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Battery Storage for Resilient Homes

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ABSTRACT Small-scale battery energy storage systems (BESS), especially for behind-the-meter applications, are still relatively expensive, but we show that it can be a potent solution to render homes resilient to storm related power outages. We present a stochastic programming model formulation to optimize PV/BESS explicitly accounting for resilience benefits these investments entail, over and above their ability to reduce cost of supply. The stochastic optimization considers uncertainties around storm related grid supply failures as well as variability of solar PV. The model includes an embedded Monte Carlo simulation module that considers storm related outage risks using climate model reanalysis data. It is a least-cost planning framework that optimizes selection of BESS, solar PV, grid supply, and diesel generator, from a home-owner's perspective. We present two case studies with low and high storm risks that demonstrate how different risk exposures can impact on the selection of alternative options to build resilience. Duals, or shadow prices, of demand-supply constraints from the model for both normal days and for storm related contingencies, provide interesting insights into the marginal cost of supply that can inform innovative pricing schemes to promote customer level resilience measures. The case study results reveal significant merits of BESS, in combination with PV, to enhance resilience. We find that in low-risk areas like Bethesda, MD, incremental PV and BESS required for a more resilient system can add \$79 (4%) to annual electricity costs for a typical household, and a considerably higher \$208 (10.6%) in Miami, FL which is at a much greater risk. These options are, however, 27% (in Bethesda) and 20% (in Florida) less expensive than the conventional solution of installing a diesel generator. These results provide insights into the value of BESS as part of a resilient and clean energy solution for households.

INDEX TERMS Stochastic optimization model, battery storage, solar panel sizing, climate resilience, smart meter data, stochastic programming, Monte Carlo simulation.

NOMENCLATURE

Indices:

t	Hours/sub-hours of the day
d	All day types
sun_d	Sunny or normal day (no storms)
$storm_d$	Stormy days
m	Months of the year
y	Solar profiles: y=1, … Y
s	Monte Carlo samples: s=1, … S

Input Parameters:

$Weight_d$	Weight associated with each day type
$Demand_{y,m,d,t}$	Hourly/sub-hourly demand
w_t	Hourly windspeed for a storm in each location in mph
p_t	Hourly probability of power outage due to winds
$\theta_{1s,t}$	Stochastic parameter with uniform distribution {0,1}
$\theta_{s,t}$	Grid supply availability, i.e., binary parameter determining whether the household can access the grid
$AvailableSolar_{y,m,d,t}$	Solar irradiance in kW/m^2 per 1 kW panels installed
$Tariff$	Cost of energy from the grid in \$/kWh
$LSPenalty$	Cost of unserved energy
ε	Penalty on solar rejection
$PanelCost$	Annualized cost in \$/kW/year of solar panels

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BuyBackRate	Price in \$/kWh which can be earned by the household by selling 1 kWh of energy to the grid
TaxDiscount	Percent of the solar panel cost subsidized by the government
SolarEfficiency	Efficiency of the solar panel
BatteryCost	Annualized cost in \$/kWh/year of BESS
BatteryEfficiency	BESS efficiency
ChargeRate	The rate in kW that the battery can charge
DischargeRate	The rate in kW at which the battery can discharge
M	Diesel generator capacity in kW (e.g., 10 kW)
DGCost	Annualized cost in \$/year of an M-kW diesel generator
HourlyDGCost	Cost of operating the diesel generator in \$/kWh

Decision Variables:

Cost	Total cost of supply
SolarInstalled	Amount of solar panels installed by the model in kW – **first stage decision**
BatterykW	Size of battery in kW to be installed – **first stage decision**
DGSelected	Binary variable denoting whether the model installs a diesel generator – **first stage decision**
$Grid_{y,m,d,t}$	Supply of energy from the grid in kWh
$Grid^{*}_{y,m,d,t,s}$	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)
$SolarReject^{*}_{y,m,d,t,s}$	Solar energy in kWh being rejected in sample s (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
$LoadShed_{y,m,storm,t,s}$	Demand in kWh that cannot be met.

I. INTRODUCTION

The United States Department of Energy found that an average household in the United States goes without power for 8 hours in a year [1]. This number varies widely among individual states: households in Florida lose power supply on average for 40 hours, whereas those in Washington, D.C. lose power supply for about 2 hours. These power outages occur for a variety of reasons, that range from natural events to intentional attacks on the power supply. A recent paper found that between 2012 and 2016, over 96.2% of power outages occurred due to the impact of severe weather [2] on transmission, and to a greater extent, on distribution networks [3]. Storms and hurricanes account for the vast majority of these outages. Resilience of a system can be defined as its ability to prepare, predict, sustain and recover from an outage [3]. This definition is applicable to the power system as a whole or one of its components, such as a household.

Households have several options available to them in terms of both supplementing or ''cleaning'' their energy supply and protecting against outages. As an example, they can install photovoltaic panels (PV), household battery energy storage systems (BESS), or small diesel/propane/natural gas fired backup generators.

Figure 1 shows the difference in probability of power outages (i.e., grid supply failures) during a typical stormy day in Bethesda (Maryland) and Miami (Florida)—two locations chosen for our illustrative case studies. These probabilities are correlated to wind gust and can be derived from climate model reanalysis data as discussed later.

Motivation for This Study: There is a growing literature on *system level* power sector resilience as the frequency and intensity of major storms are on the rise, e.g., [3]. Still, the role of BESS and solar PV is relatively unexplored compared to that of fossil fuel-based generators in providing

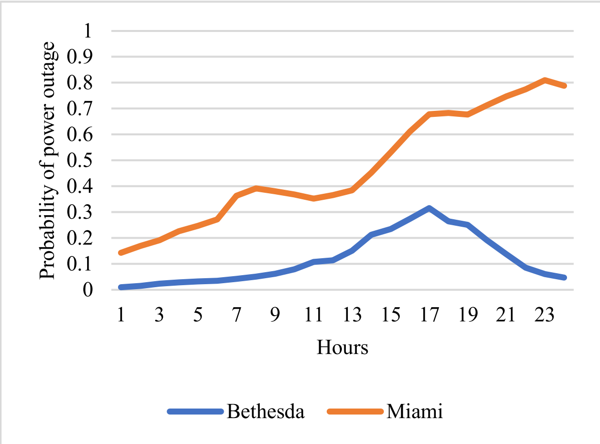

FIGURE 1. **Comparison of power outage probabilities between Bethesda and Miami.**

backup power during storms [3]. As an example, none of the commercially available tools for PV/BESS sizing analysis consider these aspects. These solar PV assessment tools are also deterministic in nature. Since the resilience problem intrinsically considers risk of outages (and variability of solar power), there is a need for stochastic optimization. We address this gap by considering how resilience can be integrated into a household-level energy supply analysis. A second motivation for this study is to understand the role uncertainty of solar resources plays in this regard and what this in turn implies for level of storage needed to render a household resilient. We consider variability of solar resource – both inter-annual and intra-annual variability – to see how PV/BESS sizing and its competitiveness against other options like diesel is influenced by it.

The concept of incremental investments to add resilience can in fact be generalized to cover other areas of study. It would, first of all, be interesting to see how households in substantially different geographies are affected by extreme weather events with different risk profiles and solar resources. Secondly, this study addresses household-level investment decisions, but the concepts and the framework can be applied to analyze the resilience needs of larger communities, mini-grids or a power system for that matter with utility-scale solar farm and BESS considered for resilience. Thirdly, these concepts can be further extended to address other sources of risks. In this study, we address power outages due to extreme winds, but the framework used in the study can be extended to include outage risks due to flooding or wildfires. Finally, the model used in the study to combine the flexibility of stochastic programming with a Monte Carlo simulation can be adapted to represent a wide variety of weather-related risks prevalent in varying parts of the globe.

Application of this study is imminent from the preceding discussion and further illustrated in case studies that we discuss in section 4. The analytical framework and the model developed can be used by property owners, rooftop PV and BESS vendors, as well as distribution utilities in order to accurately estimate the volume of PV and BESS for a building to maximize economic and resilience benefits. The study can be further used by a wider group of planning bodies and regulatory agencies to reduce dependence on fossil-fuel based back-up generation facilities. The proposed methodology can be applied immediately in the form of enhancements to the existing tools that do not consider resilience related issues. There are commercial tools developed by solar panel companies that do not in most instances co-optimize BESS. There are other tools offered by agencies such as NREL, IRENA, Google, etc that do not consider resilience either. Part of our motivation therefore is also that the proposed methodology and model can fill a useful niche in existing commercial and research grade tools.

