To Charge or not to Charge: Selfish Storage and Its Effect on Electricity Markets

ABSTRACT

The volatility of prices in modern electricity markets, caused by fluctuations in generation and fast-changing demand, can be significantly reduced by the introduction of arbitrage-oriented storage suppliers. The behavior of selfish agents that provide storage is greatly influenced by both strategic considerations and by the physical constraints of storage systems, limiting their beneficial effect on the market. In this work we use agent-based modeling to examine the effect of both these factors on the agent's behavior and the subsequent market outcome. For a market in which a single monopolistic storage provider exists, we analyze the welfare loss caused by profit-maximizing behavior of the agent, showing that in case of linear demand and supply curves, the price of anarchy is 3/4, and the monopolist extracts 2/3 of the total welfare that it adds. For smaller-scale storage, we use Markov Decision Processes (MDPs) to realistically model the physical behavior of a storage system. We then utilize this model to provide an agent-based framework to derive the bidding strategies of storage agents, and use it to analyze the effect of multiple agents on the market, empirically showing the effect of physical specifications of storage on the market equilibrium and storage saturation.

KEYWORDS

Modelling for agent based simulation; auctions and mechanism design

INTRODUCTION

Electricity markets have undergone profound changes since the last decade of the 20th century, moving from a market governed by a vertically integrated electric utility towards a competitive environment where electricity generators, consumers and retailers interact via bid-based transactions. The last two decades saw the establishment of regional and international wholesale power exchanges in Europe, Asia, South and North America, where energy is traded on both a short term (spot market) and a long-term (forward market) basis.

In spot markets, where fluctuations in production and consumption can quickly change prices, there are economic benefits that can be reaped from the introduction of energy storage. Storage can increase social welfare by transferring power between on-peak and off-peak times, as well as provide ancillary services to the market, reducing the need to over-provision the system with electricity generation that is only activated during peak demand, and mitigating price volatility stemming from the increasingly large market participation of the renewable energy sources. The arbitrage opportunities imply that private agents can supply all of these services and profit from the price differences. However, as more storage suppliers join the market, competition between them increases and reduces any gains from arbitrage. This implies that any electricity market can only sustain a certain level of storage capacity while maintaining profitability for its storage suppliers.

In this paper we analyze the effect of such arbitrage-oriented storage agents (SA's) on electricity market. The market we explore utilizes a *double-sided uniform market clearing price auction* which is used in most power exchanges. We begin by analyzing a simple setting where a single large storage provider exists, using game-theoretic tools to show that even for a completely predictable market with idealized storage, the strategic considerations of the storage agent drive it to limit the storage capacity it uses in which leads to a lower social welfare than is otherwise achievable. We then proceed to analyze the case where individual storage providers are small. Here we use an agent-based framework to examine the impact of strategic considerations on the behavior of storage owners, while taking into account the physical behavior of the storage systems used.

To summarize, our contributions are:

(1) Using a game-theoretic approach, for a linear model of the market, we derive that at least 3/4 of the optimal social welfare is obtained, and that the storage agent obtains 2/3 of the added utility as arbitrage gain.
(2) We provide a realistic model of an electric storage system (ESS) that is based on its physical attributes and models the way it deteriorates based on usage patterns.
(3) Using this model, we are able to empirically analyze the impact of multiple storage agents on the electricity market, deriving methodologies to estimate the limits of the positive effect that energy storage can have on market price volatility. We use this to evaluate how various parameters of the storage technology affect market saturation and how markets will behave once saturated.

The rest of this paper is structured as follows. First, we provide a game-theoretic analysis of a selfish storage agent's behavior in a market environment. In the following section, we describe our framework for representing an energy storage system (ESS) as an MDP, and presents an example of implementing a real-life storage system (electrochemical battery) using this framework. Next, we study the effect of such storage agents on the market through empirical simulations, and conclude.

Related Work

The beneficial effects of storage on the electricity market have been widely researched. Studies show that introducing storage to energy markets stabilizes market prices, decreases congestion, limits the market power of strategic producers [16] and decreases

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the price volatility resulting from integration of renewable sources [9]. Several studies have analyzed the social welfare effects of large-scale energy storage [7], [8], showing that the welfare gain from such storage is on the same scale as the arbitrage gain.

Studies that focus on strategic behavior of the battery show that ESS is incentivized to withhold its capacity [7] and its incentives depend on the distribution of power between the players ([5]). As far as we are aware, there are no treatments of price-of-anarchy for storage units in the literature.

Agent-based approaches have been used to propose intelligent strategies for independent suppliers [2], [4] as well as developing policies for decentralized storage management [13]. The issue of micro-storage, where storage is operated by independent home-owners [14], [15] or electric-vehicle owners [11], has received particular attention. However, these studies do not deal with the modern structure of electronic power markets, utilizing older models where price is either deterministic or set according to a predetermined load pattern.

Markov decision processes and dynamic programming have been used in multiple studies to model energy storage behavior [12], [1]. However, these models mostly use the MDP framework to model the changes in State-of-charge (SOC) of the storage systems, and the issue of performance-affecting degradation was not discussed, nor is their overall effect on the market. Furthermore, the effect of multiple storage devices on the market was not covered in any of the studies.

