Battery-Assisted Distribution Feeder Peak Load Reduction: Stochastic Optimization and Utility-Scale Implementation

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***Abstract*—In this paper, a stochastic optimization framework is developed to reduce congestion on distribution feeders using batteries, under offline and online design paradigms. Our design is customized, implemented, tested, and analyzed in a real-world testbed that was built based on a university-utility collaboration in California. Our proposed method seeks to optimize peak load at the feeder while taking into account feeder load uncertainty as well as hardware, utility, and customer constraints. We present both experimental and numerical results. Insightful observations, design trade-offs, and lessons learned are discussed.**

***Keywords*: Battery systems, feeder-level peak-load shaving, utility-scale testbed, stochastic optimization, communications.**

I. Introduction

Power distribution feeders are designed to support certain peak loads that can occur at any given time. However, if the average load is low compared to the peak load, then the feeder will be overbuilt to accommodate the peak. In fact, having a high peak load but for a short duration of time can force the utility to upgrade a feeder that would in most situations be under loaded. This sort of feeder upgrade could be costly, and therefore could be eliminated or postponed [1].

One can reduce the peak-to-average-ratio on a feeder by carefully planning to turn the local loads on and off [2], but in many cases the loads are not time shiftable. In this situation, energy storage, both stationary [3], and mobile such as electric vehicles [4], can be used to stabilize the system, offset the load, and keep the peak-to-average-ratio low. One can also combine energy storage and other customer-side resources so as to have certain customers act as microgrids [5].

The storage on the customer side can charge when the feeder load is low, and discharge when it is high, reducing the total peak. However, any such arrangement will require customers to have communication with the utility and be able to adjust their load to relieve stress on the grid during these peak load times. Of course, the utility could also improve this situation by carefully choosing the time-of-use and rate structures [6].

In this paper, we show how the above idea can work *in practice* on a utility-scale testbed that is built and operated through a university-utility collaboration in Riverside, California. First, we provide a detailed overview of the testbed and its electrical layout, energy components, and near real-time interactions with the utility's Supervisory Control and Data Acquisition (SCADA) system. Second, we analyze and characterize historical load data for a target feeder and identify the challenges, opportunities, and the needs for a battery-assisted distribution feeder peak load reduction system. Third, we provide an optimization-based framework to operate the batteries in the testbed, considering both offline and online designs and various design objectives and constraints. Finally, we present experimental and numerical results from the testbed and report several insightful and interesting observations.

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Fig. 1. The energy resources at the University of California at Riverside's CE-CERT microgrid. From left to right and top to bottom: battery racks, battery connections, battery inverter, solar panel inverters, and EV chargers.

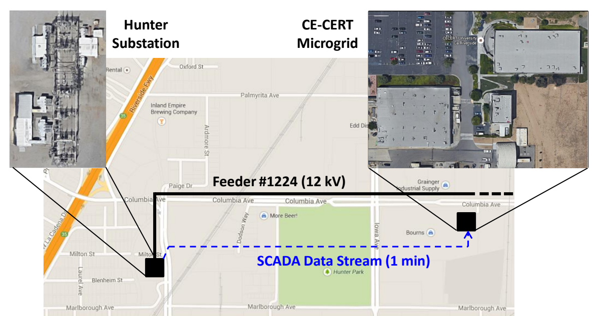

Fig. 2. The CE-CERT microgrid is served by Feeder #1224 at Hunter Substation. A secured web-based communication infrastructure provides minute-by-minute access to RPU's data acquisition system for this feeder.

II. Overview of Utility-Scale Test System

The site of this utility-scale project is in Riverside, California. This project is based on a collaboration between the University of California at Riverside (UCR) and Riverside Public Utilities (RPU). The batteries are located on-site at the

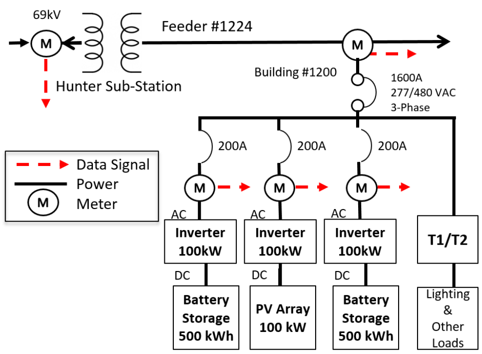

Fig. 3. The electrical layout of building #1200 at CE-CERT facility.

