

# Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets



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## HIGHLIGHTS

- Estimation of required cost reductions to make ESSs profitable for energy arbitrage.
- Comparison of 14 ESS technologies in 7 regional markets.
- Optimal sizing of ESSs to maximize the IRR for arbitrage in real-time energy markets.
- Pumped hydro, CAES, and ZEBRA ESSs result in the greatest IRR from energy arbitrage.

## ARTICLE INFO

### Article history:

Received 6 February 2013

Received in revised form 6 September 2013

Accepted 6 October 2013

Available online 29 October 2013

### Keywords:

Energy storage

Power markets

Arbitrage

## ABSTRACT

Energy storage systems (ESSs) can increase power system stability and efficiency, and facilitate integration of intermittent renewable energy, but deployment of ESSs will remain limited until they achieve an attractive internal rate of return (IRR). Linear optimization is used to find the ESS power and energy capacities that maximize the IRR when used to arbitrage 2008 electricity prices (the highest of the past decade) in seven real-time markets in the United States for 14 different ESS technologies. Any reductions in capital costs needed to achieve an IRR of 10% are solved for. Results show that the profit-maximizing size (i.e. hours of energy storage) of an ESS is primarily determined by its technological characteristics (round-trip charge/discharge efficiency and self-discharge) and not market price volatility, which instead increases IRR. Most ESSs examined have an optimal size of 1–4 h of energy storage, though for pumped hydro and compressed air systems this size is 7–8 h. The latter ESSs already achieve IRRs >10%, but could be made even more profitable with minimal cost-reductions by reducing power capacity costs. The opposite holds for Flywheels, electrical ESSs (e.g., capacitors) and a number of chemical ESSs (e.g., lead acid batteries). These could be made more profitable with minimal cost-reductions by reducing energy capacity costs.

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## 1. Introduction

Energy storage systems (ESSs) have the potential to revolutionize the way in which electrical power grids are designed and operated [1]. Presently, power grids require that the generation of electricity continuously balance the demand for it. Significant incorporation of ESSs into the grid would relax this constraint by enabling electrical energy to be withdrawn from the grid when there is excess generation and held in reserve until needed. Such reserve capacity could enable cost and emissions reductions from more efficient dispatch of generators, facilitate the integration of renewable, but intermittent power sources such as wind and solar, and provide numerous services that support grid reliability including frequency regulation, spinning reserve capacity, transmission

and distribution support [2], voltage support including VAR compensation [3], and grid stabilization during times of voltage deviation, reverse-power-flow, and over-power in distribution networks [4].

ESSs are already used for some of these purposes, but only to a minor extent [1,3,5–10]. In the United States, the focus of this study, there are 228 GW [2] of installed ESS capacity, which equates to ~20% of the nation's total generating capacity. However, just 2.5% of the total power delivered in the U.S. passes through an ESS [11], and 99% of these are pumped hydro facilities used by utilities for load balancing [2]. Furthermore, the deployment of additional pumped hydro has stalled due to (among other factors) declines in the price of natural gas and stricter environmental regulations for water use in power generation [12].

To date, ESSs other than pumped hydro have rarely been cost effective to install and/or operate. This situation may be changing with increasing capacity of intermittent wind and solar power

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generators, as these generators have fluctuating power outputs capable of increasing market price volatility [13]. This may improve revenue opportunities for ESSs engaging in price arbitrage, i.e. buying and storing energy when electricity prices are low and then selling and discharging the energy back to the grid when prices are high. The arbitrage potential of ESSs has been explored both for generic storage devices [14–16], and for specific ESS technologies in particular markets [11,17–25].

Energy storage systems can be characterized in terms of energy and power capacity, round trip efficiency, and self discharge. Energy capacity is the maximum energy a storage device can hold. Power capacity is the maximum rate at which energy can be transferred into and out of the device. Round trip efficiency is the ratio of output-to-input energy for a storage device throughout the charge and discharge of the device. And self discharge is the loss of energy due to parasitic losses in an energy storage system, where these losses may be due to mechanical friction, chemical reactions, etc., depending on the technology.

Previous studies of ESS arbitrage potential fix both the power and energy capacities, the ratio of which (i.e. energy/power capacity) determines the maximum hours of energy the device can store. However, [26] has shown that this ratio directly affects the arbitrage profitability of an ESS. Thus by arbitrarily fixing power and energy capacity, these studies do not optimally size each ESS, which may prevent the estimation of the highest potential IRR, nor do they quantify the required reduction in power and/or energy capacity capital costs to enable each ESS to yield an acceptable IRR.

Similar to [17,26], a linear optimization model is used, to solve for the maximum possible profit an ESS could achieve through price arbitrage assuming perfect foresight of past price data from a number of major U.S. real-time electric markets. In this analysis, however, the energy and power capacities of the ESS that would yield this maximum profit are also determined. The breadth of currently available storage technologies for use in power grids are evaluated, including: three that store and generate electricity via mechanical energy – pumped hydroelectric (PH), compressed air energy storage (CAES) and flywheels (FW); three devices that store energy electrically – capacitors (CAP), electrochemical double layer capacitors otherwise known as super- or ultra-capacitors (EDLC), and superconducting magnetic energy storage (SMES); and eight batteries that utilize chemical storage – lead acid (LA), nickel-cadmium (NiCd), lithium-ion (Li-ion), sodium-sulfur (NaS), sodium nickel chloride (a.k.a. ZEBRA), zinc-bromine (ZnBr), polysulfide bromide (PSB), and vanadium redox (VR).

