Resilience Metrics for Building-Level Electrical Distribution Systems with Energy Storage

Preprint

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National Renewable Energy Laboratory

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Resilience Metrics for Building-Level Electrical Distribution Systems with Energy Storage

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***Abstract*—The energy system infrastructure that delivers power to a building's loads needs to be resilient to withstand and recover from extreme outages (e.g., grid faults that leave millions of people without power during severe weather events). Building-level electrical distribution systems (BEDSs) distribute power from a building's energy sources—including the grid, solar photovoltaic (PV) panels, and batteries—to its loads, including lighting, HVAC, and plug loads. BEDS with storage can provide resilience by distributing local electricity supply to critical loads during an outage. Quantitative metrics are needed to assess the resilience improvements associated with new BEDS and storage system technologies. In this paper, we apply an existing metric, the probability of outage survival curve (POSC), to BEDS with storage and propose novel metrics that improve upon POSC. Through a simulation-based case study, we demonstrate how these metrics are impacted by the BEDS design and how they can be used to design a resilient system.**

***Index Terms*—Buildings, resilience, power distribution, metrics.**

I. Introduction

Severe power outages will likely become more common as the severity and frequency of extreme weather events increase due to climate change [1]. These outages can have devastating consequences, especially when coupled with extreme weather. For example, an unusually intense winter storm in Texas in February 2021 induced widespread power outages that left 4.5 million homes and businesses without power, some for several days. Buildings suffer the majority of the economic and human safety issues associated with such outages, given that 76% of electricity is used by buildings [2].

Economic losses from the February 2021 outages in Texas are estimated to be $130 billion [3], and there were 210 deaths [4], most of which were due to hypothermia. In particular, sixty-one percent of Texas homes use electric heating [5], so the co-occurrence of the outages with cold temperatures made it hard for the residents in those homes to keep warm. Power delivery to a building's load should be resilient, such that it can effectively withstand and recover from adverse events. Although resilience has traditionally been a qualitative concept, quantitative resilience metrics are necessary to assess, compare, and improve the resilience of energy systems.

Resilience is defined as "the ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time and composite costs and risks" [6]. Generally, the term resilience is limited to disruptions that are high-impact and low-probability [7]. Reliability is similar to resilience, and the two terms are sometimes used interchangeably in informal contexts. However, reliability differs from resilience in that it is focused on disruption events that are low impact, have a high probability of occurring, have negligible recovery time, and are highly predictable [8]. Power systems reliability metrics are well established, including System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), and Customer Average Interruption Duration Index (CAIDI) [9]. These reliability metrics are unsuitable for measuring resilience because they often exclude major outages caused by unexpected events and do not capture how well the system can recover [9]. Reliability metrics are also unsuitable for resilience because they evaluate a system's performance based on past events. The severe events relevant to resilience can be extremely rare, and little to no historical record exists to indicate their likelihood. Therefore, resilience metrics should not be based solely on past events, but instead should be useful when an event exceeds historical precedent.

Various resilience metrics have been developed for power systems, including the ratio between targeted performance and real performance [9], time of restoration [9], rapidity of restoration [9], cost of resilience [9], and network connectivity [10]. Likewise, metrics have been used to quantify the resilience of microgrids, such as statistical survivability [11], probability of outage survival curve [12] [13], and value of resilience [14]. These metrics are useful to assess the ability of energy systems to mitigate outages and the impacts of outages. However, none of the previous work has proposed resilience metrics for building-level electrical distribution systems (BEDSs) with energy storage. BEDSs distribute power from the building's sources—including the grid, solar photovoltaic (PV) panels, and batteries—to the building's loads, including lighting, HVAC, and plug loads. When there is energy storage in the building, it can remain operational during a grid outage. The design of the BEDS can impact the ability of the building to survive an outage. For example, the efficiency of a BEDS dictates how long a battery can supply power to a given load. The traditional alternating current (AC) BEDSs have been dom-

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inant since the electrification of buildings. However, increases in the number of native direct current (DC) loads and sources, such as light-emitting diode (LED), variable-frequency drive (VFD), PV, and battery systems, have spurred interest in DC BEDSs. With DC loads and sources in a modern building, DC BEDSs can have higher efficiency than the legacy AC systems [15] [16] [17]. With emerging BEDS designs, the performance of a BEDS (including its resilience) can be effectively improved with the right metrics and tools. Quantitative metrics for BEDSs with energy storage are necessary to assess and improve the systems' resilience.

