Combining a dynamic battery model with high-resolution smart grid data to assess microgrid islanding lifetime

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Abstract

In this paper, we use experimental data collected from an Austin, Texas smart grid test bed with a system-level battery energy storage model to assess the lifetime of batteries in a microgrid operating in islanded mode during a distribution-level outage. We consider a hypothetical microgrid consisting of 21 single-family detached homes and three transformer-level community energy storage (CES) battery units ranging in size from 25 kWh to 75 kWh. To describe the performance of CES batteries, we implement a dynamic behavioral circuit model capable of describing voltage transients and rate-capacity effects. We use one-minute electricity production and consumption data collected from the smart grid test bed in 2012 to assess how the timing of an electric outage affects the islanding lifetime of a residential microgrid. We contrast our results with the average outage duration reported by U.S. electric utilities to quantify how often a residential microgrid could withstand a typical outage. Our results show that increasing the amount of rooftop PV in a residential microgrid does not significantly increase how often it can withstand an average-duration outage. However, combining PV with CES extends the median islanding lifetime by up to 11.6 hours during morning outages. Based on our results, 50 kWh CES provides the best tradeoff between the cost of a CES system and its reliability benefit, allowing downstream loads to withstand an average-duration outage approximately 93% of the time.

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1. Introduction and motivation

With the rapid development of battery energy storage devices and the rising implementation of intelligent electricity distribution technologies, there has been growing interest in distribution-level battery energy storage systems [1, 2, 3]. Energy storage located at the distribution level of the grid can provide useful control services, reduce the cost of delivering electricity during peak-demand hours, integrate local intermittent renewable energy, and isolate a node of the distribution system during an electric outage to form a microgrid [1, 2, 3]. The U.S. Department of Energy defines a microgrid as “a group of interconnected loads and distributed energy resources (DERs) within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid [and can] connect and disconnect from the grid to enable it to operate in both grid-connected or island mode.” [4].

One proposed distribution-level energy storage technology is community energy storage (CES), a 25 kW battery system located at the distribution transformer [1]. The goal of this paper is to model the state of CES used to isolate downstream electric loads, so that we can approximate how long CES could provide backup power during an outage. It is difficult to gauge how long CES could isolate downstream loads because electric demand often varies widely with ambient temperature, time of day, and other factors. Furthermore, the power load placed on a battery affects its available capacity [5, 6]. To approximate how long a battery could power a microgrid, information must be known about the power load on the battery and the battery’s real-time performance.

To model the performance of CES, we use a dynamic behavioral circuit model [7]. The model has the capability to describe how the voltage and capacity of a battery vary with its duty cycle. These features are important for the purpose of this paper, because a battery powering a microgrid would have a variable load applied to it.

To approximate the load that would be applied to CES powering a microgrid during an electric outage, we use high-resolution electricity data collected by Pecan Street Inc. [8] of Austin, Texas as part of its ongoing smart grid demonstration study [9]. The study utilizes a test bed of 250 modern, green-built homes constructed after 2007, and 160 homes ranging from 10–92

years in age [10]. The homes are instrumented with electricity, gas, and water metering equipment. Of the 250 homes in the study, 185 are outfitted with rooftop solar photovoltaic (PV) panels [10], which are metered separately from electric demand. For the purposes of this paper, we utilize electric demand and PV generation data with a one-minute time resolution collected from 21 of homes with PV panels over the entirety of 2012.

The remainder of this paper is organized as follows: Section 2 introduces the concept of microgrids and discusses the dynamic battery performance modeling literature; Section 3 discusses how we implement a dynamic battery model to approximate the state of CES powering a microgrid; Section 4 shows how we combine the battery model with empirical electricity data to calculate the islanding lifetime of a microgrid powered by CES; Section 5 shows the results of our analysis; and Section 6 discusses our results and prospects for future work.

2. Background

2.1. Distributed energy resources and microgrids

For many years, the electric grid has operated within a centralized, energy-on-demand paradigm. Electric power is typically produced in a large power station located far away from electricity end users, and then sent over a long distance using high-voltage transmissions lines (electric “highways”). Transmission lines deliver electric power to a substation, which transfers the power to distribution lines (electric “roads”) that deliver electricity to end users. The entire grid operates on demand; electricity is instantaneously generated, delivered, and consumed in real-time.

