Abstract— Grid-scale energy storage systems are attracting more attention because of increased public-awareness and declining prices. However, there is still one question which needs to be answered: when utilization of Battery Storage System (BSS) is economical? To address this question, problems of simultaneously sizing BSSs and optimal power sharing—with an objective of decreasing daily operational cost–is investigated to assess the economic viability of BSSs. The assessment is carried out by specializing the problem formulation to mid-sized C&I customers associated with PG&E and by simulating scenarios that differ in the size of load, PV installation, cost of BSS and participation in Demand Response (DR). Simulation results indicate that, using price projections from DOE and Navigant, BSSs can be used to shift loads economically (savings of 10%) around the year 2019. Furthermore, the effective daily savings, when participating in DR programs, is noted to be independent of the load, and that participating in DR does not require a significantly up-sized BSS.

I. INTRODUCTION

Storage devices (specially different battery technologies) can play an important role in the smart grid era, where dynamic pricing mechanisms, demand response programs (DRPs), and demand charge (DC) will exist for almost all customers in different sectors. These devices can be utilized in peak shaving, for participating in DRPs, and to decrease DC simultaneously. The outcome will be economic benefits for both customers and utility companies. Although mass production and widespread adoption have made energy storage progressively more affordable, they are still relatively expensive. According to reports from Navigant and the U.S. Department of Energy (DOE), the price of electrochemical energy storage systems is expected to halve in cost over the next half decade [1], [2]. The question of when it is economically viable (by achieving 10% savings) to adopt BSSs, has yet to be addressed.

The problems of energy management and sizing Battery Storage Systems (BSSs) have been widely studied in literature. In [3] the authors investigate the same problem with the objective of reducing power demand cost in peak-shaving applications. While [4] provides a method to compute the smallest size of BSSs in a microgrid (MG) equipped with PV modules in order to minimize daily operational cost, in [5] a MILP is formulated to include WT installations. While works such as [6], [7] address energy management in MGs, [8] studies the energy management problem whilst participating in DRPs as offered by utilities such as PG&E. In [8], the reward earned by participating in DRPs was maximized in the absence of any energy storage systems. To the best of our knowledge, there is not a research paper to evaluate affordability of battery for such applications. This study aims to formulate battery sizing and optimal daily operation considering its lifetime in a single optimization framework. Then, based on the economic benefit for participating in DRPs and DC reduction for the customer will be evaluated for various amount of load, PV generation and battery prices.

Additionally, to ground the work in a realistic market and a group of potential adopters of BSSs, this study is presented as a case-study targeting mid-sized C&I customers (whose peak daily power consumption is in excess of 200 kW) associated with Pacific Gas and Electricity (PG&E) utility. Conclusions are drawn by simulating scenarios that differ from each other in either the size of load and PV installations, the cost of BSS and its projected life. In addition, the impact of participating in DRPs on the size of chosen BSSs is investigated.

II. PROBLEM FORMULATION

The problem is formulated as a battery sizing optimization where cost of energy from the grid, DC, battery capital cost, and the benefit of participating in the DRPs are considered. Additionally, desired battery lifetime is integrated as a hard constraint on daily energy throughput. In the proposed framework, daily battery operation is also optimized to take advantage of time-of-use (TOU) pricing structure. The most complex scenario under consideration is the one that allows for participation in DRPs. Rewards from DRPs are computed based on the nominal power consumed on days of not participating in DRPs (termed as baseline); since the BSS affects the baseline, the BSS sizing problem is formulated as one that has two objectives which are solved simultaneously--minimize the cost of electricity--of the baseline (non-eventdays) and the cost of electricity; when participating in DRPs (event-days).

A. Daily cost of electricity

The first component of the problem is daily cost of electricity. Typically, it can be broken in to energy charge and demand charge. Energy charges are computed based on the TOU rates and the power purchased from the grid, which can be represented as:

$$J_{\text{energy}} = \langle \text{TOU}, \mathbf{P}_g \rangle^{\zeta},$$

where $\mathbf{P}_g \in \mathbb{R}^{24}$ is the vector of grid powers corresponding to the hours of the day (to keep the problem tractable, every day is discretized into hours); $\zeta$ is a place holder that takes values from the set $\{\text{DR}, \text{no-DR}\}$ and helps distinguish between variables that are associated with an event-day (DR) and a non-event-day (no-DR).

