Comparing Electric Water Heaters and Batteries as Energy-Storage Resources for Energy Shifting and Frequency Regulation

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Recent technical, market, and policy developments in the electricity industry are increasing interest in and need for energy storage. We examine the potential for using the flexibility of an aggregation of tank electric water heaters as a source of virtual energy storage. Specifically, we examine the operational performance of and operating profit that is earned by a fleet of water heaters that provide energy shifting and frequency regulation. We contrast this performance and operating profit to that of a lithium-ion battery. We find that water heaters do not achieve the same level of performance or operating profit that a battery does. However, when accounting for the capital costs of the two technologies, water heaters are superior, insomuch as they have a better cost-to-profit ratio. We find that both water heaters and batteries earn significant operating profits from frequency regulation as opposed to energy shifting. Water heaters have a stronger bias towards frequency regulation, due to temporal constraints on load shifting. Relaxing these constraints improve water-heater performance slightly.

***Index Terms*—Energy storage, power-system economics, electric water heater, energy shifting, frequency regulation**

NOMENCLATURE

Common Parameters

- f_t^+ hour-t dispatch-to-contract ratio of upward frequency regulation (p.u.)
- f_t^- hour-t dispatch-to-contract ratio of downward frequency regulation (p.u.)
- t time index
- T number of hours within the optimization horizon
- $\bar{\pi}_t^d$ hour-t price of downward frequency regulation (\$/MW)
- $\bar{\pi}_t^e$ hour-t energy price (\$/MWh)
- $\bar{\pi}_t^u$ hour-t price of upward frequency regulation (\$/MW)

Battery-Specific Parameters

- P^+ charging capacity of the battery (MW)
- P^- discharging capacity of the battery (MW)
- S^+ maximum state of energy (SOE) of the battery (MWh)
- S^- minimum SOE of the battery (MWh)
- $\bar{\eta}$ charging efficiency of the battery (p.u.)

Water-Heater-Specific Parameters

- $\bar{C}$ nominal power capacity of the water heaters (MW)
- $\bar{t}$ allowable time shift of water-heater load (h)
- $\bar{\mu}_t$ hour-t water-heater availability factor (p.u.)

Battery-Specific Variables

- e_t^c scheduled hour-t battery charging (MW)
- e_t^d scheduled hour-t battery discharging (MW)
- q_t^d hour-t downward frequency regulation that is provided by the battery (MW)
- q_t^u hour-t upward frequency regulation that is provided by the battery (MW)

Water-Heater-Specific Variables

- S_t ending hour-t SOE of the battery (MWh)
- v_t binary variable that equals 1 if δ_t is positive and equals 0 otherwise
- δ_t hour-t net water-heater discharge (MW)
- δ_t^c maximum between 0 and $-\delta_t$ (MW)
- δ_t^d maximum between 0 and δ_t (MW)
- ϵ_t^c scheduled hour-t water-heater charging (MW)
- ϵ_t^d scheduled hour-t water-heater discharging (MW)
- ρ_t^d hour-t downward frequency regulation that is provided by the water heaters (MW)
- ρ_t^u hour-t upward frequency regulation that is provided by the water heaters (MW)

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I. INTRODUCTION

TECHNICAL, market, and policy developments in the electricity industry are increasing interest in energy storage [1]. Battery energy storage is seeing major recent cost declines [2]. Nevertheless, at current costs, battery energy storage is economically viable for limited applications.

Aggregations of tank electric water heaters could be a low-cost source of virtual energy storage. Water heaters act as energy storage by exploiting their load flexibility—the timing of water heating is controlled to shift energy demand. From the perspective of the electricity system this demand shifting is indistinguishable from battery charging and discharging. Using water heaters as energy-storage resources entails minimal cost, insomuch as the capital cost is borne by the water-heater owner. As of 2020 there are over 58 million residential units in United States of America with electric water heaters, which is greater than the number of natural-gas water heaters.[1] There are some incremental costs for deploying and maintaining systems to monitor and control the aggregation of water heaters, however. The primary disadvantage of using water heaters for energy storage is their limited flexibility. There is a time window within which water-heating demand can be shifted, otherwise hot-water users will be inconvenienced. Moreover, water-heating load has diurnal and seasonal patterns, which

[1] https://www.eia.gov/consumption/residential/data/2020/#waterheating

yield temporal variability in shiftable demand that is available. Given these benefits, there are legislative and policy efforts to encourage the use of electric water heaters for providing electricity-system services.

The extant literature studies technical facets of using water heaters for energy shifting and ancillary services [3]–[14]. One set of works [3], [4], [6] characterize and model water-heating loads whereas another [5], [7]–[14] examines or models the demand-response potential of such loads. Different approaches are used to represent the temperature dynamics of the tank. Single-element models assume a uniform water temperature within the tank and do not capture heat transfer between its upper and lower sections [3]–[9]. Two-element models address this shortcoming by modeling the hot and cold portions of the tank at the top and bottom, respectively [10]. Diao *et al.* [11] employ a hybrid approach that switches between one- and two-element models. They use a two-element model when the water heater is recovering and a one-element model when the water temperature reaches its maximum. A more complex approach employs single-dimensional partial differential equations, which represent the dynamics as a continuum within the tank's vertical column [12], [13].

Another body of work, which Mukherjee *et al.* [15] survey, focuses on controlling water-heater loads. One technique is selective-curtailment control, whereby the on and off states of water heaters are adjusted using a predefined logic. If this control strategy does not incorporate water-temperature measurements, hot-water users may be inconvenienced. Another approach uses a variable set point that is adjusted based on the service that is being provided. For example, some techniques use droop control that is based on a temperature set point that follows a frequency-regulation signal or a rule-based temperature set point that is based on energy prices.

A gap in this literature, which our work fills, is a direct comparison of the technical and economic performance of water heaters to other 'conventional' energy-storage technologies, such as batteries. In particular, we focus on the use of these technologies for the provision of energy shifting and frequency regulation. To our knowledge, no such direct comparisons exist. Instead, much of the technical literature [16] examines generic energy-storage technologies [17]. Some of the literature has a particular focus on battery energy storage [18]–[26], given the aforementioned recent cost reductions.

A common approach to this type of analysis is to use a price-taking model, whereby the prices for the services that energy storage provides are fixed exogenously [16]. Most price-taking models use linear or mixed-integer structures [17]–[20], [22]–[24], which we use in our work. Other modeling approaches, *e.g.*, dynamic optimization [21], [25] and deterministic policy gradients [26], can be applied, often to capture system or market dynamics. Cheng and Powell [25] use nested dynamic optimization to combine hourly, five-minute, and two-second models to co-optimize the provision of energy and frequency regulation and capture multiple timescales therein. Miao *et al.* [26] use a noise-decay method to capture uncertain real-time prices.