The physical separation between energy sources and energy users is a primary vulnerability that affects electric reliability. Temporary distribution equipment failures that disrupt the flow of current cause all downstream electric customers to lose power. Because these failures are difficult to avoid, a typical U.S. electric customer experiences 1–2 power outages a year, with each outage lasting approximately 2.5–3 hours on average [11].

Beyond the issue of power reliability, today’s grid sometimes lacks sufficient power quality for some end users. Transmission and distribution lines behave as inductors when they carry electric power over long distances. Their inductive reactance must be compensated for using banks of capacitors, power electronics, or other equipment to avoid excess reactive power

70 flow, which can potentially cause voltage sags, voltage collapse or even a
71 system-wide blackout [12].

72 Issues such as power quality and reliability have driven interest in a grid
73 with a larger share of DERs, such as energy storage, demand response, mi-
74 croturbines, fuel cells, and PV panels [13, 14, 15]. Because they are located
75 close to electricity customers, DERs have the potential to fundamentally
76 increase electric reliability and power quality. Nevertheless, centrally coor-
77 dinating and controlling a fleet of DERs poses a challenge to grid opera-
78 tors [13, 14]. One solution is to lump groups of DERs and electric loads into
79 microgrids [13, 16, 17, 18], which can behave as a single entity capable of
80 operating in both grid-connected and island mode [4].

81 In this paper, we build on our previous work [19] to evaluate the impact
82 of transformer-level CES coordinating with local PV generation and electric
83 loads to form an islanded microgrid during an electric outage.

84 2.2. Battery modeling

85 Researchers have developed numerous models to describe the performance
86 of a battery. The literature divides battery models into three major cate-
87 gories: electrochemical models, mathematical models and electrical models.
88 Electrochemical models use fundamental electrochemical and chemical equa-
89 tions to describe the transport and reaction of active species inside a battery.
90 They describe how the concentration of active species at the electrode sur-
91 face affects the overpotential required to drive an electrochemical reaction
92 to store or release energy [20]. Electrochemical models are primarily used as
93 a design tool to optimize the performance of a battery. Newman and Dees
94 have developed models of this kind for lithium-ion batteries [21, 22].

95 Mathematical models use semi-analytical or empirical equations to de-
96 scribe the system-level characteristics of a battery, such as capacity, effi-
97 ciency and voltage. Peukert’s law, which describes the relationship between
98 rate of discharge and discharge capacity, is one of the earliest mathematical
99 models [5, 6]. Other mathematical models describe a battery’s non-linear
100 capacity/recovery effects [23, 24, 25, 26] or energy efficiency [27].

101 Electrical models are equivalent circuit models that describe the system-
102 level behavior of a battery using a combination of variable voltage sources,
103 resistors, and capacitors. A number of electrical models have been developed
104 in the literature including Thévenin equivalent circuit models [28, 29, 30],
105 impedance-based models [31, 32, 33], and runtime-based models [34, 35]. A
106 behavioral circuit model developed by Chen and Rincón-Mora combines the

benefits of many of these models [7]. It accurately describes the nonlinear voltage of a battery, short-term and long-term transient effects, and nonlinear rate-capacity effects.

The objective of this paper is to describe the capabilities of a battery energy storage unit used to isolate downstream loads and provide emergency backup power during a distribution-level outage. In doing so, a large power load in excess of the battery’s capacity might be applied for a short period of time. Furthermore, unlike a battery used in typical applications, a battery used for islanding will continue to discharge until its minimum cutoff voltage is reached, where the terminal voltage behavior is highly nonlinear. Thus, it is important to utilize a model capable of describing dynamic rate-capacity effects and end-of-discharge voltage behavior. Chen and Rincón Mora’s model combines the benefits of a number of dynamic behavioral circuit models to describe both of these phenomenon without significant added complexity [7]. Thus, we select the behavioral circuit model from [7] for our analysis.

