Optimal Battery Configuration in a Residential Home with Time-of-Use Pricing

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***Abstract*—Residential energy consumption shows significant diurnal patterns that can be leveraged by energy storage devices. Batteries can store energy from either local renewable sources or from the grid when the electricity is cheaper, and provide it when the prices are higher. However, batteries are chemical devices and their efficiency and lifetime highly depends on the usage patterns. In this paper, we develop a framework that considers the physical properties of batteries, tests the feasibility of a battery deployment and finds the best battery types and configurations for a particular residential configuration. We validate the outcomes our framework through simulations that are informed by measurements. Our framework shows that up to 43% savings can be obtained with batteries, which may be lower or completely eliminated if the batteries are not used in specific configurations.**

I. Introduction and Related Work

Residential energy consumption constitutes 38% of the total energy consumption in the US, with millions of individual customers [1]. In this paper, we focus on the demand side of the residential domain to minimize the cost of home energy use. Unlike the industrial domain, residential systems are not heavily automated and are prone to inefficiency due to unpredictable user behavior. The advancements in smart grid technologies, like smart metering, allow residential energy consumption to be monitored and managed more effectively. This monitoring enables smarter technologies to be deployed in residential domain, e.g. load shifting [2], peak shaving [3], voltage regulation [3], energy arbitrage [4], etc. Load shifting [2] classifies the demand of a house as deferrable and non-deferrable and enables rescheduling of the deferrable demand. Peak shaving [3] reduces the maximum power draw of a house to avoid both peak power charges and circuit tripping. Voltage regulation [3] minimizes the voltage deviations, which are especially prevalent with the distributed energy generation.

This paper focuses on energy arbitrage in a residential home using batteries. Time-of-use (ToU) pricing is a common method used by the utilities, which set cheaper electricity prices when the demand is expected to be low and higher prices when the demand is higher. Energy arbitrage leverages these different energy prices by buying the extra energy when the prices are low, storing it in an energy storage device and then using the stored energy when the price is higher.

Several studies [4], [5], [3], [6] have investigated this idea in the residential domain and formulated optimization problems to maximize the energy cost savings. The amount of cost savings depends on how well the price difference can be used and the initial deployment cost of the batteries. Previous studies formulate the cost savings as the main optimization goal and find the capacity that maximizes the savings function [4], [5]. Additionally, some studies solve the battery capacity problem while including renewable energy from solar [3]. Some studies focus on when the batteries should be used to maximize the savings [6]. However, battery sizing and usage are not decoupled and should not be considered separately. Barnes et al. [4] combine battery sizing and scheduling for different battery technologies.

Although the previous studies consider sizing problem and battery scheduling, they consider only round trip efficiency when modeling different types of batteries, but not the non-linear battery properties. These properties include how deep and how fast the batteries should be discharged. The battery lifetime decreases with deeper battery discharges and higher discharging current [7], [8]. If the batteries are not used in the best possible way, they have to be replaced prematurely, resulting in higher system costs.

In contrast to previous work, we leverage a more detailed battery model to obtain the battery configuration for homes that have ToU pricing. Battery configuration includes type, total capacity, depth-of-discharge and average discharging current. We validate our model against battery measurements and show that it is within 5% error. Our novel framework uses this battery model and obtains a closed form inequality that can query the profitability of a battery deployment and choose the most beneficial battery configuration. We validate the results of our framework with extensive simulation studies using measured house data from MIT's REDD database [9]. As a case study, we compare two different battery technologies, lead-acid (LA) and lithium-iron-phosphate (LFP), under realistic ToU pricing schemes obtained from California ISO [10] and observe that LFP batteries are more cost effective, obtaining up to 43% more cost savings.

