Maximizing the Cost-savings for Time-of-use and Net-metering Customers Using Behind-the-meter Energy Storage Systems

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***Abstract*—The transformation of today's grid toward smart grid has given the energy storage systems (ESSs) the opportunity to provide more services to the electric grid as well as the end customers. On the grid's side, ESSs can generate revenue streams participating in electricity markets by providing services such as energy arbitrage, frequency regulation or spinning reserves. On the customers' side, ESSs can provide a wide range of applications from on-site back-up power, storage for off-grid renewable systems to solutions for load shifting and peak shaving for commercial/industrial businesses. In this work, we provide an economic analysis of behind-the-meter (BTM) ESSs. A nonlinear optimization problem is formulated to find the optimal operating scheme for ESSs to minimize the energy and demand charges of time-of-use (TOU) customers, or to minimize the energy charge of net-metering (NEM) customers. The problem is then transformed to Linear Programming (LP) problems and formulated using Pyomo optimization modeling language. Case studies are conducted for PG&E's residential and commercial customers in San Francisco.**

***Index Terms*—Energy storage, behind-the-meter (BTM), time-of-use (TOU), net metering (NEM), peak shaving, load leveling, demand charge, distribution system, optimization, Mixed Integer Nonlinear Programming (MINLP), Linear Programming (LP).**

I. Introduction

Over the last decade, the emergence of the new technologies and the changes in policies and regulations have been the fundamental drivers to transform todays power grid toward a smarter, more reliable and more distributed grid in the future [1]. This transformation has given energy storage the opportunity to provide more services to the electric grid and the customers. On the grid's side, energy storage systems (ESSs) can generate revenue streams participating in electricity markets by providing services such as energy arbitrage, frequency regulation or spinning reserves [2]. On the customers' side, ESSs can also provide a wide range of applications from on-site back-up power, storage for on-site renewable systems to solutions for load shifting and peak shaving for commercial/industrial businesses [3].

Energy storage (ES) could provide the solutions to the grid-side and customer-side challenges and at the same time create revenues for the storage owners. However, the overall economic gains of energy storage deployments are limited by the round-trip efficiency and the capital costs of the ES devices [4]. Furthermore, ES is not the only option for the above challenges. Therefore, it is critical to assess the technical and economic benefits of energy storage systems as grid-side and customer-side solutions.

In the literature, a number of works have investigated the benefits of ESSs for generation, transmission and distribution applications. In [5], a theoretical framework of planning and control was proposed to maximize the profit of battery energy storage systems (BESS) for primary frequency control. In [6–9], maximum potential revenues of ESSs for energy arbitrage and frequency regulation in different market areas were investigated. A real-time optimal dispatch algorithm is proposed in [10] to maximize ESS's revenue from energy arbitrage in the day-ahead electricity market and its contribution to transmission congestion relief. Financial benefits of BESSs in upgrade deferral of distribution networks were evaluated in [11]. Optimal operations of BESSs for mitigating PV variability and reducing transformers' losses was studied in [12]. A comprehensive review of ES benefits for grid-side applications was presented in [2].

On the other hand, very limited studies for behind-the-meter (BTM) ESSs have been published. Most of the studies focused on peak demand shaving strategies using energy storage [13–15]. In [16], an optimal demand charge management for TOU customers using energy storage was studied; however, the trade-off between of demand charge saving and energy charge increase due to ESS round-trip efficiency was not captured. In [15], a fuzzy control algorithm for BESS was proposed to reduce the peak demand of commercial/industrial customers. Optimal benefit and sizing of BESS for BTM applications were evaluated in [17] in which energy charge and demand charge reduction for commercial buildings were co-optimized. Nevertheless, the negative net consumption caused by on-site renewable energy generation was not considered.