In this paper we develop price-taking operational models of battery and water-heater energy storage. The models assume that these resources provide energy shifting and frequency regulation and are tailored based on the rules of the wholesale market that is operated by California Independent System Operator (CAISO). Our models capture all of the key operational characteristics of using batteries and water heaters for energy-storage services (or can be adapted easily to capture these, as is detailed below). As such, our models are sufficiently general to represent the use of these technologies for the provision of most any service in most any wholesale electricity market. We apply the models to three illustrative one-day examples and a full year's data from the CAISO market. We find that batteries are more profitable than water heaters, due to their greater operational flexibility and ability to use their full capacity at all times. Water heaters have limited flexibility to shift water-heating load and the amount of load that can be shifted depends upon time-variant hot-water demands. Most of the operating profits for both technologies come from providing frequency regulation. This bias is greater for water heaters, due to their flexibility constraints. The capital cost of controlling an aggregation of water heaters is much lower than that of building a battery. Thus, in net, water heaters have better cost/benefit performance.

Our paper makes three major contributions to the existing literature. First, we develop a model to optimize the operation of an aggregation of water heaters for the provision of electricity-system services. Our focus is the provision of energy shifting and frequency regulation, but the model can be generalized to capture other services. Second, we conduct a direct comparison of the operating profit and capital costs of batteries and aggregated water heaters. To the best of our knowledge, no such comparison appears in the extant technical literature. Third, we provide a detailed analysis of the trade-offs between providing frequency regulation and energy shifting and the effect thereupon of energy deployed from providing frequency regulation. Currently, CAISO is exploring modifications to its market-participation models for energy storage to account for these trade-offs, which reinforces the practical value of this third contribution of our work. We envision two types of direct beneficiaries of our findings. First, entities that promote or develop the use of water heaters as a source of virtual energy storage could use our work to quantify the benefits of such efforts. Such entities include water-heater and control-system developers, aggregators, utilities that procure services from water heaters, or regulators or legislators that set policy surrounding such use of water heaters. A second type of direct beneficiary are designers of wholesale electricity markets, who set rules that govern such use of water heaters.

The remainder of this paper is structured as follows. Section II provides our model formulations. Section III summarizes the data that underlie our case study. Section IV provides a detailed analysis of battery and water-heater operations during three illustrative day-long periods. Section V summarizes results of our year-long case study. Section VI concludes.

II. Model Formulations

Our focus is day-ahead dispatch-planning of batteries and electric water heaters, as opposed to considering the details of battery or water-heater control. As such, our model assumes hourly time increments, which is aligned with the temporal granularity of CAISO's (and most) day-ahead wholesale electricity market.

A. Battery Model

The battery model is formulated as:

$$\max \sum_{t=1}^{T} \left[\bar{\pi}_t^e \cdot \left(e_t^d - e_t^c\right) + \bar{\pi}_t^d q_t^d + \bar{\pi}_t^u q_t^u \right. \\ \left. + \bar{\pi}_t^e \cdot \left(f_t^+ q_t^u - f_t^- q_t^d\right)\right] \quad (1)$$

$$\text{s.t.} S_t = S_{t-1} - e_t^d + e_t^c/\bar{\eta} - f_t^+ q_t^u + f_t^- q_t^d/\bar{\eta}; \\ \forall t = 1, \ldots, T \quad (2)$$

$$S_{t-1} + e_t^c/\bar{\eta} + q_t^d/2 \leq S^+; \forall t = 1, \ldots, T \quad (3)$$

$$S_{t-1} - e_t^d - q_t^u/2 \geq S^-; \forall t = 1, \ldots, T \quad (4)$$

$$S^- \leq S_t \leq S^+; \forall t = 1, \ldots, T \quad (5)$$

$$P^- \leq e_t^c + q_t^d \leq P^+; \forall t = 1, \ldots, T \quad (6)$$

$$P^- \leq e_t^d + q_t^u \leq P^+; \forall t = 1, \ldots, T \quad (7)$$

$$e_t^c, e_t^d, q_t^d, q_t^u \geq 0; \forall t = 1, \ldots, T. \quad (8)$$

Objective function (1) gives total operating profit that is earned from providing energy and frequency regulation and consists of three components. The first:

$$\bar{\pi}_t^e \cdot \left(e_t^d - e_t^c\right);$$

is operating profit that is earned from scheduled energy sales and purchases. The second, $\bar{\pi}_t^u q_t^u + \bar{\pi}_t^d q_t^d$, is operating profit that is earned from providing frequency-regulation capacity. Following CAISO's market design, we allow providing different amounts of upward and downward frequency regulation, which have different prices. Not all markets separate upward and downward frequency regulation in this manner. Such markets can be captured by having a single hourly price for frequency regulation and a single variable that represents the amount of (upward and downward) frequency regulation that is provided during each hour. The final component of (1) gives operating profit that is earned from energy that is provided by the battery to fulfill its frequency-regulation obligation. For all $t = 1, \ldots, T$, we use dispatch-to-contract ratios, f_t^+ and f_t^-, to model the amount of energy that must be provided during hour t to fulfill this requirement [27], [28]. Objective function (1) measures operating profit in the sense that it captures that cost of charging energy, but not the capital cost of the battery.

Constraint set (2) gives the evolution of the battery's state of energy (SOE) from one hour to the next. We use a single parameter, $\bar{\eta}$, to reflect energy losses when the battery is charged. Our model can be generalized to include energy losses when discharging and a self-discharge rate. Constraint sets (3) and (4) ensure that fulfilling scheduled charging, discharging, and frequency regulation would not violate the battery's SOE. CAISO rules require that energy-storage resources have sufficient SOE headroom to serve their frequency-regulation commitments for at least 30 minutes, which is why q_t^d and q_t^u are halved in these constraints. These one-half coefficients can be adjusted if modeling a different market that imposes different headroom requirements on energy storage that provides frequency regulation. Constraint sets (6) and (7) impose power capacities on battery charging and discharging and (8) imposes non-negativity.

Model (1)–(8) does not include any direct cost on battery cycling. Objective function (1) does capture the opportunity cost of discharging as opposed to retaining stored energy. Moreover, the efficiency factor, $\bar{\eta}$, captures an implicit cost of energy that is lost through cycling. One could include a direct cost on battery cycling in (1). One reason to do so could be to capture the effect of battery degradation or maintenance [21], [29]. Including a degradation-related cost in (1) would reduce the extent to which the batteries are used (a larger price difference between discharging and charging energy would be needed to justify their use), which would reduce the financial performance of the batteries.