II. Battery Configuration Study

This section demonstrates how battery configuration affects the battery efficiency and lifetime. We refer to a battery configuration as the combination of depth-of-discharge (DoD) limit, discharging current, battery capacity and type. The first two properties can decrease the battery lifetime significantly if they are not adjusted properly. Their effects are highly dependent on battery type and capacity, and thus all these components should be evaluated jointly. We use state-of-health (SoH) metric to quantify the battery lifetime. SoH is defined as the maximum deliverable capacity of a battery at a given time estimated as a percentage of the initial capacity. We also

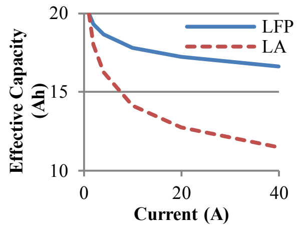

Fig.1. Effective capacity of 20Ah LA & LFP batteries

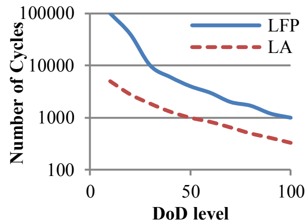

Fig.2. Cycle life of LA & LFP batteries rated at 20h [18], [19]

compare two different battery types: lead-acid (LA) and lithium-iron-phosphate (LFP). The former is a commonly used inexpensive battery type whereas the latter is more efficient but also more expensive.

We use the Coulomb Counting method presented in [8] to describe the relation between DoD level and SoH. The effects of high discharge currents on SoH are captured using model shown in [7]. Peukert's law [11] enables us to more accurately estimate a battery's effective capacity, C_{eff}. We use H to denote rated discharge time hours and obtain its value (typically 20 hours) from the data sheets [11]. Peukert's exponent, *k,* changes depending on the battery type. For LA batteries, the typical value is around 1.15 whereas for LFP batteries it is 1.05 [12]. The rated capacity, C_R , exponentially decays with discharging current $I_{discharge}$ as shown below:

$$C_{eff} = C_R * \left(\frac{C_R}{I_{discharge}*H}\right)^{k-1} * \frac{SoH}{100} \quad (1)$$

The capacity loss as the battery is used is modeled by scaling the effective capacity with SoH. We also record the total depth of discharge at the end of a discharging period as DoD_{final} to capture the effect of the current cycle on the battery lifetime (see equation 2).

Figure 1 shows the negative effect of high discharge currents on 20Ah LA and LFP batteries. The horizontal and vertical axes show the effective battery capacity and discharging current respectively. The effective capacity of the LA battery decreases faster due to its greater nonlinear behavior, represented by a larger Peukert exponent. At 40A, equivalent to 2C rate for both batteries, the LFP battery loses only 15% of its nominal capacity whereas the LA battery capacity loss is more severe, with 42%.

We update battery SoH after a complete charge/discharge cycle [8]. This update depends on the battery type, effective capacity and DoD_{final}. Deeper discharging periods are represented with larger DoD_{final} values and reduce the total number of charge/discharge cycles of a battery. We estimate the effects of DoD_{final} with a lookup table derived from effective capacity graphs similar to Figure 2 that are provided in the data sheets. In Figure 2, the horizontal axis shows the DoD level for charge/discharge at 20h discharge rate, which is defined as the discharging current draining the battery in 20h. The vertical axis is on a log scale. It shows the number of cycles a battery can sustain a particular DoD level. The available number of cycles reduces exponentially with a deeper discharge in each cycle.

We normalize the effect of one cycle with DoD_{final} value to capture its effect on the battery lifetime. Battery needs to be replaced when its SoH falls below a threshold, $SoH_{dead.}$ Battery manufacturers generally recommend 80% for this value [13] i.e. the battery has to be replaced if the maximum capacity it can provide falls below 80% of its rated capacity. If the battery has $Cycles_{DoD\_final}$ cycles with DoD_{final} value, the battery SoH is updated as:

$$SoH_{new} = SoH_{prev} - (100 - SoH_{dead}) * \frac{1}{Cycles_{DoD\_final}} * \frac{C_R}{C_{eff}} \quad (2)$$

This equation normalizes the effect of one cycle with DoD_{final} over the battery lifetime and penalizes high discharge currents. We validate the accuracy of our model using the full battery charge/discharge data available from the NASA Ames Prognostics Data Repository [14]. Our model has 4.67% average error as compared to measurements.

