Optimizing Energy Storage Participation in Emerging Power Markets

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Abstract—**The growing amount of intermittent renewables in power generation creates challenges for real-time matching of supply and demand in the power grid. Emerging ancillary power markets provide new incentives to consumers (e.g., electrical vehicles, data centers, and others) to perform demand response to help stabilize the electricity grid. A promising class of potential demand response providers includes energy storage systems (ESSs). This paper evaluates the benefits of using various types of novel ESS technologies for a variety of emerging smart grid demand response programs, such as regulation services reserves (RSRs), contingency reserves, and peak shaving. We model, formulate and solve optimization problems to maximize the net profit of ESSs in providing each demand response. Our solution selects the optimal power and energy capacities of the ESS, determines the optimal reserve value to provide as well as the ESS real-time operational policy for program participation. Our results highlight that applying ultra-capacitors and flywheels in RSR has the potential to be up to 30 times more profitable than using common battery technologies such as LI and LA batteries for peak shaving.**

I. Introduction

A sustainable energy future mandates integrating a larger portion of renewable generation into the grid. Most states in the US and several European countries already have aggressive targets to increase the share of renewables in their portfolios [1], [2]. The fact that many forms of renewable generation are intermittent by nature (e.g., wind and solar) creates significant challenges for grid operators, who need to match supply and demand in real-time. In response to this challenge, emerging ancillary power markets provide sizable monetary incentives for the consumers to perform *demand response*, which refers to a consumer adjusting its own electricity use following a set of constraints or directives given by the grid operator.

Among potential demand response program participants, data centers, electrical vehicles (EVs), and smart buildings are especially promising, and have received recent attention from the research community [3], [4], [5], [6], [7]. This attention is due to their significant flexibility in energy consumption, as well as the large cumulative power consumption levels and/or fast growth these entities provide.

One of the most promising participation opportunities for demand response comes from using energy storage systems (ESSs), which can potentially charge/discharge depending on the demand response program requirements reliably. There are a variety of energy storage startup companies [8], [9] that use ESSs to participate directly in energy market programs this way. Additionally, entities such as data centers and smart buildings, which have on-site ESSs to manage power outages, can make use of ESSs to receive monetary incentives without having to alter their internal performance. ESSs have been studied for participation in well-known power programs such as real-time pricing [10], [11] and peak shaving [12], [13], but the potential of ESS participation in many of the emerging promising demand response programs has yet to be understood, such as regulation service reserves (RSR) and contingency reserves in emerging ancillary service markets [14], [15], [16]. Some recent work has begun to survey potential market chances and evaluate maturity of ESS participation in these programs [17], [18], [19], [20]; however, in most cases, these papers use simplified participation models, e.g., an RSR model that ignores regulation accuracy constraints and penalties [21]. Besides, few work studies the decisions of reserve value and the ESS capacity planning. Furthermore, different ESS technologies (e.g., lead-acid (LA) batteries, lithium-ion (LI) batteries, ultra/super-capacitors (UC), flywheels (FW), and compressed air energy storage (CAES)) have contrasting properties [22], [23], [24], which can dramatically impact profits of participation in such programs. Systematic evaluation and comparison of the benefits of using these ESS technologies in a variety of demand response opportunities do not exist in current literature.

This paper's goal is to thoroughly evaluate, optimize, and contrast a range of ESS technologies for participation in a variety of promising demand response programs. Our method seeks to provide a strategy for the selection and management of ESSs for a broad range of consumers (data centers, EVs, smart buildings) to maximize the incentives received from ancillary power markets, and hence, to minimize the electricity cost while helping stabilize the grid. To the best of our knowledge, ours is the first paper to provide detailed models, evaluate and optimize the profits of various ESS technologies in not only traditional power market programs such as peak shaving, but also in emerging smart grid demand response such as RSR and contingency reserves, by proposing detailed reserve value and capacity planning, as well as online ESS operational policies. Our specific contributions are:

First, we provide detailed models and optimization solutions for participation of ESSs in multiple smart grid programs, including RSR, contingency reserves and peak shaving (Section III-A to Section III-C). In each model, the cost of ESS equipment, the revenue received for demand response, and constraints required by the demand response program are formulated. The net profits are optimized based on these models, and the corresponding optimal decisions of reserve value, ESS capacity planning and the operational policies are derived. The generality and wide applicability of the models and solutions distinguish this paper from previous work.

