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Resilience-Oriented Behind-the-Meter Energy Storage System Evaluation for Mission-Critical Facilities

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ABSTRACT Immunization of mission-critical facilities such as hospitals and first responders against power outages is crucial for the operators due to their significant value of the lost load, affecting citizens' lives. This paper proposes a novel evaluating framework which enables facility operators to efficiently size and optimally dispatch their behind-the-meter energy storage systems (BTM-ESS) for resiliency purposes during grid emergencies. The proposed framework, formulated as a mixed integer linear programming model, aids facility operators to quantify the impacts of various BTM-ESSs on resilience enhancement where the Avoided Loss of Load (ALOL) is incorporated as the resilience indicator. BTM-ESS is assumed to be operated in both standalone and coupled with solar photovoltaic (PV) as an onside backup generation which is a viable energy solution for more prolonged power outages. The proposed model is developed on a probabilistic energy procurement model, aiming to minimize the facility's total operation cost. The uncertainty of power outages is characterized by a set of a large number of scenarios generated by the brute-force enumeration method. Additionally, to analyze the impacts of facilities' behaviors on the BTM-ESS evaluation procedure, a set of 24 facilities from different end use sectors with various functionalities are simulated by employing our in-house-developed building simulator, which is a physics-based simulation tool. Finally, the practicality of the proposed evaluating framework is investigated through two case studies where both short and long-duration grid outages are examined based on the historical outage data adopted from New Jersey, USA. The simulation results reveal that a BTM-ESS with 4 hours discharge duration that is sized at rated power equal to 50% or more of the facility's peak load generates sufficient resilience benefits for most of the 24 representative facilities in case of short-duration power outages.

INDEX TERMS Demand-side management, energy storage, load modeling, resilience, solar power generation, system simulation.

I. INTRODUCTION

A. BACKGROUND AND PROBLEM DESCRIPTION

Based on the current global trend, severe weather events, which are the foremost cause of power outages in the US [1], are increasing in frequency, duration, and severity [2], [3]. At the same time, the vulnerability of the legacy grid has been exposed by the consequences of the recent severe weather events, such as Hurricane Irene in 2011 [4] and Hurricane Sandy in 2012 [5]. The CPI-adjusted[1] total cost of weather and climate-related events that affected the US between 2010 and 2020 has been expected to be approximately $825 billion [6]. Therefore, enhancing the system's resilience to ensure a certain level of service under severe weather events, particularly for mission-critical facilities such as hospitals and fire stations, is indispensable. Apart from utility grid hardening and reinforcement plans, which might be either traditional capacity expansion plans to ensure

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[1]Consumer Price Index, which measures the average change in the prices paid for a market basket of goods and services.

system adequacy [7] or non-wires alternatives (NWA) against traditional investments [8], critical facilities can also utilize behind-the-meter (BTM) distributed energy resources (DERs) that are configured to operate even when the utility grid is jeopardized.

By substituting, or serving as a supplement to renewable back-up powers, e.g., solar PV [9], BTM energy storage system (ESS), hereinafter BTM-ESS, can be operated at critical facilities to mitigate risks of unserved load during utility grid outages while adding benefits of zero greenhouse gas (GHG) emissions with virtually instant dispatch. Although critical facilities are different in terms of functionality and behavior, incorporating either standalone ES or solar-plus-storage systems boosts the facility's resilience by providing back-up power to avoid loss of some/all parts of the critical loads. According to the findings from our recently published technical report in [10], the costs of ESSs, which are dropping rapidly, are not currently cost-competitive for most applications. However, for resilience purposes, the economic viability of ESS highly depends on the value of lost load (VOLL)[2] and duration and frequency of the grid outages, which can justify the resilience-oriented BTM-ESS applications for mission-critical facilities. Yet the question to be answered is, "*How can different mission-critical facilities efficiently size and optimally dispatch their BTM-ESSs to achieve the desired resiliency goals under uncertain grid outages?*"

B. LITERATURE REVIEW

Multiple studies have been conducted recently in the literature addressing the resilience of the utility grid, where both traditional wires solutions and NWAs have been explored [11]–[16]. The impacts of integrating solar PV and ESS on energy-saving and resilience of office buildings within a microgrid (MG) are investigated in [17] where it is demonstrated that the MG could benefit in both cost-savings over the 20-year life cycle of the facility while increasing the amount of time it can survive a power outage. In [18], the authors introduce four resilience indices, including the expected number of lines on the outage, loss of load probability, expected demand not supplied, and the difficulty level of grid recovery, to measure the impacts of integrating MGs on the resilience of the grid. Moreover, the application of coordinated MGs in enhancing the system resilience is investigated in [19], where strategic recourse-sharing through joint-scheduling of the networked MGs is proposed.

In addressing ESS utilization in resilience applications, Zhang *et al.* analyze the use of a battery ESS and feeder automation to avoid line overloads in [20], where a multiday high-demand scenario that leads to an outage is considered. In [21], the authors investigate the effects of adding ESS as one of the proposed smart grid technologies on the frequency of long interruptions per load in a rural LV distribution network, where the number of long interruptions is seen to be reduced. In addition, a multi-objective planning and control strategy is proposed in [22], where various DERs, including distributed generation, ESS, and demand response (DR), are co-optimized in an MG application for resiliency enhancement.

Apart from the resilience applications of DERs, particularly ESSs, the technical literature is rich in terms of the research efforts tapping on modeling weather-related outages where the probabilistic methods have been mainly focused. Panteli *et al.* in [23] measure weather-dependent failure probabilities of the components expressed by the fragility curves to develop a resilience assessment procedure based on the severity of the extreme weather events, while in [24], Yodo *et al.* present a dynamic Bayesian network approach for the modeling and predictive resilience analysis for dynamic engineered systems. Also, Hussain *et al*. in [25] employ the probability distribution functions to estimate the resilience load of the electric vehicles (EVs) that is further utilized to maintain the energy level in the ESS to ensure the resilience of EVs during power outages, while in [26], a predefined set of 8 outage scenarios are considered with given consequences to optimize investment decisions on mobile ESS units.

The technical literature, however, lacks a comprehensive evaluation framework that aids mission-critical facility operators to optimize both size and dispatch of their BTM-ESSs to achieve their resiliency goals under uncertain grid outages, including short- and long-duration events. Additionally, considering the consumption patterns of the facilities with different functionalities in the performance evaluation process of the BTM-ESS for resiliency purposes is another research area that needs more investigation.

C. CONTRIBUTIONS AND PAPER STRUCTURE

This paper proposes a comprehensive framework that evaluates the performance of various BTM-ESSs for mission-critical facilities in pursuing their resilience requirements once power outages occur. Hence, a probabilistic energy procurement-based model is developed where BTM-ESSs are configured as both standalone and integrated solar-plus-storage systems while considering the uncertainty of the power outages. To extend the analysis and make the proposed framework more robust, a set of 24 mission-critical facilities with various functionalities from different end use sectors, including commercial, industrial, and residential, are simulated by employing our in-house-developed physics-based building simulator, i.e., PBS, which is an *EnergyPlus*-based tool [27] capable of fully capturing the facilities' demand patterns. It is worth mentioning that, here in this paper, we adopt the *resilience* notion as initially defined by Carlson *et al.* in [28], but modify it to be fitted for the scope of facility-level applications. Thus, resilience is defined as *the ability of a facility to anticipate, respond/adapt to, and recover from a utility grid outage*, hereinafter. Accordingly, the critical facility operator first anticipates the utility

[2]Computing VOLL is a challenging task since it strongly depends on the outage duration and frequency of occurrence, the available substitutes, and the criticality of the consequences if an outage occurs.

