Energy Storage Participation in Wholesale Markets: The Impact of State-of-Energy Management

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Wholesale electricity markets are undergoing reforms to allow greater participation of energy storage. These reforms raise questions regarding the roles of market operators in energy-storage management and the design of market-participation models and offer parameters for energy storage. This paper examines the market implications of energy-storage participation models and state-of-energy (SOE) management. To this end, we develop a bi-level stochastic optimization model, wherein the upper level represents a profit-maximizing energy-storage firm offering into a wholesale market. Lower-level problems represent market clearing under different uncertain operating conditions. Using complementarity theory and binary expansion, this model is recast as a single-level mixed-integer linear optimization problem, which can be solved using off-the-shelf software packages. We apply the model to an illustrative example and a comprehensive case study. We demonstrate that with uncertainty, self scheduling energy storage is suboptimal for the energy-storage firm. Relying on only the energy-storage firm to manage SOE can yield strategic behavior, whereby infeasible offers are submitted to affect dispatch and market prices. These findings can guide ongoing market-design reforms.

***Index Terms*—Energy storage, power system economics, power system markets, state-of-energy management, offer strategy**

NOMENCLATURE

Indices and Sets

d	index of demands from set, D
g	index of generators from set, G
h	index of hours from set, H
s	index of scenarios from set, S

Parameters

e_0	hour-0 state of energy (SOE) of energy storage (MWh)
$\bar{E}$	energy-carrying capacity of energy storage (MWh)
$O_{s,h,g}$	hour-h offer price of generator g under scenario s (\$/MWh)
$p_{s,0,g}$	hour-0 output of generator g under scenario s (MW)
$\bar{P}_g$	generating capacity of generator g (MW)
$\bar{P}_{s,h,d}$	hour-h quantity of demand d under scenario s (MW)
$\bar{P}^{\text{ch}}$	charging capacity of energy storage (MW)
$\bar{P}^{\text{dis}}$	discharging capacity of energy storage (MW)
R_g^{D}	ramp-down limit of generator g (MW/h)
R_g^{U}	ramp-up limit of generator g (MW/h)
$U_{d,h}$	hour-h utility of demand d (\$/MWh)
β	round-trip efficiency of energy storage (p.u.)
γ	target ending SOE of energy storage (p.u.)
ρ	deviation penalty (p.u.)
ϕ_s	probability with which scenario s occurs
χ^{ch}	charging cost of energy storage (\$/MW)
χ^{dis}	discharging cost of energy storage (\$/MW)

Upper-Level Variables

$b_{s,h}$	equals 1 if energy storage discharges during hour h of scenario s and equals 0 otherwise
$e_{s,h}$	ending actual hour-h energy-storage SOE under scenario s (MWh)
o_h^{ch}	hour-h charging offer price of energy storage (\$/MW)
o_h^{dis}	hour-h discharging offer price of energy storage (\$/MW)
$\bar{p}_h^{\text{ch}}$	hour-h charging offer quantity of energy storage (MW)
$\bar{p}_h^{\text{dis}}$	hour-h discharging offer quantity of energy storage (MW)
$p_{s,h}^{\text{ch,a}}$	actual hour-h energy-storage charging under scenario s (MW)
$p_{s,h}^{\text{dis,a}}$	actual hour-h energy-storage discharging under scenario s (MW)
$p_h^{\text{ch,ss}}$	hour-h self-scheduled charging of energy storage (MW)
$p_h^{\text{dis,ss}}$	hour-h self-scheduled discharging of energy storage (MW)
$\delta_{s,h}^{\text{ch}}$	hour-h charging deviation of energy storage under scenario s (MW)
$\delta_{s,h}^{\text{dis}}$	hour-h discharging deviation of energy storage under scenario s (MW)

Lower-Level Variables

$e_{s,h}^{\text{m}}$	ending hour-h energy-storage SOE under scenario s from following the market operator's dispatch (MWh)
$p_{s,h,d}$	hour-h quantity of demand d that is satisfied under scenario s (MW)
$p_{s,h,g}$	hour-h dispatch of generator g under scenario s (MW)
$p_{s,h}^{\text{ch}}$	hour-h incremental energy-storage-charging dispatch by the market operator under scenario s (MW)
$p_{s,h}^{\text{dis}}$	hour-h incremental energy-storage-discharging dispatch by the market operator under scenario s (MW)

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I. Introduction

ENERGYstorage can provide value to its owner [1] and society, *e.g.*, through improved reliability [2]–[4] or renewable-energy integration [5], [6]. As such, energy storage is seeing increasing deployment, with some projections of its installed capacity increasing seventeenfold by 2050.[1]

Despite this outlook, a barrier to energy-storage deployment is its regulatory, policy, and market treatment [7]. To this end, reforms that view energy storage equitably *vis-à-vis* other technologies are ongoing. One such example is Federal Energy Regulatory Commission (FERC) Order 841.[2] Order 841 requires FERC-jurisdictional market operators (MOs) to develop market-participation models that treat energy storage equitably with other resources for the provision of services. A question that these market reforms raise is the proper role of MOs in managing the operation of energy storage as opposed to leaving these decisions to individual agents. Order 841 provides the option for an owner to choose between managing the state of energy (SOE) of its energy storage individually or having the MO do so. Regardless of the option that is chosen, energy-storage SOE must be feasible during all times. Additionally, Order 841 envisions markets giving owners the option to self-schedule energy storage or to have it participate in the market through price-responsive offers. Thus, Order 841 gives MOs flexibility in designing markets to accommodate the participation of energy storage. As such, the objective of this paper is to evaluate these design options from the perspective of market efficiency and the potential for energy-storage owners to manipulate market outcomes.

