Maximizing Return on Investment of a Grid-Connected Hybrid Electrical Energy Storage System

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Abstract – This paper is the first to present a comprehensive analysis of the profitability of the hybrid electrical energy storage (HEES) systems while further providing a HEES design and control optimization framework to maximize the total return on investment (ROI). The solution consists of two steps: (i) Derivation of an optimal HEES management policy to maximize the daily energy cost saving and (ii) Optimal design of the HEES system to maximize the amortized annual profit under budget and system volume constraints. We consider a HEES system comprised of lead-acid and Li-ion batteries for a case study. The optimal HEES system achieves an annual ROI of up to 60% higher than a lead-acid battery-only system (Li-ion battery-only) system.

I Introduction

One of the most serious challenges in power grid design is the mismatch between electrical energy generation and consumption [1]. The consumption is fluctuating with some degree of regularity: energy consumption over the grid generally ramps up during certain hours of a day, i.e., *peak hours*, and ramps down during the other hours. In contrast the overall energy generation fluctuates within a much smaller range compared to the demand. Figure 1 shows a 24-hour profile of system load demand of the California Independent System Operator (ISO) Corporation on July 9, 2012 [2].

Today, many utility companies such as the Consolidated Edison Company of New York (conEdison) deploy time-of-day pricing policy [3] with much higher energy price during peak hours for residential users, incentivizing residential users to perform *demand side management*. There are several ways to perform demand side management. The first way is to shift the residential load demand from peak hours to off-peak hours [4][5]. This method has limited applicability since only a small fraction of the total load demand is transferrable in time. A more promising solution is to exploit electrical energy storage (EES) systems to store excess energy when the electricity price is low and supply energy for use when the electricity price is high [6]. A typical EES system may comprise of Lithium-ion (Li-ion) batteries, lead-acid batteries and/or supercapacitors. Incorporation of EES system effectively shifts the residential peak hour energy demand from the grid and results in a win-win situation: users lower their electricity bills while utility companies reduce the demands on their peak power generation capability.

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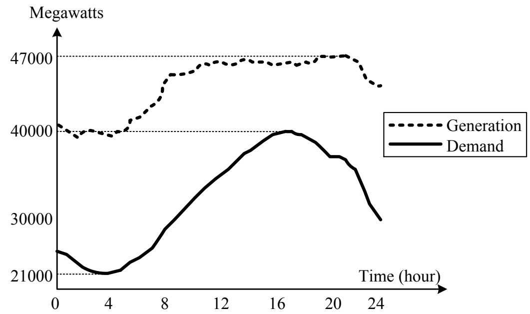

Figure 1. Electrical Energy Generation vs. Demand [2].

Consumers must be convinced before making a purchase that the EES system is profitable, similar to other investments. In other words, before the EES system reaches its end-of-life, it should be able to bring higher total energy cost saving compared to its capital cost (i.e., the purchase price of the system plus its maintenance cost).

In order to achieve maximum energy cost saving, choosing the optimal EES system size (capacity) is important since an EES system with a large size results in a higher efficacy (albeit with diminishing marginal efficacy gain) but also a higher capital cost. In addition, the amount of electrical energy cost saving also depends on the (i) (*deployment*) *efficacy* of the EES system i.e., the average daily saving in the electrical energy cost of the residential unit, and (ii) expected lifetime of the EES system. Therefore, it is equally, if not more, important to develop an optimal EES system control policy since both the efficacy and lifetime of the system strongly depend on such a policy. The policy determines the charging and discharging methods and the magnitude of charging and discharging currents. First, to enhance the EES system efficacy, the control policy should take into account the daily electric rates and the characteristics of the EES elements and chargers, or more specifically, the rate capacity effect of batteries, self-discharge of supercapacitors, and converter efficiency variation. Second, to extend the EES system lifetime, the control policy should properly maintain the depth of EES system charging/discharging during each day.