This paper presents an approach to minimize the electricity cost for time-of-use (TOU) and net-metering (NEM) customers using BTM energy storage. The approach requires the forecast data of the loads and renewable generations and the pricing data of the utilities. In this approach, a co-optimization of energy charge, demand charge and net-metering credit is performed. The cost minimization problem is formulated as a Mixed Integer Nonlinear Programming (MINLP) problem in which the linear constraints are based on the constant-efficiency energy storage model presented in [6]. The problem is then transformed to a Linear Programming (LP) problem

TABLE I
STORAGE PARAMETERS

Symbol	Storage Parameter
τ	Time period length (e.g., one hour)
H	Set of time periods in the optimization
$\overline{q}^{\mathrm{d}}$	Maximum energy sold in a single period [kWh]
$\overline{q}^{\mathrm{c}}$	Maximum energy bought in a single period [kWh]
$\overline{S}$	Maximum energy capacity [kWh]
S	State of charge [kWh]
γ_{s}	Storage efficiency over one period [%]
γ_{c}	Charge efficiency [%]
γ_{d}	Discharge efficiency [%]

using Minimax technique. In this approach, uncertainties in forecast data are not considered. The approach assumes perfect foresight of data and therefore provides the results for the best-case scenario.

The rest of the paper is organized as follows: section II presents the constant-efficiency energy storage model; section III provides details about TOU and NEM programs and problem formulations; case studies are conducted in section V; concluding remarks are found in section VI.

II. ELECTRICAL ENERGY STORAGE (EES) MODEL

An EES system is generally characterized by the following parameters:

1) Power rating [kW]: the maximum power that the EES can charge or discharge.
2) Energy capacity [kWh]: the amount of energy that the EES can store.
3) Charge efficiency, $\gamma_{\mathrm{c}}[\%]$: the charge efficiency represents the conversion losses encountered when energy is stored during charge.
4) Discharge efficiency, $\gamma_{\mathrm{d}}[\%]$: the discharge efficiency represents the conversion losses encountered when energy is released during discharge.
5) Storage efficiency, $\gamma_{\mathrm{s}}[\%]$: the storage efficiency describes the time-based losses in the EES system.

The parameters involved in storage system constraints are shown in Table I in which the maximum energy discharged and recharged in a single period τ are specified as follows:

$$\overline{q}^{\mathrm{D}} = (\text{Maximum discharge power level}) \times \tau \quad (1)$$

$$\overline{q}^{\mathrm{R}} = (\text{Maximum recharge power level}) \times \tau \quad (2)$$

For behind-the-meter applications, there are two decision variables in the optimization: the energy discharged q_i^{d} and the energy recharged q_i^{c} at time i, which are non-negative by convention. They are subjected to the following constraints :

$$0 \leq q_i^{\mathrm{c}} \leq \overline{q}^{\mathrm{c}}, \forall i \in \mathrm{H} \quad (3)$$

$$0 \leq q_i^{\mathrm{d}} \leq \overline{q}^{\mathrm{d}}, \forall i \in \mathrm{H} \quad (4)$$

Therefore, the state of charge (SOC) S_i at any time i is given by:

$$S_i = \gamma_{\mathrm{s}} S_{i-1} + \gamma_{\mathrm{c}} q_i^{\mathrm{c}} - q_i^{\mathrm{d}}/\gamma_{\mathrm{d}}, \ \forall i \in \mathrm{H} \quad (5)$$

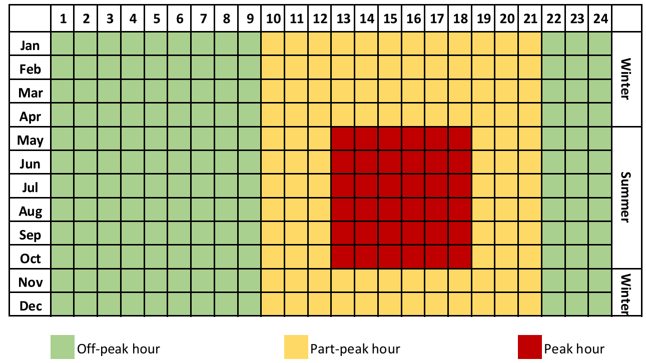

Fig. 1. An illustrative example of time schedule for regular week days

which states that the SOC at time i is the sum of the SOC at time $i-1$ and the net charging energy (adjusted by the corresponding efficiencies) [6].