The extant literature that analyzes this question can be classified along two distinguishing assumptions [8]. The first is the behavioral assumption—whether energy storage is a price-taker or behaves strategically. The price-taking assumption is used to analyze energy storage participating in energy [9], [10] and energy and reserve [11], [12] markets. Examples of the latter assumption include analyses of self-scheduling by strategic energy storage that affects market prices [13]–[16]. Mohsenian-Rad [17], [18] and De Vivero-Serrano *et al.* [19] examine strategic energy storage participating in a market through self-scheduling or other offering mechanisms. Nasrolahpour *et al.* [20] model the participation of strategic energy storage in a wholesale market with ramp-constrained generators. They assume that energy storage submits price-responsive bids and offers and that energy storage's SOE is managed by its owner. Shafiee *et al.* [21] present an algorithm to construct bid and offer curves of price-making energy storage in a wholesale electricity market. Both of these works differ from ours, in that they do not consider offer structures that energy storage could use or SOE management. The second distinguishing dimension is how energy-storage SOE is managed. One set of works [9], [10], [12]–[18], [20], [22], [23] assume that energy storage's SOE is managed by its owner. Other works [24], [25] assume MO management of energy-storage SOE. Singhal and Ela [26] analyze different proposed approaches for MOs to manage energy-storage SOE.

Thus, there is a gap in the literature in that it does not examine the market-efficiency and price-formation implications of how an MO and strategic energy storage interact. Its integration into electricity markets raises questions around the format of energy-storage offers and SOE management. Mohsenian-Rad [17], [18] and De Vivero-Serrano *et al.* [19] examine the impacts of strategic energy storage participating in a market using different offering mechanisms. However, these works do not consider the implications of SOE management thereupon. Works that examine SOE management [9], [10], [12]–[18], [22]–[26] do not consider its interaction with the offering mechanism that is available to the energy storage.

Our paper makes two key contributions towards addressing this gap. First, we use a stochastic bi-level model to analyze self-interested behavior by energy storage in an electricity market. Unlike works that assume price-taking [9]–[12], our focus is strategic behavior by energy storage. Second, we use our model to analyze the impacts of energy-storage-SOE management and the strategic variables that are available to the energy storage. This distinguishes our work from others that assume SOE is managed by the asset owner or that energy storage participates in the market solely through self-scheduling [12]–[16]. Although different offering mechanisms are investigated in the literature [17]–[19], interactions between SOE management and offering mechanisms are not examined in previous works.

Our work differs from others that optimize energy-storage sizing and placement [22]–[25]. We assume a fixed energy-storage size and focus on market participation. As such our work can be likened to others [27], [28] that examine or reveal market-design choices that can yield inefficiencies in the presence of strategic behavior. In particular, this similar body of work examines strategic behavior of market participants and its impact on market designs due to asymmetric information. Our use of a computational model, which allows us to study detailed technical constraints, SOE-management options, and offer structures, is a distinguishing characteristic *vis-à-vis* this literature. These works [27], [28] use highly stylized models that are amenable to analytic solutions but are limited in representing technical details.

The remainder of this paper is organized as follows. Sections II and III provide model formulations and our solution methodology, respectively. Sections IV and V summarize an illustrative example and comprehensive case study, respectively. Our two key findings are that being restricted to self-scheduling only is suboptimal for energy storage in the presence of uncertainty and that relying on energy storage only to manage SOE can yield infeasible dispatch schedules. There are no specific market designs that restrict energy storage to self-schedule only. We analyze a case with such a restriction to understand how it would impact market behavior and outcomes. If the MO does not manage its SOE, strategic energy storage can use an infeasible schedule to increase its profit through price and quantity impacts. Section VI concludes.

II. Model Formulations

We model existing energy storage that participates in an energy market by submitting a combination of self schedules

[1] https://www.eia.gov/analysis/studies/electricity/batterystorage/

[2] *cf.* FERC docket numbers RM16-23-000 and AD16-20-000.

and price-responsive offers for charging and discharging. Once energy-storage offers are submitted, the MO clears the market under scenarios with different supply and demand conditions. Energy-storage offers are scenario-invariant.

Thus, we model a stochastic bi-level optimization, with expected-profit-maximizing energy-storage offers determined at the upper level and stochastic market clearing at the lower level. Scenarios can represent price uncertainty from the perspective of energy storage, *e.g.*, due to stochastic offers from competing firms or loads. Bi-level modeling is used widely in the literature [19], [22]–[25] and many works assume that energy storage participates in the market using scenario-dependent price-responsive offers. Our goal is to investigate the interplay between strategic energy storage, offering mechanisms, and SOE management, while accounting for deviations between actual energy-storage dispatch and quantities that clear the market. Thus, we restrict energy storage to using a combination of scenario-invariant self schedules and price-responsive offers to participate in the market. This assumption is in-line with that which is used by Mohsenian-Rad [17].

SOE constraints are modeled in the upper-level problem by the energy storage owner and may be represented in the MO's lower-level problems. The difference between these two sets of SOE constraints is that the latter are based on the MO's dispatch of energy storage, which may differ from actual energy-storage operations, due to possible dispatch deviations. Most of the extant literature neglects dispatch deviation in modeling energy-storage SOE.

A. Lower-Level Problems

For all $s \in S$, the MO's scenario-s problem is:

$$\min_{\Omega_s^{\mathrm{L}}} \sum_{h\in H}\left(\sum_{g\in G} O_{s,h,g}p_{s,h,g} - o_h^{\mathrm{ch}}p_{s,h}^{\mathrm{ch}} + o_h^{\mathrm{dis}}p_{s,h}^{\mathrm{dis}} - \sum_{d\in D} U_{d,h}p_{s,h,d}\right); \quad (1)$$

$$\text{s.t. } p_{s,h}^{\mathrm{dis}} + p_h^{\mathrm{dis,ss}} - p_{s,h}^{\mathrm{ch}} - p_h^{\mathrm{ch,ss}} + \sum_{g\in G} p_{s,h,g} = \sum_{d\in D} p_{s,h,d}; \quad \forall h \in H; \quad (\lambda_{s,h}) \quad (2)$$

$$0 \le p_{s,h,g} \le \bar{P}_g; \quad \forall h \in H, g \in G; \quad (\mu_{s,h,g}^{1,\min}, \mu_{s,h,g}^{1,\max}) \quad (3)$$