The economic viability of using each ESS for price arbitrage based on its modeled internal rate of return in the example markets is assessed. The internal rate of return or IRR is the discount rate that would make the net present value of the investment project equal to zero. It is used here because it is independent of ESS lifetime and power/energy capacity (e.g., the IRR of a 30-year, 1 kW ESS can be directly compared to the IRR of a 5-year, 1 MW ESS). It is arbitrarily assumed that ESSs with an IRR <10% are deemed unprofitable. The minimum changes to current power and energy capacity costs for an ESS that would generate >10% IRR in the most and least profitable of the example markets are then solved for. Consequently, the results of the analysis point to what may be the most cost-effective way to improve the economics of the ESSs for price arbitrage.

Note that while this analysis is limited to the arbitrage potential of ESSs in real-time energy markets, ESSs might also be economically used in the ancillary-service, capacity, and day-ahead energy markets. The ancillary service markets include the reserve capacity market for contingency scenarios, and the frequency regulation market for high-speed, second-to-second power balancing. Both of these sub-markets might yield additional revenue opportunities for ESSs [22], but participation in the reserve capacity market alone has yet

to prove profitable [2], and there is uncertainty over how much additional “compensation” ESSs might receive in the frequency regulation market because FERC Order No. 755 (which requires markets to compensate faster-responding units such as ESSs for signal-following accuracy) has yet to be fully implemented. Uncertainty also exists in capacity markets over what payment is appropriate for ESS capacity [26]. And while the day-ahead market is similar to the real-time market, prices in the latter are generally more volatile than in the former [27,28], so if an ESS is unprofitable in the real-time market, the same is likely to be true in the day-ahead market. Hence we do not explore any of these other market options here.

## 2. Methods

### 2.1. Price arbitrage optimization model

Fig. 1a depicts our model of the simulated interaction of an ESS and a power grid for the purpose of price arbitrage. The energy  $E$  (kW h) stored in the device at time  $t$  is given by

$$E(t) = (1 - \delta)E(t - \Delta t) + [\eta P_c(t) - P_d(t)]\Delta t \quad (1)$$

where  $\delta$  is the fractional loss of energy over the interval  $\Delta t$  due to parasitic losses, or self-discharge,  $\eta$  is the roundtrip efficiency of the storage device,  $P_c(t)$  (kW) is the charging power from the grid at time  $t$  (h), and  $P_d(t)$  (kW) is the discharging power from the device at  $t$ . Note that  $E(t) = 0$  at  $t = 0$ .

The linear program for maximizing the arbitrage revenue  $r$  (\$) in a year, assuming time periods of 1 h (i.e.  $\Delta t = 1$  h) is expressed as

$$\text{Max } r = \sum_{t=1}^{n=8760} \pi(t)[P_d(t) - P_c(t)]\Delta t \quad (2)$$

subject to the following constraints

$$\begin{aligned} 0 &\leq P_d(t), P_c(t) \leq P_{\max} \forall t \\ 0 &\leq E(t) \leq E_{\max} \forall t \end{aligned} \quad (3)$$

In these Equations,  $n$  is the number of 1-h periods (i.e.  $n = 8760$  h in a year – the most optimistic estimate for it assumes there will be no maintenance downtime). The price of electricity at hour  $t$  is  $\pi(t)$  (\$/kW h),  $P_{\max}$  (kW) is the power capacity of the device (the maximum charge or discharge rate), and  $E_{\max}$  (kW h) is the device's energy capacity (the maximum energy the device can store). Fig. 1b shows a sample of the revenue-maximizing operation of the model in which the ESS charges when the price of electricity is low and discharges when it is high.

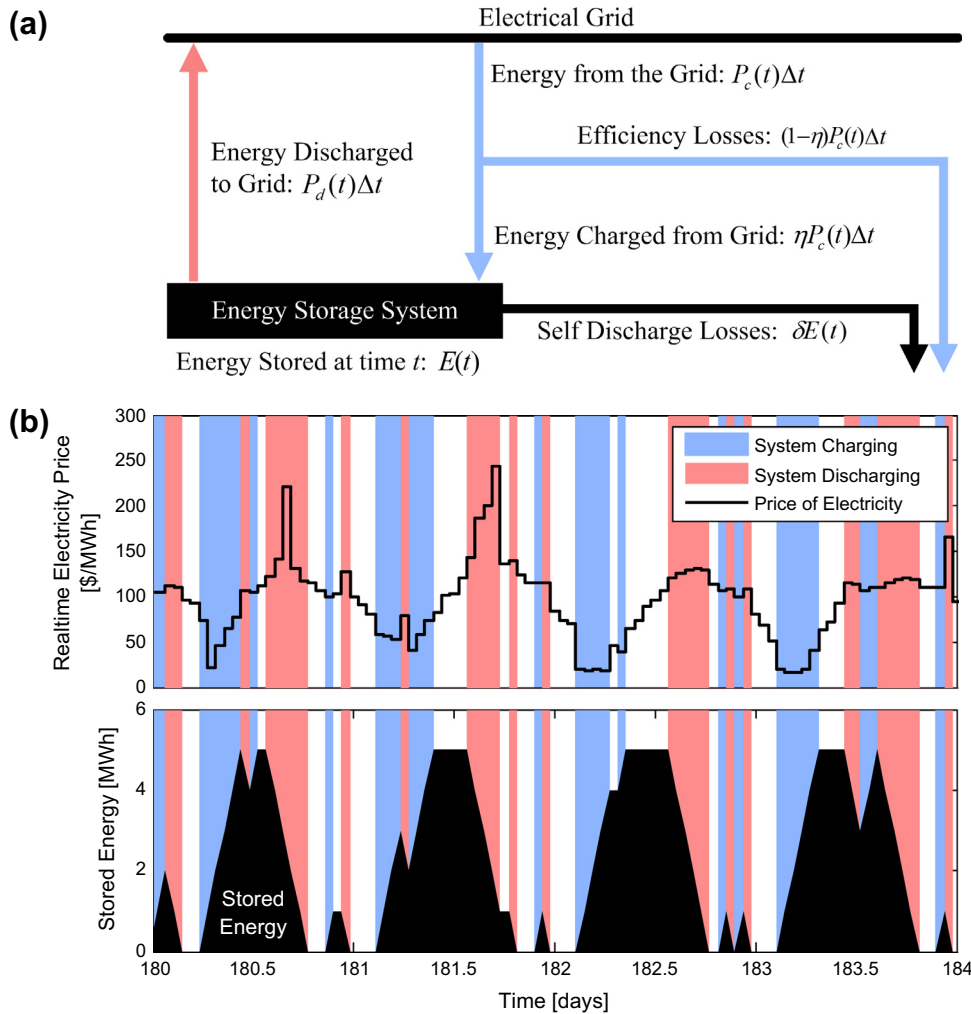
Eqs. (1)–(3) is solved using as input a yearlong time series of one-hour interval electricity price data to arrive at a representative annual revenue  $r$  for the ESS. Then,  $r$  is used to calculate the present value (PV) of the total revenue the ESS would generate over its lifetime,  $R_{PV}$  (\$) as given by

