from heat waves. Panteli *et al.* [15] was among the first to rigorously lay out the definition of phases for resilient recovery. Espinoza, Panteli and others [16] took this framework a step further to test different strategies to make the power system more robust and responsive, using an example of Great Britain. Moreno, Panteli and others [17] more recently have further reiterated the need for planning models to make the transition from a relatively simple and one-dimensional reliability criterion to multi-dimensional resilience standards. There have also been case studies that incorporate resilience considerations in practical systems including flooding risks in Bangladesh [10], impact of storms on the British transmission network [18] and impact of cyclones on household level supply in Florida [19]. It is recognized that resilience needs to be built throughout the supply chain and measures may include a vast range of options from change of power plant siting in Bangladesh [10] down to strengthening of distribution network using microgrids and distributed energy resources. The latter is increasingly being integrated into mainstream planning. There is in fact a vast literature including NREL's RE-OPT [20] and LBNL's DER-CAM [21] that deal with optimization of these energy resources.

Distributed solar PV, battery storage and other resources have been gaining popularity as their costs came down over the recent years. They also present a formidable option to enhance resilience of the system without requiring expensive hardening of the entire supply chain from utility scale generation, transmission down to distribution networks.

There is a significant amount of work to address the latter issue. Important planning and operations related analytical innovations around microgrid include incorporating real-time load recovery systems after power outages [22], optimizing the placement of microgrids to enhance power system resilience [23], economic operation of microgrids taking into consideration demand side bidding and adequacy of the grid to meet critical load [24]. Other significant developments include application of multi-objective optimization to operate microgrid networks [25], scheduling microgrid operation to improve network resilience [26] and expanding the resilience of microgrid networks via an advanced interface control system [27].

A better appreciation of distributed energy resources to specifically recognize their resilience benefits is also visible in some of the research over the past decade. For instance, Zhang *et al.* [28] developed a model specifically to optimize photovoltaic (PV) panel and battery storage capacity placements in a network to enhance resilience. This model aims to improve a network's reliability by installing PV and small-scale batteries. A reduced reliance on the grid and hence the requirement to harden the grid can save billions of dollars even for a relatively small geographic area. A similar concept is proposed in [29], wherein grid failures caused by severe weather are addressed by assets available in various islands. This means that the resilience of the overall power system is complemented by individual microgrids. This is a concept that is gaining popularity following the onslaught of hurricanes in the Caribbean and coastal parts of America. Other developments in modeling distributed energy systems include efforts to (a) incorporate electric vehicles [30], (b) smart grids to reduce storm related outages [31] and (c) demonstrate how individual power component faults can be minimized using microgrids [32].

NERC [33] in 2012 provided an overarching framework for power systems that laid out three phases of a resilient system, namely, preparedness, mitigation, and restoration. These concepts were also echoed in [15], [16] among others. These works showed how incurring a relatively small cost in planning/preparedness stage can help to lower the cost of mitigation/restoration phases. Gholami *et al.* [34] translated these concepts into a two-stage adaptive robust formulation for microgrids that can island and self-supply, to better cope with adverse weather events. Their proactive scheduling framework can be implemented to limit adverse outcomes from islanding situations.

B. SCOPE OF THIS WORK

The overview of the literature alludes to the fact that resilience of power system can be built throughout the supply chain including microgrids. The literature also amply demonstrates the role of planning. However, there are two areas where there is a need for further discussion and analytical developments, namely:

1. There needs to be a clearer articulation of a resilience standard that is grounded on the concepts of reliability but captures the multiple facets of resilience. The resilience criterion (or criteria as the case may be) then needs to be embedded into a planning framework to optimize resources explicitly considering resilience as a ''constraint''; and
2. As roof-top solar PV, BESS and smart meters enable behind-the-meter resources that can more than adequately equip households to deal with power outages, there is a need to go beyond microgrids and plan for household level electricity supply. Our previous work [19] has demonstrated that planning analysis can be extended to distributed energy resources to develop an optimal supply mix for a household that may include solar PV, BESS and diesel back-up to complement grid supply. This work also demonstrated how roof-top solar PV and BESS can form part of an effective resilience solution even in locations like Miami that are prone to severe cyclones. The present work further extends the analysis in [19] to form resilience constraints and implement the planning framework.

Section III discusses the nuances regarding the definition of resilience including a motivating example to show the impact of imposing a resilience standard on cost of electricity supply. Section IV builds on it to present a least-cost planning model that can directly embed such standards as constraints in the optimization. Section V discusses a case study for a household in Miami before Section VI draws the key conclusions and insights from the model and the case study.

II. DEFINITION OF RESILIENCE

A. RESILIENCE VS RELIABILITY

One area where better translation and integration of resilience metrics into planning is needed, relates to the difference between reliability and resilience [17]. Resilience and reliability are two closely related concepts used to determine a power system's performance during an outage. Put simply, reliability is the ''outcome'' whereas resilience is the means to achieve the outcome. Resilience can also be thought of as the ability of the supply system to bounce back. Andy Ott, ex-President of PJM, distinguishes between the two [35] by saying that reliability is a necessary condition for resilience, but the latter has many dimensions to it. In other words, reliability in general reinforces resilience, but the multi-dimensional nature of resilience means there are also trade-offs that need to be understood better. There are two other somewhat artificial distinctions between reliability and resilience, namely:

1. Resilience is often associated with extreme weather events and therefore the 'stressors' are typically different, e.g., resilience may be explicitly associated with storms as opposed to reliability that has traditionally been characterized by mechanical failures of power plants or transmission or distribution components. Resilience, therefore, needs to be characterized by specific events and the related standards need to be quite different from typical reliability metrics such as loss of load expectation (LOLE). The latter can still be used to express the outcome of a measure that adds resilience to the system. For example, if a transmission line has been designed to withstand a category 5 storm, the resilience standard will be associated with such an event, but the end result of the system achieving a lower LOLE can still be applied to characterize the outcome; and
2. Resilience is also associated with typically longer or more complex outages e.g., common mode failures where many components fail simultaneously during extreme events such as multiple plants getting flooded or multiple towers getting knocked down by a storm. This is an increasingly common phenomenon due to climate change and therefore old reliability standards that were used to mainly capture mechanical failures alone, may be superseded by a set of more complex and stringent criteria. Resilience can also be explicitly associated with the ability of the system to bounce back following an outage that is also embedded in reliability metrics such as the mean repair time.

