BSS Sizing and Economic Benefit Analysis in Grid-Scale Application

Shankar Mohan*, Ali Hooshmand†, S. A. Pourmousavi†, and Ratnesh Sharma†

***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-event-days*) 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:

$$J^{\zeta}_{energy} = \langle TOU, \mathbf{P}_g \rangle^{\zeta},$$

where $\mathbf{P}^{\zeta}_g \in \mathbb{R}^{24}$ is the vector of grid powers corresponding to the hours of the day (to keep the problem tractable, every day is discretized into hours); ζ 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

*S. Mohan is with the Department of ECE, University of Michigan, Ann Arbor, MI 48109 elemsn@umich.edu

†A. Hooshmand, S.A. Pourmousave and R. Sharma are with the Energy Management deparment at NEC Laboratories America, Inc., Cupertino, CA, USA {ahooshmand, s.pourmousavi, ratnesh}@nec-labs.com

TABLE I: Summer TOU and DC rates in Schedule E-19 [9]

Designation	TOU rate ($/kWh)	DC rate ($/kW)
Peak	0.16233	19.04
Off-peak	0.07397	–
Part-Peak	0.10893	4.42
All	–	15.07

PG&E utility. 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 peiod 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:

$$DC(\mathbf{P}_g^\zeta) = DC_{max} \cdot \|\mathbf{P}_g^\zeta\|_\infty + DC_{p-max} \cdot \|\mathbf{P}_{g,p-hours}^\zeta\|_\infty + DC_{pp-max} \cdot \|\mathbf{P}_{g,pp-hours}^\zeta\|_\infty \tag{1}$$

where $\mathbf{P}_g^\zeta, \mathbf{P}_{g,p-hours}^\zeta$, $\mathbf{P}_{g,pp-hours}^\zeta$ are vectors of the grid powers during the entire day, peak-hours and part-peak-hours, respectively; DC_{max}, DC_{p-max}, DC_{pp-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:

$$\begin{aligned} J_{DC}^\zeta &= DC_{max} \cdot P_{g,max}^\zeta + DC_{p-max} \cdot P_{g,p-max}^\zeta \\ &\qquad + DC_{pp-max} \cdot P_{g,pp-max}^\zeta \\ 0 &\le P_{g,max}^\zeta,\ P_{g,p-max}^\zeta,\ P_{g,pp-max}^\zeta \\ P_{g,i}^\zeta &\le P_{g,max}^\zeta && \forall i \in \mathbb{N}_{24} \\ P_{g,i}^\zeta &\le P_{g,p-max}^\zeta && \forall i \in \mathbb{N}_{peak-hours} \\ P_{g,i}^\zeta &\le P_{g,pp-max}^\zeta && \forall i \in \mathbb{N}_{p.p.-hours} \end{aligned} \tag{2}$$

B. Accounting for BSS cost

The daily cost associated with the BSS (Capex.) is assumed to be the same over the expected life of the BSS. Thus, the daily cost is computed as below

$$Capex = \frac{1,000,000}{365 \times n_{\text{years}}} \times \text{capex multiplier}$$

where it is assumed that a 1MWh battery costs $1,000,000 and 'capex multiplier' is a scaling factor that is used to adjust the price of the BSS system to reflect the price points of interest. The daily cost of battery is:

$$J_{Capex} = n_s \cdot Capex$$

where n_s is the number of battery units (not necessarily an integer).

C. Accounting for battery degradation

Batteries experience degradation in energy capacity and power, even at the time of being idle. Since battery capacity degradation will directly affect battery performance in the system, it is required to account for it in sizing and operation studies. Two primary causes of battery degradation are cycling and calendar aging processes. Typically, both aging processes occurs at the same time in a nonlinear fashion. In order to account for battery degradation in this paper, a nonlinear model is adapted from [10] which includes both processes, as follows:

$$q_T = 1 - k_1|E|^{k_2} - j_1 T^{j_2}$$

where E is the total cycles of energy of the battery, T is the age of battery in days and q_T is the fraction of remaining capacity. In order to accommodate the nonlinear aging model within our linear optimization framework, and to guarantee a certain lifetime, battery degradation is added as a constraint on the daily number of cycles in the formulation. This constraint is represented in terms of the positive ($P_{bnet,i}^{+\zeta}$) and negative decomposition ($P_{bnet,i}^{-\zeta}$) of the net BSS power ($P_{bnet,i}^{\zeta}$):

