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Resilience and economics of microgrids with PV, battery storage, and networked diesel generators

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ABSTRACT

Current designs and assessments of microgrids have ignored component reliability, leading to significant errors in predicting a microgrid's performance while islanded. Existing life cycle cost studies on hybrid microgrids—which combine photovoltaics (PV), battery storage and networked emergency diesel generators—also have not identified all the potential economic opportunities. Reducing the number of emergency diesel generators through reliance on PV and battery, retail bill savings, and demand response and wholesale market revenue streams are all important. This paper provides a new statistical methodology that calculates the impact of distributed energy reliability and variability on a microgrid's performance and a novel use of the optimization platform REopt to explore multiple cost savings and revenue streams. We examine the impacts for microgrids in California, Maryland, and New Mexico and show that a hybrid microgrid is a more resilient and cost-effective solution than a diesel-only system. Under realistic conditions, a hybrid microgrid can provide higher system reliability when islanded and have a lower life cycle cost under multiple market conditions than a traditional diesel generator-based system. The improved performance of the hybrid system is resilient to conditions experienced over the last 20 years in solar irradiance and sees little degradation in performance immediately after a hurricane. The cost savings to provide this more resilient backup power system as compared to a diesel-only microgrid are significant. The net present cost for a hybrid microgrid is 19% lower in New Mexico and 35% lower in Maryland than a diesel-only microgrid. In California, the net present cost of the hybrid microgrid is negative because, unlike a diesel-only microgrid, a hybrid microgrid has lower life cycle costs than the power costs without a microgrid.

1. Introduction

Current modeling tools and analyses do not properly account for the impact of distributed energy resource (DER) reliability and variability and therefore cannot properly estimate a microgrid's reliability. The primary driver for deploying a microgrid is the need for energy resiliency, or, equivalently, providing reliable power when the grid is down. Secondary value streams such as participation in demand response programs and energy markets allow a microgrid to be affordable [1], but they are not the driver. While the reliability of a microgrid system to provide power to critical loads when islanded is dependens on the reliability and availability of power from the individual DERs, [2,3], quantitative and realistic assessments of the impact of DER reliability on total system reliability are absent from the literature. Industry has recognized this issue and has highlighted this gap in our ability to assess performance [4].This paper provides a new approach for treating DER reliability and variability impacts on a microgrids islanded performance and explores for the first time their impacts on cost and performance of hybrid microgrids that use emergency diesel generators (EDG), photovoltaic solar power (PV), and battery energy storage systems (BESS). We focus on these DERs because they are the dominant sources used to provide energy for backing up critically loads. Historically almost all backup power has been provided exclusively from EDGs. Recently due to the rapid decline in PV and BESS costs they are being considered as a supplement for exclusively EDG based systems. Although other renewable energy sources such as wind or hydro power are possible, they are limited in the application in microgrids because of site constraints.

Realistic estimates for the reliability of DERs are critical in designing a microgrid. DERs' reliabilities establish an upper bound for a microgrid's probability to provide continuous power while islanded during a grid outage, because, without sufficient power, the microgrid cannot support the critical loads. The reliability of power from a microgrid also depends on the reliability of the electric distribution and communication networks; their vulnerabilities are highly site-specific, dependent on the local level of hardening and cyber protection. In addition, the impact of the distribution networks are the same for a diesel-only and a hybrid microgrid, independent of the number and size of DERs. Thus, in considering the reliability advantages and disadvantages of DER selection, the distribution conditions can be ignored. DERs also have site-specific

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vulnerabilities. They can be submerged due to local flooding or potentially damaged by extreme weather events as reported for PV systems [5]. These vulnerabilities can be greatly reduced by smart planning and engineering [5]. The reliabilities we are concerned with are the inherent reliabilities of the DERs that are set by the design and maintenance of the DER and independent of local conditions.

The impact of realistic reliability estimates for EDG based systems [6] has recently been analyzed for both microgrids and stand-alone building-tied systems [7,8]. That work provides a comprehensive review of the literature on EDG reliability and its impact on microgrids. But no similar analyses exists for hybrid systems that use a mix of PV, BESS, and EDGs. Existing studies of hybrid microgrids do not explore the potential for costs savings that can be realized by reducing the number of EDGs through reliance on PV and BESS to meet the critical loads, and do not model the impacts of EDG, PV, and BESS reliability or PV variability over short (hourly) and long time scales (years). These issues are critical when a microgrid is supporting national security or health and safety critical loads.

In this paper, we present an approach for conducting a techno-economic assessment of hybrid microgrids that use PV, BESS, and EDGs. The diesel generators in the microgrid are networked to allow parallel operation and coordinated dispatch for loads interconnected within a facility's distribution system. This study provides an approach to selecting DERs by evaluating their life cycle costs and the resilience of a microgrid when islanded. Three case studies are presented that illustrate the impact of local electricity markets and solar resources. We briefly review the literature and highlight some of the findings and limitations of: (1) existing public microgrid design software tools, (2) studies on the economic value of behind-the-meter grid-tied PV and BESS, and (3) studies on hybrid grid-tied microgrids.

1.1. Public software tools

Multiple software tools design and optimize microgrid configurations [9], buy most do not consider the impact of DER reliability, and none fully consider both grid-connected and islanded performance. Three commonly used technical-economic modeling tools: REopt [10,11], developed by the National Renewable Energy Laboratory (NREL), Hybrid Optimization Model for Multiple Energy Resources (HOMER) [12], and Distributed Energy Resource, Customer Adoption Model (DER-CAM) [13,14], developed by Lawrence Berkeley National Laboratory, currently do not take into account the reliability of the DERs that make up the microgrid. Although they discuss reliability and resilience, none consider DER reliability in determining the microgrid's performance. The Microgrid Design Toolkit (MDT) [15,16], developed by Sandia National Laboratory, calculates microgrid performance in an islanded mode using a Monte Carlo simulation to account for DER reliability. But no default recommendations on how to model the individual DER reliability are provided. Also, direct Monte Carlo simulations for rare events can be slow to converge and thus difficult to use to assess overall microgrid reliability.

1.2. Economic value of PV and BESS

The economics of behind-the-meter PV and BESS has been well studied. Many studies have assessed and optimized the economics of PV systems without storage as a function of building types [17], utility rate structure, ownership options, PV size, and PV costs [18]. Tools are available to assess PV costs for site-specific conditions [19]. Work has also been done to optimize the size and savings of behind-the-meter BESS for demand savings as a function of tariffs [20], battery sizing [21], and load profile [22]. More recently, studies have looked at combined PV and BESS behind the meter [23]. Tools are available to optimize behind the meter storage and PV for site-specific conditions [10,11].

1.3. Grid-Tied hybrid microgrids

There is a large body of literature on the role and economic value of integrating BESS into grid-tied hybrid microgrids [24]. BESS can reduce the microgrid's cost by utilizing renewable generation, peak shaving, energy arbitrage, or other market opportunities during nonemergency periods. BESS can also exploit intermittent renewable energy while islanded. Sizing of BESS is often based on grid-tied economic issues [24–26]. Little work has been done to quantify the value of resiliency provided by a hybrid microgrid over a diesel-only system during a grid outage. Improvements in resiliency due to reduced fuel consumption that results in longer islanding times has been examined [27,28] and has demonstrated the benefit of on-site renewable energy but assumed all DERs are 100% reliable. Increasing fuel reserves on-site, for most campus-like environments, is straightforward and not costly, and does not dramatically change the microgrid's performance. In all these cases, the full variability of a solar PV output is not examined, nor is the potential improvement in microgrid reliability.

The works of Hanna et al. [29,30] and Nelson et al. [31] look at the issue of component reliability on microgrid performance. Hanna et al. uses a novel optimization approach to optimize a microgrid subject to the reliability of the DERs and the value of lost load. This work is an important contribution to the microgrid literature but unfortunately did not consider realistic DER reliability estimates and did not model long duration outages that are rare but have a high impact. Nelson et al. use a Markovian statistical approach to incorporate component reliability similar to our previous work [8] and the work presented here. They treat the nonperfect reliability of EDGs based on our previous work [7] but do not explore the reliability of other DERs or their potential variability. Optimization is focused on grid-connected behavior for a single example market. The work presented here is consistent with their work but analyzes a number of key issues not previously treated, and provides the following contributions to the literature:

- A computationally simple method using Markov chains to calculate the likelihood of the DERs meeting 100% of the critical load and the mean fraction of lost load
- The impact of EDG and BESS reliability on the islanded performance of the microgrid
- The impact of both short- and long-term variability of the PV on a microgrid's islanded performance
- A novel use of REopt for optimal sizing of a microgrid's DERs that takes account of the number of EDGs, and the size of the PV and BESS
- A comparison of the resilience of a diesel-only microgrid and a hybrid microgrid
- An assessment of market condition on the relative cost and performance of a hybrid microgrid versus a diesel-only microgrid.

This work demonstrates the importance of taking into account the reliability and variability of DERs in assessing microgrid systems. Under realistic conditions, a hybrid microgrid can provide higher system reliability when islanded and have a lower life cycle cost under multiple market conditions than a traditional diesel generator-based system. The approach reported on here allows one to assess the life cycle costs and system reliability of a microgrids with multiple DER configurations. We separately calculate life cycle costs and reliability and depending on an individual sites goals an optimal system can be chosen. Thus in the paper we separately describe the system reliability and life cycle cost methodologies and results.

The analysis flow chart used in this work is illustrated by Fig. 1 which shows the integration of blue-sky (i.e. grid-connected, normal operations) economics, component reliability data, and a robust resilience performance assessment. The initial DER sizing from the blue-sky economics model incorporates some heuristic constraints for resilience, but once the true resilience performance is assessed, iteration can be made

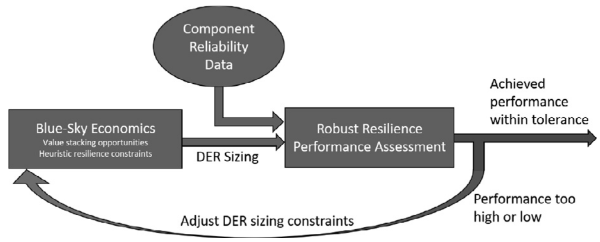

Fig. 1. The analysis flow chart used in this work which integrates economics, component reliability, and resilience performance.

on the economics with adjusted DER sizing constraints if the resilience performance is higher or lower than required.

Section 2 reviews and estimates the reliability of EDGs, PV, and BESS. Details on the values used are provided in the appendix. Section 3 discusses the approach for modeling the microgrid's system level resilience when islanded independent of cost considerations. Section 4 presents our approach for using NREL's REopt™ techno-economic optimization model for evaluating the cost-optimal sizing of PV and battery storage. Section 5 provides the conditions and assumptions for the three case studies to be presented. Section 6 provides the DER sizing and relative life cycle costs results for diesel-only and hybrid microgrids. Section 7 provides the resilience performance for diesel-only and hybrid microgrids. The optimal choice for each site will depend on the risk tolerance of the site or equivalently the level of reliability they require. The trade off between cost and reliability will always be a site specific decision based on the site's mission and financial resources. Lastly, we provide a brief discussion is provided on the results of this study, the importance of considering finite reliability and long term variability when selecting DERs for a microgrid, and additional benefits of hybrid microgrids.

2. Component reliability

In this section, we summarize our assumptions for EDG, PV, and BESS reliability. Additional details are provided in Appendix A. The focus is on a DER's reliability during a grid outage when a microgrid must island. This requires an estimate for three metrics: (1) the probability that the DER will be operationally available at a given power level when a grid outage occurs, (2) the probability the DER will start (relevant only if the DER is in a cold state before the grid outage), and (3) the probability a DER will operate at a given power capacity over the duration of the grid outage. Although grid outages can last months, they rarely last longer than a week or two, which is the focus of this assessment.

2.1. EDG Reliability

A detailed analysis of modern EDG reliabilities has shown that EDG reliability is dependent on the level of preventive maintenance [6]. If EDGs are to be used, they must be properly maintained in accordance with either government [32] or public standards [33]. We consider only well-maintained EDGs[1] Empirical data collected for fielded commercial EDGs by the U.S. Army [34] and Navy [35] provides the information required to estimate the three reliability metrics for EDGs typically used in microgrids (10 kW to 2,000 kW).