In addition to the resilience metrics for power systems and microgrids described previously, resilience metrics have also been developed for engineering systems and building structures. These include a probability distribution function with respect to impact [7], availability divided by the log of time [19], community cost normalized by Gross Regional Product [20], cumulative functionality loss integrated over probability distribution function [21], and a points rating system [22]. Of all the metrics investigated, the POSC, presented in [12] and [13], is most applicable to BEDSs. In particular, the POSC can be calculated with available data and provides a descriptive measure of the probability of surviving outages that could occur at any time throughout the year. This metric is used with REopt Lite, a techno-economic optimization tool developed by the National Renewable Energy Laboratory (NREL) [18]. Our proposed approach is to apply the POSC metric to BEDSs with energy storage, develop new metrics that are specifically intended for this application, and present a case study to illustrate how these metrics can be used. This work contributes to the body of research by investigating resilience metrics for BEDSs, introducing novel resilience metrics, developing a framework for evaluating the resilience of a BEDS, and using the framework and metrics to study the resilience of different BEDS designs. These contributions will help promote resilience evaluation in BEDSs by providing an effective way to quantify resilience.

Section II describes the POSC metric and analyzes the proposed metrics. Section III applies these metrics in a case study: a simulated commercial building with different battery storage capacities, power ratings, and configurations. Section IV discusses the advantages and disadvantages of the approach, and opportunities for future work.

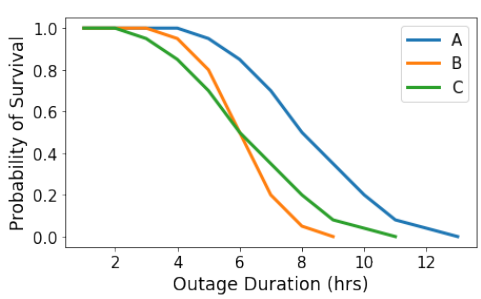

Fig. 1. Example probability of outage survival curves. Recreated from [18].

II. Resilience Metrics for Building-Level Electrical Distribution Systems

In this section, the POSC metric and the proposed metrics are described and discussed.

A. Probability of Outage Survival Curve

The POSC metric, presented in [12] and [13], shows the probability of surviving an outage for each duration. This metric is displayed on a graph with the outage duration on the x-axis and the probability of survival on the y-axis, as shown with the example curves in Fig. 1. As described in [13], this curve is calculated by simulating an outage starting at each time step in the year and finding the maximum outage duration that can be survived for each time step. An outage is considered to have been "survived" when power is maintained to the building's critical loads for the entire outage duration. Because POSC is calculated with a simulation, it requires an accurate model of the system being studied. From [13], the probability of surviving each outage duration is

$$P(d) = \frac{1}{N_s} \sum_{h \in r} \begin{cases} 1 & h > d \\ 0 & else \end{cases} \qquad for\ d \in [1, r_{max}], \quad (1)$$

where r is the set of survival times for all time steps, N_s is the number of time steps, and d is the outage duration. Some properties of POSC are:

- maximum possible range: $P \in [0, 1]$
- maximum possible domain: $d \in [1, \infty)$
- monotonically decreasing (The slope is never positive; it is either zero or negative.).

The greater the probability of survival at each outage duration, the more likely the system will withstand outages. The inverse is also true: the greater the outage duration at each probability of survival, the more likely the system will withstand outages. In Fig. 1, the A system is more resilient than both the B and C systems.

POSC is advantageous for measuring the resilience of BEDSs because it can be calculated with yearlong BEDS simulation, is easy to understand, and is independent of historical outage data. The POSC metric is independent of historical outage data because it makes no assumptions about when in the year the outage is most likely to occur. It assumes that the probability of an outage occurring is equal for all time steps. Given these advantages, the POSC metric is useful for measuring the resilience of a BEDS.

The disadvantages of POSC are that it can be ambiguous which of two curves is more resilient, it can be challenging to compare multiple POSCs directly, and it does not capture the recovery aspect of resilience. There is ambiguity when comparing two POSCs because one curve can be more resilient for part of the domain, and the other curve can be more resilient for the other part. The B system in Fig. 1 is more able to withstand outages than the C system when the outage duration is less than six, while the opposite is true when the outage duration is greater than six. This ambiguity can

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TABLE I
CHARACTERISTICS OF PROPOSED METRICS.

