Energy Management and Cost Analysis in Residential Houses using Batteries

Baris Aksanli and Tajana Rosing
Computer Science & Engineering Department
University of California San Diego
{baksanli, tajana}@ucsd.edu

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. But, 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]. Some studies solve the battery capacity problem while including renewable energy from solar [3]. Others focus on when the batteries should be used to maximize the savings [6]. Barnes et al. [4] combine battery sizing and scheduling for different battery technologies. But, battery sizing and usage are not decoupled and should not be considered separately.

The previous studies consider sizing problem and battery scheduling, but they consider only round trip efficiency when modeling different types of batteries, not the non-linear battery properties. These include how deep and how fast the batteries should be discharged. The battery lifetime decreases with deeper 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.

We leverage a detailed battery model to obtain the battery configuration for homes with 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 framework uses this model and obtains a closed form inequality that can query the profitability of a battery deployment and choose the most beneficial 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 Analysis

Battery Configuration: We define a battery configuration as the depth-of-discharge (DoD) limit, discharging current, battery capacity and type. The first two can reduce the battery lifetime significantly if they are not controlled properly. Their effects also highly depend on battery type and capacity, and thus these variables should be evaluated jointly. We use state-of-health (SoH) metric to measure the battery lifetime. SoH is defined as the maximum deliverable capacity of a battery at a given time estimated as a percentage of its nominal capacity. We compare two 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 battery model from our previous work [11] [12], which adopts Coulomb counting from [8], incorporates the effects of high discharge currents on SoH from [7], and applies Peukert's law [13] to accurately capture the effective capacity of a battery. We see that without these modeled, the effective capacity can be miscalculated by up to 42% [11] and the battery lifetime can be overestimated by up to 2.4x [12]. We validate our model using the full battery charge/discharge data from the NASA Ames Prognostics Data Repository [14]. Our model has 4.67% average error as compared to measurements.

System Framework: We next define and solve the battery configuration problem in a home with time-of-use (ToU) pricing. We assume that the house can be equipped with a battery with adjustable configuration. To simplify the problem, we assume that the house does not have any renewable sources. 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. The battery is charged during the night and discharged during the day, when the energy demand of the house is higher. We also consider the amortized cost of the battery. The total energy cost with a battery should be smaller than the energy cost without it.

We define the energy cost without using a battery, C_{nb}:

$$C_{nb} = P_{ave_h} * t_h * c_h + P_{ave_l} * t_l * c_l \tag{1}$$

where P_{ave_h} and P_{ave_l} are average power demand (W) during peak and off-peak energy prices; t_h and t_l are the durations (hour) of peak and off-peak energy price intervals; 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:

$$C_{wb} = c_h * (P_{ave_h} * t_h - E_d) + c_l * (P_{ave_l} * t_l + E_c) \tag{2}$$

where C_{wb} is the electricity cost with a battery, E_d and E_c are battery discharge and charge energy (Wh) respectively. Equation 2 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:

$$E_d = V * I_d * t_d * \gamma \tag{3}$$

$$E_d = V * I_d * H * \left(\frac{Capacity}{I_d * H}\right)^k * DoD_{limit} * \gamma \tag{4}$$

$$E_c = V * I_r * \frac{(Capacity * DoD_{limit})}{I_r} = V * Capacity * DoD_{limit} \tag{5}$$

where V is the battery voltage (V), I_d and I_r are discharge and recharge currents (A), t_d is the time (h) battery can discharge within 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 battery. Equation 4 uses Peukert's Law [13] to calculate t_d and scales the battery output with its efficiency to calculate the actual energy provided by it. Both E_d and E_c are scaled with DoD_{limit} to account for the available battery capacity, instead of the total. We also assume that the battery output is 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:

$$C_{nb} - C_{wb} > 0 \tag{6}$$

If we combine C_{nb} and C_{wb} into equation 6:

$$\left(\frac{c_{high} * \gamma}{c_{low}}\right)^{\frac{1}{k-1}} \geq H * discharging_{rate} \tag{7}$$

where discharging rate is defined in terms of C current and calculated as $\frac{I_d}{Capacity}$. We use 1C current as a reference defined as the current that drains the battery in one hour.

If the battery deployment cost is not considered, equation 7 gives the feasible configuration. An interesting observation is that this inequality is independent of the power demand of the house. There is one other restriction from equation 2:

$$P_{ave_h} * t_h - E_d \geq 0 \tag{8}$$

This inequality specifies that the discharge energy of the battery cannot be larger than the energy demand during the peak energy price interval.