B. Water-Heater Model

The water-heater model is formulated as:

$$\max \sum_{t=1}^{T} \left[\bar{\pi}_t^e \cdot \left(\epsilon_t^d - \epsilon_t^c\right) + \bar{\pi}_t^d \rho_t^d + \bar{\pi}_t^u \rho_t^u \right. \\ \left. + \bar{\pi}_t^e \cdot \left(f_t^+ \rho_t^u - f_t^- \rho_t^d\right)\right] \quad (9)$$

$$\text{s.t.} \delta_t = \epsilon_t^d - \epsilon_t^c + f_t^+ \rho_t^u - f_t^- \rho_t^d; \forall t = 1, \ldots, T \quad (10)$$

$$- M \cdot (1 - v_t) \leq \delta_t \leq M v_t; \forall t = 1, \ldots, T \quad (11)$$

$$\delta_t^c \leq -\delta_t + M v_t; \forall t = 1, \ldots, T \quad (12)$$

$$- \delta_t \leq \delta_t^c; \forall t = 1, \ldots, T \quad (13)$$

$$\delta_t^c \leq M \cdot (1 - v_t); \forall t = 1, \ldots, T \quad (14)$$

$$\delta_t^d \leq \delta_t + M \cdot (1 - v_t); \forall t = 1, \ldots, T \quad (15)$$

$$\delta_t \leq \delta_t^d; \forall t = 1, \ldots, T \quad (16)$$

$$\delta_t^d \leq M v_t; \forall t = 1, \ldots, T \quad (17)$$

$$\sum_{\tau=1}^{t} \delta_\tau^c \leq \sum_{\tau=1}^{t+\bar{t}} \delta_\tau^d; \forall t = 1, \ldots, T \quad (18)$$

$$\sum_{\tau=1}^{t} \delta_\tau^d \leq \sum_{\tau=1}^{t+\bar{t}} \delta_\tau^c; \forall t = 1, \ldots, T \quad (19)$$

$$\epsilon_t^c + \rho_t^d \leq \bar{\mu}_t \bar{C}; \forall t = 1, \ldots, T \quad (20)$$

$$\epsilon_t^d + \rho_t^u \leq \bar{\mu}_t \bar{C}; \forall t = 1, \ldots, T \quad (21)$$

$$\delta_t^c, \delta_t^d, \epsilon_t^c, \epsilon_t^d, \rho_t^d, \rho_t^u \geq 0; \forall t = 1, \ldots, T \quad (22)$$

$$v_t \in \{0, 1\}; \forall t = 1, \ldots, T; \quad (23)$$

where M is an arbitrarily large constant. Net water-heater discharging, which is represented by δ_t, $\forall t = 1, \ldots, T$, is physically different than battery charging and discharging. Water heaters discharge energy by delaying water heating, meaning that the delayed water-heating load must be served within some window of time. Water heaters charge energy by water heating, *e.g.*, pre-heating water before it is needed or recovering the water temperature following delayed water heating. These activities must be done within a limited window of time, so that the tank's water temperature remains within acceptable bounds.

Objective function (9) gives operating profit that is earned from providing energy and frequency regulation and consists of the same three components that are in (1). Objective function (9) measures operating cost in the same sense that (1) does—it does not account for the capital cost of the water heaters. Objective function (9) does not include any direct cost on water-heater cycling. In part, this modeling choice is made because it is not clear from empirical data whether water-heater cycling imposes any degradation or other direct cost (so long as water-heating is shifted within a window of time that does not disrupt hot-water use).

Constraint set (10) defines net hour-t discharging based on scheduled charging and discharging and energy requirements from providing frequency regulation. For all $t = 1, \ldots, T$, we use the convention that a positive value of δ_t means that the water heaters are being discharged in net during hour t whereas a negative value means that they are being charged. Constraint set (11) uses Big-M method to define, $\forall t = 1, \ldots, T$, the values of the binary variable, v_t, based on the sign of δ_t. v_t equals 1 if δ_t is positive and equals 0 otherwise. Constraint sets (12)–(14) employ Big-M method to linearize the definition of δ_t^c, $\forall t = 1, \ldots, T$, which is, $\delta_t^c = \max\{0, -\delta_t\}$. Constraint sets (15)–(17) do the same for δ_t^d, $\forall t = 1, \ldots, T$, which is $\delta_t^d = \max\{0, \delta_t\}$. The purpose of these variables and constraints is to decompose water-heating operations into charging and discharging actions. Constraint sets (18) and (19) impose flexibility restrictions and are akin to the SOE bounds that are imposed upon the battery by (2)–(5). Constraint set (18) ensures that $\forall t = 1, \ldots, T$, the total amount of energy that is charged into the water heaters (*e.g.*, through water pre-heating) up until hour t is discharged within the $\bar{t}$-hour flexibility window. Constraint set (19) imposes an analogous restriction on discharged energy. Collectively, these constraints ensure that the desired water temperature of the tank and comfort of the water user are maintained. Constraint sets (20) and (21) impose power constraints on water-heater charging and discharging. These constraints are time-variant, because they depend upon the water-use profile of the heaters. Constraint sets (22) and (23) impose non-negativity and binary restrictions, respectively.

III. Case-Study Data

Our case study examines the operation of the battery and water heaters over a year-long period. To this end, hourly historical year-2020 day-ahead energy and regulation-capacity prices are obtained from CAISO. Table I provides summary statistics of the market prices. Historical frequency-regulation data (hourly procurements of frequency-regulation and real-time deployment of frequency-regulation resources) are used to compute dispatch-to-contract ratios.

We examine a 10-MW lithium ion battery with an 80% roundtrip efficiency, 40-MWh energy-carrying capacity, and \$350/kWh capital cost [2]. Water heaters are modeled using data that are obtained from a private company that has an over seven-year history of aggregating and controlling electric water heaters to transact energy and frequency regulation in numerous wholesale electricity markets, including that operated by PJM Interconnection LLC. Based on their data, a standard 4.5-kW water heater provides 400 W of manageable capacity at a capital cost of \$200 (to install sensing, control, and communication equipment). We assume that the sensing, control, and communication equipment is installed on existing water heaters that are used primarily for hot-water use. Thus, the cost of the water heater itself is not included in our analysis. An aggregation of $25\,000$ water heaters has nominal charging and discharging capacities of 10 MW and a \$500/kW capital cost. Typically, the water heaters have lower charging and discharging capacities than 10 MW, because these capacities depend upon real-time water-heating demand. This dependency is modeled through the parameters, $\bar{\mu}_t$, $\forall t = 1, \ldots, T$, which are estimated using historical data from the company. These parameters are affected by environmental (*e.g.*, the inlet temperature of water) and behavioral (*e.g.*, water-usage patterns) factors. We do not model these factors directly. Rather, the data that are provided to us by the private company account for these impacts in estimating the values of $\bar{\mu}_t$, $\forall t = 1, \ldots, T$. Fig. 1 shows the average, minimum, and maximum (over the modeled year) diurnal availability factor of the water heaters. The figure shows that the water heaters have an average availability of about 50% and that availability has considerable intraday and seasonal variability. Our base case assumes that $\bar{t} = 2$. Data that are provided by the private company indicate that water-heating load can be shifted within a two-hour window with negligible thermal-energy losses and without any noticeable impact on hot-water users. As such, we do not need to model the thermodynamics of the water heaters. We contrast this base case to a case with $\bar{t} = 4$, to examine the effects of relaxing the flexibility window.