Metric	Unit Type	Least Resil.	Most Resil.
Survival Time (ST)	Time	0	∞
Survival Probability (SP)	-	0	1
Recharge Time (RT)	Time	∞	0
Recharge Index (RI)	-	∞	0
Critical Duty Cycle (CD)	-	100%	0%

make it challenging to compare how well different systems can withstand outages. Also, POSC does not capture resilience in its entirety because it does not capture the recovery ability of a system, which is an important aspect of resilience.

B. Proposed Metrics

To address the apparent shortcomings of POSC, we propose an alternative set of metrics, some of which are calculated from POSC. Unlike POSC, these metrics are numeric, such that it is always clear which system is more resilient. With numeric metrics, it is also easier to compare multiple systems with a table or bar graph. The proposed set includes metrics that capture the ability of a system to withstand outages and the ability of a system to recover from outages. Therefore, this set of metrics more effectively capture the resilience of a system.

The metrics are:

- **Survival Time (ST)**: The survival time at a specific probability level (e.g., 95% Survival Time).
- **Survival Probability (SP)**: The survival probability at a specific outage duration (e.g., 5-hour Survival Probability).
- **Recharge Time (RT)**: Time required to fully recharge energy storage.
- **Recharge Index (RI)**: Recharge time normalized by survival time.
- **Critical Duty Cycle (CD)**: Minimum duty cycle of power availability that can be survived indefinitely.

The unit type and domain of each metric are shown in Table I. ST is calculated by interpolating the POSC curve to estimate the survival time at a specific probability. Likewise, SP is calculated by interpolating the POSC curve to estimate the probability at a specific outage duration. ST and SP are easily understood metrics to indicate how well a system can withstand isolated outage events. SP is more appropriate when there is a specific outage duration that is most important, while ST is more appropriate when there is no such duration. For example, SP would be more appropriate for a building that takes 2 hours to evacuate and needs to ensure that critical services are operational for those 2 hours. Also, the choice of probability level is highly important for ST. For buildings that need to always survive, such as data centers and hospitals, the 100% probability level is most appropriate, while for buildings that can deal with outages, such as homes, the 75% probability level may be most appropriate.

Unlike ST and SP, the method for calculating RT depends on the type of energy storage. For the case study in Section III, we assume that the electrical batteries charge at a constant rate, and therefore take RT to be the capacity in kWh divided by the power rating in kW. Other types of energy storage or more accurate battery models will require RT to be calculated differently. RT is useful because it quantifies how long the system takes to fully recover after an outage so that it can be prepared for another one.

RI is calculated by dividing RT by ST at a specific probability level as in (2).

$$RI = \frac{RT}{ST}. \tag{2}$$

RI puts RT in to context, conveying how long it takes to recharge relative to how long the system can survive. As such, RI captures both how well a system can survive an outage and how well it can recover from an outage: systems that perform well with respect to RI will have both a long survival time and a short recharge time. The lesser the value of RI, the more resilient the system is.

CD is calculated with (3).

$$CD = \frac{RI}{1 + RI}. \tag{3}$$

During repeating outages, each outage will be separated by a limited amount of uptime. The duty cycle of grid availability is the ratio of uptime to the total time for that specific event. In the ideal case, the cycle of grid outages and uptimes is periodic, such that each outage has the same duration and each uptime has the same duration. The metric CD refers to the minimum duty cycle of availability that is required for the system to survive indefinitely. However, this is only guaranteed to hold for periodic outages with an outage time less than or equal to the survival time. Despite this restriction, CD is useful for conveying how capably the system can withstand repeating outages, such as rolling blackouts. The relationship between availability duty cycle and CD is shown in Fig. 2. As shown in Fig. 2a and 2b, the system can fully recover in between outages when the availability duty cycle is greater than or equal to CD. As shown in Fig. 2c, the system cannot fully recover between outages and eventually dies when the availability duty cycle is less than CD. The lesser the value of CD, the better the system can withstand repeating outages.