College of Engineering Center for Environmental Research and Technology (CE-CERT). The batteries are grouped into two 500 kWh modules, where each module is served by a 100 kW grid-connected inverter. Other on-site distributed energy resources (DERs) at CE-CERT include three solar arrays at 260 kW, 100 kW, and 100 kW nominal generation capacities, and four level-2 electric vehicle (EV) chargers, see Fig. 1.

CE-CERT is served through the 12 kV Feeder #1224 on RPU's 69 kV Hunter Capital Station, see Fig. 2. The service area for RPU spans 82 square miles. It serves electricity to over 107,000 metered electric customers in City of Riverside. In total, RPU has 14 substations on its subtransmissions system. The RPU historical peak demand is 612 MW that was recorded on September 16, 2014 during a summer heat wave.

There are three buildings at CE-CERT that are served by three separate 277/480 VAC transformers. Of interest in this project is building # 1200, where all batteries and one 100 kW solar panel are currently installed. The electric layout of this building is shown in Fig. 3. The total energy and power ratings of the available batteries are 1 MWh and 200 kW.

Our goal is to do *feeder-level peak-load shaving* by optimally operating battery resources at CE-CERT's microgrid.

RPU and CE-CERT are collaborating to explore the impact that customer power resources could have on the feeder. To facilitate this goal, RPU has provided CE-CERT with a datalink from its SCADA system through a secured communications line[1]. The following values are obtained for Feeder #1224 on a *minute-by-minute* basis: Neutral Amps, Active Power, Reactive Power, Average Phase Current, Apparent Power, and Voltage.

Of particular interest to this project is the data on active power, i.e., the feeder's load profile. Examples of such load profile are shown in Fig. 4 for the days of May 3-5, 2015. We can see that there is a major difference between the load profile on weekdays and weekends. Similar trends are observed in other weeks and months. Since the peak load is low on weekends, our focus in this project is to analyze the load profiles on weekdays. For the two sample load profiles on weekdays in Fig. 4, the peak loads are at 2.85 MW and occured at 1:55PM and 2:05PM. We can make two observations here:

- First, the peak often does not last long, which means even a relatively small energy storage might be able to make a noticeable impact on the peak load at the feeder.

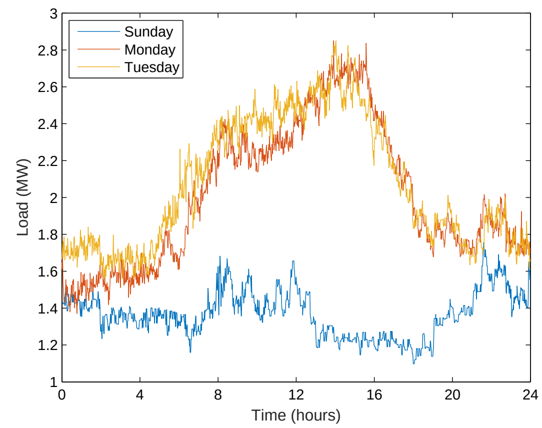

Fig. 4. Sample load profiles of Feeder #1224 from Sunday 5/3/2015 to Tuesday 5/5/2015. The load profile is different on weekdays versus weekends.

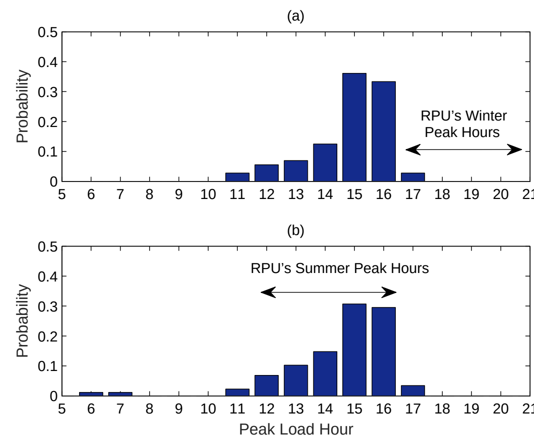

Fig. 5. The distribution of peak load hour at Feeder #1224 and its comparison with RPU's system-wide peak load hours: (a) winter; (b) summer.

- Second, the peak load at the feeder level for Feeder #1224 at Hunter substation does *not* coincide with the typical peak hours that are identified by RPU for its overall system load. As a result, RPU's existing demand response programs that are set to curtail the load during peak hours do *not* contribute to peak load shaving at Feeder #1224.