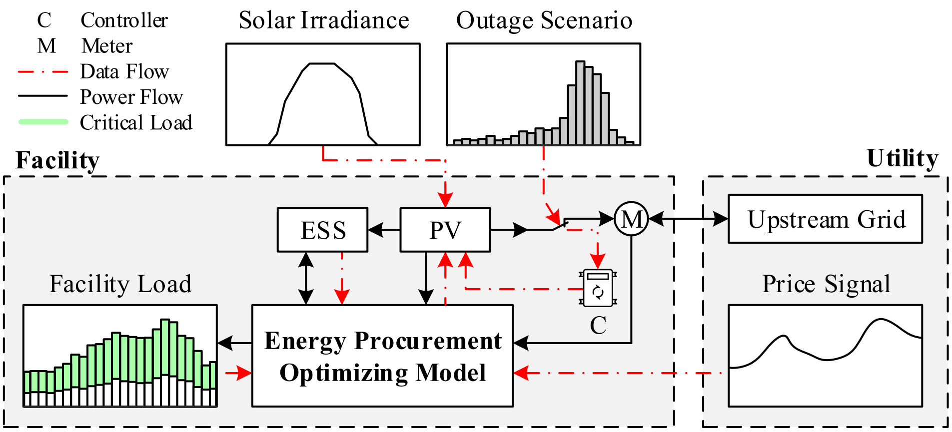

FIGURE 1. Energy procurement-based framework for a critical facility operating a BTM solar-plus-storage system for resilience purposes.

grid outages; then rapidly responds by switching off from the utility grid and becoming isolated, which is relayed by a smart controller; and lastly, optimizes the operation of its BTM-ESS to recover some/all parts of its critical loads. Fig. 1 illustrates the energy procurement-based framework for a mission-critical facility utilizing a BTM solar-plus-storage system for resilience enhancement. From the facility operator's perspective, the proposed evaluating framework anticipates the expected utility grid outages of both short- and long-duration events during the planning horizon, thence co-optimizes the BTM solar-plus-storage system dispatches based on the candidate ESS sizes to achieve the desired resiliency goals. In order to characterize the uncertainty of the utility grid outages, a scenario-based approach [29], [30], which is detailed in section II, is employed. A set of a large number of possible outage scenarios is then generated by the brute-force enumeration method [31], which samples from the probability spaces of outage-related key parameters/ features obtained from the statistical analysis of the historical grid outage databases.

Finally, to quantify the resilience impacts of various BTM-ESSs, we introduce the *Avoided Loss of Load (ALOL)*, which measures the expected energy not served under all possible grid outage scenarios over the planning horizon as a proxy indicating the value of resilience. Therefore, ALOL is measured as our resilience index, hereinafter. It should be noted that here we assume the ESS not to be used to provide grid services such as demand response [32] and/or load shifting and peak load shaving; thereby, the ESS capacity is devoted to performing its emergency power obligation during the emergency events. Depending on the operation priorities and the level of risk that facility operators can take,[3] the BTM-ESS might also be partially operated to perform energy arbitrage and/or provide grid services such as frequency regulation and directly reap market benefits alongside the dedicated capacity for resilience improvements. This way, the BTM-ESS needs to be oversized, i.e., bigger than the size needed for emergency use, to ensure the facility's resilience requirements while fulfilling the other functions. The problem of co-optimizing the dedicated capacities of the BTM-ESS for coincidentally performing various functionalities is out of the scope of this paper, but it is in order as one of our very close future works.

In summary, the core contributions of this paper can be listed as follows:

- Developing physics-based facility models that enable facility operators to capture various electricity consumption patterns in evaluating the performance of various BTM-ESSs in pursuing resiliency goals.
- Investigating the impacts of BTM-ESS's characteristics such as energy capacity, rated power, and round-trip efficiency on the resilience enhancement of a set of 24 representative mission-critical facilities to assure resilience requirements with efficiently sized and optimally dispatched BTM-ESSs.
- Exploring the outage duration impacts on the facility operation where a large number of grid outage scenarios are generated for both short and long duration outages to yield efficiently sized and optimally dispatched BTM-ESSs for sufficiently boosting the facility's resilience.

The remainder of this paper is organized as follows: The proposed probabilistic energy procurement-based BTM-ESS evaluation model is presented in section II, where the uncertainty of the utility grid outage events is first characterized using a scenario-based approach. Section II is followed by developing the probabilistic energy procurement-based model and ended up with the formulation of the ALOL as our measured resilience index. Section III represents the case studies conducted on a set of mission-critical facilities and provides the BTM-ESS evaluation results at the end. Finally, the conclusions are drawn and discussed in section IV.

[3]Mission-critical facility operators are highly risk-averse to avoid the consequent huge VOLL, affecting the whole communities and people's lives.

II. THE PROPOSED PROBABILISTIC ENERGY PROCUREMENT-BASED BTM-ESS EVALUATION MODEL

In this section, we present the mathematical formulation of our proposed facility-level BTM-ESS evaluation framework, where the impacts of ESS on the resilience of various facilities are quantified by employing an appropriate resilience index. The proposed model, which aims at determining optimal ESS dispatch under various grid outage scenarios, minimizes total energy procurement cost while penalizing the facility's load curtailments to achieve the desired resiliency goals. We develop our evaluating framework on an energy procurement-based model with both internal and external resources, where the facility operator might use on-site ESS(s) coupled with solar PV in a solar-plus-storage system and/or the utility grid when the service is available during normal blue-sky operation. It is worth mentioning that for the sake of generality, we build here the model based on a solar-plus-storage system; thereby, the standalone ESS becomes a special case that can be simulated by a set of simplifications. Also, the proposed model is formulated as a probabilistic model where the utility grid outages are represented by a finite set of scenarios that are characterized by the outage-defining features, e.g., duration and occurrence time. The mathematical formulation of the proposed model is elaborated in the following.

A. UTILITY GRID OUTAGE CHARACTERIZATION

Let $\mathcal{T}$ be the planning horizon defined as $\mathcal{T} := (0, T]$ and divided to K same-length time intervals with the i^{th} interval to be $\mathcal{T}_i := (t_{i-1}, t_i]$ with the length $\Delta t := t_i - t_{i-1}$ such that $\mathcal{T} = \bigcup_{i=1}^{K} \mathcal{T}_i$. Let us also represent the occurrence time of grid outages on this horizon by a random variable y defined over the probability space $\left(\Omega_y, \mathcal{F}_y, \mathbb{P}_y\right)$. Let Ω_y be composed of a finite discrete set of outage occurrence time scenarios defined as $y_{\omega'} : \Omega_y \mapsto \mathcal{T}_y$ and associated with a probability $\pi_{\omega'} := \mathbb{P}_y\left(\{\omega' \in \Omega_y | y = y_{\omega'}\}\right)$ such that $\sum_{\omega' \in \Omega_y} \pi_{\omega'} = 1$, where $\mathcal{T}_y := \{t_0, t_1, \ldots, t_{K-1}\}$, and $0 \leq y_{\omega'} < T,\ \forall \omega' \in \Omega_y$ holds. Further, the outage duration is another key uncertain feature which is represented by a random variable z defined over the probability space $(\Omega_z, \mathcal{F}_z, \mathbb{P}_z)$. Let Ω_z be composed of a finite discrete set of outage duration scenarios defined as $z_{\omega''} : \Omega_z \mapsto \mathbb{N}_{K_0}$ and associated with a probability $\pi_{\omega''} := \mathbb{P}_z\left(\{\omega'' \in \Omega_z | z = z_{\omega''}\}\right)$ such that $\sum_{\omega'' \in \Omega_z} \pi_{\omega''} = 1$, where $\mathbb{N}_{K_0} := \{1, 2, \ldots, K_0\}$ given that $K_0 \leq K$, thereby, $z_{\omega''} \subseteq \mathcal{T},\ \forall \omega'' \in \Omega_z$.