$$-R_g^{\mathrm{D}} \le p_{s,h,g} - p_{s,h-1,g} \le R_g^{\mathrm{U}}; \quad \forall h \in H, g \in G; \quad (\mu_{s,h,g}^{2,\min}, \mu_{s,h,g}^{2,\max}) \quad (4)$$

$$0 \le p_{s,h,d} \le \bar{P}_{s,h,d}; \quad \forall h \in H, d \in D; \quad (\mu_{s,h,d}^{3,\min}, \mu_{s,h,d}^{3,\max}) \quad (5)$$

$$0 \le p_{s,h}^{\mathrm{ch}} \le \bar{p}_h^{\mathrm{ch}}; \forall h \in H; \quad (\mu_{s,h}^{4,\min}, \mu_{s,h}^{4,\max}) \quad (6)$$

$$0 \le p_{s,h}^{\mathrm{dis}} \le \bar{p}_h^{\mathrm{dis}}; \forall h \in H; \quad (\mu_{s,h}^{5,\min}, \mu_{s,h}^{5,\max}) \quad (7)$$

$$0 \le e_{s,h}^{\mathrm{m}} \le \bar{E}; \forall h \in H; \quad (\mu_{s,h}^{6,\min}, \mu_{s,h}^{6,\max}) \quad (8)$$

$$e_{s,h}^{\mathrm{m}} = e_{s,h-1}^{\mathrm{m}} - p_{s,h}^{\mathrm{dis}} - p_h^{\mathrm{dis,ss}} + \beta \cdot \left(p_{s,h}^{\mathrm{ch}} + p_h^{\mathrm{ch,ss}}\right); \quad \forall h \in H; \quad (\mu_{s,h}^{7}) \quad (9)$$

$$e_{s,|H|}^{\mathrm{m}} = \gamma e_0; \quad (\mu_s^{8}) \quad (10)$$

where the Lagrange multiplier that is associated with each constraint is in parentheses to its right and:

$$\Omega_s^{\mathrm{L}} = \{p_{s,h,d}, \forall h \in H, d \in D; p_{s,h,g}, \forall h \in H, g \in G; e_{s,h}^{\mathrm{m}}, p_{s,h}^{\mathrm{ch}}, p_{s,h}^{\mathrm{dis}}, \forall h \in H\}.$$

Objective function (1), which is in equivalent minimization form, maximizes the social welfare that is engendered by the market. Constraints (2) enforce hourly load balance, taking account of self-scheduled energy-storage charging and discharging as well as the MO's energy-storage-dispatch instructions. Constraints (3)–(4) enforce generator-capacity and -ramping limits, respectively. Constraints (5) limit the amount of load that is served based on the quantity of demand. Constraints (6)–(7) enforce power limits on energy storage. Constraints (8) enforce limits on energy-storage SOE, if energy storage follows the MO's dispatch. Constraints (9) give the inter-hour evolution of energy-storage SOE. Constraint (10) restricts the ending energy-storage SOE, which is a heuristic approach to avoid myopic energy-storage dispatch [29].

B. Upper-Level Problem

The energy storage's problem is:

$$\max_{\Omega^{\mathrm{U}}\cup\Omega^{\mathrm{L}}} \sum_{s\in S, h\in H} \phi_s \cdot \Big[p_{s,h}^{\mathrm{dis,a}} \cdot \left(\lambda_{s,h} - \chi^{\mathrm{dis}}\right) - p_{s,h}^{\mathrm{ch,a}} \cdot \left(\lambda_{s,h} + \chi^{\mathrm{ch}}\right) - (1+\rho)\lambda_{s,h} \cdot \left(\delta_{s,h}^{\mathrm{ch}} + \delta_{s,h}^{\mathrm{dis}}\right)\Big]; \quad (11)$$

$$\text{s.t. } 0 \le p_{s,h}^{\mathrm{ch,a}} \le \bar{P}^{\mathrm{ch}} \cdot (1 - b_{s,h}); \forall s \in S, h \in H; \quad (12)$$

$$0 \le p_{s,h}^{\mathrm{dis,a}} \le \bar{P}^{\mathrm{dis}} b_{s,h}; \forall s \in S, h \in H; \quad (13)$$

$$p_{s,h}^{\mathrm{ch}} + p_h^{\mathrm{ch,ss}} = p_{s,h}^{\mathrm{ch,a}} + \delta_{s,h}^{\mathrm{ch}}; \forall s \in S, h \in H; \quad (14)$$

$$p_{s,h}^{\mathrm{dis}} + p_h^{\mathrm{dis,ss}} = p_{s,h}^{\mathrm{dis,a}} + \delta_{s,h}^{\mathrm{dis}}; \forall s \in S, h \in H; \quad (15)$$

$$0 \le e_{s,h} \le \bar{E}; \forall s \in S, h \in H; \quad (16)$$

$$e_{s,h} = e_{s,h-1} - p_{s,h}^{\mathrm{dis,a}} + \beta p_{s,h}^{\mathrm{ch,a}}; \forall s \in S, h \in H; \quad (17)$$

$$e_{s,|H|} = \gamma e_0; \forall s \in S; \quad (18)$$

$$\delta_{s,h}^{\mathrm{ch}}, \delta_{s,h}^{\mathrm{dis}} \ge 0; \forall s \in S, h \in H; \quad (19)$$

$$\bar{p}_h^{\mathrm{ch}}, \bar{p}_h^{\mathrm{dis}}, p_h^{\mathrm{ch,ss}}, p_h^{\mathrm{dis,ss}} \ge 0; \forall h \in H; \quad (20)$$

$$b_{s,h} \in \{0,1\}; \forall s \in S, h \in H; \quad (21)$$

$$(1)\text{–}(10); \forall s \in S; \quad (22)$$

where:

$$\Omega^{\mathrm{U}} = \Big\{b_{s,h}, e_{s,h}, p_{s,h}^{\mathrm{ch,a}}, p_{s,h}^{\mathrm{dis,a}}, \delta_{s,h}^{\mathrm{ch}}, \delta_{s,h}^{\mathrm{dis}}, \forall s \in S, h \in H; o_h^{\mathrm{ch}}, o_h^{\mathrm{dis}}, \bar{p}_h^{\mathrm{ch}}, \bar{p}_h^{\mathrm{dis}}, p_h^{\mathrm{ch,ss}}, p_h^{\mathrm{dis,ss}}, \forall h \in H\Big\};$$

and:

$$\Omega^{\mathrm{L}} = \bigcup_{s\in S} \Omega_s^{\mathrm{L}}.$$

Objective function (11) maximizes expected energy-storage profit and consists of three terms in the brackets. The first two terms represent operating profit from actual energy-storage charging and discharging. For all $s \in S, h \in H$, $\lambda_{s,h}$ is the hour-h market-clearing price under scenario s. The costs of discharging and charging energy storage, which appear in these first two terms, could reflect degradation that is associated with energy-storage use. The third term in (11) represents a penalty, which is proportional to the prevailing price, for the energy storage deviating from the dispatch that clears one of the corresponding lower-level problems.