$$\begin{aligned} -P_{bnet,i}^{+\zeta},\ P_{bnet,i}^{-\zeta} &\le 0 && \forall i \in \mathbb{N}_{24} \\ P_{bnet,i}^{+\zeta} + P_{bnet,i}^{-\zeta} &= P_{bnet,i}^{\zeta} && \forall i \in \mathbb{N}_{24} \\ -P_{bnet,i}^{+} \le -P_{bnet,i}^{\zeta} \mid P_{bnet,i}^{-\zeta} &\le P_{bnet,i}^{\zeta} && \forall i \in \mathbb{N}_{24} \\ \sum_{i=1}^{24} P_{bnet,i}^{+\zeta} - P_{bnet,i}^{-\zeta} &\le E^* \end{aligned} \tag{3}$$

where

$$E^* = \exp\left(\frac{1}{k_2}\log\left(\frac{1}{k_1}(1 - q_T - j_1 n^{j_2})\right) - \log(n)\right)$$

and is the limit on daily maximum number of cycles derived as the inverse of the degradation model and using the desired life, n (in days), of the BSS. Associated with this set of constraint, the following regularizing cost (to avoid unnecessary battery usage) is required.

$$J_{ET}^\zeta = \gamma_1 \sum_{i=1}^{24} P_{bnet,i}^\zeta$$

where γ_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:

$$
\begin{aligned}
u_{dr_s,i} - u_{dr_e,i} &= u_{dr,i} - u_{dr,i-1} && \forall i \in \mathbb{N}_{24} \backslash \{1\} \\
u_{dr_s,i} + u_{dr_e,i} &\leq 1 && \forall i \in \mathbb{N}_{24} \\
u_{dr_s,i} &\leq u_{dr,i+k} && \forall i \in \mathbb{N}_{24} \\
u_{dr_e,i} &\leq 1 - u_{dr,i+k} && \forall i \in \mathbb{N}_{24} \\
u_{dr,i} &\leq u_{g,i} && \forall i \in \mathbb{N}_{24}
\end{aligned} \tag{4}
$$

where $k \in \{j \in \mathbb{N}_{24} \mid i + j \leq 24\}$, $u_{dr_s,i}$ and $u_{dr_e,i}$ are binary variables that serve as indicators of the start and end hours of participating in the DR programs, respectively; u_{dr} 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 $\mathbf{P}_{g-pick}$ 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:

$$
\begin{aligned}
-P_{g-pick,i} &\leq 0 && \forall i \in \mathbb{N}_{24} \\
P_{g-pick,i} &\leq K u_{dr,i} && \forall i \in \mathbb{N}_{24} \\
P_{g-pick,i} &\leq P_{g,i}^{\text{no-DR}} && \forall i \in \mathbb{N}_{24} \\
P_{g,i}^{\text{no-DR}} - P_{g-pick,i} &\leq M(u_{g,i}^{\text{DR}} - u_{dr,i}) && \forall i \in \mathbb{N}_{24}
\end{aligned} \tag{5}
$$

$$
\begin{aligned}
0 \leq P_{g,i}^{\text{DR}} - P_{dr,i} &\leq M(u_{g,i} - u_{dr,i}) && \forall i \in \mathbb{N}_{24} \\
P_{dr,i} &\leq K u_{dr,i} && \forall i \in \mathbb{N}_{24} \\
Q \cdot u_{dr,i} &\leq P_{g-pick,i} - P_{dr,i} && \forall i \in \mathbb{N}_{24}
\end{aligned} \tag{6}
$$

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} 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 DR_{reward} being the dollar value of the reward per kW of power reduced:

$$
J_{DR} = DR_{reward} \sum_{i=1}^{24} (P_{g-pick,i} - P_{dr,i}) \tag{7}
$$

Bear in mind that the baseline load profile to compute reward is P_{g-pick} 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:

$$
J_{energy}^{\text{no-DR}} + J_{DC}^{\text{no-DR}} + J_{ET}^{\text{no-DR}} \leq \langle TOU, \mathbf{P}_{bl} \rangle + DC(\mathbf{P}_{bl}) \tag{8}
$$

where $P_{bl,i} = \max(P_{l,i} - P_{pv,i}, 0)$. $P_{pv,i}$ 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 study, 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:

$$
0 \leq P_{sl,i}^{\zeta},\ P_{sd,i}^{\zeta},\ P_{sb,i}^{\zeta} \leq P_{pv,i} \quad \forall i \in \mathbb{N}_{24} \tag{9}
$$

where $P_{pv,i}$ is the maximum hourly power output from the PV installation. In an effort to avoid the possible solution where BSS accept power from the PV installation and support the load simultaneously, the following additional term is introduced in the cost function:

$$
J_{pv}^{\zeta} = \gamma_2 \sum_{i=1}^{24} P_{sb,i}^{\zeta}
$$

where γ_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).