The second issue above is better understood by examining the feeder load profiles over several months and comparing them with RPU's seasonal peak hours. The results are shown in Fig. 5. The analysis of the Summer peak is based on the data from June 1, 2015 to September 30, 2015; and the analysis of the Winter Peak is based on the data from March 12, 2015 to May 30, 2015 and October 1, 2015 to October 11, 2015. We can see that typical Winter peak hour at Feeder #1224 is very different from the typical peak hour across the RPU system. This could be due to the fact that Feeder #1224 is connected to mostly commercial buildings, where the peak load almost always occurs during business hours. This further confirms the goal of our project to conduct peak load reduction at *feeder-level* through a *localized solution*, rather than a system-wide solution. It also shows the conflict between the best ways to run the battery as a financial asset at CE-CERT to lower its own electricity bill versus the best ways to run the battery to contribute to feeder-level peak load reduction.

[1]The authors would like to thank Alan Woodcock, Alan Lee, Ed Sponsler, and Alex Vu for their help in establishing the communications line.

III. Optimal Battery Operation

Throughout this section, we assume that the charge and discharge schedules of the batteries can be controlled on intervals of length 15 minutes. That is, to avoid excessive use of batteries, we may not switch from a charge cycle to a discharge cycle or vise versa in a time period earlier than 15 minutes. Accordingly, time is divided into *time slots* of length 15 minutes. The charge and discharge status of the batteries at time slot τ is denoted by $x[\tau]$, where τ can take a number between 1 to 96 to span an entire day. We also denote the average load at time slot τ by $l[\tau]$, where $l[\tau] = \frac{1}{15}\sum_{t=1}^{15} l(t)$. Here, $l(t)$ is the feeder load at minute t, matching the time resolution in RPU's SCADA system. Both $l[\tau]$ and $l(t)$ are random variables. In contrast, $x[\tau]$ is a decision variable.

A. Offline Optimization

In this paper, we refer to a design as *offline*, if the decisions on charging and discharging are made once at the beginning of each day based on historical data and such decisions are *not* updated as more data becomes available during the day. Since our approach is optimization-based, next, we separately discuss the objective function(s) and the constraints.

1) Objective Function: The primary goal of this project is to exploit CE-CERT batteries for peak load reduction at Feeder #1224. Nevertheless, we note that there are three distinct objectives that one could take into account while formulating an optimization problem in the context of this paper:

- Feeder Peak Load
- Battery Health and Longevity
- Customer Utility Bill

Next, we start off by formulating an objective function that addresses the primary goal of minimizing the feeder peak load:

$$\underset{x}{\textbf{minimize}} \quad \max_{1\leq\tau\leq 96} \; \mathbb{E}\{l[\tau]+x[\tau]\}, \tag{1}$$

where $\mathbb{E}$ denotes mathematical expectation. Here, we seek to minimize the maximum feeder load, i.e., the peak load across all 96 time slots during the day. Note that, $x[\tau]$ takes a *positive* value if we charge the battery and a *negative* value if we discharge the battery. The expected value is calculated based on historical data by applying a *weighted average* to the past 10 weekdays, i.e., the past two weeks. The weights are selected proportional to the *cross-correlation* among the seasonal historical data on different days, as shown in Fig. 6.

Due to the use of $\max$ function, there are infinite solutions to problem (1), however, to improve battery health, we would like to narrow down the solution space to include only those solutions in which the battery is exercised as little as possible. To this end, we can add a new term to the objective function:

$$\underset{x}{\textbf{minimize}} \quad \max_{1\leq\tau\leq 96} \mathbb{E}\{l[\tau]+x[\tau]\} + \epsilon \sum_{\tau=1}^{96} |x[\tau]|, \tag{2}$$

where ϵ is a small positive number. The second term is to penalize any battery activity, whether charging or discharging. If we increase ϵ, then it starts creating a *trade-off* between peak-load reduction and battery health considerations.

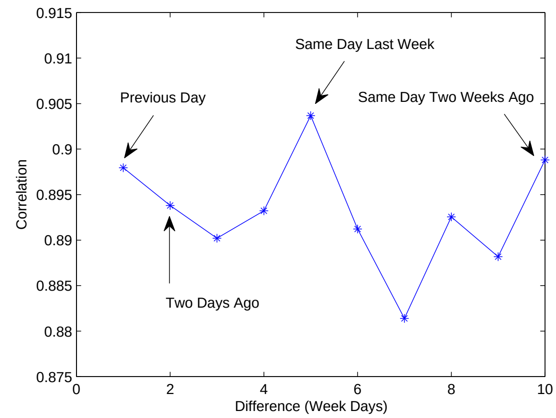

Fig. 6. The correlation of any weekday to weekdays over the past two weeks.