Constraints (12)–(13) impose power limits on energy-storage charging and discharging, respectively, and allow energy storage to operate only in one of charging or discharging mode during each hour of each scenario. Constraints (14)–(15) define actual energy-storage charging and discharging and deviations. Constraints (16)–(18) pertain to energy-storage SOE. Constraints (16) impose SOE bounds, (17) define hourly SOE evolution, and (18) restrict the ending SOE. Constraints (19)–(20) and (21) impose, respectively, non-negativity and integrality restrictions on variables. Constraints (22) embed the MO's problems into that of the energy storage.

III. Solution Methodology

Model (11)–(22) is a bi-level optimization with nonlinearities. We address the inherent computational difficulties as follows.

A. Conversion from Bi-Level to Single-Level Problem

For all $s \in S$, (1)–(10) is linear and satisfies the Slater condition. Thus, $\forall s \in S$, an optimal solution to (1)–(10) can be characterized by its necessary and sufficient Karush-Kuhn-Tucker conditions [30], which are (2), (9)–(10), and:

$$O_{s,h,g} - \lambda_{s,h} - \mu^{1,\min}_{s,h,g} + \mu^{1,\max}_{s,h,g} - \mu^{2,\min}_{s,h,g} + \mu^{2,\max}_{s,h,g} + \mu^{2,\min}_{s,h+1,g} - \mu^{2,\max}_{s,h+1,g} = 0; \forall h \in H, g \in G; \tag{23}$$

$$-U_{d,h} + \lambda_{s,h} - \mu^{3,\min}_{s,h,d} + \mu^{3,\max}_{s,h,d} = 0; \quad \forall h \in H, d \in D; \tag{24}$$

$$-o^{\text{ch}}_{h} + \lambda_{s,h} - \mu^{4,\min}_{s,h} + \mu^{4,\max}_{s,h} - \beta\mu^{7}_{s,h} = 0; \quad \forall h \in H; \tag{25}$$

$$o^{\text{dis}}_{h} - \lambda_{s,h} - \mu^{5,\min}_{s,h} + \mu^{5,\max}_{s,h} + \mu^{7}_{s,h} = 0; \forall h \in H; \tag{26}$$

$$-\mu^{6,\min}_{s,h} + \mu^{6,\max}_{s,h} + \mu^{7}_{s,h} - \mu^{7}_{s,h+1} = 0; \forall h \in H; \tag{27}$$

$$0 \le p_{s,h,g} \perp \mu^{1,\min}_{s,h,g} \ge 0; \forall h \in H, g \in G; \tag{28}$$

$$p_{s,h,g} \le \bar{P}_g \perp \mu^{1,\max}_{s,h,g} \ge 0; \forall h \in H, g \in G; \tag{29}$$

$$-R^{\text{D}}_{g} \le p_{s,h,g} - p_{s,h-1,g} \perp \mu^{2,\min}_{s,h,g} \ge 0; \quad \forall h \in H, g \in G; \tag{30}$$

$$p_{s,h,g} - p_{s,h-1,g} \le R^{\text{U}}_{g} \perp \mu^{2,\max}_{s,h,g} \ge 0; \forall h \in H, g \in G; \tag{31}$$

$$0 \le p_{s,h,d} \perp \mu^{3,\min}_{s,h,d} \ge 0; \forall h \in H, d \in D; \tag{32}$$

$$p_{s,h,d} \le \bar{P}_{s,h,d} \perp \mu^{3,\max}_{s,h,d} \ge 0; \forall h \in H, d \in D; \tag{33}$$

$$0 \le p^{\text{ch}}_{s,h} \perp \mu^{4,\min}_{s,h} \ge 0; \forall h \in H; \tag{34}$$

$$p^{\text{ch}}_{s,h} \le \bar{p}^{\text{ch}}_{h} \perp \mu^{4,\max}_{s,h} \ge 0; \forall h \in H; \tag{35}$$

$$0 \le p^{\text{dis}}_{s,h} \perp \mu^{5,\min}_{s,h} \ge 0; \forall h \in H; \tag{36}$$

$$p^{\text{dis}}_{s,h} \le \bar{p}^{\text{dis}}_{h} \perp \mu^{5,\max}_{s,h} \ge 0; \forall h \in H; \tag{37}$$

$$0 \le e^{\text{m}}_{s,h} \perp \mu^{6,\min}_{s,h} \ge 0; \forall h \in H; \tag{38}$$

$$e^{\text{m}}_{s,h} \le \bar{E} \perp \mu^{6,\max}_{s,h} \ge 0; \forall h \in H. \tag{39}$$

Ramping restrictions (4) introduce a time dynamic in the MO's problem. Thus, there is a time dynamic in (23). Constraints (23) that correspond to hour $h = |H|$ have the same form that appears in (23), however the $\mu^{2,\min}_{s,h+1,g}$ and $\mu^{2,\max}_{s,h+1,g}$ terms vanish, because these Lagrange multipliers do not exist. Constraints (9), which give the inter-hour evolution of energy-storage SOE, introduce a similar time dynamic in the MO's problem and in (27). Constraints (27) that correspond to hour $h = |H|$ do not have a $\mu^{7}_{s,h+1}$ term.