$$
\begin{aligned}
C_{i+1}^{\zeta} &= C_i^{\zeta} - P_{b_{net},i}^{\zeta} && \forall i \in \mathbb{N}_{24} \\
P_{b,i}^{\zeta} + P_{g,i}^{\zeta} + P_{sl,i}^{\zeta} &= P_{l,i} && \forall i \in \mathbb{N}_{24} \\
P_{sl,i}^{DR} + P_{sd,i}^{DR} + P_{sb,i}^{DR} &= P_{pv,i} && \forall i \in \mathbb{N}_{24} \\
P_{b_{net},i}^{\zeta} &= P_{b,i}^{\zeta} - P_{sb,i}^{\zeta} && \forall i \in \mathbb{N}_{24} \\
n_s \cdot c_{min} \cdot C_{rated} \leq C_i^{\zeta} &\leq n_s \cdot c_{max} \cdot C_{rated} && \forall i \in \mathbb{N}_{24} \\
C_1 &= C_{24} \\
0 &\leq P_{g,i}^{\zeta} && \forall i \in \mathbb{N}_{24} \\
P_{b,min} \leq P_{b,i}^{\zeta} &\leq P_{b,max} && \forall i \in \mathbb{N}_{24}
\end{aligned} \tag{10}
$$

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_{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:

$$
\min J \ ,\ \text{st., Eqns. (2)} - (10)
$$

where

$$
\begin{aligned}
J = \lambda \cdot \big(&J_{energy}^{\text{DR}} + J_{DC}^{\text{DR}} + J_{ET}^{\text{DR}} + J_{pv}^{\text{DR}}\big) \\
+(1-\lambda) \cdot \big(&J_{energy}^{\text{no-DR}} + J_{DC}^{\text{no-DR}} + J_{ET}^{+\text{no-DR}} + J_{pv}^{\text{no-DR}}\big) \\
&- J_{DR} + J_{Capex}
\end{aligned}
$$

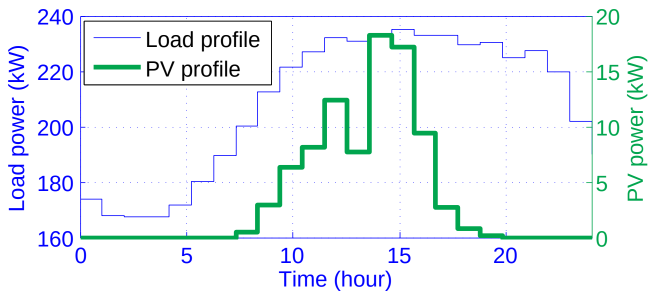

Fig. 1: Sample power profiles of the load and PV installation

and λ ($\in$ $[0, 1]$) 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 $[10\%, 100\%]$ 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 /kW) and SLRP ($0.1 /kW). 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

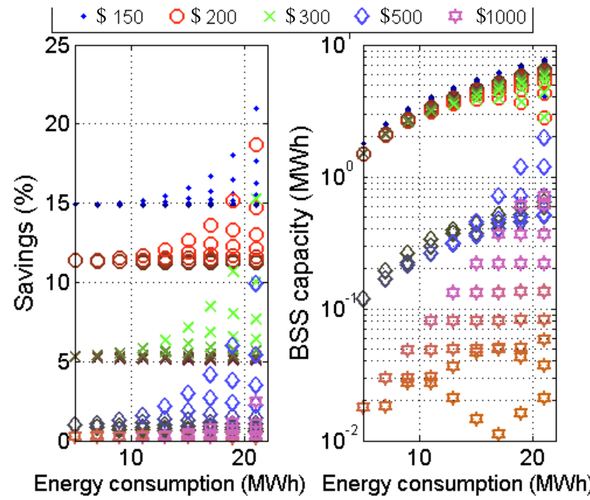

Fig. 2: Impact of varying load levels, PV penetration and BSS capex

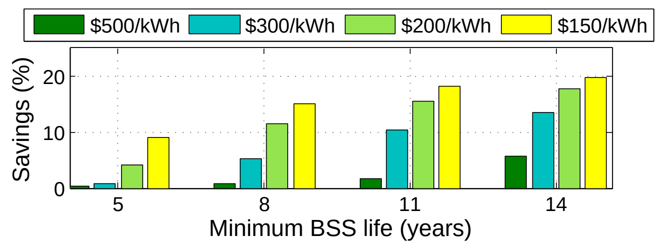

Fig. 3: Impact of varying expected BSS lifetime

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.