Table I shows a typical TOU and DC rates in summer for...
The TOU rates are classified into peak, off-peak, and part-peak rates, and the cost of energy consumption is simply the energy in each period multiplied by the given rates. Demand Charge, on the other hand, is more complicated. DC rates are divided into peak, part-peak, and all-month, and is computed as a function of the maximum load seen by the grid at different times of the month. However, since this work focuses only on daily optimization, it is assumed that all days in the month are identical and hence the daily demand charge is proportionally scaled. The DC function can be represented as:

\[
DC(P_g^\infty) = DC_{\text{max}} \cdot \|P_g^\infty\| + DC_{p-\text{max}} \cdot \|P_{g,p-\text{hours}}^\infty\| + DC_{pp-\text{max}} \cdot \|P_{g,pp-\text{hours}}^\infty\|
\]

where \(P_g^\infty, P_{g,p-\text{hours}}^\infty, P_{g,pp-\text{hours}}^\infty\) are vectors of the grid powers during the entire day, peak-hours, and part-peak-hours, respectively; \(DC_{\text{max}}, DC_{p-\text{max}}, DC_{pp-\text{max}}\) are the rates associated with the entire day, peak, and part-peak, respectively, according to Table I.

Equation (1) can be linearized by introducing auxiliary variables \(P_{g,max}, P_{g,p-max}\) and \(P_{g,pp-max}\), representing the maximum grid power during the different periods of DC rates. Accordingly, the DC cost function and constraints can be rewritten as follows:

\[
J_{DC} = DC_{\text{max}} \cdot P_{g,max} + DC_{p-\text{max}} \cdot P_{g,p-max} + DC_{pp-\text{max}} \cdot P_{g,pp-max}
\]

\[
0 \leq P_{g,max}^i, P_{g,max}^i, P_{g,pp-max}^i \quad \forall i \in \mathbb{N}_24
\]

\[
P_{g,pp-\text{hours}}^i \leq P_{g,pp-max}^i \quad \forall i \in \mathbb{N}_peaks-\text{hours}
\]

\[
P_{g,pp-\text{hours}}^i \leq P_{g,pp-max}^i \quad \forall i \in \mathbb{N}_pp-\text{hours}
\]

\[
J_{ET} = \gamma_1 \sum_{i=1}^{24} P_{bnet,i}^\infty
\]

where \(\gamma_1\) is a small number (0.001 in this study).

**D. Allowing Demand Response Participation**

PG&E offers five different Demand Response (DR) programs to businesses of which two, namely Demand Bidding Program (DBP) and Scheduled Load Reduction Program (SLRP), are being considered in this study. The DBP is a penalty free DR program to reduce the load by a user-determined amount. Participants in DBP are given a day ahead notice where they are asked to indicate the time of the day during which the participant will reduce the load and the amount of reduction. In return, participants receive a reward of $0.5/kWh of actual energy reduction without any financial penalty for failure. In SLRP, on the other hand, the participants commit to reduce their load during at most three events every week between month of June and September. Three non-overlapping SLRP events occur every day between 8:00 and 20:00 hours with each lasting four hours. The participant is restricted to choose no more than one event per day. More details about these programs can be found in [11]. To address these requirements, the following...
constraints are enforced:
\[
\begin{align*}
  u_{dr,i} - u_{dr,i} & = u_{dr,i} - u_{dr,i-1} & \forall i \in \mathbb{N}_{24} \setminus \{1\} \\
  u_{dr,i} + u_{dr,i} & \leq 1 & \forall i \in \mathbb{N}_{24} \\
  u_{dr,i} & \leq u_{dr,i+k} & \forall i \in \mathbb{N}_{24} \\
  u_{dr,i} & \leq 1 - u_{dr,i+k} & \forall i \in \mathbb{N}_{24} \\
  u_{dr,i} & \leq u_{g,i} & \forall i \in \mathbb{N}_{24}
\end{align*}
\]

where \( k \in \{j \in \mathbb{N}_{24} \mid i + j \leq 24\} \), \( u_{dr,i} \) and \( u_{dr,i} \) are binary variables that serve as indicators of the start and end hours of participating in the DR programs, respectively; \( u_{dr,i} \) is a binary variable that will be 1 during the period of participation and is 0 at other times; and \( u_{g,i} \) is a binary variable that takes 1 when power is drawn from the grid.