$$R_{PV} = (r - c_{om}) \sum_{i=1}^{L(N_c)} \frac{1}{(1 + \rho)^i} \quad (4)$$

Here  $c_{om}$  is the annual operations and maintenance (O&M) cost,  $\rho$  is the discount rate, and  $L(N_c)$  is the lifetime of the storage device, which, for many technologies, depends on the number of times the ESS is cycled per year.

$$L(N_c) = \min \left\{ \frac{L_c}{N_c}, L_y \right\} \quad (5)$$

In Eq. (5),  $L_y$  is the maximum lifetime of the device in years,  $L_c$  is the lifetime of the device in cycles, and  $N_c$  is the average number of cycles per year, measured as the total energy charged annually to the device divided by the energy capacity of the device.



**Fig. 1.** ESS operation in energy markets. (a) Flowchart of the general model of interaction between an energy storage device and the grid. Roundtrip efficiency losses are incurred at the time of charge, and at each time step there are self-discharge losses based on the level of stored energy. (b) Sample of four days of revenue-maximizing operation showing hourly real-time price variations (upper) and stored energy (lower) for a 1 MW/5 MW h ideal ESS.

For the overnight capital cost of the ESS,  $C$ , a linear function of energy and power capacity is assumed. Here,  $c_E$  and  $c_P$  are the capital cost of energy (\$/kWh) and capital cost of power (\$/kW), respectively.

$$C = E_{\max}c_E + P_{\max}c_P \quad (6)$$

The energy-to-power capital cost ratio (CCR) is represented as  $c_E/c_P$ , while the hours of energy storage at the maximum discharge rate is given by  $E_{\max}/P_{\max}$ .

$R_{PV}$  and  $C$  are used to calculate the IRR by solving Eq. (7) for the discount rate that yields zero net present value.

$$-C + (r - c_{om}) \sum_{i=1}^{L(N_c)} \frac{1}{(1 + IRR)^i} = 0 \quad (7)$$

Note that this is a nonlinear equation, which is solved via the Newton–Raphson technique.

## 2.2. Storage device parameter assumptions

Eqs. (1)–(7) require input values for roundtrip efficiency, self-discharge rate, energy capacity, power capacity, and the operational lifetime of the device, the latter being dependent on the number of charge/discharge cycles. Estimates for these parameters for each of the 14 ESSs were obtained from [1,2,8,15,29,30], and are given in Table A.1 in the Appendix. Table A.1 also contains

the most recent publicly reported values for the capital costs required by Eqs. (4) and (7). For this analysis, benchmark parameter and cost estimates were chosen from [1] for consistency since they include estimates for all of the ESSs analyzed in this study, while acknowledging that the true costs of these systems are rapidly changing.

Capital costs include the per-unit-energy capacity, per-unit-power capacity, power conversion system (PCS), and balance-of-plant (BOP) costs. The PCS costs are for all the components linking the storage device to the power grid including power conditioning equipment, control systems, power lines, transformers, system isolation equipment, and safety sensors. The BOP costs encompass construction and engineering costs, land, access routes, taxes, permits, and fees. These costs were included within the power and energy capital cost estimates of each system presented in Table A.1. It is assumed that each capital cost component for an ESS (i.e. power and energy capacity costs) scales linearly [1,31], so IRR will not vary with system size. For example, a 2 MW h/2MW system will yield twice the arbitrage value of a 1 MW h/1MW system, but since the former would also cost twice as much as the latter, the IRR for this ratio of power and energy capacities in the ESS will remain the same.

With the exception of CAES, fixed and variable O&M costs for the ESSs tend to be negligible [30], so they are omitted. CAES on the other hand requires natural gas, so its variable operating cost

could be significant. For this analysis, natural gas costs of \$5/MCF are assumed.

### 2.3. Electricity price data

The arbitrage potential of the 14 ESSs is assessed using 2008 locational marginal price (LMP) data from major nodes in seven U.S. wholesale electricity markets. The nodes are examples of many in the markets and so are not meant to be representative of them but rather illustrate the range of price volatility across the markets. The nodes are New York City in NYISO, the Houston zone in the ERCOT, the American Electric Power (AEP) LMP in PJM, Ameren in SPP, Alliant Energy Corporation (AEC) in MISO, San Francisco in CAISO, and the northeastern Massachusetts/Boston region in ISO-NE. Year 2008 was chosen because prices exhibited high volatility, and in some months reached the highest average electricity prices of the last decade [32].