Finally, we can combine the objectives on feeder peak load reduction and customer utility bill reduction as follows[2]:

$$\begin{aligned}\underset{x}{\textbf{minimize}} \quad \max_{1\leq\tau\leq 96} \mathbb{E}\{l[\tau]+x[\tau]\} &+ \epsilon_1 \sum_{\text{On-Peak}} x[\tau] \\ &+ \epsilon_2 \sum_{\text{Mid-Peak}} x[\tau],\end{aligned} \tag{3}$$

where $\epsilon_1 > \epsilon_2 > 0$. The new terms tend to *penalize charging during on-peak and mid-peak hours*. They act as knobs to control the *trade-off* between lowering CE-CERT's own electricity bill versus reducing peak load at feeder-level. Note that, one may choose ϵ_1/ϵ_2 equal to the ratio of the electricity prices during on-peak hours and mid-peak hours.

2) Constraints: Several constraints need to be considered in order to assure proper operation of the battery systems. Some of these constraints are imposed by physical systems, while some others are required due to some operational considerations. Next, we mathematically model different constraints.

Let $SoC[\tau]$ denote the state-of-charge at the end of time slot τ. We can model the changes in state-of-charge as follows:

$$SoC[\tau] = SoC[\tau-1] + x[\tau]/4 \quad \tau = 1,\ldots,96, \tag{4}$$

where $SoC[0]$ denotes the *initial state-of-charge* at the beginning of the day. The second term is the energy that is charged into or drawn from the battery during the time slot. It is obtained by dividing charging or discharging power $x[\tau]$ in kW by four, which is the number of time slots in each hour.

For the model in (4), we implicitly assumed that the batteries are ideal. Next, suppose $\sigma \leq 1$ and $\delta \geq 1$ denote the *charge efficiency* and *discharge efficiency* parameters of the batteries, respectively. Under ideal efficiency, we have $\delta = \sigma = 1$. We can capture the impact of non-ideal efficiency as follows:

$$SoC[\tau] = SoC[\tau-1] + \sigma x^c[\tau]/4 - \delta x^d[\tau]/4, \quad \forall\tau, \tag{5}$$

where $x^c[\tau] \geq 0$ is the scheduled charge rate and $x^d[\tau] \geq 0$ is the scheduled discharge rate. The following constraints can

[2]The fixed, i.e., uncontrollable, part of the CE-CERT load is not considered in the optimization objective because it does not have impact on the solution.

capture the relationship between $x[\tau]$, $x^c[\tau]$, and $x^d[\tau]$:

$$x[\tau] = x^c[\tau] - x^d[\tau] \tag{6}$$

$$0 \leq x^c[\tau] \leq \theta[\tau]x^{\max} \tag{7}$$

$$0 \leq x^d[\tau] \leq (1-\theta[\tau])x^{\max}, \tag{8}$$

where $\theta[\tau]$ is an *auxiliary binary variable* and $x^{\max}$ is the maximum charge and discharge rate of the battery inverters. Since $\theta[\tau]$ takes only 0 or 1, it can force the batteries to be either charging ($\theta = 0$) or discharging ($\theta = 1$), but not both.

Another constraint is about the charge and discharge rates:

$$-x^{\max} \leq x[\tau] \leq x^{\max}, \quad \forall \tau. \tag{9}$$

For the battery inverters at CE-CERT, $x^{\max} = 200$ kW.

In practice, the state-of-charge for batteries should be kept within certain ranges that assure the health of the battery:

$$C^{\min} \leq SoC[\tau] \leq C^{max} \quad \forall \tau, \tag{10}$$

where $0 \leq C^{\min} \leq C^{\max} \leq C^{\text{full}}$. For the batteries at CE-CERT, we have $C^{\min}=0.2$, $C^{\max}=0.9$, and $C^{\text{full}}=1$ MWh.

Recall from Section III.A. that the considerations with respect to reducing the customer utility bill could be addressed by adding the two new terms into the objective function in (4). However, one may still want to restrict the charging of the batteries to hours other than RPU's system-wide peak-hours. This can be achieved by imposing the following constraints:

$$x[\tau] \leq 0 \quad \forall \tau \in \text{Peak Hours}. \tag{11}$$

Finally, we may enforce the following constraint to keep the state-of-charge at the end of each day to always be above a minimum level to assure energy availability:

$$SoC^{\min} \leq SoC[96], \tag{12}$$

where $SoC^{\min} \geq C^{\min}$ is a design parameter.