An appropriately designed control policy should thus find a balance between the daily energy cost reduction and the lifetime extension. For example, the conEdison electric rate during summer has the energy price for peak hours nearly thirty times the rate for off-peak hours. The EES system should store as much energy as possible so as to lower the energy consumption in the peak periods. In other seasons, the system may store less energy since the difference in price in peak vs. off-peak hours is smaller, so as to increase the EES system lifetime.

State-of-the-art EES system deployments are mainly homogeneous, i.e., they comprise a single type of EES elements, such as Li-ion batteries, lead-acid batteries, or supercapacitors. Nevertheless, none of the existing EES elements can simultaneously fulfill all the desired features of an ideal EES system, e.g., high charge/discharge efficiency, high energy density, low cost per unit capacity and long cycle life [7]. The overall performance of a homogeneous EES system is limited by characteristics of the underlying EES elements, thereby discouraging the application of EES systems in households.

A novel technology aiming at overcoming the above limitations, the hybrid EES (HEES) system, is gaining popularity [7][8]. A HEES system comprises of several heterogeneous EES elements and is therefore able to exploit the strengths of each type of EES element while hiding their weaknesses. Design considerations and control policies of the HEES systems have been proposed [9][10][11] to help realize the potential benefits. Despite these research efforts, the wide application of the HEES system is significantly restrained by the lack of more practical information, especially a properly designed energy management system and the analysis of *return on investment* (ROI) calculated by net profit divided by cost.

This paper presents a unified framework for the optimal design and control of a HEES system targeting at exploiting its potential for energy cost saving. First, we derive the optimal HEES control algorithm to maximize the daily energy cost saving with a given specification of the HEES system (in terms of types and capacities of different EES banks). This management algorithm properly controls the charging and discharging of each EES bank. We further improve this management policy by adding limits on the depth of discharge (DoD) of the battery banks for lifetime extension. Based on the optimal control algorithm, we find the optimal design and specification of the HEES system, taking into consideration the battery's cycle life, energy density, investment discount factor and system maintenance fee in the optimization framework. This optimal HEES design maximizes the amortized annual profit under a monetary budget constraint and a total volume constraint. We take Li-ion batteries, lead-acid batteries, the time-of-day electric pricing policy of conEdison [3], and one-year-long load profile of a multi-family house as a case study. We show that an optimally designed HEES system with energy management obtains an ROI of up to over 5%. Compared to the average of lead-acid battery-only EES system and Li-ion battery-only EES system, the HEES system improves the ROI by up to 60%.

The rest of this paper is organized as follows. Section II describes our optimization for daily performance: finding the optimal charging/discharging policy for daily energy cost saving. Section III presents our second optimization: maximizing the amortized annual profit by choosing proper EES capacity and DoD values. The paper is concluded in Section IV.

II. Daily Energy Cost Saving Maximization

First of all, it is important to develop an optimal HEES system management policy to achieve the maximum daily energy cost saving for a given HEES system specification

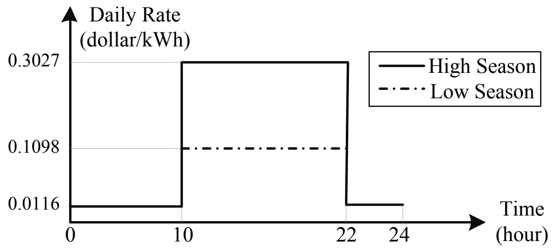

Figure 2. Daily Time-of-Day Energy Pricing.

(i.e., EES bank types and capacities) and an electricity usage (load) profile. This section first provides background about time-of-day pricing and HEES system characteristics. We formulate the problem and develop the solution to the problem to find the maximum daily energy cost saving with a given HEES system specification. We refer to the problem as the "*daily-cost-saving problem*" or the DCS problem for short. We then adjust the optimization result by considering the DoD in order to preserve the lifetime of EES banks for further improvement.

A. Daily Time-of-Day Energy Pricing

Because of the high electricity usage during peak hours, most utility companies provide customers with an alternative pricing policy, called *time-of-day pricing*. In particular, the electricity energy price per kWh during a day is shown in Figure 2, in which high season is from June to September, and others are low season.