When using RI and CD, the probability level needs to be specified because they are calculated with ST at a specific probability level. For example, one might use RI 95% or CD 95%. ST and SP indicate how well a system can withstand an outage, while RT and RI indicate how well a system can recover from an outage, and CD indicates how well a system can withstand repeating outages. CD, in particular, can be useful for understanding how well a system can survive rolling blackouts. Each of these metrics alone is not intended to capture resilience in its entirety. Rather, each metric captures a piece of resilience, and when used together, they are intended to help the user understand the resilience of a particular BEDS. Because these metrics are computed from the POSC, they also require an accurate model of the BEDS being studied. The model of a

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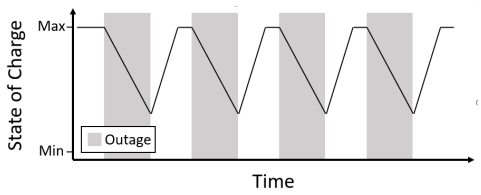
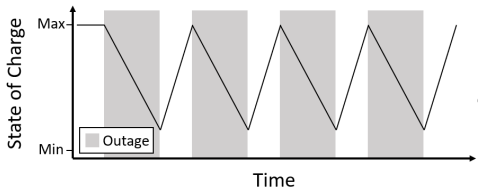
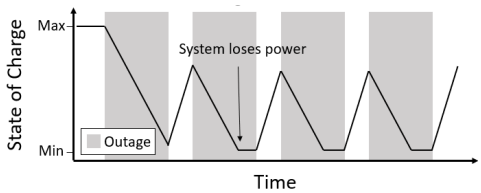


(a) Availability duty cycle > CD



(b) Availability duty cycle = CD



(c) Availability duty cycle < CD

Fig. 2. The state of charge of the energy storage during repeated outages of different availability duty cycles.

real BEDSs can be created by collecting timestamped power measurements at the location of the energy storage systems in the BEDS. Such a model can be used to compute the resilience metrics because it specifies the power that needs to be supplied by the energy storage system during an outage.

Although these metrics only capture the resilience of a BEDS with storage to grid outage, we see grid outage as the most relevant type of event for resilience. Extreme hazards, which are the focus of resilience, may damage the BEDS itself, but this would likely render the entire building unusable. If the extreme hazard results in a grid outage, on the other hand, then the building would still be usable, but power would need to be maintained.

III. Commercial Building Case Study

To demonstrate how these metrics can be used, we applied them to a commercial building model with different battery storage configurations. This section discusses the building model specifications, the simulation approach, and the computed metrics for this building.

A. Building Model

The building model is the commercial reference building model (CRBM) from [23] that has been retrofitted with LED lighting, as presented in [24]. The building is a medium-sized office building in Seattle, Washington, with three floors and was built in the 1980–2000 era. The BEDS for this building utilizes 480Y/277V and 208Y/120V.

When an outage occurs, only critical loads are used. For this study, all of the loads on the first floor were assumed to be critical loads. In the simulation, we considered the system to have survived an outage when power was maintained to all of the critical loads and did not consider the cases where a portion of the loads were powered (partial survivability). There are two different battery storage configurations: centralized or distributed. The BEDS with centralized battery storage has a single battery connected to the main panel, while the BEDS with distributed battery storage has a battery connected to each critical load panel. The nominal total battery capacity is selected to be 250 kWh, as this provides enough power to supply the building's load (in total) for approximately 24 hours. The diagram of the building model with critical loads and battery storage configurations is shown in Fig. 3.

Centralized battery storage systems are often used for load shifting or to store excess renewable energy generation. However, here we assume that the centralized storage is dedicated to resilience, such that it is kept at full charge until an outage occurs. Distributed battery storage systems are more often uninterruptible power supply (UPS) systems, which are dedicated to resilience. The batteries in the distributed configuration are sized according to the total energy at the branch in the network. The panels HM1, HL1, and LP1 are, on average, responsible for 29.6%, 38.0%, and 32.4% of the critical load, respectively. Therefore, the capacities of batteries 1, 2, and 3 are 29.6%, 38.0%, and 32.4% of the total capacity, respectively.