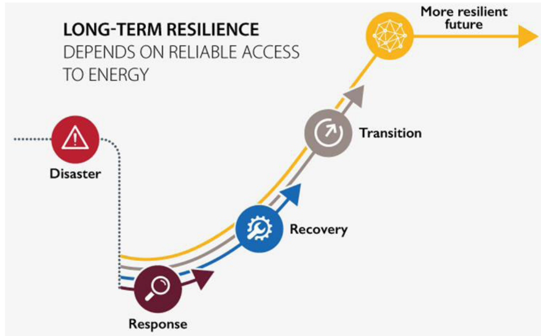

FIGURE 1. Characteristics of a resilient system.

Figure 1 shows different phases of a system following a disaster including the response, recovery and transition phase until normal operation is restored. Resilience focuses on all of these phases [15]–[19], [33] including the initial depth of the outage, what back-up measures are in place to sustain critical operation/load, what responses can be taken to restore supply, etc. Resilience is about the entire process and how the system should be designed to render it reliable.

The underlying metrics for these do not have to be substantially different and indeed reliability is measured in terms of the depth, duration and frequency of outages and mean repair time. These are also useful to design and measure the resilience performance of a system. There are, however, trade-offs among these attributes with significant cost implications. Building a resilient system must combine these attributes carefully and understand such cost implications. Depth of outage in this analysis has been calculated as the fraction of hourly load that is not being supplied in an outage and the outage frequency as the number of hours during which outages occur in a year. The expected unserved energy (EUE) of the outage is also used to denote the kiloWatt-hours of household load that could not be met because of the outages.

B. DISCUSSION ON APPROACH

This work investigates the trade-offs in designing a resilient household supply system, though the concepts apply to a bulk power system as well. Household power supply outages and measure resilience metrics are simulated including outage duration, the quantity of power lost and the fraction of lost power, and the frequency of the outages. Designing a resilient household system may require a complex criterion that combine these facets. As an illustrative example, consider the following set of criteria that may stipulate a resilience standard:

Install sufficient capacity of diesel, PV and battery storage to ensure that (*i*) *minimum 20% of the power supply is always available; (ii) there are no more than x outage of the remaining 80% of the power supply in any year including category 5 storms; (iii) total power outage in a year should not exceed y kWh and (iv) full power supply should be restored within z hours.*

If the parameters concerning critical load, such as the number of outages linked to the probability of an extreme weather event (a storm in this case) or the desired restoration time, are tightened, the investment requirements may increase sharply. For example, there may be a larger number of solar panels and BESS needed and/or a back-up diesel generator. It should also be borne in mind, however, that a naïve solution including one that does not consider any investment in PV/BESS/diesel may face a steep cost due to frequent, deep and long duration outages. The naïve solution will typically not meet the resilience standard but is a benchmark for cost and other parameters that can be compared with resilient solutions.

The current literature has laid out the concepts and solution methodologies at a high level. However, the planning process to build in resilience including how to characterize supply failure risks from extreme weather events in a practical way is not yet fully developed. As the role of distributed energy resources grows with the possibility of these resources also contributing to resilience at the customer end is a significant issue that can enhance their business cases. Planning analysis is equally applicable for a customer end to understand if solar PV, BESS etc. can be usefully deployed not only to reduce electricity bill, but also improve resilience of supply at a lower cost (than say install a diesel generator). It will require building in the planning analysis a resilience standard and assessing the performance of alternative investment strategies both in terms of their costs and resilience performance. The trade-off between cost of supply and resilience at a household level supply system has not been explored in the literature to date. An extension to the planning model is proposed to build resilience standard and used data from our previous analysis [19] to construct cases that can quantify this trade-off.

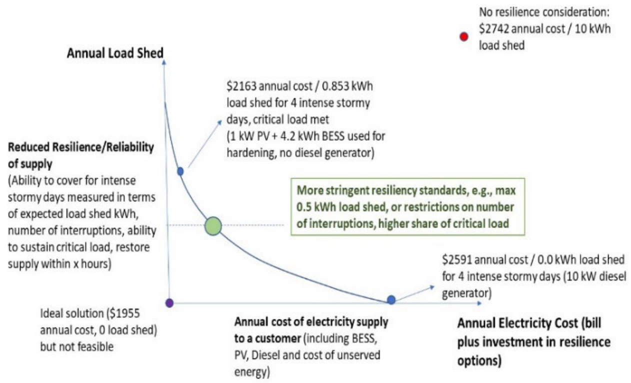

FIGURE 2. **Trade-off in designing a household electricity supply system.**

C. DIFFERENCE WITH OTHER APPROACHES

It is worth clarifying the specific contribution of this study. There have been many dozens of resilience metrics proposed, as is evidenced by an NREL literature survey [36] among others e.g., [13], [37], [38]. This study does not attempt to formulate a new resilience metric. The focus of this study is to showcase different methods of hardening power supply and hence increasing electricity resilience in a household. It can be misleading to conclude that resilience is achieved as soon as any one of the resilience metrics is reduced, which is quite common including our previous work [19].

Resilience standards will typically need to cover more than one attribute to cover the physical event and customer requirements. This is accomplished by adding additional metrics and thus forming a more nuanced definition of resilience and reliability for use in an analytical model. This necessarily allows for a higher degree of refinement in power system analysis and opens the path for analysis to match individual system needs as is discussed in the methodology section. A uniform holistic resilience/reliability metric is not advisable because every household's needs is different including depth, frequency, coverage of critical loads and expected unserved energy.

D. A MOTIVATING EXAMPLE

An example may be helpful demonstrate the key issues around supply costs, alternative investment strategies and reliability performance. Figure 2 illustrates the trade-off using data from our previous work [19] for a typical household in Miami, Florida that faces relatively high risk of power outages from cyclones. Specifically,

1. The ''ideal solution'' is generated using the optimization model developed in [19] ignoring weather driven outages. This leads to the lowest supply cost estimated at $1955 with perfectly reliable grid-supply as no investment is needed for resilience purposes. The ideal solution is not achievable in reality because the area is prone to storms including severe ones for 3-4 days in a year;
2. The naïve solution with ''No or low resilience consideration'' brings out the risk of facing 10 kWh of outages through a typical year and the household costs (including

a penalty on cost of unserved energy) jumps to \$2742; and

3. There is a continuum of efficient solutions each of which delivers certain degree of resilience by investing in alternative levels of investment choices with varying costs. As the system is hardened (higher resilience), annual cost of electricity increases (hence the y-axis represents an arbitrary measure of reduced resilience/reliability to show that a lower annual cost of electricity implies less reliability/resilience). For instance, the household supply can be made 100% reliable by investing in a 10 kW generator with a cost of \$2591 (which is expensive but still lower than the naïve solution); or it can substantially lower annual supply cost to \$2163 by investing in 1 kW PV plus 4.2 kWh BESS system, but have a small exposure to load shed up to 4 times in a year totaling less than 1 kWh. The precise solution will of course depend on the resilience standard that will need to be built in the planning methodology.