Many areas, such as Los Angeles, require mandatory time-of-day pricing for customers whose average monthly electrical energy consumption reaches or exceeds a threshold in the preceding year [12]. The significant difference in energy price between peak hours and off-peak hours encourages customers especially with high electrical energy consumption to shift electricity usage from peak hours to off-peak hours.

B. EES elements and the HEES system

Among dozens of types of EES elements in the market, the most commonly used ones are lead-acid batteries, Li-ion batteries, and supercapacitors.

The lead-acid batteries are among the cheapest types of EES elements, yet they suffer from short lifetime, low *energy density,* and significant *rate capacity effect* compared to Li-ion batteries or supercapacitors. The first two factors, namely battery lifetime and energy density, are discussed in Section III. The rate capacity effect specifies the fact that the available discharging time of a battery is dependent on its discharging current. Peukert's law [13] gives a numerical expression for a battery with *nominal full-charge capacity* Q (in Ah), *reference discharge current* I_{ref} and actual discharge current I_{disch}:

$$T = \frac{Q}{I_{ref}} \left(\frac{I_{ref}}{I_{disch}} \right)^{k} \tag{1}$$

where T is the actual time to discharge the battery using current I_{disch}. The reference current I_{ref} is commonlyassumed to be the constant current that can fully discharge the battery in 20 hours if not explicitly provided [13]. The Peukert constant k reflects the efficiency of the discharging process. The Peukert constant of lead-acid batteries (1.3 to 1.4) is higher than that of Li-ion batteries (around 1.1).

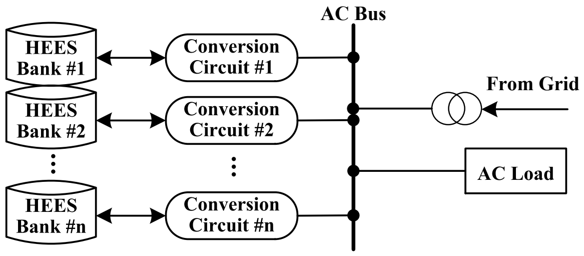

Figure 3. HEES System Structure.

We define the *equivalent current* I_{eq} as:

$$I_{eq} = (\frac{I_{disch}}{I_{ref}})^k I_{ref} \tag{2}$$

I_{eq} specifies the actual rate of charge loss inside a battery. Thus the Peukert's law can also be expressed using I_{eq}:

$$Q = TI_{eq} \tag{3}$$

Furthermore, we must consider the capital cost of EES elements while building a HEES system. This cost can be represented in the form of unit (energy) price, which is the cost per unit of delivered energy (\$/Wh). The unit price of a battery can therefore be written as its dollar cost divided by its nominal full-charge capacity Q and terminal voltage V_{bat}:

$$p = \frac{\text{Dollar Cost}}{QV_{bat}} (\$/\text{Wh}) \tag{4}$$

Compared to lead-acid or Li-ion batteries, supercapacitors are far too expensive for residential users to perform load shaping; namely, the unit price of supercapacitors (i.e., the dollar cost divided by stored energy $\frac{1}{2}CV^2$ when they are fully charged) is \$20-50/Wh while that of lead-acid is \$0.1-0.2/Wh [7]. This makes the break-even time unacceptably longer when that when using supercapacitors in the residential HEES system.

Figure 3 shows the structure of a grid-connected HEES system. The power conversion circuits are employed in our system structure since we use batteries to supply power for AC loads. These power conversion circuits are non-ideal and cause certain amount of power dissipation due to *IR loss* (i.e., voltage drop due to the internal resistance of the interconnects constituting the circuits) and switching power losses. We use 0.95 as the power conversion efficiency of the DC-AC converters (also known as inverters).

C. Problem formulation and solution

One observation is made from above aiming at maximizing daily energy cost saving: The battery capacity gets best utilized by using full range of its capacity every day. If we do not fully discharge the batteries during peak hours, or if we do not fully charge the batteries during off-peak hours, the unused capacity is wasted.