Using these conditions, (11)–(22) can be converted to a single-level optimization problem by replacing (22) with (2), (9)–(10), and (23)–(39), $\forall s \in S$, and expanding the variable set to include all of the Lagrange multipliers of (1)–(10).

B. Linearizing Complementary-Slackness Conditions

Complementary-slackness conditions (28)–(39) are nonlinear. This is because a condition of the form:

$$f(x) \le 0 \perp \zeta \ge 0; \tag{40}$$

is equivalent to:

$$f(x) \le 0;$$
$$\zeta \ge 0;$$
$$f(x)\zeta = 0;$$

which is nonlinear in x and ζ. Complementary-slackness condition (40) can be linearized by introducing an auxiliary binary variable, which we denote as ξ, and replacing (40) with:

$$-M\xi \le f(x) \le 0;$$
$$M \cdot (1 - \xi) \ge \zeta \ge 0;$$

so long as M is sufficiently large [31]. We employ this linearization, which requires one auxiliary binary variable be added to the variable set for each of (28)–(39).

Selecting suitable values for M can be challenging. If M is too small, the model can become infeasible, whereas large values of M can result in poor computational performance. We select large starting values for M and reduce the values iteratively until we obtain the tightest value for which the complementary-slackness conditions hold [20].

C. Linearizing Objective Function (11)

Objective function (11) contains bilinear terms in which $\lambda_{s,h}$ multiplies one of $p^{\text{ch,a}}_{s,h}$, $p^{\text{dis,a}}_{s,h}$, $\delta^{\text{ch}}_{s,h}$, or $\delta^{\text{dis}}_{s,h}$. We linearize these using binary expansion [32], which is an approximation (unlike the linearization approaches that we discuss in Sections III-A–III-B). The approximation error can be controlled by the choice of the discrete values that $p^{\text{ch,a}}_{s,h}$, $p^{\text{dis,a}}_{s,h}$, $\delta^{\text{ch}}_{s,h}$, and $\delta^{\text{dis}}_{s,h}$ are assumed to take in the binary expansions.

D. Model Solution

Employing the linearizations that are outlined in Sections III-A–III-C yields a single-level stochastic mixed-integer linear optimization problem. This problem can be solved using an off-the-shelf optimization package and, due to the use of binary expansion, gives an approximate solution to (11)–(22). As a post-processing step, we verify that a solution to the linearized model satisfies original complementary-slackness conditions (28)–(39).

IV. Example

This section uses seven variants of a three-hour, four-generator example to illustrate our proposed model and to demonstrate the impact of market-design choices on market efficiency and energy-storage behavior and profit. Table I summarizes the offer and constraint parameters of the generators. Unless stated otherwise, these parameters are assumed to be constant across time and scenarios and we assume that $e_0 = 0$, $\bar{P}^{\mathrm{ch}} = 15$, $\bar{P}^{\mathrm{dis}} = 20$, $\bar{E} = 100$, $\beta = 1.0$, $\chi^{\mathrm{ch}} = \chi^{\mathrm{dis}} = 0$, and $\rho = 0.5$.

TABLE I
Generator Data for Example

g	$\bar{P}_g$	$O_{s,h,g}$	$R_g^{\mathrm{D}} = R_g^{\mathrm{U}}$
1	100	12	15
2	75	20	20
3	50	50	25
4	50	300	50

The model is programmed using `GAMS` version 34.3.0 and solved with `Gurobi` version 9.1.1 using the cloud-based NEOS Sever for Optimization [33]. The examples take between 2 s and 10 s to solve. Memory requirements and computation times can increase rapidly if more operational periods or units are considered, especially because of the need to use binary expansion to provide a reasonable approximation of the bilinear terms in (11). The results in this section demonstrate that three operating periods is sufficient for our goal of understanding through simple examples how market-design choices impact energy-storage behavior.

A. Case 1: No Uncertainty or Ramping Constraints

Our first case relaxes generator-ramping constraints and assumes no uncertainty. The hourly loads, which have arbitrarily high utilities, are 120 MW, 240 MW, and 130 MW, respectively. Because there is no uncertainty, the energy storage self-schedules 15 MW of charging during hour 1 and the stored energy is discharged during hour 2 (*i.e.*, price-responsive offers are unnecessary). There are no deviations by the energy storage and $\forall s \in S, h \in H$ the energy-storage SOE levels that are given by $e_{s,h}$ and $e^{\mathrm{m}}_{s,h}$ are identical.

We investigate energy-storage behavior further by examining two other market conditions. First, if we fix $p_h^{\mathrm{ch,ss}} = p_h^{\mathrm{dis,ss}} = 0, \forall h \in H$, energy storage submits price-responsive offers that result in the same dispatch that is self-scheduled absent the restriction. Second, if (8)–(10) are relaxed in the MO's problem, energy storage operates in the same way as when the MO manages energy-storage SOE. Thus, this case shows that absent uncertainty, the structure of energy-storage offers (*i.e.*, having the ability to self-schedule or not) and the MO managing energy-storage SOE have no bearing on energy-storage participation in or efficiency of the market.

B. Case 2: Capacity Withholding

This case retains the assumptions of no uncertainty and relaxed generator-ramping constraints that are considered in case 1 but the hourly loads are changed to 120 MW, 210 MW, and 240 MW, respectively. As such, absent energy-storage operation, the energy price increases successively from one hour to the next. One may expect energy storage to charge 15 MW and 5 MW during the first two hours and to discharge 20 MW during hour 3. However, optimized energy-storage offers entail self-scheduling 15 MW of charging and discharging during hours 1 and 3, respectively, and no hour-2 charging. This operational profile is optimal because if energy storage discharges 15 MW during hour 3, generator 4 is marginal during hour 3 and sets the hour-3 energy price equal to \$300/MWh. Conversely, if energy storage discharges 20 MW during hour 3, generator 3 becomes marginal and sets the hour-3 energy price equal to \$50/MWh. Thus, capacity withholding increases energy-storage profit by about 38% relative to energy storage behaving as a price taker. This benefit of capacity withholding is consistent with other analyses [9].