In both DRPs, baseline plays an important role since the amount of reduction in load as seen by the grid, and hence the resulting rewards is computed by comparing the grid load during event and baseline. To isolate the baseline, another vector of decision variables labeled \( P_g \) is introduced which is zero at hours when not participating in DR on event-days and is equal to the baseline at other hours. The following constraints are enforced on this vector:
\[
\begin{align*}
  -P_g & \leq 0 & \forall i \in \mathbb{N}_{24} \\
  P_g & \leq K u_{dr,i} & \forall i \in \mathbb{N}_{24} \\
  P_g & \leq P_{g,\text{DR}} + P_{g,\text{no-DR}} & \forall i \in \mathbb{N}_{24} \\
  0 & \leq P_{g,\text{DR}} - P_{dr,i} & \leq M(u_{g,i} - u_{dr,i}) & \forall i \in \mathbb{N}_{24} \\
  P_{dr,i} & \leq K u_{dr,i} & \forall i \in \mathbb{N}_{24} \\
  Q \cdot u_{dr,i} & \leq P_g - P_{dr,i} & \forall i \in \mathbb{N}_{24}
\end{align*}
\]

where \( Q \) is the program specific constant that determines the minimum reduction in grid power when participating in DRPs (10 in DBP and 100 in SLRP); \( K \) and \( M \) are arbitrary large constants \( (M, K > Q) \); \( P_{dr,i} \) is the grid power during the hours when participating in DRPs on event-days. Therefore, reward for participating in DRPs is computed as follows with \( D_R \text{reward} \) being the dollar value of the reward per kW of power reduced:
\[
J_{DR} = D_R \text{reward} \sum_{i=1}^{24} (P_g - P_{dr,i})
\]  

Bear in mind that the baseline load profile to compute reward is \( P_g \) and not \( P_l \) which is the load profile without BSS.

Additionally, since the DR cost function, \( J_{DR} \), is not strictly a sum of positive quantities, it is necessary to ensure that the optimal solution does not culminate in negative savings. Negative savings are likely to occur on non-event-days when the potential for increasing savings during event-days comes at the expense of operational cost on non-event-days. It occurs because we solve event-days and non-event-days simultaneously. To overcome this situation, the following constraint is enforced which ensures that the operational cost during non-event-day is not any more than when not using a BSS:
\[
J_{\text{energy}}^{\text{no-DR}} + J_{\text{DC}}^{\text{no-DR}} + J_{ET}^{\text{no-DR}} \leq (TOU, P_b) + DC(P_b) \quad (8)
\]

where \( P_b = \max(P_{i,i} - P_{pv,i}, 0) \), \( P_{pv,i} \) is hourly PV generation, if any exists.

E. Accounting for PV installation

As a result of policies and efforts from policy makers and energy industry, more commercial facilities are considering PV installation for further economic benefits. So a possible scenario in which PV installation exists in the facility should be considered in the formulation. In this model, it is assumed that PV generation can be curtailed, if needed. Furthermore, PV generation is decomposed into three components: 1) Load support \( (P_{sl}) \); 2) BSS charging \( (P_{sb}) \); and 3) dispatched power \( P_{sd} \); each of these power components are constrained as follows:
\[
0 \leq P_{sl,i} + P_{sd,i} + P_{sb,i} - P_{pv,i} \quad \forall i \in \mathbb{N}_{24}
\]  

where \( \gamma_2 \) is a small number. When PV installation is not present, it is to be enforced that \( P_{pv} \) is identically zero.