In these real-time market nodes, the price of electricity is determined by supply and demand and is typically struck in the hour preceding the settlement interval. Since the majority of real-time markets have at most a 1-h interval, and this is the periodicity of the data available from all markets, a 1-h interval is assumed for this analysis. The means and standard deviations of 2008 prices among are plotted in Fig. A.2. Note that during this time period, the nodes/zones with the greatest price volatility (as measured by the standard deviation) were (1) Houston, (2) New York, and (3) San Francisco, while those with the least volatility (measured by standard deviation of price) were (1) AMRN, (2) AEP, and (3) AEC.

## 3. Results and discussion

### 3.1. Model sensitivity

The arbitrage revenue of an ESS depends on the round-trip efficiency and self-discharge of the device, as well as on its energy-to-power capacity ratio or hours of energy storage. We also informally refer to this as the system size. Fig. 2 illustrates how the arbitrage revenue calculated by the model changes among the different real-time markets as one model input is varied and the other two are held constant. The plots in this figure are for a 1 MW ESS having ideal base values of 0% self-discharge, 100% round-trip efficiency, and 30 h of energy storage respectively. Also shown beneath the plots are graphs of the published ranges of these parameters for the 14 ESSs.

In general, arbitrage revenue decreases as daily self-discharge of an ESS increases because more electricity must be purchased to keep the ESS sufficiently charged for dispatch (Fig. 2a). Most of the ESSs analyzed here have low (<5%) daily self-discharge (Fig. 2d), but there are a number of devices that lose a significant amount of energy over the course of a day. The worst are FWs, which lose all of their stored energy within 24 h (Fig. 2d) due to friction in the system's bearings. Daily losses of 20–40% also occur in CAP, EDLC, and NaS storage systems, while SMES and ZEBRA systems lose 15% (Fig. 2d).

In contrast to self-discharge, arbitrage revenue increases as round-trip efficiency increases because less energy and thus less revenue is lost as the energy is transferred between the ESS and the grid during charging and discharging. All of the ESSs analyzed here have an efficiency  $\geq 60\%$ . With one exception, the most efficient of these are the same devices that suffer from high self-discharge, i.e. FWs, EDLCs, NaS, SMES and ZEBRA storage systems. The exception is Li-ion batteries, which not only have among the highest (90–98%) efficiencies but also are among the lowest (0.1–0.3% per day) self-discharge.

Arbitrage revenue also increases with increasing hours of energy storage in an ESS, but nonlinearly. Revenue grows rapidly as energy storage rises from 0 to 5 h but then approaches an asymptote at storage capacities of  $\geq 15$  h due to the diurnal periodicity of electricity prices. As a result, ESS storage capacities of less than or equal to about half a day can extract the majority of arbitrage revenue.

Note that revenue also depends on the real-time market that the ESS is operating in. Of the markets analyzed, Houston is the most profitable while Boston is the least, being <60% as lucrative as Houston. Recall that Houston was the most volatile market; its standard deviation was almost double that of the second most volatile market, New York City. Boston on the other hand was among the least volatile with a standard deviation of about a third to a quarter that of Houston.

### 3.2. Arbitrage potential of current ESS technologies

The simulated maximum IRRs for the 14 ESSs in the seven example real-time markets are plotted in Fig. 3. Also included in the figure are the associated optimal system sizes for each ESS, i.e. the hours of storage that yield the maximum IRRs. Both of these results were generated by running the arbitrage model for the profit maximizing size of each ESS in each market using the ranges of round-trip efficiency, daily self-discharge, operational lifetime, and power and energy capital cost estimates for the ESS from [1] listed in Table A.1.