Finally, combining the two probability spaces, i.e., Ω_y and Ω_z, the yielded utility grid outage scenario, which is defined as a sequence of outage occurrence time and duration scenarios τ_ω and associated with a probability π_ω, is modeled as:

$$\tau_\omega := \{(y_{\omega'}, z_{\omega''})\, | y_{\omega'} \in \mathcal{T}_y, z_{\omega''} \in \mathbb{N}_{K_0}\}, \tag{1}$$

$$\pi_\omega := \{\pi_{\omega'} \times \pi_{\omega''} | \omega' = 1, \ldots, |\Omega_y|, \omega'' = 1, \ldots, |\Omega_z|\} \tag{2}$$

such that $\sum_{\omega \in \Omega} \pi_\omega = 1$, where Ω is the Cartesian product $\Omega_y \times \Omega_z$, and the notation $|.|$ shows the cardinality of a set.

A large number of possible outage scenarios can then be generated by sampling or enumeration from the yielded probability space stemming from the utilities' historical grid outage databases. In the case studies presented in section III, the brute-force enumeration method [31] is implemented to generate a large number of possible utility grid outage scenarios. The characterized outage scenarios are then used to develop the proposed probabilistic energy procurement-based model, which is elucidated next.

B. PROBABILISTIC ENERGY PROCUREMENT-BASED MODEL

The objective function of the model, which is to minimize the total energy procurement costs of the facility over the study horizon $\mathcal{T}$ while penalizing the facility load curtailments, is formulated as:

$$\min_{P^{UG}_{\omega t}, P^{PV,X}_{\omega t}, P^{LC}_{\omega t}} \sum_{\omega \in \Omega} \pi_\omega \left\{ \sum_{t \in \mathcal{T}} \left\{ \lambda_t \left(P^{UG}_{\omega t} - P^{PV,X}_{\omega t} \right) + \nu_t P^{LC}_{\omega t} \right\} \Delta t \right\} \tag{3}$$

where $P^{UG}_{\omega t}$ and $P^{PV,X}_{\omega t}$ are purchased power from the grid and excess power generated by solar PV and sold to the utility in scenario ω at time t, respectively. In objective function (3), $P^{LC}_{\omega t}$ models the facility's load curtailment in scenario ω at time t, which is penalized by a sufficiently large positive number at time t, denoted by ν_t; and λ_t is the utility electricity price at time t. Here we assume that the excess power generated by PV that is sold to the utility in grid-connected operation is compensated at the utility's electricity price, which is consistent with the current FERC Order 745 regulations [33]. Note that in the islanded operation, the excess solar PV power is decreased by the facility's smart controller. The objective function (3) is subject to the energy procurement-based operational constraints (4)-(11) through which power exchanges with the utility in grid-connected mode, and dispatches of ESS, solar PV, and load curtailments in both grid-connected and islanded operation modes are co-optimized.

Let us assume that the power purchased from the utility in scenario ω at time t, i.e., $P^{UG}_{\omega t}$, is split into two components, the power which supplies the demand, $P^{UG,D}_{\omega t}$, and the power which charges the ESS, $P^{UG,S}_{\omega t}$. Thus, the power purchased from the utility is modeled as:

$$P^{UG}_{\omega t} = \begin{cases} P^{UG,D}_{\omega t} + P^{UG,S}_{\omega t} & \forall t \in \mathcal{T} - [y_\omega, y_\omega + z_\omega)\,, \omega \\ 0 & \forall t \in [y_\omega, y_\omega + z_\omega)\,, \omega \end{cases} \tag{4}$$

Also, in the proposed model, the facility's solar PV power in scenario ω at time t, denoted by $P^{PV}_{\omega t}$, is decomposed into three components including the power which supplies the demand, $P^{PV,D}_{\omega t}$, the power which charges the ESS, $P^{PV,S}_{\omega t}$, and the excess power, $P^{PV,X}_{\omega t}$, which is either sold to the utility during grid-connected operation or decreased by the facility's smart controller during the utility grid outages. This way, the facility's solar PV power is formulated as:

$$P^{PV}_{\omega t} = P^{PV,D}_{\omega t} + P^{PV,S}_{\omega t} + P^{PV,X}_{\omega t} \quad \forall t, \omega \tag{5}$$

where $P^{PV,X}_{\omega t} = 0$ over $t \in [y_\omega, y_\omega + z_\omega)$ for all ω.

