

Over-voltage Disconnection of DER Inverters: Assessing Customer Savings

William Cesar de Carvalho* Elizabeth Louise Ratnam*
Lachlan Blackhall* Alexandra von Meier** Alan Murray***

* *The Australian National University, Australia (e-mail:
william.decarvalho, elizabeth.ratnam, lachlan.blackhall@anu.edu.au).*

** *The University of California Berkeley, USA (e-mail:
vonmeier@berkeley.edu)*

*** *Independent, Australia (e-mail: alan@atmurray.net)*

Abstract:

Distributed energy resource (DER) owners experience a loss in economic benefits due to prolonged and/or frequent inverter disconnection. In this paper, we investigate the economic savings that customers accrue when combining rooftop solar photovoltaic (PV) generation with battery storage systems, considering a time-of-use pricing tariff and the steady-state over-voltage disconnection of inverters. In particular, we compare four quadratic program (QP) optimization-based approaches to designing the charge and discharge schedule of residential batteries. The objective of the first optimization-based approach is to increase the economic savings that PV customers with battery storage accrue. The next two approaches additionally modulate the power to and from the grid, reducing the occurrence of inverter-based disconnection for improved economic savings. By contrast, the fourth approach directly manages customer-based power flows to and from the electric grid to smooth distribution load curve peaks and valleys, without explicitly considering energy savings that accrue to customers. By means of a case study, we observe the over-voltage disconnection of residential-scale inverters decreases with the proliferation of behind-the-meter batteries until an integration level of 60% is reached. At battery integration levels beyond 60%, the fourth grid-focused optimization-based approach continues to improve the grid voltage preventing inverter-based disconnections.

Keywords: economic savings, over-voltage, inverter disconnection, battery storage, solar PV.

1. INTRODUCTION

The recent rapid increase in electrical power generation from grid-integrated, customer-owned solar photovoltaic (PV), has led to distribution network operators facing significant operational challenges. At times when customer-owned PV generation exceeds the local demand, excess power is released to the distribution network. Customers supply voltages increase when excess power is delivered to the electrical grid, potentially creating concern for over-voltage conditions. To manage voltages within an appropriate range, a number of different approaches have been adopted by distributors, such as limit maximum power export to the grid at 70% of the installed PV capacity (see Marra et al. (2014)) and restrict new installations of solar PV (see Sayeef et al. (2012)). When voltage rise is significant, PV inverters are commanded to disconnect from the grid to prevent unacceptable high voltage levels on the feeder, Sayeef et al. (2012) and Collins and Ward (2015). The subsequent loss of renewable power generation resulting from PV disconnection or curtailment limits opportunities to store and dispatch the energy resource at a later time, reducing potential economic savings that solar PV would otherwise accrue, Collins and Ward (2015).

Among several methods for mitigating voltage rise and increasing the grid-connection of solar PV, is home- and

business-scale battery storage solutions, see Porteous et al. (2018). As the technology continues to improve and prices fall, a greater number of PV customers are grid-connecting battery to provide both energy independence and, more frequently, increased economic benefits. Specifically, economic drivers such as time-of-use pricing have spurred customers to consider profit-based optimization algorithms for designing the scheduling of battery storage charge and discharge cycles, Ranaweera and Midtgard (2016).

Several authors have investigated approaches to balance distributor and customer benefits using home-battery co-located with solar PV. Ranaweera and Midtgard (2016) propose an objective function to maximize savings for customers while addressing voltage rise by limiting (with the battery) PV power exports to the grid. Several rule-based and voltage dependent control approaches for PV and battery inverters are proposed by von Appen et al. (2014). The authors also consider PV self-consumption and the economic savings that accrue to the customer. Jayasekara et al. (2014) and Marra et al. (2014) propose different optimization-based approaches to improve grid conditions and minimize operational costs for owners in terms of extending the battery life expectancy. Wang et al. (2015) integrates batteries with solar PV by reserving specific amounts of the battery capacity to different tasks.

Although the aforementioned studies have provided important contributions to better integrate battery storage in the grid, they have not considered the disconnection of inverters caused by voltage rise. A typical threshold for disconnection is 1.10 p.u. Inverter disconnection impacts both battery storage control strategies and the economic savings that customers would otherwise accrue. The grid impact of wide-spread and frequent, inverter-based disconnection, is of growing concern to distribution network operators, Collins and Ward (2015), Sayeef et al. (2012), Tonkoski et al. (2012), Wang et al. (2012), De Brabandere et al. (2004), and Ueda et al. (2008).