THE MONOPOLISTIC STORAGE AGENT

In this section we analyze the behavior of a single storage provider. We remove from the model any uncertainty about future prices, and consider ideal storage units in order to focus purely on the cost of selfish behavior by the agent.

Market Model

We adopt a model of the market that uses double-sided uniform market clearing price (MCP) auction. This auction mechanism is adopted in most power exchanges around the world, such as EEX and NordPool [3]. In this auction model, every trader in the market submits a *market bid*, which is a 2-tuple (v, p) where v is the *volume* of energy submitted for trade and p is the *limit price* of the bid, e.g. the minimal price for the bid to sell energy and the maximal price for the bid to buy energy.

Definition 1. Let $\{(v_1^{\text{Pr}}, p_1^{\text{Pr}}), (v_2^{\text{Pr}}, p_2^{\text{Pr}}), \dots\}$ be the *sell* bids sorted from lowest to the highest price offer. Then, we define the *supply curve* $\text{Pr}(v) = p_N^{\text{Pr}}, s.t. N = \min_n (\sum_{i=1}^n v_i^{\text{Pr}} \geq v$. The *demand curve* is defined similarly for the set $\{(v_1^{\text{Co}}, p_1^{\text{Co}}), (v_2^{\text{Co}}, p_2^{\text{Co}}), \dots\}$ of *buy* bids sorted.

Definition 2. The uniform market clearing price auction is an auction that for a set of *buy* bids $\{(v_1^{\text{Co}}, p_1^{\text{Co}}), (v_2^{\text{Co}}, p_2^{\text{Co}}), \dots\}$ and for the set of *sell* bids $\{(v_1^{\text{Pr}}, p_1^{\text{Pr}}), (v_2^{\text{Pr}}, p_2^{\text{Pr}}), \dots\}$, determines the *market clearing volume* as

$$mv = \max_V s.t. \exists N_V, M_V : \sum_{i=1}^{N_V} v_i^{\text{Co}} \geq V, \sum_{i=1}^{M_V} v_i^{\text{Pr}} \geq V, \\ p_{N_V}^{\text{Co}} \geq p_{M_V}^{\text{Pr}}$$

The *market clearing price* is then $mp = p_{N_V}^{\text{Co}} + p_{M_V}^{\text{Pr}}/2$, and every agent participating in the auction pays and is paid according to it. The resolution of the trade is as follows: the *buy* bids $1 \dots N_V - 1$ and the *sell* bids $1 \dots M_V - 1$ are satisfied fully; the bids N_V, M_V are satisfied partially, so that the volumes $V - \sum_{i=1}^{N_V} v_i^{\text{Co}}$ and $V - \sum_{i=1}^{M_V} v_i^{\text{Pr}}$ are transferred to the bidders accordingly.

In this section, we treat the case of a market with large amount of infinitesimally small consumers and producers. In this case, the piecewise-constant demand and supply curves behave like a continuous functions. Note that both curves are monotone, with demand curve monotonically descending and supply curve monotonically ascending. For the sake of analysis in this section, we assume that both curves are strictly monotone (and therefore invertible) and differentiable.

To model the different behaviors of the market, we introduce the notion of *market state*. Each market state is characterized by a demand and supply curve. In this section, we assume two market states: DAY, with supply curve $\text{Pr}_d(x)$ and demand curve $\text{Co}_d(x)$ and NIGHT, with curves $\text{Pr}_n(x)$ and $\text{Co}_n(x)$ accordingly, s.t. $\text{Co}_d(0) > \text{Co}_n(0)$. We further assume that consumers and producers bid truthfully, i.e. offer the energy bids at their true valuation.

We define the storage agent as an agent who can offer buying bids to the market, and can offer a selling bid after a successful buying bid, i.e., that the agent's storage is either charged or not, and that bids are for exactly the amount of energy the agent chooses to store.

In the case of a agent's *buy* bid of size α at price pr, let v_{pr} be the market volume s.t. $\text{Co}(v_{pr}) = pr$. Then the updated consumption curve becomes:

$$\text{Co}^*(x) = \begin{cases} \text{Co}(x) & 0 \leq x < v_{pr} \\ pr & v_{pr} \leq x < v_{pr} + \alpha \\ \text{Co}(x - \alpha) & x \geq v_{pr} + \alpha \end{cases}$$

In case of a *sell* bid, we update the production curve in the similar fashion.

Definition 3. For a given demand and supply curve, let mv be the market volume of the round and mp be the market price. We define the **social welfare** of the market as:

$$W = \int_0^{mv} \text{Co}(x) - \text{Pr}(x) dx$$

If the agent is participating in the trade with a bid of size α and price pr_b, the social welfare of the market is defined as:

$$W = \int_0^{mv} \text{Co}(x) - \text{Pr}(x) dx - \alpha |pr_b - mp|$$

Note that we exclude the storage agent's welfare ($\alpha |pr_b - mp|$) from the market, as it does not gain utility from acquiring electricity. Instead, we introduce the definition of the agent's *gain*:

Definition 4. For a storage agent that successfully bought a volume of energy α for the price mp_1 and sold it for the price mp_2, the *gain* is defined as $G = \alpha(mp_2 - mp_1)$