TABLE I
Summary Statistics of Market Prices for Case Study

	Minimum	Mean	Median	Maximum
$\bar{\pi}_t^e$	-10.34	34.78	29.66	$1\,062.64$
$\bar{\pi}_t^d$	0.00	9.45	6.84	207.26
$\bar{\pi}_t^u$	0.10	9.81	5.92	962.54

IV. Illustrative Day-Long Examples

Before summarizing complete case-study results in Section V, we examine battery and water-heater operations during three illustrative one-day periods. The three days—14 August, 2020, 14 December, 2020, and 22 April, 2020—have, respectively, relatively high, average, and low prices. For each example the optimization models are solved using a 48-hour optimization horizon. Hours 25–48 are included to ensure that the battery's SOE, which is assumed to be at its minimum as of the beginning of each day, is not depleted fully as of the end of hour 24 [30]. The water heaters are assumed to begin as of hour 1 of each day without any previous charging or discharging. Hours 25–48 are included in the optimization horizon to ensure that charged and discharged energy as of the end of hour 24 can be replenished during the following day. For simplicity, we assume in these examples that $\bar{\eta} = 1.0$, to illustrate how the battery is operated independent of energy

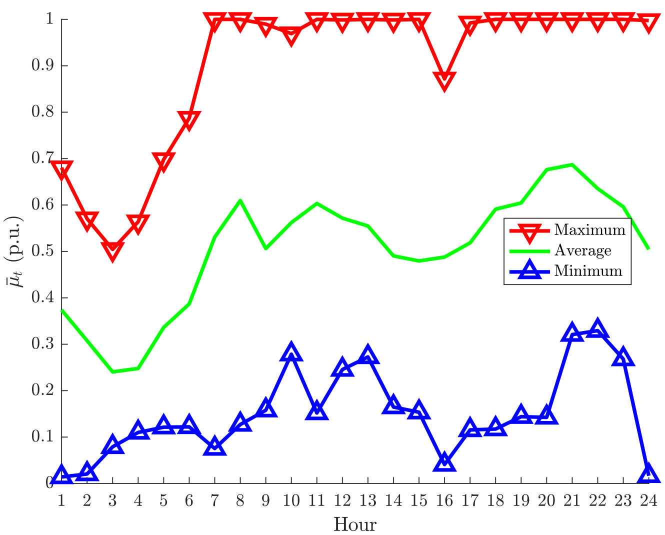

Fig. 1. Maximum, average, and minimum diurnal water-heater availability factors for case study.

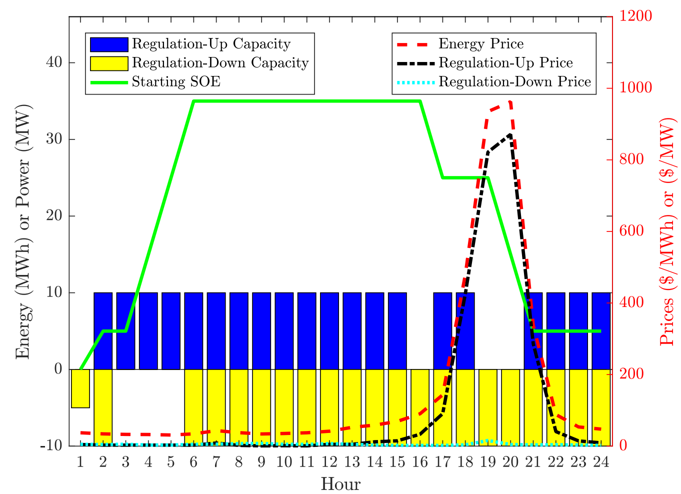

Fig. 2. Prices and optimized battery dispatch with zero f_t^+ and f_t^- during high-price day.

losses. Assuming a lower value of $\bar{\eta}$ does not change our results qualitatively, but results in less battery cycling. We begin with cases without energy dispatch from providing frequency regulation, *e.g.*, $f_t^+ = 0$ and $f_t^- = 0$, $\forall t = 1, \ldots, T$. Then we consider cases with non-zero values for these parameters.

A. $f_t^+ = 0$ *and* $f_t^- = 0$, $\forall t = 1, \ldots, T$

1) *High-Price Day*

Fig. 2 summarizes market prices and battery operations during the high-price day. Although they are positive, we use the convention in this and other figures of showing regulation-down capacities below the horizontal axis. Given the high evening energy prices, the battery's overall strategy is to charge energy during the morning when energy prices are relatively low and to discharge and sell energy during the evening. When possible, the battery provides frequency regulation, which can be limited by power and energy constraints. For instance, because its starting hour-1 SOE is zero, the battery can provide only downward frequency regulation during hour 1. As another example, the battery charges at its power capacity during hours 3–5 and (6) prevents the battery from providing downward frequency regulation simultaneously with this charging. The battery can provide both upward and downward frequency regulation during hours that the battery neither is charging nor discharging (*e.g.*, hours 2, 6–15, 17–18, and 21–24).

Energy shifting is profit-maximizing only when the associated revenues outweigh foregone revenues from not providing frequency regulation. The battery discharges during hour 16, when the energy price is \$90.41/MWh, as opposed to during hours 17 or 18, when the energy prices are \$143.29 and \$479.23/MWh, respectively. The reason for this behavior is that upward-frequency-regulation prices during hours 16–18 are \$33.20/MW, \$90.74/MW, and \$425.46/MW, respectively. As such, it is profit-maximizing to discharge during hour 16 and provide upward frequency regulation during hours 17 and 18.

Fig. 3 summarizes prices and the optimized operation of the water heaters with $\bar{t} = 2$ for the same day that is shown in Fig. 2. We use the convention in this and other figures of showing discharging below the horizontal axis. The figure shows water heaters operating under two significant constraints. First, the two-hour limit on load shifting allows for relatively little energy shifting. The capacity factor of the battery charging that is shown in Fig. 2 is about 14.58% as opposed to 5.40% for the water heaters. The trade-off between providing energy shifting and frequency regulation is another limiting factor in providing energy shifting. Despite the energy price peaking above \$930/MWh during hours 19 and 20, it is not profit-maximizing for energy storage to discharge energy during these hours. This is not profit-maximizing because with the two-hour load-shifting window, the lowest-priced charging energy that could be used to discharge during hours 19 and 20 costs \$88.24/MWh. The fact that prices for upward frequency reserves are above \$820/MW makes it preferable to provide frequency regulation during hours 19 and 20. Fig. 4 summarizes the operation of the water heaters with $\bar{t} = 4$. Having $\bar{t} = 4$ yields significantly more charging and discharging—the charging capacity factor of the water heaters increases to 34.84%—due to the relaxed flexibility constraint.

The second limitation on water-heater operations is the time-varying nature of the water-heating load. During the high-price day, the availability factor of the water heaters reaches a maximum of 62.00% and averages 37.79%.