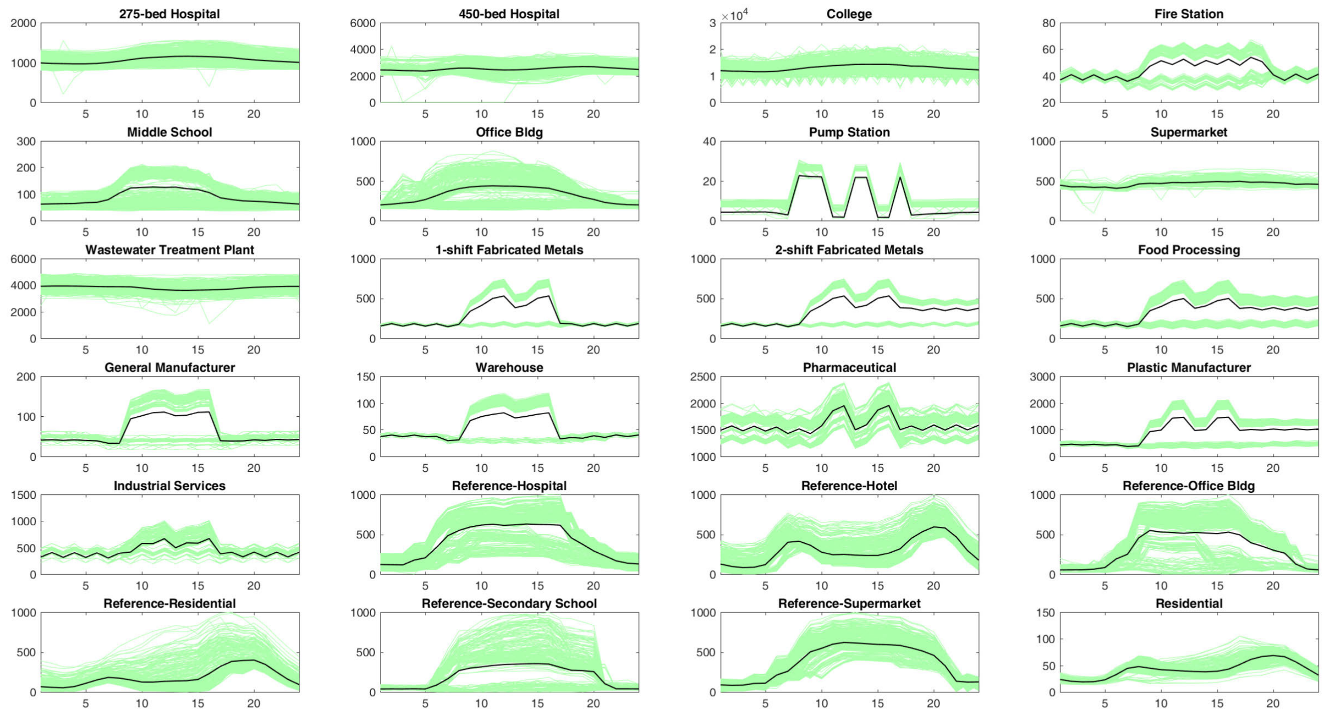

FIGURE 2. 24-hour demand profiles of representative facilities in kW over a year with the average in black line.

Further, the facility's generic ESS, which is coupled with a solar PV in a solar-plus-storage system, is modeled as:

$$P^{UG,S}_{\omega t} + P^{PV,S}_{\omega t} \leq (1-\beta_{\omega t})\overline{P}^{S} \quad \forall t, \omega \tag{6}$$

$$P^{S,D}_{\omega t} \leq \beta_{\omega t}\overline{P}^{S} \quad \forall t, \omega \tag{7}$$

$$\beta_{\omega t} \in \{0, 1\} \quad \forall t, \omega \tag{8}$$

$$\underline{E}^{S} \leq E^{S}_{\omega t} \leq \overline{E}^{S} \quad \forall t, \omega \tag{9}$$

$$E^{S}_{\omega t} = (1-\epsilon)\, E^{S}_{\omega(t-1)} + \left(\eta^{C}\left(P^{UG,S}_{\omega t} + P^{PV,S}_{\omega t}\right) - \frac{P^{S,D}_{\omega t}}{\eta^{D}}\right)\Delta t \quad \forall t, \omega \tag{10}$$

where the binary variable $\beta_{\omega t}$ models the charge/discharge status of ESS in scenario ω at time t with corresponding charging power $P^{UG,S}_{\omega t} + P^{PV,S}_{\omega t}$ and discharging power $P^{S,D}_{\omega t}$, which are limited to the ESS rated power $\overline{P}^{S}$ in (6) and (7). Considering charge and discharge efficiencies to be η^{C} and η^{D}, the dynamic energy balance of the ESS assuming its self-discharge denoted by ϵ is formulated in (10), where the energy capacity of ESS is bounded in (9) over $\mathcal{T}$ for all ω. The facility's supply-demand balance equation is then formulated as:

$$P^{UG,D}_{\omega t} + P^{PV,D}_{\omega t} + P^{S,D}_{\omega t} = D_t - P^{LC}_{\omega t} \quad \forall t, \omega. \tag{11}$$

Constraint (11) ensures that the power purchased from the utility to supply the demand, and the power generated by the solar PV to compensate some/all parts of the demand, and the discharged power from the ESS balance the facility's total demand subtracted by the load curtailments in scenario ω at time t.

C. RESILIENCE INDEX OF A MISSION CRITICAL FACILITY

Each grid outage scenario may result in a different amount of lost load, i.e., unserved load during an outage; thereby, the resilience index needs to be defined as the expected lost load stemming from the enumerated outage scenarios throughout the planning horizon $\mathcal{T}$. Therefore, we define *Avoided Loss of Load (ALOL)* as the resilience indicator, which aids facility operators in determining their efficient sizes of optimally dispatched BTM-ESSs, which assure the desired resiliency goals against utility outages. The ALOL, which we consider as the facility's resilience index hereinafter, is modeled as:

$$\text{ALOL} = \left(1 - \frac{\mathbb{E}\left[\mathbf{P}^{LC}_{\omega}\right]}{\text{D}}\right) \times 100\% = \left(1 - \frac{\sum_{\omega\in\Omega}\pi_{\omega}\left(\sum_{t\in\mathcal{T}} P^{LC}_{\omega t}\Delta t\right)}{\sum_{t\in\mathcal{T}} D_t \Delta t}\right) \times 100\% \tag{12}$$

where $P^{LC}_{\omega t}$ is the facility's load curtailment in scenario ω at time t, and D_t is the facility's load at time t, thereby, $\text{D} := \sum_{t\in\mathcal{T}} D_t\Delta t$ and $\mathbf{P}^{LC}_{\omega} := \sum_{t\in\mathcal{T}} P^{LC}_{\omega t}\Delta t$ are defined accordingly. Note that D designates the facility's total load over $\mathcal{T}$, and $\mathbf{P}^{LC}_{\omega}$ is a $(|\Omega| \times 1)$-dimensional vector of total load curtailments over $\mathcal{T}$ for $\forall\omega \in \Omega$. Note that $\mathbb{E}[.]$ is the expectation operator.

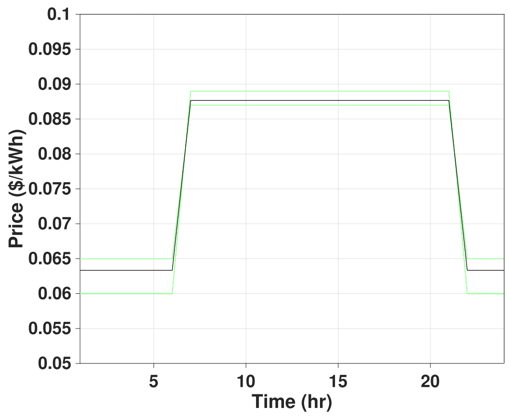

FIGURE 3. Hourly day-ahead electricity price of the utility over a year with the average in black line.

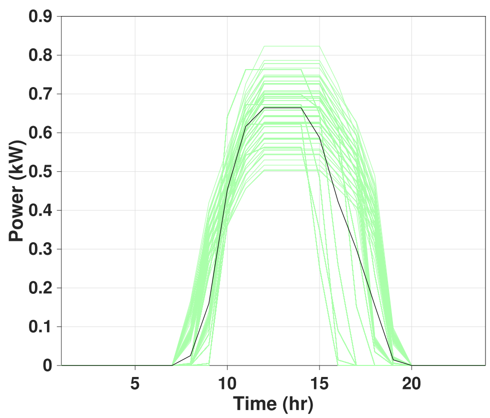

FIGURE 4. Hourly 1-kW scaled solar power output over a year with the average in black line simulated by *Trnsys* for a site located in NJ, USA.

In summary, equations (1)-(12) present our proposed probabilistic energy procurement-based BTM-ESS evaluation model for mission-critical facilities that is formulated as a mixed-integer linear programming problem and can be solved using commercial solvers.