In summary, the motivation of our study is to ensure resilience analysis is put into practice and decision makers at all levels including homeowners can make investment decisions on PV/BESS sizing that explicitly recognize the associated resilience benefits.

The remainder of this paper is organized as follows: Section 2 provides a survey of the existing literature in this area. Section 3 describes the stochastic model that is developed to perform the analysis, followed by case studies in Section 4. Section 5 summarizes the key findings of the analysis.

II. LITERATURE SURVEY

There is a substantial literature on usage of optimization tools for managing residential load. Capehart *et al.* [4], published in the 1980s showed how household electricity costs can be reduced by lowering their consumption during the peak. Since then, there have been many developments in the general area of home energy management system (HEMS). Rahman and Bhatnagar [5] and Wacks [6] are important examples of this. Rahman and Bhatnagar [5] discusses the advantages of computerized energy management systems and how they perform in comparison to mechanical controllers. Khatib *et al.* [7] describes available methods for optimizing system level PV capacity.

We have focused on four key aspects of the literature, namely: (a) operational simulation of a household level energy system; (b) optimization of PV and BESS capacity and diesel generators; (c) smart meter data to inform optimization; and (d) customer-level-resilience represented through a Monte Carlo simulation.

Literature on HEMS has grown over the years. There have been significant developments in embracing smart grid, rooftop PV, and BESS. Beaudin and Zariepour [8] provides a good overview of the recent literature on HEMS on these topics. Simulation of household level energy system operation, as opposed to capacity optimization, has also grown over the years. Zhao *et al.* [9] introduced an advanced Energy Management Controller (EMC) design and includes an optimal power scheduling scheme for each appliance. The proposed power scheduling method in Zhao *et al.* [9] would effectively strengthen the stability of the power system while also reducing costs. Zhou *et al.* [10] extends the concept of a smart HEMS to consider renewable energy sources such as solar, biomass, wind, etc. HEMS capabilities have been progressively extended to prioritize appliances [11], include demand response combined with storage [12], and electric vehicles (EV) [13]. Hosseinnezhad *et al.* [14], [15] uses artificial intelligence techniques to solve the HEMS scheduling problem. Hosseinnezhad *et al.* [14] demonstrates benefits of using a self-healing strategy that will sectionalize an isolated area of the distribution system into island partitions to provide reliable power supply to the critical loads continuously. It shows how an intelligent network reconfiguration strategy can add to system resilience. Hosseinnezhad *et al.* [15] presents a HEMS with day-ahead management and real-time regulation. Their case studies show that the model can reliably locate the optimal operating scenario. Shareef *et al.* [16] is a recent summary of the HEMS applications.

Falling costs of BESS in recent years has encouraged combining PV with it to provide stable power supply. Both linear and nonlinear mixed integer programming (MIP) models have been used to optimize PV and BESS capacity [17]–[22]. Zhao *et al.* [17] co-optimizes BESS and PV for microgrids and households. Zhao *et al.* [17] makes significant progress in improving accuracy of solar panel sizing analysis by introducing an additional penalty for battery-life loss. Their analysis involves maximizing the life of the BESS. Zhou *et al.* [18] also performs this co-optimization using a comprehensive nonlinear MIP (MINLP) model that considers alternative pricing schemes. Results from Zhou *et al.* [18] indicate that economics of PV under a standard tariff policy is not attractive. However, it is economic to install a PV-only system under a stepwise power tariff, whereas the PV together with BESS can only be justified under a time-of-use and real-time-pricing tariff. Hemmati [19] and Hemmati and Saboori [20] adopt a similar approach. Hemmati and Saboori [20] introduces uncertainty in PV output using a Monte Carlo simulation model to minimize annual utility bills of customers. The analysis in Hemmati and Saboori [20] indicates that it is possible to achieve a net-zero energy model if both PV and BESS are installed. Okoye and Solyali [21] used an integer programming model to determine the optimal PV and BESS capacity in Nigeria that reduces the usage of diesel. Analysis of the annualized costs in [21] demonstrates that the PV system is not only environmentally friendly, but also 30% cheaper than the conventional alternative of diesel generators. Erdinc *et al.* [22] used a mixed integer programming model to co-optimize distributed generation, storage and demand response. Their work was a significant step forward in HEMS analysis through the integration of BESS in the model.

Accurate load profiles are critical to PV/BESS capacity optimization and operation including resilience considerations, that can come from smart meter data. Smart meter data analytics until 2019 [23], however, shows limited application of it in PV/BESS sizing. There has been some application of it to identify demand response measures (e.g., [24]). Dyson *et al.* [24] presents a new method for assessing demand-response potential of residential air-conditioning using smart-meter data from 30,000 households in Northern California. Liang *et al.* [25] used smart meter data from 5,000 installations to analyze the number of solar panels needed to render the system net zero energy (NZE) but did not perform a capacity optimization. Case studies from Liang *et al.* [25] include actual feeder topology in Duke Energy North Carolina service areas to demonstrate the impact of an NZE strategy on customer bills and power flow changes in the distribution system. Chatterji and Bazilian [26] used smart meter data to optimize selection of PV, BESS and EV charging mode using a stochastic mixed integer programming model. Analysis of PV and BESS in [26] as well as [18] showed that even with low cost of BESS in recent years, it is hard to justify behind-the-meter application of storage without time-of-use, special EV tariffs [26] or subsidies [18]. Past analyses however did not consider the resilience benefits of BESS.

Power system resilience is a topic that connects to multiple sources of risks including severe weather events, cyber security, and conflict. Our work focuses specifically on the extreme weather driven outages and building resilience at a household level. As we noted, Houser *et al.* [2] conclusively demonstrated how vast majority of the recent power outages in the US were caused by the impact of severe weather on the infrastructure. This is also evident from the data presented by the Energy Information Administration (EIA), which in recent years, shows a breakdown of the role of the weather events [1]. References [27]–[29] analyze methods of improving system resilience in different locations of the world. O'Neil-Carrillo and Irizarry-Rivera [27] shows how a combination of microgrids, PV, and BESS can be applied to hurricane-prone Puerto Rico to improve power system resilience. Their proposed solution includes a 'grid of microgrids' that essentially comprise 2 kW PV and 10 kWh BESS for 200,000 customers who are particularly vulnerable to hurricanes. Although this solution comes at a significant cost \$1.4 billion, they aptly make the point that "*it's just a fraction of what the Puerto Rico government has proposed spending on an enhanced central grid*." Panteli *et al.* [28] provides an analysis of the key concepts of power system analysis. They also analyzed methods to harden Great Britain's transmission network. Bristow [29] presents a resilience assessment for the city of Toronto using a novel methodology. This analysis considers the interdependencies of multiple infrastructures in an investigation of Toronto's ability to efficiently recover from extreme events.

This concept is further explored in Guidotti *et al.* [30], who present a sophisticated methodology for modeling correlated infrastructure networks. Interdependence in infrastructure is also considered in Bie *et al.* [31], wherein a framework for power system resilience evaluation is presented along with a load restoration framework. This methodology places emphasis on new technologies such as topology reconfiguration and distribution automation. In order to accurately assess the resilience of power systems, Panteli and Mancarella [32] present a conceptual framework that makes use of a sequential Monte-Carlo-based time-series simulation model to compute random weather-related events and considered time dependent failure probabilities of system components. An important contribution of their work is an integration of the 'fragility curve' concept in power system resilience analysis for applying weather- and time-dependent failure probabilities to system components. Duque *et al.* [33] presents a comprehensive optimization framework that dispatches oil tank trucks to supply resources based on another model that predicts demand for diesel based on historic weather forecasts. Although [33] does not consider renewable resources to impart resilience, it highlights the complexities and costs associated with usage of diesel as a back-up resource. Their work also introduces a logistic regression model that predicts the probability of a power outage from wind gust speeds which forms the basis of storm outages probabilities in our analysis.