B. Online Optimization

In an *online* design, the charge and discharge schedules are updated as more data becomes available during the day. To do so, we propose to replace the expected values in (1)-(3) with *conditional expected values*, where the conditions are with respect to the new data that becomes available during the day. For example, suppose we are at time slot κ, where $\kappa = 1, \ldots, 96$. Accordingly, we know the realizations of random variables $l[1], \ldots, l[\kappa-1]$. We have also already implemented the charge and discharge schedules $x[1], \ldots, x[\kappa-1]$. Next, we want to select the charge and discharge schedules $x[\kappa], \ldots, x[96]$. We still need to obtain the expected values of $l[\kappa], \ldots, l[96]$, but subject to observations $l[1], \ldots, l[\tau-1]$. Mathematically, we can rewrite (1) as follows:

$$\underset{x}{\textbf{minimize}} \quad \max_{\kappa \leq \tau \leq 96} \mathbb{E}\{l[\tau] + x[\tau] \mid l[1], ..., l[\kappa-1]\}. \tag{13}$$

The objective functions in (2) and (3) can be reformulated similarly. For $\kappa = 1$, the objective function in (13) reduces to (1). However, the two formulations are different for $\kappa > 1$.

The online optimization method works as follows. Initially, i.e., right after midnight, the charge and discharge schedule is set according to the solution of problem (1). Then, at 15 minutes past midnight, the charge and discharge schedule is updated for the remaining 95 time slots based on the solution of problem (13) for $\kappa = 1$. After that, at 30 minutes past midnight, the charge and discharge schedule is updated for the remaining 94 time slots based on the solution of problem (13) for $\kappa = 2$. This process continues throughout the day.

We use *cross-correlation* to calculate conditional expected values. At each time slot τ, we obtain the cross-correlation between $l[1], \ldots, l[\kappa]$ and the feeder load during the same time frame on a previous day. The historical data from such previous day is included in the calculation of the expected value only if the correlation is above a threshold $\tau_{\text{th}} = 0.75$.

Last but not least, please note that the choices of constraints are not different for our proposed online and offline designs.

IV. Experimental and Numerical Results

A. Experimental Results

The experimental results for implementing the proposed design at the CE-CERT / RPU test site are shown in Figs. 7 and 8. Here, the operation of the batteries at CE-CERT was scheduled during the whole day on November 2, 2015 based on the optimal solution of problem (1), subject to equations (4), (9), (10), (11), and (12). The optimization was done in an offline fashion, i.e., the charge and discharge schedule was decided right before mid-night and it was not altered during the day. From the results in Fig. 7, our proposed design was able to reduce the peak-load on the feeder by 97 kW, which is very promising considering the relatively small power rating of the battery inverters and also the randomness in feeder load.

As for the results in Fig. 8, we can make some interesting observations. First, the SoC for the second battery suddenly droped to $C^{\min}$ at 4 PM. This is due to the nature of Lithium Ion batteries and the way the Battery Management System (BMS) operates. Unless the battery is fully charged or fully discharged, the SoC that the BMS reports is an *estimation*. Without regular calibration, the reported and actual SoC can *drift apart* over time. At Event 1, the true SoC was much lower than what the BMS reported. As the battery reached a very low SoC, the BMS was able to *recalibrate*, updating the value. Since the SoC was lowered to below $C^{\min}$, the battery then stopped discharging. Therefore, in practice, the SoC must be carefully calculated and the drift must be accounted for.

The second observation is about the gradually increasing difference between the experimental SoC and the analytical SoC. This is due to the *non-ideal efficiency* of the battery and inverter. This leads to the SoC slowly drifting downward throughout the day. This can be taken into account by using the system efficiency constraints in (5)-(8) in the optimization.

B. Numerical Results

The experimental results in the previous section are promising and show how the proposed approach can result in reducing the peak load at distribution feeder. However, in order to make solid conclusions about the proposed schemes, one needs to conduct similar experiments for several weeks and months and also for different choices of objective functions and constraints. While this is what we intend to ultimately do

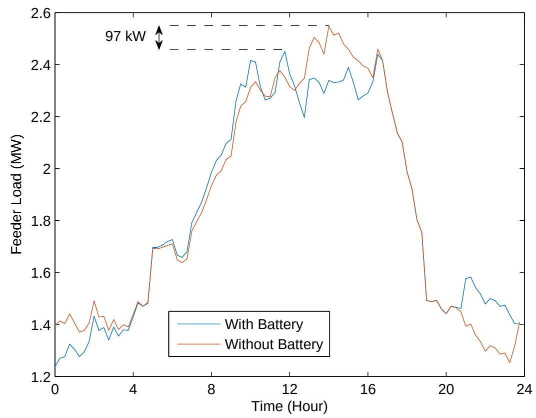

Fig. 7. Experimental result for peak feeder-load reduction on 11/2/2015.