B. Building-Level Electrical Distribution System Simulation

The operation of the BEDS was simulated to determine the outage survival time for each time step. An object-oriented Python module was created to solve for the voltage and current at all locations for any BEDS configuration. The module does not consider any transient dynamic effects in the BEDS. Instead, it solves the BEDS assuming that the power only flows in one direction and that there is a particular power loss through each component. Components with bidirectional power flow, such as battery controllers, are modeled as two separate components: one for when the power is flowing one direction, and another for when the power is flowing the other direction. The module uses efficiency curves for the converters to determine the efficiency according to the loading level. The module also allows batteries to be simulated based on specific dispatch rules. The user specifies the distribution system as a directed network graph, where the nodes have net-zero power flow and the edges represent components such as wires, converters, or circuit breakers. The network must be hierarchical, where the top node has no inputs, the bottom nodes have one input and no outputs, and all other nodes have exactly one input. The user specifies the load profile for the bottom nodes, which is used to find the powers at each node from the bottom up.

A network representing the test building was created with all of the components defined. The hourly data for each load was generated with EnergyPlus [25]. To test the module, the normal operation of the building was simulated for each hour

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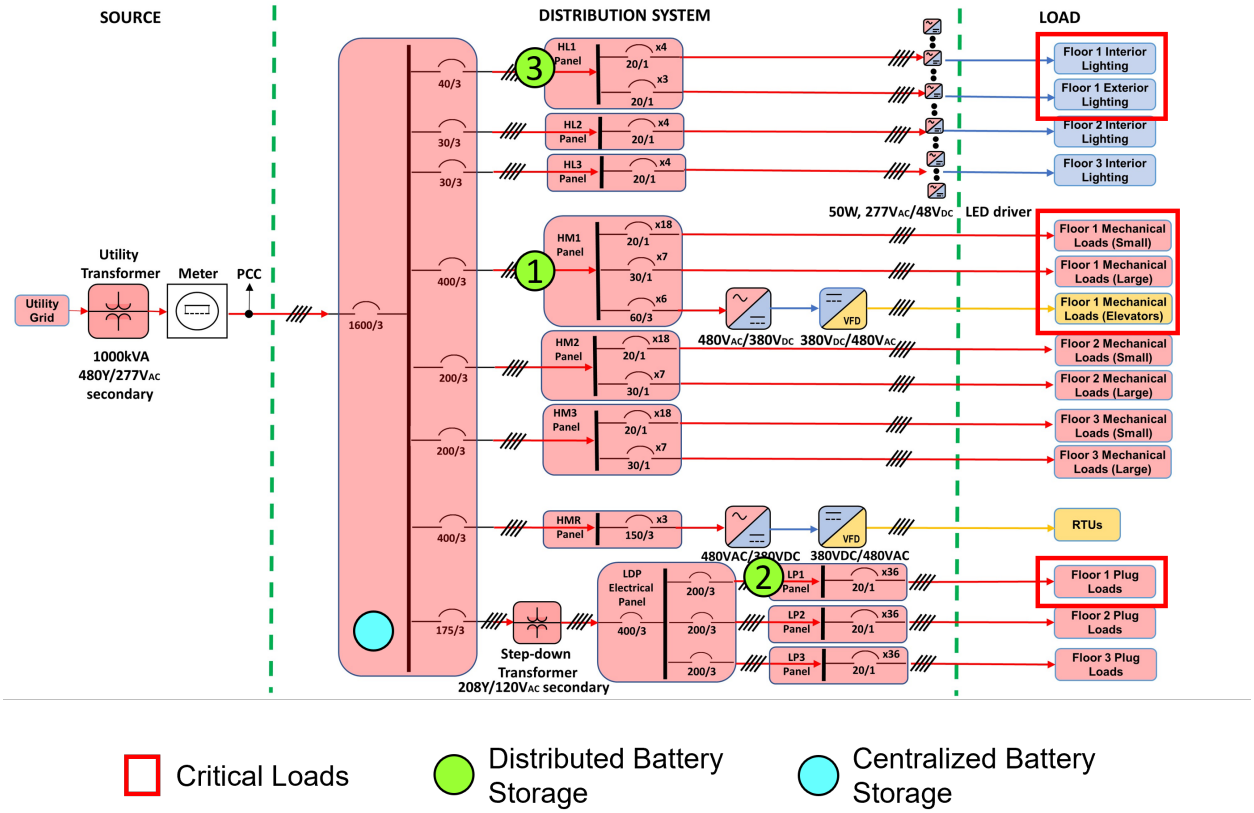

Fig. 3. Building-level electrical distribution system model with critical loads and battery storage locations. (Original image Credit: Moazzam Nazir/NREL [24]).

in the year. Next, versions of the building distribution system were created for two different battery configurations. To get outage survival data, the simulation was started at each hour of the year, and the batteries attempted to meet all of the load at each following hour. Once there was unmet power at the top of the network, the simulation ended, and the survival time was recorded for that starting hour.