We charge both EES banks until they are full with constant current during off-peak hours. However, it is much more complicated to decide the discharging rate of the battery backs for the peak hours. In order to maximize the daily energy cost saving, the optimal discharging policy should take into consideration both the load profile and the power loss caused by rate capacity effect. As is mentioned in (2), the actual charge decreasing rate inside a battery is a superlinear function of its discharging current. We should hence keep the discharging currents as steady as possible to reduce the power loss from rate capacity effect. In a word, the HEES management policy should find balance between stabilizing discharging currents and matching the load profile.

We formulate the DCS problem as follows:

Given:

1) Battery capacity (in Ah): Q_x, Q_y (x stands for Li-ion and y stands for lead-acid as a case study in this paper);
2) Battery's terminal voltage: V_{bat};
3) The 24-hour electrical energy price: $r_i, i = 1, \ldots, 24$. (We define the peak hours index set as $PK = \{11,12,\ldots,22\}$, and base hours index set as $BS = \{1,2,\ldots,10,23,24\}$);
4) Residential load power profile $P_i^{load}, i = 1, \ldots, 24$;
5) Batteries' rate capacity effect coefficients k_x, k_y;
6) DC-AC converters' power conversion efficiency: η.

Find: Discharge current $x_{11}, \ldots, x_{22}$, $y_{11}, \ldots, y_{22}$ of two battery banks during peak hours. Indices 11 to 22 indicate peak hours, from 10:00 AM to 9:59 PM.

Maximize: The daily energy cost saving:

$$\begin{aligned} DCS &= \sum_{i=1}^{24} r_i P_i^{load} - \sum_{i\in BS} r_i (P_i^{load} + \frac{x_c + y_c}{\eta} \cdot V_{bat}) \\ &\quad - \sum_{i\in PK} r_i \big(P_i^{load} - \eta(x_i + y_i)V_{bat}\big) \qquad (5) \\ &= \sum_{i\in PK} r_i \eta \cdot (x_i + y_i) V_{bat} - \sum_{i\in BS} r_i \frac{x_c + y_c}{\eta} V_{bat} \end{aligned}$$

where $x_c = \frac{1}{12}\sum_{i\in PK}(\frac{20x_i}{Q_x})^{k_x}\frac{Q_x}{20}$, $y_c = \frac{1}{12}\sum_{i\in PK}(\frac{20y_i}{Q_y})^{k_y}\frac{Q_y}{20}$.

Subject to:

1) Battery capacity constraint:

$$\sum_{i\in PK}(\frac{20x_i}{Q_x})^{k_x}\frac{Q_x}{20} \le Q_x, \sum_{i\in PK}(\frac{20y_i}{Q_y})^{k_y}\frac{Q_y}{20} \le Q_y \tag{6}$$

where $\frac{Q_x}{20}$ and $\frac{Q_y}{20}$ are the reference discharge current.

2) Load power constraint:

$$\eta(x_i + y_i) \cdot V_{bat} \le P_i^{load}, i = 11 \sim 22 \tag{7}$$

The DCS problem is a convex optimization problem since it has convex objective function as well as convex inequality constraints. This problem is solved optimally in polynomial time using standard optimization tools [14].

In this simulation we use conEdison's time-of-day electric rate and single-family house electricity usage data for 365 days in a year as the load profile [3]. The maximum saving of the j^{th} day is expressed as a function $f_j(Q_x, Q_y)$ of Li-ion battery capacity Q_x and lead-acid battery capacity Q_y. By summing up the daily optimization results, we get the *maximum annual cost saving function*:

$$F(Q_x, Q_y) = \sum_{j=1}^{365} f_j(Q_x, Q_y) \tag{8}$$

$F(Q_x, Q_y)$ is shown in Figure 4. The results are stored in a look-up table (LUT) for the next step optimization. As can be seen from this figure, the maximum annual energy cost saving has diminishing marginal gain as the battery capacities increase.