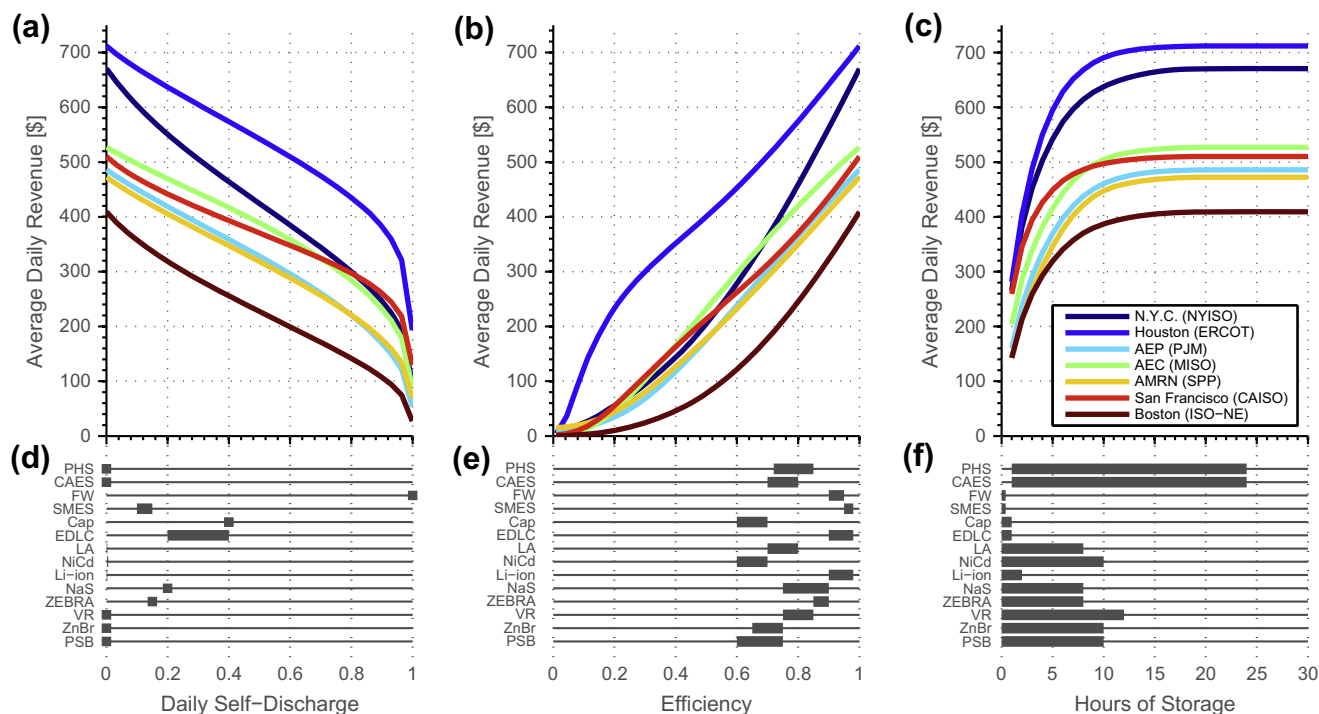
With the exception of FW, mechanical ESSs appear to have the greatest IRR potential (Fig. 3). FW has negative IRRs for all performance characteristics in all markets, but when the best performance characteristics for PHS and CAES are modeled, both achieve IRRs well in excess of 10% in every market except Boston. Note though that the IRR for CAES is sensitive to fuel costs for natural gas, and that if the latter is raised from \$5/MCF to \$10/MCF, CAES becomes substantially less profitable (Fig. 3). The optimal size for PHS and CAES ranges between 2 and 14 h of energy storage. For FW, it is  $\leq 1$  h, which is ineffectual for real-time markets with one-hour settlement periods and explains why the IRRs for FW are so low, as self-discharge would dissipate most of the energy from the device if stored for an hour or more.

The IRRs for Chemical ESSs are generally poor. The exception is ZEBRA ESSs, which yield among the highest IRRs modeled. The only other chemical ESS to achieve an IRR >10% is LA, but only in the Houston market in the most optimistic case. For all other chemical ESSs, maximum IRRs fall below the 10% threshold and in most cases are negative. The optimal storage capacities for chemical ESSs range from  $\sim 1.5$  to 6 h (Fig. 3).

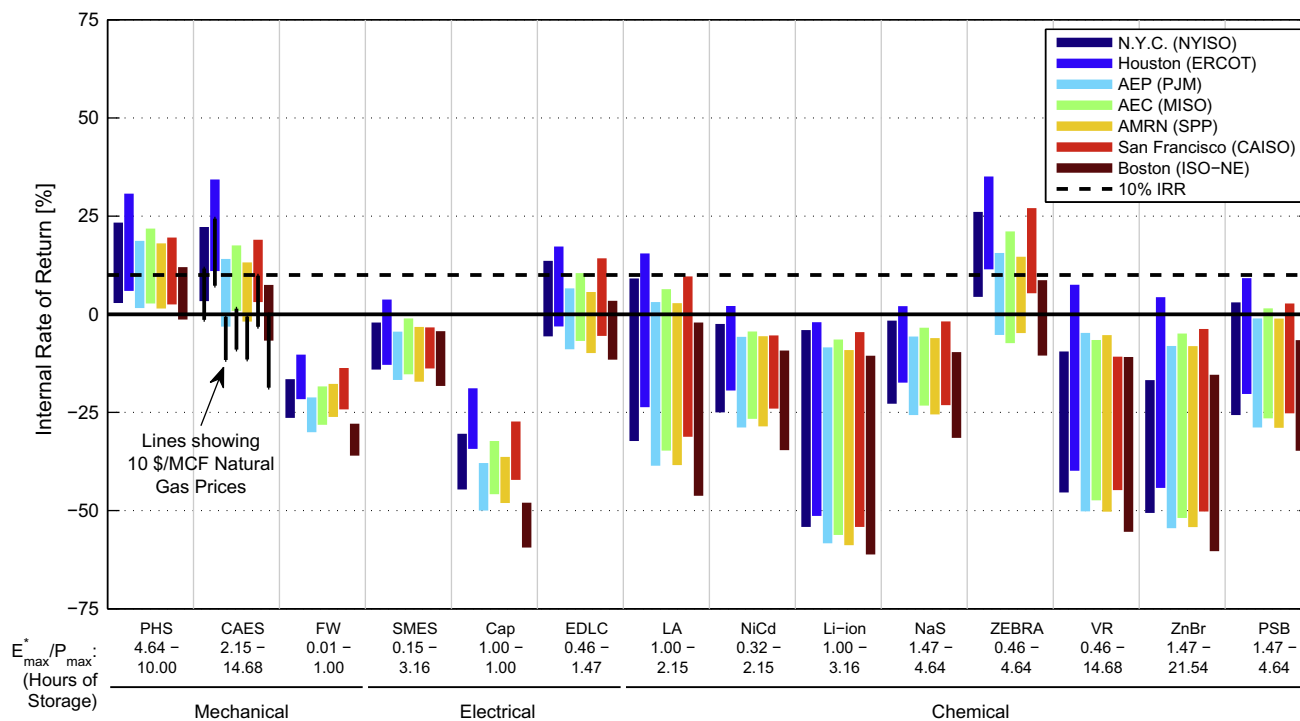
The modeled IRRs for the electrical ESSs are similar to those for the chemical ESSs. EDLC achieves maximum IRRs >10% in Houston, New York City and San Francisco, but is unprofitable in the other locations. SMES and CAP are unprofitable under all circumstances with the IRRs for CAP being among the lowest modeled. This is because like FW, the optimal hours of energy storage for CAP are  $\leq 1$  h, and thus not suited for price arbitrage in hour-ahead real-time markets (Fig. 4).