2) *Medium-Price Day*

Fig. 5 summarizes market prices and battery operations during the medium-price day, which has price patterns that are the most common (during the year that we model) of the three illustrative examples. As is common during many days (in California and other electricity markets with high penetrations of solar generation), there are two price peaks. Midday prices are suppressed by solar-energy availability. As such, the battery has two charging and discharging cycles as opposed to only one during the high-price day (*cf.* Fig. 2). Battery operations during the medium-price day exhibit many

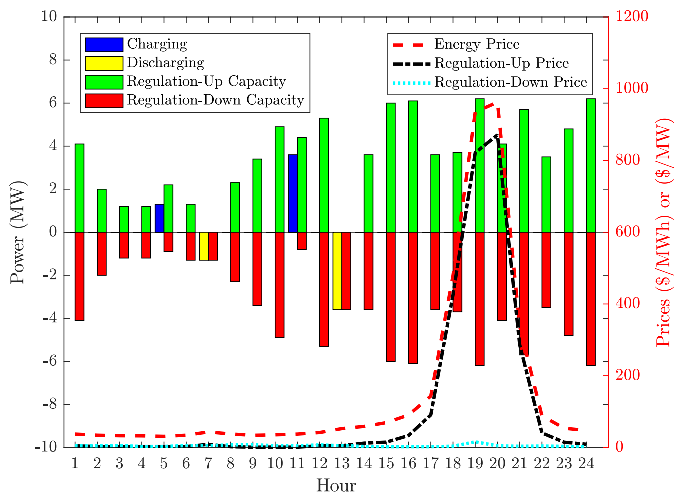

Fig. 3. Prices and optimized water-heater dispatch with $\bar{t} = 2$ and zero f_t^+ and f_t^- during high-price day.

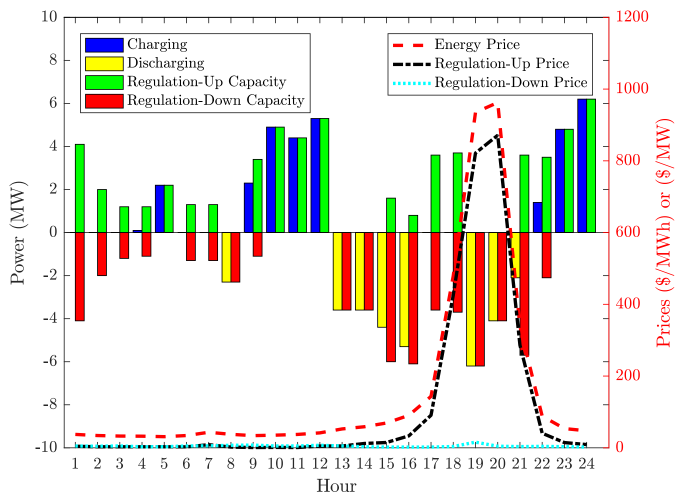

Fig. 4. Prices and optimized water-heater dispatch with $\bar{t} = 4$ and zero f_t^+ and f_t^- during high-price day.

of the same qualitative properties that we observe during the high-price day. When possible, the battery provides upward and downward frequency regulation simultaneously. The provision of upward or downward frequency regulation is limited during hours that the battery schedules discharging or charging, respectively. We observe also the trade-off in how the battery schedules charging, discharging, and frequency regulation. The battery discharges during hour 6, when the energy price is \$39.97/MWh, as opposed to during hour 7, when the energy price is \$52.04/MWh. It discharges during hour 6 because the price of upward frequency regulation is considerably higher during hour 7 (\$27.10/MW) relative to during hour 6 (\$5.00/MW).

Fig. 6 summarizes prices and the optimized operation of the water heaters with $\bar{t} = 2$ for the same day that is shown in Fig. 5. As is the case during the high-price day, the water heaters are used considerably less than the battery for energy shifting (the charging capacity factor of the water heaters is 5.40% as opposed to 18.75% for the battery). However, the

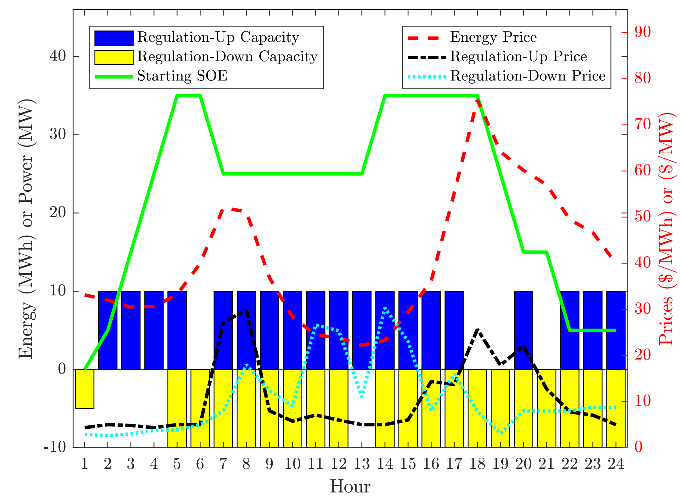

Fig. 5. Prices and optimized battery dispatch with zero f_t^+ and f_t^- during medium-price day.

two-hour flexibility window does allow the water heaters to capture both peaks in the energy prices. If $\bar{t}$ is relaxed to equal 4 (for sake of brevity, we do not include a figure for this case), the water heaters' charging capacity factor increases to 12.13%.

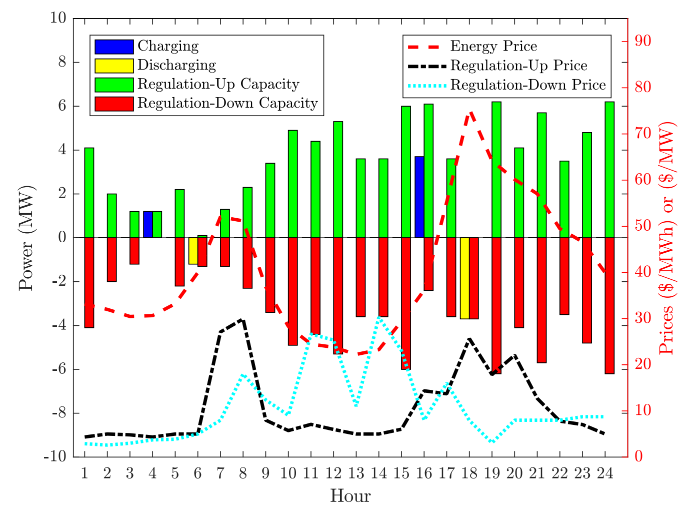

Fig. 6. Prices and optimized water-heater dispatch with $\bar{t} = 2$ and zero f_t^+ and f_t^- during medium-price day.

3) Low-Price Day

Fig. 7 summarizes market prices and battery operations during the low-price day. As with the medium-price day, many low-price days have two price peaks, as is shown in Fig. 7. These two price peaks are due to solar generation suppressing midday prices. The battery follows the same operational strategy as during the medium-price day, except with less total energy shifting. During both high- and medium-price days, the battery's SOE reaches a maximum of 35 MWh. While this is less than the 40-MWh SOE limit, it is the highest SOE that allows the battery to provide 10 MW of downward frequency regulation. During the low-price day, the battery's SOE reaches a maximum of 25 MWh. The maximum battery

SOE is lower because the lower prices during this day reduce profit opportunities from energy shifting. Water heaters with $\bar{t} = 2$ and $\bar{t} = 4$ are operated in the exact same manner during this day. They provide frequency regulation only and no energy shifting. This lack of energy shifting is due to very small energy-price differences during the course of the day and relatively high revenue opportunities from providing frequency regulation.

