Optimal Battery Charging in Smart Grids with Price Forecasts

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***Abstract*—In this paper, we consider a residential cluster in which some of the households own home batteries. The battery owners have forecasts of future prices for optimally utilizing the long-term flexibility of the battery. These forecasts become increasingly uncertain the further we look into the future.**

The home batteries are individually too small to influence prices, collectively however, they have enough capacity to have an influence. We study three possible scenarios: (i) Each household controls its own battery to maximize its own profits; (ii) The battery owners coordinate their strategies to maximize the collective battery profits; (iii) The battery owners coordinate their strategies to maximize the overall cluster profits. For (i) we formulate an algorithm for a single price taker battery based on Stochastic Dynamic Programming. Through simulation with realistic data we find that this solution performs well for one isolated home battery and remains stable when used by every battery in the cluster. Additionally, we formulate an algorithm based on Stochastic Dynamic Programming for scenarios (ii) and (iii). Using simulation with realistic data we find that scenarios (ii) and (iii) outperform scenario (i), and that from a cluster perspective, scenario (iii) is more beneficial than scenario (ii). We conclude that incentives have to be put in place to promote the right use of storage in the future grid.

***Index Terms*—smart grid, agent strategies, battery storage, stochastic dynamic programming, emergent behavior.**

I. Introduction

Electrical energy storage is recognized as an essential element in the future energy grid [1]. Batteries are capable of reducing system costs and increasing the stability in grids with high ratios of renewable energy sources [2]. And, even though current battery technology is still too expensive to reach large scale grid parity, the production cost estimates have been dropping at an average rate of 14% per year over the period 2007-2014 [3], indicating grid parity will be reached in the near future.

Existing literature on the optimal control of batteries focuses primarily on batteries too small to influence the electricity market (i.e. they are price takers). Some consider combining batteries with renewable energy production in order to increase reliability of the supply-side [4], while others combine batteries with microgrids to increase their reliability [5], or reduce costs [6]. The related problem of optimally charging EV batteries can be solved using order statistics [7].

Aside from batteries as price takers, some literature focuses on batteries as price makers ([8][9]). However, to the best of our knowledge, no study has compared different control methods for a large number of batteries who are individually price takers, but collectively price makers. The contributions of this paper, which is based on [10], are:

- the derivation and validation of optimal charging strategies based on Stochastic Dynamic Programming (SDP), taking into account price forecasts and their uncertainty;
- the performance comparison of different possible scenarios involving a cluster with home batteries which are collectively price makers (defined as scenario (i)-(iii) in Section II) using simulation with realistic data.

The remainder of this paper is structured as follows. The problem is introduced in Section II. Section III and IV contain the mathematical formulation, the SDP solution, and simulation results for respectively the price taker and price maker problem. Finally, the paper is concluded in Section V.

II. Problem Formulation

The setting we consider in this paper involves a residential cluster of 200 households, each with their own electric vehicle (EV), participating in a smart grid with 30% renewable generation (combined wind and solar). Some of the households own home batteries, which can be charged or discharged (within capacity constraints) to compensate for, or even benefit from, price fluctuations due to changes in demand and supply. We assume that price forecasts are available (e.g. based on weather forecasts and historical demand data), but that these forecasts are uncertain: At each time we know only the current price with certainty, and the forecasting error on future prices increases with their distance in time.

For simplicity we assume that home batteries are the only flexible devices in this cluster, and all other demand and supply is fixed. We neglect the aspects of taxation and network constraints. Having no taxes within the cluster has the advantage that there is no added value to storing and using electricity within the same household, compared to trading it within the cluster. This means that locational aspects within the cluster are irrelevant, and we can model the home batteries as independent entities rather than devices within a household.

There are several options as to how the batteries will be controlled: the battery owners may or may not choose to participate in a collective strategy, and different objectives for this strategy are possible. We compare three scenarios:

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(i) Each household controls its own battery separately to maximize its profits;
(ii) The battery owners coordinate their strategies to maximize the collective battery profits (*selfish*);
(iii) The battery owners coordinate their strategies to maximize cluster profits (*selfless*).

The batteries owned by households are individually too small to influence electricity prices (i.e. they are price takers), collectively however, they have enough capacity to influence prices (i.e. they are price makers). When fully coordinating their actions, and assuming that all batteries have the same characteristics, this collection of batteries can be modeled in an aggregated way, as one large battery.