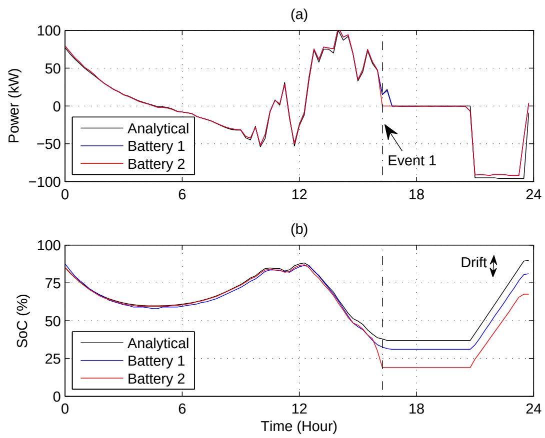

Fig. 8. Experimental results for operation of two battery modules on 11/2/2015: (a) charge and discharge powers; (b) state-of-charge.

in this project in the future, at this point, we can still benefit from conducting numerical studies based on the historical SCADA data that RPU has collected at Feeder #1224.

The results are shown in Fig. 9. Here, we compare nine different design combinations. On one hand, a design can be offline, online, or ideal. An ideal design is when we know the feeder load profile in advance, which serves as an upper-bound on the best performance possible. On the other hand, a design can be based on the different objective in (1), (2), or (3). Next, we summarize multiple interesting observations that we made.

First, an online design outperforms an offline design. This is because an online design makes *corrective actions* in operating the batteries. Recall from Section III.B. that such corrective actions are made systematically within the framework of conditional expectation and cross-correlation analysis. Therefore, statistically, we expect better results for an online design once we implement it in the experiment in Section IV.A.

Second, the *resource bottleneck* is the power rating of the inverters, but not the energy rating of the batteries. This is because *almost always*, the ideal design could reduce the feeder peak load by 200 kW. The only exception was one single day in Summer when the peak time lasted for multiple hours and the energy rating of the battery became binding as well. Therefore, it is safe to argue that we can significantly

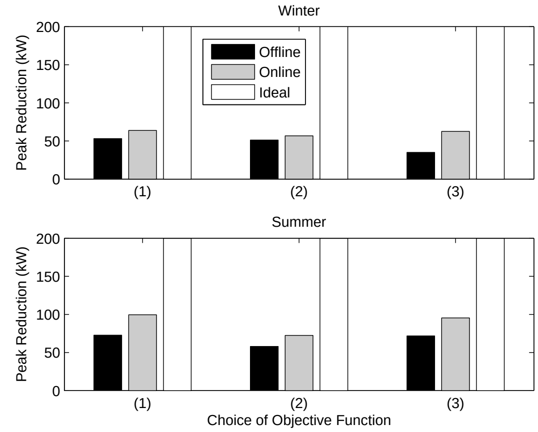

Fig. 9. Comparing different methods in reducing the feeder peak load.

increase the peak load shaving capability of the batteries at CE-CERT if we only upgrade the grid-connected inverters.

Third, the Summer peak reduction is more than the Winter peak reduction. Due to the conflict between the system- and feeder-level peak hours, see Fig. 5, the constraints in (11) are more restrictive in Winter. In contrast, in Summer, the peak system load and the peak feeder load coincide, allowing the battery to be utilized more freely for feeder peak load shaving.

V. Conclusions

An analytical stochastic optimization framework together with experimental and numerical results from a utility-scale testbed were presented to design, implement, and test the idea of conducting peak load reduction at a distribution feeder using batteries. Both offline and online optimization approaches were discussed. The latter resulted in better peak load reduction as it takes better advantage of a minute-by-minute data stream from the feeder's SCADA system to the battery system controller. It was also shown that the feeder peak load and the utility-defined peak hours may not be aligned, confirming the need for a localized solution for feeder-level peak load reduction, rather than a system-wide solution. The real-world experiment of the design platform showed considerable reduction of the feeder peak. It also showed many operational issues that were not foreseen in the numerical analysis, such as the need to carefully calibrate BMS state-of-charge estimates and to take into account operational efficiency/SoC drift.

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