D. DoD-Aware DCS Optimization

The optimal solution of the above DCS problem assumes full charge and discharge of both batteries during off-peak hours and peak hours, respectively. However,

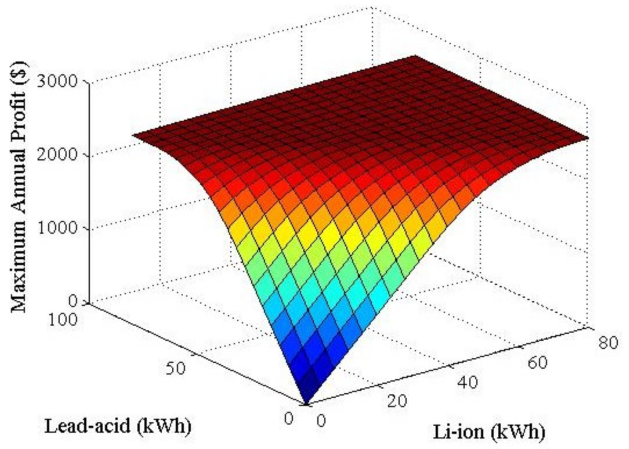

Figure 4. Maximum Annual Energy Cost Saving.

fully charging and discharging of batteries result in fast capacity degradation, and thereby significantly shorten the battery lifetime [15][16]. Using only part of the battery capacities extends the service time of the HEES system, and probably brings in more profit than using full capacity in the long run. Based on this observation, we should re-consider the DCS problem by adjusting limitations on usable capacities. This section shows that this is implemented by limiting maximum DoDs of battery banks. More importantly, we reduce this DoD-aware DCS problem to an original DCS problem with equivalent battery capacities.

We define the DoD of a battery during a discharge process to be the ratio of charge loss to the *full charge capacity* (FCC) in our model. For example, if a battery's initial charge is 90% of its FCC and it gets discharged to have 40% of its FCC before the next charging begins, then the DoD of this discharge process is 0.5. According to the Li-ion battery model in [15], a battery can get its lifetime extended by storing less energy and maintaining smaller charge swings during each cycle. This conclusion is translated into the following policy: if a maximum DoD is set, the energy management system should function in such a way that the battery banks cannot be charged more than the maximum DoD during off-peak hours, and get fully discharged during peak hours.

Assume the maximum DoD of Li-ion battery is d_x and that of lead-acid battery is d_y. Let $\hat{f}_i(Q_x, Q_y, d_x, d_y)$ denote the maximum daily energy cost saving of the j^{th} day achieved by optimizing the DoD-aware DCS problem. We then prove that it is an underestimation to use $f_i(d_x^{\frac{1}{k_x}} Q_x, d_y^{\frac{1}{k_y}} Q_y)$ to approximate the DoD-aware optimization result:

$$\hat{f}_i(Q_x, Q_y, d_x, d_y) \geq f_i(d_x^{\frac{1}{k_x}} Q_x, d_y^{\frac{1}{k_y}} Q_y) \tag{9}$$

First, the battery capacity constraints in the original DCS problem formulation should be changed accordingly as follows:

$$\sum_{i \in PK} (\frac{20x_i}{Q_x})^{k_x} \frac{Q_x}{20} \leq d_x Q_x, \sum_{i \in PK} (\frac{20y_i}{Q_y})^{k_y} \frac{Q_y}{20} \leq d_y Q_y \tag{10}$$

or equivalently:

$$\sum_{i \in PK} (\frac{20x_i}{d_x^{\frac{1}{k_x}} Q_x})^{k_x} \frac{Q_x}{20} \leq Q_x, \sum_{i \in PK} (\frac{20y_i}{d_y^{\frac{1}{k_y}} Q_y})^{k_y} \frac{Q_y}{20} \leq Q_y \tag{11}$$

Table 1
Estimation error percentage of different days.

Day	Q_x	Q_y	d_x	d_y	f_i	$\hat{f}_i$	Δ(%)
1	20	20	0.6	0.6	2.185	2.210	1.14
100	5	20	0.6	0.6	1.361	1.382	1.45
200	10	10	0.8	0.8	4.191	4.199	0.171
300	20	5	0.6	0.9	1.469	1.478	0.563

The DCS problem with result $f_i(d_x^{\frac{1}{k_x}} Q_x, d_y^{\frac{1}{k_y}} Q_y)$ is therefore proved to have the same constraints with its equivalent DoD-aware problem.