III. CASE STUDY AND NUMERICAL RESULT

A. INPUT DATA AND TEST MISSION CRITICAL FACILITY SET

In order to sufficiently explore our proposed BTM-ESS evaluation framework, we consider various mission-critical facilities with different functionalities and from different end-use sectors, including commercial, industrial, and residential. The test facility set, which is illustrated in Fig. 2, includes 24 critical facilities from both well-fitted facilities to the state of New Jersey (NJ) climate zone and the US Department of Energy (DOE) reference buildings [34]. Also, we employ our in-house-developed physics-based building simulator, i.e., PBS, which is an *EnergyPlus*-based tool [27], to simulate the hourly load profile of each facility over a year. The resulted dataset on the estimated 8,760-hour load profiles can be found at http://dx.doi.org/10.17632/rfnp2d3kjp.1, which is an open-source online data repository hosted at Mendeley Data [35]. Moreover, Figs. 3 and 4 depict the

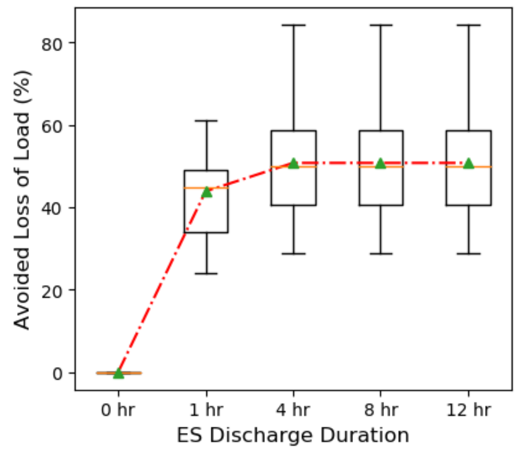

FIGURE 5. Impact of energy capacity on avoided loss of load for standalone ESS with rated power of 25% of peak load of each facility–*Case I*.

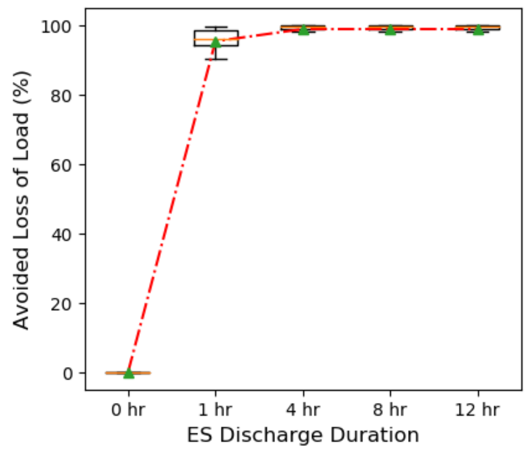

FIGURE 6. Impact of energy capacity on avoided loss of load for standalone ESS with rated power of 100% of peak load of each facility–*Case I*.

utility's electricity price and the one-kW scaled solar PV output power located in NJ and simulated by *Trnsys* [36], respectively.

For the generic ESS in our studies, regardless of the size and in both standalone ES and solar-plus-storage systems, we assume the round-trip efficiency to be 85%; self-discharge to be 0.001%; the initial state-of-charge (SoC) to be 100%; and the minimum and maximum SoCs to be 10% and 100%, respectively. Also, the coupled solar PV in the case of a solar-plus-storage system is sized to be 80% of the facility's peak load, which is the maximum annual load of the facility in kW.

To generate utility grid outage scenarios, including both short- and long-duration outages, we deploy the NJ's 2018 historical power outage data, including the occurrence time and duration of the reported outages, to model the grid outage scenarios [37]. From the extracted outage data, the following characteristics are assumed.

- Mar., May, and Sept. are highly affected months.
- Short-duration outages mostly occur from 15:00 to 17:00 and last between 1 to 3 hours.
- Long-duration outages last between 1 to 7 days.

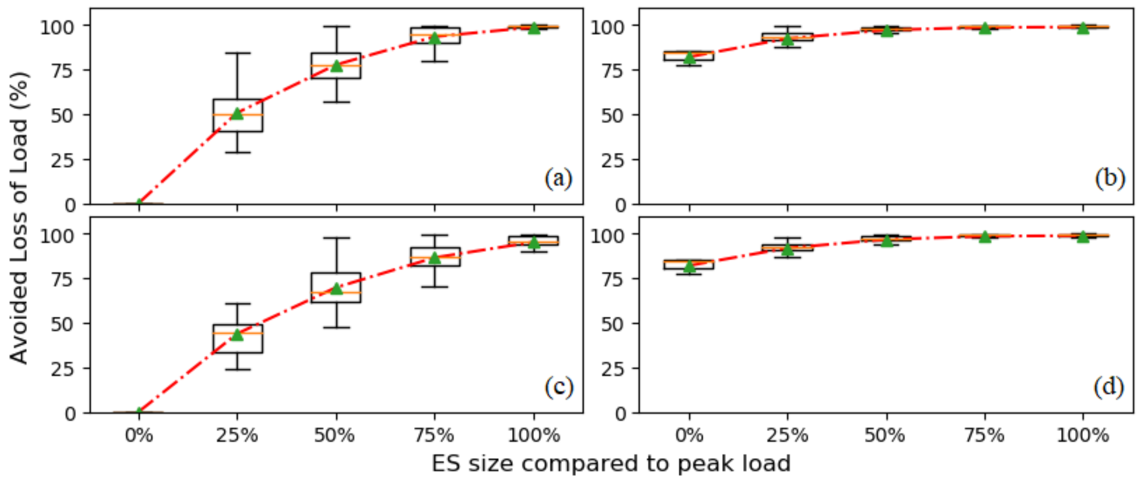

FIGURE 7. **Impact of ESS rated power on avoided loss of load in both standalone ES and solar-plus-storage systems–*Case I*: (a) standalone ES with 4-hr discharge duration, (b) solar-plus-storage with 4-hr discharge duration, (c) standalone ES with 1-hr discharge duration, (d) solar-plus-storage with 1-hr discharge duration.**

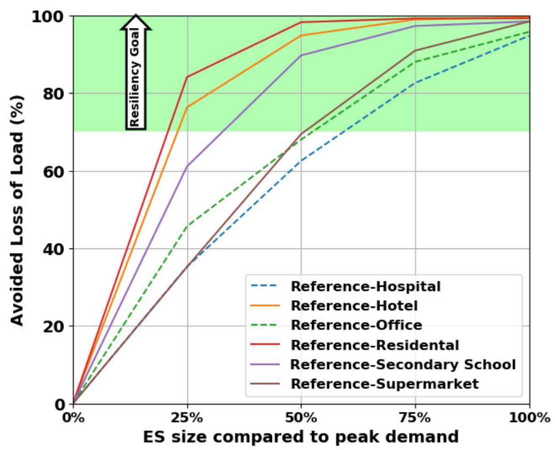

FIGURE 8. **Impact of ESS rated power on supplying 70% of critical load for 6 DOE reference facilities in standalone ESS with 1-hr discharge duration–*Case I*.**

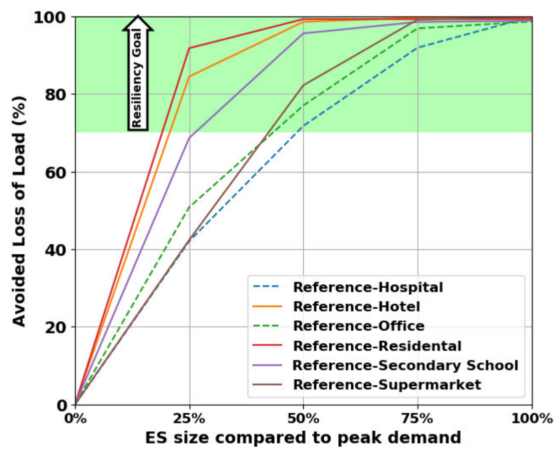

FIGURE 9. **Impact of ESS rated power on supplying 70% of critical load for 6 DOE reference facilities in standalone ESS with 4-hr discharge duration–*Case I*.**

Therefore, we implement a brute-force enumeration method [31] to pay heed to all possible scenarios stemming from the characteristics mentioned above for both short- and long-duration grid outage scenarios while satisfying the energy procurement problem constraints for each mission-critical facility. The two case studies and the simulation results are expounded in the next section.