The first reliability metric, Operational Availability (OA), captures the likelihood the EDG is available at the start of a grid outage (the formulas for all reliability metrics are provided in Appendix A). The OA metric can change based on maintenance schedules, repair times, and annual failure rates. The OA of a well-maintained EDG has been shown

[1] Well maintained means that at a minimum follows the recommended maintenance practices defined in government and commercial guidance.

Table 1
Mean reliability metrics and 90% confidence intervals [8].

Metric	Low Reliability (90% confidence)	Mean Reliability	High Reliability (90% confidence)
MTTF	1180 hours	1662 hours	2410 hours
FTS	0.17%	0.13%	0.10%

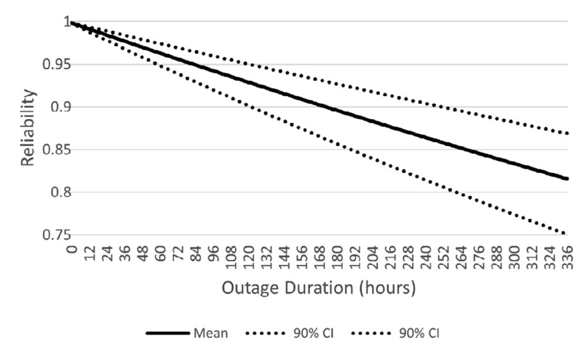

Fig. 2. Mean and 90% confidence interval reliabilities for a well-maintained EDG for outages up to two weeks [8].

to be very high, 99.98% [8]. This high availability reflects the small number of EDG runs per year, and thus the small number of potential failures per year that require repairs. EDGs are run almost exclusively for testing or during a grid outage and therefore rest in a cold state for most of the year. Their yearly operation is limited to 200 hours (for nonemergency use) by the Clean Air Act regulations, and most run less than that. Because of this usage pattern, it is important to include the potential failure to start (FTS).

To address runtime failures and the irregular use of EDGs, the EDG is assumed to successfully start and carry the load, and then a mean time to failure (MTTF) is defined that captures failures while the EDG is running. The MTTF is not dependent on the reliability of the grid or how often the EDG is tested. This metric is defined by total runtime and the number of failures that occur while running. The mean and 90% confidence intervals for the FTS and the MTTF previously reported [8] based on the Army's and Navy's empirical data are provided in Table 1. These reliability metrics are more than an order of magnitude better than seen in poorly maintained commercial EDGs in this size range [36].

We further assume the EDG is in its "useful life period" [37] and therefore the runtime failure rate (the inverse of the MTTF) is constant. Thus, the reliability, $R(t)$, of an EDG at time t during an outage is given by:

$$R(t) = OA(1 - FTS)e^{\frac{-t}{MTTF}} \tag{1}$$

Fig. 2 illustrates the reliability of a single EDG from the start of a grid outage out to 2 weeks.

Fig. 2 illustrates the dominant impact of the MTTF on the predicted reliability of an EDG. The OA and FTS impacts are not visible in Fig. 1 due to the scale of the reliability axis.

2.2. PV Reliability during an outage

The reliability of a PV system (PV modules, inverters, and balance of system) is defined as the available generation capacity of the PV system, not the delivered power. The delivered power is highly variable due to changes in the local solar irradiance, which affects power output. The delivered power variability is treated separately. To characterize PV reliability during a grid outage we need to estimate only two of the metrics (OA and MTTF), because the PV is never in a cold state waiting to be turned on.

We are concerned with modern utility-scale PV systems greater than one megawatt (MW). In Appendix A, we demonstrate that a utility-scale

PV system's availability is typically greater than 99% and the capacity may decline on the order of 1%. Thus, the PV reliability is high enough to ignore its impact when modeling a hybrid microgrid system. The infrequent and modest loss of capacity is small compared to the large variation of power due to changes in solar irradiance. This conclusion may not hold for small residential systems.

2.3. BESS Reliability during an outage

We are interested only in the performance when a grid outage occurs and the microgrid system is in an islanded mode. BESS reliability can be defined as the likelihood the storage capacity is above a predefined threshold (i.e. its ability to be charged to that level) relative to its nameplate value. To quantitatively characterize the BESS reliability during a grid outage, we need to know both the OA and the MTTF during the grid outage. The reliability of a BESS depends on both their design and operation. Stationary storage batteries consist of multiple cells, which can be connected in different configurations [38]. The reliability depends on the details of the manufacturer's design and on the operation of the battery. Its temperature, age, and cycling history (frequency of cycles and depth of discharge) can all affect reliability. MTTF estimates have both a calendric and cycling dependency [39]. Our goal is to estimate a reasonable range of reliability values. We use a range of values from the literature and from commercial BESS manufacturers to identify reliability estimates to be used in our case studies.

A BESS may not be available to support a hybrid microgrid when an outage occurs due to maintenance or repair activities. Manufacturers report availability from 97% to greater than 99% for Li-ion BESS in MW-scale systems [40]. Availability quoted by manufacturers can be overly optimistic and may be based on limited testing. The case studies in this work examine a range of OA from 95% to 100% and use 97% as a representative estimate.

The probability the BESS stops functioning at a level necessary to support a microgrid that is islanded for less than 2 weeks is very small. The anticipated battery degradation rates for systems is inconsequential over a two-week period and can be ignored. Manufacturer's estimates for MTTF are over 50,000 hours [41] and calculations [42] made for a 1-MW/500-kW Li-ion battery for frequency regulation application predict an MTTF of over 8 years (>70,000 hours). Thus, if a BESS is available at the start of a grid outage, we can assume it will remain operational for the next few weeks.

3. Reliability modeling

This section describes how to model the expected performance of a hybrid microgrid during a grid power outage. The approach described here has been validated in [43]. The reliability is calculated using a Markov chain approach independent of the economic optimization, which is conducted using REopt, as described in the next section. These two approaches can be run sequentially to identify an optimal system. The hybrid microgrid consists of networked diesel generators, PV panels, and battery storage. To calculate the expected performance of the backup system for a given outage, we first determine the initial probabilities of being in each system state, which is dependent on the number of working generators and the battery initial state of charge (SOC). The battery initial state of charge is determined by the economic dispatch calculated using REopt. We assume that sufficient diesel fuel is available to operate the EDGs for the duration of the outage. We then iteratively execute the following procedure:

1. Update system state probabilities to reflect chance of generators failing.
2. Calculate solar, generator, and battery output for each system state.
3. Subtract system output from critical load to determine amount (if any) of unmet critical load in each system state.
4. Use unmet critical load and system state probabilities to calculate performance metrics.
5. Use battery output in each system state to update system state probabilities.

The following subsections describe each step in detail.

3.1. Initial system state and generator failure

The performance of a microgrid system during an outage depends on the system configuration, when the outage occurs, and the outage duration. The system configuration is determined by the size and number of EDGs, along with the PV and battery sizes. Critical load and PV output varies across the year, so the chance of survival depends on when an outage occurs. EDGs can fail to start or run during the outage, and batteries have limited storage capacity, which results in the probability of outage survival decreasing with outage duration.

The following five factors describe the system configuration: number of EDGs N, EDG maximum capacity K_G, solar capacity K_S, battery inverter size K_I, and battery effective energy capacity K_B. Battery systems are often kept from fully charging or discharging to decrease battery degradation. Therefore, the effective energy capacity may only be a fraction of rated energy capacity.

The system state is determined by the number of working generators and battery SOC. The number of EDGs is denoted n which ranges from 0 to N. We discretize the potential battery states of stored energy into M+1 bins (to allow the SOC to be included in the Markov chain), indexed with m ranging from 0 to M. The kWh increment of each bin is denoted h, where $h = K_B/M$. Bin m denotes $b = m * h$ kWh of stored energy. This discretization may lead to some calculation error, but will be small for a sufficiently large M. In our simulations we set $M = 200$.

The probability of the system being in each state is represented by the $N + 1$ by $M + 1$ matrix $\mathbf{A(t, d)}$, with element $a_{n,m}(t, d)$ denoting the probability of the state consisting of n working generators and having a battery charge in bin m. In each outage hour, $\mathbf{A}$ is updated to reflect the new probabilities of being in each state.

Let $q_B(m, t)$ denote the probability that the battery initial charge falls into bin m at the beginning of an outage starting at time t. This allows for uncertainty regarding the battery charge at the start of an outage. The battery SOC will often be given by a known economic dispatch, in which case $q_B(m, t)$ will be 1 for the initial bin and zero for all others.

Let $q_G(n)$ denote the probability that n generators successfully start at the beginning of the outage. The likelihood of one generator failing is independent of whether another generator failed, which means $q_G(n)$ is:

$$q_G(n) = \binom{N}{n} (OA(1 - FTS))^n (1 - OA(1 - FTS))^{N-n} \tag{2}$$

Equation (2) is the combinatorics equation for the probability that n out of N generators will successfully start. The initial system state probabilities are as follows:

$$A(t, 0) = \begin{bmatrix} q_G(0)q_B(0, t) & \dots & q_G(0)q_B(M, t) \\ \vdots & q_G(n)q_B(m, t) & \vdots \\ q_G(N)q_B(0, t) & \dots & q_G(N)q_B(M, t) \end{bmatrix} \tag{3}$$

A generator may be available and start, but then fail to run at some point during the outage. We use a constant hourly failure to run probability, denoted FTR, which is the inverse of the mean time to failure when the generator is running. If n generators are running in a given hour, then the likelihood that k generators will be running in the next hour is given by $p(n, k)$:

$$p(n, k) = \binom{n}{k} (1 - FTR)^k FTR^{n-k} \tag{4}$$

Let $\mathbf{P}$ denote the matrix of transition probabilities:

$$\mathbf{P} = \begin{bmatrix} p(0, 0) & \dots & p(N, 0) \\ 0 & p(n, k) & \vdots \\ 0 & \dots & p(N, N) \end{bmatrix} \tag{5}$$

In each hour, we update the system state to account for generator failures:

$$\mathbf{A}(t, d+1) = \mathbf{P}\mathbf{A}(t, d) \tag{6}$$

3.2. Microgrid dispatch and unmet critical load

We denote outage start time as t, current outage duration as d, and critical load as $L(t+d)$. The quantity of solar generation is given by:

$$Q_S(t+d) = K_S * F(t+d) \tag{7}$$

where $F(t+d)$ is the solar power factor in hour $t+d$.

EDG dispatch is limited by EDG capacity times the number of working EDGs. The maximum potential output from n working EDGs, each with a capacity K_G, is given by:

$$Q_G(n) = K_G * n \tag{8}$$

In hours when the PV and EDG are unable to meet critical load, the battery system can discharge to fill in the gap; in hours where the PV and EDGs have excess capacity the battery can recharge. Battery systems experience efficiency losses while charging and discharging. The battery requires b/E kWh to increase charge by b and requires to discharge by $b * E$ to output b. When $Q_S(t+d) + Q_G(n) \leq L(t+d)$, then the battery discharges Q_B^D:

$$Q_B^D(t, d, b, n) = \min\left(Eb, K_I, L(t+d) - Q_S(t+d) - Q_G(n)\right) \tag{9}$$

Equation (9) describes that the battery discharge is the minimum of stored energy, maximum power output, and the amount of energy required to meet net critical load. When $Q_S(t+d) + Q_G(n) \geq L(t+d)$, the battery uses Q_B^C to charge:

$$Q_B^C(t, d, b, n) = \min\left((K_B - b)/E, K_I, (Q_S(t+d) + Q_G(n) - L(t+d))\right) \tag{10}$$

Equation (10) says the amount of battery charging is the minimum of the available storage capacity in the battery, maximum power output, and excess generation available.

Unmet critical load is given by $Q_U(t, d, n, b)$:

$$Q_U(t, d, n, b) = \max(0, L(t+d) - Q_S(t+d) - Q_G(n) - Q_B^D(t, d, n, b) + Q_B^C(t, d, n, b)) \tag{11}$$

Therefore, given the current system state in terms of the number of working generators n and battery SOC b, we can determine whether the system will meet critical load for an outage starting in hour t for outage duration d or whether the system will need to shed critical load.