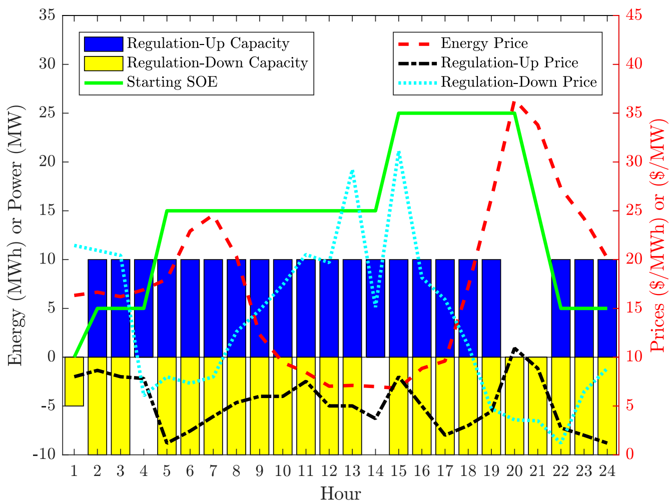

Fig. 7. Prices and optimized battery dispatch with zero f_t^+ and f_t^- during low-price day.

B. Non-Zero Values of f_t^+ and f_t^-

Assuming non-zero values of f_t^+ and f_t^- changes the trade-off between energy shifting and providing frequency regulation. This change is due to frequency regulation impacting the SOE of the battery or requiring offsetting water-heater charging or discharging. Thus, this case with non-zero f_t^+ and f_t^- gives rise to what we term indirect charging and discharging, or indirect energy shifting. Indirect energy shifting is the effect of frequency regulation, through the values of f_t^+ and f_t^-, $\forall t = 1, \ldots, T$, on the battery or water heaters. CAISO and other market operators aim to have an energy-neutral frequency-regulation signal. Thus, the impact of indirect energy shifting on the battery and water heaters is exacerbated if they provide an imbalanced mix of upward and downward frequency regulation.

In some cases, indirect energy shifting may be preferable to direct energy shifting, because the energy storage captures frequency-regulation-capacity payments to supplement energy-transaction settlements. For example, it can be preferable to undertake indirect charging as opposed to direct charging during an hour with a higher price for downward frequency regulation than the price for upward frequency regulation. The price data that underlie our examples and case study show such correlations—hours with low energy prices tend to have higher prices for downward frequency regulation than for upward frequency regulation. This relationship tends to be reversed during hours with high energy prices.

We examine the same three illustrative examples that are examined in Section IV-A.

1) High-Price Day

Fig. 8 summarizes market prices and battery operations during the same day that is summarized in Fig. 2. The battery follows the same overall strategy with non-zero values of f_t^+ and f_t^- as is shown in Fig. 2—it charges energy during low-price hours to sell during the evening peak.

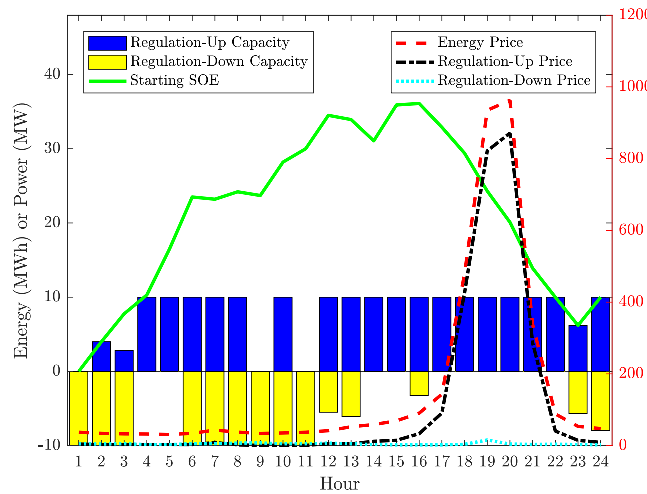

Fig. 8. Prices and optimized battery dispatch with non-zero f_t^+ and f_t^- during high-price day.

There are two key differences in battery operations with non-zero values of f_t^+ and f_t^-. First, the battery does non-trivial amounts of indirect energy shifting with non-zero values of f_t^+ and f_t^-. The battery's SOE reaches a peak of 36.10 MWh, which is followed by a low of 6.20 MWh, as of the beginning of hours 16 and 23, respectively, of the day that is shown in Fig. 8. A total of 33.03 MWh of energy is charged directly during hours 4, 5, 14, and 15. The remaining 3.07 MWh is charged indirectly. In addition, the battery schedules no direct discharging, meaning that the battery discharges entirely through the provision of upward frequency regulation. This behavior reflects the aforementioned relationship between high prices for energy and upward frequency regulation.

The fact that the battery relies upon indirect energy shifting gives the second key operational difference with non-zero values of f_t^+ and f_t^-. All of Figs. 2–7 show that energy storage tends to provide equal amounts of upward and downward frequency regulation with zero f_t^+ and f_t^-. With non-zero f_t^+ and f_t^-, there is more unbalanced frequency-regulation provision, which allows controlling the SOE indirectly through frequency-regulation deployments.

The trade-off between direct and indirect energy shifting depends upon the relative values of the three market prices. The hour-14 upward and downward frequency-regulation prices are \$12.04/MW and \$2.90/MW, respectively. As such, direct charging is preferable to indirect charging during hour 14, because direct charging allows providing 10 MW of upward frequency regulation simultaneously. Indirect charging would require providing more downward and less upward frequency regulation, which would reduce operating profit.

Fig. 9 summarizes prices and the optimized operation of the water heaters with $\bar{t} = 2$ during the high-price day. The key difference between water-heater operations with zero and non-zero values of f_t^+ and f_t^- is that with non-zero values, it is profit-maximizing for the water heaters to exploit indirect energy shifting during the evening energy-price peak. Non-zero values of f_t^+ and f_t^- make this a profit-maximizing strategy for the water heaters because they can capture revenues from both energy and upward frequency regulation during hours 18–21 through indirect discharging. Energy charging is achieved through pre-heating water during hours 16 and 17 and deferring water heating until hours 22 and 23. Relaxing the flexibility of the water heaters with $\bar{t} = 4$ yields an operational profile that is qualitatively similar to what is shown in Fig. 9. A figure for this case is excluded for sake of brevity.

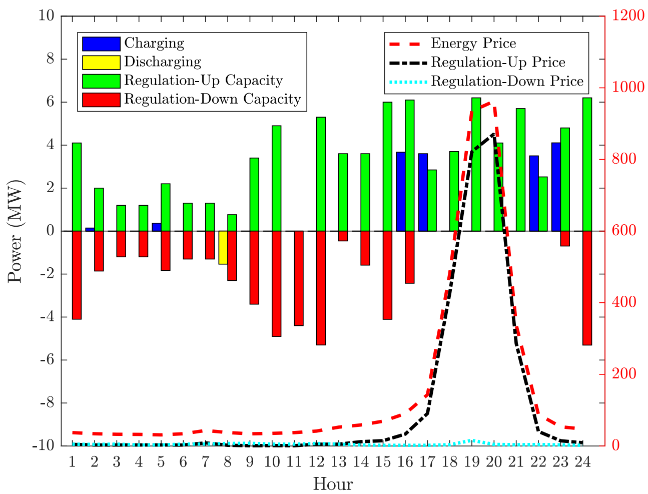

Fig. 9. Prices and optimized water-heater dispatch with $\bar{t} = 2$ and non-zero f_t^+ and f_t^- during high-price day.