The SOC must be within its physical limits as described in the following constraint:

$$0 \leq S_i \leq \overline{S}, \forall i \in \mathrm{H} \quad (6)$$

It should be noted that the "available" capacity at time i is $\gamma_{\mathrm{d}} S_i$ because of the discharge efficiency. Therefore, $\overline{S} = X/\gamma_{\mathrm{d}}$ where $X(kWh)$ is the rating capacity given in the system specification data.

If zero net charging (i.e., the SOC at the last period is equal to the initial SOC) is required, the following constraint must be met:

$$\sum_{i \in \mathrm{H}} \gamma_{\mathrm{c}} q_i^{\mathrm{c}} - q_i^{\mathrm{d}}/\gamma_{\mathrm{d}} = 0 \quad (7)$$

III. MINIMIZING THE TOTAL ELECTRICITY COST FOR TOU AND NEM CUSTOMERS

A. TOU and NEM pricing

TOU pricing is the rate structure in which energy and peak power prices are time-dependent [18]. TOU rates are often set in advance and do not adjust during a contract period. Different utilities have different time schedules; however, they are commonly classified as followings:

- Hour: peak hours, part-peak hours and off-peak hours.
- Day: regular week days, weekend days and holidays.
- Month: summer months and winter months.

Fig. 1 shows an illustrative example of a time schedule for regular week days through out a year, in which summer and winter off-peak hours are both [9pm to 9am], winter part-peak hours are [9am to 9pm] while summer part-peak hours are [9am to 12am] and [6pm to 9pm], summer peak hours are [12am to 6pm]. For holidays and weekend days, all hours are off-peak. Table II shows an example of TOU energy rates applied on the above time schedule.

For commercial and industrial customers, demand charges are also billed along with energy charges. Demand charges are often based on the highest 15-min (or hourly) average power within a month [19]. Higher demand rates can also

TABLE II
AN EXAMPLE OF TOU RATES

	Summer	**Winter**
Off-peak	0.09 \$/kWh	0.08 \$/kWh
Part-peak	0.11 \$/kWh	0.10 \$/kWh
Peak	0.15 \$/kWh	-

be applied to the highest demand occurred during part-peak and peak hours. Setting the higher energy and demand rates at peak hours gives TOU customers the incentives to shift or decrease their consumption during those hours to lower their bills, which in return helps the utilities to better manage their total peak load.

For the customers who own renewable energy systems (e.g., rooftop PV systems and small wind turbines), the net energy generated to the grid after the customers' usage can be compensated under net metering (NEM) programs [20]. For example, NEM allows solar customers to export power to the grid when their PV systems generation excesses their demand. The net energy exported to the grid will then be used to offset the customers' monthly consumption, or be credited to the customers periodically based on the market prices. NEM encourages the deployment of distributed renewable energy systems at the customers' sites which lowers the customers energy bills and reduces the transmission and distribution losses [21].

The above pricing mechanisms are often considered as part of demand response programs which credit the customers for the flexibility in their energy consumption [22]. In order to benefit from those rate structures, the utility customers must have the ability to change their total loads in a manner that lowers their monthly electricity bills without interrupting their operations (commercial/industrial customers) or sacrificing their conveniences (residential customers). Energy storage systems (ESSs) - with the ability to absorb (charge) and inject (discharge) energy - could provide a solution for that problem. For example, commercial/industrial customers could benefit from TOU rate differences by charging their ESSs during off-peak hours when rates are low (energy and demand rates) and then discharging them during peak hours when rates are high. ESSs could also be used by NEM customers for storing the excess renewable energy when the load is low and use that energy later when the load is high. In this case, the customers can increase their savings by avoiding selling their renewable energy at low whole-sale price and buying the energy later at much higher retail price.

Given the limitations in ESSs' energy capacities and their round trip efficiencies, the economic gains of the above applications are highly dependent on the ESSs' sizes and operations. Therefore, to justify the deployments of ESSs for BTM applications, it is essential to optimize these factors to maximize the overall benefits for the customers.