3.3. Performance criteria

We use two performance criteria to determine system reliability for a given outage duration d. The first is to determine the likelihood the microgrid meets critical load. Let $x(t, d)$ denote the probability of critical load being met in outage hour d of an outage starting at t:

$$x(t, d) = \sum_{n=0}^{N} \sum_{m=0}^{M} a_{n,m}(t, d)\, \mathbb{1}_{Q_U(t,d,n,b)=0} \tag{12}$$

Where T denotes the number of time periods and $\mathbb{1}_{Q_U(t,d,n,b)=0}$ is 1 whenever the system has sufficient generation to meet critical load. In other words, sum the elements of the state probability matrix, in which the system meets critical load.

In the absence of any information on the time during the year outages are likely to occur, one typically assumes outages are equally likely in each hour of the year, then the probability the microgrid will meet critical load in an outage of duration d, denoted $X(d)$, is:

$$X(d) = \left(\frac{1}{T}\right) \sum_{t=1}^{T} x(t, d) \tag{13}$$

If outages are expected to be non-uniformly distributed, $X(d)$ can account for differences in the chance of an outage occurring in a given hour by weighting each $x(t, d)$ with the probability of an outage occurring in hour t. The second performance criteria is the expected percentage of load shed in a given outage hour, which is given by $y(t, d)$:

$$y(t, d) = \left(\frac{1}{L(t+d)}\right) \sum_{n=0}^{N} \sum_{b=0}^{B} a(n, b; t, d)\, Q_U(t, d, n, b) \tag{14}$$

$Y(d)$ gives the expected percentage of load shed in outage hour d:

$$Y(d) = \left(\frac{1}{T}\right) \sum_{t=1}^{T} y(t, d) \tag{15}$$

A more reliable system will have a higher $X(d)$ and a lower $Y(d)$: a higher probability of survival and a lower expected percentage of load shed.

3.4. Update battery state

The battery may charge to store excess generation or discharge to help meet critical load. Charging and discharging will change the system state, which in turn changes the probability of meeting future critical load. In the state probability matrix $A(t, d)$, the number of working generators is indicated by the row and the binned battery charge is indicated by the column. Therefore, a change in battery charge shifts probabilities horizontally along a row to a different column.

The element in n, m will shift to the $m'_{n,m}$'th column, where m' is given by:

$$m'_{n,m} = m - round\left(\frac{Q_B^D(t,d,n,mh)}{Eh}\right) + round\left(\frac{Q_B^C(t,d,n,mh)E}{h}\right) \tag{16}$$

In equation (16) round denotes rounding to the nearest integer. Equation (16) says the battery charge decreases by the number of bins worth of discharge and increases by the number of bins worth of charging. We set $A'(t, d)$ as an $N+1$ by $M+1$ matrix, with each element defined as follows:

$$a'_{n,m}(t, d) = \sum_{i=0}^{M} a_{n,i}(t, d)\, \mathbb{1}_{m'_{n,i}=m} \tag{17}$$

In other words, we sum all of the state probabilities shifted into the given battery bin. Finally, we set $A(t, d) = A'(t, d)$.

4. Economic modeling

This study uses NREL's REopt techno-economic optimization model for evaluating the cost-optimal sizing of solar PV and battery storage. REopt is a planning tool formulated as a mixed-integer linear program to optimally size and dispatch the DERs and storage-based assets given the historical building loads and rate tariffs for a specific site [11,44]. The optimization model performs hourly economic dispatch for a year and uses financial discounting parameters (e.g. discount rate, escalation rates) to determine the life cycle cost of energy over the analysis period (e.g. 20 years). The model has perfect-foresight of the site load and energy prices, so the resulting DER investment economics represents the theoretical potential. The REopt model capabilities leveraged for this project are shown in Fig. 3, including consideration of solar PV and battery storage for retail electric bill savings opportunities. In this work, additional features were developed to consider (1) avoided cost of the diesel-only microgrid's EDGs, (2) demand response revenues, and (3) wholesale market revenues. The objective function of the model is to minimize the life cycle cost of energy, which includes capital investment, operating and maintenance cost, utility electric bills, and negative costs such as demand response and wholesale market revenue streams.

Three site locations across the United States were selected to observe the variation in economic results based on several unique attributes: (1)

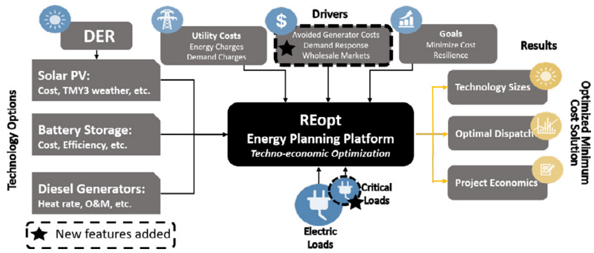

Fig. 3. The REopt™ techno-economic optimization tool used in this analysis. Source: [11].

solar resource, (2) retail electric rate tariff, and (3) opportunities for demand response and wholesale markets. REopt uses the PVWatts™ application programming interface (API) [45] within the model to estimate the solar production profile based on typical meteorological year data and default performance parameters. The retail electric rate tariffs are based on actual tariffs at the three sites modeled. Research was conducted to evaluate the demand response and wholesale market opportunities available for each site. The same electric load profile and critical load was used for each site. Additional information related to the three site locations is given in Section 5.

4.1. Avoided EDG costs

The diesel-only microgrid is assumed to have an $N+1$ reliable configuration where the peak critical load is between the electric capacity of $N-1$ and N EDGs. Reducing the number of EDGs by adding PV and BESS is explored as one of the value streams for a hybrid microgrid. Because reducing EDGs has implications for the resilience performance and REopt does not explicitly calculate this performance, a heuristic approach was taken to estimate any additional power and/or energy capacity required by the battery to achieve economic credit for reducing an EDG.

In the heuristic, the battery was forced to discharge in the grid-tied economic dispatch when the critical load exceeded the capacity of the $N-1-N_{\text{EDG Reduced}}$, where $N_{\text{EDG Reduced}}$ is the decision variable for the number of EDGs reduced. This ensured the net critical load could be met by EDG in case a power outage were to imminently occur. This dispatch requirement by the battery may or may not result in a larger battery size than what REopt would have otherwise sized based on the other economic benefits. The actual reliability performance of the microgrid with PV, battery, and a reduced number of EDGs is evaluated using the Markov chain reliability model to compare against the diesel-only microgrid. The reliability performance then determines if more, fewer, or the same number of EDGs should be removed than the result of the initial heuristic approach.

4.2. Retail bill savings, demand response and wholesale markets

The details of the economic modeling methodology, including retail bill savings, demand response, and wholesale markets are included in Appendix B.

4.3. Life cycle cost inputs

Table 2 lists the life cycle cost analysis inputs for the REopt model based on financial parameters that would be used for military-based projects [40].

Table 3 lists the DER and microgrid cost parameters used in the REopt model. The PV capital and O&M cost are based on NREL's 2019 Annual Technology Baseline estimates for commercial-scale systems [46]. The power and energy portion of battery storage capital cost is calculated independently. The power-specific cost ($/kW) represents the cost of the power converter and other power electronics, and the energy-specific cost ($/kWh) represents the cost of the battery storage modules. The costs used in this analysis are in line with recent data for commercial- and industrial-scale systems [47]. There is also an assumed replacement cost of half of the initial power- and energy-specific capital cost incurred in year 10.

The estimate for microgrid capital and O&M costs are intended to be inclusive of the following hardware and software equipment: switchgear upgrades, information technology (IT) hardware, operational technology (OT) hardware, market participation software, communications, monitoring, and metering improvements, and upgraded power control system (PCS) that meets IEEE, UL, and/or IEC standards. Other system-related equipment and maintenance costs included are foundational work and buildings, engineering, procurement, and construction (EPC), grid interconnection engineering, HVAC systems for DER, land and right-of-way preparation and access, shipping, testing and commissioning, and personnel training. These estimates are based on similar size microgrids [40]. Items not included in the microgrid costs include distribution system upgrades and line extensions, substation upgrades, and operating permits.

Table 2
Financial parameters for life cycle cost analysis.

	Value	Units
Analysis Period	20	years
Discount Rate	6%	
General Inflation Rate	2.2%	
Electricity Escalation Rate	2.2%	
Diesel Fuel Escalation Rate	2.2%	

Table 3
DER and microgrid cost parameters.

	Value	Units
Solar PV		
Capital	1600	$/kW
Fixed O&M	12	$/kW/yr
Battery Storage		
Capital, Power	500	$/kW
Capital, Energy	300	$/kWh
Capital Power Replacement	250	$/kW
Capital, Energy Replacement	150	$/kWh
Fixed O&M	12.5	$/kW/yr
Variable O&M	0.0003	$/kWh
EDG		
Capital	750	$/kW
Fixed O&M	9.3	$/kW/yr
Microgrid		
Capital	4000	$k
Fixed O&M	133	$k/yr

5. Site information

To illustrate the economic and resilience performance of a hybrid microgrid as compared to a diesel-only microgrid, we examine three cases that explore the diversity of electricity markets in the United States and solar resources. We use the same electric load profile for each campus. The diesel-only microgrid has an N + 1 reliable configuration at all three sites. The three sites are located in California, Maryland, and New Mexico. They cover a diversity of utility rate structures and local electricity market conditions seen across the United States. Table 4 lists the DER performance inputs used in the analysis. Performance estimates for solar PV are consistent with REopt defaults [11] which leverage default values used in PVWatts [45]. Battery storage round trip efficiency is based on estimates from industry experts [40] and this represents a power conversion efficiency of 96% and battery module round trip efficiency of 92% (where net round trip efficiency equals $96\% \times 92\% \times 96\%$). EDG

Table 4
DER performance parameters .

	Value	Units
Solar PV		
Production Calculator	PVWatts™	
Resource Dataset	TMY3	
Tilt	30.4	deg
Losses	14%	
DC to AC Ratio	1.1	
Inverter Efficiency	96%	
Balance of System Efficiency	86%	
Annual Degradation	0.5%	
Battery Storage		
Round Trip Efficiency	81.3%	
Minimum State of Charge	20%	
EDG		
Diesel-only Number	15	
Electric Capacity	750	kW
Heat Rate	12,040	btu/kWh

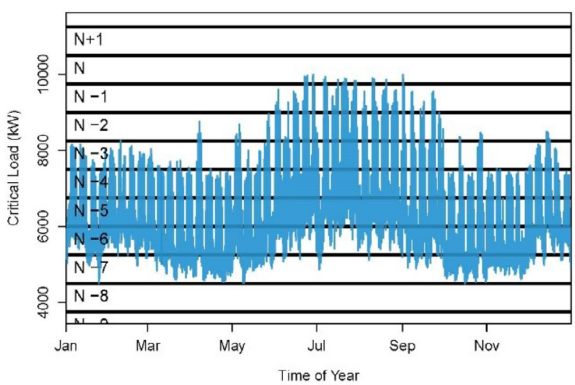

Fig. 4. Modeled campus critical load profiles. The horizontal lines indicate the number of 750 kW EDG to satisfy conventional N + x reliability.

performance parameters are based on estimates from industry experts [40].

5.1. Electric load

A realistic and representative hourly load profile was used to represent a large campus with a peak hourly load of 20 MW, of which 50% is deemed to be critical. The load profile was generated by scaling an existing hourly campus load profile for a military base [7,8]. The load profile is representative of load profiles seen in large universities [48], large active military installations [49], midsize airports [50], and research hospital complexes. Fig. 4 shows the hourly critical load profile. The full campus load profile is simply twice this. In our previous work [8], we examined the sensitivity of a diesel based microgrid's performance to details of the load profiles. We showed that the differences are modest, less than the variation due to uncertainty in the reliability metrics of the DERs. Uncertainty or stochastic behavior in the load profile will not have a major impact on the predictions or reliability. Thus, we consider only a single fixed load profile.

5.2. EDGs

The diesel-only microgrid is assumed to have fifteen 750-kW EDGs to serve the critical load during an outage. This is an N + 1 reliable configuration. Reducing the number of EDGs by adding PV and BESS is explored as one of the value streams for a hybrid microgrid. The size of the EDGs was selected based on engineering estimates. For efficiency in maintenance and testing, all EDGs were assumed to be the same size. Increasing the size of an EDG leads to an increased total capacity and a higher capital cost. Decreasing their size leads to a larger number of EDGs and an increased O&M cost. Finally, EDGs should not be run under low load. Fully participating in market opportunities requires that EDGs size remain modest. These considerations dictated the selection of 750-kW EDGs. The impact of this selection was considered in calculating system reliability and shown to have little impact on the results.