3. Model development and transformation

Chen and Rincón-Mora’s model describes the state of a battery using two coupled electrical circuits, as shown in Figure 1. The “battery lifetime circuit” on the left-hand side of Figure 1 estimates a battery’s state of charge based on the current input, I_{batt} . The capacitor $C_{capacity}$ integrates the coulombs of charge flowing into and out of the battery, and the resistor $R_{self-discharge}$ models how state of charge naturally decreases over time in the absence of an external charging current or float voltage. The circuit components combine to produce a voltage at node V_{SOC} corresponding to the battery’s state of charge. The “voltage-current characteristics circuit” on the right-hand side of Figure 1 estimates a battery’s terminal voltage based on the current input and state of charge (V_{SOC} from the battery lifetime circuit). The variable potential source $V_{OC}(V_{SOC})$ models how open-circuit voltage varies with state of charge, and the series resistor R_{series} and two parallel RC networks consisting of $R_{transient,S}$, $C_{transient,S}$, $R_{transient,L}$, and $C_{transient,L}$ model how the battery’s terminal voltage dynamically changes under a variable applied current, I_{batt} . Each of these circuit components has parameters defined by a variable function fit to experimental performance data [7]. The details of the experimental procedure for extracting the model parameters are described in the literature [7, 36, 37].

Figure 1: The battery lifetime circuit describes the dynamic nature of a battery’s state of charge, and the voltage-current characteristics circuit describes how the terminal voltage of a battery is dynamically affected by state of charge and current load. Figure adapted from [7].

143 We use this model to describe the performance of a CES unit. Spec-
 144 ifications for proposed transformer-level CES are available from American
 145 Electric Power, a major U.S. electric utility [1]. The specifications were de-
 146 veloped by a consortium of large U.S. electric utilities and other relevant
 147 stakeholders under the organization of the Electric Power Research Institute
 148 (EPRI). The specifications discuss the size, placement, roundtrip efficiency,
 149 energy capacity and power capacity of CES. The given functional specifica-
 150 tions for CES are shown in Table 1.

Table 1: Functional specifications for community energy storage were developed by American Electric Power, the Electric Power Research Institute and other relevant stakeholders [1].

Parameter	Specification
Power Capacity	25 kW
Energy Capacity	25, 50, or 75 kWh
AC-AC Roundtrip Efficiency	>85%
Enclosure Dimensions (W×D×H)	38" × 40" × 35"

151 We assume that CES uses batteries with a lithium-ion chemistry. Based
 152 on performance characteristics reported in the literature [38, 40, 41], lithium-
 153 ion is the battery chemistry most likely to meet the CES specification's re-
 154 quirements for roundtrip efficiency and dimensions. Chen and Rincón-Mora
 155 experimentally extracted the model parameters for an 850-mAh TCL PL-
 156 383562 polymer lithium-ion battery cell. We assume that this battery has a
 157 similar dynamic character to batteries that would be used in a CES unit. The
 158 model parameters for the specified cell are given in the following equations:

$$C_{capacity} = 3060 \text{ F} \quad (1)$$

$$V_{OC} = -1.031e^{-35V_{SOC}} + 3.685 + 0.2156V_{SOC} - 0.1178V_{SOC}^2 + 0.3201V_{SOC}^3 \text{ V} \quad (2)$$

$$R_{series} = 0.1562e^{-24.37V_{SOC}} + 0.07446 \text{ } \Omega \quad (3)$$

$$R_{transient,S} = 0.3208e^{-29.14V_{SOC}} + 0.04669 \text{ } \Omega \quad (4)$$

$$C_{transient,S} = -752.9e^{-13.51V_{SOC}} + 703.6 \text{ F} \quad (5)$$

$$R_{transient,L} = 6.603e^{-155.2V_{SOC}} + 0.04984 \text{ } \Omega \quad (6)$$

$$C_{transient,L} = -6056e^{-27.12V_{SOC}} + 4475 \text{ F} \quad (7)$$

159 With the model parameters established, one can build a physical circuit
 160 model using software such as Cadence PSpice or MathWorks SimPowerSys-
 161 tems. We transform the physical model into a mathematical model, increas-
 162 ing modeling software compatibility and performance. Kirchoff's circuit laws
 163 are used to extract the mathematical equations that describe the dynamic
 164 state of the behavioral circuit model components, resulting in the following
 165 nonlinear differential equations:

$$\dot{V}_{SOC} = -\frac{I_{batt}}{C_{capacity}} \quad (8)$$

$$\dot{V}_{transient,S} = \frac{I_{batt}}{C_{transient,S}} - \frac{V_{transient,S}}{R_{transient,S}C_{transient,S}} \quad (9)$$

$$\dot{V}_{transient,L} = \frac{I_{batt}}{C_{transient,L}} - \frac{V_{transient,L}}{R_{transient,L}C_{transient,L}} \quad (10)$$

$$V_{batt} = V_{OC} - I_{batt}R_{series} - V_{transient,S} - V_{transient,L} \quad (11)$$

166 Using Equations 8–11, the model for an individual cell can be readily
 167 implemented in any modeling platform capable of numerically integrating
 168 coupled nonlinear differential equations. We implement the model for an
 169 individual battery cell in MathWorks Simulink.