We then update equation 6 with the amortized battery cost:

$$Savings = C_{nb} - C_{wb} - C_b > 0 \tag{9}$$

where C_b is the amortized cost of the deployed battery:

$$C_b = \frac{Battery\ Deplyment\ Cost}{Battery\ Lifetime} \tag{10}$$

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

$$Battery\ deployment\ cost = c_{unit} * Capacity \tag{11}$$

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

$$Battery\ Lifetime = \frac{Cycles_{DoD}}{(H * discharging_{rate})^{k-1}} \tag{12}$$

where $Cycles_{DoD}$ is the number of charge/discharge cycles that the battery can perform with given DoD value. By combining equations 10, 11, 12 into equation 9:

$$c_h * \gamma * (H * discharging_{rate})^{2-2k} - c_l \geq \frac{10^5 * c_{unit}}{DoD_{limit} * V * Cycles_{DoD}} \tag{13}$$

The constant 10^5 appears due to the conversion between kWh → Wh and \$ → ¢. Equation 13 is the generalized version of equation 7, testing the feasibility of a battery deployment under ToU pricing with a peak and an off-peak price. The advantages of this closed form inequality are:

- 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 test if a battery configuration is feasible before the deployment.

Capacity Analysis: We analyze the capacity for both LFP and LA batteries, for which the Peukert exponent is 1.05 and 1.15 respectively. For both, the optimal capacity is on the order of 10^5 Ah. But, we know that the capacity is limited by equation 8, i.e. the optimal capacity 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.

Discharging Current Analysis: The discharging current should be adjusted so that the expected battery lifetime is close to the battery shelf life. Lower discharging current does not bring any benefits, as the battery lifetime does not improve further beyond its shelf life. The expected shelf life is 10 years for both LA and LFP batteries [3]. For a house-sized 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.

Depth-of-discharge Analysis: The optimal depth-of-discharge limit depends highly on the battery type. For this analysis we use the data from [11] for LA and LFP batteries along with our battery model. The most beneficial DoD limit for LFP and LA batteries are 50% and 20-30% respectively.

III. 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 1. 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.

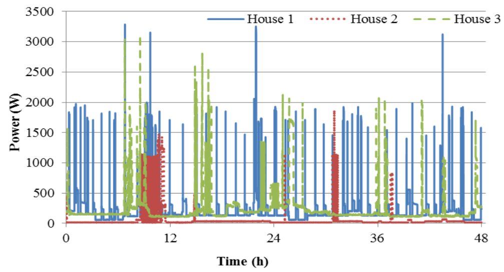

Fig. 1. Power demand profile of 3 houses from MIT REDD database [9]

We assume that these residences have two-level time-of-use (ToU) electricity prices, representing off-peak and peak electricity prices. We obtain these prices by taking the minimum and maximum limits of the CAISO market price (Figure 2) during the day [10]. In Table I, we apply the peak between 7am and 11pm and off-peak in the rest of the day [15].

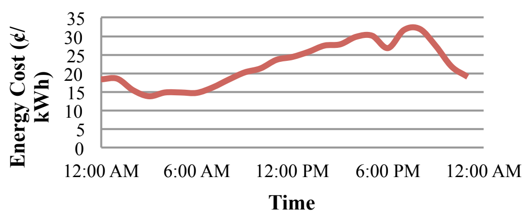

Fig. 2. Market electricity pricing from California ISO [10]

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

We simulate the power profile of a house for a single day, corresponding to average, with different battery configurations. 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.

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 [18]	1.05 [18]
Battery shelf life	10 years [3]	10 years [3]
Battery efficiency	80% [4]	92% [4]
Battery nominal voltage	12V [11]	

Case 1: First, we study the case where the off-peak and peak prices are 10 and 35 ¢/kWh, respectively. This corresponds to CAISO pricing data we have [10]. Before carrying our simulation study and battery lifetime analysis, we put the battery parameters in equation 13 and see that the inequality is:

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

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. Also, simulation results show that the LFP battery brings profit only for DoD values between 50-70%, and C/20 discharging current rate. When the discharging 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. With this configuration the LFP battery lifetime is around 8 years.