In this paper we assess the customer and utility benefits of scheduling the charge and discharge of residential battery storage co-located with solar PV, considering the impact of distributed energy resource (DER) inverter disconnection. We consider four quadratic program (QP) optimization problems to define the day-ahead battery charge and discharge schedule. The first QP, referred to as customer focused-QP (CF-QP), increases operational savings for the battery owner while reducing battery cycling. The next two QPs, referred to as balanced-QP (B-QP) and alternate balanced-QP (AB-QP) respectively, are two approach variations to balancing customer operational savings against PV self-consumption. By contrast, the objective function of the fourth QP, referred to as grid-focused-QP (GF-QP), is to flatten the residential load curve to improve supply voltages. Our contribution is to provide a novel analysis of a range of QP approaches, benchmarking the impact on customer savings in cases where the over-voltage disconnection of inverters occurs. Numerical simulations are carried out on the IEEE 13 Node Test Distribution Feeder (13NF) that we populate with hundreds of residential systems that include solar PV and battery storage. The 13NF is a challenging feeder in terms of voltage regulation, proving to be appropriate to illustrate the impacts of over-voltage disconnection of inverters. Real time-varying data from the Australian Capital Territory (ACT), shown by Shaw et al. (2019), is used for residential loads and rooftop PV generation.

This paper is organized as follows. In Section 2 we describe the residential system composed of load, rooftop solar PV generation and battery storage. The four optimization-based approaches for battery charge/discharge scheduling are presented in Section 3. The distribution network and simulation results are included in Section 4.

2. RESIDENTIAL SYSTEM

Fig. 1 illustrates the residential system considered, where $k \in \{1, \dots, s\}$ is the time index and $l(k)$, $g(k)$, $x_1(k)$, $x_2(k)$ denote average power flows (in kW) across time interval $((k-1)\Delta, k\Delta)$, respectively. Let $T = s\Delta$, where $[0, T]$ represents the battery charge/discharge scheduling horizon. That is, we introduce notation similar to that in Ratnam et al. (2016).

The residential system represented in Fig. 1 includes separate inverters for the solar PV and battery storage, that facilitate the disconnection of DER when steady-state voltages measured at the point of common coupling (PCC) exceed an over-voltage threshold. The DER over-voltage trip protects both the devices and the surrounding grid

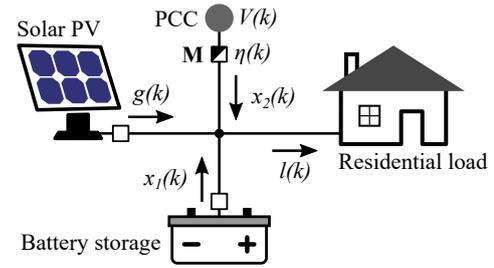


Fig. 1. Residential system with average power flows depicted for load $l(k)$, solar PV $g(k)$, the battery $x_1(k)$, and power to and from the grid $x_2(k)$. Arrows indicate the positive power flow direction. The PCC depicts the node where the customer is connected to the utility.

electrical infrastructure as discussed by Sayeef et al. (2012) and Wang et al. (2012). The DER inverter disconnection is either a physical separation from the system through a switch device or a virtual disconnection in which inverters set their power output to zero as discussed by the Electric Power Research Institute (2016). In both cases, $g(k) = x_1(k) = 0$, when $V(k) > 1.10$, where $V(k)$ is the steady-state voltage magnitude (in per unit) across time interval $((k-1)\Delta, k\Delta)$, as measured at the PCC.

Fig. 1 also depicts the bi-directional meter M , which applies a time-of-use (TOU) price $\eta(k)$ (in \$/kWh) across time interval $((k-1)\Delta, k\Delta)$. We also consider the financial policy of net metering, where the customer is billed for energy consumption at the same rate as they are compensated for exported energy to the grid. The power balance equation for Fig. 1 is

$$x_2(k) = l(k) - g(k) - x_1(k), \quad (1)$$

where x_2 represents the grid power provided to the residential system. Positive values of $x_2(k)$ indicate power flow to the residence and negative values correspond to power exported to the grid from the residence. Battery power $x_1(k)$ is considered positive when discharging and negative when charging and is limited by