Restricting energy storage to price-responsive offers or self-scheduling only and the MO managing SOE or not have no impacts on the market outcome. As with case 1, this result is due to the lack of uncertainty.

C. Case 3: Uncertainty

This case assumes load uncertainty through two equiprobable scenarios and no generator-ramping constraints. The hourly scenario-1 and -2 loads are 240 MW, 120 MW, and 240 MW and 120 MW, 240 MW, and 120 MW, respectively. The load and price patterns differ between the two scenarios. Thus, it is suboptimal for the energy storage to rely solely on self-schedules and it uses price-responsive offers to yield different operational patterns under the two scenarios. Under scenario 1, 15 MW are charged and discharged during hours 2 and 3, respectively, whereas charging and discharging occur during hours 1 and 2, respectively, under scenario 2. Expected prices, loads, and generators' profits are not impacted by energy storage. However, generation cost decreases 30% (relative to having no energy storage), meaning that there are productive-efficiency gains that translate into energy-storage profit.

If we fix $\bar{p}_h^{\mathrm{ch}} = \bar{p}_h^{\mathrm{dis}} = 0, \forall h \in H$ and restrict the energy storage to self-scheduling only, it earns zero expected profit. Energy storage earns zero expected profit because any revenue that is earned under one scenario from a self schedule yields an exact countervailing loss under the other scenario, which is consistent with other analyses [17].

D. Case 4: Self-Scheduled Deviation

This case assumes no generator-ramping constraints, two equiprobable load scenarios, and $\bar{p}_h^{\mathrm{ch}} = \bar{p}_h^{\mathrm{dis}} = 0, \forall h \in H$. The hourly scenario-1 and -2 loads are 170 MW, 200 MW, and 240 MW and 170 MW, 230 MW, and 140 MW, respectively. We contrast cases in which (8)–(10) are enforced and relaxed in the MO's problem.

If the MO's problem includes (8)–(10), energy storage self-schedules 15 MW of charging during hour 1, which is followed by 5 MW and 10 MW of discharging during hours 2 and 3, respectively. The hour-1 price is \$50/MWh, the hour-2 prices are \$50/MWh and \$300/MWh under scenarios 1 and 2, respectively, and the hour-3 prices are \$300/MWh and \$20/MWh under scenarios 1 and 2, respectively. It is suboptimal for energy storage to increase hour-2 discharging, as doing so would make generator 3 marginal under scenario 2 and reduce the hour-2 price to be equal to \$50/MWh.

If (8)–(10) are relaxed in the MO's problem, the energy storage self-schedules 15 MW of charging and 10 MW of simultaneous discharging during hour 1, which is followed by 5 MW and 15 MW of discharging during hours 2–3. The energy storage deviates from the 10 MW of hour-1 discharging, which yields a penalty. However, this self schedule is beneficial to the energy storage because its 10 MW of scheduled discharging suppresses the hour-1 price 60% relative to not self-scheduling the discharging. Under each of scenarios 1 and 2 there is a 5-MW discharging deviation during hours 2 and 3, respectively. The timing of these deviations are scenario-dependent because the deviation penalty is proportional to the energy price—the hour-2 price and deviation penalty are lower than their hour-3 counterparts under scenario 1 and *vice versa*.

The profit loss that results from the deviation penalty during hours 2–3 under one scenario is offset by a countervailing profit increase under the other. Overall, expected energy-storage profit increases 30% if (8)–(10) are relaxed relative to if they are enforced. This increase in energy-storage profit comes with an 8% decrease in expected generator profit and a 3% increase in expected consumer welfare. These calculations do not account for possible changes in real-time prices that may impact remuneration (*e.g.*, when the MO must clear the real-time imbalance market due to the dispatch deviations).

E. Case 5: Price-Responsive Deviation

This case assumes no generator-ramping constraints and two equiprobable load scenarios with 120-MW, 230-MW, and 200-MW and 170-MW, 240-MW, and 120-MW hourly loads under the two scenarios, respectively. Both with and without (8)–(10) enforced in the MO's problem, the energy storage charges 15 MW during hour 1 under both scenarios. Under scenario 1, it discharges 5 MW and 10 MW during hours 2 and 3. Under scenario 2, it discharges 15 MW during hour 2. Energy storage does not discharge the full 15 MW during hour 2 under scenario 1, because doing so would suppress the hour-2 price by making generator 3 marginal.

Although energy-storage operations are identical with and without (8)–(10) enforced, the offers and MO's dispatch differ between the two cases. Specifically, if (8)–(10) are relaxed, the energy storage structures its offers so it is dispatched to discharge 10 MW simultaneously (to the 15 MW charged) during hour 1 under scenario 2. The energy storage deviates from this 10 MW of discharging, incurring a penalty. However, its discharging dispatch prevents generator 3 from being dispatched during hour 1 under scenario 2, which reduces the hour-1/scenario-2 price from \$25/MWh with (8)–(10) enforced to \$20/MWh with (8)–(10) relaxed.

Relaxing (8)–(10) increases expected energy-storage profits by 3% relative to enforcing the constraints. This profit increase comes with a 4% decrease in expected prices and generator profits and a 2% increase in expected consumer welfare.

F. Case 6: Ramping Constraints

This case assumes no uncertainty and enforces generator-ramping constraints using the limits that are reported in Table I. The hourly loads are 170 MW, 150 MW, and 194 MW and generators 1 and 2, respectively, have 100-MW and 15-MW initial production levels. If (8)–(10) are enforced in the MO's problem, it is optimal for energy storage to charge and discharge 5 MW during hours 2 and 3, respectively. It is suboptimal for the energy storage to shift more than 5 MW between hours 2 and 3, because doing so would increase the hour-2 price of charging energy.

Actual energy-storage operations are identical if (8)–(10) are enforced or relaxed in the MO's problem. However, with the constraints relaxed, energy storage schedules 20 MW of discharging during hour 2 simultaneously with the 5 MW of charging. The energy storage deviates from the scheduled discharging, for which it incurs a deviation penalty. This scheduled discharging is beneficial to the energy storage because it reduces the hour-2 dispatch of generator 2, which forces the dispatch of generator 4 during hour 3 (due to all of generators 1–3 having binding ramping constraints). The resultant spike in the hour-4 price increases expected energy-storage and generator profits by 1300% and 90%, respectively, relative to if (8)–(10) are enforced in the MO's problem. Expected consumer welfare decreases by 29% if (8)–(10) are relaxed, relative to a case in which they are enforced.