Definition 5. Let α_{self} be the size of the bid that maximizes the agent's gain, and α_{soc} be the size of the bid that maximizes the market's social welfare gain with nonnegative agent's gain. We define *price of anarchy* as:

$$PoA = \frac{\Delta W(\alpha_{self}) + \Delta G(\alpha_{self})}{\Delta W(\alpha_{soc}) + \Delta G(\alpha_{soc})}$$

and the *revenue extraction ratio* as:

$$RER = \frac{\Delta G(\alpha_{self})}{\Delta W(\alpha_{self}) + \Delta G(\alpha_{self})}$$

The PoA and RER quantify two important aspects of the tradeoff between the agent's personal gain and the market's surplus. The former helps us to understand how degrading is the storage agent's selfish behavior to the social welfare gain of the whole market; the latter quantifies the amount of social surplus the agent is able to extract as personal revenue. It is clear, therefore, that from the market's perspective, we are interested in high PoA and low RER (at the extreme, an RER of 1 means that while we seem to gain from the addition of storage to the market, all these gains end up in the hands of the storage agent, which does not benefit the rest of the market at all).

Influence of the Agent on Social Welfare

To prove further claims we first prove supportive lemmata:

Lemma 6. *Given the demand and supply curves Co(x) and Pr(x), the social welfare of the market for the successfully resolved buy bid (α, b) or sell bid (α, s) of the storage agent is identical to the welfare for successfully resolved buy bid $(\alpha, Co(0))$ and sell bid $(\alpha, 0)$ accordingly.*

Proof. Let us show w.l.o.g that the social welfare in the case of buying at Co(0) is equal for buying at other price for a given bid size α: Let x_m, y_m be the market volume and price for both cases, y_b the agent's price bid, and $x_b = \mathrm{Co}^{-1}(y_b)$.

The social welfare for $x_b = 0, y_b = \mathrm{Co}(0)$ is

$$W_a = \alpha y_m + \int_{\alpha}^{x_m} \mathrm{Co}(x-\alpha)dx - \int_0^{x^m} \mathrm{Pr}(x)dx$$

Using basic algebraic manipulation, it can be shown that the social welfare for general y_b, x_b is:

$$W_{gen} = \int_0^{x_b} \mathrm{Co}(x) - \mathrm{Pr}(x)dx + \alpha y_b - \int_{x_b}^{x_b+\alpha} \mathrm{Pr}(x)dx + \int_{x_b+\alpha}^{x_m} \mathrm{Co}(x-\alpha) - \mathrm{Pr}(x)dx = W_a$$

□

Lemma 7. *There exist a bid size α, for which, if the agent sells α energy during day and buys α energy during night, it achieves the optimal social welfare.*

Proof. We break the proof into several claims:

Claim 7.1. *There exist x_m^d, x_m^n and α, such that $Co_n(x_m - \alpha) = Pr_n(x_m)$ and $Co_d(x_m) = Pr_d(x_m - \alpha)$*

As the demand and supply curves are invertible in the domain $x > 0$, let $\mathrm{Pr}_d^{-1}(y), \mathrm{Pr}_n^{-1}(y)\mathrm{Co}_d^{-1}(y)$ and $\mathrm{Co}_n^{-1}(y)$ be the inverse functions of $\mathrm{Pr}_d(x), \mathrm{Pr}_n(x), \mathrm{Co}_d(x)$ and $\mathrm{Co}_n(x)$ accordingly (note that monotonicity is preserved and also $\mathrm{Co}_d^{-1}(y) \geq \mathrm{Co}_n^{-1}(y)\ \forall 0 \leq y \leq \mathrm{Co}_d(0)$). We define the function

$$f(y) = (\mathrm{Co}_d^{-1}(y) - \mathrm{Pr}_d^{-1}(y)) - (\mathrm{Pr}_n^{-1}(y) - \mathrm{Co}_n^{-1}(y))$$

As all the inverse functions are continuous, and also $\mathrm{Pr}_d^{-1}(y), \mathrm{Pr}_n^{-1}(y)$ are strictly increasing and $\mathrm{Co}_d^{-1}(y), \mathrm{Co}_n^{-1}(y)$ strictly decreasing in the domain $0 \leq y \leq \mathrm{Co}_d(0)$, then $f(y)$ is continuous and strictly monotone in this domain. Let x_d^*, y_d^* signify the market volume and price in the DAY period, and x_n^*, y_n^* signify the market volume and price in the NIGHT period. Then,

$$f(y_n^*) = (\mathrm{Co}_d^{-1}(y_n^*) - \mathrm{Pr}_d^{-1}(y_n^*)) - (\mathrm{Pr}_n^{-1}(y_n^*) - \mathrm{Co}_n^{-1}(y_n^*))$$
$$= (\mathrm{Co}_d^{-1}(y_n^*) - \mathrm{Pr}_d^{-1}(y_n^*)) - 0 \geq 0$$

Similarly,

$$f(y_d^*) = 0 - (\mathrm{Pr}_n^{-1}(y_d^*) - \mathrm{Co}_n^{-1}(y_d^*)) \leq 0$$

Therefore, according to the intermediate value theorem, there exists a point y^* s.t. $f(y^*) = 0$. Let $x_m^d = \mathrm{Pr}_d^{-1}(y^*), x_m^n = \mathrm{Pr}_n^{-1}(y^*)$and $\alpha = \mathrm{Co}_d^{-1}(y^*) - \mathrm{Pr}_d^{-1}(y^*) = \mathrm{Pr}_n^{-1}(y^*) - \mathrm{Co}_n^{-1}(y^*)$ It is then clear that $\mathrm{Co}_n(x_m - \alpha) = \mathrm{Pr}(x)$ and $\mathrm{Co}_d(x) = \mathrm{Pr}(x_m - \alpha)$.