$$-\underline{\beta} \leq x_1(k) \leq \bar{\beta}, \quad \forall k \in \{1, \dots, s\}, \quad (2)$$

where $\underline{\beta}$ and $\bar{\beta}$ is the maximum charging and discharging rates in kW, respectively. We denote by $E(k)$ the battery state of charge (in kWh) at time $k\Delta$, such that

$$E(k) = E_0 - \sum_{j=1}^k x_1(j)\Delta, \quad \forall k \in \{1, \dots, s\}, \quad (3)$$

where E_0 is the initial state of charge of the battery in kWh. The state of charge is limited by

$$0 \leq E(k) \leq C, \quad \forall k \in \{1, \dots, s\}, \quad (4)$$

where C is the energy capacity of the battery (in kWh). At the end of the battery charge/discharge scheduling horizon, let the final state of charge be

$$E(s) = E_f, \quad (5)$$

where E_f is the scheduled state of charge at time T (in kWh). The simple battery model is consistent with Ratnam et al. (2016), and more complex models such as Reniers et al. (2018) are possible.

We define the PV savings denoted by Ψ_g , and the battery savings denoted by Ψ_{x_1} , accrued by a customer over the period $[0, T]$ by

$$\Psi_g := \sum_{k=1}^s \Delta\eta(k)g(k), \quad \Psi_{x_1} := \sum_{k=1}^s \Delta\eta(k)x_1(k).$$

3. PROBLEM FORMULATION

In this section we present four optimization-based approaches for scheduling the charge and discharge of residential battery storage. The first approach aims to maximize energy savings accrued through charging and discharging residential battery storage. The second and third approach aims to balance the self-consumption of PV generation against increasing the energy savings accrued through charging and discharging residential battery storage. By contrast, the fourth approach flattens the residential load curve at the PCC, and in this way seeks to improve the supply voltage to reduce the occurrence of DER over-voltage disconnection.

3.1 Customer-focused CF-QP

The objective function of the CF-QP is designed to increase economic savings that accrue to residential battery owners whilst reducing battery cycling. Specifically,

$$\begin{aligned} \min_{x_1} \quad & \sum_{k=1}^s w(x_1(k))^2 - \Delta\eta(k)x_1(k) \\ \text{s.t.} \quad & (2) - (5), \end{aligned} \quad (6)$$

where w is a weight designed to increase or reduce the importance of the battery cycling (first term in the objective function). To increase the economic savings (second term in the objective function), we incorporate the day-ahead time-of-use prices ($\eta(k)$ for all $k \in \{1, \dots, s\}$), provided by the electricity retailer.

3.2 Balanced B-QP

The objective function of the B-QP is designed to balance increases in economic savings that accrue to residential battery owners against promoting the self-consumption of solar PV. Specifically, as proposed in Ratnam et al. (2016),

$$\begin{aligned} \min_{x_1, x_2} \quad & \sum_{k=1}^s w(x_2(k))^2 - \Delta\eta(k)x_1(k) \\ \text{s.t.} \quad & (1) - (5), \end{aligned} \quad (7)$$

where the grid power is weighted by w . Here the first term is designed to reduce peak power flows from the grid to the customer, and promotes the self-consumption of PV generation, which is balanced against the second term designed to increase economic benefits associated with battery storage scheduling.

3.3 Alternate Balanced AB-QP

Over-voltage conditions in distribution networks typically occur during low load periods and when PV generation output peaks, Jayasekara et al. (2014). As such, we design the AB-QP with the same objective function as the B-QP, but modify the power balance equation constraint to emphasize the charging of the battery when PV generation peaks. Let $\hat{g}(k)$ be the processed PV generation defined as

$$\hat{g}(k) := \frac{(g(k))^2}{\|g\|_\infty}, \quad \forall k \in \{1, \dots, s\}, \quad (8)$$

where $\|g\|_\infty := \max_{k \in \{1, \dots, s\}} |g(k)|$, and then (1) in (7) is replaced by

$$\hat{x}_2(k) = l(k) - \hat{g}(k) - x_1(k), \quad (9)$$

in the AB-QP formulation. This straightforward modification decreases PV exports during peak solar production, preventing over-voltage disconnection of inverters.