G. Case 7: Uncertainty and Ramping Constraints

This case enforces generator-ramping constraints and assumes load uncertainty with two equiprobable scenarios. The hourly scenario-1 and -2 loads are 170 MW, 190 MW, and 230 MW and 170 MW, 240 MW, and 190 MW, respectively. The generators have the same hour-0 generation levels as under case 6. Both with and without (8)–(10) enforced in the MO's problem, the energy storage relies on price-responsive offers for market participation. Self-scheduling only is suboptimal in this case because any revenue that a self-schedule earns under one scenario is offset by losses under the other scenario [17].

If (8)–(10) are enforced in the MO's problem, optimal energy-storage operations entail charging and discharging during hours 2 and 3, respectively, under scenario 1. Although the hour-2 load is greater than hour-1 load, the hour-2 price is lower than the hour-1 price, due to the impact of a binding generator-ramping constraint. Energy storage does not operate under scenario 2 in this case, because the hourly energy prices are \$300/MWh, \$300/MWh, and \$20/MWh, respectively, which does not yield a profitable operating profile.

If (8)–(10) are relaxed in the MO's problem, scenario-1 energy-storage operations are identical to the case in which the constraints are enforced. Scenario-2 operations differ with the constraints relaxed. Specifically, energy storage is dispatched to discharge 20 MW and charge 10 MW simultaneously during hour 1 and to discharge 10 MW during hour 2. The simultaneous energy-storage discharging and charging reduces the hour-1/scenario-2 price to be equal to \$20/MW, which creates a profit opportunity for the energy storage despite its paying a deviation penalty for not discharging during hour 1. Relative to a case in which (8)–(10) are enforced, relaxing these constraints increases expected energy-storage profit 78% and decreases expected generators' profits 19%. Generator-profit losses stem from the hour-1/scenario-2 price decreasing 83%. In addition, relaxing (8)–(10) reduces expected generation cost 14% and load-weighted energy prices 20%.

Restricting energy storage to using price-responsive offers only has no impact on its operation or expected profit. However, if energy storage is restricted to self-scheduling only and (8)–(10) are enforced, it earns zero expected profits. Restricting energy storage to self-schedule only and relaxing (8)–(10) reduces expected energy-storage profit 94% and increases expected consumer welfare 13% relative to allowing price-responsive offers with (8)–(10) relaxed.

V. Case Study

This section summarizes the results of a case study, which is based on year-2015 data for the wholesale electricity market that operates in Alberta, Canada. The average, minimum, and maximum year-2015 system loads are 9 162 MW, 7 203 MW, and 11 229 MW, respectively. Following the model formulations that are presented in Section II, we assume that the market employs a single-bus model. This assumption is consistent with the policy goal of the government of Alberta to have a congestion-free electricity system.[3] We assume that $\bar{E} = 200$, $\bar{P}^{\mathrm{ch}} = \bar{P}^{\mathrm{dis}} = 40$, $\beta = 0.9$, $\chi^{\mathrm{ch}} = \chi^{\mathrm{dis}} = 0$, and $\rho = 0.5$. The case study illustrates that the energy storage is sufficiently large to impact market prices. Thus, we perform a comparison to a perfectly competitive case, wherein the operation of energy storage is optimized by the MO based on its true operating costs and characteristics. We construct three equiprobable load scenarios by using load data that correspond to three consecutive days. Alberta's electricity system has about 200 generators, which are represented in our case study using 14 archetypal generators [34]. Data regarding the modeled generator fleet can be found in the work of Nasrolahpour *et al*. [34]. The case study is implemented using the computational platform that is used for the examples. The case studies take between 16 s and 6 min. to solve.

Table II summarizes the breakdown of expected social welfare that is engendered in cases with (8)–(10) enforced or relaxed and with or without the energy storage being restricted to self-scheduling only (as opposed to being able to submit self schedules *and* price-responsive offers). Following the results that are presented in Section IV, relaxing (8)–(10) and relying only upon energy storage to manage its SOE increases expected energy-storage profit by about 5% relative to enforcing (8)–(10). Expected energy-storage profit increases with (8)–(10) relaxed because the energy storage can schedule charging or discharging that it does not deliver but which change generator dispatch and prices. Although the energy storage must pay for replacement energy and a 50% deviation penalty, such a strategy is beneficial.

As is observed in cases 3–5 and 7 of our example, load uncertainty implies that energy storage must rely upon price-responsive offers so its operational profile can be adapted to

[3] *cf.* decision number 22942-D02-2019 of Alberta Utilities Commission.

TABLE II
BREAKDOWN OF EXPECTED SOCIAL WELFARE ENGENDERED IN CASE STUDY WITH OPTIMIZED ENERGY-STORAGE OFFERS

Constraints (8)–(10)	Only Self Schedules	Expected Welfare ($ thousand)		
		Energy Storage	Generator	Consumer
Enforced	No	3.366	17 060	39 880
Relaxed	No	3.523	16 750	40 190
Enforced	Yes	1.227	16 720	40 220
Relaxed	Yes	1.227	16 720	40 220

individual scenarios. Indeed, restricting energy storage to using price-responsive offers and not allowing it to self-schedule yields solutions that are identical to those that are summarized in the first two rows of Table II, which correspond to cases in which the energy storage can use price-responsive offers and self schedules. Expected energy-storage profit decreases by 64% if energy storage is restricted to self-scheduling only. This profit decrease stems from a self schedule that is profitable under one scenario yielding a revenue loss under another. If energy storage is restricted to self-scheduling only, relaxing (8)–(10) do not yield profit increases.