As the discussion above alludes to, it is necessary to develop a methodology and framework to examine these solutions associated with alternative resilience standards. The remainder of this paper discusses a methodology and provides results from a case study for a typical household in Florida.

III. METHODOLOGY

This study presents a planning methodology that incorporates resilience standards as a constraint for a household level energy supply system. As noted in the preceding discussion, such a standard will typically need to explicitly recognize key stressors such as the risk of storms and multiple dimensions of a standard. This model builds on [19] to include the following additional considerations:

a. Explicit consideration of grid supply outage depth, frequency, expected unserved energy and outage duration based on NASA's MERRA-2 climate model reanalysis data on wind risk [39];
b. Setting a resilience standard that the household supply optimization needs to consider, i.e., the planning model needs to find the least-cost mix of grid supply, roof-top solar PV, BESS and diesel, subject to meeting demand as well as the resilience standard. Put differently, our previous work [19] shows how addition of BESS/diesel generation etc. enhances resilience of the system but does not build in it a specific resilience standard in the analysis to drive the selection; and
c. More specifically, the planner to represent multiple dimensions and objectives intrinsic in a resilience standard that were discussed in the preceding section, namely, depth, frequency, duration, total load shed, etc.

A. AN OVERVIEW OF THE MODEL

The model is formulated as a stochastic mixed integer linear programming (MILP) problem which considers historic load data, solar resource profiles and hourly windspeeds corresponding to a household location. It is used to minimize the annual household electricity costs including electricity purchase costs (utility costs), (annualized) investments in solar, BESS, or other back-up generation facilities, some of which may be needed to reduce exposure to weather driven outage risks. The model represents a typical year using a few representative day types (e.g., Normal, Sunny and Stormy) that includes days of potential supply outages due to storms. Outages for Stormy days are represented using a number of outage samples (s) developed from the wind risk distribution for the area. Least-cost investments in solar PV, BESS and diesel are influenced by the resilience standard which is in turn determined by the outage probability due to storms. No other stressor is considered in the analysis, but the basic construct can be applied to other sources of outages, e.g., transformer outages or upstream HV grid failures. The modeling framework is general to accommodate multiple households or a mini-grid, for multiple years, day types, different sources of risks that can be sampled and investment choices that can encompass different types of back-up generator, storage and solar panels.

B. MATHEMATICAL FORMULATION

The variables '*Grid**', '*GridCharge**', '*SolarExport**' and '*SolarReject*' are recourse variables for the storm day type defined for each outage sample s.

The objective function sums the total annual cost of electricity. It is calculated by taking the annualized cost of the installed capacities of PV and BESS and combining it with the cost of energy from the grid as well as any penalties associated with unused solar energy and load shed. Any revenue earned through net metering is subtracted from the annualized cost. The objective function is defined as follows:

$$\begin{aligned}
&Cost \\
&= SolarInstalled * PanelCost \\
&\quad *TaxDiscount + BatterykW * BatteryCost \\
&\quad +DieselGenSelected * DieselGenCost \\
&\quad + \sum_{y,m,sun,t} Weight_{sun} \left(\left(Grid_{y,m,sun,t} \right. \right. \\
&\quad \left. +GridCharge_{y,m,sun,t} \right) * GridCost \\
&\quad -SolarExport_{y,m,sun,t} * BuyBackRate \\
&\quad \left. +SolarReject_{y,m,sun,t} * \boldsymbol{\varepsilon} \right) \\
&\quad + \sum_{y,m,storm,t,s} Weight_{storm} \left(\left(Grid^{*}_{y,m,storm,t,s} \right. \right. \\
&\quad \left. +GridCharge^{*}_{y,m,storm,t,s} \right) * GridCost \\
&\quad -SolarExport^{*}_{y,m,storm,t,s} * BuyBackRate \\
&\quad +SolarReject^{*}_{y,m,storm,t,s} * \boldsymbol{\varepsilon} \\
&\quad \left. +DieselSupply_{y,m,d,t,s} * HourlyDieselCost \right) \Big) /s \quad (1)
\end{aligned}$$

Other equations relating to the model's function are not included in discussion of this study to keep this section focused. A full description of the model including all of the equations can be found in reference [19]. The additional equations that represent resilience constraints, and key equations from [19] that are essential to understand the new additions are presented here.

There are three key balances (2)-(4) central to the optimization, namely:

- Equation (2) that represents the overall demand-supply balance for the household for each period of a "stormy" day when grid supply may be prone to outages and load shed may occur absent sufficient solar, battery and/or back-up diesel capacity;

$$\begin{aligned} &SolarInHouse^{*}_{y,m,storm,t,s} + (1-\theta_{s,t})Grid^{*}_{y,m,storm,t,s} \\ &\quad + BatteryOut^{*}_{y,m,storm,t,s} \\ &\quad * BatteryEfficiency + DieselSupply_{y,m,storm,t,s} \\ &\quad + LoadShed_{y,m,storm,t,s} \\ &= Demand^{*}_{y,m,storm,t,s} \end{aligned} \tag{2}$$

- Equation (3) shows the balance for the solar PV system:

$$\begin{aligned} &SolarExport^{*}_{y,m,storm,t,s} + BatteryIn^{*}_{y,m,storm,t,s} \\ &\quad + SolarReject^{*}_{y,m,storm,t,s} \\ &\quad + SolarInHouse^{*}_{y,m,storm,t,s} \\ &= Solar^{*}_{y,m,storm,t,s} \end{aligned} \tag{3}$$

- Equation (4) represents the balance for the battery storage system:

$$\begin{aligned} &BatteryLevel^{*}_{y,m,storm,t,s} \\ &\quad = BatteryIn^{*}_{y,m,storm,t} \\ &\quad\quad - BatteryOut^{*}_{y,m,storm,t,s} \\ &\quad\quad + GridCharge^{*}_{y,m,storm.t,s} \\ &\quad\quad + BatterykW \in t = 1 \end{aligned} \tag{4}$$

- Additional constraints included in the model are defined below. Expected unserved energy is found by taking the sum of the *LoadShed* kWh and dividing by the total number of Monte Carlo samples. This metric is important for finding the *quantity* of energy lost in an outage:

$$EUE = \sum_{y,m,storm,t,s} (LoadShed_{y,m,d,storm,s})/S \tag{5}$$

- Outage depth is calculated by taking the maximum fraction of load shed over demand. This metric is important for finding the *fraction of energy* lost in an outage:

$$Depth = Max_{y,m,storm,t,s}\left(\frac{LoadShed_{y,m,storm,t,s}}{Demand_{y,m,storm.t.s}}\right) \tag{6}$$