2) *Medium-Price Day*

Fig. 10 summarizes market prices and battery operations during the medium-price day. Contrasting this with Figs. 5 and 8 shows qualitatively similar battery operations in this case. The key difference is that with non-zero values of f_t^+ and f_t^-, the energy prices justify only a single charging/discharging cycle during the day, as opposed to the two cycles that are shown in Fig. 5. There are some small SOE fluctuations during hours 4–11 in Fig. 10, which are due to frequency-regulation energy deployments. The battery SOE reaches a peak of 35 MWh as of the beginning of hour 17. Only 9.25 MWh of this energy is charged directly. The remaining energy is obtained through the deployment of downward frequency regulation. There is no direct discharging during this day. The battery's SOE reaches 19.30 MWh after the peak in the energy prices only through providing upward frequency regulation.

Water-heater operations are qualitatively similar to the aforementioned cases, and figures summarizing their operations are excluded for sake of brevity.

3) *Low-Price Day*

Fig. 11 summarizes market prices and battery operations during the low-price day. Overall battery operations are qualitatively similar during this day with zero and non-zero values of f_t^+ and f_t^-—the energy prices justify a single energy-

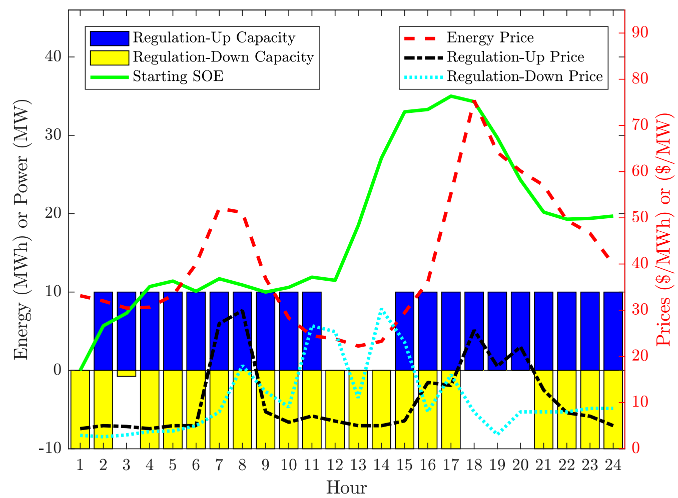

Fig. 10. Prices and optimized battery dispatch with non-zero f_t^+ and f_t^- during medium-price day.

shifting cycle. The key difference is the use of indirect energy shifting with non-zero values of f_t^+ and f_t^-. With non-zero values of f_t^+ and f_t^-, the battery's SOE reaches a peak of 30.70 MWh, of which 22.52 MWh is sold during the day. Only 10 MWh of direct discharging is scheduled during hour 22. The remainder of energy shifting is through providing frequency regulation.

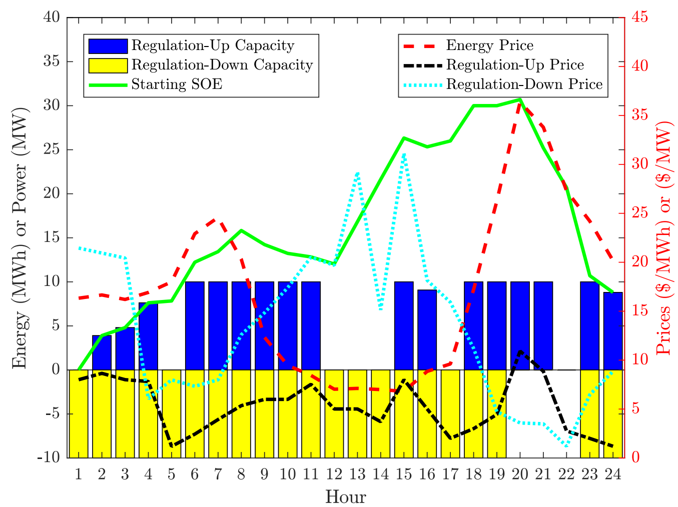

Fig. 11. Prices and optimized battery dispatch with non-zero f_t^+ and f_t^- during low-price day.

It is profit-maximizing to sell energy through direct discharging because of the relatively low hour-22 frequency-regulation prices. The battery could collect two revenue streams through indirect discharging. However, the relatively low dispatch-to-contract ratio means that the battery would forego on the volume of energy that is sold to collect a relatively small frequency-regulation payment. As such, it is preferable to sell energy during this hour through direct discharging.

Fig. 12 summarizes market prices and the optimized operation of the water heaters with $\bar{t} = 2$ during the low-price day. The key difference between operations with zero and non-zero values of f_t^+ and f_t^- is that direct discharging is profit-maximizing during some hours in the latter case. With zero values of f_t^+ and f_t^-, the water heaters provide frequency regulation only. With non-zero values of f_t^+ and f_t^-, the water heaters charge indirectly during hours 17 and 18, when downward-frequency-regulation prices are relatively high, to provide 26.39 MW of direct discharging during hour 19. This direct discharging offsets 11.99 MW of indirect charging. This strategy is profitable because the water heaters maximize the amount of frequency regulation that they are able to provide (based on hour-19 hot-water use) and collect energy payments from direct discharging when the energy price is relatively high.

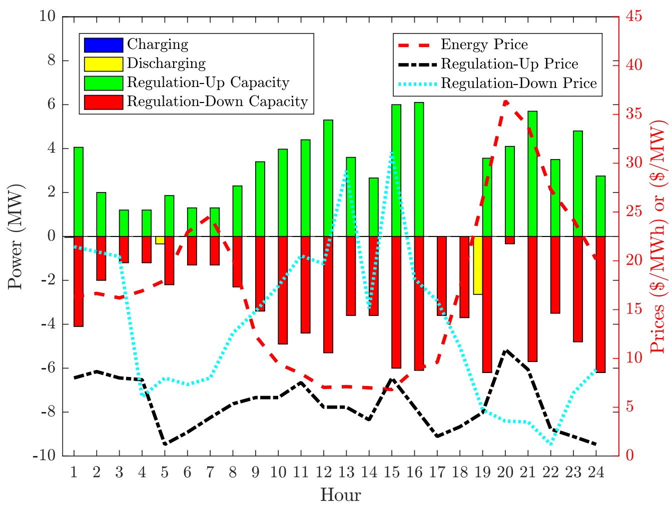

Fig. 12. Prices and optimized water-heater dispatch with $\bar{t} = 2$ and non-zero f_t^+ and f_t^- during low-price day.

Water-heater operations with $\bar{t} = 4$ is qualitatively similar to the operations that are shown in Fig. 12, and a figure that summarizes this case is excluded for sake of brevity.