Alternatively, the battery capacity in the system could be provided by one high capacity battery owned by the network operator, aiming at improving the overall cluster performance, or an independent investor, aiming at maximizing his own profits. Given our setting and assumptions, from a modeling perspective the first case is equivalent to scenario (iii), and the second case is equivalent to scenario (ii).

As a basis for our analysis, we first develop and discuss the optimal charging strategy for a single battery acting as a price taker (Section III). In Section IV, the developed approach is then adapted to the price maker scenarios (i)-(iii).

III. Analysis Price Taker

A. Modeling and Analysis

We start by looking at a single battery acting as a price taker in the electricity market. The goal of the battery is to optimize its charging strategy based on the current price and forecasts of future prices, in order to maximize its own profit. In this model we assume that the maximum charging speed equals the maximum discharging speed and, w.l.o.g., we set this speed to 1. The set of all possible actions is then given by $U = [-1, 1]$, with $u < 0$ representing discharging and $u > 0$ representing charging.

Combining the efficiency[1] η and the write-off costs[2] κ gives us the following reward for the battery at time t given action $u_t \in [-1, 1]$ and price p_t:

$$R(u_t, p_t) = -u_t^+ (p_t + \sqrt{\eta}\kappa) - \eta u_t^- p_t, \tag{1}$$

with $u_t^+ = \max(u_t, 0)$, and $u_t^- = \min(u_t, 0)$.

If the future prices were known with certainty, the optimal charging strategy could be found using dynamic programming, with as state variable the state of charge (SOC) of the battery, x_t. The dynamic programming equation is given by:

$$V_t^*(x_t) = \max_{u_t \in U_t} \left[R(u_t, p_t) + V_{t+1}^*(x_t + u_t) \right], \tag{2}$$

with $U_t = [\max(-1, -x_t), \min(1, x_{\max} - x_t)]$, so that we never attempt to discharge more than is currently in the battery and never charge beyond its capacity ($x_{\max}$). If we had perfect foresight and hence knew future prices with certainty, solving this equation would provide the optimal charging strategy.

In most smart grid settings however (e.g. [11]), future prices are not known in advance. Therefore we assume that only the current price p_t is known, and forecasts $P_{t+1}, \ldots, P_{t+L}$ are available up to L time units ahead. In addition, we assume the distributions of these forecasts to be independent with known probability density functions $f_{P_t}(\cdot)$. In order to take this uncertainty into account, we have to extend the state space of the dynamic program in (2) with the current price p_t. The state at time t is now given by (x_t, p_t).

Let $V_t(x_t, p_t)$ be the maximum expected profit in the interval $t, \ldots, t+L$, given that the state at time t is (x_t, p_t). Then $V_t(x_t, p_t)$ can be determined by iteratively solving the following Stochastic Dynamic Programming (SDP) equations:

$$V_{t+L+1}(x, p) = cx, \text{ with } c \text{ the long-run average price,} \tag{3}$$

$$\begin{aligned} V_\tau(x_\tau, p_\tau) = \max_{u_\tau \in U_\tau} & \left[R(u_\tau, p_\tau) \right. \\ & \left. + \mathbb{E}_{P_{\tau+1}} \left(V_{\tau+1}(x_\tau + u_\tau, P_{\tau+1}) \right) \right], \text{ for } \tau \le t+L, \end{aligned} \tag{4}$$

with $U_\tau = [\max(-1, -x_\tau), \min(1, x_{\max} - x_\tau)]$. Equation (3) denotes the value of the energy left over in the battery at the end of the planning window.

Given the definitions of $R(u, p)$ and $V_{t+L+1}(x, p)$, it is straightforward to calculate the maximum for $V_{t+L}(x, p)$ for given x and p. For each time $\tau = t, \ldots, t+L$, in order to calculate $V_{\tau-1}(x_{\tau-1}, p_{\tau-1})$ we first have to compute the expectation $\mathbb{E}_{P_\tau}(V_\tau(x_\tau, P_\tau))$ in (4). Define:

$$\begin{aligned} \hat{V}_\tau(x_\tau) &= \mathbb{E}_{P_\tau}(V_\tau(x_\tau, P_\tau)) \\ &= \mathbb{E}_{P_\tau}\left(\max_{u_\tau} \left[R(u_\tau, P_\tau) + \hat{V}_{\tau+1}(x_\tau + u_\tau) \right] \right). \end{aligned}$$

Due to the monotonicity of the optimal action w.r.t. the price, and because of the piecewise linearity of both (1) and (3), the set of optimal actions reduces to the discrete set $U_\tau^d = \{\max(-1, -x_\tau), 0, \min(1, x_{\max} - x_\tau)\}$.