III. Optimal Battery Configuration Analysis

We next define and solve the battery configuration problem in a home with time-of-use (ToU) pricing [15]. For this study, we assume that the house can be equipped with a battery whose configuration, e.g. capacity, discharging current, depth-of-discharge (DoD) limits, are determined through optimization. To simplify the problem, we assume that the residence does not have any renewable sources, such as solar or wind. Since a majority of homes in the USA do not have any form of renewable energy, this is a reasonable assumption. We exploit the energy price difference by storing cheaper energy in the battery using the stored energy when energy prices are higher. When redirecting the energy flow through a battery, we consider the conversion losses and nonlinear battery behavior.

Time of use pricing has a peak price during the day, c_h, and an off-peak price c_l [4], during the night. As a result, the battery is charged during the night and discharged during the day, when the energy demand of the house is actually higher. Furthermore, we also consider the amortized cost of the battery and take that cost into consideration when we decide if a battery configuration is profitable. The total energy cost with a battery (including the amortized battery cost) should be smaller than the energy cost without using a battery.

We define the energy cost without using a battery:

$$C_{nb} = P_{ave_h} * t_h * c_h + P_{ave_l} * t_l * c_l \quad (3)$$

where C_{nb} is the electricity cost without batteries, P_{ave_h} and P_{ave_l} are average power demand (W) during peak and off-peak energy prices respectively; $t_h$and t_l are the durations (hour) of peak and off-peak energy price intervals respectively; and c_h and c_l are peak and off-peak energy prices in terms of (¢/kWh). This energy cost is calculated for a single day. Accordingly:

$$C_{wb} = c_h * (P_{ave_h} * t_h - E_d) + c_l * (P_{ave_l} * t_l + E_c) \quad (4)$$

where C_{wb} is the electricity cost with a battery, $E_d$and $E_c$are battery discharge and charge energy (Wh) respectively. Equation 4 subtracts the cost of energy that can be provided by the battery and adds the cost of the energy required for the battery charge. We add the battery cost to C_{wb} later separately. We calculate E_d and $E_c$as follows:

$$E_d = V * I_d * t_d * \gamma \quad (5)$$

$$E_d = V * I_d * H * \left(\frac{Capacity}{I_d*H}\right)^k * DoD_{limit} * \gamma \quad (6)$$

$$E_c = V * I_r * \frac{(Capacity*DoD_{limit})}{I_r} = V * Capacity * DoD_{limit} \quad (7)$$

where V is the battery voltage (V), I_d and I_r are discharge and recharge currents (A), t_d is the time (h) that battery can discharge within the DoD limit, DoD_{limit} (%), H is the rated battery hour (h), $Capacity$ is the total battery capacity (Ah), γ is the battery efficiency, and k is the Peukert exponent of the investigated battery (no unit). Equation 6 leverages Peukert's Law [11] to calculate t_d and scales the battery output with the battery efficiency to calculate the actual energy provided by the battery. Furthermore, both E_d and E_c are scaled with DoD_{limit} to account for the depth-of-discharge limit because we may not use the total available battery capacity. This formulation also assumes that the battery does not power the entire home and its output can be combined with the grid in any amount.

If a battery deployment is profitable, the cost with batteries should be smaller than the cost without them:

$$C_{nb} - C_{wb} > 0 \tag{8}$$

If we combine C_{nb} and C_b into the above equation, we obtain the following simplified inequality:

$$\left(\frac{c_{high} * \gamma}{c_{low}}\right)^{\frac{1}{k-1}} \geq H * discharging_{rate} \tag{9}$$

where discharging rate is defined in terms of C current and calculated as $\frac{I_d}{Capacity}$. We use 1C current as a reference which is defined as the discharging current that drains a battery in one hour, e.g. for a 20Ah battery this current is 20A.