Claim 7.2. *Let y_d, y_n be the market prices during day and night accordingly. As long as $y_d > y_n$, the agent can improve the social welfare of the system by selling an infinitesimal Δ_b during day and buying Δ_b during night.*

Let x_d, x_n be the market volumes during day and night accordingly, and $x_d^* = x_d + \delta_{day}, x_n^* = x_d + \delta_{day}$ be the market volumes in case the agent trades as described. W.l.o.g, the new consumption and production curves are:

$$\mathrm{Co}_n^*(x) = \begin{cases} \mathrm{Co}_n(0) & 0 \leq x < \Delta_b \\ \mathrm{Co}_n(x - \Delta_b) & x \geq \Delta_b \end{cases}$$

$$\mathrm{Pr}_n^*(x) = \begin{cases} 0 & 0 \leq x < \Delta_b \\ \mathrm{Pr}(x - \Delta_b) & x \geq \Delta_b \end{cases}$$

The welfare change during the day is

$$W_{day} = \int_0^{x_d} \mathrm{Co}_d(x)dx - \int_0^{x_d} \mathrm{Pr}_d(x)dx$$

$$W_{day}^* = \int_0^{x_d^*} \mathrm{Co}_d(x)dx - \int_{\Delta_b}^{x_d^*} \mathrm{Pr}_d(x-\Delta_b)dx - \overbrace{\Delta_b y_d^*}^{\text{agent's welfare}} =$$
$$= \int_0^{x_d^*} \mathrm{Co}_d(x)dx - \int_0^{x_d^*-\Delta_b} \mathrm{Pr}_d(x)dx - \Delta_b y_d^*$$
$$= W_{day} + \int_{x_d}^{x_d^*} \mathrm{Co}_d(x)dx + \int_{x_d^*-\Delta_b}^{x_d} \mathrm{Pr}_d(x)dx - \Delta_b y_d^*$$

Similarly, the welfare change during the night:

$$W_{night}^* = W_{night} + \int_0^{\Delta_b} \mathrm{Co}_n(0)dx - \int_{x_n^*-\Delta_b}^{x_n} \mathrm{Co}_n(x)dx - \int_{x_n^*}^{x_n} \mathrm{Pr}_n(x)dx - \Delta_b(\mathrm{Co}_n(0) - y_n^*)$$

Using the infinitesimality of Δ_b:

$$\Delta W_{day} + \Delta W_{night} = \int_{x_d}^{x_d^*} \text{Co}_d(x)dx + \int_{x_d^*-\Delta_b}^{x_d} \text{Pr}(x)dx + \int_0^{\Delta_b} \text{Co}_n(0)dx - \int_{x_n^*-\Delta_b}^{x_n} \text{Co}_n(x)dx - \int_{x_n}^{x_n^*} \text{Pr}(x)dx - \text{Co}_n(0)\cdot\Delta_b - \Delta_b(y_d^* - y_n^*)$$

$$\approx \text{Co}_n(0)\cdot\Delta_b + (\delta x_d)\cdot y_d + (\Delta_b - \delta x_d)\cdot y_d - (\Delta_b - \delta x_n)\cdot y_n - (\delta x_n)\cdot y_n + -\text{Co}_n(0)\cdot\Delta_b - \Delta_b(y_d^* - y_n^*) + \text{O}(\delta x_n^2 + \delta x_d^2)$$
$$= \Delta_b(y_d - y_n) - \Delta_b(y_d^* - y_n^*) + \epsilon$$

Because of infinitesimality of Δ_b, we assume that $\delta y_d = y_d - y_d^* = \text{Co'}_d(x_d)\delta x_d, \delta y_n = y_n^* - y_n = \text{Pr'}_n(x_d)\delta y_d$, and also:

$$\delta x_n = \frac{\text{Co'}_n(x_n)}{\text{Co'}_n(x_n) - \text{Pr'}_n(x_n)}\Delta_b \quad \delta x_d = \frac{\text{Pr'}_d(x_d)}{\text{Pr'}_d(x_d) - \text{Co'}_d(x_d)}\Delta_b$$

$$\epsilon \approx \frac{1}{2}(-\delta x_n\delta y_n - (\Delta_b - \delta x_n)\delta y_n - \delta x_d\delta y_d - (\Delta_b - \delta x_d)\delta y_d) = \frac{1}{2}\Delta_b(-\delta y_n - \delta y_d)$$

Altogether, the difference in social welfare is:

$$\Delta W_{day} + \Delta W_{night} = \Delta_b(\delta y_d + \delta y_n) + 1/2\Delta_b(-\delta y_n - \delta y_d) = 1/2\cdot\Delta_b\delta y_n + 1/2\Delta_b\delta y_d > 0 \tag{1}$$