C. Calculated Metrics

First, the POSC metric was calculated for both distributed and centralized storage with a total battery capacity of 250 kWh for both. These curves are shown in Fig. 4. The centralized curve is above the distributed curve when the outage duration is greater than 1 hr, indicating a higher probability of survival for all outage durations greater than 1 hr. This suggests that the centralized storage configuration is better able to withstand outages. This result is likely due to the differing load profiles for each set of critical loads. For the centralized storage, the battery can deliver more energy to the loads that need it, while for the distributed storage, there is only a limited amount of energy available to be used at each part of the network. As a result, the centralized storage is better able to withstand isolated outages.

Next, the battery size was varied for both the centralized and distributed battery storage configurations. The outage survival curves for centralized storage and distributed storage are shown

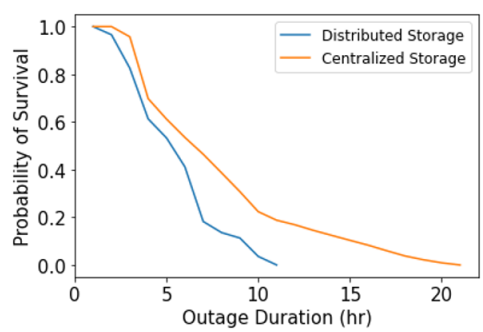

Fig. 4. Probably of outage survival curve for distributed and centralized battery configurations. The total battery capacity is 250 kWh for both.

in Fig. 5 and Fig. 6, respectively. As expected, the probability for each duration increases as the battery capacity increases. However, the graph profile remains relatively similar as the battery capacity is varied.

The data from these curves were then used to compute the proposed metrics. ST 95%, ST 90%, and ST 75% are shown in Fig. 7. According to the ST 95% metric, the centralized storage configuration is substantially better for withstanding outages. However, the margin between centralized and distributed storage decreases for ST 90% and again for ST 75%. This illustrates how the choice of probability level impacts the

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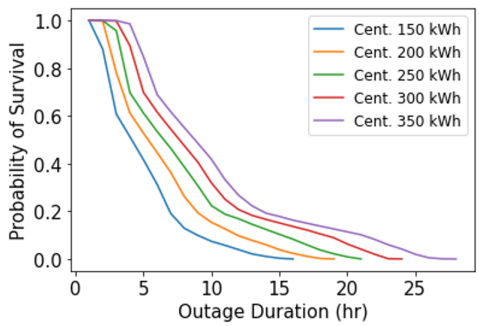

Fig. 5. Probably of outage survival curve for centralized battery storage configuration for varying battery capacities.

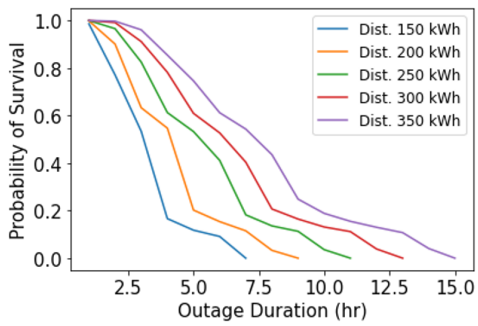

Fig. 6. Probably of outage survival curve for distributed battery storage configuration for varying battery capacities.

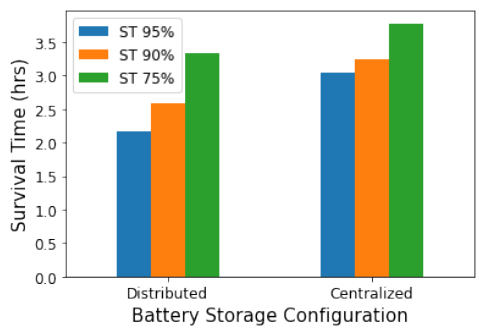

Fig. 7. Survival Time (ST) metrics for a building-level electrical distribution system with distributed and centralized storage configurations.