TABLE III
NOMENCLATURES

Symbol	**Description**
m	Month m
$\mathrm{P_i}$	TOU energy price at time i [\$/kWh]
$\mathrm{P_i^s}$	Market energy price at time i [\$/kWh]
α_i	Binary variable at time i
q_i^{c}, q_i^{d}	Decision variables: ESS charged and discharged energy at time i [kWh]
q_i^{ld}, q_i^{re}	Load and renewable energy at time i [kWh]
$\mathrm{C_E^m}$, $\mathrm{C_N^m}$, $\mathrm{C_D^m}$	Energy, net-metering and demand charges [\$]
$\mathrm{D_{max}^m}$, $\mathrm{D_{pk}^m}$, $\mathrm{D_{ppk}^m}$	Rates for maximum demand and highest demands during peak and part-peak hours [\$/kW]
$\mathrm{H^m}$, $\mathrm{H_{pk}^m}$, $\mathrm{H_{ppk}^m}$	Sets of hours, peak hours and part-peak hours of month m

B. Problem formulations

The cost minimization problem can be formulated as follows where variables and all parameters are defined in Table III.

$$\min\{\mathrm{C_E^m} + \mathrm{C_N^m} + \mathrm{C_D^m}\} \tag{8}$$

s.t. (3), (4), (6) and (7), where

$$\mathrm{C_E^m} = \sum_{i\in \mathrm{H^m}} \alpha_i q_i^{\mathrm{net}} \mathrm{P}_i \tag{9}$$

$$\mathrm{C_N^m} = \sum_{i\in \mathrm{H^m}} (1-\alpha_i) q_i^{\mathrm{net}} \mathrm{P}_i^{\mathrm{s}} \tag{10}$$

$$\mathrm{C_D^m} = \max_{i\in \mathrm{H^m}}\{q_i^{\mathrm{net}}\}\mathrm{D_{max}^m} + \max_{j\in \mathrm{H_{pk}^m}}\{q_j^{\mathrm{net}}\}\mathrm{D_{pk}^m} + \max_{k\in \mathrm{H_{ppk}^m}}\{q_k^{\mathrm{net}}\}\mathrm{D_{ppk}^m} \tag{11}$$

with $q_i^{\mathrm{net}} = q_i^{\mathrm{ld}} - q_i^{\mathrm{re}} + q_i^{\mathrm{c}} - q_i^{\mathrm{d}}$ and α_i ($\forall i \in \mathrm{H^m}$) is binary and defined as follows:

$$\alpha_i = \begin{cases} 1 & \text{if } q_i^{\mathrm{net}} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

The above problem is categorized as a Mixed Integer Nonlinear Programming (MINLP) problem which is difficult to solve directly. In this paper, we tackle this problem by removing binary variables in (9) and (10) using the following technique:

$$\alpha_i q_i^{\mathrm{net}} = \begin{cases} q_i^{\mathrm{net}} & \text{if } q_i^{\mathrm{net}} \geq 0 \\ 0 & \text{otherwise} \end{cases} \Rightarrow \alpha_i q_i^{\mathrm{net}} = \max\{q_i^{\mathrm{net}}, 0\} \tag{13}$$

$$(1-\alpha_i) q_i^{\mathrm{net}} = q_i^{\mathrm{net}} - \alpha_i q_i^{\mathrm{net}} = q_i^{\mathrm{net}} - \max\{q_i^{\mathrm{net}}, 0\} \tag{14}$$

Therefore, (9) and (10) can be rewritten as follows:

$$\mathrm{C_E^m} = \sum_{i\in \mathrm{H^m}} \max\{q_i^{\mathrm{net}}, 0\} \mathrm{P}_i \tag{15}$$

$$\mathrm{C_N^m} = \sum_{i\in \mathrm{H^m}} (q_i^{\mathrm{net}} - \max\{q_i^{\mathrm{net}}, 0\}) \mathrm{P}_i^{\mathrm{s}} \tag{16}$$

The problem now has become a Linear Minimax problem which can be transformed to a Linear Programing problem

[23] by replacing the max terms in the objective function by the representative variables together with the corresponding constraints:

- Representative variables:

$$q_{\max}^{\mathrm{m}} \text{ represents } \max_{i \in \mathrm{H}^{\mathrm{m}}}\{q_i^{\mathrm{net}}\}$$
$$q_{\mathrm{pk}}^{\mathrm{m}} \text{ represents } \max_{j \in \mathrm{H}_{\mathrm{pk}}^{\mathrm{m}}}\{q_j^{\mathrm{net}}\}$$
$$q_{\mathrm{ppk}}^{\mathrm{m}} \text{ represents } \max_{k \in \mathrm{H}_{\mathrm{ppk}}^{\mathrm{m}}}\{q_k^{\mathrm{net}}\}$$
$$q_i^{+} \text{ represents } \max\{q_i^{\mathrm{net}}, 0\}$$

- Corresponding constraints:

$$q_i^{\mathrm{net}} \leq q_{\max}^{\mathrm{m}}, \forall i \in \mathrm{H}^{\mathrm{m}} \quad (17)$$
$$q_j^{\mathrm{net}} \leq q_{\mathrm{pk}}^{\mathrm{m}}, \forall j \in \mathrm{H}_{\mathrm{pk}}^{\mathrm{m}} \quad (18)$$
$$q_k^{\mathrm{net}} \leq q_{\mathrm{ppk}}^{\mathrm{m}}, \forall k \in \mathrm{H}_{\mathrm{ppk}}^{\mathrm{m}} \quad (19)$$
$$q_i^{\mathrm{net}} \leq q_i^{+}, \forall i \in \mathrm{H}^{\mathrm{m}} \quad (20)$$

It is important to note that $\mathrm{C}_{\mathrm{D}}^{\mathrm{m}} = 0$ if there are no demand charges for the customers. In that case, variables $q_{\max}^{\mathrm{m}}$, $q_{\mathrm{pk}}^{\mathrm{m}}$ and $q_{\mathrm{ppk}}^{\mathrm{m}}$ and constraints (17), (18) and (19) are removed.

IV. Case Studies

In this section, case studies are conducted for PG&E's customers in San Francisco including: 1) A medium-size commercial TOU customer; 2) A typical-size residential TOU and NEM customer. The consumption data of the residential and the commercial customers are given in [24]. The dataset provides simulated hourly load profiles for residential and commercial buildings based on the DOE's Building America House Simulation Protocol [25] and the DOE's commercial reference building models [26]. The solar PV generation data used in these case studies are generated using NREL's PVWatts [27]. The optimization problems are formulated using Pyomo optimization modeling language [28]. Different sizes of energy storage are investigated. Charge and discharge efficiencies are assumed to be 94% in all cases. The state of charge of the ESS is maintained at 50% at the beginning of each month.

A. Case 1 - A medium-size commercial TOU customer

The medium-size commercial customer considered in this case is a large hotel as defined in [26]. Hourly load profiles for a year based on TMY3 weather data [29] is given in [24]. The maximum demand every month exceeds 500kW, therefore, it is assumed that the customer follows PG&E's TOU schedule E19 [30] for medium demand TOU service. To benefit from NEM in this case, a large renewable system is required, which is often not practical. Thus, to better evaluate the impact of ESS's deployment, we assumed that there is no renewable systems installed at the customer's site. The time schedule of E19 is described in Fig. 1. The energy and demand rates are summarized in Table IV.

Multiple sizes of the ESS are considered as follows:

- The power rating varies from 100kW to 800kW with 100kW step size.
- The energy rating varies from 0.5MWh to 20MWh with 0.5MWh step size.