- Outage frequency is calculated by taking the sum of all hours of load shed and dividing by the number of samples. This metric is important for finding the *duration* of an outage:

$$Frequency = \sum_{y,m,storm,t,s} \left(\frac{LoadShedEvent_{y,m,storm,t,s}}{S}\right) \tag{7}$$

- The formulation for the binary variable $LoadShedEvent_{y,m,storm,t,s}$ is defined as follows:

$$\begin{aligned} &LoadShedEvent_{y,m,storm,t,s} \\ &\quad = 1 \quad \forall\, LoadShed_{y,m,storm,t,s} > 0 \end{aligned} \tag{8}$$

$$\begin{aligned} &LoadShedEvent_{y,m,storm,t,s} \\ &\quad = 0 \quad \forall\, LoadShed_{y,m,storm,t,s} = 0 \end{aligned} \tag{9}$$

- $LoadShedEvent_{y,m,storm,t,s}$ holds each individual hour of outage and, therefore, adding this variable across all the samples, as is done in the Frequency metric, returns the *duration* of outage.
- The resilience constraints are implemented in the model using the following equations which requires each individual attribute from surpassing a certain threshold:

$$EUE < EUELimit \tag{10}$$

$$Depth < DepthLimit \tag{11}$$

$$Frequency < FrequencyLimit \tag{12}$$

The case study results in the next section discuss the implications of using individual reliability standards like EUE vis-à-vis composite resilience standards.

IV. CASE STUDY FOR A HOUSEHOLD

This section describes the results for an illustrative case study using solar and wind resource profiles for Miami, Florida. The annual supply outage duration for Miami due to frequent storms is estimated at 38 hours [40]. The model is set up for a single year in hourly resolution for three representative days.

A. KEY ASSUMPTIONS

Key assumptions used in the analysis are as follows:

1. The model uses a total installed cost of \$3000/kW for a PV system [19], and \$300/kWh for fully installed BESS. A 10 kW diesel generator (commensurate with the 9.94 kW peak demand for the household) is considered as an option that has an up-front cost of \$5000 (or \$515 per annum for a 10kW generator in annualized cost). Solar PV costs represent commercial quotes and battery costs are based on the NREL projections. These investment costs are annualized assuming a 10-year lifespan for BESS and 25-year life for solar PV and diesel generator.
2. Energy from the grid is assumed at a flat tariff of 15.65 c/kWh.
3. Load is represented for a year using three representative days: Normal (311-312 days per year with a peak demand of 2.64 kW), Sunny (50 days per year with a peak demand of 9.94 kW) and Stormy (3-4 days with a peak demand of 2.73 kW). The number of unusually stormy days based on extreme wind gust data is four for Miami, although the gust speed and hence probability of outage is much higher.
4. The solar PV capacity factors for Normal, Sunny and Stormy day-types are 18%, 25%, and 10%, respectively.

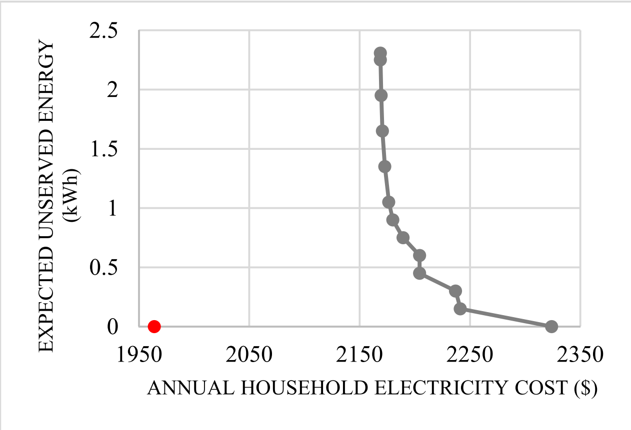

FIGURE 3. Trade-off between expected unserved energy and cost for a household in Miami.

5. Cost of unserved energy (*LoadShedPenalty* parameter) is set at $20/kWh. Baik *et al.* 42] presents a survey that shows a very wide range of cost of unserved energy resulting from resilience considerations from less than $1/kWh to $76/kWh. The baseline estimate of $20/kWh assumed for this study is high but representative of residential customers in the US.
6. A full account of all other inputs is provided in [19] and are not repeated here.

B. DISCUSSION OF RESULTS

The model is used to show the impact of different resilience standards and show how different dimensions of it may interact and the overall impact of a standard on household electricity supply cost and investment mix. Figure 3 shows how EUE varies with annual household cost. Additional details including PV and BESS selections are provided in Table 1.

There are several important points to note:

1. The red point represents a deterministic outcome that does not consider extreme weather events, i.e., there is no investment towards resilience and there are also no damage costs considered. Hence, it is not a realistic/feasible outcome although most traditional planning models will typically develop such plans that are devoid of any resilience consideration. As in Figure 2, it is included in the plot to show the 'ideal' but infeasible solution. It is termed 'ideal' because it has the least cost as well as unserved energy, as if extreme weather events can be ignored without any consequence. It should be noted that the ideal solution picks 5 kW of PV, but very little BESS as part of the optimal solution reflecting that PV is economic for the household, but BESS at the assumed costs are still not very attractive.
2. Once resilience constraints are considered (from row 2 onwards), there is an extra kW of PV selected but more importantly significant level of BESS is also selected to guard against storm related outages. EUE level in row 2 (Table 1) is small at 2.31 kWh for the year. This is because the household daily peak load is typically low around 2.4 kW on average the exposure to risk is also a relatively low number of hours impacted by extreme weather events. It is also possible to reduce the EUE value further without significant additional investments - mostly in the form of a marginal increase in BESS volume.
3. Annual cost to harden the electricity supply to the household increases by only $12 to bring EUE down below 1 kWh. This is of course is significant because it saves only (2.31-0.9) or 1.41 kWh of EUE for the year making an already reliable supply even better at an average cost of $12/1.41 or $8.5/kWh of EUE. The cost benefit of the additional investment would depend on the preference of the household and the underlying resilience standard.
4. It should also be noted from Figure 3 that there are near vertical steps in the cost curve suggesting close to zero increase in cost for some segments. To reduce EUE from 0.6 kWh to 0.45 kWh, for instance, requires no additional investment in BESS or PV. This is because some reductions in EUE may simply require altering the operation of the BESS without any additional investments. BESS operation can be adjusted to preserve stored energy on a stormy day that can be achieved at very little additional cost to buy grid power during other hours.
5. However, if the household seeks the perfectly reliable supply (0 EUE), the last 0.4 kWh can take a disproportionate amount of incremental PV/BESS or a diesel generator at a cost over $250 per avoided kWh of EUE.
6. It is still cheaper to reach 0 kWh of EUE using a combination of solar panels and BESS rather than using a diesel generator. The annual cost of reaching 0 kWh of EUE using solar panels and BESS is $2324, which is considerably cheaper than the annual cost of $2600 using the diesel generator. Although PV and BESS are capital

TABLE 1. Model results for varied EUE limits.