This concludes the proof of Lemma 7. □

Lemma 8. *Let α_{self} the volume of agent's bid maximizing its gain, and $x_d^s, x_n^s, y_d^s, y_n^s$ be the resulting market volumes and prices for night and day. Then, $x_d^s, x_n^s, y_d^s, y_n^s, \alpha_{self}$ satisfy:*

$$\alpha_{self}\left(\frac{Pr'_n(x_n^s)Co'_n(x_n^s)}{Co'_n(x_n^s) - Pr'_n(x_n^s)} + \frac{Co'_d(x_d^s)Pr'_d(x_d^s)}{Pr'_d(x_d^s) - Co'_d(x_d^s)}\right) = y_d^s - y_n^s \tag{2}$$

Proof. Agent's gain for increasing its bid size α by Δ_b is:

$$\Delta G = \Delta_b(y_d^* - y_n^*) - \alpha(\delta y_d + \delta y_n) \tag{3}$$

The optimal bid size is reached when the gain from increasing the bid is equal to zero:

$$\Delta G = 0 = \Delta_b(y_d^* - y_n^*) - \alpha(\delta y_d + \delta y_n)$$
$$\alpha(\Delta_b\cdot\frac{\text{Pr'}_n(x_n)\text{Co'}_n(x_n)}{\text{Co'}_n(x_n) - \text{Pr'}_n(x_n)} + \Delta_b\cdot\frac{\text{Co'}_d(x_d)\text{Pr'}_d(x_d)}{\text{Pr'}_d(x_d) - \text{Co'}_d(x_d)})$$
$$= \Delta_b(y_d - y_n - \delta y_n - \delta y_d) = \Delta_b(y_d - y_n) - \underbrace{\Delta_b(\delta y_d + \delta y_n)}_{\text{negligible for}\Delta_b\to 0}$$
$$\alpha\left(\frac{\text{Pr'}_n(x_n)\text{Co'}_n(x_n)}{\text{Co'}_n(x_n) - \text{Pr'}_n(x_n)} + \frac{\text{Co'}_d(x_d)\text{Pr'}_d(x_d)}{\text{Pr'}_d(x_d) - \text{Co'}_d(x_d)}\right) = y_d - y_n$$

□

Price of Anarchy and Revenue Extraction

Lemma 9. *For linear demand and supply curves, RER = 2/3*

Proof. In the linear case, the differences of profit and gain for bid size $a >> 0$ are equal to the linearized gains from Δb increment listed in the previous section. Additionally, as the derivatives of the curves are constant, we can define:

$$\left|\frac{\text{Pr'}_n(x)\text{Co'}_n(x)}{\text{Co'}_n(x) - \text{Pr'}_n(x)}\right| = z_n \quad \left|\frac{\text{Co'}_d(x)\text{Pr'}_d(x)}{\text{Pr'}_d(x) - \text{Co'}_d(x)}\right| = z_d$$

Therefore, according to 8, α_{self} satisfies:

$$\alpha_{self}\,(z_n + z_d) = y_d^s - y_n^s$$

The agent's gain in this case is:

$$\Delta G(\alpha_{self}) = \alpha_{self}(y_d - y_n) = \alpha_{self}^2\,(z_n + z_d)$$

The difference in the welfare is, according to Equation 1:

$$\Delta W(\alpha_{self}) = 1/2\alpha_{self}(\delta y_d + \delta y_n) = 1/2\alpha_{self}(\alpha_{self} z_n + \alpha_{self} z_d) = 1/2\alpha_{self}^2\,(z_n + z_d) \tag{4}$$

Therefore, the RER is

$$\frac{\Delta G(\alpha_{self})}{\Delta W(\alpha_{self}) + \Delta G(\alpha_{self})} = \frac{\Delta G(\alpha_{self})}{\frac{1}{2}\Delta G(\alpha_{self}) + \Delta G(\alpha_{self})} = \frac{2}{3}$$

□

Lemma 10. *For linear demand and supply curves, PoA = 3/4*

Proof. For the linear system, it can be shown that $\alpha_{soc} = 2\alpha_{self}$: Let y_d, y_n be the initial prices, and $y_d^{soc} = y_n^{soc}$ the price for the scenario when the optimal warfare is reached. From the definition of α_{soc}:

$$y_d^{soc} = y_d - \alpha_{soc} z_d = y_n + \alpha_{soc} z_n = y_n^{soc} \Rightarrow$$
$$y_d - y_n = \alpha_{soc}(z_d + z_n)$$

Similarly for α_{self}:

$$\alpha_{self}\,(z_n + z_d) = y_d - \alpha_{self} z_d - (y_n + \alpha_{self} z_n) = \alpha_{soc}(z_d + z_n) - \alpha_{self}(z_d + z_n)$$
$$2\alpha_{self}(z_d + z_n) = \alpha_{soc}(z_d + z_n)$$

Plugging back into 4:

$$\Delta W(\alpha_{soc}) = \frac{1}{2}\alpha_{soc}^2\,(z_n + z_d) = \frac{1}{2}4\alpha_{sel}^2\,(z_n + z_d) = 2\Delta G(\alpha_{self})$$

We will then note that as the storage agent buys and sells the energy for the same price when it maximizes the social welfare, therefore:

$$\Delta G(\alpha_{soc}) = 0$$

Then:

$$PoA = \frac{\Delta W(\alpha_{self}) + \Delta G(\alpha_{self})}{\Delta W(\alpha_{soc})} = \frac{1/2\cdot\Delta G(\alpha_{self}) + \Delta G(\alpha_{self})}{2\Delta G(\alpha_{self})} = \frac{3}{4}$$

□

We have found therefore that in the case of linear market, while the equilibrium welfare is reasonably close to the optimal welfare, most of the welfare in the equilibrium is extracted by the agent as personal revenue and the other participants are only slightly better off.