TABLE IV
E-19 Schedule's TOU Rates

	Summer	Winter
Off-peak energy	0.08651 \$/kWh	0.09317 \$/kWh
Part-peak energy	0.11333 \$/kWh	0.10779 \$/kWh
Peak energy	0.15384 \$/kWh	-
Part-peak demand	5.18 \$/kW	0.12 \$/kW
Peak demand	18.64 \$/kW	-
Maximum demand	16.08 \$/kW	16.08 \$/kW

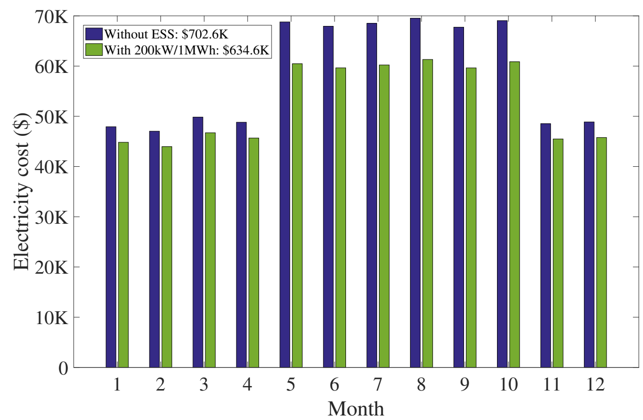

Fig. 2. Monthly electricity bills with 200kW/1MWh ESS

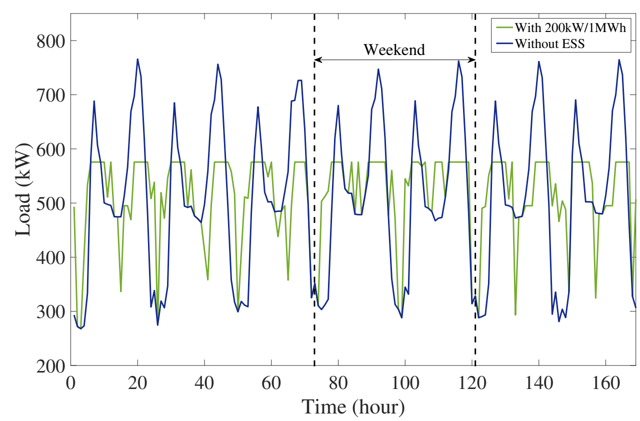

Fig. 3. Case 1 - Net loads during the first week of June

Fig. 2 shows the optimal monthly costs when integrating 200kW/1MWh ESS. We can see that there are better savings during the summer months (May to October). This is because bigger rate differences between peak and part-peak/off-peak hours create higher margin for energy arbitrage. As seen in Fig 3, the peak load is significantly shaved by charging the ESS during off-peak and part-peak hours and discharging during peak hours. There is also a tendency that ESS charges at higher rate during weekends. This is due to the fact that the peak

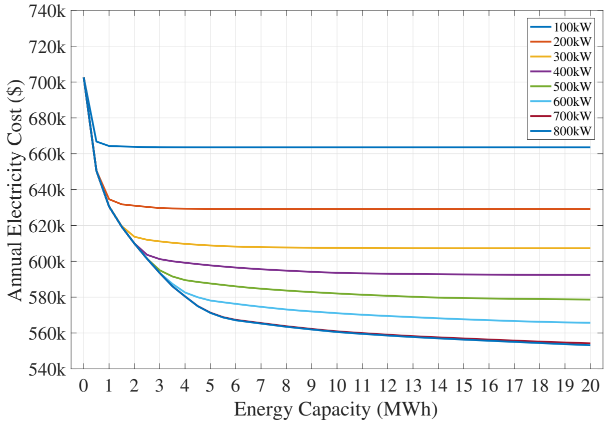

Fig. 4. Case 1 - Sensitivity of annual electricity bill to ESS size

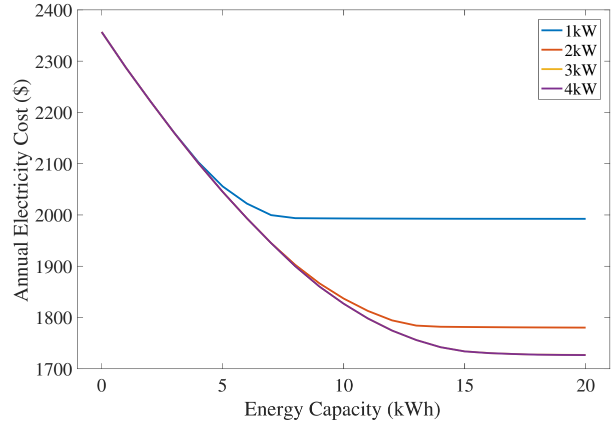

Fig. 5. Case 2 - Sensitivity of annual electricity bill to ESS size

energy and demand rates are only applied to the week days. Overall, the annual electricity bill is reduced from $702,600 (without energy storage) to $634,600 (with 200kW/1MWh energy storage system).