3.4 Grid-focused GF-QP

The objective function of the GF-QP is designed to exclusively improve grid voltages by flattening the residential load curve measured at the PCC. Specifically,

$$\begin{aligned} \min_{x_2} \quad & \sum_{k=1}^s (x_2(k))^2 \\ \text{s.t.} \quad & (1) - (5). \end{aligned} \quad (10)$$

The optimization problem is presented in the standard QP formulation in Ratnam et al. (2015). By reducing grid active power at the residence premises, the GF-QP approach potentially prevents voltage rise and thus economic losses caused by the frequent disconnection of inverters.

4. ASSESSING THE BENEFITS

In the numerical simulations that follow, the 13NF from Kersting (2001) represents the distribution network (see Fig. 2). We replace the original spot loads with aggregated residential systems. Real time-varying data from the Next Generation (NextGen) Energy Storage program at the ACT, Australia, is used for residential loads and solar PV generation, see Shaw et al. (2019). The NextGen data has been collected from de-identified customers since 2016. A clean NextGen dataset was obtained using the cleaning process presented in Shaw et al. (2019), which excised both errors and customers with anomalous data. The cleaning process resulted in a 100-customer dataset for the entire year of 2018, which is used in this study. It is worth mentioning that each one of the 100 customers has their own solar PV system with a tailored power capacity.

Customers from this clean dataset were aggregated at each of the node on each phase (i.e., each point where there were a spot load in the 13NF) until the aggregated peak load reached approximately the original spot load value (in kW). A total of 1503 customers were connected to the 13NF, each one represented by the residential system shown in Fig. 1, although not all customers considered have a battery storage. To reach 1503 customers from the dataset, we repeated the selection of the 100 customers.

To calculate the unbalanced three-phase power flow for each k interval, residential loads, PV generation and battery power are represented by constant PQ model. Solar PV and battery are considered to operate at unity power factor, whereas the load power factor is considered to be equal to the respective original spot load. It is worth mentioning that the tap positions of the voltage regulator transformer is fixed at the original positions throughout the numerical simulations.

Each QP is executed at the beginning of each day (midnight) to obtain the day-ahead battery charge and discharge profile. With the exception of the CF-QP, each approach requires a day-ahead forecast of the load and the

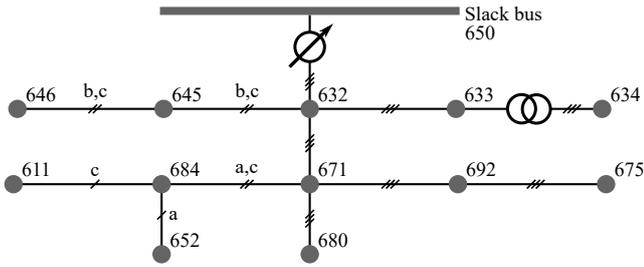


Fig. 2. Diagram of IEEE 13 Node Test Feeder (13NF).

PV generation, which we emulated as per Ratnam et al. (2016). PV and battery inverters are configured to disconnect when voltage exceeds 1.10 p.u. as in Sayeef et al. (2012) and Tonkoski et al. (2012). The same parameters are adopted for every residential battery. The maximum continuous power of the battery is considered to be 5 kW for both charging and discharging ($\underline{\beta} = \bar{\beta} = 5$) and the energy capacity C is 10 kWh. To prevent an energy-shifting bias, both the initial and final state of charge are selected as 2 kWh ($E_0 = E_f = 2$). However, note that E_0 is selected only at the beginning of the first day of the simulated week, whereas on the following days E_0 will be automatically updated to the battery state of charge at midnight. Although the battery is scheduled to achieve E_f at the end of each day, it will not necessarily be E_f , since over-voltage disconnections will shutdown the battery for the duration of the over-voltage.

Load $l(k)$ and PV generation $g(k)$ data are 5 minutes average power flows, $\Delta = 5/60$ hour, the time window T is 24 hours, and $s = 288$. The TOU tariff $\eta(k)$ is based on an Australian distributor that serves the de-identified customers from the NextGen dataset, Shaw et al. (2019) and Evoenergy (2019). Specifically, $\eta(k) = 0.03154$ for $k = \{1, \dots, 84, 265, \dots, 288\}$ (off-peak price from midnight to 7 am and from 10 pm to midnight), $\eta(k) = 0.06438$ for $k = \{109, \dots, 204, 241, \dots, 264\}$ (shoulder price from 9 am to 5 pm and from 8 pm to 10 pm) and $\eta(k) = 0.14131$ for $k = \{85, \dots, 108, 205, \dots, 240\}$ (peak price from 7 am to 9 am and 5 pm to 8 pm). Batteries are allocated proportionally to the number of customers connected at each node.