B. RESULTS AND DISCUSSIONS

Depending on the grid outage duration, two case studies, namely *Case I* and *Case II*, are investigated where the avoided loss of load is calculated as a risk measure in pursuing resiliency goals. In *Case I*, short-duration grid outage scenarios are considered, while in *Case II* long-duration outage scenarios are taken into account. In addition, the standalone ES and solar-plus-storage systems are analyzed and compared in both cases to show the impacts of coupled back-up solar PV on the evaluation of ESS for the set of facilities shown in Fig. 2. Evaluation of the ESS in both standalone ES and solar-plus-storage systems leads us to delineate the effectiveness of the proposed model in efficiently sizing and optimally dispatching the ESS for resiliency purposes, which enables the facility operators to respond to their needs under the grid outage circumstances effectively.

The optimization models for the case studies are solved using Gurobi 9.0 Python-API *gurobipy* [38] on a system with a Core i7-8700 processor at 3.20 GHz and 64 GB of RAM. Note that the computation time for simulating either of the cases for each facility over a year was within 10 minutes.

1) CASE I–SHORT-DURATION GRID OUTAGE

In this case, short-duration utility outage scenarios are generated by the brute-force enumeration method enumerating the outage durations of 1 to 3 hours, each of which starts at 15:00, 16:00, or 17:00 every day over three months of Mar., May, and Sept., which ends up with $3 \times 3 \times 92$ equiprobable

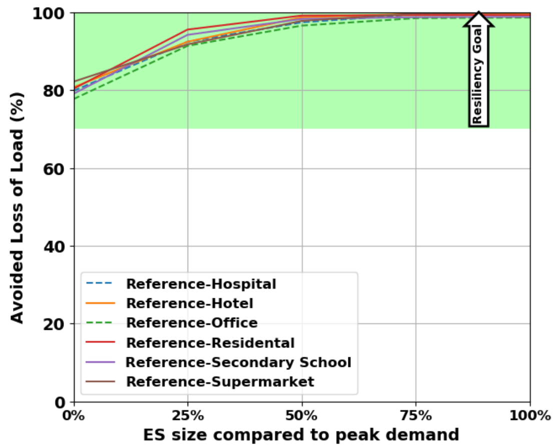

FIGURE 10. Impact of ESS rated power on supplying 70% of critical load for 6 DOE reference facilities in solar-plus-storage system with 1-hr discharge duration–*Case I*.

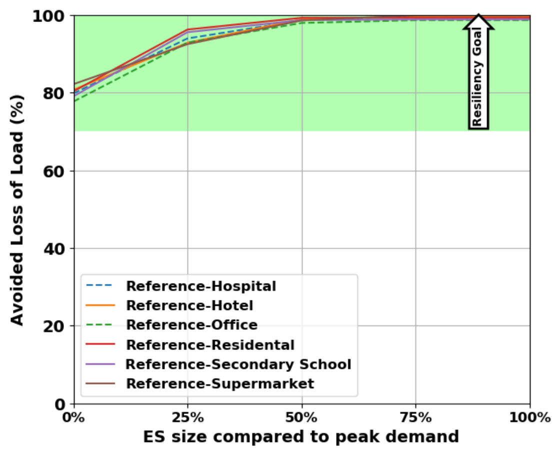

FIGURE 11. Impact of ESS rated power on supplying 70% of critical load for 6 DOE reference facilities in solar-plus-storage system with 4-hr discharge duration–*Case I*.

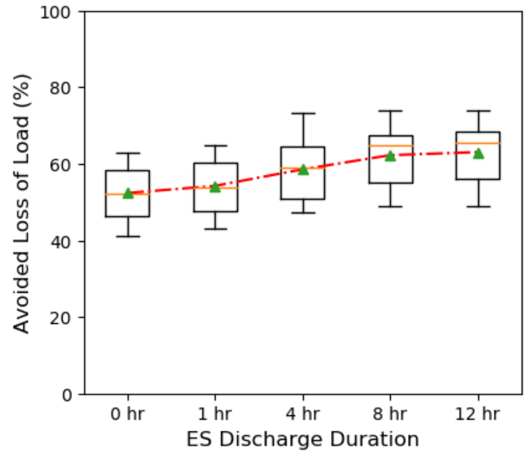

FIGURE 12. Impact of energy capacity on avoided loss of load for a solar-plus-storage system with ESS rated power of 25% of peak load of each facility in 7-day outage scenarios–*Case II*.

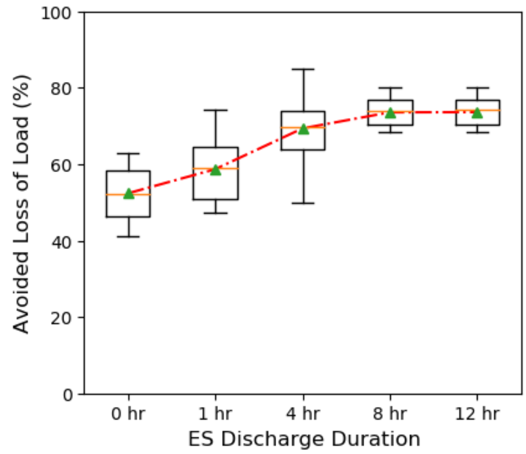

FIGURE 13. Impact of energy capacity on avoided loss of load for a solar-plus-storage system with ESS rated power of 100% of peak load of each facility in 7-day outage scenarios–*Case II*.

scenarios in total. Fig. 5 depicts the impact of ESS energy capacity (discharge duration) on the avoided loss of load for a standalone ESS with rated power equal to 25% of the peak load of each facility. It can be observed that a standalone ESS with a 4-hour discharge duration with rated power equal to 25% of the peak load suffices to avoid approximately 50% of loss of load on average in this case study. Moreover, Fig. 5 shows that the marginal value added by increasing the discharge duration to more than 4 hours significantly diminishes. However, the marginal value added by increasing the rated power of ESS leads to a substantial increase in avoided loss of load on average, which is illustrated in Fig. 6 for a standalone ESS with rated power equal to 100% of the peak load of each facility.