The sensitivity of annual cost to ESS's size are given in Fig 4. It is observed that the total annual cost at each ESS's power rating decreases as the energy rating increases. The rate of the decrease is high at first but significantly slowing down at the "knee point" of the curve. This is the point where energy arbitrage and peak shaving are limited by the power rating. The costs are bounded by the 800kW-curve. This is because the maximum load is 775kW. Any power ratings higher than the maximum load do not increase the chance for peak shaving.

B. Case 2 - A typical-size residential TOU and NEM customers

The typical-size residential customer considered in this case is a three-bedroom house as defined in [25]. Hourly load profiles for a year based on TMY3 weather data [29] is given in [24]. The following assumptions are considered in this case:

- The customer participates in TOU program under PG&E's schedule E-TOU/Option-B [31] in which peak hours are from 9am to 4pm on non-holiday weekdays year round. The pricing details are given in Table V.
- 5kW PV rooftop system is installed at the customer's site.
- The NEM energy price is $0.03/kWh [32].
- The NEM credit is calculated monthly.

Multiple sizes of the ESS are considered as follows:

- The power rating varies from 1kW to 5kW with 1kW step size.
- The energy rating varies from 1kWh to 20kWh with 1kWh step size.

Results are shown in Fig. 5 and 6. As seen in Fig. 6, the energy sold to the grid is reduced by charging the ESS when renewable energy generation exceed the customer's consumption. The ESS then discharges to reduce consumption during peak hours. The peak-shaving in this case is not significant.

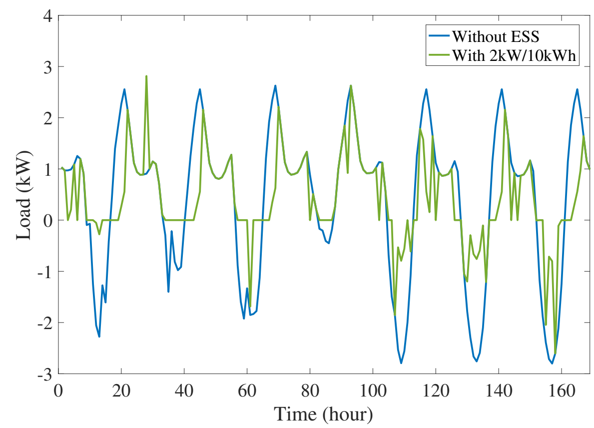

Fig. 6. Case 2 - Net loads during the first week of June

TABLE V
ETOU-B'S RATES

	Summer	**Winter**
Off-peak energy	0.26029 $/kWh	0.20708 $/kWh
Peak energy	0.36335 $/kWh	0.22588 $/kWh

This is because there is no peak demand charge and the energy price differences between peak and off-peak hours are small.

The sensitivity of annual cost to ESS's size in this case is very similar to that of case 1. It should be noted that in Fig. 5 the 3-kW and 4-kW curves are too close to differentiate; however, based on the results the costs are bounded by the 4-kW curve. This is due to the fact that the net load in this case is always less than 4kW. Thus, increasing the ESS's power rating beyond 4kW will be unnecessary.

V. CONCLUSIONS

In this paper, the benefits of behind-the-meter ESSs for TOU and NEM customers have been reviewed. A MINLP is formulated to minimize the monthly electricity cost of the customer. The problem is then transformed to an LP problem using the Minimax technique. Case studies have been conducted for PG&E's customers in San Francisco. The results show energy storage can significantly reduce electricity cost by peak shaving and load shifting for the commercial customer and by storing excess renewable energy for the residential customer. The sensitivity of annual electricity cost to ESS's sizes is also investigated. Future work in this area would consider the uncertainties of forecast errors as well as include a non-linear energy storage model.

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