170 Assuming that battery cells can be ideally lumped, the model for an
 171 individual cell can be scaled up to describe CES units with specifications
 172 matching those in Table 1. We develop models for 25 kWh, 50 kWh, and 75
 173 kWh CES units. For each of these units, we calculate the number of battery
 174 cells required so that a discharge from “full” ($V_{SOC} = 1$, $V_{cell} = 4.2$ V) to
 175 “empty” ($V_{cell} = 3$ V) with a constant power load of 25 kW delivers the
 176 corresponding rated energy capacity. Table 2 shows the number of cells con-
 177 nected in series/parallel required to match the energy capacities specified in
 178 Table 1. While real-life CES units might utilize cells with a capacity greater
 179 than 850 mAh, a number of large lithium-ion battery packs have been de-
 180 signed using thousands of small cells in lieu of larger cells. For example, the
 181 Tesla Roadster electric vehicle uses 6,831 cylindrical 18650 lithium-ion cells
 182 in its 53 kWh battery pack [39]. Furthermore, this assumption permits im-
 183 plementation of Chen and Rincón-Mora’s experimentally-determined model
 184 parameters [7] without comprehensive information about CES battery per-
 185 formance characteristics or the specific design of an integrated CES system.

Table 2: We calculate the number of 850-mAh TCL PL-383562 polymer lithium-ion bat-
 tery cells required to meet the CES power and energy capacity requirements specified in
 Table 1.

Power Capacity	Energy Capacity	Number of Battery Cells
25 kW	25 kWh	8,250
25 kW	50 kWh	16,087
25 kW	75 kWh	23,925

186 In addition to an appropriate battery pack, a CES unit requires a recti-
 187 fier/inverter to convert the battery’s DC electricity into AC electricity ap-
 188 propriate for the power grid, and vice versa. We assume a one-way AC-DC

189 and DC-AC energy efficiency of 93% for the inverter/rectifier bridge con-
 190 necting the battery pack to the grid, consistent with values reported in the
 191 literature [40, 42].

192 Figure 2 illustrates how we use a behavioral-circuit model of a single
 193 battery cell to describe the dynamic voltage of a CES unit as a function
 194 of its instantaneous power load. In the following section, we input real-life
 195 smart grid data to the model to assess the microgrid capabilities of CES.

Figure 2: Our model describes the dynamic voltage of CES battery cells as a function of the power load applied to the CES unit. The power flowing to/from the grid is converted in a rectifier/inverter bridge, and then input to the CES unit’s battery pack. The flow of DC power is equally divided amongst each of the battery cells, so that a single-cell battery model can be used to describe the dynamic voltage of an integrated CES system.

196 4. Microgrid System Simulations

197 CES and other grid-connected battery systems have the rapid power-
 198 delivery capability required to provide frequency control for a small power
 199 system consisting of a handful of energy sources and energy sinks. This abil-
 200 ity permits distributed energy storage to provide reliable power to an isolated
 201 microgrid during an electric outage. If distributed energy sources are avail-
 202 able (e.g. rooftop PV panels), local battery storage can balance electricity
 203 production with demand, maintaining power quality and reliability even in
 204 the presence of intermittent energy production and consumption [43, 44].