We prioritize increases in economic savings over other objectives when assigning the optimization weights w . That is, we carefully select $w = 10^{-5}$ for the CF-QP and $w = 10^{-4}$ for the B-QP and AB-QP. In this way, these weights work as bias factor to improve battery charge and discharge scheduling. Although these values seem insignificant, it is important to note that the savings term in the objective function is intrinsically multiplied by small values such as $2.6 \cdot 10^{-3}$.

4.1 Case study

We consider data from 21-27 July 2018, a sequence of sunny days corresponding to PV generation peaks on the distribution network. The feeder-level aggregated load, PV generation and battery power are shown in Fig. 3 for the last day (27 July 2018), with the battery schedule corresponding to the CF-QP approach. A total of 601 residential customers (40% of customers with battery) on the 13NF are following the CF-QP battery charge and discharge schedule.

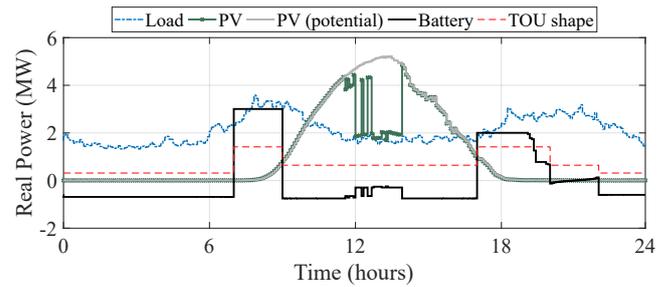


Fig. 3. Aggregate residential load, PV generation and battery power for 13NF – with the CF-QP battery schedule implemented. PV(potential) corresponds to the absence of inverter over-voltage disconnections.

In Fig. 3, we observe battery storage discharging (providing power) during the morning and evening peak pricing periods. The charging occurs overnight during the off-peak pricing period and also during the shoulder pricing period (between the morning and evening peak). As the CF-QP approach does not consider load and PV generation data, battery storage scheduling results in a flat power profile for each pricing period.

The simulation results for the entire week for each of the four QP approaches to scheduling battery storage are presented in Fig. 4. In Fig. 4(a) we observe sharp variations on the aggregated PV generation due to inverter disconnections when voltages exceed 1.1 p.u. We observe that the disconnection of inverters occurs during peak PV generation periods when the afternoon load is low. We note that many residential inverters are switched off for considerable intervals, specially on the the fifth day.

Simulation results for B-QP and AB-QP are presented in Fig. 4(b) and (c), respectively. We observe that both approaches reduce the disconnection of inverters. Also, with the AB-QP approach we observe no major disconnection of inverters on the last day, suggesting further improvement in supply voltages. In Fig. 4(d) we observe the GF-QP does not reduce over-voltage disconnection further, when compared to the AB-QP approach.

Table 1 presents the average savings per customer accrued in the simulated week - considering the four QP battery scheduling approaches. PV savings represent the average savings accrued per solar PV customer (1503 customers) through generating electricity. Battery savings represent the average saving accrued per battery storage customer (601 customers) through charging and discharging the home battery. It is worth mentioning that the potential PV generation across the week is the same for all four cases, and so increases in PV savings corresponds to a reduction in PV inverter disconnections caused by over-voltage. We observe that AB-QP, by improving grid supply voltages, increases the customer solar PV savings. In comparing the CF-QP to the GF-QP approach, we observe GF-QP improves PV savings, however, the battery savings are drastically reduced. Recall that the objective of the CF-QP battery scheduling approach is to increase savings customers with battery storage accrue. However, we observe inverter disconnection results in reduced battery savings (when compared to B-QP and AB-QP). Furthermore, the battery savings are greater for the AB-QP approach, sug-