If the battery deployment cost is not considered, equation 9 gives the feasible battery configuration. An interesting observation is that this inequality is independent of the power demand of the house. However, there is one other restriction from equation 4:

$$P_{ave_h} * t_h - E_d \geq 0 \tag{10}$$

This inequality specifies that the discharge energy of the battery cannot be larger than the energy demand during the peak energy price interval because the home cannot use more energy than its demand.

In order to calculate the actual savings, we also need to consider the amortized battery cost. We update the equation 8:

$$Savings = C_{nb} - C_{wb} - C_b > 0 \tag{11}$$

where C_b is the amortized cost of the deployed battery:

$$C_b = \frac{Battery\ Deplyment\ Cost}{Battery\ Lifetime} \tag{12}$$

The deployment cost of the battery is computed as the market price of the battery:

$$Battery\ deployment\ cost = c_{unit} * Capacity \tag{13}$$

where c_{unit} is the unit battery cost in terms of \$/Ah. We also calculate the expected lifetime of the battery with the battery configuration defined with DoD_{limit}, I_d and $Capacity$. We assume that the battery has one complete charge/discharge cycle per day:

$$Battery\ Lifetime = \frac{Cycles_{DoD}}{(H * discharging_{rate})^{k-1}} \tag{14}$$

where $Cycles_{DoD}$ is the number of charge/discharge cycles that the battery can perform with given DoD value. By combining equations 12, 13, 14 into equation 11:

$$c_h * \gamma * (H * discharging_{rate})^{2-2k} - c_l \geq \frac{10^5 * c_{unit}}{DoD_{limit} * V * Cycles_{DoD}} \tag{15}$$

The constant 10^5 appears as a result of the conversion between kWh → Wh and \$ → ¢. Equation 15 is the generalized version of equation 9. It tests the feasibility (nonnegative cost savings) of a battery deployment under ToU pricing with a peak and an off-peak price. However, equation 10 should still be satisfied as a pre-requisite for equation 15. The advantages of this closed form inequality are as follows:

- It is simple and the feasibility of a configuration can be tested independently of the energy demand of the house (The best configuration still depends on the house demand).
- It shows the tradeoff between the peak and off-peak energy prices and battery unit price.
- It determines how the battery should be used, e.g. discharging current, depth of discharge etc.
- It can estimate if a battery configuration is feasible before the deployment.

Next, we analyze the critical points of the savings function in terms of battery capacity, discharging current and DoD limit. We use equation 11 as our savings function and combine with C_{nb}, C_{wb}, and C_b from equations 3, 4, and 12 respectively. This savings function calculates the benefits of the battery deployment ($C_{nb} - C_{wb}$) and also considers the amortized initial deployment cost of the battery, C_b.

Capacity Analysis: We first compute the partial derivative of the savings function and set it to zero to obtain the optimal capacity (equation 11). Then, we analyze the capacity for both LFP and LA type of batteries, for which the Peukert exponent is 1.05 and 1.15 respectively. For both types of batteries the optimal capacity is on the order of 10^5 Ah or larger. However, we also know that the capacity of the battery is limited by equation 10. Therefore, with this analysis, we can say that the battery capacity can be scaled up to the limit introduced by equation 10. The optimal capacity value only depends on the power profile of the given house. If the capacity is further increased, the savings obtained by exploiting the electricity price difference cannot justify the additional battery capacity because it is not used. For the power profiles of the homes we use in our study, this capacity ranges between 100-500Ah.