Second, the proposed models and optimal solutions enable, for the first time in the literature, a thorough comparison of the benefits of different ESSs for participation in demand response opportunities (Section III-D). We highlight the ESS technology

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that is the most appropriate for each power program (and vice-versa). Results show that UC is the most profitable ESS for RSR, while LI battery is the best choice for peak shaving. Also, we show that none of today's typical ESSs can earn positive net profits from providing contingency reserves.

Finally, in addition to evaluation with offline optimization solutions, this paper proposes heuristic practical online policies for provisioning with different types of ESSs in RSR program (Section III-A4), which is the most profitable program among those studied. As opposed to the offline solution, our online solution does not require information of RSR signal in advance, and thus, is applicable for real-life use. The solution adaptively leverages the tolerable RSR signal tracking errors for pursing larger profits. Our solution is able to satisfy all constraints and thus guarantee the feasibility of the provision, while still achieving significant profits.

II. Energy Storage Systems

Storage technologies are becoming more cost-effective and wide spread and, at the same time, more lucrative market participation opportunities are emerging. In this paper, we focus on five popular ESSs, namely, lead-acid (LA) batteries, lithium-ion (LI) batteries, ultra/super-capacitors (UC), flywheels (FW), and compressed air energy storage (CAES). In the following, we briefly highlight important characteristics of each. The interested reader can refer to prior work [12], [22], [24] for more information.

Lead-Acid (LA) batteries are widely used in daily life, e.g., in car batteries. They have very low self-discharge loss rates, which makes them suitable for the demand response programs with long durations, e.g., hours. Additionally, they have moderate energy cost and power cost, and therefore are robust under different market scenarios. However, the key disadvantage of LA batteries is the relatively small number of charge/discharge cycles and shorter float life. LA batteries can only be used for several thousand circles.

Lithium-Ion (LI) batteries are also widely used in our daily life, and have similar characteristics to LA batteries. The key difference is that LI batteries have relatively higher costs, longer lifetimes, more cycles, and higher efficiency.

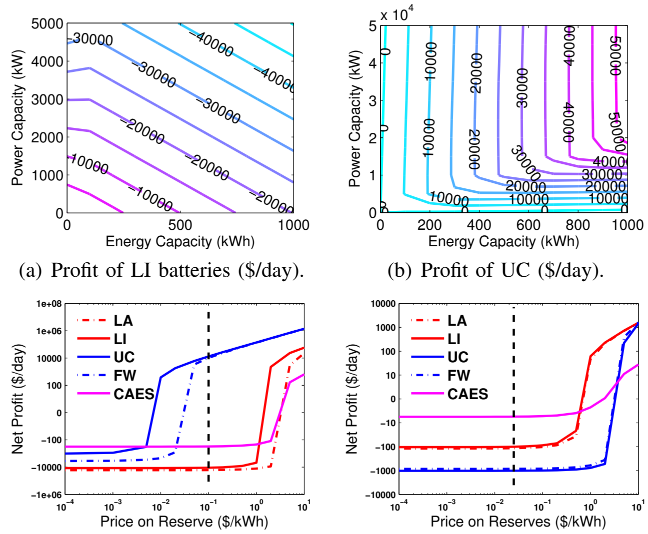
Ultra/super-Capacitors (UCs) differ dramatically from LI and LA batteries. UCs have an extremely high tolerance for frequent charging/discharging. Additionally, UCs have high efficiency and power density. However, they have a high energy cost (around \$10,000/kWh) and high self-discharge rate.

Flywheels (FWs) represent a middle ground between LI/LA batteries and UCs. Like UCs, they have high efficiency and power density, but also high energy cost and a high self-discharge rate.

Compressed Air Energy Storage (CAES) has a very low energy cost and self-discharge rate. However, it has a very slow ramping time (10 min vs. 1ms in the other four ESSs). This means that it cannot adapt quickly, which limits participation of CAES in some market programs. Additionally, it has a very low energy density (large space needed) and a high power cost.

III. Market Opportunities for Energy Storage Systems

In this section, we propose detailed models of ESS participation in various electricity market programs, including RSR, contingency reserves, and peak shaving. Then we compute optimal solutions and evaluate the potential benefits of each type of ESS in participating these energy market opportunities. We derive the optimal selections of ESS energy and power capacities, as well as the optimal ESS operational policy (including the amount of reserves to provide, and the solution of how to dynamically charge and discharge over time, etc.) for maximizing profit. After that, we evaluate applying these ESSs with today's typical capacities, and conduct sensitivity analysis of the maximal net profit on the price of reserves. We also propose online heuristic policies for ESSs participating in RSR. Finally, we compare the benefits of these ESSs participating in each program.