V. Case-Study Results

Table II summarizes the operating profits that are earned with zero and non-zero values of f_t^+ and f_t^- by the battery and water heaters during the three illustrative days that are examined in Section IV. Non-zero values of f_t^+ and f_t^- reduce battery profits during the medium- and low-price days (relative to the case with zero values of f_t^+ and f_t^-), while this impact is reversed for high-price days. Water-heater profits are higher during the high- and low-price days with non-zero values of f_t^+ and f_t^-. These varied operating-profit effects are due to frequency regulation having different impacts on the battery as opposed to water heaters. The operating profits that are reported in Table II represent the marginal value during these days of the energy storage to the CAISO system and to the energy-storage owner [31], [32].

The primary benefit to water heaters of non-zero values of f_t^+ and f_t^- is that energy shifting becomes more economically viable. With zero values of f_t^+ and f_t^-, the time limit on shifting water-heating loads restricts the ability of the water heaters

TABLE II
Energy-Storage Operating Profits Earned ($ Thousand) During High- (HP), Medium- (MP), and Low-Price (LP) Days

Technology	Zero f_t^+ and f_t^-			Non-Zero f_t^+ and f_t^-		
	HP	MP	LP	HP	MP	LP
Battery	24.19	5.37	3.61	33.17	4.90	3.47
Water Heater						
$\bar{t} = 2$	13.37	2.04	1.75	18.69	2.02	1.75
$\bar{t} = 4$	13.97	2.22	1.75	19.60	2.14	1.81

to exploit high energy prices. This restriction is exacerbated by the trade-off between providing frequency regulation as opposed to energy shifting (*cf.* Fig. 3 and the accompanying discussion). There is some benefit to a battery from indirect energy shifting with non-zero values of f_t^+ and f_t^-. However, this benefit is relatively small during many days, because the operational flexibility of the battery allows it to provide much more frequency regulation and energy shifting than the water heaters are able to provide.

Table III summarizes the overall financial performance of the battery and water heaters with the two different flexibility windows, assuming non-zero values of f_t^+ and f_t^-. The operating profits that are reported in Table III consider the full year, as opposed to only the three days that are examined in Section IV. The battery is assumed to begin with $S_0 = S^-$ and the water heaters are assumed to begin as of hour 1 of the year without any previous charging or discharging. Following from our analysis in Section IV, annual operating profit of the battery is almost twice as high as that of the aggregated water heaters if $\bar{t} = 2$. If the water heaters can be operated with greater flexibility (*i.e.*, with $\bar{t} = 4$), this operating-profit gap is reduced slightly. With current cost estimates, the battery is nearly three times as expensive as the water heaters. We do not account for any actual or perceived cost to the hot-water users, because we assume that the flexibility window is chosen so as not to inconvenience them. If they bear such costs, that should be incorporated into our cost estimates. We use the ratio between capital cost and annual operating profit as a back-of-the-envelope estimate of the net benefit of the two energy-storage technologies. On the basis of this metric, the water heaters outperform the battery.

TABLE III
Capital Costs and Operating Profits of Energy-Storage Technologies

Technology	Capital Cost ($ Million)	Annual Operating Profit ($ Million)	Cost-To-Profit Ratio
Battery	14	1.689	8.3
Water Heater			
$\bar{t} = 2$	5	0.979	5.1
$\bar{t} = 4$	5	1.028	4.9

The cost-to-profit ratios that are reported in Table III assume that the year that we model in our case study is representative of conditions that impact energy-storage revenues during the life of a battery or water-heater aggregation. Our operating-profit estimates rely upon year-2020 energy and frequency-regulation prices and the seven-year history of water-heater data that provide our case-study inputs. We do not consider the potential degradation of the energy-storage media. The data that are provided to us by the water-heater aggregator do not show any notable degradation from using water heaters in this manner. Many modern batteries carry multi-year warranties.[2] Thus, considering degradation may reduce the net benefit of batteries relative to water heaters, insomuch as a cost-to-profit ratio of 8.3 means that a battery may be nearing the end of its usable life once operating profits recover the upfront capital cost.

VI. Conclusions

This paper examines the performance of an aggregation of tank electric water heaters as a source of virtual energy storage and compares it to battery energy storage. To do so, we develop models to optimize battery and water-heater operations. We focus on using energy storage for energy shifting and frequency regulation, but our model is sufficiently general that other market-priced services could be incorporated and considered. Our models are structured for the CAISO market and we apply them to a case study that is based on CAISO data. Nevertheless, our models can be adapted to study other wholesale electricity markets with different rules. For instance, the one-half coefficients in (3) and (4) can be changed to reflect the headroom requirement of a different market. As another example, the parameter and variable definitions can be changed to capture a market that does not separate upward and downward frequency regulation into two separate products.

We conduct a detailed examination of three illustrative days and consider cases with zero and non-zero values of f_t^+ and f_t^-. We find that the greater operational flexibility of the battery yields higher operating profit compared to the water heaters under all of the cases that we examine. Electric water heaters face two significant operating constraints. They are restricted by the window of time within which water-heating loads are able to be shifted without impacting water-user comfort. In addition, the ability of water heaters to charge and discharge during any given hour depends on that hour's water-heating demand. Relaxing the window of time within which water-heating loads can be shifted yields some small operating-profit increases.

Providing energy shifting is profit-maximizing only if the associated operating profit outweighs the operating-profit loss from foregone provision of frequency regulation. The operating profit that is earned from energy shifting depends upon the price difference between the discharging and charging energy. The operating profit that is earned from providing frequency regulation depends upon the frequency-regulation price, the dispatch-to-contract ratio, and the price difference between the discharging and charging energy. The flexibility window limits the economic viability of water heaters providing energy shifting, which makes water heaters ideal for providing frequency regulation. Although the battery provides significant amounts of frequency regulation as well, a larger portion of its operating profit is derived from energy shifting.

Overall, the water heaters outperform the battery when accounting for capital costs. However, future battery costs could be lower than they are today, *e.g.*, some estimates of $\$150$/kWh by 2050 [2]. Such cost reductions could improve the economic case for battery energy storage. Improvements in water-heater control, sensing, and communication can yield further reductions in the cost of this technology. Such improvements could be spurred by current legislative and regulatory levers that are encouraging or requiring the deployment of controllable water heaters (*e.g.*, learning-by-doing effects) [33]. The cost estimates that we use for the water heaters assume that control, sensing, and communication equipment is added to existing water heaters. If dedicated water heaters must be built for this application, their costs should be incorporated into our estimates.

We use a price-taking model, which assumes that the prices are fixed exogenously. This is an appropriate modeling approach to estimate the value to the bulk electricity system and the asset owner of marginal energy-storage capacity. Other modeling approaches would be needed to understand how the value of battery or water-heater energy storage changes as the penetrations of these or other technologies change [34]. Another natural extension of our work would be to model operating profits over multiple years.

Our models are fully deterministic, meaning that the decision maker knows all prices, dispatch-to-contract ratios, and water-use patterns *a priori*. In practice these data must be estimated or forecasted, which can impact energy-storage operations and operating profits that are earned [35]. Simple techniques, such as backcasting, can have fairly good performance relative to the perfect-foresight benchmark that we examine [17]. No doubt this is an important consideration that should be examined if batteries or water heaters are being used to provide energy shifting or frequency regulation. We do not focus on this issue, because our goal is to benchmark the operational and financial performance of water heaters relative to a battery.

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