5.3. PV Resource

All economic calculations are based on PVWatts and typical meteorological year (TMY) 3 solar resources (as described in Section 4) for the three locations. These results are also used for determining the reliability performance for the hybrid microgrid at the three sites. As discussed in Section 7, the impact of solar variability on the reliability of a hybrid microgrid while islanded is explored using 20 years of hourly solar resource data from the National Solar Radiation Database [51] and a modeled solar profile for a hurricane-induced grid outage at the Maryland site.

5.4. Retail electric rates

Table 5 describes the electric rate tariffs for the three sites. All three sites have demand charges, and two of the three sites (not the Maryland site) have time-of-use energy charges.

5.5. Demand response programs

The California site has the Capacity Bidding Program (CBP) offered by the Southern California Edison (SCE) utility for demand response. The CBP prohibits fossil-based generation, so EDGs cannot participate [52]. The CBP is a capacity-based program that calls on sites to reduce load during certain time periods (e.g., 2 p.m. to 6 p.m.), and the value is significantly higher during June through September compared to other months. The load baseline from which the load reduction is calculated is the site's average load during the same hours from the 10 previous nonevent business days or 4 previous nonevent nonbusiness days. The minimum load reduction during all event hours in a month multiplied by the month's capacity price equates to the awarded capacity payment for that month. In REopt, the historical event days and hours for 2018 were used to implement the CBP participation by the battery.

The New Mexico site's local utility, El Paso Electric Company, offers a demand response program called the Load Management Program. This program offers a yearly capacity-based payment for curtailing load. There is a maximum of four curtailment events per year with a maximum aggregated duration of 15 hours per year [53].

The Maryland site is within the PJM ISO region, and PJM offers a capacity-based demand response program called Capacity Performance; this is the same public capacity market in which transmission-sited generators participate. There is a requirement to reduce load for a duration of up to 12 hours [54], so the battery storage capacity credit is typically based on the energy capacity divided by twelve (unless it has enough energy to sustain its rated capacity for more than 12 hours, in which case the capacity credit is equal to the power capacity). Table 6 lists the capacity payments for all three sites' capacity-based demand response programs.

5.6. Wholesale market opportunities

The most common method of DERs participating in CAISO wholesale markets is through the Proxy Demand Response (PDR) model, which is a CAISO-sponsored demand response program. Sites or DERs participate in PDR through a registered Scheduling Coordinator, which interfaces directly with the ISO. The available markets under this model include Day-Ahead and Real-Time Energy, as well as Spinning and Non-Spinning Reserve ancillary services [55]. However, the site does not receive wholesale market compensation for any power exported to the grid during participation (they may still receive retail credit for export,

Table 5
Electric rate tariff and diesel fuel cost for each site.

	California	New Mexico	Maryland	Units
Summer On-Peak Energy	0.328	0.128	N/A	$/kWh
Summer Mid-Peak Energy	0.108	N/A	0.088	$/kWh
Summer Off-Peak Energy	0.062	0.037	N/A	$/kWh
Winter Mid-Peak Energy	0.078	N/A	0.067	$/kWh
Winter Off-Peak Energy	0.068	0.037	N/A	$/kWh
WAPA Energy	0.058	N/A	N/A	$/kWh
WAPA % of energy purchases	50%	N/A	N/A	
Summer Monthly Demand	8.8	12.8	9.3	$/kW/mo
Winter Monthly Demand	8.8	21.3	9.3	$/kW/mo
Monthly Fixed Charges	2110	220	4035	$/mo
Diesel Price	2.97	2.59	2.74	$/gal

Table 6
Capacity-based demand response program prices.

	Value	Units
CBP avg four summer months	13	$/kW/mo
CBP avg eight non-summer months	1.8	$/kW/mo
El Paso Electric Co Load Mngmt.	48	$/kW/yr
PJM Capacity Performance	63	$/kW/yr

Table 7
Optimal PV and battery sizing and avoided EDG results.

	California	New Mexico	Maryland	Units
Solar PV Size	8200	5000	4000	kW
Battery Power Size	4300	400	1900	kW
Battery Energy Size	12,900	1000	3800	kWh
EDGs Avoided	3 (2,250)	2 (1,500)	2 (1,500)	count (kW)

if offered by the local utility). A new product call PDR-Load Shift Resource (PDR-LSR) was recently added for battery storage in order for them to receive credit for charging during negative price hours—the PDR without LSR does not otherwise provide an opportunity for the unique nature of battery storage to controllably "increase load" at times of over-supply/under-demand. However, the PDR-LSR still does not allow for arbitraging wholesale energy other than when the locational marginal price (LMP) is negative [56]. Battery storage participation in the PDR-LSR program for both DAM and RTM energy markets and spinning reserve was modeled in this analysis.

The New Mexico site is in a regulated-utility territory, and there is no access to wholesale energy or ancillary service markets.

The Maryland site has access to all of the PJM wholesale markets, and this is offered through several PJM demand response programs [57]. The relevant markets include Day Ahead and Real Time Energy, Synchronous (spinning) Reserve, and Frequency Regulation. The notable difference between PJM's offerings and CAISO's PDR is the availability of the Frequency Regulation market. However, the value of frequency regulation for BTM battery storage is limited because following a regulation down signal may increase the site's demand charges. Similar to PDR, the site does not receive compensation for energy exported to the grid, and there is no opportunity to arbitrage wholesale energy with battery storage because there is no mechanism to "buy" power. Battery storage and EDG participation in both DAM and RTM energy markets and spinning reserve was modeled in this analyis, and battery storage could also participate in frequency regulation.

Nonspinning reserve was not included in this analysis because it would never be chosen over the spinning reserve market for which EDGs and battery storage are capable of providing. Because PV is nondispatchable and reduces the site load similarly each day, PV was assumed to not participate in wholesale markets.

6. Sizing and costs results

The REopt economic optimization results for solar PV and battery storage sizing are shown in Table 7 (the exact sizing result from the optimization model was rounded to the nearest 100 kW [and 100 kWh for battery energy] and then re-run through the model). The heuristic dispatch requirement implemented in REopt for battery storage to reduce EDGs (described in Section 4.1) resulted in an EDG reduction of two for the California site and one for the New Mexico and Maryland sites. The reliability performance model determined that one additional

Table 8
California site life cycle cost breakdown.

	Pre-Microgrid	Diesel-only Microgrid	Hybrid, Wholesale	Units
Energy	115.865	106.517	89.079	$M
Demand Charge	26.028	23.814	19.628	$M
Capital Cost	-	12.438	31.476	$M
Fixed O&M	-	3.317	5.144	$M
Variable O&M	-	-	0.032	$M
EDG Fuel	-	8.102	4.483	$M
Demand Response	-	-	(2.328)	$M
Wholesale Markets	-	-	(5.832)	$M
Total Life Cycle	141.893	154.187	141.682	$M
Net Present Cost	-	12.294	(0.211)	$M

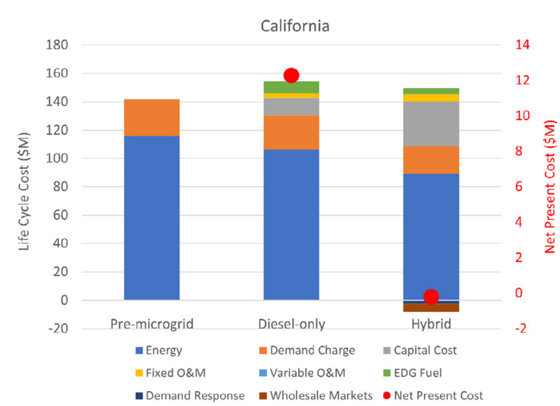

Fig. 5. California site life cycle cost breakdown.

EDG could be removed while still exceeding the diesel-only microgrid reliability performance, and this is reflected in the *EDGs Avoided* results in Table 7.

Table 8 and Fig. 5 show the life cycle cost results for the California site. The California site has the largest sizing of PV and battery due to significant value from retail bill savings, demand response, and wholesale markets. The value achieved by the addition of PV and battery is large enough to offset the added cost of the microgrid, and this is the only site to have a positive net present value. That is, in this scenario, the hybrid microgrid not only has lower total life cycle cost than the EDG-only microgrid, but the facility realizes lower costs with the hybrid microgrid

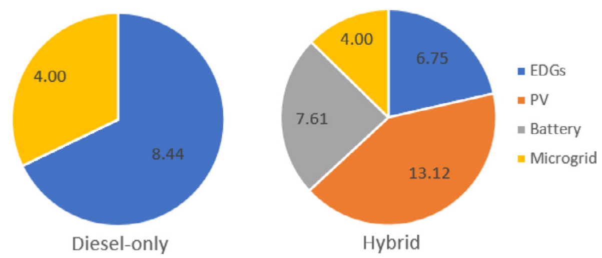

Fig. 6. California site capital cost breakdown in units of $M.

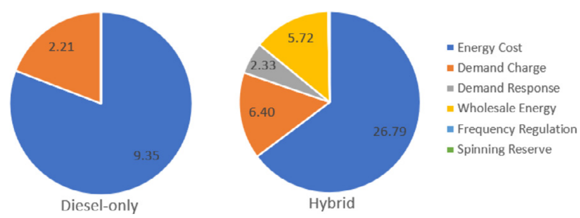

Fig. 7. California site savings and revenues by value stream type in units of $M.

Table 9
New Mexico site life cycle cost breakdown.

	Pre-Microgrid	Diesel-only Microgrid	Hybrid, Wholesale	Units
Energy	66.536	65.643	60.148	$M
Demand Charge	47.392	40.296	35.899	$M
Capital Cost	-	12.438	19.944	$M
Fixed O&M	-	3.317	4.027	$M
Variable O&M	-	-	0.099	$M
EDG Fuel	-	5.159	3.668	$M
Demand Response	-	(6.020)	(5.284)	$M
Wholesale Markets	-	-	-	$M
Total Life Cycle	113.928	120.832	118.403	$M
Net Present Cost	-	6.904	4.476	$M

than without any microgrid. This site also has the largest difference in net present cost compared to the diesel-only microgrid of all the sites, and this is largely due to PV offsetting the high cost of energy and diesel EDGs being prohibited from participating in demand response. The battery achieves a significant reduction in demand charges, and the diesel fuel cost is reduced by about half. The large PV and battery size also enable the most avoided EDGs of all the sites.

Fig. 6 shows a comparison of the capital cost breakdown between the diesel-only microgrid and the hybrid microgrid. The PV and battery add about $21M in capital cost, while the avoided EDGs reduce just under $2M in capital cost. Fig. 7 shows the breakdown of life cycle *savings* and *revenues* (i.e., negative costs) by value stream type. Energy cost savings is the largest portion of total savings for both microgrids, but the hybrid microgrid increases the savings by just under 200%. Demand charge savings also increases by about 200%, and revenue from demand response and wholesale markets accounts for 20% of all the savings and revenues.

The New Mexico site has a large PV size but a modest battery size. Table 9 and Fig. 8 show the life cycle cost results for the New Mexico site. The net present cost for the hybrid microgrid is about 35% lower than to the diesel-only microgrid. The cost reduction comes from energy savings, demand charge reduction, and reduced diesel fuel consumption. The EDGs achieve significant demand response revenue, and reducing the two EDGs results in a reduction of demand response revenue for the hybrid microgrid. The net benefit of reducing EDGs is still positive with the reduction of EDG capital cost.

Table 10 and Fig. 9 show the life cycle cost results for the Maryland site. The Maryland site has the smallest PV size of the three sites, but it has a large battery size relative to the PV size. The net present

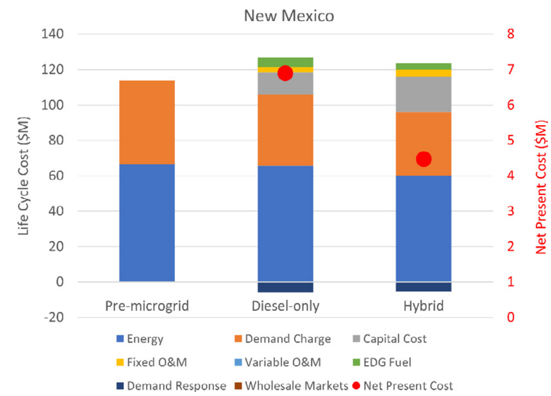

Fig. 8. New Mexico site life cycle cost breakdown.