EUE Limit (kWh)	Cost ($)	PV Installed (kW)	BESS Installed (kWh)
0*	1964	5	0.333
2.31	2168	6	4.182
2.25	2169	6	4.235
1.95	2169	6	4.509
1.65	2170	6	4.826
1.35	2173	6	5.142
1.05	2176	6	5.489
0.90	2180	6	5.729
0.75	2189	6	6.268
0.60	2204	6	6.914
0.45	2204	6	6.914
0.30	2237	6	8.164
0.15	2241	7	8.108
0	2324	7	10.289

**This case did not have resilience considered in its analysis*

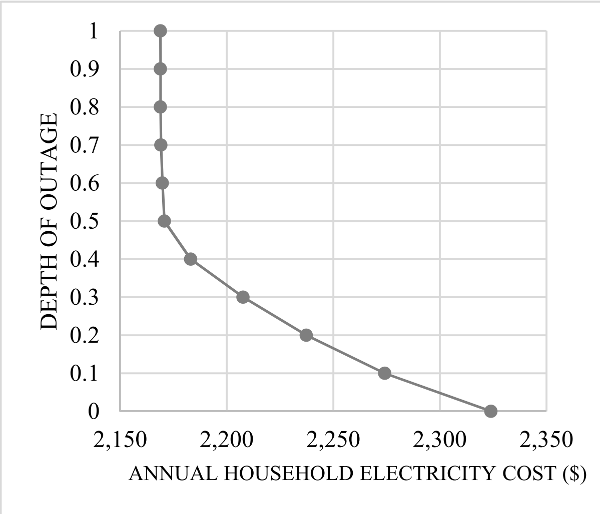

FIGURE 4. Trade-off between depth and cost for a household in Miami.

intensive, they are also modular that can be matched more precisely to the household demand pattern. In comparison, diesel generator size tends to be more discrete and often oversized relative to household demand (e.g., 5, 10, 15, 20 kW) and as such the diesel option ends up being more expensive. In other words, investment in a 10-kW generator in this case is a significant overinvestment that costs the household an additional $276 each year.

Next, it is shown how the depth of outage (i.e., number of kW lost) can influence investment decisions and system cost. Table 2 and Figure 4 summarize results that gradually reduce depth of outage from 1 kW down to zero.

Table 2 also reports the EUE for these cases to show how storm related outages impact on it. As depth of outage reduces, it naturally improves other reliability performance metrics too including EUE. However, constraining depth alone tries to maintain the system cost unchanged and the pattern of resource usage that may also increase as happens to be the case for a depth of 1 kW. In other words, there are intrinsic trade-offs among different aspects of resilience. This is an important consideration in developing a resilience standard that considers multiple dimensions simultaneously. An EUE standard alone may be quite blind to the requirement of capping the depth of outage that may be important for certain requirements, e.g., critical load in a building.

It is again clear that there is very little additional cost to lower the depth of outages from 1 kW to 0.5 kW, and it should be noted that this is efficiently accomplished through incremental increases in BESS capacity. If the BESS kW/kWh is optimized properly, a household is able to contain the depth of outage to half, albeit the reduction in annual EUE may not be as significant. Nevertheless, it may be a significant relief to maintain critical load for half a kW with just a $1.86 increase in annual cost. It is also a cost-effective means to achieve 0.907 kWh reduction in annual outages. Beyond an outage depth of 0.5, the costs increase by larger increments. Going

TABLE 2. Model results for varied outage depth limits.

Outage Depth	Cost ($)	PV Installed (kW)	BESS Installed (kWh)	EUE (kWh)
1	2168	6	4.182	3.078
0.9	2168	6	4.195	3.058
0.8	2168	6	4.207	3.041
0.7	2168	6	4.167	3.1
0.6	2168	6	4.193	3.061
0.5	2170	6	4.815	2.171
0.4	2183	6	5.911	1.061
0.3	2207	6	7.042	0.515
0.2	2237	6	8.173	0.219
0.1	2274	6	9.158	0.068
0	2323	7	10.289	0

from a depth of 0.5 to 0.4 requires an additional $12.32 in annual costs, and the increments continue to rise until the $49.86 increment between the 0.1 and 0 depth values. This is because the capacity of BESS required to power the household needs to step up considerably. The household can meet its objective to contain depth as well as EUE primarily using BESS with 1 kW increase in panel size only for the last step.

It is worth repeating that specifying an outage depth of 0 is equivalent to specifying an EUE value of 0, so the quantity of BESS and PV is the same in both scenarios.

The final metric explored in this study is the frequency of outages which is calculated by summing the hours of outage across each sample. The frequency of outages focuses on the duration that the household can supply power without relying on the grid. As an example, a frequency value of 0.8 means the household can supply power for 4 of the 5 hours of an outage. This is materially different from the other metrics of power outages and places less emphasis on the kWh of outages. In forming their resilience standard, some customers may place a significant emphasis on avoiding frequent short-duration outages. This may have a bigger impact on BESS sizing compared to EUE or depth of outage, and in some cases may even reduce the size of the solar panel needed to meet the standard at the expense of a bigger battery.

Improving the incumbent household's resilience with outage frequency is achieved through incremental investments in BESS, as with the other metrics. The key difference is that the incremental cost to improve outage frequency is more variable than in other metrics. The annual cost between an outage frequency of 0.8 and an outage frequency of 0.43 is $0.98, yet the difference between outage frequencies of 0.1 and 0.07 is $9.56. However, bringing the frequency of outage (and hence depth/EUE too) down to zero may cost a disproportionately high $92 per year.