Second, according to the original DCS estimation, the charging current of Li-ion bank in off-peak hours in the objective function (5) becomes:

$$x'_c = \frac{1}{12} \sum_{i \in PK} \left(\frac{20x_i}{d_x^{\frac{1}{k_x}} Q_x} \right)^{k_x} \frac{d_x^{\frac{1}{k_x}} Q_x}{20} = \frac{1}{12} \sum_{i \in PK} \left(\frac{20x_i}{Q_x} \right)^{k_x} \frac{d_x^{\frac{1}{k_x}-1} Q_x}{20} \tag{12}$$

Note that $k_x > 1$, making $\frac{1}{k_x} - 1 < 0$. With $d_x \leq 1$, we know $d_x^{\frac{1}{k_x}-1} \geq 1$. We then have:

$$x'_c \geq x_c = \frac{1}{12} \sum_{i \in PK} (\frac{20x_i}{Q_x})^{k_x} \frac{Q_x}{20} \tag{13}$$

This means the original DCS problem overestimates the charging cost during off-peak hours, making it an underestimation of the total cost saving. Therefore, (9) is proved. ∎

We randomly pick different days in both high season and low season to investigate the actual error of this underestimation compared to the DoD-aware result. Simulation results show that this error is less than 2%. Table 1 shows results of four days with different capacities and maximum DoD limits.

The DoD-aware maximum annual energy cost saving may be approximated as:

$$\hat{F}(Q_x, Q_y, d_x, d_y) \geq F(d_x^{\frac{1}{k_x}} Q_x, d_y^{\frac{1}{k_y}} Q_y) \tag{14}$$

III. Amortized Annual Profit Maximization

In this section, we discuss the problem of finding the optimal design and specification of the HEES system maximizing annual ROI. The monetary budget and the system volume limit are given, making the amortized annual net profit an equivalent criterion (i.e., objective function.) to the annual ROI. We take the HEES system comprising Li-ion and lead-acid batteries for a case study based on current unit price of lead-acid battery and both the current and predicted unit price of Li-ion battery.

A. Calculation of Average Annual Profit

The following four factors are taken into consideration to provide more practical and accurate estimation of the amortized annual profit:

1) Cycle life: Generally speaking, a battery is regarded to be at the end of its lifetime when its capacity becomes lower than 80% of its initial capacity [15]. Both Li-ion and lead-acid batteries have their lifetime superlinearly extended if they are charged and discharged with a smaller DoD. This can be shown more clearly in Figure 5. For example, the cycle life of a Li-ion battery with 75% DoD is 4605 cycles, more than three times that of 100% DoD, 1560 cycles.

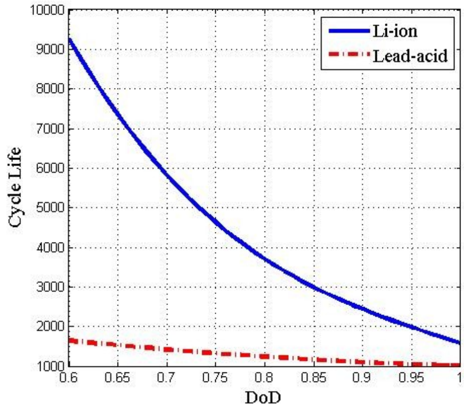

Figure 5. Cycle life vs. DoD of Li-ion and Lead-acid batteries.