(a) Profit of LI batteries (\$/day). (b) Profit of UC (\$/day).

(c) Impacts of price for RSR. (d) Impacts of price for CR.

Fig. 1. (a), (b) and (c) are ESSs in RSR, and (d) is ESSs in CR.

A. Regulation Service Reserves (RSR)

Historically, RSRs were mainly provided by centralized generators, but market rules are changing to encourage demand-side participation. This emerging demand response opportunity is quite attractive due to the high payments comparable to the real-time market price [25], [14]. RSR programs are typically quite demanding for participants. Each RSR provider is obligated to modulate its power to track an RSR signal β_t broadcast every 4 seconds (this defines the length of one time slot) by the independent system operator (ISO) [25]. The signal is between $[-1, 1]$, with an average of zero over long time intervals. It is updated every 4 seconds in increments that do not exceed $\pm 4/\tau$, where τ is in 100-300 seconds [15].

1) Problem Formulation: A provider receives $\Pi^{RS} \cdot R$ revenue for providing R (kW) amount of reserves, where Π^{RS} is the price of reserves. The revenue is reduced based on the tracking error of the RSR signal, i.e., $|u_t - R\beta_t|$, where u_t is the power rate. The overall daily revenue received from RSR participation ($T = 1$ day) is:

$$Revenue_{RS} = \Pi^{RS} R - \theta \cdot \Pi^{RS} (\frac{1}{T} \sum_{t=1}^{T} |u_t - R\beta_t|), \quad (1)$$

where θ is the penalty coefficient on the tracking error.

The provider may lose the RSR contract if the constraint on signal tracking performance is violated. We formulate this using a probabilistic constraint:

$$\sum_{t=1}^{T} \mathbb{I}_{\{|\frac{u_t}{R\beta_t} - 1| \le \rho_1\}} \ge \rho_2 T \quad (2)$$

where ρ_1 and ρ_2 are parameters set by the ISO. This equation shows that the probability of tracking error at each time t, (i.e., $|u_t - R\beta_t|$) that is smaller than $\rho_1 R|\beta_t|$ should be greater than or equal to ρ_2. The overall optimization formulation of ESSs in RSR is:

$$
\begin{aligned}
\max_{E_{cap},P_{cap},R,\mathbf{r},\mathbf{d},\mathbf{u},\mathbf{e}} \quad & \Pi^{RS}R - \theta\cdot\Pi^{RS}\frac{1}{T}\sum_{t=1}^{T}|u_t - R\beta_t| \\
& -(\Pi^{P,d}P_{cap} + \Pi^{E,d}E_{cap}), \\
\textbf{s.t.} \quad & \sum_{t=1}^{T}\mathbb{I}_{\{|\frac{u_t}{R\beta_t}-1|\le\rho_1\}} \ge \rho_2 T, \\
& e_t = e_{t-1} - \mu e_{t-1} + r_t - d_t,\ \forall t\in[1,T], \\
& u_t = r_t/\eta - d_t,\ \forall t\in[1,T], \\
& 0\le r_t \le \frac{P_{cap}}{\gamma},\ 0\le d_t\le P_{cap},\ \forall t\in[1,T], \\
& (1-DoD)E_{cap}\le e_t\le E_{cap},\ \forall t\in[0,T], \\
& d_{t+1}-d_t \le \frac{P_{cap}}{T^{ramp}},\ \forall t\in[1,T-1], \\
& P_{cap}\ge 0, E_{cap}\ge 0, R\ge 0.
\end{aligned}
\tag{3}
$$

In the formulation, P_{cap} (in kW) and E_{cap} (in kWh) represent the power capacity and energy capacity of the ESS, $\Pi^{P,d}$ (in \$/kW) and $\Pi^{E,d}$ (in \$/kWh) are the corresponding daily prices amortized by the lifetime of ESSs[1]. The lifetime is determined by the face-plate lifetime, the maximal charge/discharge cycles and the real charge/discharge frequencies when the ESS is in use. r_t, d_t, u_t and e_t are the charge, discharge, overall power rate and the total energy stored in the ESS at time t. We use $\mathbf{r}$, $\mathbf{d}$, $\mathbf{u}$ and $\mathbf{e}$ to denote the vectors of r_t, d_t, u_t and e_t, respectively. μ is the self-discharge rate, η is the energy charging efficiency, γ is the ratio of discharge rate to charge rate, DoD is the Depth of Discharge, which helps guarantee the lifetime of the equipment. T^{ramp} is the time for ESS to ramp up the discharge rate from 0 to P_{cap}. The objective function is to maximize the net profit of the participation, which equals to the revenue for providing reserves (reduced by the tracking error) minus the amortized cost of ESS equipment. The constraints are imposed by both the demand response program (RSR here) and the ESS technology (including the charge/discharge rates and the amount of energy stored, constrained by power/energy capacities, DoD and ramp up rate, etc). Due to the space limitation, interested readers can refer to an extended version of this text [26] for details in problem formulation. The decision variables of this optimization problem are:

- Power and energy capacities of ESS, i.e., (P_{cap}, E_{cap});
- The amount of reserve to provide, i.e., R;
- $\mathbf{r}$, $\mathbf{d}$, $\mathbf{u}$ and $\mathbf{e}$, which represent how the ESS is operated dynamically, i.e., the operational policy.

2) Case Study: To evaluate the potential value from RSR program, we solve the above optimization formulation for the types of ESSs introduced before. We use parameters defined by prior work [12]. The RSR signal β_t that we use is a real 24-hour signal from PJM [25]. Additionally, $\rho_1 = 0.2$, $\theta = 1$ and $\Pi^{RS} = \$0.1$/kWh based on today's markets [14].

The probabilistic constraint makes Eq.(3) not straightforward to solve. To simplify the problem, we first study the case of $\rho_2 = 1$, in which the probabilistic constraint in Eq.(2) can be transformed to a deterministic constraint:

$$\left|\frac{u_t}{R\beta_t} - 1\right| \le \rho_1, \forall t\in[1,T]. \tag{4}$$

Heuristic solutions of $\rho_2 < 1$ are discussed in Section III-A3.

At the current reserve prices ($\Pi^{RS} = \$0.1$/kWh), the optimal solution of Eq.(3) for LA, LI batteries and CAES are all $P^*_{cap} = E^*_{cap} = R^* = 0$, which demonstrates that there is no net profit of LA, LI batteries or CAES to participate in RSR program, i.e., the ESS cost of them is always larger than the revenue received from the program, no matter what the power and energy capacities are used or how they are operated dynamically. On the other hand, there is no feasible optimal solution of Eq.(3) for UC and FW: the net profit keeps increasing as P_{cap}, E_{cap} and R increase, which demonstrates that the maximal net profit is large for UC and FW, as long as sufficiently large power and energy capacities can be offered. This highlights that the revenue earned by UC and FW from RSR is always larger than the amortized cost of the ESS.

TABLE I. A SELECTION OF TODAY'S TYPICAL CAPACITIES OF ESSS, BASED ON SPACE CONSTRAINTS.

	LA	LI	UC	FW	CAES
P_{cap} (kW)	1,000	1,000	20,000	10,000	20
E_{cap} (kWh)	250	250	250	250	250

We then study the sensitivity of net profit to energy, power capacities. Fig.1(a) and Fig.1(b) present the optimal net profit (the negative value represents that the cost of ESS is larger than the revenue, hence the net profit is less than 0) for varying energy and power capacities (E_{cap}, P_{cap}), and for LI batteries and UC respectively, in contour plots. LA batteries have similar results to LI batteries, and FW is similar to UC. From the figures, we see that for LA/LI batteries, the net profits of participating RSR are always negative, and the larger capacities of them are used, the higher cost there would be. On contrary, for UC and FW, a larger (E_{cap}, P_{cap}) creates larger net profit.

The main factors that lead to such differences among ESSs are related to the characteristics of the ESSs. Since the RSR signal changes rapidly (every 4 seconds) and bidirectionally, in order to track it, RSR providers must have a large power capacity and large charge/discharge cycles. A large energy capacity, however, is not necessary, as the RSR signal has an average of zero over longer time intervals. UC and FW perfectly match these RSR characteristics: they have extremely high tolerance for frequent charging/discharging, high efficiency and power density, and relatively low power capacity cost, whereas under the high charge/discharge frequency in RSR, the lifetime of LA or LI batteries is shortened to less than 10 days due to the limited life cycle, which results in great cost and thus they no longer gain any net profit from RSR participation. CAES is even more limited due to the very large ramp up delay in discharge and the extremely small power density.