C. COMBINED METRICS

As the introductory section states, a resilience standard may have multiple dimensions and may vary across different types of customers (or even across customers within a group). While this study does not attempt to formulate an ideal resilience/reliability metric, the proposed model allows users to formulate their own metrics according to their individual needs. The proposed model allows users to modify its constraints, meaning users can define a system that meets their own limits for annual EUE, outage depth, and frequency. This study recognizes that users' energy needs vary widely and that they may prefer to prioritize one metric over another. For example, should a user require that certain appliances stay powered in their home despite an outage, they would place more emphasis on hardening the supply to lower outage depth rather than outage frequency. If the user also desires that EUE for the year be limited below a threshold, the model can be run using both constraints simultaneously. This section presents results for constraints constituting all three metrics: EUE, outage depth and outage frequency.

Table 3 summarizes model outputs for various scenarios. The results from these cases are fundamentally not different from the ones presented in the preceding discussions. More stringent reliability/resilience constraints result in higher annual energy costs. However, the combined metrics lead to a set of results that provide a few additional insights.

1. A judicious selection of resilience standard is needed because some standards are easier to meet than others.
    a. *Rows 2 vs 1:* As an example, focusing on the first two cases - incremental household electricity costs to reduce outage depth are relatively low. To go from an outage depth of 0.75 to 0.5 kW requires an incremental cost of only \$2 despite preventing 0.83 kWh (i.e., from 3 kWh to 2.17 kWh) of load shed with no explicit constraint on EUE. If the resilience standard was set to tolerate non-essential load of only half a kW, an extra kW of PV (noting that 5 kW of PV is economic without any resilience requirement) and around 4.5 kWh of BESS could do the job well to with barely any increase in annual supply cost;
    b. *Rows 2 vs 7:* In comparison, scaling outage depth from 0.75 to 0.55 requires an additional annual cost of \$36 when EUE is limited to 1 kWh. If the additional (3 kWh less 0.6 kWh, or) 2.40 kWh of load shed is worth saving at that cost, an increase in BESS capacity from 4.8 kWh to 6.9 kWh may be economic; and
    c. *Row 2 vs 14:* Further, in the most stringent case in row #14 where depth, frequency and EUE are all minimal, the increase in cost is (\$2289 less \$2168 or) \$121. The BESS size is almost doubled, and an extra kW of PV is also needed. This supply mix of course ensures any prospect of load shed is almost wiped out apart from a tiny 100 Watt of non-essential load, the rest of it is always met, etc. Such a service quality at an extra cost of \$10 per month in bill may well be attractive to some customers and this solution is still a lot cheaper than one that requires a diesel generator.
2. *Row 4 vs rows 5,6 and 13:* Incremental investments to lower outage frequency are remarkably cheap. To reduce outage frequency from a value of 1 to 0.9 costs only \$4, and to further harden it to a value of 0.55 or eliminate nearly 40% of outage instances costs an additional \$4. A comparison of row 4 against 13 shows that if the household is interested in a standard that eliminates 80% of the outage instances and would like to treat only 0.1 kW of load as non-critical, the annual cost increase is \$104.
3. *Row 2 vs rows 3, etc:* EUE is the costliest of the three metrics to lower. Marginal cost of EUE reduction goes up rapidly - it only costs \$1 to harden from 3 to 2.8 kWh of load shed). Reducing EUE standard from 1 kWh (row 9) to 0.4 kWh (row 10), on the other hand, costs an additional \$18. The willingness to pay for the incremental kWh of reliability for most customers will probably lie somewhere in this range.

TABLE 3. Model results for combined constraints.

	EUE Limit (kWh)	Depth	Frqy	Cost (\$)	PV (kW)	BESS (kWh)	Load shed (kWh)
1	*	0.50	*	2170	6	4.8	2.17
2	*	0.75	*	2168	6	4.8	3.00
3	3	0.75	*	2169	6	4.3	2.80
4	3	0.50	*	2170	6	4.8	2.20
5	3	0.75	0.90	2174	5	5.3	1.80
6	3	0.75	0.55	2178	6	5.6	1.30
7	1	0.75	0.55	2204	6	6.9	0.60
8	1	0.25	0.55	2241	6	7.6	0.40
9	1	0.25	0.20	2255	6	8.1	0.30
10	0.4	0.25	0.20	2273	6	8.1	0.23
11	0.4	0.10	0.20	2289	7	9.2	0.07
12	0.4	0.50	0.20	2226	6	7.8	0.30
13	2	0.10	0.20	2274	9	9.1	0.09
14	0.4	0.10	0.50	2289	7	9.2	0.07

**** There were no constraints in place for these metrics in these cases***

4. In summary, the cases presented here show that the proposed planning model informed explicitly by the dominant source of risk (i.e., storms in this case) can be useful in exploring the multiple facets of resilience to choose a solution that best fits an intended resilience standard. It may also be noted that the multiple dimensions have trade-offs among themselves in some areas, while they can also complement each other, depending on the supply mix chosen. It is important to explore the solution space and understand these relationships.

V. CONCLUSION

A. SUMMARY AND KEY INSIGHTS

This study proposes a multi-dimensional resilience constraint and implements it in an analytical planning model for a household level power supply analysis. The three resilience criteria analyzed in this study address three core aspects of a household's resilience in power outages: the total quantity of lost energy, outage depth, and outage frequency. The three metrics represent complex resilience considerations such as coverage of category 5 storms that may occur with certain probability but still allow for certain tolerable level number of outage events in a year, of a specified maximum duration and a cap on the total annual unserved energy. By implementing these three metrics as constraints in an analytical model, it is possible to characterize desired resilience outcomes linking it to the probability of extreme weather events, coverage of critical loads, and other attributes. It is also instructive to understand how these three metrics complement each other and the cost implication for each individual metric to inform useful resilience standards. While there are ongoing efforts to standardize resilience metrics and standards at a system level e.g., [40], customer level resilience standard is yet to receive much attention. The model and analysis presented in this work may be helpful in setting such standards.

The Miami case study reveals that it is possible to create a highly resilient system which meets the criteria of relatively low outage frequency, low outage depth and low expected unserved energy up to certain level without a drastic increase in annual electricity supply cost. It also however shows that the perfectly reliable system would incur disproportionately high level of investments in BESS/diesel and solar PV. It is important to recognize this trade-off between cost and resilience in designing a reliable household supply system that may in turn also hold significance for investing less towards the resilience of the upstream distribution system.

The model may be a useful tool that may be used by retailers, regulators, individual businesses and households as well as solar and battery storage service providers to design the best electricity supply system. Most of the data can be obtained including customer load profile from smart meters, renewable profile data from publicly available resources like MERRA-2, etc. Absent such an analysis, it is easy to overestimate the need for investments like a large diesel generator and underestimate the need for battery storage.