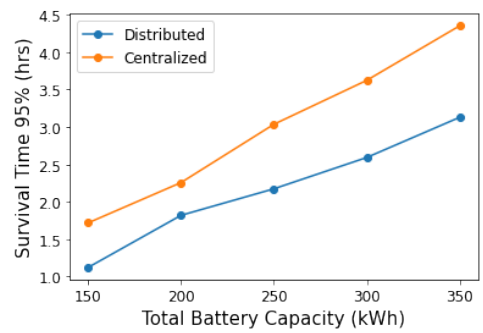

Fig. 8. Survival Time (ST) 95% metric for different battery storage capacities and configurations.

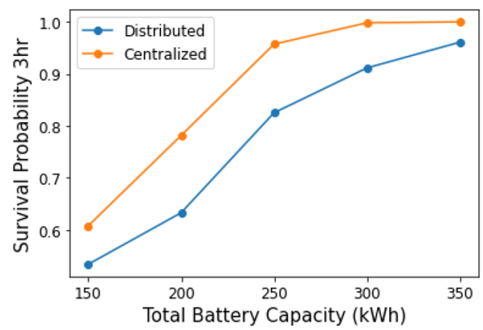

Fig. 9. Survival Probability (SP) 3-hr metric for different battery storage capacities and configurations.

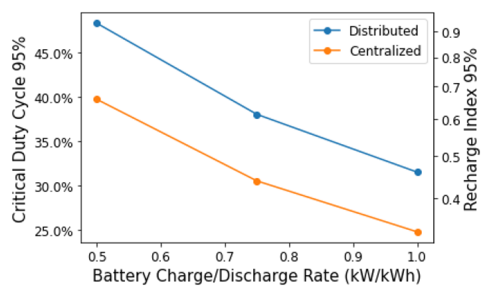

Fig. 10. Critical Duty Cycle (CD) 95% and Recharge Index (RI) 95% metrics for different battery charge/discharge rates and configurations.

measured survival time.

ST 95% for all battery capacities and configurations is shown in Fig. 8. The relationship between total battery capacity and ST 95% is approximately linear. The centralized storage configuration has a greater ST 95% for all battery capacities. Large total battery capacity is important for ST 95%.

Fig. 9 shows the SP 3-hr metric for all battery capacities and configurations. These curves have a notably different shape than the ST curves, as they approach a value of one with an approximately exponential shape. This means that additional battery capacity has a diminishing impact on SP 3-hr. Therefore, for SP 3-hr, additional battery capacity has an increasingly small impact.

In order to understand how RT, RI, and CD perform, we also varied the battery's power rating. Fig. 10 shows RI and CD for different charge/discharge rates. The charge/discharge rate displayed in Fig. 10 is the battery power rating, in kW, divided by the battery capacity, in kWh. This quantity, which is referred to as the E-rate, is equal to $1/RT$. Therefore, RT decreases as the E-rate increases. Fig. 10 shows that RI 95% and CD 95% also decrease as the E-rate increases. A higher power rating will improve the system's ability to recover from isolated outages, as indicated by RT and RI, and its ability to withstand repeating outages, as indicated by CD.

All metrics for the distributed and centralized configurations with a total battery capacity of 250 kWh are shown in Table II. For this total battery capacity, the centralized configuration

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TABLE II
METRICS FOR DISTRIBUTED AND CENTRALIZED BATTERY CONFIGURATIONS.

	ST 95% (hr)	SP 3-hr	RT (hr)	RI 95%	CD 95%
Dist.	2.17	0.83	1.00	0.46	31%
Cent.	3.04	0.96	1.00	0.33	25%

TABLE III
METRICS FOR BATTERY SELECTION.

Battery Capacity (kWh)	ST 90% (hr)	CD 90%	
		1-hr RT	2-hr RT
150	1.93	34%	51%
200	2.49	29%	45%
250	3.25	24%	38%
300	3.97	20%	34%
350	4.69	18%	30%

outperforms the distributed configuration for every metric, except for RT.

D. Designing the Building-Level Electrical Distribution and Energy Storage Systems

In this section, the metrics are used to select the battery configuration and sizes that are most appropriate for this particular application. This will show how the metrics can be used to appropriately design a BEDS with energy storage.