TABLE III. Optimal Battery Capacity For Case 1 Pricing

	LA		LFP	
	Capacity (Ah)	**Savings ($)**	**Capacity (Ah)**	**Savings ($)**
H1	N/A		359	298
H2			138	89
H3			324	233

Case 2: In this case, we increase the gap between off-peak and peak electricity prices. We see that equation 13 is satisfied for:

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

We have a larger set of profitable configurations due to the larger price difference. Table IV shows the optimal battery configurations and the corresponding cost savings with case 2 pricing. Compared to case 1, the optimal LFP capacities slightly increase due to elevated price difference. 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. The optimal DoD levels for LA and LFP batteries are 20% and 60% respectively. LA battery limits DoD level more strictly since its performance degrades significantly with deeper discharges. 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 and reduce the battery replacements. Our analysis concludes that the capacity should be increased instead of the discharging current.

TABLE IV. Optimal Battery Configuration For Case 2 Pricing

	LA				LFP			
	Cap. (Ah)	**DoD**	**Cur. Rate**	**Savings ($)**	**Cap. (Ah)**	**DoD**	**Cur. Rate**	**Savings ($)**
H1	624	20%	C/20	481	359	60%	C/20	1145
H2	255	20%	C/20	166	138	60%	C/20	413
H3	497	20%	C/20	352	325	60%	C/20	1006

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

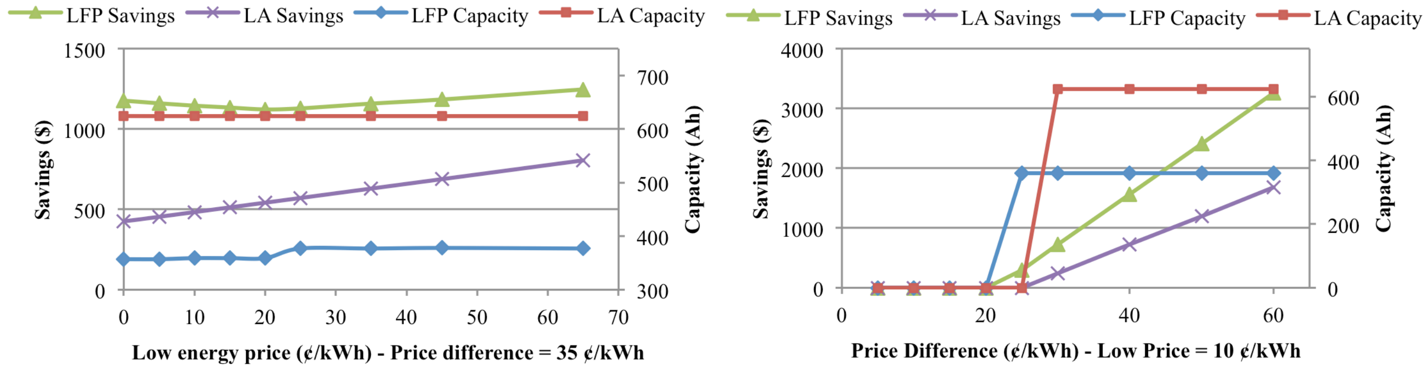

Fig. 3. Savings&capacity vs. price differences using House 1 power profile. a) Fixed 35 ¢/kWh price difference with changing low energy price, b) Increasing price difference with fixed 10 ¢/kWh low energy price

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, 29% on average.

Pricing Analysis: We study both a fixed price difference with varying low energy price (Figure 3.a) and a varying price difference with fixed low energy price (Figure 3.b) using the power profile of House 1. We select House 1 due to its higher demand, so that the effects of price changes are more visible. 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 dollars and the other represents the best capacity value in Ah. The x-axis shows the varying low energy price in Figure 3.a and the price difference in Figure 3.b. We set the price difference to 35¢/kWh in Figure 3.a because it is the lowest that we observe savings for the LA battery.

We see that the best capacity is almost fixed across different pricing schemes, supporting the fact that the best capacity depends highly on the power demand of the house. In Figure 3.a, the LA battery performs better as the low energy price gets higher. 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. In Figure 3.b, the LA battery needs larger price difference to obtain savings, but even with larger price difference, 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 3 for clarity. However, for both graphs, 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.

IV. CONCLUSION

Residential homes can benefit from using batteries to exploit electricity price differences applied by utilities. But, previous work neglected the effects of the nonlinear properties of the batteries. We develop a framework that models the nonlinear behavior of the batteries and tests the feasibility of a battery deployment. 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 show 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.

ACKNOWLEDGEMENT

This work was supported in part by TerraSwarm, one of six centers of STARnet, a Semiconductor Research Corporation program sponsored by MARCO and DARPA.

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