2) Maintenance cost: Figure 5 illustrates that Li-ion batteries usually have 3-4 times the lifetime of lead-acid batteries. Normally different types of batteries do not break down together. It is uneconomical to discard or replace the whole HEES system as soon as one battery bank reaches its end-of-life. Instead, replacing the aged battery bank with a new one can restart the HEES system with lower extra cost. Apart from the purchase cost of new batteries, the replacement of devices also adds up to the total capital cost since it requires maintenance personnel to come by and restore the system. We use M to denote one-time maintenance fee of battery installation or replacement.
3) Discount factor: The *discount factor* reflects the time value of money, indicating that there is a difference between the future value of a payment and the present value of the same payment. The HEES system is an investment, for which the lifetime may be 10 years or more, making the discount factor non-negligible. Different from certificate of deposit (CD), the HEES system investment has maintenance cost, which gets paid from accumulated saving in proceeding years. Therefore, we must consider the discount factor γ when amortizing the maintenance cost, in terms of 5-year CD annual percentage yield of 2% i.e., $\gamma = 1/(1+2\%) = 0.9804$. The detailed calculation is provided in the next subsection.
4) System volume: we must limit the overall volume of the HEES system since it targets at residential usage. Our problem formulation uses the reciprocal of battery volumetric energy density, referred to as the *unit volume*, which is its volume divided by the maximum stored energy. The lead-acid batteries' average unit volume is 12.5L/kWh, much higher than that of Li-ion batteries: 2L/kWh [18].

B. Problem Formulation

The calculation of amortized annual net profit of installing a HEES system comprises of two parts: cost and gain. The gain of a HEES system is the annual saving derived in Section II.

Cost of a HEES system includes the purchase cost of the batteries and maintenance fee when they are installed or replaced. For a certain battery's whole lifetime, its cost (dollar cost plus maintenance) is one-time investment and thus should be amortized. Let p_x denote the unit price of Li-ion battery. The cost of installing a new Li-ion bank with capacity Q_x is $Q_x p_x + M$. Assume a_x is the amortized annual cost. The amount of money a_x has the same value with $a_x \cdot \gamma^{-1}$ of the next year, and $a_x \cdot \gamma^{-2}$ of the year after next, etc. Hence we have:

$$a_x + a_x \cdot \gamma^{-1} + a_x \cdot \gamma^{-2} + \cdots + a_x \cdot \gamma^{-L(d_x)+1} = Q_x p_x + M \tag{15}$$

$$a_x = (Q_x p_x + M) \times \frac{1-\gamma^{-1}}{1-\gamma^{-L(d_x)}} \tag{16}$$

where $L(d_x)$ is Li-ion battery lifetime as a function of its DoD d_x. The amortized cost is similar for lead-acid battery.

Taking all the aforesaid factors into consideration, we formulate the annual profit problem as follows.

Given:
1) LUT of high season energy cost saving and low season saving: HT, LT;
2) Unit price of Li-ion and lead-acid batteries: p_x, p_y;
3) Unit volume of Li-ion and lead-acid batteries: v_x, v_y;
4) One-time maintenance fee: M;
5) Discount factor γ;
6) Budget B for initial investment and total volume limit V.

Find: Li-ion capacity and maximum DoD Q_x, d_x; lead-acid capacity and maximum DoD Q_y, d_y.

Maximize: amortized annual profit:

$$\begin{aligned}&\text{Annual Profit} = \text{Annual Saving} - \text{Annual Cost}\\ &= \hat{F}(Q_x, Q_y, d_x, d_y)\\ &-(Q_x p_x + M)\cdot\frac{1-\gamma^{-1}}{1-\gamma^{-L(d_x)}} - \left(Q_y p_y + M\right)\cdot\frac{1-\gamma^{-1}}{1-\gamma^{-L(d_y)}}\end{aligned} \tag{17}$$

Subject to:
1) Budget constraint: $Q_x p_x + Q_y p_y + M \le B$;
2) System volume constraint: $Q_x v_x + Q_y v_y \le V$.

The linear constraints of the annual profit problem define a bound for variables Q_x, Q_y. We use three-dimensional search through all values of d_x, d_y along this bound to derive an optimal annual profit.