The building used in this case study is a simulated office building that will downgrade normal business operation and keep only critical loads during an outage event. For this study, we assume that the first floor loads (which have been deemed critical) include a data center, as well as lighting and ventilation for the first floor. We can assume that this data center contains the information technology services necessary for people to work from home, but does not support any critical services, such as websites. Therefore, the system should maintain power to the critical loads until everyone evacuates, and the data center should remain operational as long as possible. Assuming that people need 1 hr to leave the building, SP 1-hr is appropriate. Because the data center's operation is important, but not safety-critical, the ST 90% metric is appropriate as well. CD 90% is also important to ensure that the system can recover and be ready for a second outage or rolling blackouts. The target values for each metric are:

- ST 90% $>$ 4 hr
- SP 1-hr $=$ 1.00
- CD 90% $<$ 50%.

Considering that businesses usually operate 8 hr per day, a 4-hr ST is likely all that is necessary to ensure that there is not a major interruption. The SP 1-hr should be 1.0 because of the safety hazards associated with people being in the building without emergency lighting and ventilation.

Given the analysis in the previous section, centralized battery storage will be used to ensure sufficient resilience. For this example, we can assume that two different battery technology options are available: one with 1-hr RT and the other with 2-hr RT. The metrics for each battery capacity and RT are shown in Table III. SP 1-hr is not included in Table III as it is 1.0 for all of the battery capacities. A 300-kWh battery with a 2-hr RT meets the target metric values. Therefore, a battery should be selected with minimum specifications of 300-kWh capacity and 150-kW power rating.

IV. CONCLUSION

In this work, we identified existing metrics and developed new metrics for quantifying the resilience of a BEDS. We then applied these metrics to a commercial office building case study and showed how varying the battery storage capacity and configuration impacted the resulting metric values. Next, we used these metrics to appropriately select the energy storage system for this building. Overall, this case study shows how the metrics can be useful for assessing the resilience of a BEDS with energy storage.

The case study revealed the advantages and disadvantages of the proposed metrics. The advantages of these metrics are that they:

- can be calculated from BEDS simulations,
- are easy to understand,
- each describe a specific aspect of resilience, so some combination of the metrics can be customized for a specific application,
- are not based on historical data, so they measure the resilience to unprecedented outages,
- can be used with BEDS that have different types of energy storage.

These advantages allow the metrics to be used by a wide audience, including building designers, members of the public, government officials, and researchers. The metrics can also be used to understand the resilience of a BEDS to predicted or expected events because they are not based on historical data. Researchers could use these metrics to study how predicted changes in the frequency and duration of grid outages will impact buildings.

The disadvantages of these metrics are that they:

- require an accurate model of BEDS, and
- do not capture the resilience from other types of adverse events besides grid outage.

To compute these metrics, a model is needed. This might limit the use of the metrics because it requires the user to have an accurate BEDS model for the specific building.

In future research efforts, the authors will collect data from DC BEDSs across the United States, use the data to develop BEDS models, and use the proposed metrics to quantify the resilience of DC BEDSs. In this future work, DC BEDSs will also be assessed according to other performance metrics, such as those presented in [24]. Other future research opportunities include applying the resilience metrics to different BEDS configurations (DC, hybrid AC/DC), sources (PV, wind), and energy storage types (mechanical, thermal). Specifically, applying these metrics to unconventional BEDS, such as DC,

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would help quantify the impacts of these proposed BEDS on resilience. These metrics could also be used to optimize the system design, such as the size of battery and PV, to maximize the resilience. The software tool developed in this research effort could be used to model these different scenarios. Another opportunity for future work is to restrict the time of day when the survival time is calculated. For example, an office building that is being used from 8 a.m. to 5 p.m. is not as concerned with outages at night, so the survival times could be calculated for working hours only. Additionally, the resilience metrics presented here could be holistically applied to building-level energy systems, including electricity, thermal, and natural gas systems. Future work could also build on the case study presented here to investigate BEDSs with both centralized and distributed energy storage. Centralized systems have more flexibility than distributed systems, but distributed systems have less loss between the storage and the load. As centralized and distributed storage each have their benefits, there should be an optimal amount of centralized and distributed storage to maximize resilience.

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