Discharging Current Analysis: The optimization process minimizes the discharging current in order to maximize the battery lifetime. The discharging current should be adjusted so that the expected battery lifetime is close to the battery shelf life. Otherwise, lower discharging current does not bring any benefits because the battery lifetime does not improve further beyond its shelf life. The expected shelf life is generally 10 years for both LA and LFP batteries [3]. For a 100-500Ah battery, the discharging current should be at rate C/10-C/20 to obtain the maximum benefits from a battery deployment. If the power demand of the house increases, the battery capacity should be increased instead of increasing the discharging current. In this case, the additional demand justifies the extra capacity and the battery lifetime can still be maximized with lower discharging current.

Depth-of-discharge Analysis: The optimal depth-of-discharge limit depends highly on the battery type. For this analysis we use the data from Figure 2 for LA and LFP batteries along with our battery model shown above. The most beneficial DoD limit for LFP and LA batteries are 50% and 20-30% respectively.

In summary, we can conclude from our analysis of the savings function in equation 11 that:

- The battery capacity should be adjusted to meet the energy demand of the given house during the high pricing intervals.
- The selected discharging current should be as low as possible, so that the expected battery lifetime is close to the battery shelf-life.
- The optimal DoD level depends on the battery type. For LFP it is around 50% and for LA it is around 20-30%.

IV. Results

In this section, we leverage our model to analyze three different houses from the MIT REDD database [9]. The power profiles of these houses are shown in Figure 3. Although all three houses show diurnal patterns, their power profiles have great diversity. House 1 has the largest demand and exhibits duty cycling of some appliances such as HVAC. The demands of House 2 and 3 are lower than House 1. The former has less frequent and smaller demand whereas the latter may require frequent and higher instantaneous power compared to House 2.

We assume that these residences have two-level time-of-use (ToU) electricity prices, representing off-peak and peak electricity prices. Figure 4 shows how the market electricity prices fluctuate in California as provided by the California ISO database [10]. Since we model two-level ToU pricing, we take the minimum and maximum limits of the price during the day to represent off-peak and peak electricity pricing. We apply peak pricing between 7am and 11 pm and off-peak pricing during the rest of the day [15]. Table I shows two different ToU pricing schemes that we use for comparison purposes.

TABLE I. ToU Prices

	Time Interval	Pricing Case 1	Pricing Case 2
Peak	7am – 11 pm	35 ¢/kWh	45 ¢/kWh
Off-peak	11 pm – 7 am	10 ¢/kWh	10 ¢/kWh

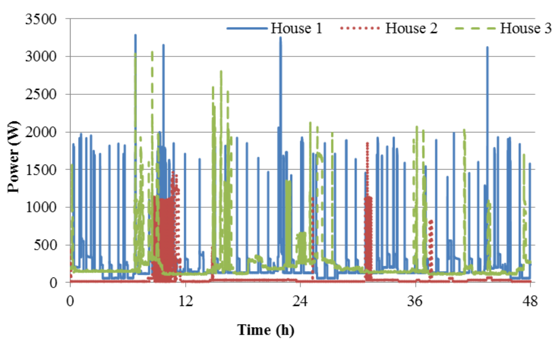

Fig. 3. Power demand profile of 3 houses from MIT REDD database [9]

We simulate the power profile of a house for a single representative day, corresponding to average, with different battery configurations, i.e. battery type, capacity, DoD limit and discharging current rate. We refer to this process as load simulation. We use the results of load simulation as representative of the usage pattern of the battery going forward. We then perform battery analysis to estimate the lifetime of the battery and calculate the amortized battery cost. Table II shows the battery related parameters we use in our battery analysis. Battery lifetime analysis uses the data from Figure 2 to get a relationship between the number of charge/discharge cycles and various DoD levels.