Yan *et al.* [34] introduced a sophisticated framework and an algorithm to reduce customer operational costs, also integrating electric vehicle (EV) charge scheduling in a commercial building. Their analysis shows that operational costs in a commercial building can be lowered while also increasing tolerance to uncertain power outages. This algorithm includes battery storage and PV generation. Their model makes use of hourly load data sourced from a commercial building. It should be noted though that the model in [34] is an operational planning model in which the capacity for BESS/PV is pre-fixed.

As the discussion above alludes to, there are several elements of a holistic framework for addressing resilience issues. These include *inter alia* assessment of storm probability [33], stochastic optimization [26] and Monte Carlo technique [32], and operational simulation of storm resilience [34]. Yet, there is no comprehensive framework and model we are aware of that brings these elements together to analyze contribution of PV/BESS towards resilience of supply for a household customer.

III. METHODOLOGY

This paper builds on our previous work [26] to extend an optimization model that determines optimal PV and BESS size, and includes the following considerations (*the specific additions to the methodology in [26] are shown in italics*):

(a) hourly smart meter load data at a household level to represent load, including variability in load across different years in conjunction with solar insolation and *extreme weather events (namely, storms in our case studies);*
(b) co-optimization of solar and battery capacity to minimize household utility bills while matching the load, solar and *weather driven outage profiles*;
(c) analysis of solar irradiance and wind data available in the public domain (e.g., NASA's MERRA-2) to represent (i) hourly variability of solar within a year and also inter-annual variability; and *(ii) extreme wind speed representing stormy conditions that may cause grid supply failures;*
(d) stochastic modeling as an integral part of the optimization of (i) multiple solar profiles to capture inter-annual variability; and *(ii) storm related power outages;*
(e) explicit consideration of net metering policy for the state/country, including restrictions on quantity of kWh that can be exported to the grid, *which holds interesting implications for selection of BESS for resilience and marginal cost of supply*;
(f) *customer-level resilience through investments in BESS and/or back-up generation facility based on grid failure probability driven by wind gust speed;*
(g) *integrated assessment of investment decisions on such hardening measures (namely, additional PV and BESS specifically to cover storm related outage risks and also an option to install diesel generator to provide power in case of power outages);*
(h) *operational decisions for grid supply, solar usage in-house and export to grid, BESS charging and discharging decisions and back-up generation for both normal and contingency conditions (namely storm related outages) including coverage of critical loads;*
(i) *economic load-shedding beyond critical load, in the case it is too expensive to invest in hardening measures relative to the cost of unserved energy; and*
(j) *elicit shadow prices or marginal cost of supply at a household level for normal and contingency conditions that may provide insights into investments needed for hardening distribution system infrastructure.*

A. OVERVIEW OF THE MODEL

The model is formulated as a mixed integer linear programming (MILP) problem which considers historic smart meter load data, solar resource profiles and hourly windspeeds corresponding to a household location. It is used to minimize the annual household electricity costs including (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 selection of the core mixed-integer programming modeling framework is done on the premise that it is robust and well established in the domain of power system planning including most system planning and market related applications. Stochastic optimization including stochastic programming and Monte Carlo simulation have been fully embedded in the same framework to ensure that the results are robust, can be implemented through production-grade commercial optimization solvers, and ensures the optimal solution with a high degree of reliability and hence fully replicable.

The stochastic optimization framework adopted for the analysis is generic and can consider any type of outages and related hardening measures. The use cases consider storm related outages and diesel generators as a back-up because these are shown as a dominant source of risk and hardening

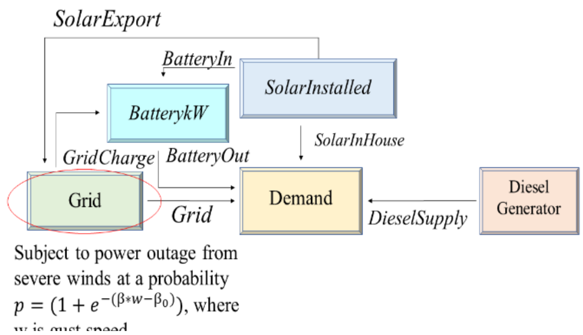

FIGURE 2. **Model schematic.**

option for most parts of US, including Florida [33] which is our key focus.

The model selects a discrete PV size and decides whether to install a back-up generation option. It makes second stage hourly/sub-hourly decisions to meet demand including critical load. Electricity supply options for the household include energy from grid, solar panels, BESS, or diesel generators, subject to the uncertainties on solar availability, which we represent using different historic solar profiles [26], as well as grid supply failures [33]. The household can also sell energy to the grid when it is profitable to do so (following the applicable net metering and other regulations). If (non-critical) demand cannot be met using all of these options, load will be shed and penalized at a predetermined cost of unserved energy. We adopt the reduction in expected unserved energy arising from storms as a measure of system resilience.

Solar PV decisions are driven by policy parameters which include tax incentives for PVs, and net metering (or similar) limits prevailing in most states. A schematic overview of the model with variable names is provided in Figure 2 and shows how the demand in the household is met by different sources.

The model considers uncertainties around availability of solar power as well as grid supply failures. It is cast as a stochastic programming problem with multiple solar profiles for the former, and a Monte Carlo process for the latter. The Monte Carlo framework adopted in the present model is generic and can work with any probability distribution with additional weather or other sources for supply failures. The model uses representative days. We have, for instance, used three representative days for our illustrative case studies discussed in a subsequent section that correspond to a "Normal", "unusually sunny (Sunny)", and "unusually stormy (Stormy)" days. The precise number of representative days depends on the load characteristics and can be determined using a proper clustering technique as has been discussed in [35]. Data for wind speeds and solar irradiance are taken from NASA's climate reanalysis model, MERRA-2 [36]. As Figure 2 depicts, the probability of grid power loss can be approximated as a nonlinear function of wind gust. Duque et al [33] has estimated the coefficients as: $\beta = 0.0889$ and $\beta_0 = -6.388$ which we have adopted for our case studies. Duque et al [33] have also considered a number of other explanatory variables to power losses including flooding and concluded that gust speed is the only significant one, albeit it is quite possible that power outages in other jurisdictions may require additional considerations [3]. We have represented unusually stormy day power outage probabilities as shown in Figure 1. The optimization model embeds a Monte Carlo simulation containing a large number of samples to represent the effects of power outages on BESS/diesel generator sizing decisions. Each sample represents a "contingency" event of grid supply failure for one or more hours. The model chooses remedial/recourse measures to cover for the contingency, e.g., BESS discharge or diesel generation, which in turn determines investment decisions in (additional) BESS or installation of diesel generator. Decision variables associated with the contingencies are denoted with a superscript (*) for each contingency state/sample. The precise number of samples depends on the number of representative days and other options included in the model. In our experiments we varied the number from 100 to 1000 with relatively small impact on the level of accuracy beyond the first 100 samples.

B. OPTIMIZATION MODEL

The objective function for the model defines cost of the household's electricity as Cost. The total electricity supply cost for the household comprises:

a. The annualized capital cost of PV and BESS;
b. The annualized capital cost of the diesel generator;
c. Cost of diesel generation;
d. Cost of energy from the grid; and
e. Penalties associated with load shed and rejected solar energy.