F. Accounting for operating constraints

Operating constraints such as power balance and maximum/minimum values of decision variables are mathematically represented in Eqn. (10).
\[
\begin{align*}
  C^i_{i+1} & = C^i - P_{\text{best,i}}^c & \forall i \in \mathbb{N}_{24} \\
  P_{b,i} + P_{g,i} + P_{sl,i} & = P_{i,i} & \forall i \in \mathbb{N}_{24} \\
  P_{\text{DR}}^i + P_{\text{DR}}^g + P_{sb,i} & = P_{pv,i} & \forall i \in \mathbb{N}_{24} \\
  P_{\text{best}}^i + P_{bi} - P_{sb,i} & \forall i \in \mathbb{N}_{24} \\
  n_s \cdot c_{\min} \cdot C_{\text{rated}} & \leq C^i_{i+1} & \forall i \in \mathbb{N}_{24} \\
  C_1 & = C_{24} \\
  0 & \leq P_{g,i} & \forall i \in \mathbb{N}_{24} \\
  P_{b,\min} & \leq P_{b,i} & \leq P_{b,\max} & \forall i \in \mathbb{N}_{24}
\end{align*}
\]

where \( P_b \) is the power output of the BSS; \( C \) is the State of charge (SOC) of the BSS (in kWh); \( c_{\min} \) and \( c_{\max} \) are the fractions of minimum and maximum SOC as a ratio of total capacity of BSS; and \( C_{\text{rated}} \) is the nominal capacity of each BSS module. In this study, battery SOC at the end of the day is enforced to be the same as battery SOC at the beginning of the day (i.e., \( C_1 = C_{24} \)).

G. Final Problem formulation

Using the constraints and components of the different objective functions described in previous sub-sections, the final optimization problem is formulated as:
\[
\min J \quad \text{st., Eqns. (2) – (10)}
\]

where
\[
J = \lambda \cdot (J_{\text{energy}} + J_{\text{DC}} + J_{ET} + J_{pv}) + (1 - \lambda) \cdot (J_{\text{energy}}^\text{no-DR} + J_{\text{DC}}^\text{no-DR} + J_{ET}^\text{no-DR} + J_{pv}^\text{no-DR})
\]

\[
- J_{DR} + J_{\text{Capex}}
\]
and $\lambda (\in [0, 1])$ is the relative weight that penalizes the operational cost on event-days; superscripts no-DR and DR correspond to variables that belong to non-event days and event days, respectively.

Based on the above formulation and the information available about the DRPs, the individual cases of DBP ($\lambda = 0.05$) and SLRP ($\lambda = 0.13$) are simulated based on their occurrences over a year.

III. Simulation Framework and Results

In this paper, a grid-connected micro-grid including load, PV installation and BSS system (where BSS size will be determined by the proposed approach) is considered as a case study. The hourly load profile used hereon was derived from publicly available data from PG&E [12] pertinent to Medium Commercial TOU customers; Fig. 1 charts a sample load profile and that of a PV installation used (when applicable). For simulations that attempt to study the influence of varying size of loads and PV installations, the basic power profiles depicted in Fig. 1 are scaled. The BSS under consideration is assumed to be modular and scalable with each module having a capacity of 15 kWh. The entire BSS, regardless of its capacity, is assumed to have a discharging and charging power limit of 1MW. In an effort to reduce the number of integer variables in the subsequent optimization problems, it is assumed that the number of modules takes rational values. Finally, it is assumed that the battery SOC is limited to $10\%$ and $100\%$ of the total capacity of the cell. Additionally, SOC at the end of the day should be equal to the SOC at the beginning of the same day, which is considered to be 50%.

The MG under consideration is assumed to participate in PG&E Schedule E-19 pricing structure. Table I summarizes the Summer time rates for both energy and demand charge. The rewards for the DRPs under consideration are: DBP ($0.5 /kWh$) and SLRP ($0.1 /kWh$). The optimization problem in Sec. II-G is used to study the economic feasibility of using ESSs to reduce daily operating cost for varying values of Capex, total load levels and different extents of PV penetration.