Table 10
Maryland site life cycle cost breakdown.

	Pre-Microgrid	Diesel-only Microgrid	Hybrid, Wholesale	Units
Energy	117.885	117.259	112.936	$M
Demand Charge	27.532	24.502	22.145	$M
Capital Cost	-	12.438	20.353	$M
Fixed O&M	-	3.317	4.122	$M
Variable O&M	-	-	0.011	$M
EDG Fuel	-	2.631	2.051	$M
Demand Response	-	(7.839)	(7.125)	$M
Wholesale Markets	-	-	(3.491)	$M
Total Life Cycle	145.417	152.307	151.002	$M
Net Present Cost	-	6.891	5.586	$M

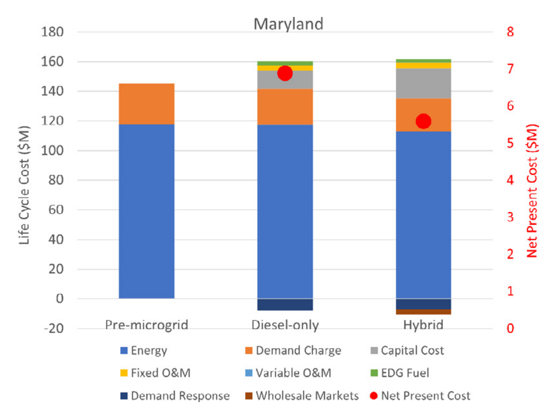

Fig. 9. Maryland site life cycle cost breakdown.

cost for the hybrid microgrid is about 19% lower than the diesel-only microgrid. The battery achieves significant revenue from the frequency regulation market. The breakdown of wholesale revenue is about 60% from frequency regulation, 39% from energy, and less than 1% from spinning reserve. The demand response revenue is reduced compared to the diesel-only microgrid because of the reduced EDGs.

Each site has different attributes that favor the economics of PV and battery storage differently. PV sizing is significant at all three sites, with the primary value of retail bill savings. Battery storage is sized to varying degrees at all three sites based on various levels of value stacking opportunities in retail bill savings, demand response, and wholesale markets (except New Mexico). California has a demand response program (CBP) that is favorable for battery, but the 12-hour runtime requirement for the capacity-based DR programs at the other two sites limits the value. Wholesale markets provides significant revenue for the two sites in which wholesale markets exit (California and Maryland). At the Maryland site, battery benefits from PJM's frequency regulation market, but

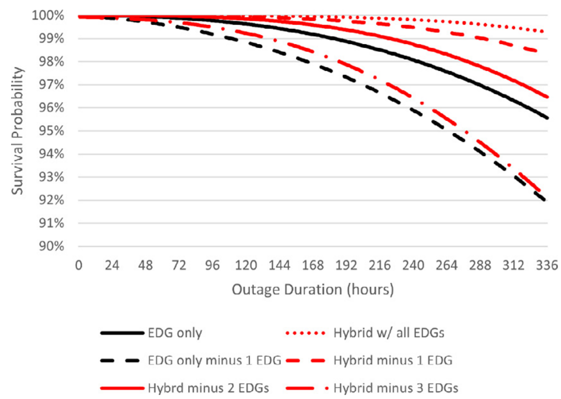

Fig. 10. Survival probability at Maryland site for outages up to 14 days (336 hours) for a diesel-only and hybrid microgrid with reduced number of EDGs.

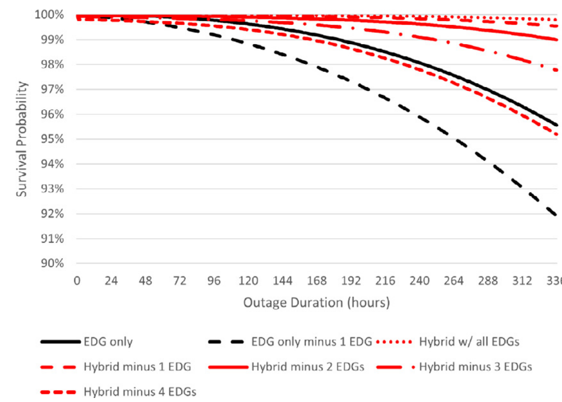

Fig. 11. Survival probability at California site for outages up to 14 days (336 hours) for a diesel-only and hybrid microgrid with reduced number of EDGs.

participation can increase demand charges for behind-the-meter DERs. These value streams allow battery to be sized large enough to reduce EDGs and provide additional cost savings to the microgrid.

7. Reliability performance results

Multiple metrics can be estimated for the performance of a microgrid. We focus on survival probability, the likelihood that all critical loads have power at a given time during an outage. The survival probability metric provides a stringent criterion where any critical load not served is considered a failure. It best illustrates the differences in performance as a function of DER selection. Other metrics, such as the mean fraction of lost critical load, have also been calculated and show identical relative performance between a diesel-only and hybrid microgrid. Other commonly used reliability indices such as loss of load probability (LOLP) or loss of load expectation (LOLE) can be easily calculated if one assumes an annual probability of grid outages frequency and duration. We focus on survival probability because it is independent of the grid's performance and is dependent only on the microgrid's performance. The resiliency of a microgrid system during a long duration outage also depends on the repairability of a failed EDG during the outage. The mean time to failure for EDGs is 37 [8] hours, which is already relatively long. These results reflect repairs during short outages or testing. During a multiday outage, it is unlikely that staff and equipment will be readily available to make the needed repairs. Thus, we treat the EDGs in our analysis below as unrepairable for the duration of an outage

7.1. Hybrid and diesel only microgrids

First, we consider the annual average performance of diesel-only and hybrid microgrids. These results represent the performance of a microgrid, assuming an outage can start with equal probability at any time during the year. (Later in this section, we will demonstrate how the performance of the microgrid varies as a function of the date and time the outage begins.) Illustrated below is the survival probability assuming mean reliability for the EDGs and 97% availability for the BESS for the optimized hybrid systems as defined in Section 6. Results are shown for the Maryland site (Fig. 10) and the California site (Fig. 11).

Adding cost-effective PV and BESS to the diesel-only microgrid leads to a more reliable microgrid system. Additional cost savings can be achieved by removing one or two EDGs while still surpassing the diesel-only microgrid's performance. Removing a single EDG leads to more than $500,000 reduction in capital costs and approximately $7000 per year in O&M costs. In fact, one could remove three EDGs or 20% of the total generator capacity and have a performance nearly identical to the diesel-only microgrid. The diesel-only microgrid was designed with an N + 1 reliability in terms on the number EDGs. Removing only one EDG (i.e., reducing the diesel-only microgrid to an N reliability) can be seen to lead to a significant deficit in performance. Nearly identical results are found for the New Mexico case, which has roughly the same size PV system as the Maryland site (see Table 11).

The California site, due to greater economic opportunities, has a larger PV and BESS than either the Maryland or New Mexico sites. Due to the larger PV and BESS, up to three EDGs can be eliminated (20% of the generator capacity) while maintaining better survivability performance than diesel-only microgrid, and a fourth can be eliminated without a significant impact on performance. This is very different than the reduction seen in going from N + 1 reliable to N reliable diesel-only microgrid. These results hold true even when one considers the uncertainties in EDG reliability estimates as listed in Table 2.

For all three sites the hybrid microgrid with a reduced number of EDGs (two less at the Maryland and Nevada site and three less at the California site) has a higher mean survival probability for the entire outage duration. Similar results are found for mean lost load at all three sites. These results assumed no constraints on the amount of diesel fuel. The hybrid microgrids are more fuel-efficient. They consume 23% less fuel at the California site to 10% less fuel at the Maryland site. Thus any limitation in available diesel fuel would further enhance the performance of the hybrid microgrid relative to the diesel only microgrid. These results are for a system of 750-kW networked EDGs. But they hold for EDGs of different sizes. Larger EDGs will require fewer EDGs to achieve an N + 1 configuration. For example, a 1,500-kW EDG based diesel-only microgrid for a 10MW peak critical load requires only 8 EDGs as compared to the 15 used for a set of 750-kW EDGs. Although the absolute value of the survival probability and mean lost load will change slightly the relative performance advantages of the hybrid system are nearly identical. It is important to recognize that if we had ignored the EDG reliability, an N + 1 as well as an N reliable diesel-only microgrid would be incorrectly predicted to have a 100% survival probability for the entire 2-week outage.

Up to this point, we have presented annual average survivability results. Variability in the load and the solar resource can increase or decrease the likelihood that the DERs can produce sufficient power, and, therefore, the survival probability is dependent on when an outage starts. Thus for a given 2-week outage the survival probability is unlikely to decline monotonically and the impact of EDG reliability is even greater when one considers outages during peak load times. Fig. 12 illustrators the performance for a 2-week outage starting at 5 a.m. the third week of August at the Maryland site. This is a period of peak critical load.

The survival probability does decline over the two weeks for both systems but has large decreases correlated with hours of peak load. These dips are not seen in the annual average survival probability because averaging over outage start time removes them. The hybrid system has much smaller decreases due to the impact of the BESS and PV. This

Table 11
The mean survival probability at two weeks and the fraction of the year where the survival probability is below 90%.

Systems	Diesel Only Microgrid	Hybrid Microgrid at California Site	Hybrid Microgrid at Maryland Site	Hybrid Microgrid at New Mexico Site
Mean Survival Probability	95.6%	97.8%	96.2%	96.3%
Minimum Survival Probability	20.7%	64.0%	27.7%	27.0%
Fraction of year Survival Probability is below 90%	13.4%	3.3%	6.8%	6.1%

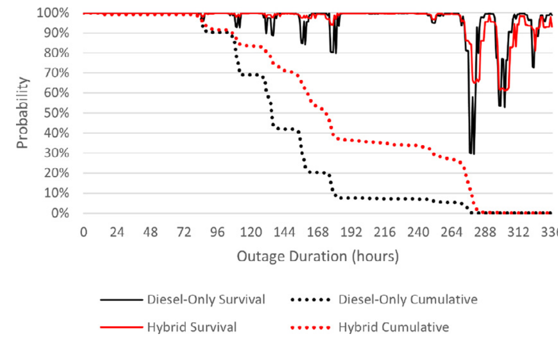

Fig. 12. The survival and cumulative probability for a 2-week outage in late August at the Maryland site.

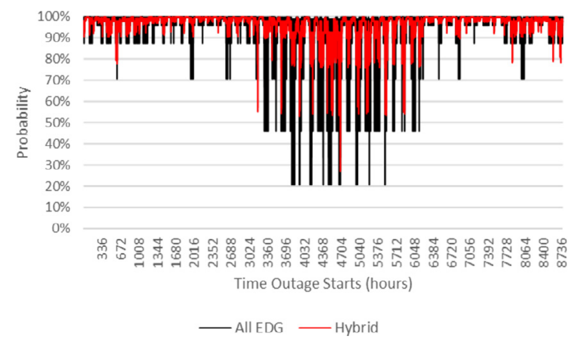

Fig. 13. Survival probability at the Maryland site at two weeks for a diesel only (All EDG) and hybrid microgrid with two fewer EDGs as function of the hour in the year the outage starts.

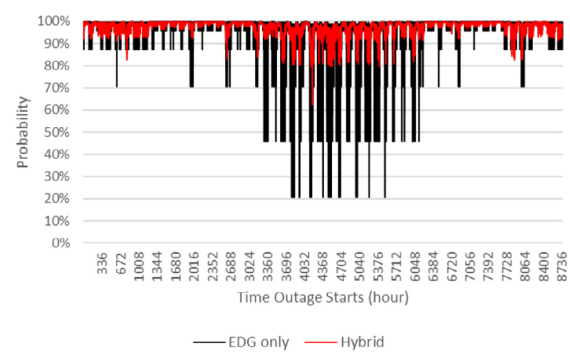

Fig. 14. Survival probability at the California site at two weeks for a diesel only (All EDG) and hybrid microgrid with three fewer EDGs as function of the hour in the year the outage starts.

is an important performance difference when one has critical loads that cannot recover from short-term loss of power.