205 We utilize electric load and PV energy production data collected from
 206 21 homes in Austin, Texas to show the capabilities of CES used to power

207 an islanded microgrid during an electric outage. Each of the homes has
 208 south-facing and/or west-facing rooftop PV panels installed. Table 3 contains
 209 information about each of the 21 homes’ PV array size, electricity use and PV
 210 energy production. The data were recorded with one-minute time resolution.
 211 This level of resolution is important for our analysis because it allows us to
 212 approximate islanding lifetime to the nearest minute. If, for example, we used
 213 a dataset with hourly time resolution, we would only be able to reasonably
 214 approximate islanding lifetime to the nearest hour. Furthermore, the one-
 215 minute resolution of the electricity data allows us to capture the effect of
 216 large, short-duration power loads on CES. Hourly averaged electricity data,
 217 for example, would mask the occurrence of short-term power spikes. We use
 218 data from calendar year 2012 to show how seasonal and diurnal variability in
 219 electricity use and PV energy production affects the lifetime of CES powering
 220 a microgrid.

221 We consider a hypothetical microgrid composed of those 21 homes. Be-
 222 cause a residential transformer typically serves 5–8 homes, we assume these
 223 21 homes are served by three residential transformers and three CES units,
 224 with 7 homes allocated to each transformer and CES unit.

225 In normal operation, the microgrid freely exchanges energy with the main
 226 power grid, and we assume CES batteries are kept fully charged in antici-
 227 pation of an unexpected power outage. At the precise moment that power
 228 from the grid is interrupted, CES batteries isolate the microgrid and provide
 229 backup power until they reach their minimum acceptable voltage (3 V per
 230 cell), and their energy is depleted. Because islanding is an emergency func-
 231 tion that would only occur a handful of times each year, we assume that CES
 232 can provide up to 1.5 times its rated power capacity during islanding. We
 233 consider three microgrid configurations: (1) CES is deployed in a residential
 234 neighborhood with no PV panels installed; (2) CES is deployed in a residen-
 235 tial neighborhood where approximately half of the homes have rooftop PV
 236 panels installed; and (3) CES is deployed in a residential neighborhood where
 237 every home has rooftop PV panels installed. These three scenarios contrast
 238 the present, centralized power system with a system that has a large share
 239 of rooftop PV. Considering these three scenarios also illustrates the relative
 240 benefit of deploying energy storage in a neighborhood with a high penetration
 241 of PV panels versus a neighborhood with little or no PV penetration.

242 In the first scenario, the three CES units equally provide all of the electric
 243 power required by the 21 homes comprising the microgrid, essentially acting
 244 as an uninterruptible power supply (UPS) until CES batteries are depleted

Table 3: We utilize electricity production and consumption data collected from 21 Austin, Texas homes with south and/or west-facing rooftop PV panels. The PV array size, total energy use, and total energy production for each of the homes is shown here.

House ID	South-Facing PV Capacity (kW)	West-Facing PV Capacity (kW)	Total 2012 Energy Use (MWh)	Total 2012 Energy Production (MWh)
1	4	2.25	6.52	8.65
2	4	2.25	7.49	8.98
3	2.5	3.5	10.39	7.86
4	2.21	3.92	9.74	8.03
5	1.96	3.92	9.16	8.29
6	4.25	3.92	7.55	6.45
7	6.25	0	10.13	6.54
8	3.43	3.43	13.37	10.08
9	4	0	7.76	6.01
10	5.15	0	6.85	7.84
11	0	4.8	14.7	6.05
12	4.66	0	12.68	7.09
13	0	4.5	10.71	5.72
14	0	5.25	13.85	6.96
15	4	0	5.94	5.02
16	No Data	No Data	12.71	8.89
17	6.25	0	12.41	9.12
18	5.92	0	9.52	6.47
19	2.04	4.07	21.77	9.01
20	4.25	0	10.43	5.79
21	2.04	4.07	12.67	8.35
Aggregate	66.89	45.88	226.35	157.19

245 or grid power is restored.

246 In the second and third scenarios, the three CES units equally match
247 electricity production from local PV systems with the electric demand of
248 the 21 homes comprising the microgrid. During periods of high solar PV
249 power production, CES batteries might be unable to capture solar electricity
250 because they are fully charged. In this case, solar energy that would overload
251 CES batteries is curtailed and lost. At all other times, CES captures solar
252 PV electricity and powers the microgrid until CES batteries are depleted
253 or grid power is restored. It should be noted that we assume the DER
254 interconnection standards of IEEE 1547 [45] do not apply to our hypothetical
255 microgrid. Presently, IEEE 1547 mandates that grid-tied solar power DC-
256 AC inverters automatically disconnect from the grid during an outage [45].
257 We assume that inverters in our hypothetical microgrid do not disconnect
258 during an outage, so that PV electricity can be used to power the microgrid
259 in islanded mode.