Next we focus on the RSR participation of different ESS technologies with today's typical capacities. In practice, the power and energy capacities of ESSs usually have upper bound limitations due to the restrictions of manufacturing techniques, unit prices and space constraints. Table I lists a selection of today's typical capacities of different types of ESSs referring to recent work [12], [22], [23], [24], estimated mainly based on space constraints[2]. The power capacity of CAES is small due to its extremely small power density. The optimal net profit and the corresponding optimal R^* of these typical ESSs in RSR are listed in the 3^{rd} row of Table III[3]. From the table, today's typical UC or FW can provide around 6MW RSR, and gain more than \$10,000 net profit a day, which are close to the

[1]The life span of an ESS is normally years with one-time upfront purchase/installation cost, yet participation in a demand response program can span a year, a month, or even a day. In order to handle the mismatch in time granularity, we amortize the upfront cost evenly over the lifespan of the ESS.

[2]Since we have taken the cost and unit price information into account in the problem formulation, we no longer consider it as a problem in determining typical capacities of ESSs here.

[3]All results listed in Table III are the optimization solutions of Eq.(3) when E_{cap} and P_{cap} are given as in Table I.

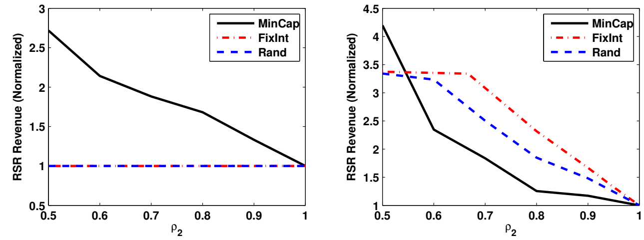


Fig. 2. The revenue of providing RSR via varying ρ_2, for LI batteries (in 2(a)) and UC (in 2(b)), with three heuristic offline solutions, respectively. The revenue is normalized to the value of $\rho_2 = 1$.

power consumption and the cost of a data center with 10,000-20,000 servers. The cost of this typical UC or FW is around \$4 million, which can be paid back in less than one year by receiving RSR credit.

Fig.1(c) shows the optimal net profit via varying reserve price Π^{RS}, for different types of ESSs with their capacities fixed and given in Table I. The black dashed line represents where the current market reserve price is around. From the figure, LI, LA batteries and CAES start to gain net profit (the value of the net profit is larger than 0) when the reserve price Π^{RS} is beyond \$1/kWh.

3) Heuristic Solutions for the Probabilistic Constraint: We propose three heuristic offline solutions to deal with the probabilistic constraint in Eq.(2) when $\rho_2 < 1$. The key idea behind these solutions is to determine when the signal should be tracked within the tolerance ρ_1 (i.e., satisfying Eq.(4)), and when the tolerance can be violated. Three solutions are:

RandSelect: Randomly select $\rho_2 T$ time intervals in $[1, T]$ to satisfy Eq. (4).

MinCapSelect: Select $\rho_2 T$ time intervals in $[1, T]$ with smallest $|\beta_t|$ to satisfy Eq.(4). This design is based on the fact that tracking RSR signal at the time interval t with larger $|\beta_t|$ requires larger power capacity.

FixIntSelect: Equally distribute $T - \rho_2 T$ time intervals that are allowed to violate the Eq.(4) in $[1, T]$. This is for the purpose of enabling the policy to adjust amount of energy stored in ESSs without closely tracking once a while.

Fig.2 shows the optimal RSR revenue solved based on Eq.(3) with these three solutions via varying ρ_2, for LI batteries and UC with typical capacities listed in Table I, respectively. ρ_1 is fixed at 0.2. Note that since we use the typical capacities in all cases, the cost of ESS is fixed. Thus, it is equivalent to make comparisons of these three methods based on either the RSR revenue, i.e., $Revenue_{RS}$ or the net profit originally used in the objective function of Eq.(3). In the figure, all the revenues are normalized by the revenue at $\rho_2 = 1$.

From Fig.2(a), *MinCapSelect* always achieves largest revenue for LI batteries when ρ_2 varies. The charge/discharge capacities, i.e., the power capacity are the main bottleneck for LI batteries to offer more reserves, while *MinCapSelect* can help reduce the requirement on power capacity by only tracking small $|\beta_t|$ and giving up tracking large $|\beta_t|$, hence enabling LI batteries to provide additional reserves. The results for UC, however, are different. The power capacity is no longer the bottleneck, as today's typical UC has a much stronger power capacity compared to its energy capacity. As a consequence, energy capacity turns out to be the bottleneck. In that case, *MinCapSelect* does not help, and is even worse than the random algorithm *RandSelect*. A solution that is able to utilize the limited energy capacity in a more efficient way can provide more reserves and earn higher revenue. *FixIntSelect* becomes a better solution shown in Fig.2(b), because it equally distributes time points where constraint violations are allowed across the whole time frame, so that the energy amount stored in ESS can be adjusted periodically and uniformly. Fig.2 also shows that the optimal revenue increases when ρ_2 decreases. Relaxing the signal tracking constraints by decreasing ρ_2 in general offers more flexibilities for ESSs to participate the RSR program, and therefore, enables them to gain larger profits.