In order to solve the expectation of the maximum in (4), we use the monotonicity of the optimal action w.r.t. the price again, this time to split the expectation of the maximum into three parts, one for each action. The corresponding regions of the state space are bounded by the inequalities:

$$R(1, p) < \hat{V}_{\tau+1}(x_\tau + 1) - \hat{V}_{\tau+1}(x_\tau), \tag{5}$$

$$R(-1, p) > \hat{V}_{\tau+1}(x_\tau) - \hat{V}_{\tau+1}(x_\tau - 1). \tag{6}$$

Buying energy ($u_\tau = 1$) is optimal when inequality (5) holds, selling energy ($u_\tau = -1$) is optimal when inequality (6) holds, and doing nothing ($u_\tau = 0$) is optimal when neither holds. The expectation in (4) can now be found by numerical integration over the three regions.

We can now deduce the expected best action to be taken at the current time t by solving the following equation:

$$\hat{u}_t(x_t) = \arg\max_{u_t} \left(R(u_t, p_t) + \hat{V}_{t+1}(x_t + u_t) \right).$$

[1] In order to keep the storage levels within a limited set of discrete values, the choice was made to settle the round trip efficiency (η) when discharging, as opposed to taking $\sqrt{\eta}$ into account when charging and $\sqrt{\eta}$ into account when discharging. This means that only charging can happen at full speed and discharging happens at $\sqrt{\eta}$ times the maximum speed.

[2] While we do not take the charging efficiency into account to stay within a limited number of discrete storage levels, we will take it into account when it comes to the write-off costs (κ). As mentioned before, $1 - \sqrt{\eta}$ of the energy is lost in charging and therefore never reaches the battery, so the write-off costs per cycle are $\sqrt{\eta}\kappa$.

Using this equation and a sliding window, which looks L time units ahead at each point in time, we can calculate the optimal expected value over an entire time frame using:

$$V_{total} = \sum_{t=1}^{T} R\left(\hat{u}_t\left(x_0 + \sum_{\tau=1}^{t-1} \hat{u}_\tau, p_t\right), p_t\right), \tag{7}$$

with x_0 the initial SOC of the battery, and T the end of the time frame (e.g. 50 days in Section III-B).

B. *Numerical Results*

In this section we compare the SDP solution from (7) with its theoretical upper bound (2), and with two other benchmarks.

1) Data: We scale realistic data for the demand of 200 households from [12], to match the annual average Dutch household demand of 3000 kWh. Additionally, we consider realistic EV driving patterns from [13], and let 200 EVs charge uniformly between their arrival at home at the end of the day and their departure the following day.

The data for the renewable supply in the network consists of solar and wind data from the Belgian network in 2015, available at [14]. The 15-minute interval data is converted to hourly data, and it is scaled such that it satisfies on average 30% of the total demand in the system.

For calculating price forecasts, we use Belgian data [14] on day-ahead forecasts for wind and solar production as well as forecasts for the system demand. Since these forecasts are day-ahead forecasts, they lack accuracy on the short term. This is handled by reducing the forecasting error using linear regression. An illustrative example of the data can be found in Figure 1.

For converting the Belgian demand and supply data and forecasts into price data and forecasts, we use the exponential model from [15], describing the merit order curve of the German electricity grid:

$$\pi_t(x) = e^{\frac{l'_t(x)-a}{b}} + z_t, \tag{8}$$

with l'_t the normalized load, $a = -0.860$ the horizontal shift, and $b = 0.421$ the scaling factor. The normalized load is given by $l'_t(x) = \frac{x - E_t^w - E_t^s}{l_{\max}}$, with E_t^w the generated wind energy at time t, E_t^s the generated solar energy, and $l_{\max}$=383 kWh the maximum difference between demand and renewable supply.