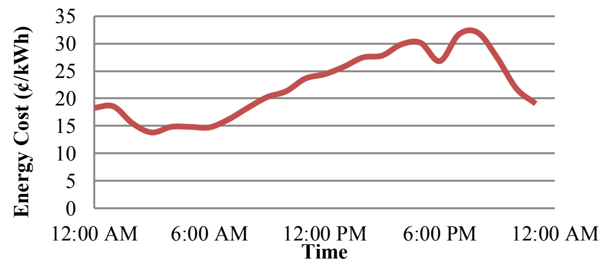

Fig. 4. Market electricity pricing from California ISO [10]

TABLE II. Battery Parameters

Input	LA Value	LFP value
Battery unit price -rated with 20h	2 \$/Ah [16]	5 \$/Ah [17]
Peukert's exponent	1.15 [12]	1.05 [12]
Battery shelf life	10 years [3]	10 years [3]
Battery efficiency	80% [4]	92% [4]
Battery nominal voltage	12V [18], [19]	

Case 1: First, we study the pricing case where the off-peak and peak electricity prices are 10 and 35 ¢/kWh, respectively. This pricing corresponds to CAISO pricing data we have [10]. Before carrying our simulation study and battery lifetime analysis, we first put the battery related parameters in equation 15 and observe that the inequality is:

- Satisfied for LFP when DoD level is between 50-70%
- Not satisfied for LA at any DoD level

Therefore, we expect savings for only LFP battery and for only a narrow range of DoD values. We run simulations both to validate the feasibility conclusions of our framework and to find the best configurations. When we run our simulations, we find the optimal battery capacity for the case 1 pricing. Table III shows the results. LA battery does not result in any savings as we expected from our initial analysis. In contrast, LFP battery brings profits for all three houses. The optimal capacity changes depending on the power profile of the house. Since House 1 is the one with the highest demand, it can benefit more from larger capacity batteries. House 2 leads to the smallest battery as its power demand is low compared to the others.

TABLE III. Optimal Battery Capacity For Case 1 Pricing

	LA		LFP	
	Capacity (Ah)	**Savings (\$)**	**Capacity (Ah)**	**Savings (\$)**
House 1	N/A		359	298
House 2			138	89
House 3			324	233

We present the detailed analysis of the optimal battery configuration in Figure 5. The graph in Figure 5 stands for House 1 when the battery capacity is optimized, i.e. a 359 Ah LFP battery. The graphs show the savings in y-axis in terms of dollars with changing DoD values in x-axis. Individual lines represent different discharge current rates. For this study, we have 4 different discharging current rates, i.e. 20h, 10h, 4h, 2h rates, corresponding to C/20, C/10, C/4 and C/2 respectively. The total savings for each battery configuration are presented over the respective battery lifetime value.

The simulation results verify the outcomes of the theoretical approach. The results show that the LFP battery brings profit only for DoD values between 50-70%. We can also observe that other than C/20 discharging current rate, we do not get any savings. When the discharging current rate is increased, both battery lifetimes and the effective battery capacity decrease, preventing us from taking full advantage of the price differences and do not get any cost savings. Although we present results of only House 1 in Figure 5, the other two houses have similar results. Thus, we conclude that for the case 1 pricing the optimal battery configuration is achieved with LFP batteries, 60% DoD limit, C/20 discharging current and the capacity matching the house demand. With this configuration the LFP battery lifetime is around 8 years.

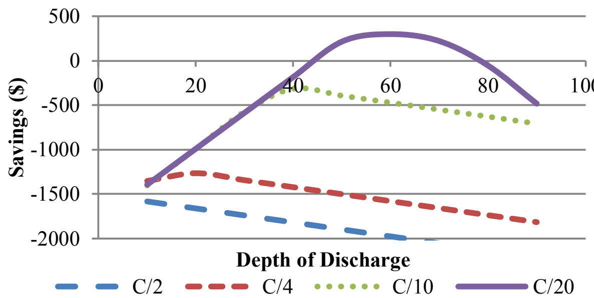

Fig. 5. Savings vs. DoD for House 1 with optimal capacity

Case 2: In this case, we increase the gap between off-peak and peak electricity prices and evaluate both the accuracy of our framework and the profitability of different battery configurations. When we use equation 15, we see that the inequality is satisfied for:

- LFP when DoD level is between 30% - 80%
- LA when DoD level is between 10% - 70%

Here we have a larger set of profitable battery configurations due to the larger price difference. Table IV shows the optimal battery capacity values and the corresponding cost savings when using case 2 pricing. Compared to case 1, the optimal LFP capacities slightly increase because the price difference helps justify the additional battery capacity. LA batteries become a feasible option. The optimal LA capacities are larger than LFP because of their highly nonlinear behavior, lower efficiency and cheaper unit cost. We again observe that the power profile of the house affects the optimal capacity.