260 For each scenario, we simulate 8,784 independent outages corresponding
261 to hypothetical electricity service interruptions occurring at the beginning of
262 each hour of 2012 (a leap year). We use the results observed from these sim-
263 ulations to show the expected islanding lifetime of the microgrid at different
264 times of the day during different seasons of the year.

265 5. Results and Discussion

266 The model developed in Section 3 is used to describe the state of CES
267 batteries in response to a stepwise-constant power load consistent with data
268 collected from a smart grid test bed. We model CES islanding a microgrid
269 during hypothetical outages beginning each hour of 2012, and record the
270 results. In the course of our study, we found that diurnal variations in electric
271 demand and PV production have the greatest influence on the distribution
272 of observed islanding lifetimes. Seasonal variations in demand only have
273 a profound effect during summer months (June, July, and August), when
274 air conditioning use significantly increases electric demand. Thus, we focus
275 on the diurnal variation in observed islanding lifetimes to draw conclusions
276 about the effect of utilizing transformer-level CES.

277 Figures 3–5 use boxplots to show the observed islanding lifetimes of the
278 three CES units considered (25, 50, and 75 kWh). A boxplot summarizes
279 observed data by showing upper and lower quartiles, the median, and out-
280 liers [46]. In Figures 3–5, whiskers extend up to 1.5 times the interquartile

281 range of the upper and lower quartiles. Any points beyond the whiskers are
 282 considered outliers, and appear as points.

283 To contextualize the islanding lifetimes observed in this study, Figures 3–5
 284 also show the average U.S. outage duration reported by electric utilities [11].
 285 U.S. electric utilities typically quantify their electric reliability using two in-
 286 dices, the system average interruption frequency index (SAIFI) and the sys-
 287 tem average interruption duration index (SAIDI) [11, 47]. SAIFI indicates
 288 how often the average electricity customer experiences a sustained power
 289 interruption and is defined mathematically as in Equation 12 [47]. SAIDI
 290 indicates the total duration of interruption for the average electricity cus-
 291 tomer and is defined mathematically as in Equation 13 [47]. The customer
 292 average interruption duration index (CAIDI) can be computed from the com-
 293 mon reliability indices SAIFI and SAIDI and is mathematically defined as
 294 in Equation 14 [47]. CAIDI represents the average time required to restore
 295 electrical service after an outage [47]. We use SAIDIs and SAIFIs reported
 296 by 123 U.S. electric utilities [11] to calculate the average U.S. CAIDI (2.73
 297 hours).

$$\text{SAIFI} = \frac{\sum \text{Total Number of Customers Interrupted}}{\text{Total Number of Customers Served}} \quad (12)$$

$$\text{SAIDI} = \frac{\sum \text{Customer Interruption Durations}}{\text{Total Number of Customers Served}} \quad (13)$$

$$\text{CAIDI} = \frac{\sum \text{Customer Interruption Durations}}{\sum \text{Total Number of Customers Interrupted}} = \frac{\text{SAIDI}}{\text{SAIFI}} \quad (14)$$

298 How often the microgrid could withstand an average-duration outage is
 299 indicated by the number of observations greater than the average of CAIDIs
 300 reported by U.S. electric utilities. We report how often various CES microgrid
 301 configurations could withstand an average outage in Table 4.

302 Figure 3.a shows that 25 kWh CES alone can withstand the vast majority
 303 of outages occurring outside the hours of 2:00–8:00 pm, when demand for
 304 electricity peaks. The median of observed islanding lifetimes only falls below
 305 the average U.S. CAIDI during this peak-demand period. Overall, 25 kWh
 306 CES alone can withstand an average-duration U.S outage approximately 68%
 307 of the time.

308 Adding photovoltaic panels to the CES microgrid does not significantly
 309 increase the number of average-duration outages avoided. Comparing the

Figure 3: To gauge the reliability benefit of utilizing 25 kWh CES, we show the distribution of islanding lifetimes observed from simulated outages occurring at the beginning of each hour. The data are contrasted with the average of CAIDIs reported by U.S. electric utilities. 25 kWh CES alone can withstand the vast majority of outages occurring outside the hours of 2:00–8:00 pm, when electric demand peaks. The addition of PV to the microgrid significantly increases the median islanding lifetime between 3:00 am and 3:00 pm, but does not affect the results for outages occurring after 5:00 pm. Because this cut-off point coincides with peak-demand hours, increasing PV penetration from 0% to 100% only increases the number of avoided average-duration outages from 68% to 82%.