C. Optimization Results

We take Li-ion and lead-acid batteries as a case study. Figure 6 gives the derived maximum annual profit under two different (B, V) constraints, compared with Li-ion battery-only EES system and lead-acid battery-only system. In Figure 6, the HEES system achieves 56.95% more annual net profit than a lead-acid battery bank and 59.11% more than a Li-ion battery bank under \$3000 budget and 100L volume constraint. The ROI of HEES system may be significantly higher than that of Li-ion battery-only EES

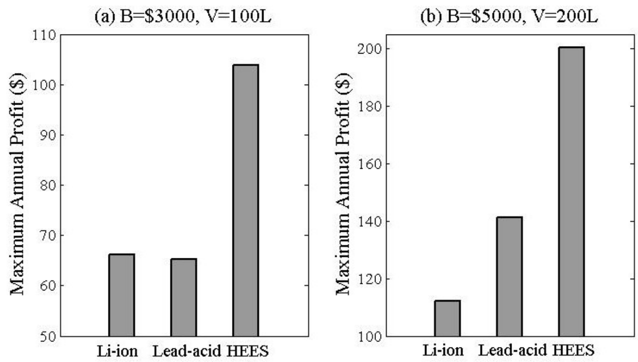

Figure 6. Maximum Annual Profit with Different Constraints.

Table 2.
Annual Profit Results with Current Battery Prices.

Budget ($)	Volume (L)	Lead-acid (kWh)	Li-ion (kWh)	Annual Profit ($)	Annual ROI
1000	50	3.86	0.81	34.88	3.49%
3000	50	3.23	4.53	76.65	2.55%
3000	100	7.38	3.58	103.87	3.46%
3000	200	15.67	1.69	158.30	5.28%
5000	30	0	8.84	112.12	2.24%
5000	50	2.68	8.22	118.95	2.38%
5000	100	6.84	7.25	145.93	2.92%
5000	200	15.08	5.39	200.36	4.01%

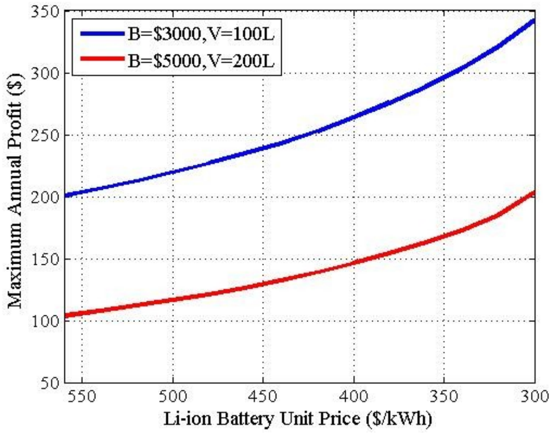

Figure 7. Maximum Annual Profit with Decreasing Li-ion Cost.

system when budget is tight or lead-acid battery-only EES system when volume is small. It is therefore more convincing to compare the ROI of the HEES system with the average of these two EES systems. Results show that this improvement of the ROI of the HEES system reaches 60%.

Table 2 shows optimization results using current prices of lead-acid and Li-ion batteries. The HEES system structure achieves 5% ROI with a budget of $3000 and volume constraint of 200L. The table proves the diminishing marginal efficacy gain, comparing the ROI of ($1000, 50L), ($3000, 50L) and ($5000, 50L). It also proves the intuitive conclusion that lead-acid batteries take a larger proportion for a tight budget and Li-ion instead for a small space.

In addition, our optimization framework can easily handle changing constraints and other practical constraints such as the weight of HEES system together with system volume upper bound. For example, according to [19], the unit cost of Li-ion batteries is expected to be at $0.3/Wh in 2015. Figure 7 shows annual profit increases rapidly with decreasing Li-ion battery cost.

IV. Conclusion

The lack of ROI analysis greatly hinders the wide application of HEES systems for home users. Consumers have no idea how much can be saved on their electric bills with the investment in building and maintaining the system. This paper provides such a practical analysis with latest real data and shows the potential of making profit by investing in HEES systems. First, the daily energy cost saving problem with given battery capacity and load profile is characterized as a convex optimization problem which can be solved optimally. Based on its result, we provide an HEES design framework that can maximize annual profit. Real data of New York electric rates and single-family house load profile as a case study show that our optimized HEES system reaches an annual ROI of over 5%, which is 60% higher than the average ROI of lead-acid battery-only system and Li-ion battery-only system.

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