4) Online policies for RSR: Prior offline solutions are based on the fact that RSR signal is known a priori, which is not the real case in practice. RSR signal is broadcast to demand side every few second in real time. We propose heuristic online ESS operational policies for RSR participation, where no information on the RSR signal is required in advance. The online policies handle the following problems: given the types and capacities of the ESS (i.e., assuming the ESS has been setup), how much reserve should be provided and how the ESS should be operated so that higher revenue from RSR participation can be gained and the feasibility of the participation is guaranteed.

As discussed before, *MinCapSelect* provides the highest revenue for LI and LA batteries in the offline solution, and *FixIntSelect* is the best for UC and FW. We design the online operational policies for LI and LA batteries based on the *MinCapSelect* solution and the policies for UC and FW based on the *FixIntSelect*. Due to the space limitation, the detailed operational policies are provided in the extended version [26].

Unlike the offline solution, in which the RSR signal is known ahead, thus an optimal R can be calculated directly from the optimization formulation, the R_{onl} for the online policies is required to be carefully estimated. We propose an approach to learn R_{onl} from historical offline solutions, as $R_{onl} = \lambda R_{min}$, where R_{min} is the minimum of the offline optimal R in the past 12 hours (the signal has been known in those hours, so offline optimal R can be calculated), λ is a discount value. We use R_{min} and select λ to avoid aggressive estimation of R_{onl}, and to guarantee feasibility of our policies. We select $\lambda = 90\%$ for LI batteries and $\lambda = 75\%$ for UC, because LI batteries have more stable results, much smaller provision and are less sensitive to variations of ρ_2 than UC shown in offline solutions.

We evaluate both the feasibility and the efficiency of our online policies. Detailed experiments are in the extended version [26]. Experimental results show that these safely estimated R_{onl} together with our operational policies satisfy all constraints and, thus, are feasible solutions in all test cases, for both LI batteries and UC, which shows that the feasibility of such online policies is guaranteed with high confidence. In addition, these policies still receive promising revenues, though there is (as expected) a noticeable gap compared to offline solutions, due to the lack of RSR signal information, and the safe estimation of the reserve value R_{onl}. There is the following tradeoff: an aggressive online policy may bring the revenue close to optimal offline solutions, while the real-time feasibility of such solution decreases at the same time.

B. Contingency Reserves

In ancillary markets, contingency reserves are used to respond to loss of power supplies during generation or line failures. They are typically called by the market less than once a day, and some of them are called even less than once a year. A call typically lasts from several minutes to a few hours. Reserves that are able to respond immediately are known as *spinning reserves*, whereas reserves that require more time to respond are called *non-spinning reserves*. For example, NYISO provides 10-minute spinning and 10-minute non-spinning reserves. Another type of reserves, the *operating reserves*, are also provided by NYISO, as supplements of other reserves. Operating reserves have longer reaction time but also last longer, e.g., more than 30 minutes [14]. 10-minute spinning reserves have the highest price while the price of 30-minute operating reserves is the lowest. All these prices are significantly lower than that of RSR. Overall, due to the much lower frequency of calls as well as the lower price of the reserves, the revenue received from contingency reserve provision is much lower than revenue from RSR provision.

1) Problem Formulation: The revenue of contingency reserves can be modeled as:

$$Revenue_{CR} = \Pi^{CR} R, \tag{5}$$

where R is the amount of contingency reserves provided and Π^{CR} is the price of the reserve. Unlike RSR, the contingency reserve provision is single directional with:

$$r_t = 0, \quad d_t = R, \ \forall t \in [T_S, T_E], \tag{6}$$

where $[T_S, T_E]$ is a subset of $[1, T]$, representing that only at some t during a day, an ESS is used to provide contingency reserves. For the rest of the day, the ESS is not used. When providing contingency reserve, the ESS keeps discharging at the fixed rate as the reserve value R. In order to provide the maximal amount of reserves, an ESS is charged to its full energy capacity before response, i.e.,

$$e_{T_S} = E_{cap}. \tag{7}$$

The rest of equations in the optimization problem for ESS in contingency reserves are similar to those in RSR in Eq.(3).