TABLE IV. OPTIMAL BATTERY CAPACITY FOR CASE 2 PRICING

	LA		LFP	
	Capacity (Ah)	**Savings ($)**	**Capacity (Ah)**	**Savings ($)**
House 1	624	481	359	1145
House 2	255	166	138	413
House 3	497	352	325	1006

Table V summarizes the optimal battery configurations for three houses using case 2 pricing. We present the configuration for each house (including capacity, DoD limit and discharging current rate) resulting in the best savings shown in Table IV. The optimal DoD levels for LA and LFP batteries are 20% and 60% respectively. LA battery limits DoD level more strictly because its performance degrades significantly when it is discharged deeper. Consequently, LFP battery requires less capacity because it is allowed to discharge deeper. In contrast, the discharging current should be scaled as low as possible to maximize the battery lifetime in order to increase savings. Decreasing the battery capacity with higher discharging current is another solution to decrease the total cost of batteries. However, reduced battery lifetime leads to frequent battery replacements, and thus we get lower profits. Therefore, we can conclude from our analysis that the battery capacity should be increased instead of increasing the discharging current.

TABLE V. OPTIMAL BATTERY CONFIGURATION FOR CASE 2 PRICING

	LA			LFP		
	Capacity	**DoD**	**Dis. Cur. Rate**	**Capacity**	**DoD**	**Dis. Cur. Rate**
House1	624	20%	C/20	359	60%	C/20
House2	255	20%	C/20	138	60%	C/20
House3	497	20%	C/20	325	60%	C/20

The maximum savings of LFP batteries is $1145, $413 and $1006 for House 1, 2 and 3 respectively. The savings are $481, $166 and $352 for LA batteries. These savings are observed over the expected lifetime of the batteries. The expected battery lifetime values for LFP and LA for the best battery configuration are 8 and 4 years respectively. When we compare these different technologies over the same time interval, we see that LFP battery still brings 19%, 24% and 43% more savings for House 1, 2 and 3 respectively. For case 2 pricing, we can say that LFP batteries are 29% more profitable than LA batteries on average.

In both pricing cases, LFP batteries are more profitable compared to LA batteries even though they are more expensive. The former are more feasible because of its more linear battery behavior and longer cycle life. In contrast, the latter may have significant performance degradation due to its nonlinear battery behavior as well as larger energy losses. As a result, LA batteries require the difference between off-peak and peak electricity pricing to be larger. In the next part, we further analyze different pricing options and show how the optimum configuration and the savings change with these options.

Pricing Analysis: In this part, we analyze the price differences in more detail. We study both a fixed price difference with varying low energy price and a varying price difference with fixed low energy price. Figure 6.a shows the results of fixed price difference whereas Figure 6.b outlines the outcomes of varying price difference using the power profile of House 1. We select House 1 because its demand is higher, and consequently, the effects of price changes are more visible than the other two houses. Both graphs have two y-axes, where the primary one stands for the savings obtained through the lifetime of the battery (8 years for LFP and 4 years for LA) in terms of dollars and the other one represents the best capacity value in Ah. The x-axis shows the varying low energy price in Figure 6.a and the price difference in Figure 6.b. We set the price difference to 35¢/kWh in Figure 6.a because it is the lowest that we observe savings for the LA battery. We also set the low energy price in Figure 6.b to 10¢/kWh to be compatible with Figure 4.