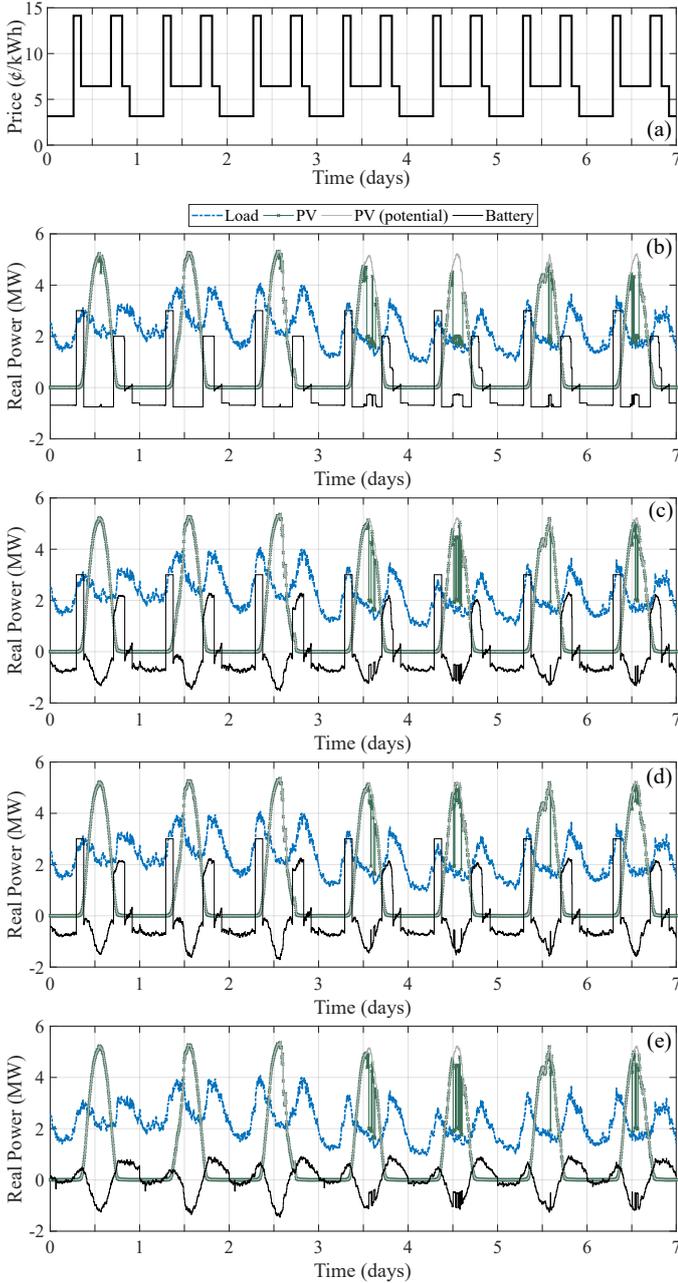


Fig. 4. (a) TOU tariff. Aggregated residential: load, PV generation, and battery power corresponding to (b) CF-QP; (c) B-QP; (d) AB-QP; and (e) GF-QP.

gesting an appropriate balance between improving grid voltage and earnings for battery owners.

In Fig 5 we present the savings accrued in the week for each customer. Savings accrued during the week for one customer are calculated by adding Ψ_g of each day. Similarly, battery savings are calculated by adding Ψ_{x_1} of each day in the week. In Fig 5(a) we observe that some battery owners enjoyed higher earnings than others, although all batteries were scheduled to accrue the exact same savings under the same TOU tariff. The variation in customer savings is attributed to the customer location in the 13NF, that is, voltage rise occurs more frequently on some nodes and customers experiencing more frequent inverter disconnections. Customers more affected by over-

Table 1. Average savings accrued per customer ¹

	CF-QP	B-QP	AB-QP	GF-QP
PV savings	\$7.86	\$8.45	\$8.67	\$8.36
Battery savings	\$12.60	\$12.73	\$12.90	\$2.34

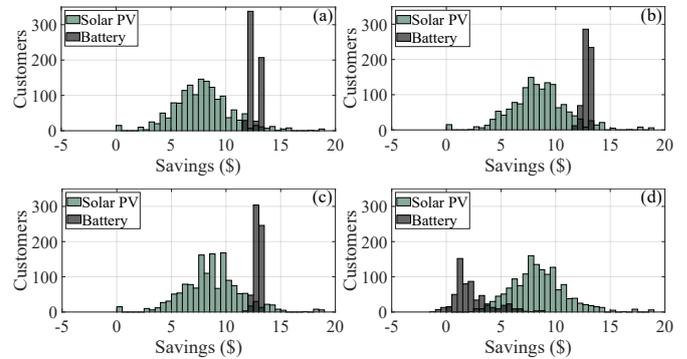


Fig. 5. Distribution of customer savings accrued in the week from PV generation and from battery storage: (a) CF-QP; (b) B-QP; (c) AB-QP; and (d) GF-QP.

voltage disconnection are mainly connected at the nodes at the end of the feeder on phases in which the tap position is higher. Nodes 675 and 611 contain shunt capacitors connected and are specially affected by voltage rise during high PV generation. It can be seen in Fig 5(b) and (c) that B-QP and AB-QP have a similar distribution of savings, although AB-QP enables customers to accrue more earnings. In Fig 5(d) we observe that the majority of battery owners accrued just a few dollars in the week. Furthermore, we observe cases where battery storage scheduling corresponds to an economic loss for some customers.