SMALL-SCALE STORAGE AGENTS

We now turn our attention to scenarios in which there are multiple storage providers in the market. We utilize MDPs to derive their trade behavior and focus on the effects that the physical properties of storage units have on the market once it is saturated.

General Model

We now want to model the behavior of the agent as it stems from the physical properties and physical deterioration of the ESS. Such modeling can be easily done using stationary discrete-time Markov Decision Process (MDP). A MDP is a 5-tuple (S, A, T, R, γ), where S is the states set, A is possible actions set, $T_a(s, s') = \Pr(s'|s, a)$ is the transition probability from state s to state s' after performing action a, $R_a(s, s')$ is a reward from the transition between s and s' by performing an action a, and γ is a discount factor signifying how gains from future events are discounted relative to immediate gains.

To represent the storage agent, we define the MDP as follows: the state set is defined $\mathcal{S} = \mathcal{IS} \times \mathcal{M}$, where $\mathcal{M}$ is the set of market states and $\mathcal{IS}$ is the set of ESS's inner states. To capture the deterioration of the ESS's performance, we define the *health* parameter, which represents the ESS's physical state. The internal state space is therefore $\mathcal{IS} = \mathcal{H} \times \mathcal{E}$ where $\mathcal{H} = \{h_0, h_1 \ldots\}$ is the set of the health states, and $\mathcal{E} = \{e_1, e_2, \ldots\}$ is the set of state-of-charge (SOC) states, signifying the amount of energy currently stored in the ESS,

The action set $\mathcal{A}$ of the MDP represents the bids that the agent can submit to the electricity market. For the storage agent, $\mathcal{A} = \{BUY, SELL\} \times \mathcal{W} \times C + \mathcal{SA}$, where $\mathcal{W} = \{w_0, w_1 ...\}$ is the set of energy volumes that the ESS can sell in one round, while $C = \{c_0, c_1 ...\}$ is discrete set of bid limit prices. $\mathcal{SA}$ represents a set of agent's special actions.

The transition function, T, is derived from the physical model of a ESS and from the agent's model of the market, and the reward function $\mathcal{R}$ represents the financial gain or loss to the agent as a result of the trade and is defined by the market pricing model. We represent the market by a set of states $\mathcal{M}$. The transition between the market states can be either deterministic, similar to previous section, or stochastic. In each state, the market's behavior is determined by a success probability function $p^{succ}(a)$ and an expected reward function $r^{succ}(a)$. As we are dealing with small agents, we assume that the volume does not affect the success probability, and if the bid resolves successfully, all the bid volume is transferred.

We assume a probability distribution on the market prices that predicts the success of any bid. In a real market, the agent can empirically compute such distribution using price history and assume that any buying bid higher than the market price and any selling big lower than the market price will resolve successfully. Let $f_{pr}(pr)$ be the price probability distribution, for a bid $a = (BUY, v, pr_i)$ the success probability is $p^b_{succ}(a) = F_{pr}(pr_i)$ and expected reward is $r^{succ}(a) = v \cdot MP_b(pr_i)$, where $MP_b(pr_i) = E_{pr}[pr | pr \leq pr_i]$. Similarly, the success and reward for the bid $a = (SELL, v, pr_i)$ are $p^s_{succ} = 1 - F_{pr}(pr_i)$ and $r^{succ}(a) = v \cdot MP_s(pr_i) = v \cdot E_{pr}[pr | pr \geq pr_i]$.

We consider selfish agents that strive to maximize the discounted profit by arbitrage, that is by buying energy at low price and selling it at higher price. Therefore, the optimal policy of the MDP can be used as the agent's bidding strategy. In this paper, we used policy iteration to compute the optimal policy for the agent.

A Physical Model of Electric Storage

To demonstrate how our framework can model a storage system whose performance and aging are characterized, we will use Li-Ion batteries whose performance and deterioration are well-covered in the literature. Studies focusing on ESS aging typically distinguish between calendar ageing, resulting from calendar life duration of a ESS, and cycling ageing, resulting from charging and discharging activity of the ESS. Both these mechanisms affect two parameters that define the battery's performance: *capacity*, the maximal amount of energy the battery can store; and *efficiency*, the fraction of energy lost in the charge and discharge process. In electrochemical batteries, the efficiency is mainly dependent on battery's internal resistance. We use the work of [10], which gives the connection between the internal resistance, the charging current (which determines a fraction of battery's capacity charged in a given timeslot), and efficiency.