Fig. 1 shows expected profit that is earned by energy storage with different power capacities and market-participation models. The five sets of bars on the left correspond to cases in which energy storage is restricted to self-scheduling only whereas the bars on the right remove this restriction. The bottom of each stacked bar summarizes expected energy-storage profit if (8)–(10) is enforced in the MO's problem. The top of each stacked bar shows incremental expected profit that energy storage earns if these constraints are relaxed.

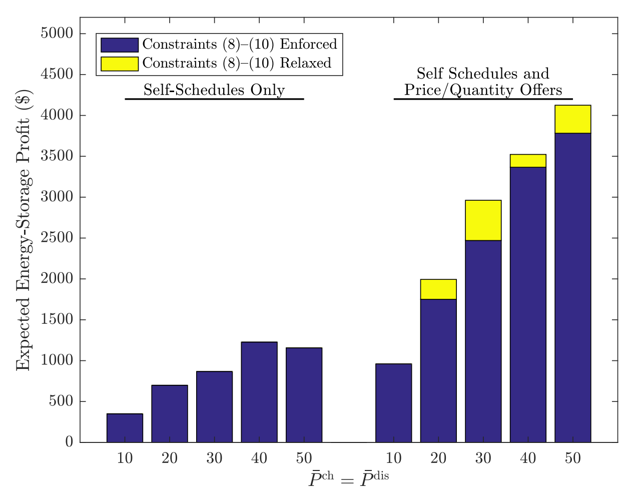

Fig. 1. Expected energy-storage profit in case study with different power capacities and market-participation models.

Expected energy-storage profit is increasing in energy-storage capacity and restricting energy storage to be able to self-schedule only yields significant profit losses compared to its using price-responsive offers. Enforcing or relaxing (8)–(10) has no impact on energy-storage profit if energy storage is restricted to self-scheduling only. There is no profit impact in this case because with self schedules only, there is limited opportunity for energy storage to manipulate prices through infeasible offers.

Finally, we compare the results that are summarized in Table II to two additional cases, which are summarized in Table III. The first case that is summarized in Table III assumes that energy storage behaves perfectly competitively. Under such an assumption, energy storage offers the amounts of charging and discharging of which it is physically capable into the market at cost. The second case that is summarized in the table assumes no energy storage, meaning that the market clears load against generation resources only.

TABLE III
BREAKDOWN OF EXPECTED SOCIAL WELFARE ENGENDERED IN CASE STUDY WITH PERFECTLY COMPETITIVE AND NO ENERGY STORAGE

Case	Expected Welfare ($ thousand)		
	Energy Storage	Generator	Consumer
Perfectly Competitive	0.857	4 862	52 089
No storage	n/a	4 896	52 052

Contrasting the first case in Table III to the cases that are summarized in Table II shows that except for a case in which the MO does not enforce (8)–(10) and the energy storage is not restricted to self scheduling only, strategic behavior by energy storage has limited effects on social welfare. Conversely, the second case that is summarized in Table II yields close to 18% social-welfare losses compared to the perfectly competitive case. Thus, (relative to perfect competition) the price manipulation that is possible if (8)–(10) are relaxed allows energy storage to increase its profit by about $3 000, but at a nearly $10 million consumer-welfare loss. This finding suggests that the price manipulations that are possible if (8)–(10) are relaxed can be detrimental to consumers.

The final case in Table III shows that (relative to perfect competition) social-welfare losses without energy storage are on-par with social welfare losses under the first and last two cases that are summarized in Table II. Thus, our results should be cautionary for market designers and policymakers. Energy-storage development should be encouraged so long as sound designs for integrating energy storage into wholesale markets are employed [35]–[38].

VI. CONCLUSION

This paper adds to the literature that examines the integration of energy storage into electricity markets. Unlike much of the literature, we relax the price-taking assumption and focus on strategic behavior by energy storage that can influence prices. We use our modeling framework to examine the trade-offs that are inherent in how energy storage participates in the market. We demonstrate that it is suboptimal to have energy storage self-schedule only if there is uncertainty, because its operational profile cannot be tailored to real-time system conditions. This finding is consistent with other analyses [17] and important, as there are cases in which MOs or regulators object to MOs controlling the dispatch of energy storage [39].

We show that relying on energy storage to manage its SOE can result in infeasible dispatch schedules that are profitable to the energy storage. This profitability arises from the price impacts of energy-storage operations and the examples in Section IV demonstrate the underlying mechanisms. An infeasible schedule can yield lower-price charging energy or higher-price discharging energy. Generator-ramping constraints exacerbate energy storage's incentives to manipulate energy prices in this manner. This finding regarding ramping constraints is consistent with other analyses that demonstrate profitable manipulation of ramping constraints [40]. The profitable infeasible energy-storage dispatch schedules that we find are reminiscent of market participants exploiting congestion-management schemes profitably [41]. Thus, market designers and policymakers should pay attention to the incentive properties of market designs, insomuch as they may mitigate or exacerbate these perverse incentives. Our modeling approach can be used to this end. Our results show that the impact of infeasible dispatch schedules on other market participants varies. Depending on whether energy storage manipulates the cost of charging or discharging energy, generators and consumers may benefit or lose relative to enforcing (8)–(10).

FERC Order 841 provides flexibility in how markets are designed, structured, and reformed to allow the participation of energy-storage resources. This includes flexibility surrounding the structure of offers into the market and SOE management. Our work shows that restricting energy storage to self scheduling is suboptimal for an owner to maximize potential energy-storage value. Contemporaneously, we find that relying upon owners to manage energy-storage SOE can result in price manipulation through infeasible schedules. The breakdown to generators and consumers of the resultant welfare effects of these price manipulations depends on whether the price of charging or discharging energy is manipulated. However, our case study that is based on real-world data shows a pronounced impact on consumers. Therefore, as markets are reformed in response to FERC Order 841 (or similar market reforms are undertaken in other jurisdictions), policymakers and market designers should be cognizant of the need to mitigate such perverse market outcomes.

Other areas for future research including examining the provision of other market services, *e.g.*, ancillary services and capacity. In addition, the literature proposes other market-participation models for energy storage [26], which could be examined using our modeling framework. Another area of study is to examine strategic behavior by multiple energy-storage firms, energy storage and generators, or other mixes of strategic market participants.

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