Figure 4: To gauge the reliability benefit of utilizing 50 kWh CES, we show the distribution of islanding lifetimes observed from simulated outages occurring at the beginning of each hour. The data are contrasted with the average of CAIDIs reported by U.S. electric utilities. Increasing CES energy capacity from 25 kWh to 50 kWh has the greatest effect on the number of avoided average-duration outages. Overall, 50 kWh CES alone can withstand 93% of average-duration power outages. Because PV panels do not significantly affect the results observed during peak-demand hours, increasing PV penetration from 0% to 100% only increases the percentage of avoided outages from 93% to 98%.

Figure 5: To gauge the reliability benefit of utilizing 75 kWh CES, we show the distribution of islanding lifetimes observed from simulated outages occurring at the beginning of each hour. The data are contrasted with the average of CAIDIs reported by U.S. electric utilities. Increasing the energy capacity of CES to 75 kWh gives the microgrid the ability to ride through 100% of average-duration outages, regardless of the amount of rooftop PV panels available. As was the case for 25 kWh and 50 kWh CES, the minimum observed islanding lifetimes occur during peak demand hours, when the addition of PV to the microgrid does not significantly increase islanding lifetime. Thus, increasing the PV penetration from 0% to 100% does not significantly affect the minimum islanding lifetime observed for the 75 kWh CES microgrid.

Table 4: We simulate microgrid islanding during thousands of independent, hypothetical outages occurring each hour of calendar year 2012, and record the observed islanding lifetimes. This table shows how often various configurations of the hypothetical, 21-home microgrid could withstand an average-duration U.S. outage.

Simulated islanding lifetimes longer than an average U.S. outage (%)			
CES Unit Size (kWh)	Homes with PV panels installed (%)		
	0	48	100
25	68	79	82
50	93	97	98
75	100	100	100

observed islanding lifetimes shown in Figures 3.a–3.c shows that increasing the penetration of PV in the microgrid has almost no effect on the results for outages occurring after 5:00 pm. While this result might seem counterintuitive, it follows from the fact that electricity production from rooftop PV panels peaks early in the afternoon. On average, PV electricity production from our hypothetical 21-home microgrid peaked at approximately 1:00 pm. Furthermore, by 5:00 pm the aggregate level of PV generation fell below one third of its peak value, on average. By 7:00pm, PV electricity production usually stopped completely. Crucially, this cut-off point occurs during peak-demand hours, when 25 kWh CES alone cannot typically withstand an average-duration outage. Thus, even increasing PV installation from 0% of homes to 100% of homes only increases the percentage of avoided outages from 68% to approximately 82% for 25 kWh CES.

Increasing the energy capacity of CES from 25 kWh to 50 kWh has the greatest effect on the number of average-duration outages avoided. Because of its greater energy capacity, 50 kWh CES alone can power the microgrid long enough to withstand an average-duration outage 93% of the time. Figure 4.a shows that 50 kWh CES alone could withstand all average-duration outages occurring outside the hours of 11:00 am–10:00 pm. Similar to the results for 25 kWh CES, comparing the observed islanding lifetimes shown in Figures 4.a–4.c shows that increasing the penetration of PV in the microgrid has little effect on the results for outages occurring between 5:00 pm and 9:00 pm—coinciding with peak-demand hours. Thus, increasing the PV installation from 0% of homes to 100% of homes only increases the percentage

334 of avoided outages from 93% to 98%.

335 Increasing the energy capacity of CES from 50 kWh to 75 kWh gives
336 the microgrid the ability to withstand 100% of average-duration outages,
337 regardless of the amount of rooftop PV panels available. As was the case
338 for 25 kWh and 50 kWh CES, the minimum observed islanding lifetime for
339 75 kWh CES occurs during peak-demand hours, approximately 2:00–8:00
340 pm. At the same time, adding PV to the 75 kWh CES microgrid does not
341 significantly affect the results for outages occurring between 5:00 pm and 8:00
342 pm. Thus, the minimum observed islanding lifetime is essentially unchanged
343 from the addition of PV panels to the 75 kWh CES microgrid.