These costs are included in the objective function of the model, which is defined in Equation (1).

$$
\begin{aligned}
&Cost \\
&= SolarInstalled * PanelCost * TaxDiscount + BatterykW \\
&\quad * BatteryCost + DGSelected * DGCost \\
&\quad + \sum_{y,m,sun,t} Weight_{sun}\big(\big(Grid_{y,m,sun,t} + GridCharge_{y,m,sun,t}\big) \\
&\quad * GridCost - SolarExport_{y,m,sun,t} * BuyBackRate \\
&\quad + SolarReject_{y,m,sun,t} * \boldsymbol{\varepsilon}\big) + \sum_{y,m,storm,t,s} Weight_{storm} \\
&\quad \times \Big(\Big(Grid^{*}_{y,m,storm,t,s} + GridCharge^{*}{}_{y,m,storm,t,s}\Big) \\
&\quad * GridCost - SolarExport^{*}{}_{y,m,storm,t,s} \\
&\quad * BuyBackRate + SolarReject^{*}_{y,m,storm,t,s} * \boldsymbol{\varepsilon} \\
&\quad + DieselSupply_{y,m,storm,t,s} * HourlyDGCost \\
&\quad + LoadShed_{y,m,storm,t,s} * LSPenalty\Big) / S \qquad (1)
\end{aligned}
$$

In order to introduce storm-driven power outages to the model, the following equation is used based on Duque *et al.* [33] to relate hourly windspeeds to the probability of a grid failure:

$$p_t = (1 + e^{-(0.0889 w_t - 6.388)}) \tag{2}$$

These probabilities are used in another equation which decides whether grid supply is ($\theta_{s,t} = 0$) or not ($\theta_{s,t} = 1$) available to the household:

$$\theta_{s,t} = \begin{cases} 1, & \theta_{1s,t} \leq p_t \\ 0, & \theta_{1s,t} > p_t \end{cases} \tag{3}$$

Equation (4) defines how total supply from grid, solar panels and BESS, meets the hourly demand for day-types when there are no power outages. It should be noted that this equation integrates the round-trip BESS efficiency by scaling down the output of BESS:

$$\begin{aligned} &SolarInHouse_{y,m,sun,t} + Grid_{y,m,sun,t} \\ &\quad + BatteryOut_{y,m,sun,t} * BatteryEfficiency \\ &= Demand_{y,m,sun,t} \end{aligned} \tag{4}$$

This equation is modified for the Stormy day-type. It is defined over each of the samples and includes important details:

a. Energy from the grid is only accessible when $\theta_{s,t} = 0$;
b. Load can additionally be met by the diesel generator; and
c. Hourly demand that cannot be met through any of the available provisions can be shed.

The modified equation is defined as follows:

$$\begin{aligned} &SolarInHouse^*_{y,m,storm,t,s} + (1 - \theta_{s,t}) Grid^*_{y,m,storm,t,s} \\ &\quad + BatteryOut^*_{y,m,storm,t,s} * BatteryEfficiency \\ &\quad + DieselSupply_{y,m,storm,t,s} + LoadShed_{y,m,storm,t,s} \\ &= Demand^*_{y,m,storm,t,s} \end{aligned} \tag{5}$$

The duals, or shadow prices, associated with equations (4) and (5) represent the marginal cost of supply to the household for Normal/Sunny and Stormy days, respectively. For example, the shadow prices for storm related contingencies associated with equation (5) are as follows:

$$\lambda_{y,m,d,t,s} = \partial(Cost)/\partial(Demand_{y,m,d,t,s}) \tag{6}$$

The household can only access energy from a M-kW diesel generator if it has been selected:

$$DieselSupply_{y,m,storm,t,s} \leq M * DGSelected \tag{7}$$

Solar energy production is limited by solar resource as well as the size of the system installed. It should be noted the model does not account for changes in PV efficiency due to changes in solar insolation level and cell temperature. Although these can be incorporated into the model, we have chosen to keep the model computationally tractable by assuming a constant average panel efficiency as is typical of most planning studies:

$$\begin{aligned} Solar_{y,m,sun,t} \leq AvailableSolar_{y,m,sun,t} * SolarInstalled \\ * SolarEfficiency \end{aligned} \tag{8}$$

This equation is also modified for the Stormy day-type and defined over each of the samples:

$$\begin{aligned} Solar^*_{y,m,storm,t,s} \leq AvailableSolar_{y,m,storm,t} * SolarInstalled \\ * SolarEfficiency \end{aligned} \tag{9}$$

The energy generated by the solar panels can then be either:

a. Used in the household to meet the hourly demand,
b. Sent into the BESS for later use,
c. Sold to the grid, or
d. Be rejected.

This is reflected in the following equation:

$$\begin{aligned} &SolarExport_{y,m,sun,t} + BatteryIn_{y,m,sun,t} \\ &\quad + SolarReject_{y,m,sun,t} + SolarInHouse_{y,m,sun,t} \\ &= Solar_{y,m,sun,t} \end{aligned} \tag{10}$$

This equation is defined over each of the samples for the Stormy day-type:

$$\begin{aligned} &SolarExport^*_{y,m,storm,t,s} + BatteryIn^*_{y,m,storm,t,s} \\ &\quad + SolarReject^*_{y,m,storm,t,s} + SolarInHouse^*_{y,m,storm,t,s} \\ &= Solar^*_{y,m,storm,t,s} \end{aligned} \tag{11}$$

In order to reflect the net-metering policy in the state, the following equation is defined to restrict the amount of energy that can be exported to the grid. The model stipulates that the quantity of solar energy exported cannot exceed the quantity of energy used in-house:

$$\sum_{m,sun,t} SolarExport_{y,m,sun,t} \leq \sum_{m,sun,t} SolarInHouse_{y,m,sun,t} \tag{12}$$

This equation is defined once more over each of the samples for the Stormy day-type:

$$\begin{aligned} &\sum_{m,storm,t,s} SolarExport^*_{y,m,storm,t,s} \\ &\qquad \leq \sum_{m,storm,t,s} SolarInHouse^*_{y,m,storm,t,s} \end{aligned} \tag{13}$$

The following equation defines the energy balance for the BESS for the first hour of the day, namely, the battery can be charged through the PV systems or through the grid.

$$\begin{aligned} &BatteryLevel_{y,m,sun,t=1} \\ &\quad = BatteryIn_{y,m,sun,t} - BatteryOut_{y,m,sun,t} \\ &\qquad + GridCharge_{y,m,sun.t} \end{aligned} \tag{14}$$

This equation is defined over each of the samples for the Stormy day-type and includes an additional change: the household starts the Stormy day-type with a fully charged battery. This is because households can be expected to prepare for disastrous storms ahead of time based on weather forecast.

$$\begin{aligned} &BatteryLevel^*_{y,m,storm,t,s} \\ &\quad = BatteryIn^*_{y,m,storm,t} - BatteryOut^*_{y,m,storm,t,s} \\ &\qquad + GridCharge^*_{y,m,storm.t,s} + BatterykW \in t = 1 \end{aligned} \tag{15}$$

The following equation defines the energy balance of the BESS for all other hours of the day:

$$\begin{aligned} &BatteryLevel_{y,m,sun,t} \\ &\quad = BatteryLevel_{y,m,sun,t-1} + BatteryIn_{y,m,sun,t} \\ &\qquad - BatteryOut_{y,m,sun,t} + GridCharge_{y,m,sun.t} \quad \forall t \neq 1 \end{aligned} \tag{16}$$

For the Stormy day-type, this equation is defined over each of the samples:

$$\begin{aligned} &BatteryLevel^{*}_{y,m,storm,t>1,s} \\ &\quad = BatteryLevel^{*}_{y,m,storm,t-1,s} + BatteryIn^{*}_{y,m,storm,t,s} \\ &\qquad - BatteryOut^{*}_{y,m,storm,t,s} + GridCharge^{*}_{y,m,storm.t,s} \end{aligned} \tag{17}$$

The charge and discharge rates for the battery are predefined and incorporated as follows:

$$BatteryIn_{y,m,sun,t} \leq BatterykW * ChargeRate \tag{18}$$
$$BatteryOut_{y,m,sun,t} \leq BatterykW * DischargeRate \tag{19}$$
$$BatteryIn^{*}_{y,m,storm,t,s} \leq BatterykW * ChargeRate \tag{20}$$
$$BatteryOut^{*}_{y,m,storm,t,s} \leq BatterykW * DischargeRate \tag{21}$$

The model is implemented using GAMS (General Algebraic Modeling System [38]) and solved using the CPLEX Barrier algorithm. The stochastic version of the model for 1000 Monte Carlo samples, 3 solar resource profiles, and 3 representative days contains 0.8 million variables, 0.6 million constraints, and 2.3 million non-zeroes. It solves in roughly 45 seconds on an i7-9750H (ninth generation) processor with 32 GB RAM.

IV. CASE STUDY RESULTS

This section presents findings for two illustrative cases for: (a) Bethesda, MD which typically exhibits relatively low storm related outage risks, and (b) Miami, FL which has almost five times as many hours of outages. Both cases use the same smart meter load and solar irradiance data (i.e., identical solar profile[1]) to maintain comparability across these two cases in terms of the hardening decisions. In other words, the probability of storm related outage is the key parameter that is different across the two locations so that we can directly compare the resilience measures across these. For Bethesda, the probability estimates suggest an annual outage duration of 8 hours. This is very similar to the average outage for households across the United States [2]. Annual outage duration in Miami is estimated at 38 hours which also aligns well the average outage duration in the state of Florida [2].