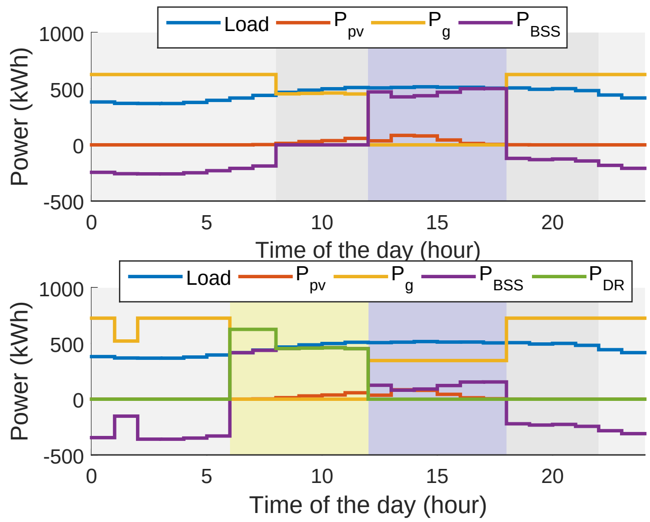

Fig. 4: Example solution of the co-optimization problem when sizing BSS accounting for participation in DR (DBP); optimal power profile on (a) non-event-day (b) event-day

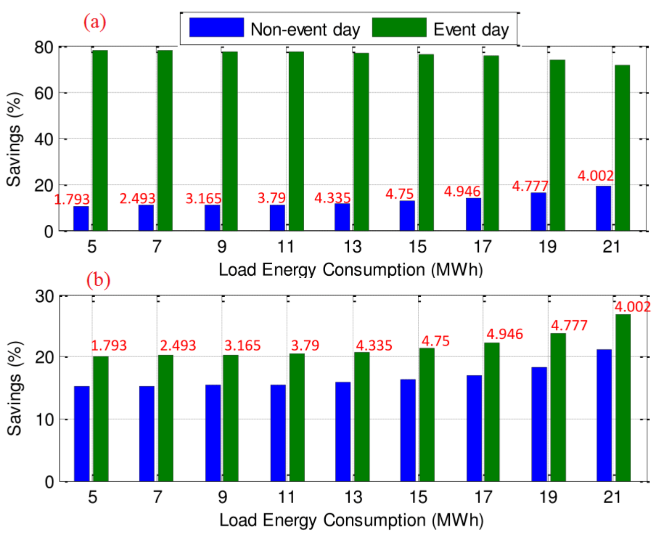

Fig. 5: Potential for participating in DR; (a) Demand Bidding Program (DBP) (b) Scheduled Load Reduction Program (SLRP)

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 are very infrequent and hence such returns are not sustainable. On the other hand, participating in SLRP does increase savings on event-days by $\sim$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

[1] ABES-14 Navigant Research - Advanced Batteries for Utility-Scale Energy Storage, 2014.

[2] Grid Energy Storage - December 2013, Department of Energy, 2013 `http://goo.gl/tGcLgR`, Retrieved 06-Jul-2015.

[3] Oudalov, A.; Cherkaoui, R. and Beguin, A., Sizing and Optimal Operation of Battery Energy Storage System for Peak Shaving Application Power Tech, 2007, IEEE Lausanne, 2007, 621-625.

[4] Ru, Y.; Kleissl, J. and Martinez, S. Storage Size Determination for Grid-Connected Photovoltaic Systems Sustainable Energy, IEEE Transactions on, 2013, 4, 68-81.

[5] Chen, S.; Gooi, H. and Wang, M., Sizing of Energy Storage for Microgrids, Smart Grid, IEEE Transactions on, 2012, 3, 142-151.

[6] Chaouachi, A.; Kamel, R.; Andoulsi, R. and Nagasaka, K. Multi-objective Intelligent Energy Management for a Microgrid Industrial Electronics, IEEE Transactions on, 2013, 60, 1688-1699.

[7] Zhang, Y.; Gatsis, N. and Giannakis, G. Robust Energy Management for Microgrids With High-Penetration Renewables Sustainable Energy, IEEE Transactions on, 2013, 4, 944-953.

[8] Tarasak, P.; Chai, C. C.; Kwok, Y. S. and Oh, S. W. Demand Bidding Program and Its Application in Hotel Energy Management Smart Grid, IEEE Transactions on, 2014, 5, 821-828.

[9] Electric Schedule E-19, PG&E, Retrieved 06-Jul-2015, `http://goo.gl/4J1508`.

[10] F. Matthey, T. Kamijoh, K. Takeda, S. Ando, T. Nomura, T. Shibata, A. Honzawa; Cost-benefit analysis tool and control strategy selection for lithium-ion battery energy storage system, 2015.

[11] PG&E Energy Management and Demand Response, `http://goo.gl/w4VMcX`, Retrieved 01-March-2016.

[12] Static Load Profiles 2000, `http://goo.gl/mzZjlF`, Retrieved 02-Jun-2015.