344 We have shown that adding PV to a CES microgrid does not significantly
345 increase how often it can withstand an average-duration outage. This result is
346 a product of the fact that peak electric demand occurs in the early evening,
347 when PV production is unavailable, and will not become available again
348 for approximately 12 hours. Nevertheless, it is important to note how PV
349 increases the median observed islanding lifetime outside peak demand hours.
350 Figure 6 shows how increasing the amount of PV installed affects the median
351 observed islanding lifetime for 25, 50, and 75 kWh CES microgrids. For all
352 CES sizes, adding PV panels to the system increases the median islanding
353 lifetime by up to 11.6 hours from the 0% PV case for outages occurring in
354 the early morning. The addition of PV is especially beneficial for outages
355 occurring in the early morning hours because PV generation typically exceeds
356 electric demand in the middle of the day. After an early-morning outage, CES
357 batteries can often discharge to meet electric demand until PV production
358 exceeds demand, charge while PV production exceeds demand, and then
359 discharge once again to cover electric demand into the evening—allowing
360 CES to power downstream loads far longer than it could without PV panels
361 present. The additional islanding lifetime provided by PV would be valuable
362 during a major outage event lasting far longer than average, such as an outage
363 caused by a hurricane.

Figure 6: While adding PV to a CES microgrid does not significantly increase how often it can withstand an average-duration outage, adding PV increases the median observed islanding lifetime by up to 11.6 hours from the 0% PV case for outages occurring in the early morning or late evening. The median islanding lifetime increases suddenly after 2:00 am for 25 kWh CES, 10:00 pm for 50 kWh CES, and 8:00 pm for 75 kWh CES. These sudden increases are transition points where CES batteries either have enough energy to power the microgrid until solar energy production begins, or CES batteries are depleted before sunrise.

6. Conclusion and Future Work

In this paper, we transformed and implemented a dynamic, system-level battery model to describe the state-dependent performance of a lithium-ion battery CES system. We then combined our CES model with one-minute electricity consumption and production data collected from an Austin, Texas smart grid test bed to simulate a microgrid operating in islanded mode. We simulated 8,784 independent islanding events occurring at the beginning of each hour of 2012, and recorded the observed islanding lifetime of the microgrid.

Our results show how the configuration of a CES microgrid affects how often it can withstand an average-duration U.S. outage, and the distribution of islanding lifetimes observed at various times of day. Based on our results, increasing the amount of PV in a CES microgrid does not significantly increase how often it can withstand an average outage, because peak electric demand occurs in the evening when PV production is low. On the other hand, increasing the amount of PV in the microgrid while retaining the CES increases the median islanding lifetime by up to 11.6 hours compared to the 0% PV case.

Based on our results, 50 kWh CES is most likely the best choice for an average U.S. electric utility interested in using CES to increase the reliability of its power system. 50 kWh CES alone provides enough backup energy to power downstream loads for at least the duration of an average U.S. outage 93% of the time. Furthermore, combining rooftop PV with 50 kWh CES significantly increases the median islanding lifetime for all outages occurring outside the hours of 4:00–10:00 pm, when electric demand peaks.

25 kWh CES is less desirable because it can only withstand 68% of average-duration outages without PV panels present. Furthermore, adding PV panels to a 25 kWh CES microgrid does not increase the median islanding lifetime outside the hours of 2:00 am–5:00 pm. 75 kWh CES is also less desirable than 50 kWh CES because it does not provide a significant incremental benefit over 50 kWh CES. Assuming that the cost of a CES unit roughly scales with its energy capacity, it is unlikely the additional reliability benefit of 75 kWh CES compensates for its increased cost.

Future work should explore the tradeoffs that exist for the decision to curtail electric load or deplete CES batteries. During an extended outage scenario, such as after a hurricane, it may be desirable to interrupt individual electric loads to extend the lifetime of an isolated CES microgrid.

401 Quantifying the value of extending islanding lifetime versus the cost of cur-
402 tailed load is a difficult exercise requiring knowledge about the preferences of
403 electric customers within the microgrid. It would be valuable to explore these
404 tradeoffs to reveal best practices for microgrid control during an extended
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