Figure 6 shows that the optimum battery capacity is almost fixed, even though the pricing policy changes. Thus, we can say that the best capacity depends highly on the power demand of the house. In Figure 6.a, the LA battery performs better as the low energy price gets higher. However, for realistic (lower off-peak prices) cases, the LFP battery is more profitable. It compensates for its higher unit cost with long battery lifetime and higher efficiency. The advantages of these properties of

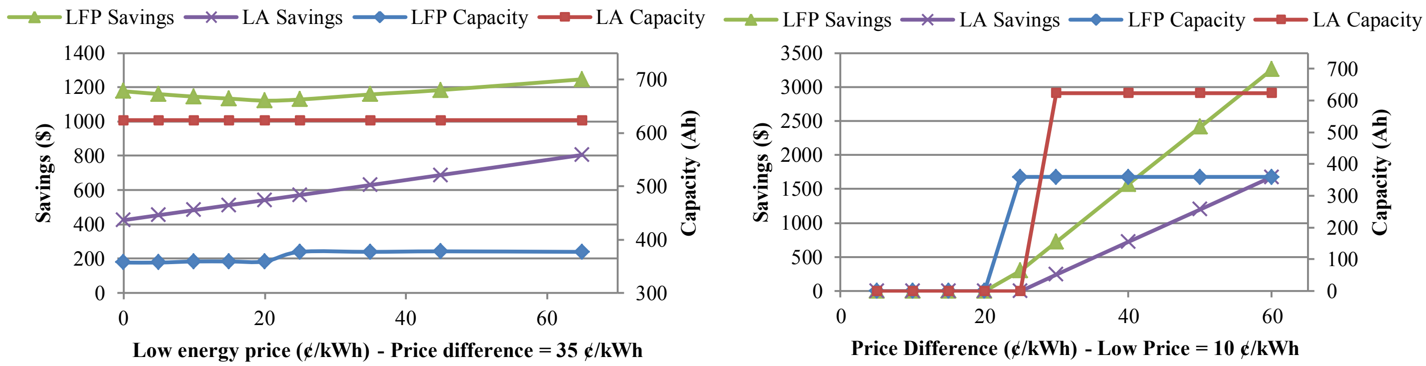

Fig. 6. Savings&capacity vs. price differences using House 1 power profile. a) Fixed 35 ¢/kWh price difference with changing low energy price, b) Increasing price difference with fixed 10 ¢/kWh low energy price

LFP battery are more visible in Figure 6.b. We see that the LA battery requires the price difference to be larger to obtain savings, but even if the price difference gets larger, the LFP is up to 3x more profitable than the LA battery. We do not show the DoD level and discharging rate results in Figure 6 for clarity. However, for both graphs in Figure 6, we observe that the best DoD values are 20% and 60% for LA and LFP batteries respectively. Also, the optimal discharging rate for all the cases is C/20. Once more, our framework shows the importance of choosing not only the optimal capacity but also the optimal battery type, discharging current rate and DoD level because we may not obtain the full benefits of the best battery capacity with a wrong battery configuration (see Figure 5). Our framework also provides tight bounds for the profitability of a battery configuration and our simulation results validate the accuracy of these bounds.

V. CONCLUSION

Residential homes can benefit from using batteries to exploit electricity price differences applied by utilities. Previous work mainly focused on optimizing the capacity of the battery when deployed in a home, but largely neglected how the nonlinear properties of the batteries can affect the savings. In this paper, we develop a framework that models the nonlinear behavior of the batteries and tests the feasibility of a battery deployment and helps to find the best configuration. We also show that if the battery usage is not configured properly, even the optimal battery capacity may not result in savings. We validate the accuracy of our battery model against battery measurements and the results of our framework with real house data from the MIT REDD database. We compare LA and LFP batteries with two different ToU pricing cases with our framework and demonstrate that both batteries need to be specifically tuned to obtain savings, which is missed by previous work. We also show that LFP batteries are up to 43% more profitable even though they are more expensive.

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