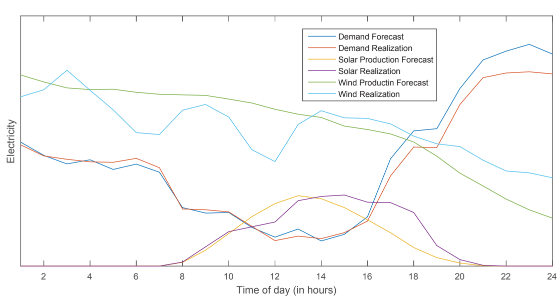

Fig. 1. An illustrative example of the data and forecasts on August 27, 2015

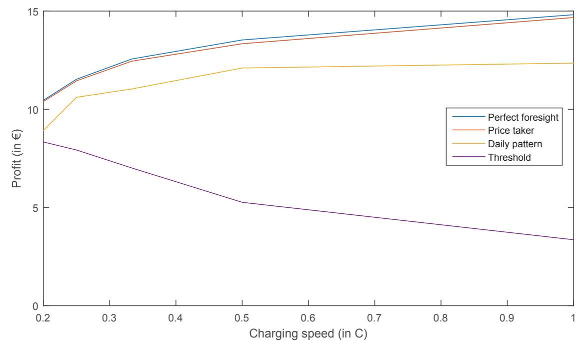

Fig. 2. Comparison of profits using two different benchmarks, the SDP of the price taker model, and perfect foresight for 200 households

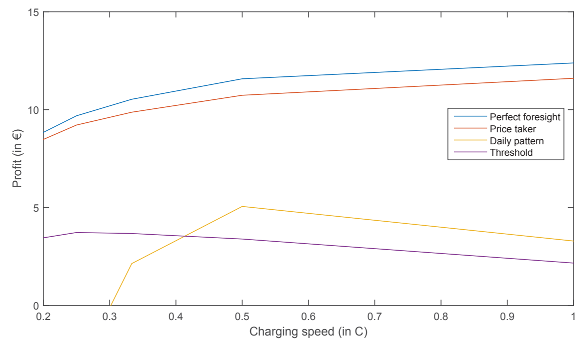

Fig. 3. Comparison of profits using two different benchmarks, the SDP of the price taker model, and perfect foresight for the Belgian grid

2) Results: For batteries with different charging speeds, we compare the results of four different strategies: the threshold and daily pattern benchmarks described below, the solution of the SDP in (7), and the upper bound given by (2).

The threshold benchmark buys energy below a certain threshold and sells energy above another threshold. The thresholds are chosen equidistant from the average price such that when energy is bought for the lower threshold and sold for the upper threshold, we turn even.

The daily pattern benchmark looks at the average daily price pattern over the entire year and uses it to buy energy during the n cheapest hours and sell energy during the n most expensive hours of the average day, with n the number of hours it takes to fully charge the battery.

The results for a period of 50 days are shown in Figure 2 for batteries with a round-trip efficiency of 90%, zero initial charge, a maximum battery capacity of 20 kWh, and write-off costs of 0.01€/kWh. The values on the x-axis denote the charging speeds (i.e. the fraction of the battery capacity $x_{\max}$ which can be charged in one hour). These results show that the SDP solution remains within 99% of the solution with perfect foresight, and it significantly outperforms both benchmark methods. The daily pattern benchmark outperforms the threshold method, because the energy prices in this setting follow a distinctive daily pattern.

Figure 3 shows the results for the same battery in the setting of the entire Belgium grid. This setting also includes industrial demand, and most of the battery profits are not gained from a daily pattern, but from significant changes in demand and renewable energy production. Therefore the daily pattern benchmark performs significantly worse than in the setting of Figure 2. Our SDP solution suffers only a minor loss in performance and remains within 92% of the solution with perfect foresight.

IV. Analysis Price Maker

In this section we look at what happens if the actions of the battery do have an influence on the price. This could happen if multiple price taker batteries all use the SDP strategy from (7) and inadvertently become a collective price maker (scenario (i) in Section II), or if one entity controls this group of batteries in a centralized way, e.g. an energy broker (scenario (ii)) or a network operator (scenario (iii)). We will start by deriving a strategy for the last two cases, recalling from Section II that a group of batteries can be modeled as one large battery if their battery characteristics are the same.

A. Modeling and Analysis

Large parts of the price maker model are similar to the model presented in Section III-A. Therefore we will only discuss the differences in this section.