2) Case Study: We focus on the 10-minute spinning reserve as an example of contingency reserves, as it is expected to have the highest revenue. Π^{CR} = \$0.025/kW is selected for the 10-minute spinning reserve based on today's market information [14]. We assume the 10-minute spinning reserve is called once a day in our case, and $T_E - T_S = 10$min.

The optimal solution for all five ESSs in contingency reserve are: $P^*_{cap} = E^*_{cap} = R^* = 0$, which shows that none of five ESSs gain net profit by only providing contingency reserves at today's market reserve price, no matter what the power and energy capacities are used, and how they are operated. The larger the capacities (E_{cap}, P_{cap}) are used, the more reserves R that an ESS can provide, however, as well as the higher the cost of ESS would be, and the cost is always larger than the revenue from providing R.

The 4^{th} row in Table III shows results of maximal net profit of contingency reserve and corresponding amount of reserve for today's typical ESS capacities, i.e., (E_{cap}, P_{cap}) given from Table I. It highlights that none of today's typical ESSs earn profit from contingency reserves at today's reserve prices. Contingency reserves are demanding in terms of energy capacity (as opposed to power capacity), though the power capacity cannot be too low either. From the table, LA and LI batteries perform better than UC and FW, because of their lower price on energy capacity and relatively low self-discharge rate, but still not well enough to be profitable. Fig.1(d) presents the optimal net profit via varying reserve prices Π^{CR} for different ESSs. LI and LA batteries start to gain profit when the price is close to \$1/kWh, whereas the critical points of CAES, UC and FW are around \$5-8/kWh.

TABLE II. OPTIMAL SOLUTIONS FOR PEAK SHAVING.

	LA	LI	UC	FW	CAES
P^*_{cap} (kW)	$1.30 * 10^3$	769.19	148.39	147.85	645.36
E^*_{cap} (kWh)	$2.15 * 10^3$	$2.40 * 10^3$	29.82	29.93	$1.83 * 10^3$
Profit (\$/day)	607.40	592.57	326.68	354.08	933.94
R^*(kW)	377.75	399.04	148.39	147.85	388.80

C. Peak Shaving

The electricity bill charged monthly by utilities to large commercial and industrial power consumers, i.e., the operational expenditure (op-ex), typically consists of two parts: (i) the energy charge and (ii) the charge for the peak power during the month. The peak power is the maximum in the month of average power over each 15-30 minute duration. The price of the peak power (i.e., the op-ex peak power price) is around \$12/kW/Month currently. In addition, the one-time cost of building power infrastructure to provide capacities to satisfy the peak power requirements, i.e., the capital expenditure (cap-ex), is around \$10-20/W on peak power based on current estimates [12]. Thus, cutting peak power is an important way to reduce costs. This approach, termed peak shaving, is common and ESS provides a key method for implementation.

1) Problem Formulation: When participating in peak shaving, an ESS that shaves R amount of power from the peak power can gain revenue:

$$Revenue_{PS} = \Pi^{PS} R, \tag{8}$$

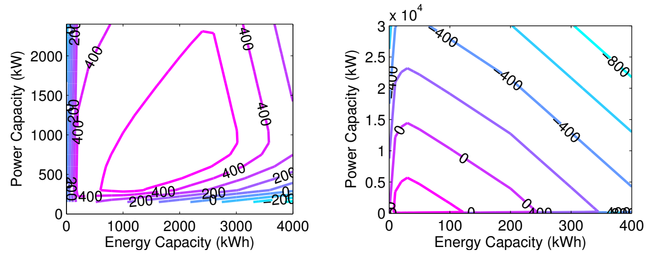
where Π^{PS} is the overall price on shaved power, i.e., the summation of the amortized capital (cap-ex) price and operational (op-ex) peak power price. The peak shaving constraints in formulation, i.e., $Constraint_{PS}$ are:

$$\begin{aligned} 0 \le p_t + u_t \le max(p_t) - R, \ \forall t \in [1, T], \\ e_0 = e_T, \end{aligned} \tag{9}$$

where p_t is the power curve before peak shaving, and $max(p_t)$ is the original peak power. u_t is the power change rate from the view of system level. $p_t + u_t$ is the new power curve after peak shaving, and $max(p_t) - R$ is the new peak power. $e_0 = e_T$ represents that energy stored in ESS is kept the same at the beginning and in the end of the time frame (in our study T = 1 day). The rest of equations in the optimization problem for ESS in peak shaving are similar to those in RSR in Eq.(3).