B. LIMITATIONS AND POSSIBLE EXTENSIONS

This study makes a simple but useful demonstration of how resilience can be built into planning of electricity supply of a household that can be extended to other applications including system level planning. There are however some limitations of the study that need to be borne in mind in doing such extensions and they also open the possibility to do further work in this area. A general limitation is that this analysis does not consider all available measures of resilience and limit the set of options to PV, BESS and diesel. There could be other forms of storage, other cleaner forms of back-up generation and grid strengthening /mini grids that could be considered. There are other limitations, namely, there are other attributes of resilience that are ignored together with uncertainties around load, probability of failure of PV/BESS/diesel itself when these resources are needed during a grid outage, etc.

The study outcomes are contingent on the demand profile assumed for the study which is representative of a medium/low electricity demand household; on specific storm risks in the Miami area and costs of resilience options assumed for this analysis. While the general conclusion on PV/BESS being cheaper than diesel may be applicable to many other cases, it needs to be tested with a wide range of input parameters covering different geographies with potentially very different risk profiles.

Due to the study being based on a single household in Miami, it is not possible to consider resilience metrics such as response time which are otherwise integral to comprehensive analysis of resilience. Response time, or the ability for a system to be able to respond to and mitigate an outage, is a core part of the definition of resilience and as such extensions to this model for it to be informed by more detailed data would be a useful addition.

This study does not consider the possibility that each individual component of the system can fail. In other words, it is assumed that the PV, BESS and diesel generators are perfectly reliable. Outage probability is restricted to the grid supply only and does not extend to backup power supplies. The possibility that solar panels or diesel generators could potentially fail, is not considered in this study. It is, in fact, possible that all three components this study considers (diesel generators, solar panels and BESS) can be severely damaged in a hurricane [40], [41]. This is also an additional consideration that will need to be built into the analysis to see if they have a major impact on the selection of resilience options.

REFERENCES

[1] D. T. Ton and W.-T.-P. Wang, "A more resilient grid: The U.S. Department of energy joins with stakeholders in an R&D plan," *IEEE Power Energy Mag.*, vol. 13, no. 3, pp. 26–34, May 2015.
[2] S. Chandramowli and F. F. Felder, "Climate change and power systems planning—Opportunities and challenges," *Electr. J.*, vol. 27, no. 4, pp. 40–50, May 2014, doi: 10.1016/j.tej.2014.04.002.
[3] M. T. H. van Vliet, J. R. Yearsley, F. Ludwig, S. Vögele, D. P. Lettenmaier, and P. Kabat, "Vulnerability of US and European electricity supply to climate change," *Nature Climate Change*, vol. 2, no. 9, pp. 676–681, Sep. 2012, doi: 10.1038/nclimate1546.