In order to analyze the impacts of BTM back-up solar PV on the evaluation of ESS, the avoided loss of load is measured in a solar-plus-storage system where the solar PV is sized to be 80% of the peak load of each facility, while the rated power of the ESS is assumed to be either 25% or 100% of the peak load of each facility. Fig. 7 depicts the impacts of different ESS rated power with both 1 and 4 hours of discharge durations on the avoided loss of load for both standalone ES and solar-plus-storage systems in *Case I*. As can be seen from Fig. 7(b) and (d), solar PV alone, i.e., with 0% ESS rated power, that is sized at 80% of the facilities' peak loads, can avoid more than 75% of the load losses on average over the 24 critical facilities. Therefore, a small ESS with rated power equal to 50% of the peak load of each facility adequately supplies the loads when coupled with onsite solar PV in *Case I*. However, the avoided loss of load for the standalone ESS highly correlated with the ESS rated power compared to the peak load of each facility.

Now, in order to demonstrate the impacts of ESS on the resiliency of each facility in more detail, we adopt a subset of our test 24-facility set, including the 6 DOE reference facilities. Although the criticality level of the facility varies based on the functionality and the operator objectives, here we assume the resiliency goal for each facility is to cover 70% of the load, thereby, the critical load of each facility is considered to be 70% in this case.

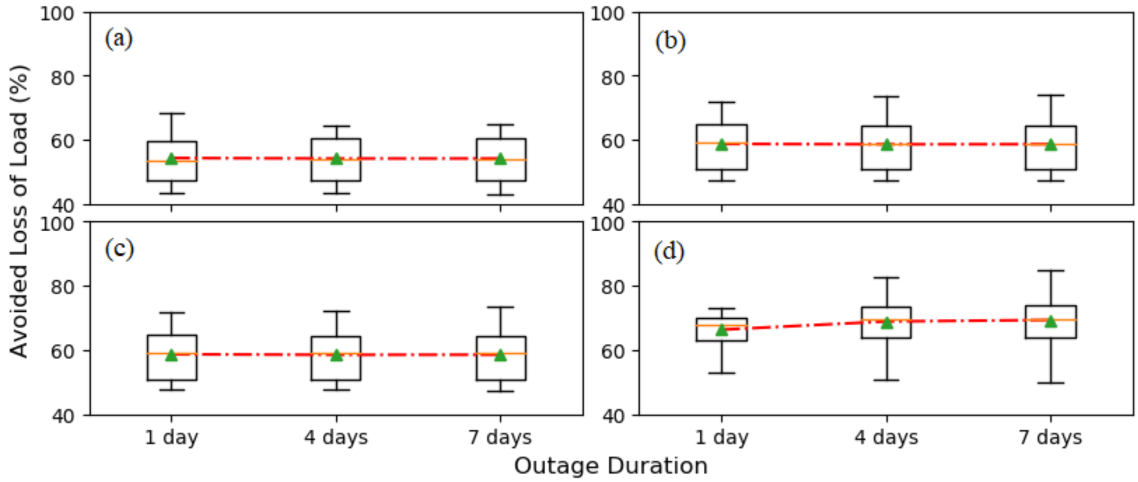

FIGURE 14. Impact of grid outage duration on avoided loss of load in solar-plus-storage systems–*Case II*: (a) ESS rated power of 25% with 1-hr discharge duration, (b) ESS rated power of 100% with 1-hr discharge duration, (c) ESS rated power of 25% with 4-hr discharge duration, (d) ESS rated power of 100% with 4-hr discharge duration.

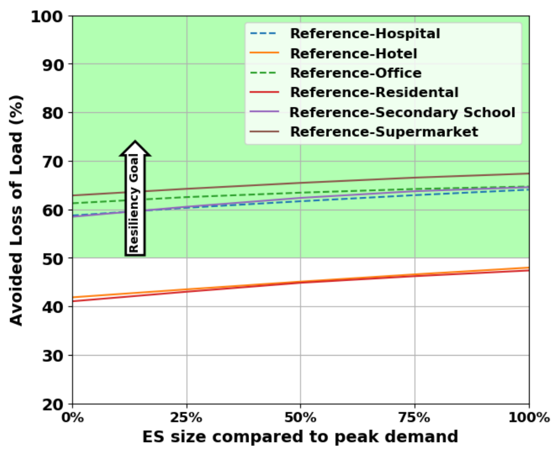

FIGURE 15. Impact of ESS rated power on supplying 50% of critical load for 6 DOE reference facilities in solar-plus-storage system with 1-hr discharge duration–*Case II*.

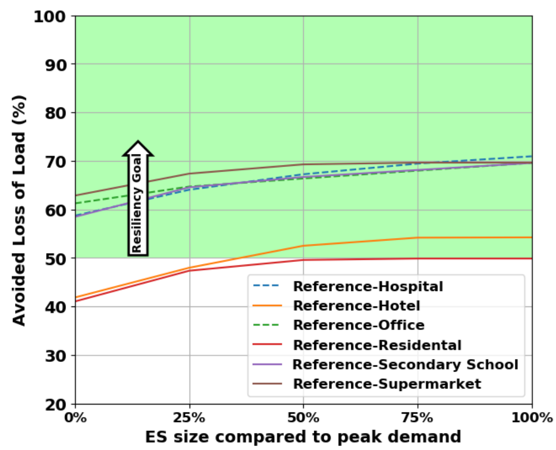

FIGURE 16. Impact of ESS rated power on supplying 50% of critical load for 6 DOE reference facilities in solar-plus-storage system with 4-hr discharge duration–*Case II*.

Figs. 8 and 9 illustrate the impacts of the ESS rated power on the avoided loss of load for each DOE reference facility and standalone ESS with 1- and 4-hour discharge durations, respectively. From Figs. 8 and 9, it can be seen that an ESS with a 1-hour discharge duration requires a higher power rated comparing with 4-hours ESS to supply 70% critical load (60% and 50% of the peak load of each facility, respectively). Moreover, it is observed that a 1-hour discharge duration ESS with rated power equal to 25% of the peak load in standalone ESS is sufficient for supplying 70% critical loads of both Residential and Hotel facilities in *case I*.

Figs. 10 and 11 illustrate the impacts of the ESS rated power on the avoided loss of load for each DOE reference facility and solar-plus-storage systems with 1- and 4-hour discharge durations, respectively. From Figs. 10 and 11, it can be seen that an onsite solar PV with rated power equal to 80% of the peak load of each DOE reference facility is sufficient for supplying the desired 70% resiliency goal in *Case I*.

Therefore, the presented results for the standalone ESS indicate that ESS sizing is highly case-sensitive in achieving the desired resiliency goals, while a cost-benefit analysis has to be conducted to compromise the present tradeoffs appropriately.

2) CASE II–LONG-DURATION GRID OUTAGE

In this case, long-duration grid outage scenarios are generated by the brute-force enumeration method, which enumerates the outage durations of 1 to 7 days, each of which starts from the beginning day of our considered three months, including Mar., May, and Sept., which ends up in 7×92 equiprobable scenarios in total. Since the long-duration outage scenarios occur in extended periods, standalone ESS as energy-finite resources cannot provide reliable back-up power to mitigate the risk of load loss. However, a coupled back-up solar PV in a solar-plus-storage system can be a viable solution for the facility operator if properly sized.