We use the work of [6] to model the ageing of the battery. The latter shows that the deterioration of parameters is proportional to the *charge throughput* Q, which signifies the total amount of energy that was charged and discharged from the battery

$$C_{cyc} = 1 - \beta \cdot \sqrt{Q} \tag{5}$$

$$R_{cyc} = 1 + \beta_r \cdot Q \tag{6}$$

The MDP definition for this type of battery is as follows: we define a set of properties for the battery: $R_{nom}, V_{nom}, C_{nom}$, that signify nominal resistance, voltage and capacity accordingly (these parameters are derived from the technical specifications of the battery and define its initial behavior); capacity deterioration factor β and resistance deterioration factor β_r. For the set of health states $\mathcal{H} = \{h_0, h_1 \ldots\}$ we define a set of capacities $C = \{c(h_0), c(h_1) \ldots\}$, s.t. $c_i \leq 1 \forall i$. The *charge throughput* Q is then defined as $Q(h_i) = 1 - c(h_i)/\beta$, and the internal resistance $R(h_i) = R_c yc(h_i) * R_{nom}$ is computed according to equation 6. For the set of bid volumes $\mathcal{W} = \{w_0, w_1 ...\}$ we define the *efficiency function*:

$$\eta(h_i, w_j) = \frac{w_j / C_{nom} * R(h_i)}{V_{nom}}$$

This function is based on the model presented in [10]. In addition, we define a *DEAD* state, which signifies that the battery has deteriorated to the state it cannot store energy, and a *FORBIDDEN* state used to signify impossible transactions.

For an agent which at round t in a state (h_i, e) and submits a bid $a = (BUY, w, c)$ and the bid succeeds as the market is resolved with market price mp, we define the following transition and reward

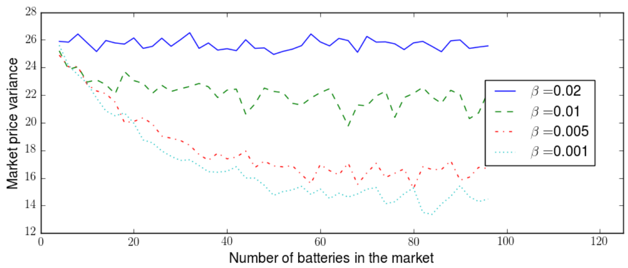

Figure 1: The evolution of market price variance

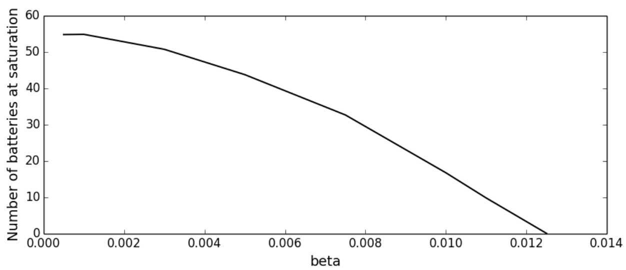

Figure 2: The storage capacity of the market

rules:

$$e^{t+1} = e + w \leq c(h^{t+1}) \tag{7}$$

$$T((h_i, e), a, (h_{i+1}, e \pm w) = p_{succ} \cdot \frac{w}{Q(h_{i+1}) - Q(h_i)} \tag{8}$$

$$R((h_i, e), (B, w, pr), (h_i, e + w)) = -\frac{w \cdot MP(pr_i)}{\eta_{h_i}(w)} \tag{9}$$

$$R((h_i, e), (S, w, pr), (h_i, e - w)) = \eta_{h_i}(w) \cdot w \cdot MP(pr) \tag{10}$$

Where 7 means that resulting SOC level cannot be higher than the battery's capacity; 8 means determines deterioration mechanics as a result of charge/discharge; and 9, 10 define how the agent pays for energy loss due to inefficiency, effectively buying more energy than is charged into the ESS, and selling less energy that discharged from it. In addition, to model calendar ageing, each turn, independent of chosen actions, the battery has a probability p_{cal} to drop to the next health level.

In addition to the trading action set, we define $\mathcal{SA} = \{\mathcal{N}, \mathcal{R}\}$. $\mathcal{N}$ (no action) is an action of not submitting a bid, as it is essential for a market trader to be able to abstain from trading if the market conditions are not beneficial. $\mathcal{R}$ (replace) is an action that returns the battery to state of full health with 0 energy, paying the battery cost c_b, effectively symbolizing the trader buying a new battery and discarding the old one. This action can be used both to model the market for longer periods, keeping the agents in the trade as the storage systems are deteriorating, and to observe the situations when the trader prefers to replace the battery even though it is still functional to some degree.

EXPERIMENTAL RESULTS

We now deploy the agent models described in Section 3 in a simulation environment that resembles the real-world electricity market, to empirically analyze the effect of multiple agents on the electricity market, given the agents' physical limitations and profitability objectives.

We use battery parameters, adapted from the Li(NiMnCO)O_2 186500 battery cell described in [6], with $V_{nom} = 3.6, R_{nom} = 0.007, \beta_c = 0.005, \beta_r = 0.0001$, and $p_{cal} = 0.00016$. As the capacity of a single cell is negligible relatively even to residential markets, we use a system of 150 such batteries as a basic storage agent. The agent is basing its decisions on empirical price distributions, aggregating the results over a predefined historic horizon.