[4] E. O'Neill-Carrillo and A. Irizarry-Rivera, "How to harden Puerto Rico's grid against hurricanes," *IEEE Spectr.*, vol. 56, no. 11, pp. 42–48, Nov. 2019. [Online]. Available: https://spectrum.ieee.org/energy/policy/how-to-harden-puerto-ricos-grid-against-hurricanes
[5] M. A. Mohamed, T. Chen, W. Su, and T. Jin, "Proactive resilience of power systems against natural disasters: A literature review," *IEEE Access*, vol. 7, pp. 163778–163795, 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8894433
[6] J. Sieber, "Impacts of, and adaptation options to, extreme weather events and climate change concerning thermal power plants," *Climatic Change*, vol. 121, no. 1, pp. 55–66, Nov. 2013.
[7] S. C. Parkinson and N. Djilali, "Robust response to hydro-climatic change in electricity generation planning," *Climatic Change*, vol. 130, no. 4, pp. 475–489, Jun. 2015.
[8] D. J. Sailor, M. Smith, and M. Hart, "Climate change implications for wind power resources in the Northwest United States," *Renew. Energy*, vol. 33, no. 11, pp. 2393–2406, Nov. 2008.
[9] S. Jerez, I. Tobin, R. Vautard, J. P. Montávez, J. M. López-Romero, F. Thais, B. Bartok, O. B. Christensen, A. Colette, M. Déqué, G. Nikulin, S. Kotlarski, E. van Meijgaard, C. Teichmann, and M. Wild, "The impact of climate change on photovoltaic power generation in Europe," *Nature Commun.*, vol. 6, no. 1, p. 10014, Dec. 2015.
[10] N. Mukhi, "Building climate resilience into power system planning: The case of Bangladesh," World Bank, Washington, DC, USA, Tech. Rep. ACS23320, 2017. [Online]. Available: http://documents.worldbank.org/curated/en/296731513710765160/Building-climate-resilience-into-power-system-planning-the-case-of-Bangladesh
[11] M. Kezunovic, I. Dobson, and Y. Dong, "Impact of extreme weather on power system blackouts and forced outages: New challenges," in *Proc. 7th Balkan Power Conf.*, 2008, pp. 1–5.
[12] S. N. Rezaei, L. Chouinard, S. Langlois, and F. Légeron, "Analysis of the effect of climate change on the reliability of overhead transmission lines," *Sustain. Cities Soc.*, vol. 27, pp. 137–144, Nov. 2016.
[13] H. H. Willis and K. Loa, *Measuring the Resilience of Energy Distribution Systems*. Santa Monica, CA, USA: RAND Corporation, 2015.
[14] D. Shelar, S. Amin, and I. A. Hiskens, "Evaluating resilience of electricity distribution networks via a modification of generalized benders decomposition method," *IEEE Trans. Control Netw. Syst.*, vol. 8, no. 3, pp. 1225–1238, Sep. 2021.
[15] M. Panteli and P. Mancarella, "The grid: Stronger, bigger, smarter?: Presenting a conceptual framework of power system resilience," *IEEE Power Energy Mag.*, vol. 13, no. 3, pp. 58–66, May/Jun. 2015.
[16] S. Espinoza, M. Panteli, P. Mancarella, and H. Rudnick, "Multi-phase assessment and adaptation of power systems resilience to natural hazards," *Electr. Power Syst. Res.*, vol. 136, pp. 352–361, Jun. 2016, doi: 10.1016/j.epsr.2016.03.019.
[17] R. Moreno, M. Panteli, P. Mancarella, H. Rudnick, T. Lagos, A. Navarro, F. Ordonez, and J. C. Araneda, "From reliability to resilience: Planning the grid against the extremes," *IEEE Power Energy Mag.*, vol. 18, no. 4, pp. 41–53, Jul. 2020.
[18] G. Fu, S. Wilkinson, R. J. Dawson, H. J. Fowler, C. Kilsby, M. Panteli, and P. Mancarella, "Integrated approach to assess the resilience of future electricity infrastructure networks to climate hazards," *IEEE Syst. J.*, vol. 12, no. 4, pp. 3169–3180, Dec. 2018.
[19] E. Chatterji and M. D. Bazilian, "Battery storage for resilient Homes," *IEEE Access*, vol. 8, pp. 184497–184511, 2020, doi: 10.1109/ACCESS.2020.3029989.
[20] D. Cutler, D. Olis, E. Elgqvist, X. Li, N. Laws, N. DiOrio, A. Walker, and K. Anderson, *REopt: A Platform for Energy System Integration and Optimization*. Golden, CO, USA: National Renewable Energy Laboratory, Sep. 2017. [Online]. Available: https://www.nrel.gov/docs/fy17osti/70022.pdf
[21] S. Mashayekh, M. Stadler, G. Cardoso, and M. Heleno, "A mixed integer linear programming approach for optimal DER portfolio, sizing, and placement in multi-energy microgrids," *Appl. Energy*, vol. 187, pp. 154–168, Feb. 2017.
[22] C. Chen, J. Wang, F. Qiu, and D. Zhao, "Resilient distribution system by microgrids formation after natural disasters," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 958–966, Mar. 2016.
[23] R. Eskandarpour, H. Lotfi, and A. Khodaei, "Optimal microgrid placement for enhancing power system resilience in response to weather events," in *Proc. North Amer. Power Symp. (NAPS)*, Sep. 2016, pp. 1–6.
[24] A. G. Tsikalakis and N. D. Hatziargyriou, "Operation of microgrids with demand side bidding and continuity of supply for critical loads," *Eur. Trans. Elect. Power*, vol. 21, no. 2, pp. 1238–1254, 2011.
[25] S. Cano-Andrade, M. R. Von Spakovsky, A. Fuentes, C. L. Prete, B. F. Hobbs, and L. Mili, "Multi-objective optimization for the sustainable-resilient synthesis/design/operation of a power network coupled to distributed power producers via microgrids," in *Proc. ASME Int. Mech. Eng. Congr. Expo. Amer. Soc.*, Nov. 2012, pp. 1393–1408.
[26] A. Khodaei, "Resiliency-oriented microgrid optimal scheduling," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1584–1591, Jul. 2014.
[27] P. Li, P. Degobert, B. Robyns, and B. Francois, "Implementation of interactivity across a resilient microgrid for power supply and exchange with an active distribution network," in *Proc. CIRED Seminar, SmartGrids Distrib.*, 2008, pp. 1–4.
[28] B. Zhang, P. Dehghanian, and M. Kezunovic, "Optimal allocation of PV generation and battery storage for enhanced resilience," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 535–545, Jan. 2017.
[29] L. Che, M. Khodayar, and M. Shahidehpour, "Only connect: Microgrids for distribution system restoration," *IEEE Power Energy Mag.*, vol. 1, no. 12, pp. 70–81, Jan./Feb. 2014.
[30] M. McGranaghan, M. Olearczyk and C. Gellings, *Enhancing Distribution Resiliency: Opportunities for Applying Innovative Technologies*. Palo Alto, CA, USA: EPRI, 2013.
[31] R. J. Campbell, *Weather-Related Power Outages and Electric System Resiliency*. Washington, DC, USA: Congressional Research Service, Aug. 2012.
[32] Z. Bie, Y. Lin, G. Li, and F. Li, "Battling the extreme: A study on the power system resilience," *Proc. IEEE*, vol. 105, no. 7, pp. 1253–1266, Jul. 2017.
[33] *Severe Impact Resilience: Considerations and Recommendations*, North Amer. Electr. Rel. Corp., Atlanta, GA, USA, 2012.
[34] A. Gholami, T. Shekari, and S. Grijalva, "Proactive management of microgrids for resiliency enhancement: An adaptive robust approach," *IEEE Trans. Sustain. Energy*, vol. 10, no. 1, pp. 470–480, Jan. 2017.
[35] A. Ott. (Dec. 2018). *Reliability and Resilience: Different Concepts, Common Goals*. [Online]. Available: https://insidelines.pjm.com/reliability-and-resilience-different-concepts-common-goals/
[36] C. Murphy, E. Hotchkiss, K. Anderson, C. Barrows, S. Cohen, S. Dalvi, N. Laws, J. Maguire, G. Stephen, and E. Wilson, "Adapting existing energy planning, simulation, and operational models for resilience analysis," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-6A20-74241, 2020. [Online]. Available: https://www.nrel.gov/docs/fy20osti/74241.p
[37] H. Sabouhi, A. Doroudi, M. Fotuhi-Firuzabad, and M. Bashiri, "Electrical power system resilience assessment: A comprehensive approach," *IEEE Syst. J.*, vol. 14, no. 2, pp. 2643–2652, Jun. 2020, doi: 10.1109/JSYST.2019.2934421.
[38] M. Mahzarnia, M. P. Moghaddam, P. T. Baboli, and P. Siano, "A review of the measures to enhance power systems resilience," *IEEE Syst. J.*, vol. 14, no. 3, pp. 4059–4070, Sep. 2020, doi: 10.1109/JSYST.2020.2965993.
[39] W. McCarty, W. McCarty, M. J. Suárez, R. Todling, A. Molod, L. Takacs, C. A. Randles, A. Darmenov, M. G. Bosilovich, R. Reichle, and K. Wargan, "The modern-era retrospective analysis for research and applications version 2 (MERRA-2)," *J. Clim.*, vol. 30, no. 14, pp. 5419–5454, 2017.
[40] T. Houser, J. Larsen and P. Marsters, *The Real Electricity Reliability Crisis*. New York, NY, USA: The Rhodium Group, Oct. 2017.
[41] J. Marqusee and D. Jenket, "Reliability of emergency and standby diesel generators: Impact on energy resiliency solutions," *Appl. Energy*, vol. 268, Jun. 2020, Art. no. 114918.
[42] S. Baik, A. H. Sanstad, N. Hanus, J. H. Eto, and P. H. Larsen, "A hybrid approach to estimating the economic value of power system resilience," *Electr. J.*, vol. 34, no. 8, Oct. 2021, Art. no. 107013.

EMON CHATTERJI is currently pursuing the degree with the Department of Electrical and Computer Engineering, University of Maryland, College Park, MD, USA.

KATE ANDERSON is currently pursuing the Ph.D. degree in advanced energy systems with Colorado School of Mines. She leads the Modeling and Analysis Group, National Renewable Energy Laboratory, and conducts research to quantify and value energy resilience.

MORGAN D. BAZILIAN is currently a Professor and the Director of the Payne Institute, Colorado School of Mines.