In this study, the value of BSS Capex is drawn from the set of prices in $\{150, 200, 300, 500, 1000\}/kWh$ which is the set of estimated/projected cost of BSS in the years $\{2023, 2020, 2017, 2015, 2013\}$. The projected values of Capex are extracted from a Navigant report [1]. Figure 2 shows the results for the case with varying load levels, PV penetration and BSS Capex. The simulation trials represented are such that the PV penetration never exceeds 15%\(^1\) of the maximum load demand. Results are computed assuming that the life of the BSS is 11 years.

In each figure, the different base colors represents a different value of Capex—for example, markers in red correspond to a capex of $200 /kWh$. In addition, markers of the same shape have color gradient that reflects the contribution of PV installation with respect to the load; lighter the color of the marker, greater the contribution of PV power.

From Fig. 2, it is observed that the load level (total energy consumed by the load over the entire day) does not impact net savings; although higher load levels, understandably, utilize a bigger BSS to achieve the same daily cost reduction. Secondly, the effective savings is intrinsically tied to the cost of the BSS; cheaper the BSS, greater the potential for savings. Finally, it is noted that larger the size of the PV installation (in energy output), the higher the potential for increasing daily savings. This is to be expected since increasing PV outputs affords the user to increase BSS size to effectively reduce daily operational cost. Using the projections of Navigant and expectations of DOE, by the year 2019, it may be possible to reduce the daily expense by $\sim 10\%$.

Since the expected battery lifetime adds a limit to the number of daily cycles, its impact on the solutions is investigated. Figure 3 presents a comparison between the computed daily achievable savings for different values of Capex and the expected lifetime when there is no PV available. From Fig. 3, it can be seen that the effective daily saving is monotonically

\(^1\)For establishments which have a bigger PV presence, PG&E offers an alternate pricing scheme—Option R.
Fig. 4: Example solution of the co-optimization problem when sizing BSS accounting for participation in demand response (DBP); optimal power profile on (a) non-event-day (b) event-day.

Fig. 5: Potential for participating in demand response (DR); (a) Demand Bidding Program (DBP) (b) Scheduled Load Reduction Program (SLRP).

increasing with respect to the expected life of the BSS; longer the expected life, the greater the savings. This trend is the result of the fact that constraint in Eqn. (3) is not active and cannot shape the savings curve.

Figure 4 presents a sample result of the optimization for the case when studying the impact of participating in the DR programs under consideration. Whilst subfigure (a) traces the power trajectory of load and other energy sources throughout the day on a non-event-day, subfigure (b) shows power profiles on an event-day. The yellow section of subfigure 2 corresponds to the period during which the system is participating in demand response. From subfigure (a) it can be noted that the BSS primarily helps to move part of the load from peak periods into the off-peak and part-peak hours. It further reduces energy cost and demand charges for the system. On the event day though, because of the reward, the grid power gets altered to increase negative cost by load reduction through DRPs.

Figure 5 shows the expected savings for different levels of load during both a non-event-day and an event-day in the presence of PV installation. By comparing Fig. 5 with Fig. 2, it can be noticed that co-optimization reduces the achievable savings on any non-event-day. This is expected because participating in DBP could potentially make the rewards outweigh the cost of energy. However, according to information available from SDG&E, the frequency of DBP events is very infrequent and hence such returns are not sustainable. On the other hand, participating in SLRP does increase savings on event-days by ∼5% and is more frequent than SLRP (possibly 13% of the year). It should be noted that by virtue of the way the optimization problem was formulated, the calculated size of BSS with or without participating in DRPs are similar. Thus, it may be possible to be opportunistic and participate in DR with an existing BSS installation.

IV. CONCLUSION

In this work, the problem of BSS sizing for a grid-connected micro-grid was studied by co-optimizing for the size of the BSS and corresponding optimal power sharing among different components in the network. Using simulation studies in which the load, size of PV installation, cost and life of the BSS were perturbed, it was concluded that by around the year 2019, it can be expected that using BSS for the sole purpose of reducing energy and demand charge related expenditure will be economically viable. Furthermore, using the BSS sized based solely on TOU and DC rates, it may be possible to make significant gains by participating in DRPs such as DBP.

REFERENCES