2) Case Study: We generate p_t from a real HP workload trace collected from a data center that consists of 5,000 servers. The peak power of this trace is 1MW, commonly seen in today's mid-size data center, and matches with the typical capacities of ESSs. Unlike the optimal solution of RSR or contingency reserves that is either 0 or maximal capacity allowed (i.e., no feasible optimal solution), the optimal solution of peak shaving can be in between. Table II lists the optimal solutions of different ESSs for peak shaving. All these optimal solutions lead to positive net profit. CAES has the maximal optimal net profit, though the corresponding capacities in the optimal solution is unrealistic due to its extremely small power and energy densities. LA and LI batteries have larger optimal net profit than UC and FW, though UC and FW can gain promising profit with very small capacities.

Fig.3(a) and 3(b) show the optimal net profit for varying energy and power capacities (E_{cap}, P_{cap}) in peak shaving, for LI and UC, respectively. These contour plots present where the optimal solution for each ESS is located. Fig.3(a) also shows that LI batteries can gain profit from peak shaving in most cases, except when the power capacity is very small. In Fig.3(b), the profit of UC is larger than 0 only when both



(a) Profit of LI batteries ($/day). (b) Profit of UC ($/day).

Fig. 3. ESSs in peak shaving.

TABLE III. COMPARING THE OPTIMAL NET PROFIT OF MULTIPLE TYPES OF ESSS (WITH E_{cap}, P_{cap} LISTED IN TABLE I) IN PARTICIPATING DIFFERENT PROGRAMS.

	LA		LI		UC		FW		CAES	
	Profit	R^*	Profit	R^*	Profit	R^*	Profit	R^*	Profit	R^*
RSR	-16.4k	0.17	-11.1k	0.29	13.0k	5.95	10.3k	5.94	-0.3k	0.004
CR	-0.12k	1.00	-0.10k	1.00	-1.02k	1.50	-0.85k	1.49	-0.006k	0.02
PS	0.41k	0.20	0.44k	0.20	- 0.46k	0.21	-0.31k	0.20	0.31k	0.13

[a]the unit of profit and R^* in table are $/day and MW.
[b]CR: contingency reserve; PS: peak shaving.

power and energy capacities are small, which shows that the marginal increase of the credit received from peak shaving by enlarging UC capacities is smaller than the increase in UC capacity cost. In addition, results show that CAES is always able to gain profit in peak shaving though large profit is not practical due to the limitations of power and energy densities.

Next, considering today's typical ESS capacities in peak shaving, the last row in Table III shows the optimal net profit and the corresponding optimal shaved power R^* of ESSs with typical capacities in Table I, and under today's cap-ex and op-ex market prices. From the table, UC and FW fail to gain net profit, whereas LA, LI and CAES earn net profit around $300-400 per day.

D. Discussion

We provide the optimal net profit of each ESS technology across the programs in Table III for today's typical capacities and market reserve prices. From the table, LA, LI batteries and CAES gain profit from peak shaving, whereas UC and FW gain profit from RSR. None of them gain profit from contingency reserve, due to its low price and low calling frequency. The maximal profit earned from emerging RSR (by today's typical UC or FW) is up to 30 times of the maximal profit that can be earned from traditional peak shaving program (by LA or LI batteries), which shows that there is a great opportunity for an ESS to gain significant profit from RSR provision in today's ancillary market. For providing RSR, UC and FW are the best choices due to their extremely high tolerance for frequent charging/discharging, high efficiency and power density, and relatively low power capacity cost, while LA, LI batteries and CAES are better choices for peak shaving, or contingency reserves (though are not profitable), because of their relatively lower cost on energy capacity and lower self-discharge rate.

IV. CONCLUSION

In this paper, we have modeled and studied the optimization solutions that maximize the net profit of various ESSs in different demand response programs. Our results show that typical UC and FW are the most profitable selections for RSR, while common battery techniques such as LI and LA batteries are the best choices for peak shaving. None of today's ESS technologies can earn positive net profits from merely providing contingency reserves. More importantly, applying UC/FW in RSR has the potential to be up to 30 times more profitable than LI/LA batteries for peak shaving. Additionally, we have proposed online policies for managing ESS participation in RSR program, the novel but most profitable option according to our studies. Our online policies guarantee the feasibility of RSR provisions, while also achieving significant profits.

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