### 3.3. Cost reductions to ESS power and energy capacity that achieve arbitrage profitability

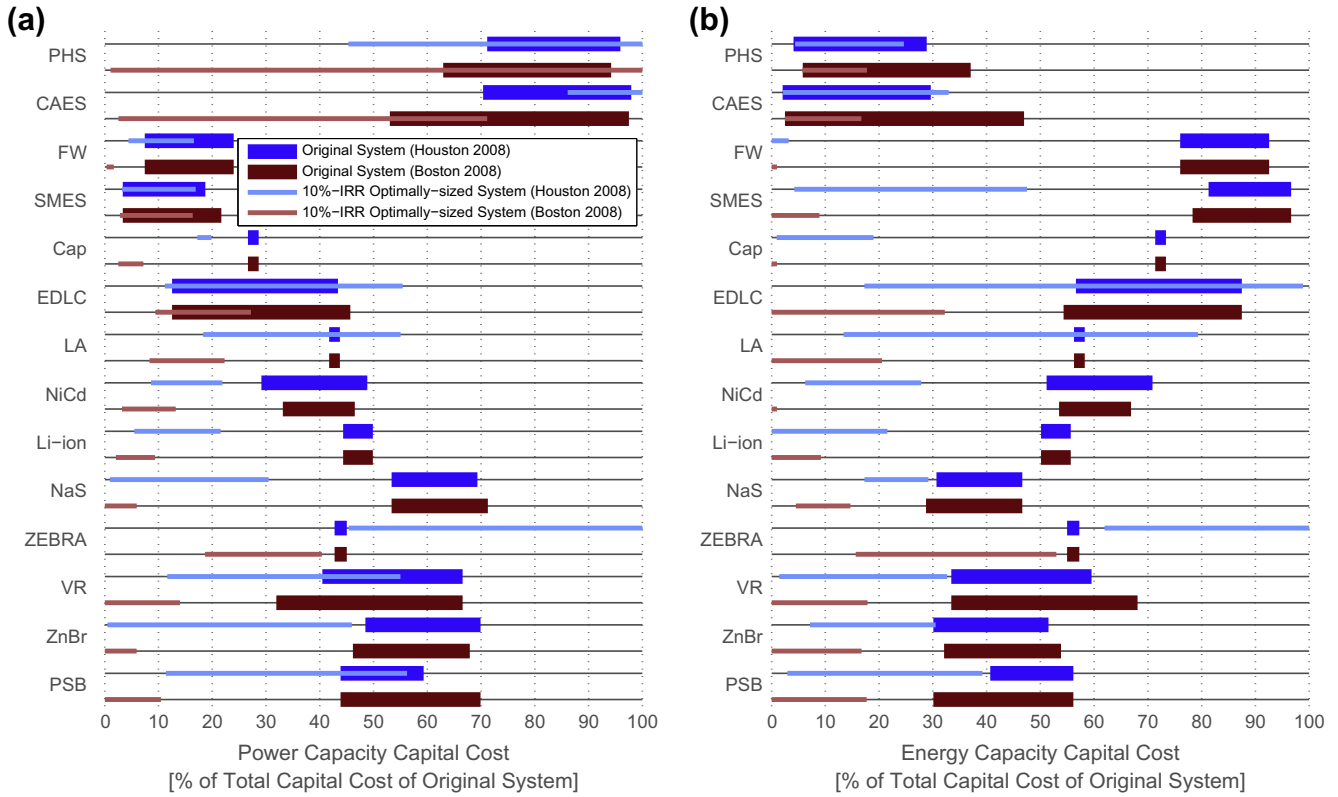
In constructing Fig. 3, the price arbitrage model was used to calculate the range of profit maximizing sizes for each ESS (i.e.  $P_{\max}^*$  and  $E_{\max}^*$ ) and the maximum potential revenues they could earn in the 2008 markets studied. Using those values, the reductions in power and energy capital costs were determined which enable the ESS to earn a 10% IRR in each market.



**Fig. 2.** Effect of device parameters on revenue. Demonstrates the effect of varying (a) daily self-discharge, (b) efficiency, and (c) the hours of storage capacity on the maximum average daily revenue from electricity price arbitrage at the selected nodes in different markets, assuming a 1 MW ESS. The modeled ESSs are ideal (100% efficiency, 0% self-discharge, and 30 h of storage capacity) except for the parameter being varied on the horizontal axis. The ranges of the daily self-discharge and efficiency, and hours of storage for the 14 devices in this study are presented in (d), (e), and (f) respectively, with values from Chen et al. [1].



**Fig. 3.** IRR comparison for all technologies across 7 markets. This figure shows the IRR for each ESS and market. Each IRR-range was formed by simulating the best-case and worst-case estimates for efficiency, self-discharge, device lifetime, and costs based on estimates of those parameters from [4]. Each simulated device was optimally sized to maximize the lifetime IRR of the ESS by holding the power capacity constant at 1 MW and varying the energy capacity to determine the number of hours of storage that maximized IRR; since we assume costs scale linearly this is the optimal value for this system at all scales. These IRR-maximizing values of storage-hours are shown below the plot, and the ranges represented the value in the worst case and the value in the best case, averaged across the markets. For CAES a natural gas price of 5 \$/MCF was assumed; the black lines show the result of increasing the price of natural gas to 10 \$/MCF.