Industrial processes are often difficult to start after only an hour outage and the products being manufactures can be a total loss. Outages to critical health care functions can lead to loss of life and military operations can often not recover from outages. To illustrate this we show in Fig. 11 the probability of a failure to provide power to 100% of the critical load having at any time (the cumulative probability). The larger deceases in the survival probability seen in the diesel-only system leads to a more rapidly declining cumulative survival probability. Now it is likely that not all the critical loads on a campus are sensitive to loss of power for only an hour. In that case, a microgrid could shed those loads to insure the high priority loads are not lost.

Over the year, the performances at the end of a 2-week outage for the Maryland and California sites are shown in Fig. 13 and 14.

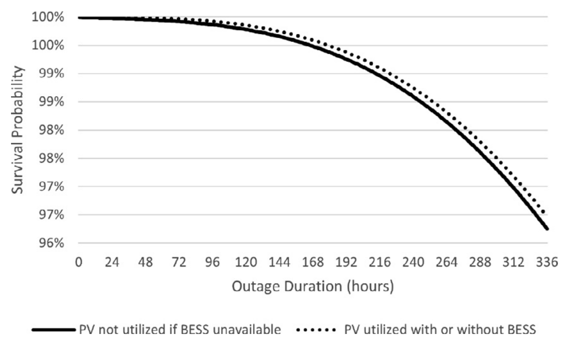

Fig. 15. Survivability or the probability of meeting 100% of the critical load for outages up to 14 days (336 hours) as a function of PV usage when a BESS is available 97% of the time.

In both locations, the variability in performance for the diesel-only microgrid is significantly larger than the optimized hybrid microgrid. Similar results are found at the New Mexico site. The variability in the diesel-only microgrid during peak summer loads can have a very low probability (as low as 21%) for providing sufficient power to the critical loads even though it has been designed to have a N + 1 reliability. This is expected, as it only requires the loss of two out of fifteen EDGs to lose the ability to meet the peak critical load. The hybrid microgrid's number of EDGs has been selected to yield a slightly better average annual performance, but this also yields a significantly lower variability in the probability to survive the outages over the year even when one accounts for the expected variability in solar power. The much larger BESS and PV that was allowed due to market conditions in California shows a dramatic difference in performance variability across the year. Thus providing not only a lower cost and higher average performance but a more robust energy resilience at all times.

Table 11 illustrates the difference in the mean annual performance and the fraction of time during the year the system's ability to support all the critical loads drops below 90%.

The diesel-only microgrid's performance is independent of location, as the load profile has been assumed to be the same at all three sites. The California hybrid microgrid has three fewer EDGs than the diesel only, and both the hybrid microgrids at Maryland and New Mexico sites have two fewer EDGs. Similar results are found for mean lost load for all three sites.

In assessing a microgrid's reliability performance, customers should specify both the minimum average survival probability for a given outage duration and any constraints on how low that performance can drop as a function of time of year for each critical load.

7.2. Impact of battery reliability

Reliability for the new generation of stationary Li-ion BESS is uncertain. The largest concern is the fraction of time the BESS will be unavailable due to repairs or maintenance activities. The lack of long-term empirical data sets makes it difficult to validate any predictions. In the system reliability predictions above, we have taken a conservative approach by assuming the BESS is available only 97% of the time and that if not available the PV system cannot contribute while islanded. Equivalently, if the BESS is not available, the microgrid defaults to operate as a diesel only microgrid. A microgrid can, if designed for it, use PV resources while islanded without a BESS [58] but most do not. Below we show the impact of this assumption and the expected change in performance as a function of BESS availability. Fig. 15 shows the impact on hybrid microgrid performance if the PV is unavailable when the BESS is unavailable. The performance of a hybrid microgrid for the Maryland case where two EDGs have been eliminated is shown.

The difference is very minor. After a 2-week outage there is only a 0.2% difference in performance, a factor of 4 to 5 times smaller than the difference between the diesel-only microgrid and these hybrid microgrids. We have assumed that the BESS is available 97% of the time. This is less than many vendors quote. The sensitivity of our results to this assumption is shown in Fig. 16. The performance of a hybrid microgrid for the Maryland case where two EDGs have been eliminated as function of BESS availability ranging from 95% to 100% is shown, assuming that the PV is not utilized when the BESS is unavailable.

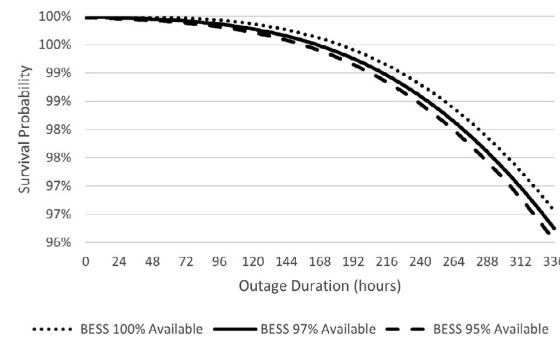

Fig. 16. Survivability or the probability of meeting 100% of the critical load for outages up to 14 days (336 hours) as a function of BESS is availability.

Table 12
The survival probability statistics for 19 years of solar conditions at a Maryland site.

System	Min	P5	P10	Mean	P90	P95
Diesel Only	0.2067	0.7062	0.8738	0.9556	0.9996	0.9996
Hybrid	0.2717	0.9184	0.9259	0.971	0.9993	0.9999

Again, these are small differences and demonstrate that trends shown for the performance differences between an optimized hybrid microgrid and a diesel-only microgrid are not sensitive to our assumptions of BESS availability.

7.3. Impact of solar variability

The results presented above are for an assumed solar power profile that is typical (TMY3) for the three sites. The hourly variability seen in a typical year, as illustrated in Figs. 12 and 13, lead to less variability in a hybrid microgrid's performance than the variability seen in a diesel-only microgrid due to changes in the critical load profile. But a TMY solar profile does not capture the long-term variability over years that can be seen in solar energy, nor does it account for extreme events such as the impact of a hurricane, often the cause of long duration grid outages.

Long-term variability can be examined by looking at actual solar irradiance over roughly the last two decades. We examined the impact at the Maryland site which is expected to have the greatest variability. Nineteen years of local solar irradiance data was used to calculate the survival probability and mean lost load for outages starting at every hour in the year. The resulting survival probability statistics at the end of a 2-week outage are shown in Table 12.

The optimized hybrid microgrid that has two fewer EDGs outperforms the diesel-only microgrid even when considering nearly two decades of solar conditions.

A larger concern for systems that rely on PV for backup power is what happens after an extreme weather event such as a hurricane. Long duration outages in some part of the world are heavily associated with hurricanes. Outages caused by hurricanes can also have significant cloud cover for the days following the event, which reduces the ability of PV to contribute as a backup power source. Increased cloudiness caused by hurricanes does decrease the solar irradiance, but only for a few days, far less than often assumed. Detailed analysis of the ability of PV to provide energy during 18 hurricanes that made landfall in the contiguous United States from 2004 to 2017 [59] shows that, prior to landfall and within 3

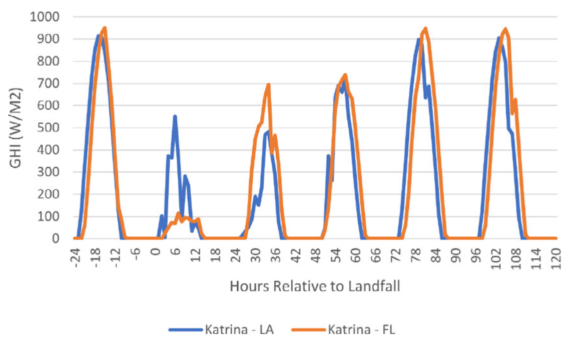

Fig. 17. The Global Horizontal Irradiance (GHI) relative to the hour hurricane Katrina made landfall in Louisiana (Katrina-LA) and Florida (Katrina-FL).

days after solar irradiance conditions almost always returns to normal. Fig. 17 illustrates the local solar irradiance relative to when Hurricane Katrina made landfall in Florida and Louisiana.

Solar power production is directly proportional to the global horizontal irradiance (GHI) at the PV's location. There is a significant decrease in GHI for 24 hours after landfall, but it rises steadily over the next 48 hours.

Assuming the local PV system survives the hurricane, we examined the impact of the increased cloudiness on the hybrid microgrid's survival probability for a system located in Maryland. We examined an early date in hurricane season, August 19, at 5 a.m., to model a stressful condition when the load is near its summer peak. We assumed that the PV power output is reduced to 20% for the first day, 40% for the second day, and 70% on day three relative to TMY levels. Even for this stressful case, the hybrid microgrid shows an imperceptible change in its survival probability, which continues to be higher than seen in the diesel-only system.

8. Conclusions

The design of microgrids often ignores the reliability of the individual DERs and the full set of opportunities to reduce life cycle cost. The statistical methodology presented here calculates the impact of realistic reliability and variability on a microgrid's performance during an extended grid outage. Ignoring these reliabilities leads to serious errors in predicted microgrid performance while islanded. Using REopt, we show that the economic impacts of avoided costs from reducing the number of emergency diesel generators, retail bill savings, and demand response and whole-sale market revenue all are important. We have demonstrated for sites in California, Maryland, and New Mexico that a hybrid microgrid (which utilizes a combination of solar power, battery energy storage, and networked emergency diesel generators) can offer a more cost-effective and resilient solution than diesel-only microgrids that rely only on a network of emergency diesel generators. It is expected that these results will hold true at most locations in the United States. The driver for microgrid deployment is the need for resilient power when the grid is down. The cost savings to provide this resilient backup power from a hybrid microgrid as compared to a diesel-only microgrid are significant. The net present value for a hybrid microgrid is 19% lower in New Mexico and 35% lower in Maryland than the diesel-only microgrid. In California, the net present value cost of the hybrid microgrid is negative. The hybrid microgrid has a lower life cycle cost for the campus than the power costs without a microgrid. These differences are primarily driven by the market conditions in the three locations. These economic predictions use realistic capital and O&M costs for all components and real electric tariffs and market prices. But they do not consider the potential need for and costs of the campus' distribution system upgrades and line extensions. These costs are very site-specific and can be significant. For all three sites the hybrid microgrid, with two or three emergency diesel generators removed, provides higher system level reliability and is more resilient than diesel-only system. The mean survival probability to provide 100% of the required power for all critical loads, assuming an outage can start at any time during the year, is slightly higher for these hybrid systems than an N+1 reliable diesel-only system and much higher than a simple N reliable diesel-only system over a 2-week outage. The improvement in performance is more dramatic when you consider survival probability as a function of when an outage occurs. This varies due to the load variability and for the hybrid microgrid also due to the variability of solar resources. The diesel-only microgrid shows far greater variability in its probability of survival performance while islanded throughout the year. A diesel-only microgrid drops to below 90% for 13% of the year, while hybrid microgrids drop below 90% between 4% and 7% of the year depending on the battery size and solar resources. The improved performance of the hybrid system is resilient to changes seen over the last 20 years in solar condition at all three sites and sees little degradation in performance immediately after a hurricane, assuming the system survives. Thus, both from a cost and performance perspective hybrid microgrids should always be considered in designing a microgrid. Both a hybrid and diesel-only microgrid system offers a much more resilient [7,8] and cost-effective [60] system than a traditional system of building-tied generators. For any microgrid, cyber vulnerabilities and weaknesses associated with the on-campus distribution system need to be considered. Cyber vulnerabilities can be addressed by appropriate cyberdefense procedures and distribution system reliability can be improved by appropriate maintenance and mitigation practices.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Jeffrey Marqusee previously served as the Director of ESTCP, the funding source for this work

CRediT authorship contribution statement

Jeffrey Marqusee: Conceptualization, Validation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **William Becker:** Methodology, Software, Writing - original draft, Visualization. **Sean Ericson:** Methodology, Software, Writing - original draft.

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Appendix A. Component Reliability Details

The results cited in the body of the paper on EDG reliability were derived from empirical data collected for fielded commercial EDGs by the U.S. Army [34] and Navy [35] (see Table A.13). This data provides the information required to estimate the three reliability metrics for EDGs typically used in microgrids (10 kW to 2,000 kW).