In this section we assume that the battery (or coordinated group of batteries) knows its influence on the price. We will refer to the battery that tries to maximize its own profits as the *selfish* battery (as in scenario (ii)) and the battery that works for the overall cluster benefit as the *selfless* battery (as in scenario (iii)).

The only difference between the models for the selfless and selfish battery is the reward function. Let q_t be the aggregated cluster demand (including the battery) at time t, given by:

$$q_t = \left(1 - (1-\eta)\,\mathbb{1}_{\{u_t<0\}}\right) u_t + d_t,$$

with $\mathbb{1}$ the indicator function, and d_t the aggregated cluster demand excluding the battery. Let $\pi_t(q_t)$ be the price function at time t, given by (8). Now the reward function for the selfish battery is given by:

$$R\left(u_t, d_t, \pi_t\right) = -u_t^+ \pi_t\left(q_t\right) - u_t^+ \sqrt{\eta}\kappa - \eta u_t^- \pi_t\left(q_t\right),$$

with $u_t^+ = \max\left(u_t, 0\right)$, and $u_t^- = \min\left(u_t, 0\right)$.
The reward function for the selfless battery is given by:

$$R\left(u_t, d_t, \pi_t\right) = -q_t^+ \pi_t\left(q_t\right) - u_t^+ \sqrt{\eta}\kappa - \eta q_t^- \pi_t\left(q_t\right),$$

with $q_t^+ = \max\left(q_t, 0\right)$, and $q_t^- = \min\left(q_t, 0\right)$.
Using the perfect foresight solution (2) with either of these reward functions again provides an upper bound for the achievable profit.

In our setting, however, we do not assume perfect foresight. The optimal charging strategies are again based on forecasts for the future wind and solar production as well as the future demand. Forecasts will be denoted by '$\hat{\ }$'.

Since our actions affect the electricity price, our future actions influence the distribution of the stochastic price forecast P_t. Assuming the forecast comes from the location-scale family, we can separate the location and the scale. The location is given by $\pi\left(x\right)$, and we introduce stochastic variable Z_t to capture the scale, with $\mathbb{E}Z_t = 0$ and probability density function $f_{Z_t}\left(z\right)$. In order to keep the notation clear, define: $\hat{R}\left(u_t, d_t, \hat{\pi}_t, Z_t\right) = R\left(u_t, d_t, g_t\right)$, with $g_t\left(x_t\right) = \hat{\pi}_t\left(x_t\right) + Z_t$.
The SDP equation for scenarios (ii) and (iii) now becomes:

$$\begin{aligned} &V_{t+L+1}\left(x, z\right) = cx, \text{ for some price } c. \\ &V_\tau\left(x_\tau, z_\tau\right) = \max_{u_\tau \in U_\tau} \Big[\hat{R}\left(u_\tau, d_\tau, \hat{\pi}_\tau, z_\tau\right) \\ &\qquad + \mathbb{E}_{Z_{\tau+1}}\left(V_{\tau+1}\left(x_\tau + u_\tau, Z_{\tau+1}\right)\right)\Big], \text{ for } \tau \le t+L, \end{aligned} \quad (9)$$

with $U_\tau = \left[\max\left(-1, -x_\tau\right), \min\left(1, x_{\max} - x_\tau\right)\right]$.

Solving this set of equations requires the same expectation of a maximum as we have seen in the price taker model. However, this time the reward function is no longer piecewise linear, and therefore the space of optimal actions can no longer be reduced to U_τ^d. Instead we approximate the optimum numerically, by finely discretizing the action space and for each discrete action finding the subset of the state space for which this action is optimal. This allows us to calculate the expectation in (9) and recursively find the optimal action at time t.

B. Numerical Results

In the price maker setting of this section, the optimal strategy influences future prices and vice versa. In contrast to the price taker setting of Section III-B, we need to re-run our simulations over the same period of 50 days multiple times in order to reflect this circular dependence. After each iteration the forecasts will be updated using $\hat{p}_{t,j}^k = \epsilon_{t,j} + p_t^{k-1}$, with t the point in time we are looking at, j the number of hours we look into the future, $\epsilon_{t,j}$ the error in the original forecast, and p_t^{k-1} the realized price at time t in the previous iteration. Each individual price taker battery is willing to buy maximum energy when inequality (5) holds and sell maximum energy when inequality (6) holds.