The model is set up for a single year in hourly resolution for three representative days. The model uses a total installed cost of \$3000/kW for a PV system, and \$300/kWh for fully installed BESS. We assume a 10 kW diesel generator (commensurate with the 9.94 kW peak demand for the household) that has an up-front cost of \$5000 [37] (or \$515 pa for a 10 kW generator in annualized cost). Solar PV costs represent commercial quotes [26] and battery costs are based on the NREL projections [38]. These investment costs are annualized assuming a 10-year lifespan for BESS and 25-year life for solar PV and diesel generator.

The solar PV capacity factors for Normal, Sunny and Stormy day-types are 18%, 25%, and 10%, respectively. We have considered two additional solar profiles: a high capacity factor resource profile wherein the capacity factor for all day types is 20% higher, and a low capacity factor resource profile wherein the capacity factor for all day-types is 20% lower. These additional profiles are considered in subsection D only – all other cases in subsections A-C use the average solar resource profile only.

Energy from the grid is assumed at a flat tariff of 15.65 c/kWh. A high penalty of \$20/kWh that represents the high end of the estimate by LBNL [39] is imposed on any unserved energy. 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 three for Bethesda, and four for Miami, although the gust speed and hence probability of outage is much higher for the latter.

We first present the results for five key scenarios for each location, namely:

(a) **No Power Outage** scenario that represents the *status quo,* wherein outage risks are ignored in making decisions on PV/BESS;
(b) **Base Case** wherein these storm related outage risks and all available mitigation options (PV, BESS and diesel) are considered;
(c) **No Resilience Consideration**, which essentially takes the decision from the No Power Outage scenario, does not consider *any* mitigation option but then imposes the outages to assess the impact of a naïve non-resilient solution;
(d) **No BESS** that repeats the Base Case but drops BESS from the set of options; and
(e) **No Solar or BESS** which also drops solar from the set of options, leaving diesel as the only source of energy in an outage.

A. CASE STUDY 1: BETHESDA

Key findings for the Bethesda case study are summarized in Table 1 and discussed below.

1. The "No Power Outage" scenario serves as a reference for both the cost and PV/BESS/diesel sizing decisions. The model chooses to install a 4 kW PV system, and no BESS or diesel generator, purely on economic ground. The electricity supply cost to the household including the annualized cost of solar PV, is \$1955, which is the lowest

[1]There is relatively low difference in solar irradiance across the two locations in any case. A comparison of solar irradiance data between Miami and Bethesda shows that the mean capacity factor varies by only 0.4% [36].

TABLE 1. **Comparison of scenarios: Bethesda.**

	Exp. Annual Cost ($)	PV (kW)	BESS (kWh)	Diesel Gen (kWh)	Load shed (kWh)
No power outage	1955.2	4	0	0	0
Base Case	2034.2	5	1.4	0	0.54
No resilience consideration	2115.2	4	0	0	2.69*
No BESS	2471.0	4	0	2.69	0
No solar or BESS	2587.4	0	0	3.59	0

* *The model could not meet the critical demand for this scenario.*

among all cases. The results for this case were obtained by neglecting power outages and these are representative of the vast majority of the current models [17]–[26] including commercial tools that ignore resilience issues. Although the models in the literature optimize PV (and BESS in some cases such as [18], [26]), they do not consider grid supply outages that are left to be covered with more expensive solutions like fossil fuel based generation. A naïve least-cost solution such as this one saves some investments in PV/BESS, but the true cost incorporating that of unserved energy due to outages, can outweigh these investment costs, as we see in the 'No Resilience Consideration' scenario;

2. The "Base Case" shows the model's results when no restrictions are placed on PV or BESS installations and power outage are considered. The PV size increases to 5 kW PV system and 1.4 kWh of BESS is also included in the optimal mix. Put differently, the extra kW of PV and 1.4 kWh of BESS are added purely from a resilience perspective. The additional total investment cost of $3,420 ($3,000 for 1 kW of PV and $420 towards 1.4 kWh of BESS) may seem substantial. The solution however does not include installation of a diesel generator which would have cost $5000. Additional investment in PV/BESS is warranted to prevent unserved energy due to storm related outages. As the Puerto Rico study [27] discussed, such investments are not only economic from a household point of view (over diesel) but may also obviate the need to harden the distribution system. Expected unserved energy is 0.544 kWh which is deemed to be economic despite a high ($20/kWh) cost of unserved energy imposed. Investments in infrastructure to guard against very low probability events can be very expensive – an issue that has been noted in the literature including [27], [29], [31], [33] and we revisit this point in a later sub-section;
3. The "No Resilience Consideration" case uses the "No Power Outage" investments i.e., 4 kW of PV and no BESS, and as a result has much higher expected unserved energy of 2.69 kWh. As some of the earlier studies – notably [18] and [26] – have also observed, justification for BESS given its high cost is difficult, but miss the point that they can be useful to cover for grid supply failures. System costs including costs of outages in this case is higher than the Base Case that demonstrates some investment in resilience is beneficial even for areas that are not at major risk of storm related outages;
4. The "No BESS" case prohibits the model from installing BESS. To supply the household with energy during outages, the model installs a diesel generator which eliminates the unserved energy, however the annual cost for the household jumps by $436 or 21% relative to the Base Case. The model installs only 4 kW of PV in this case. This scenario also demonstrates that solar PV alone does not contribute significantly to resilience in this case and cannot obviate the investment in back-up generation; and
5. The "No solar or BESS" scenario prohibits the installation of both PV and BESS. The diesel generator installed in this case supplies the household 3.59 kWh of energy during the outages. System cost goes up further by $553 or 27%, relative to the Base Case. The cost impact is higher than the 'No BESS' case which shows the contribution solar PV makes both in terms of economic supply and displacing a small number of units of diesel generation during power outages;

The difference between the costs in the "No Power Outage" and the "Base Case" scenarios indicates that the additional sizing recommendations are not significantly expensive. It adds only $78.94 or 4% to annual cost.

The value of PV and BESS is further demonstrated in Figure 3, which shows how these two resources are used on the Stormy day for each of the 1000 samples for the Base Case. Daily contribution of PV and BESS in terms of kWh during power outage are added and the values are sorted according to the daily discharge from the BESS. It is clear that BESS can complement solar well during major outage events. Following the terminology used by Panteli *et al.* [28], a combination of PV and BESS can add resilience during Phase I

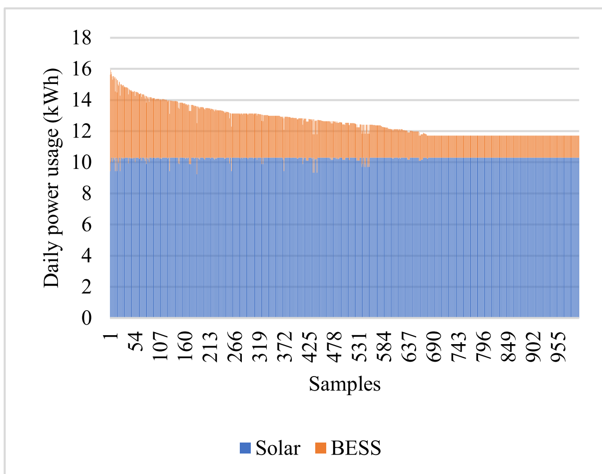

FIGURE 3. **Daily usage from PV and BESS across 1000 samples for the Stormy day during power outage: Bethesda "Base Case".**

(Disturbance Progress) as well as Phase II (Post Disturbance Degraded State). BESS performs multiple cycles during the day with the battery charged by PV and for intermittent periods when power supply is restored. There may be some outages that cannot be served by PV and BESS, depending on the level of capacity installed. However, the model does not select a diesel generator because the probability of such an event is very low and the investments needed for it are not economic.