The first reliability metric, OA, captures the likelihood the EDG is available at the start of a grid outage; this is defined in A.1.

$$OA = \frac{I - t_{ol}}{I} \tag{A.1}$$

Table A.13
Empirical data sets used to determine EDG reliability.

Source	# EDGs	EDG Years of Observation
Army [34]	304	2298
Navy [35]	239	1280

where l is the EDG lifetime and t_{ol} is time offline due to repairs and maintenance. The FTS metric is defined as:

$$FailuretoStartProbability(FTS) = \frac{n_{fts}}{n_{ats}} \tag{A.2}$$

where n_{fts} is the number of failures to start and n_{ats} is the number of attempts to starts.

The MTTF defined that captures failures while the EDG is running is defined by:

$$MTTF = \frac{t_r}{n_{rtf}} \tag{A.3}$$

where t_r is the total runtime and n_{rtf} is the number of failures while running or run-time failures. Using these definitions and the empirical data the values of the EDG reliability metrics provided in the body of the paper were derived.

The justification for assuming a PV's reliability does not need to be considered given the large variability due to changes in solar conditions is provided below.

The availability of a PV system at the start of a grid outage depends on both the rate of system failures and the time it takes to make repairs. A system that can be repaired very quickly will still have a high availability even if the failure rate is high. One can estimate the availability by measuring the actual energy yield in the field divided by the ideal energy yield. This is measured in the field as well as stipulated in contract guarantees [61]. Contractual guaranteed availability is typically between 97% and 99% but is found as high as 99.5%. Contract guarantees reflect not what is achieved but what is safe to guarantee with high confidence, as well as the value that customers place on the metric. Empirical data supports a higher value for availability. For example, 5 years of data from a 4.6-MW system in Arizona demonstrated an availability of 99.9%, and surveys of utility-scale PV systems on average have shown a 99.5% availability [62]. A recent large-scale survey of PV systems has found that failures in utility-scale systems are low, and almost all involve subcomponents that lead to only a partial loss of power [63]. This infrequent and modest loss of capacity is small compared to the large variation of power due to changes in solar irradiance and leads us to assume that for our modeling purposes the PV system is 100% available.

To estimate the loss of power during a grid outage, we consider a simplified common PV design using centralized inverters. We do not include components associated with grid connection because we are concerned with reliability when islanded.

The simplified design of a PV system with centralized inverters is shown in A.18.

Where Component 1 is string connectors and protectors (fuses), Component 2 is the DC combiner box containing a string monitoring unit and a DC disconnect, and Component 3 is a transformer. The system has n strings, each with m modules connected to a central inverter, and the overall system has P inverters. A similar block diagram can be constructed for PV systems using string inverters. Current estimates for PV component reliability are listed in A.14 [64]. These failures rates are for failure of one individual component, not all of them or of the system.

Given the designs illustrated above, a simple fault tree can be created for the system. Combining components that are in series results in a three-tier tree shown in Fig. A.19, where $\lambda_1 = \lambda_{\text{transformer}}$, $\lambda_2 = \lambda_{\text{DC combiner}} + \lambda_{\text{central inverter}}$, and $\lambda_3 = m\lambda_{\text{module}} + \lambda_{\text{string connector}} + \lambda_{\text{string protector}}$.

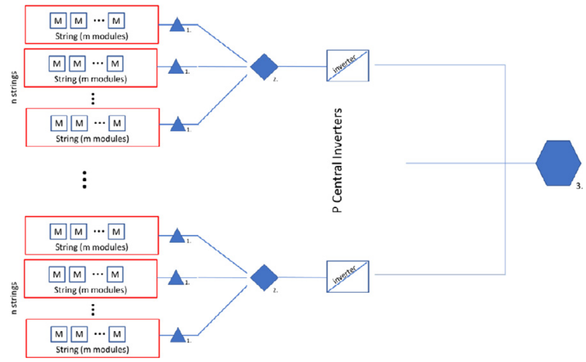

Fig. A.18. PV system with central inverters.

Table A.14
PV component failure rates [64].

Component	λ **Failure Rate 10^{-6} per hour**
PV modules	0.035
String connector	0.0056
String protector	0.063
DC combiner[a]	3.14
Central inverter[b]	74
String inverter	15.1
AC combiner[c]	0.21
Transformer	2.01

[a] The DC combiner box is assumed to have a string module monitor, DC switch, terminal screws, fuses, and DC cables in series (see [5]).
[b] The inverter reliabilities include the DC and AC circuit breakers associated with the inverters.
[c] The AC combiner box is assumed to have AC cables, fuses, and terminal blocks in series.

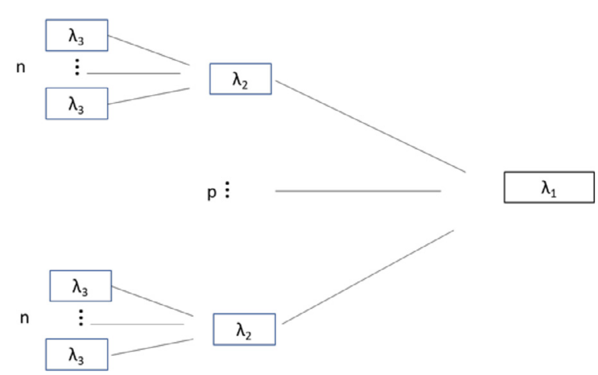

Fig. A.19. Fault tree model for PV system .

Any failure in the fault trees above will lead to a reduction in the PV's capacity. We define the cumulative probability of a component in tier i to be working at time t during an outage as:

$$R_i(t) = e^{-\lambda_i t} \tag{A.4}$$

And the cumulative probability that it fails as:

$$F_i(t) = 1 - R_i(t) \tag{A.5}$$

For a system of N components in parallel, the cumulative probability that k components are working is:

$$P_i(k, N) = \frac{N!}{k!(N-k)!} R_i^k F_i^{N-k} \tag{A.6}$$

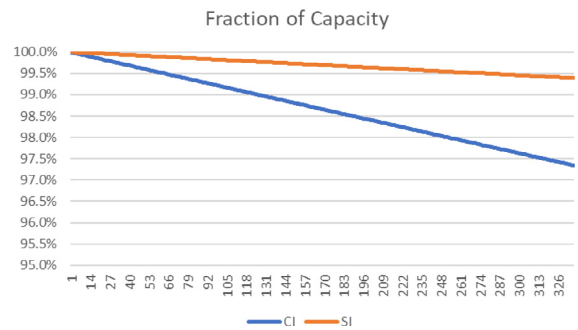

Fig. A.20. PV Fraction of Capacity.

The fraction of power that flows through a given tier i if k component out of N are operating is k/N. Thus, for the central inverter system, the expected fraction of capacity relative to capacity at the start of the outage is simply:

$$C(t) = R_1(t)R_2(t)R_3(t) \tag{A.7}$$

The fractional power capacity is independent of the number of inverters, but it does depend on the length of the string. A similar analysis can be made for PV systems with string inverters. Fig. A.20 shows the mean fractional power capacity as a function of outage duration for a central inverter system (CI) and a string inverter system (SI) assuming 24 modules per string.

Appendix B. Economic Modeling Details

B1. Retail bill savings

The conventional value stream for behind-the-meter DERs is retail electric bill savings. The electric rate tariff typically includes both energy rates ($/kWh) and demand charges ($/kW), and both of these may vary by season, weekday/weekend, and time of day. Energy cost is calculated based on the energy consumed (kWh) during the time window(s) of the energy rate, while demand charges are based on the peak 15-minute consumption interval of the demand charge time window (REopt performed an hourly analysis, so the peak *hourly* load is used instead). Battery storage is particularly suited for demand charge reduction (i.e., peak shaving) if the electric load has short duration spikes in demand because the battery can charge off-peak to reduce those peak periods with a relatively small energy requirement. Battery storage can also perform energy arbitrage to reduce energy cost if there is a large difference between the off-peak and on-peak energy rate.

B2. Demand response

Demand response is another common revenue stream for behind-the-meter DERs, but there are rules and requirements that may limit the value of participation by different DER types. The purpose of traditional demand response programs is to reduce demand during grid emergency events or peak system load times that would otherwise result in outages due to insufficient generation or transmission/distribution failures. These programs are of10 administered through the local utility, but some are offered by an ISO. Additionally, wholesale markets, such as energy and ancillary services, are accessible by behind-the-meter DERs in some ISO regions through demand response mechanisms. To distinguish between traditional emergency and capacity-based demand response programs, the participation in wholesale markets by a demand response mechanism is categorized as *wholesale markets*, as described in Section B.3.

For participation in demand response and wholesale markets, our modeling assumes that 80% of the revenue goes to the site, the remaining 20% is taken by entities which enable participation in the programs. In CAISO, these entities are called Scheduling Coordinators. In PJM, these entities are called Curtailment Service Providers.

Table B.15
Wholesale market modeling parameters.

	Value	Units
Market rules		
Minimum power to participate	100	kW
Frequency regulation		
Dispatch fraction	0.6	
Duration of energy neutrality	2	hr
Spinning reserve		
Dispatch fraction of cleared capacity	0.25	

B3. Wholesale markets

Wholesale market participation opportunities were also added to the REopt model in this work, and this section describes the modeling methodology. The *market rules* listed in Table B.15 represent parameters used for all markets.

B3.1. Energy

There are two different wholesale energy markets: day-ahead market (DAM) and real-time market (RTM). The DAM is bid into by EDGs the day before they are dispatched, and the RTM is typically bid and cleared about an hour before the EDGs are dispatched. The demand side of the market (including electricity purchases by a battery) also submits bids to purchase energy in these markets. The RTM is required to correct the difference between forecasted supply and demand, which are transacted in the DAM.

The basis of selling energy in the DAM and RTM for retail customers is by reducing load relative to the average site load during the same hours on the previous 5 (PJM [57]) to 10 (CAISO [65]) days. The previous days included in the average are similar in terms of weekday versus weekend and only include nonparticipating hours. Because PV is nondispatchable and it reduces the site load similarly each day, PV was assumed to not participate in the energy market. Battery storage was assumed to participate in both DAM and RTM energy markets, so it was able to choose the highest price between the two markets during a given hour.

B3.2. Ancillary services

The three main ISO/RTO-administered ancillary service markets are frequency regulation, spinning reserve, and nonspinning reserve. Frequency regulation is a fast-responding market that maintains the frequency of the electric grid within certain limits, and EDGs are required to follow a dispatch signal which may change every 2–4 seconds. Some ISO have a single frequency regulation market (e.g., PJM, ISO-NE), and some have separate regulation up and down markets (e.g., CAISO, ERCOT).

The REopt model uses an *hourly* time interval for the dispatch, so reduced-order parameters were implemented for evaluating the requirements of following the frequency regulation signal. The *dispatch fraction* is defined for reduced-order modeling as the fraction of the cleared power capacity that actually dispatches to follow the frequency regulation signal in a given hour. As an example, using a dispatch fraction of 0.6, if 100 kW is cleared in the market, the energy throughput into and out of the battery is 60 kWh. This allows for the accounting of energy lost due to inefficiency of the battery that needs to be made up by charging outside of the participating window. Eq. B.1 defines the energy loss ($E_{Loss}(t)$) during a given hour of participation in frequency regulation up and down.

$$E_{Loss}(t) = \frac{P_{RU,avg}(t)}{\eta_{out}} - \frac{P_{RD,avg}(t)}{\eta_{in}} \tag{B.1}$$

Where $P_{RU,avg}(t)$ and $P_{RD,avg}(t)$ is the average power dispatched from and to the battery for regulation up and down respectively, and η_{in} and η_{out} is the efficiency into and out of the battery, respectively. We can define the *Dispatch Fraction* using the average dispatched power $P_{avg}(t)$ relative to the cleared capacity $C(t)$ in regulation up and down as:

$$DispatchFraction = \frac{P_{avg}(t)}{C(t)} \tag{B.2}$$

For the PJM market, the frequency regulation is a single market (not separated into up and down markets), so $C_{RU}(t) = C_{RD}(t) = C(t)$ and the regulation signal is conditionally symmetric, so $P_{RU,avg}(t) = P_{RD,avg}(t) = \left|P_{avg}(t)\right|$. Eq. B.1 therefore can be reformulated as:

$$E_{Loss}(t) = C(t)\left[\frac{1}{\eta_{out}} - \eta_{in}\right] DispatchFraction \tag{B.3}$$

The second parameter for frequency regulation is the *duration of energy neutrality*, which is the number of hours over which the frequency regulation signal has equivalent energy dispatched to up and down regulation. This parameter ensures the battery has enough energy capacity to follow a continuous full power up or down signal in the worst-case scenario. Table B.15 shows the value used for this analysis. Eq. B.4 is the constraint on the maximum regulation up capacity based on the *duration of energy neutrality (D.E.N.)*, the battery's current stored energy ($E_{stored}(t)$), and its minimum energy state (E_{min}). Eq. B.5 is the constraint on the maximum regulation down capacity based on the battery's current stored energy ($E_{stored}(t)$) and its maximum energy capacity (E_{max}). For a single frequency regulation market, the single cleared capacity $C(t)$ is constrained by both Eq. B.4 and Eq. B.5.

$$C_{RU}(t) <= (E_{stored}(t) - E_{min})\frac{D.E.N}{2} \tag{B.4}$$

$$C_{RD}(t) <= (E_{max} - E_{stored}(t))\frac{D.E.N.}{2} \tag{B.5}$$

Spinning reserve is a market that compensates a generator for the *capability* to be dispatched and ramp up to its cleared capacity within 10–30 minutes, and it needs to be able to maintain that capacity for about an hour. Generators are often cleared in the market and receive payment without actually being dispatched. Nonspinning reserve is similar to spinning reserve except that the asset has more time to respond to a dispatch signal (1 h or more), and the compensation is lower than spinning reserve accordingly. The dispatch assumption for spinning reserve is 25% of the participating capacity in each hour to account for energy requirements of the battery and fuel cost of the EDG, as shown in Table B.15. Nonspinning reserve was not included because it would never be chosen over the spinning reserve market for which EDGs and battery storage are capable of providing.