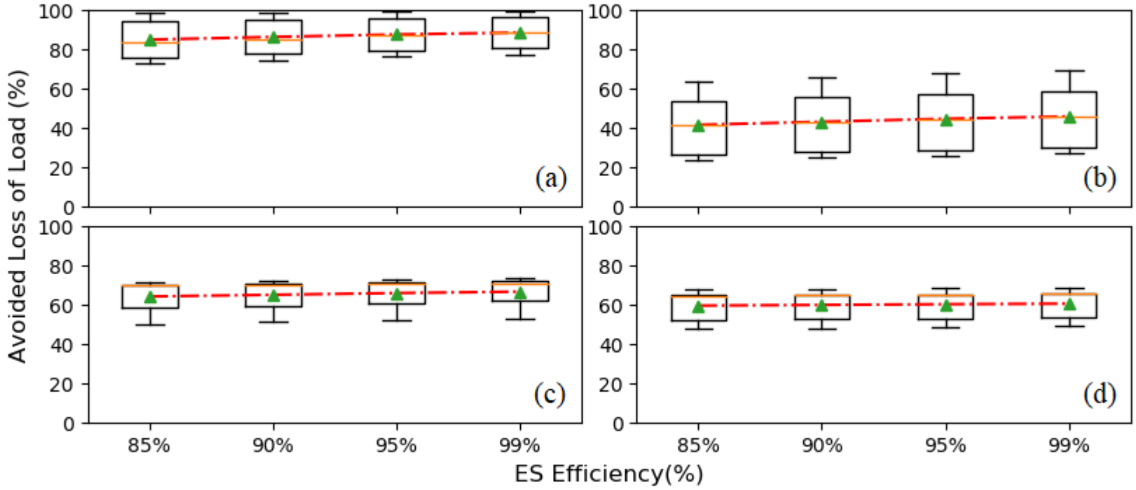

FIGURE 17. Impact of ESS round-trip efficiency on resiliency improvement under short-duration (a,b) and long-duration (c,d) outage scenarios: (a) standalone ES with 1-hr discharge duration and rated power of 100%, (b) standalone ES with 1-hr discharge duration and rated power of 25%, (c) solar-plus-storage with 1-hr discharge duration and rated power of 100%, (d) solar-plus-storage with 1-hr discharge duration and rated power of 25%.

Figs. 12 and 13 illustrate the impacts of ESS energy capacity (discharge duration) on the avoided loss of load for solar-plus-storage systems with ESS rated power equal to 25% and 100% of the peak load of each facility, respectively, where 7-day outage scenarios are taken into account. We will show that the outage duration does not affect the facility's resilience with solar-plus-storage later in this section. It can be observed that increasing ESS discharge duration from 1 to 4 hours has a considerable impact, while the marginal value added by increasing the discharge duration to more than 4 hours dramatically declines. Therefore, resilience enhancement for a facility equipped with a solar-plus-storage system is highly correlated with the ESS discharge duration and rated power.

Fig. 14 depicts the impacts of grid outage durations spanning from 1 to 7 days on the avoided loss of load for solar-plus-storage systems with ESS rated power of 25% and 100% of the peak load of each facility with 1- and 4-hour discharge durations. From Fig. 14, it can be observed that in solar-plus-storage systems with sufficient solar irradiance, outage duration does not have noticeable impacts on the facility's resilience; thereby, our claim on considering a reduced set of long-duration outage scenarios including 7-day outages holds (see Figs. 12 and 13). Furthermore, from Fig. 14, it can be seen that increasing the ES rated power to 100% of the facility's peak load increases the avoided loss of load by approximately 10% for all outage scenarios, particularly for 4- and 7-day outages.

Similar to the *Case I*, in order to investigate the resilience analysis of each facility in-depth, we adopt the set of 6 DOE reference facilities in *Case II* as well. Here we assume the resiliency goal for each reference facility is set to be 50% of its peak load. Figs. 15 and 16 demonstrate the impacts of the ESS rated power on the avoided loss of load for each DOE reference facility and solar-plus-storage systems with 1- and 4-hour discharge durations, respectively. From Figs. 15 and 16, it can be seen that Hospital and Supermarket can achieve the resiliency goal of supplying 70% of the loads by an ESS with higher rated power than 75% of the facility's peak load and with 4-hour discharge duration, while an ESS with 1-hour discharge duration is not able to support solar PV in backing-up the 70% or even 50% of the load regardless of the ESS rated power.

3) SENSITIVITY ANALYSIS ON ESS ROUND-TRIP EFFICIENCY

In this section, the impacts of ESS round-trip efficiency, which is attributed to different ESS technologies, are quantified for all facilities by measuring ALOL under various outage scenarios. Note that the round-trip efficiencies are assumed to be in the range of 85% to 99%, where the values between 85% and 95% are consistent with the assumptions made by the Massachusetts Energy Storage Initiative in [39], while the round-trip efficiency of 99% fairly reflects the ideal case allowing us to get the optimistic results in terms of round-trip efficiency. Fig. 17 illustrates the impacts of ESS round-trip efficiency on resiliency improvements under both short- and long-duration outage scenarios. From Fig. 17, it can be observed that the resiliency improvement under short-duration outages is in the range of 2% to 13.0%, while for the long-duration outages, the improvement is in the range of 1.5% to 8%.

IV. CONCLUSION

This paper proposed an evaluating framework that aids mission-critical facility operators to efficiently size and optimally dispatch their behind-the-meter energy storage systems (BTM-ESSs) for achieving their desired resiliency goals. A probabilistic energy procurement-based model was developed where the brute-force enumeration method was employed to generate a set of a large number of outage scenarios to characterize the grid outage uncertainty for both short and long-duration outages. We also measured the Avoided Loss of Load (ALOL) as a resilience index to quantify the impacts of various BTM-ESSs on resilience enhancement. To consider the impacts of the facilities' consumption patterns and behaviors on our proposed evaluation framework, a set of 24 mission-critical facilities from different end use sectors were simulated using our in-house-developed physics-based building simulator, namely PBS.

The simulation results showed that in case of short-duration outage scenarios, a standalone ESS with a 4-hour discharge duration and a rated power equal to 50% or more of the facility's peak load, engenders the desired resilience benefits of serving 70% of the critical loads on average for most of the 24 representative facilities. In the presence of solar PV, and assuming that it is appropriately sized to meet 80% of the peak load, a small ESS within 25% of the peak load suffices for achieving the desired resiliency goals of 80% or more. Overall, for the 24 representative mission-critical facilities we investigated, the solar-plus-storage system can serve all critical loads almost 100% of the time in case of short-duration power outage scenarios. For long-duration outage scenarios, however, standalone ESS had less value as an energy-finite resource. Even an ESS with a 1-hour discharge duration could not support solar PV in backing-up the desired 50% of the critical loads for the 6 DOE reference facilities, regardless of the ESS rated power. The simulation results also revealed that, among the 6 DOE reference facilities, Hospital and Supermarket could achieve the resiliency goal of supplying 70% of the critical loads by an ESS with higher rated power than 75% of the facility's peak load and 4-hour discharge duration.

Future works include co-optimizing the dedicated capacities of a BTM-ESS to simultaneously perform several functionalities where proper control strategies are needed to stack up various applications. Moreover, developing more advanced methods and tools to accurately estimate the grid outages and their consequences which enable more accurate decision-making, as well as developing an integrated scheduling model capable of co-optimizing the operation of the BTM-ESS and the potential flexible loads to boost the resilience of the facility proactively, are in order.

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