The simulation environment consists of N consumers and M producers, each with a constant limit price that is randomly sampled from distribution p_{lim}. Every turn, the consumer or producer has a chance p_{app} to appear on the market. The agents submit buying and selling bids to a market matching engine that calculates the MCP. To simulate on-peak and off-peak periods, the following mechanism is used: every turn the appearing probabilities of either consumers or producers are changed by a random factor $p_{corr} \approx \mathcal{U}[p_{corr}^{min}, p_{corr}^{max}]$. Thus, two price populations are created. In our simulations, we choose the parameters $p_{app}, p_{corr}^{min}, p_{corr}^{max}$ so that the average prices of the two populations would be $mp_{low}^{avg} = 4.0, mp_{high}^{avg} = 18.0$, reflecting exemplary on- and off-peak prices in US electricity market.

To track the market's performance for different amounts of storage agents, we introduce them into the market in small groups of j agents at a time, with intervals of i rounds. Every time a new group of agents enters the market, we want the other agents to adjust their behavior to the new market situation. To prevent simultaneous change of behavior of a large mass of agents that will lead to market oscillations, we perform policy recalculation for the agents in u groups evenly spaced between new agent injections; therefore, for b agents in the market, every i/u rounds b/u agents are updated.

For the sake of the simulation, we define the *saturation point* of the market as the point where the valuation of an individual agent in the market drops below the battery cost.

Figs. 1 and 2 show the results of simulations for $u = 10, N = M = 100, i = 3000, j = 2, p_{corr}^{min} = 0.3, p_{corr}^{max} = 0.7$. Fig 1 shows the evolution of price variance in the market as more and more storage agents enter the market, and how it is affected by the battery's capacity deterioration parameter. It is clear from the graph that even small changes in the capacity deterioration (that can be caused by physical factors such as storage condition) strongly affect the smoothing effect of the storage on the market, and even for near-ideal values of a parameter, some degree of price volatility remains. Fig. 2 shows the average amount of agents in the market once it reached the saturation point. Here, as well, we can see that even for very low values of the deterioration parameter, the storage capacity of the market is bounded and the number of storage agents that can retain profitability is of the same order as the number of other players in the market.

To empirically visualize the price of anarchy for realistic batteries in this setting, we compute the optimal social welfare in the following way: for every τ rounds, we aggregate all the market

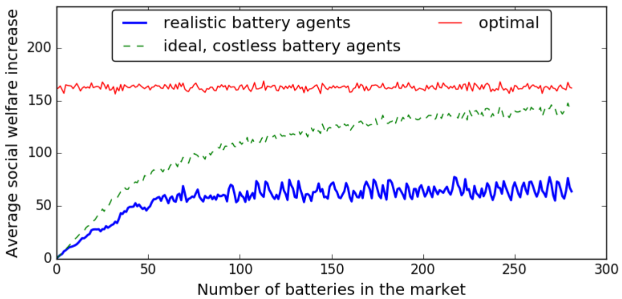

Figure 3: The social welfare increase

orders given and construct supply and demand curves from the aggregated orders. The optimal welfare is therefore the area between the supply and demand curves (this is equivalent to assuming that electricity can be traded across time and maximizes the welfare during this window).

Fig. 3 shows the social welfare of the market with increasing amount of realistic batteries, compared to the effect of increasing amount of ideal ($R_{nom} = 0, \beta \to 0, \beta_r \to 0, p_{cal} \to 0$), costless batteries on the market. Note that both physical effects of aging and the cost of a new battery must be nullified to produce "altruistic" behavior in the battery. It is clear from the graph that the battery's physical limitations and its initial cost prevent it from effectively mitigating the price gaps; however, as the physical limitations of the battery are removed, it can effectively bring the market to the optimal social welfare. This experiment can be used to calculate empirically the "price of anarchy" for realistic storage systems; the ratio between the social welfare will of course change depending on the battery's properties and cost.

CONCLUSIONS

In this paper we explored the behavior of smart selfish storage providers, and have examined the factors that can limit the beneficial effect of storage on an auction-based electricity market. In the case of large, monopolistic energy storage provider, we show the impact of strategic considerations on the agent's behavior, deriving the price of anarchy and revenue extraction ratio. Further study is needed to understand bounds for these measures for more complicated markets.

For the case of small-scale storage, we show how the physical characteristics of the storage system can affect the behavior of agents and limit their effect on the market. By using MDPs, we develop a framework that can be used to easily translate empirical deterioration analysis of an ESS into a bidding strategy in a competitive multi-state market. This can be done even with basic MDP solution techniques, such as policy iteration; however, as this method is polynomial in state number, more advanced techniques such as used in [1] could be used for more complex models to decrease computation time. While we use a specific example of a chemical battery, the framework can be used to model the influence of different kinds of storage systems and include more sophisticated market pricing models.

Due to the generalistic character of the framework, it can be used to address a wide range of problems; such as analyzing specific markets to understand the economic potential of storage; analyzing particular storage technologies to understand their maturity for arbitrage in competitive markets; examining models of renewable generation inclusion in large- and small-scale markets, etc. It is clear to us that the issue of influence of individual storage agent's physical properties and strategic considerations on the behavior of electricity market in general demand further research.

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