References

[1] Stadler M, Cardoso G, Mashayekh S, Forget T, DeForest N, Agarwal A, et al. Value streams in microgrids: a literature review. Applied energy 2016;162:980–9.
[2] Gamarra C, Guerrero JM. Computational optimization techniques applied to microgrids planning: a review. Renewable and Sustainable Energy Reviews 2015;48:413–25.
[3] Hare J, Shi X, Gupta S, Bazzi A. Fault diagnostics in smart micro-grids: a survey. Renewable and Sustainable Energy Reviews 2016;60:1114–24.
[4] Jones RB. How Reliable Is Your Microgrid? An insurer's perspective on risk drivers for distributed resources. July: Public Utilities Fortnightly; 2015.
[5] Elsworth J, Geet OV. Solar photovoltaics in severe weather: cost considerations for storm hardening PV systems for resilience. NREL/TP-7A40-75804 2020.
[6] Marqusee J, Jenket D. Reliability of emergency and standby diesel generators: impact on energy resiliency solutions. Applied energy 2020;286(11491):8.
[7] Marqusee J, Ericson S, Jenket D. Emergency Diesel Generator Reliability and Installation Energy Security. National Renewable Energy Laboratory; 2020.
[8] Marqusee J, Ericson S, Jenket D. Impact of emergency diesel generator reliability on microgrids and building-tied systems. Applied energy 2021;285(116437).
[9] Fenga W, Jina MB, Liua X, Baoa YC, Marnaya C, Yaod C, et al. A review of microgrid development in the united states – a decade of progress on policies, demonstrations, controls, and software tools. Applied energy 2018;228:1656–68.
[10] NREL. REopt: Renewable Energy Integration and Optimization. 2020a. URL https://reopt.nrel.gov/.
[11] Cutler D, Olis D, Elgqvist E, Li X, Laws N, DiOrio N, Walker A, Anderson K. REopt: A Platform for Energy System Integration and Optimization. NREL; 2017.
[12] Homer. Homer energy. 2020. URL https://www.homerenergy.com/.
[13] LBNL. Distributed Energy Resources - Customer Adoption Model (DER-CAM). 2020. URL https://building-microgrid.lbl.gov.
[14] Marnay C, Venkataramanan G, Stadler M, Siddiqu AS, Firestone R, Chandran B. Optimal technology selection and operation of commercial building microgrids. IEEE Trans Power Systems 2008;23:3.
[15] SNL. Microgrid design toolkit. 2020. URL https://www.sandia.gov.
[16] Eddy J, Miner N, Stamp J. Sandia'S microgrid design toolkit. The Electricity Journal 2017;30:62–7.
[17] Zhang J, Knizley A, Cho H. Investigation of existing financial incentive policies for solar photovoltaic systems in u.s. regions. Energy 2017;5:974–96.
[18] Davidson C, Gagnon P, Denholm P, Margolis R. Nationwide Analysis of US. Commercial Building Solar Photovoltaic (PV) Breakeven Conditions. National Renewable Energy Laboratory; 2015.
[19] NREL. SAM: System Advisor Model. 2020b. URL https://sam.nrel.gov/.
[20] Fisher MJ, Apt J. Emissions and economics of behind-the-meter electricity storage. Environmental sciences : an international journal of environmental physiology and toxicology 2017;51:1094–101.
[21] Yan X, Zhang X, Chen H, Xu Y, Tan C. Techno-economic and social analysis of energy storage for commercial buildings. Energy Convers Manage 2014;78:125–36.
[22] Long M, Simpkins T, Cutler D, Anderson K. A statistical analysis of the economic drivers of battery energy storage in commercial buildings. North American Power Symposium (NAPS); 2016. doi:101109/NAPS20167747918.
[23] McLaren J, Laws N, Anderson K, DiOrio N, Miller J. Solar-plus-storage economics: what works where, and why? The Electricty Journal 2019;32:28–46. doi:10.1016/j.tej.2019.01.006.
[24] Alsaidan I, Alanazi A, Gao W, Wu H, Khodaei A. State-of-the-art in microgrid-integrated distributed energy storage sizing. Energies 2017;10:1421. doi:10.3390/en10091421.
[25] Santillán-Lemus FD, Minor-Popocatl H, Aguilar-Mejía O. Optimal economic dispatch in microgrids with renewable energy sources. Energies 2019;12:181. doi:10.3390/en12010181.
[26] Liu J, Chen Z, Xiang Y. Exploring economic criteria for energy storage system sizing. Energies 2019;12:2312.
[27] Anderson K, Laws N, Marr S, Lisell L, Jimenez T, Case T, Li X, Lohmann D, Cutler D. Quantifying and monetizing renewable energy resiliency. Sustainability 2018;10:4.
[28] Cook JJ, Hotchkiss E, Li X, Cruce J. Planning for the storm: considering renewable energy for critical infrastructure resilience. Journal of Emergency Managements 2020;18.
[29] Hanna R, Disfani VR, Kleiss Jl. Reliability evaluation for microgrids using cross-entropy monte carlo simulation. In: International I, editor. Conference on Probabilistic Methods Applied to Power Systems (PMAPS). Boise; 2018. p. 1–6.
[30] Hanna R, Disfani VR, Haghi HV, Victor DG, Kleissl J. Improving estimates for reliability and cost in microgrid investment planning models. J Renewable Sustainable Energy 2019;11.
[31] Nelson J, Johnson NG, Fahy K, Hansen TA. Statistical development of microgrid resilience during islanding operations. Applied energy 2020;279.
[32] DoD. Unified Facility Criteria (UFC) UFC 3-540-01: Engine Driven Generator Systems for Prime and Standby Power Applications; 2017. URL https://www.wbdg.org
[33] NFPA. 110 Standard for Emergency and Standby Power Systems; 2019.
[34] Thompson C, Hale PJ, Arno R. Decanting the data: the gold book presents equipment reliability refreshment. IEEE Transactions on Industry Application 2012;482.
[35] Fehr SJ. Emergency Diesel-Electric Generator Set Maintenance and Test Periodicity. s.l. : Doctor of Philosophy (PhD). Old Dominion University; 2017. doi:1025777/q2nk-n411. URL https://digitalcommons.odu.edu/emse_et
[36] Du Y, Burnett J, Chan SM. Reliability of standby generators in hong kong buildings. IEEE transactions on industry applications 2003;39:6.
[37] Birolini A. Reliability Engineering Theory and Practice. sl Springer; 2007.
[38] Chatzinikolaou E, Rogers DJ. A comparison of grid-connected battery energy storage system designs. IEEE Transactions on Power Electronics 9 2017;32.
[39] Smith K, Saxon A, Keyser M, Lundstrom B, Cao Z, Ro A. Life prediction model for grid- connected li-ion battery energy storage system. sl : National Renewable Energy Laboratory NREL/CP-5400-67102 2017.
[40] Marqusee J, Olis D, Becker W, Ericson S, Schultz C. The value of battery storage in military microgrids. ESTCP 2020. URL https://www.serdp-estcp.org
[41] Altman D. Advanced Phasor-based Control of Energy Storage Microgrids. ESTCP; 2020. URL https://serdp-estcp.org
[42] Arifujjaman M. A comprehensive power loss, efficiency, reliability and cost calculation of a 1 MW/500 kwh battery based energy storage system for frequency regulation application. Renewable energy 2014;74:158–69.
[43] Colonnese A, Lavoi B, Molta P, Nowak K, Takle H, Winkler E, Gonata C. Demonstrating the benefits of long-duration, low-cost flow battery storage in a renewable microgrid. Tech. Rep.. ESTCP; 2020.
[44] Becker W, Miller E, Mishra P, Jain R, Olis D, Li X. Cost reduction of school bus fleet electrification with optimized charging and distributed energy resources. 2019 North American Power Symposium 2019;978-1-7281-0407-2/19.
[45] NREL. PVWatts API. 2020c. URL https://developer.nrel.gov/docs/solar/pvwatts/v6/.
[46] NREL. Annual Technology Baseline. 2019. URL https://atb.nrel.gov.
[47] BloombergNEF. Energy Storage System Costs Survey 2019. 2019. Table 4.
[48] Ke X, Jiang A, Lu N. Load profile analysis and short-term building load forecast for a university campus. IEEE Power and Energy Society General Meeting 2016.
[49] DoD. Annual Energy Management and Resilience Report Fiscal Year 2018; 2019. URL https://www.acq.osd.mil

[50] Manana A, Ortega S, Manana M. Characterization and analysis of energy demand in airports. Energies 2017;10.
[51] NREL. National solar radiation database. 2020d. URL https://nsrdb.nrel.gov/.
[52] Edison S.C.. Schedule CBP Capacity Bidding Program. 2019. Cal. PUC Sheet No. 65879-E.
[53] El Paso Electric Company. El Paso Electric Company's 2020 Load Management Program. 2020.
[54] CPower. Understanding PJM Capacity Demand Response Changes. 2019. URL https://cpowerenergymanagement.com.
[55] CAISO. PDR-DERP-NGR Summary Comparison Matrix. 2020. URL http://www.caiso.com.
[56] CAISO. Energy Storage and Distributed Energy Resources Phase 3. 2018a.
[57] PJM Day-Ahead, Real-Time Market Operations. PJM Manual 11: Energy & Ancillary Services Market Operations. 2020.
[58] Rezkallah M. Comprehensive controller implementation for wind-PV-Diesel based standalone microgrid. IEEE transactions on industry applications 2019;55:5416–28.
[59] Cole W, Greer D, Lamb K. The potential for using local PV to meet critical loads during hurricanes. Solar Energy 2020;205.
[60] Marqusee J, Schultz C, Robyn D. Power Begins at Home: Assured Energy for U.S. Military Bases. Noblis; 2017.
[61] Klise GT, Balfour J. A best practice for developing availability guarantee language in photovoltaic (PV) o&m agreements. sl: Sandia National Laboratory SAND2015-10223 2015.
[62] Hunt K, Blekicki A, Callery R. Availability of utility-scale photovoltaic power plants. In: IEEE 42nd Photovoltaic Specialist Conference, 42; 2015.
[63] Jordan DC, Dirk M, Bill D, Chris B, Teresa. PV Field reliability status-analysis of 100 000 solar systems. Prog Photovolt Res Appl 2020:1–16.
[64] Baschel S, Koubli E, Roy J, Gottschalg R. Impact of component reliability on large scale photovoltaic systems' performance. Energies 2018;11:1579.
[65] CAISO. California Independent System Operator Corporation Fifth Replacement FERC Electric Tariff. 2018b.