Figure 4 shows the cluster profit per kWh of battery capacity for the results obtained using perfect foresight combined with the selfless reward function, the collective price maker model in which all batteries use the price taker strategy (scenario (i)), and the selfish and selfless price maker models (scenarios (ii) and (iii)). The cluster profit on the y-axis is defined as the difference in costs between the cluster without batteries, and the cluster with batteries. This figure shows that there is a significant difference between the scenarios as the battery capacity increases. The cluster profit of coordinated selfless control (scenario (iii)) gets within 99% of the profit of the model with perfect foresight and selfless control, while the value of coordinated selfish control (scenario (ii)) is 42% lower for the largest batteries. Using price taker strategies in the price maker grid (scenario (i)) is beneficial for the cluster even though the batteries' collective influence on the price is

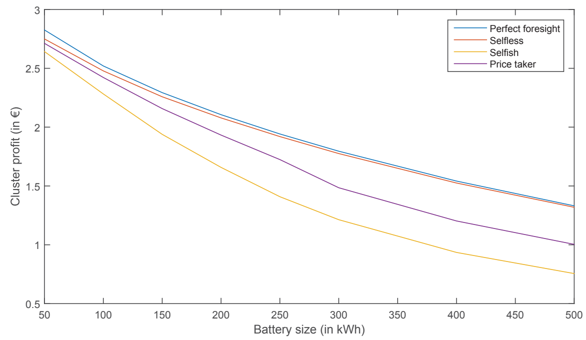

Fig. 4. Comparison of cluster profits for different battery sizes, using the selfless and selfish strategies, the price taker strategy, and perfect foresight.

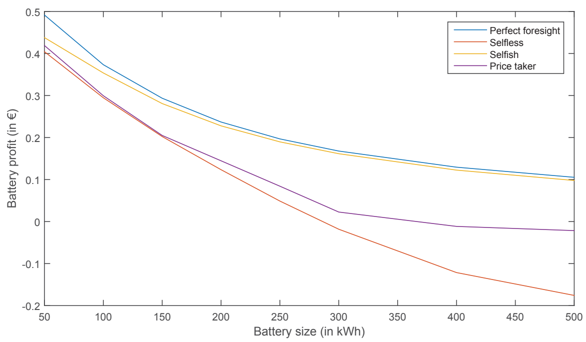

Fig. 5. Comparison of battery profits for different battery sizes, using the selfless and selfish strategies, the price taker strategy, and perfect foresight.

ignored in their strategies, and from a cluster level perspective scenario (i) even performs better than the selfish strategy.

The battery profits for the different scenarios are compared in Figure 5. The selfish strategy of scenario (ii) performs best, and gets close to the perfect foresight solution using the selfish reward function. Both the selfless battery of scenario (iii) and the group of price taker batteries (scenario (i)) incur losses for large battery sizes.

Combining both figures, we can conclude that the selfless batteries and the price taker batteries (scenarios (iii) and (i)) incur individual battery losses. Therefore, in a smart grid without incentives, the rational choice for a group of home batteries is to use the selfish strategy of scenario (ii) in order to maximize their own profits, resulting in a cluster which benefits little from the batteries' flexibility.

On the other hand, in scenario (iii) the cluster profits obtained by using the battery flexibility in a selfless way are high, but the battery profits are negative for large total battery capacities, actually making it unprofitable for any household to own a home battery. Hence, in order to promote both the investment by households in home batteries, and the selfless strategy of scenario (iii) which maximizes cluster profits, financial incentives (e.g. government subsidies) should be considered.

V. Concluding Remarks

Using SDP to control a price taker battery gives near-optimal solutions that clearly outperform the two chosen benchmarks, and were shown to remain within 92% of the solution with perfect foresight in simulations with realistic data. This solution was shown to remain stable and profitable on the cluster level, even when used by enough batteries to collectively influence the prices.

However, the performance can be improved even further, either by coordinating the actions of the batteries to increase their individual profits, or by having the batteries cooperate to collectively reduce system costs. From a system level perspective, coordinated selfless batteries are up to 42% more beneficial to the system than coordinated selfish batteries. However, for large combined battery capacities, selfless batteries incur individual losses, while being selfish leads to individual profits. For this reason, governments can play an essential role in incentivizing the right use of storage.

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