In Fig. 6 we present average savings accrued in the same week for different proportions of customers with battery storage. In Fig. 6(a) we observe that AB-QP battery scheduling provides moderately higher savings from PV generation until we reach 60% of customers with battery storage. When 50% and 60% of customers install battery storage, AB-QP prevents all cases of over-voltage disconnection for PV inverters. In the context of total earnings (from PV and battery storage) for all customer in the network, we observe AB-QP provides higher savings until we reach 60% of customers with battery storage.

We observe in Fig. 6(b) that for low percentages of customers with battery storage, CF-QP provides higher savings for battery owners than the other approaches. Here, the population of battery storage is not significant enough to prevent widespread over-voltage disconnections. In Fig. 6(b) we also observe the average earnings from battery for the GF-QP approach is low for all percentages of battery populations, suggesting that the distributor would be required to incentivize such an approach.

From the case study we observe that, except for GF-QP, customer savings decrease once the battery population reaches 70% – attributed to more frequent over-voltage

¹ Saving values are shown as the amount accrued during 21-27 July 2018 period only. Note that if a similar over-voltage disconnection pattern repeats over that year, the average difference between AB-QP and GF-QP, for instance, would have been of \$565, considering a customer with both PV and battery storage.

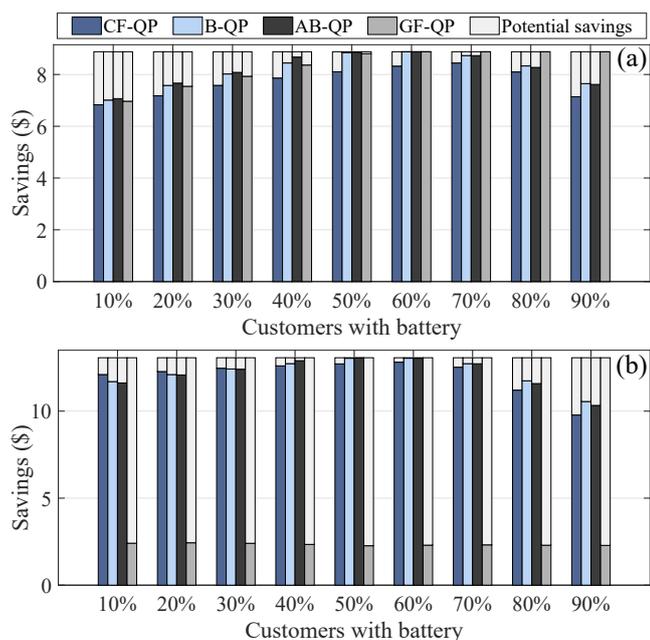


Fig. 6. Average savings accrued in the week considering different percentage of customers with battery on the distribution network. (a) PV generation savings; and (b) battery storage charge and discharge savings.

inverter disconnections on the grid. With customer-owned battery populations of 70% or more, the morning discharge of battery storage becomes significant, which creates voltage rise resulting in the disconnection of inverters. By limiting the morning discharge of battery storage (through inverter disconnection), charging during peak PV generation periods is also limited, resulting in further over-voltage inverter disconnections.

GF-QP battery scheduling considers grid power to and from the PCC of the residential system. As such, battery charge and discharge schedules according to GF-QP do not necessarily assist the grid if the residence does not contribute to the general demand profile of the distribution feeder. Battery scheduling approaches that directly consider customer savings according to TOU tariffs, at times improve the general demand profile of the feeder. Accordingly, voltages across the feeder are potentially improved with price-based schemes, reducing inverter disconnection attributed to voltage-rise. Future work to incorporate reactive power control of inverters will potentially further reduce inverter disconnection attributed to voltage-rise. A more extensive low-voltage network model will also be considered in future work to increase diversity across customer voltage profiles.

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