**Fig. 4.** ESS capital cost reductions to achieve 10% IRR. The power capacity capital costs (a) and energy capacity capital costs (b) are shown for the most and least profitable markets (Houston and Boston, respectively). The ranges of the current capital costs components (thick lines), are  $P_{\max}^* c_{p_0}$  for power capital costs (a) and  $E_{\max}^* c_{e_0}$  for energy capital costs (b). The ranges of the capital costs that enable a 10% IRR (thin lines) are  $P_{\max}^* c_p^*$  for power capital costs (a) and  $E_{\max}^* c_e^*$  for energy capital costs (b). These values were calculated by determining the smallest percent reduction in power and energy capacity capital cost that would achieve a 10% IRR, assuming the optimally-sized values for the system from Fig. 3. This method is derived in Appendix A. All values are normalized by the total capital cost of the current system,  $P_{\max}^* c_{p_0} + E_{\max}^* c_{e_0}$ .

Given the expected annual revenue of an ESS,  $r$ , along with its operational lifetime and O&M costs (Table A.1), Eq. (7) can be rewritten to solve for the total cost of the ESS that yields a 10% lifetime IRR in that market, or  $C^*$

$$C^* = R_{PV} = (r - c_{om}) \sum_{i=1}^{L(N_c)} \frac{1}{(1 + 0.1)^i} \quad (8)$$

Combining this equation with Eq. (6) (see Section 1 of the SI) the following equations for the capital cost of power and energy were derived.

$$c_p^* = \frac{\frac{1}{c_{p_0}} - \frac{P_{\max}^*}{E_{\max}^* c_{e_0}} \left[ 1 - \frac{R_{PV}}{E_{\max}^* c_{e_0}} \right]}{\frac{1}{c_{p_0}^2} + \left[ \frac{P_{\max}^*}{E_{\max}^* c_{e_0}} \right]^2} \quad (9)$$

$$c_e^* = \frac{R_{PV}}{E_{\max}^*} - \frac{R_{PV}}{P_{\max}^*} c_p^* \quad (10)$$

Here,  $c_p^*$  and  $c_e^*$  are the power and energy capital costs associated with a 10% IRR, and  $c_{p_0}$  and  $c_{e_0}$  are the current power and energy capital costs. Thus  $P_{\max}^* c_{p_0}$  and  $E_{\max}^* c_{e_0}$  are the current ESS capital costs for power and energy capacity, respectively, while  $P_{\max}^* c_p^*$  and  $E_{\max}^* c_e^*$  are the power and energy capacity costs that allow for a 10% ESS IRR and when summed give  $C^*$ . These are the least-cost change from  $P_{\max}^* c_{p_0}$  and  $E_{\max}^* c_{e_0}$  (as defined in Eqs. (A3–A6)). Henceforth,  $P_{\max}^* c_p^*$  and  $E_{\max}^* c_e^*$  will be referred to  $P_{\max}^* c_p^*$  and  $E_{\max}^* c_e^*$  as the target power and energy capacity costs, respectively.

Fig. 4 compares the current vs. target power and energy capacity costs for the 14 ESSs as percentages of the total current cost for each ESS, i.e.  $C_0 = P_{\max}^* c_{p_0} + E_{\max}^* c_{e_0}$ , so the comparison reflects what fraction of an investment in these systems would go towards

power and energy capacity. As in Fig. 3, the ranges in percentages account for the ranges in the reported input values for ESS round-trip efficiency, self-discharge and power/energy capital costs (Table A.1). And since the current power and energy capital costs are different from the target capital costs, the cost ranges differ in both value and width for each ESS (e.g., the energy capacity capital costs for SMES).

The comparison between current and target capacity costs is shown for both the Houston (blue lines, Fig. 4) and Boston prices (red<sup>1</sup> lines, Fig. 4), which (respectively) are the most and least profitable locations included in the analysis. Note that power/energy capacity costs for an ESS are roughly the same in both markets, indicating that the  $P_{\max}^*$  and  $E_{\max}^*$  of the ESS, the only market-dependent parameters in this model, are about the same for Houston and Boston. This suggests that the profit-maximizing size of ESSs is determined primarily by the capital cost of power and energy capacity for the ESS and not the market where it participates (see Section 2 of the SI).

In terms of current cost percentages (thick lines, Fig. 4), there is a significant difference in the relative expense of power vs. energy capacity among the ESSs. For example, power capacity costs would represent ~65–95% of the total cost for an optimally sized PHS and CAES, while for FW and SMES, energy capacity costs make up ~75–95% of the total cost. Chemical ESSs as a whole have power and energy capacity costs that appear to be more balanced, with many of these ESSs spanning a 50–50-price split between the power and energy components. However, the percentage ranges indicate that at present there is a tendency for power capacity costs to be more

<sup>1</sup> For interpretation of color in Fig. 4, the reader is referred to the web version of this article.

significant in LA, NiCd, Li-ion, and ZEBRA ESSs, and energy capacity costs to be more significant in NaS, VR, ZnBr, and PSB systems.

Target costs for power and energy capacity (thin lines, Fig. 4) would typically be less than current costs (thick lines, Fig. 4), but in a several cases may be more, implying that system costs could increase and still achieve a 10% IRR. The clearest example of the latter is PHS, which has a current power capacity cost that falls below the target cost in both the Houston and Boston markets. Consequently, even though the current energy capacity cost for PHS meets or exceeds that needed for a 10% IRR in these markets, the overall IRR for PHS ends up exceeding 10% even in Boston.