Figure 4 further shows an average hourly profile for the Stormy day across all 1000 samples for the Base Case. It should be noted that when the grid is unavailable, solar energy alone provides the household's energy, although its availability on the Stormy day is limited. BESS supplements the grid later in the day when solar energy is not available. The role of BESS and hence additional investments in BESS become more critical if the solar resource quality drops. The operational analysis conducted by Yan *et al.* [34] also showed that if the actual solar availability differs significantly, BESS state of charge will vary greatly through rapid discharge. This is a consideration that will need to be built in sizing of the BESS.

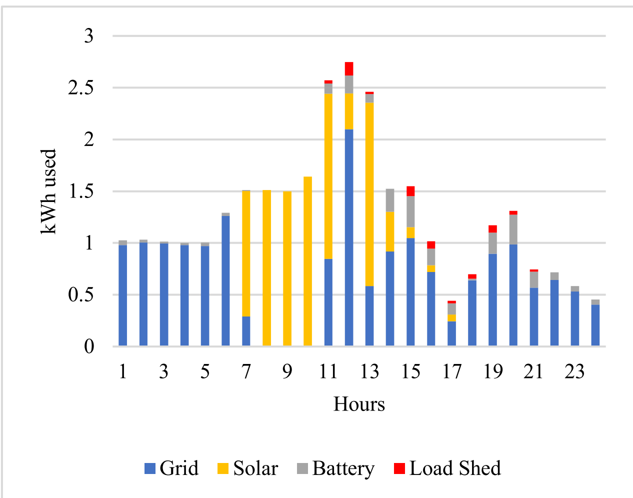

FIGURE 4. Energy balance (averaged across all samples) during Stormy day: Bethesda "Base Case."

B. CASE STUDY 2: MIAMI

The Miami case study shows how the investment and operational decisions change when the frequency and duration of the power outages are significantly increased. The load profile is unchanged from the Bethesda case study for the results to be comparable including the identical reference 'No Power Outage' scenario.

Table 2 shows the model's results for the remaining four scenarios:

1. The "Base Case" still installs 5 kW of PV but BESS level increases significantly to 4.2 kWh. There is therefore a greater need for hardening relative to Bethesda driven by significantly higher risk of outages, and hence the annual electricity cost for the household goes up. There is however no diesel generator selected albeit the expected unserved energy rises to 0.85 kWh. The expected unserved energy is below 1% of the total demand for the Stormy day, and a tiny fraction of the annual demand which does not warrant additional investments in BESS let alone diesel. This is a significant finding because diesel remains the mainstay for back-up power in the state of Florida [33] and US in general [37];
2. The "No Resilience Consideration" case shows a sharp increase in annual costs (including the cost of expected unserved energy) demonstrating a naïve plan that does not consider resilience will prove very expensive in Miami. In fact, the critical load cannot be met in many of the contingencies;
3. The "No BESS" scenario is almost identical to that for Bethesda which installs 4 kW of PV and the diesel generator. This is a more expensive hardening measure compared to the Base Case but avoids 100% of the outages. We again see that solar on its own is less effective and the combination of PV and BESS is critical for it to be a potent measure for resilience; and
4. The "No solar or BESS" scenario is also quite similar which relies entirely on the diesel generator to supply power to the household and as a result diesel generation goes up from 9.91 kWh to 13.6 kWh. Annual cost for the household goes up further by $117 mainly because lower cost solar PV generation is not available.

TABLE 2. Comparison of scenarios: Miami.

	Exp. Annual Cost ($)	PV (kW)	BESS (kWh)	Diesel Gen (kWh)	Load shed (kWh)
Base Case	2162.9	5	4.2	0	0.853
No resilience consideration	**2742.7**	4	0	0	9.91*
No BESS	2474.7	4	0	9.91	0
No solar or BESS	2591.3	0	0	13.6	0

* *The model could not meet the critical demand for this scenario.*

The Miami Base Case finds that the model responds primarily by increasing the BESS capacity to meet demand during outages. This comes at an annual cost $207.70 higher than the "No Power Outage" scenario. This additional investment in BESS allows the model to restrict unserved energy to 0.853 kWh during the outages. The additional total investment for Miami is $4,260 (1 additional kW of PV and 4.2 kWh of BESS). This is a significant investment for a household but still cheaper than buying, operating and maintaining a diesel genset. The additional PV and BESS also lower requirement to buy from the grid for vast majority of normal days, and therefore offer additional benefits that partly offset the investment.

The "No BESS" and "No Solar or BESS" cases in Bethesda and Miami end up being quite similar, and both are significantly more expensive than the optimal solution in the Base Case. As Figure 5 (Base Case) demonstrates, BESS plays a significant role in meeting demand during evening in the contingencies when the storm related outage probabilities are high. These cases indicate that BESS is essential to the mix for it to complement PV during Normal and Sunny days *and* add resilience for the Stormy day. Compared to the Base Case, the "No BESS" case costs an additional \$311.80, which is a significant benefit relative to its (annualized) cost.

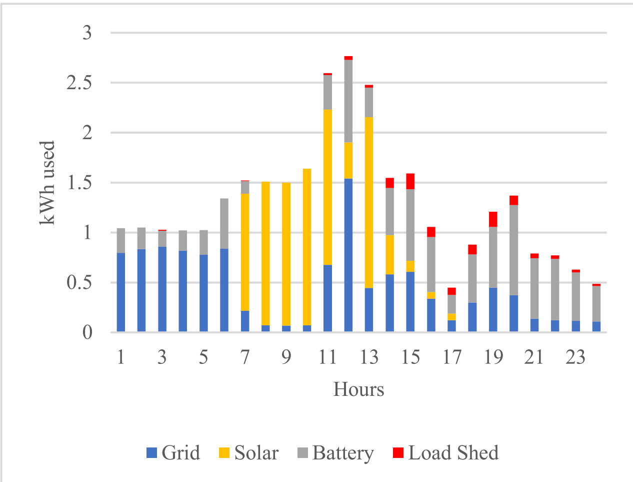

FIGURE 5. **Energy balance (averaged across all samples) during Stormy day: Miami "Base Case."**

C. COMPARISON OF CASE STUDIES

It is useful to compare the annual cost increase relative to the "No Power Outage" case for Bethesda and Miami for all four scenarios (Figure 6). This is essentially the (annualized) cost a customer pays to build resilience.

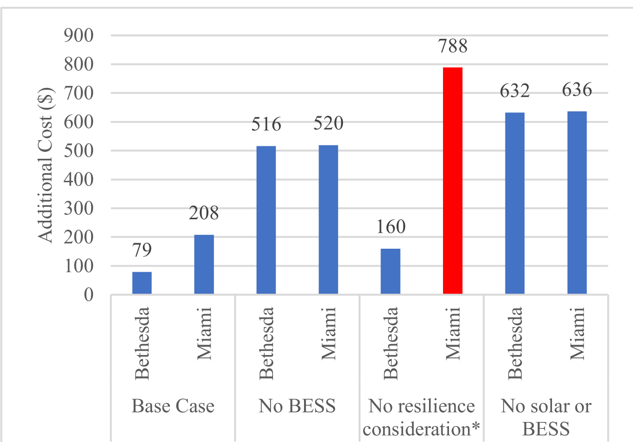

FIGURE 6. **Cost to build resilience: annual electricity cost increase relative to "No Power Outage" scenario - Bethesda vs Miami. ****The model could not meet the critical demand for this scenario.***

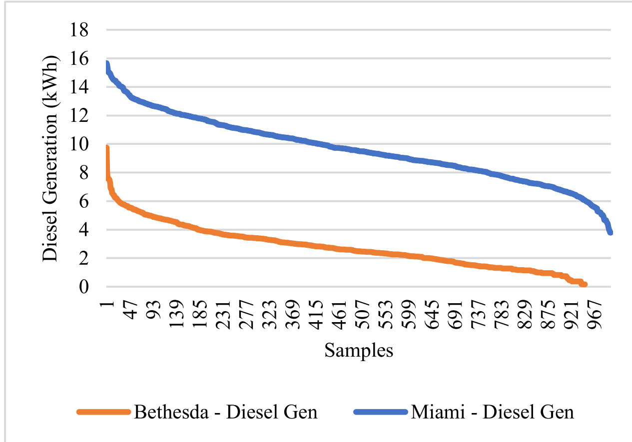

FIGURE 7. **Cumulative distributions of diesel generation: "No BESS."**

As Figure 6 shows:

- A typical household in a low storm-risk zone (i.e., Bethesda) will see only \$79 increase in annual costs, compared to \$208 in Miami. The difference is mostly due to the additional investment needed in BESS in Miami;
- However, the benefit of the added investment for Miami is much greater at \$788 compared to \$160 in Bethesda when we look at the "No Resilience Consideration" scenario. The incremental investments in BESS (and PV) for hardening are indeed justified in both cases, but the benefit to cost ratio for Miami, i.e., 788/208 or 3.78, is almost double that for Bethesda, i.e., 160/78 or 2.05. In other words, while hardening requirements may be greater in areas that are more susceptible to outages, the associated benefits may also be disproportionately high;
- Absent BESS, both households would need a diesel generator. Since the expected unserved energy is typically a small fraction of the overall demand even in Miami, the recourse operational costs for extra diesel generation is small compared to the investments needed in the generator. The "No BESS" scenario cost impact therefore ends up being similar in both cases, differentiated by only \$2 towards the extra diesel generation cost in Miami. It should be noted that the additional investment in diesel is *not* justified in Bethesda but for the coverage of critical load (which is treated as a hard constraint in the model). This has significant ramification for the implied levelized cost of diesel being extremely high for Bethesda; and
- Similarly, the "No Solar or BESS" scenario also renders the two households with similar costs. As noted before, these costs are higher compared to the "No BESS" scenario because cheaper solar PV generation is dropped from the supply mix.

Figure 7 for the "No BESS" scenario provides additional insights into the nature of the contingencies for which the diesel generation across the samples is a good proxy. As the cumulative distribution of diesel generation across 1000 samples show, Miami consistently has higher diesel generation across the whole range including a minimum of 4 kWh.

Figure 8 highlights the implied levelized cost of diesel generation which is extremely high for Bethesda at an average of \$96.52/kWh. In fact, in some of the samples with very low diesel generation, these costs approach an astronomical \$1000/kWh. It underlines how unprofitable investment in diesel generation can be. It adds over \$500 to the annual cost but it is rarely used making it a very expensive insurance. The levelized costs for Miami in comparison are far lower than that for Bethesda, but they also range from \$8.3/kWh at the lowest end to \$27.5/kWh at the highest end, making it a very expensive resource.

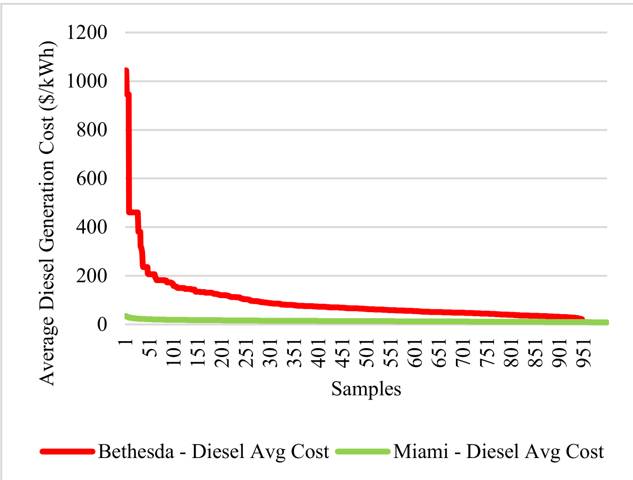

FIGURE 8. **Cumulative distributions of average diesel generation cost: "No BESS."**

Although the findings of the two case studies presented are to some extent tied to the storm probabilities for the two locations as well as the household load characteristics, some of the conclusions can be generalized, namely:

- The role played by BESS in adding resilience is critical. Absent a consideration of resilience benefits, BESS is still relatively expensive and often do not form part of optimal supply mix. Benefits associated with avoided expected unserved energy not only due to storm, but also an unreliable grid in general, can be critical for it to be part of the optimal portfolio;
- Regions where the storm probability and intensity are high – as is the case for Miami – BESS has a more significant role to play;
- The combination of PV and BESS is important as these two resources tend to complement each other. While PV alone cannot fulfil the role, BESS also benefits from a cheaper source of generation. As our previous analysis [26] has demonstrated, a drop in PV cost helps to make a stronger case for BESS. If resilience benefits are considered, this complementarity would become even stronger going forward; and
- The combination of rooftop PV and BESS even at their relatively high cost in the US seems to push diesel out of the mix and even in high risk areas like Miami. This is a very significant finding. It holds great promise for developing countries where the grid is less reliable and the cost of solar is lower in places like India. Clean distributed energy resources have significant potential to displace diesel as a back-up resource.

TABLE 3. **Varying solar resource profiles: base case.**

	All Solar Profiles		Low Solar Profile	
	Bethesda	Miami	Bethesda	Miami
Cost (\$)	2043.0	2175.2	2188.6	2370.0
PV (kW)	5	5	0	2
BESS (kWh)	1.4	4.2	1.7	5.0
Load shed (kWh)	0.5	0.9	0.9	1.0

Note: Diesel generator was not selected for any of these scenarios.

D. ANALYSIS OF SOLAR PROFILES AND PRICING

Finally, we turn to a discussion on another source of uncertainty, namely, variability in solar profiles that is shown to have a significant impact on selection of solar [26], [35] as well as BESS. In order to illustrate this issue, we have added two additional scenarios (Table 3):

1. "All Solar Profiles": a high solar profile as well as a low profile are added to the model, i.e., we consider the average profile together with a profile 20% lower than the average as well as a profile 20% higher than the average in a single model; and
2. "Low Solar Profile": in which we consider only the Low solar profile that will typically lead to a lower selection of solar PV. This scenario also acts as a stress test for solar PV/BESS selection for resilience purposes.

As Table 3 shows, addition of solar profiles has almost no impact on the PV/BESS selection. On the other hand, if we were to rely on a Low Solar Profile only, Bethesda would see no solar PV at all in the mix and Miami would also consider only 2 kW instead of 5 kW of solar PV. BESS volume, however, increases for both locations as there is less contribution from PV during contingency events. There is also a slight increase in the expected unserved energy level, albeit no diesel generator is selected in either location. This analysis highlights the need to carefully select the solar profile. Ideally, a broad range of profiles should be selected for the investment decisions to be fully informed about the inter-annual variability, rather than restricting the choice to a specific low or high solar year. As [26] notes, variability of solar is not considered in the commercially available tools in any shape or form. This is particularly important for selection of PV as well as BESS for resilience considerations. PV and

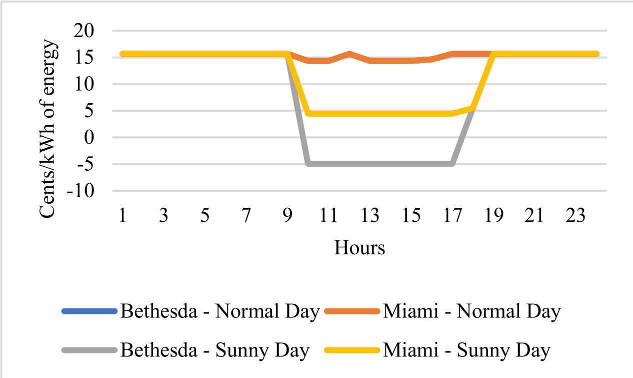

FIGURE 9. Marginal cost of energy as it varies through the Sunny and Normal days in Bethesda and Miami – All Solar Profiles (Base Case).

BESS selections are intricately linked and as the analysis above demonstrates – relying on a single solar profile can lead to quite distorted and sub-optimal outcomes.

Duals (or marginal costs) associated with the demand-supply balance constraint in the model (Equations 4 and 5) provides interesting insights into how the underlying grid/PV/BESS resources are used and the impact of the net metering policy. Prices differ significantly across the day types. Figure 9 shows prices for Normal and Sunny days for the All Solar Profiles scenario (Base Case that allows PV and BESS to be selected).

Normal day spot prices coincide for both locations at the grid supply cost of 15.65 c/kWh, or just marginally below it at 14.33 c/kWh which is the tariff obtained under the net metering policy. The latter prices occur when there is surplus solar that can be sold back to the grid *and* the restriction on solar export (Equations 10 and 11) imposed by the net metering policy can be met by charging the BESS with surplus solar. In other words, every kWh of solar fed back to the grid may require a unit to be consumed in-house or stored on the battery for later use at home. A marginal cost of 14.33 c/kWh occurs when this condition is met.