CAES, EDLC, LA, and ZEBRA are the next most promising ESSs in terms of profitability. All have current power and energy capacity costs that fall 5% to >50% (ZEBRA power costs) below the maximum target costs needed for the volatile Houston market. However, all these ESSs also have current power and energy capacity costs that are up to 40–50% more than the target costs facing low-volatility prices in Boston.

The current power and energy capacity costs for all the remaining ESSs exceed the target costs for these capacities in both the Houston and Boston. For certain systems, this excess can be small when considering either the power or energy capacity cost alone. For example, current power capacity costs for FW and SMES exceed target costs by only 5–10% (thin vs. thick lines, Fig. 4a), but current energy capacity costs for these systems would also need to be reduced some 70–90% to become profitable and thus bring total costs enabling the ESSs to yield an overall IRR of >10%.

This discrepancy between power and energy capacity costs for uneconomic ESSs highlights what cost reductions in these ESSs would be most effective. Returning to FW and SMES systems, current energy capacity costs constitute 75–95% of the total cost for these systems, so the most effective way to increase the IRR of these systems would be to lower energy capacity cost. The same generally holds for EDLC and CAP, and to a lesser extent for LA, NiCd and ZEBRA. For CAES and PHS, however, power capacity costs dominate, and their reduction would be the quickest way to raise IRR.

These modeling results should be viewed as first-order estimates of the changes to power and energy capacity capital costs that might make ESSs profitable for price-arbitrage in real-time electric markets. Some of the modeling assumptions used undoubtedly overestimate ESS profitability, including perfect foresight of electricity prices, and that ESSs charge and discharge at the same rate. Other assumptions, however, likely underestimate ESS profitability, such as that capital costs scale linearly with ESS size. There are economies of scale in a number of energy technologies (e.g., power plants) and it is possible that larger ESSs may achieve higher IRRs than found in this model. Use of the most recent publicly available price estimates for ESSs will likely underestimate profitability. However, these published values of costs should be seen as benchmarks only, given that the results on the estimated required cost reductions necessary to achieve profitability can be readily interpreted for alternative price data. The potential effect of other assumptions is unclear. For example, to estimate required power and energy capacity cost reductions for an ESS, it was assumed that  $P_{\max}^*$  and  $E_{\max}^*$  would remain unchanged, when those cost reductions may result in a different profit-maximizing size and thus a different  $P_{\max}^*$  and/or  $E_{\max}^*$ . The wide range of current technological and cost parameters considered in this analysis, however, likely compensates for uncertainties introduced by the modeling assumptions used in this work.

#### 4. Conclusions

Among the ESSs compared in this study, the results indicate that PHS and CAES ESSs currently have the greatest potential for

price arbitrage, with ZEBRA systems demonstrating similar potential, only to a lesser degree. However, this analysis also indicates how these systems might be further improved. ZEBRA systems can become more profitable by either power or energy capital cost reductions, or improvements in device efficiency (reducing wasted energy). For PHS and CAES, the greatest IRR increase would come from reductions in power capital costs. The latter ESSs require specialized siting, while ZEBRA systems do not. However, ZEBRA is a relatively new energy storage technology with cost and technology parameter estimates that are not as certain and established as PHS.

Assuming best performance characteristics, EDLC and LA ESSs could also be profitable if optimally sized and operated in the most volatile markets: LA, due to low capital cost and moderate efficiency, and EDLC, due to high efficiency and long lifetime. However, LA batteries have lower cycle lifetimes and EDLCs have relatively high power capacity costs, both of which would need to be improved for any significant economic performance gains.

The majority of ESSs will be optimally sized at 4 or less hours of energy storage (Fig. 3) due to the higher cost of energy capacity for most technologies (Table A.1), especially electrical and chemical systems. Optimal sizes for PHS and CAES are larger because it is cheaper to add energy capacity to these ESSs by enlarging water/air reservoirs than to increase power capacity by building more or larger turbines. The converse is true for FW, which has considerably greater energy capacity costs than power capacity costs. The high self-discharge of these ESSs reduces their optimal sizes so far below 4 h that these systems are currently unsuitable for price arbitrage in real-time markets.

However, FW and other ESSs that may be uneconomic for real-time markets could still possess significant economic potential for other applications, particularly in ancillary service markets. For example, the high self-discharge and high energy capital costs that make FW a poor choice for energy markets may be largely irrelevant for frequency regulation where the need is for frequent high-power, low-energy cycling.

ESSs are poised to play a major role in large-scale power systems, but this will require well-informed decisions regarding the direction of further research, development, and deployment efforts to reduce costs. This analysis not only provides an overview of the state of current and emerging ESS technologies for price arbitrage in real-time electric markets, but also a framework for understanding how the costs of these systems need to be reduced to make them profitable. An alternative to capital cost reductions is revenue enhancement which can be achieved through participation in the capacity and ancillary services markets. Any policy to promote renewable energy and efficient operation of existing generating resources needs to pay special attention to market design so that ESSs can participate and be fairly compensated for the flexibility and value they add to the systems in which they operate.

#### Acknowledgements

Joseph DeCarolus, Josiah Knight and Richard Newell are thanked for their insightful suggestions. Kyle Bradbury received funding through a Graduate Research Fellowship from the National Science Foundation. Lincoln Pratson received funding from Department of Energy Grant DE-FE0001943. Dalia Patino-Echeverri received funding from the National Science Foundation through the Center for Climate and Energy Decision Making (SES-0949710).

#### Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.apenergy.2013.10.010>.

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