On the Sunny day, however, solar surplus amount is high and we see the marginal costs dropping to 4.33 c/kWh for Miami and even negative [(-)4.93] c/kWh for Bethesda during the day time hours. The household in Miami installs higher level of BESS and as such has more ability to store energy to lower the impact on marginal cost. These low-price events essentially reflect that there is excess solar, especially associated with the High solar profile, that cannot be consumed in-house or be stored. If the household demand increases during these hours, it would cost only 4.33 c/kWh in Miami and would even *reduce* household electricity cost by 4.93 c/kWh in Bethesda. A reduction in cost may occur because every unit of solar consumed in-house also allows the household to earn extra revenue from selling solar power back to the grid. This is equivalent to the negative price phenomena observed in wholesale electricity markets and holds interesting implications for household level pricing to shape distributed PV/BESS investment decisions.

Figure 10 shows marginal costs or duals associated with the demand-supply balance for the Stormy day (Equation 5).

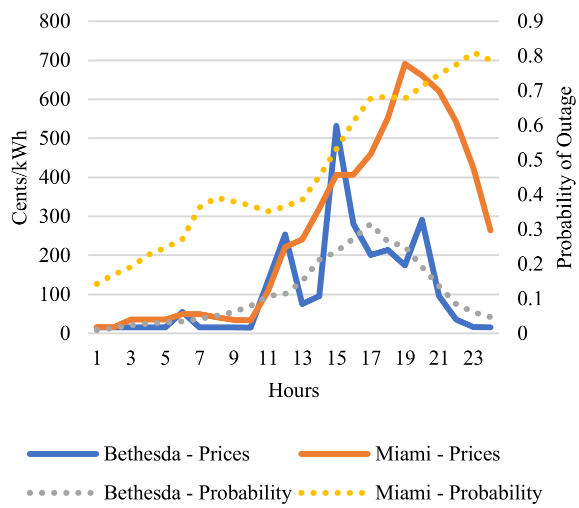

FIGURE 10. Marginal cost of supply for the Stormy day in Bethesda and Miami as it varies with the probability of power outage - Base Case.

These prices are an order of magnitude higher than that for the Normal day and are in several dollars per kWh. These contingency prices are associated with outages and reflect additional BESS/PV investments that are needed to cover for such events during high demand periods. For instance, a combination of high demand (1.52 kW) and significant probability of outage occurs at 2 PM that shows the expected contingency price for this hour (i.e., average across all 1000 samples) to peak at \$5.31/kWh. Similarly, Miami has a high probability and demand combination that occurs at 7 PM that leads to a stronger price peak of \$6.90/kWh. These prices are high because the incremental investment needed for hardening is ultimately associated with few extreme events. For instance, if 1 kWh of additional BESS that costs \$34 pa (in annualized terms) is needed to cover for 4-8 hours of outage events in a year, the levelized cost of this investment would be in the range of \$4.2-8.5/kWh. It should be noted however that the prices in Figure 10 are still significantly lower than that for a diesel option that range from \$8.3-27.5/kWh for Miami.

Figure 11 shows the daily average prices for Miami for the "All Solar Profile (Base Case)" for individual samples. It reveals that for approximately half of the samples (of Stormy day), daily average prices are low at 16.5 c/kWh which is the BESS efficiency-adjusted grid supply cost. However, the other half of samples exhibits very high prices rising up to \$12.55/kWh.

In addition to the physical investment decisions that the model produces, the marginal cost information elicited from the model can also be a useful guide for devising innovative pricing schemes for customers to adopt the right mix and level of investments needed. As the penetration of rooftop PV with BESS increases over the coming years throughout the world, consumers and utilities both would need to consider such

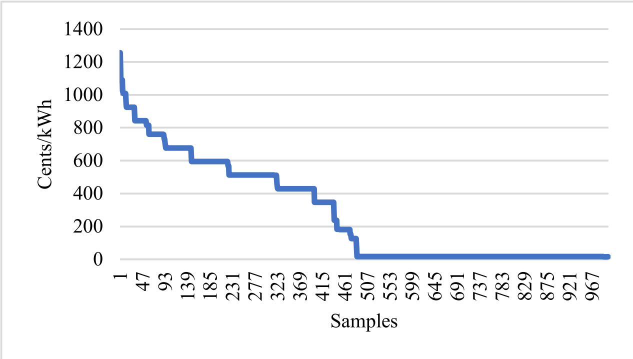

FIGURE 11. Cumulative distribution of marginal supply costs for all 1000 samples in Miami– Base Case.

innovative pricing schemes to make the right sizing decisions and buy/sell power from/to the grid. These prices may also be useful comparators to decide if hardening should be done at an individual customer level or at a greater scale at the grid level. While spot prices may need to increase considerably in high-risk areas to justify investments in additional PV/BESS – the alternative to harden the entire distribution system may well prove to be even more expensive as the discussion for Puerto Rico [27] suggests.

V. CONCLUDING REMARKS

The rapidly falling costs of PV and BESS provide sufficient motivation to study their applications in households including their competitiveness against fossil fuel-based back-up generation for adding resilience. Absent such considerations, behind-the-meter residential BESS are still relatively expensive [18], [26] compared to other applications [40]. System-level hardening strategies to address power system resilience are well documented and there is a rich and growing literature on the topic. However, there is relatively less coverage of customer-level resilience outside of traditional fossil fuel generators [33], [37]. The proposed model attempts to fill this gap in the existing literature and uses a stochastic programming methodology that explicitly captures resilience issues as well as variability in solar PV output that in turn determines the sizing of PV as well as BESS. We present an analysis on how storm-related grid supply failures can be minimized through an optimized mix of BESS/PV. The modeling framework also provides a way to compare and contrast PV/BESS options with more conventional options such as diesel generators in terms of costs as well as resilience of the household against weather driven outages.

These issues have been explored through a series of case studies for two locations with varying frequency and duration of storm related outages. We have extended this analysis further by observing the effect of solar resource profile variations, i.e., inter-annual variability, on PV/BESS sizing decisions. The shadow prices of a household level supply model are also studied as these can provide insights into the variability of marginal cost of supply that are useful in shaping tariff structure and incremental costs for hardening infrastructure at the household level.

We illustrate these key findings through an application of the model for two case studies in Bethesda (Maryland) that has relatively low risk exposure to storms, and Miami (Florida) that has much a greater exposure to storms and hurricanes. Our analysis shows that:

- Changes in storm risk exposure can have significant impacts on sizing decisions, but PV/BESS in both Bethesda and Miami remain the least-cost solution for resilience and 20%-27% cheaper than a diesel-based solution;
- In fact, if PV/BESS options are eliminated to force a diesel based solution in a low-risk area like Bethesda, the imputed cost of diesel generation works out on average at $96.52/kWh making it an *extremely* expensive resource that should be avoided;
- Additional volume of PV and BESS are needed exclusively for resilience purposes. Specifically, additional BESS volume needed for a high-risk area like Miami is three times that of Bethesda, albeit it still is significantly cheaper than diesel;
- Additional PV and BESS for resilience can add $79 to the expected annual electricity supply cost for Bethesda, compared to $208 in Miami. This is, however, important because absent these additional investments, critical load cannot be met even in Bethesda that has low risk exposure representative of an average US household; and
- Finally, the peak marginal cost of supply associated with storm related contingencies can be very high, e.g., $5.31/kWh for Bethesda and $6.90/kWh for Miami at their peak when high demand and high storm risk conditions coincide. This is inevitable because the expected unserved energy even for a high-risk area like Miami is relatively small for which the incremental investments need to be recovered. These prices can be useful in comparing measures for system level vis-à-vis customer end resilience.

These findings support the need for a stochastic optimization framework to integrate resilience considerations. These also demonstrate how PV and BESS can already be a more economic solution than diesel. As we have noted at the outset, the analytical construct adopted here can be extended and generalized to cover other sources of risk and additional geographies. The scope of analysis can also extend beyond households to include mini-grids and systemwide analyses. The proposed model can fill in a niche area to enhance the existing commercial and research grade tools used for PV/BESS that do not consider resilience aspects.

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