Energy Storage State-of-Charge Market Model

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Abstract—This paper introduces and rationalizes a new model for bidding and clearing energy storage resources in wholesale energy markets. Charge and discharge bids in this model depend on the storage state-of-charge (SoC). In this setting, storage participants submit different bids for each SoC segment. The system operator monitors the storage SoC and updates their bids accordingly in market clearings. Combined with an optimal bidding design algorithm using dynamic programming, our paper shows that the SoC segment market model provides more accurate representations of the opportunity costs of energy storage compared to existing power-based bidding models. The new model also captures the inherent SoC-dependent operational characteristics of energy storage. We benchmark the SoC segment market model against an existing single-segment model in price-taker and price-influencer simulations. The simulation results show that compared to the existing power-based bidding model, the proposed model improves profits by 10–56% in the price-taker case study; the model also improves total system cost reduction from storage by around 5%, and helps reduce price volatilities in the price-influencer case study.

Index Terms—Dynamic programming, energy storage, power system economics.

I. INTRODUCTION

ENERGY storage resources, especially battery energy storage, are entering wholesale electricity markets at a surging rate. The battery capacity connected to the California Independent System Operator (CAISO), the power system operator and market organizer of the state of California, has increased from 488 MW at the end of 2020 to 4,367 MW as of Sep 2022 and is expected to near 10 GW in 2026 [1], [2], [3]. According to EIA Annual Electric Generator Report, with increasingly installed energy storage capacity flatten the ancillary service market price, majority of energy storage participants starting to focus on arbitraging in wholesale energy markets [4].

Integrating energy storage resources into wholesale electricity markets requires the development of new models. In centralized electricity markets, which cover most regions in North America, participants must bid using a resource model representing their operational characteristics in the market clearing. For example, thermal generators submit power segment bids stemming from their heat rate curves and other operation or cost parameters, including startup costs, no-load costs, ramp rates, and minimum up and down time [5]. However, energy storage resources have distinctly different operational characteristics compared to thermal generators and need different bidding parameters. The FERC (Federal Energy Regulatory Commission) has recognized this need and issued Order 841, which requires that future electricity market designs “account for the physical and operational characteristics of electric storage resources through bidding parameters or other means” [6].

Managing storage state-of-charge (SoC) is critical for energy storage participants. The storage opportunity cost depends on SoC, and various storage operation factors, including degradation rates and efficiencies, depend on power rating and SoC [7], [8], [9]. Managing SoC is achievable in day-ahead markets with a 24-hour optimization horizon but is not effective in real-time markets [10]. Currently, most system operators allow storage to participate in markets by self-scheduling or submitting both charge and discharge bids [11]. Storage has complete control over its SoC in self-scheduling but loses the flexibility to react to actual system conditions, decreasing revenue potential and social welfare. Managing SoC through existing bidding models is difficult as storage participants cannot update their bids in a timely manner based on SoC [12].

This paper introduces a storage market model that allows storage participants to effectively manage their economic bids based on SoC and better represents SoC-dependencies of energy storage physical and operational characteristics. The main contribution is five-fold:

- We introduce an SoC segment market model for energy storage participation to economically manage their SoC in wholesale electricity markets. The model allows energy storage to submit power rating, efficiency, and charge and discharge bids by segments according to the SoC ranges.
- We incorporate SoC-dependent physical parameters into our previous storage bidding algorithm to generate time-varying SoC-dependent charge and discharge bid curves.
- We combine the proposed market model with the optimal bidding algorithm to benchmark the proposed model with existing market models in terms of system costs, price results, and storage revenue in price-taker and price-influencer cases.
For storage models whose parameters are independent of SoC, we model SoC-dependent bids as linear programming in real-time markets. Results show the proposed model reduces total system costs and price volatility with little effect on the computation time.

For storage models whose physical parameters are dependent of SoC, we model SoC-dependent bids using mixed-integer linear programming, in which integer variables are required to model the inherent non-convexity. Results show modeling the SoC dependency in day-ahead (multi-period) and real-time markets can significantly reduce system costs and price volatilities, and improve storage revenue, but have to trade-off computation time.

We organize the remainder of the paper as follows. Section II reviews related literature. Sections III and IV present the proposed market model and the bidding algorithm. Sections V and VI describe case studies under price-taker and price-influencer settings. Section VII concludes this paper.

II. LITERATURE REVIEW

A. Energy Storage Market Models

Independent system operators and regional transmission organizations (ISOs/RTOs) across North America are implementing new market rules to reduce barriers to energy storage participation, facilitated by FERC Order 841 [13]. In current and upcoming market designs, most system operators are allowing storage to bid as a combination of a generator and a flexible load in day-ahead or real-time markets [11], [14]. Dispatching energy storage using market bids requires marginal changes to the market clearing model as it simply combines two existing market models. The upcoming market design can schedule storage in day-ahead markets since the unit commitment model used to clear the market considers a 24-hour operation horizon, through which the storage SoC can be optimally managed using intertemporal constraints [15].

Distinct from the day-ahead market, generating resources in real-time energy markets are cleared 5 minutes ahead of the dispatch. Real-time market prices are more volatile than day-ahead due to more constrained generator status and demand forecast errors. Therefore, real-time markets may offer higher arbitrage profits for storage [8], [16], and real-time dispatch better utilizes storage’s near-instantaneous response speed to compensate for demand and renewable fluctuations. However, incorporating storage in real-time markets is non-trivial. In most North American systems, real-time markets only consider a single time step, while CAISO and the New York Independent System Operator include a short look-ahead horizon to address commitment and ramping constraints. This look-ahead horizon is too short to capture daily demand and price patterns to effectively manage storage SoC constraints while incorporating a longer horizon increases the computation cost significantly and may fail to meet the 5-minute dispatch frequency [15], [17].

A key challenge of incorporating storage into real-time markets is quantifying the opportunity cost. The system operator cannot incorporate a sufficiently long look-ahead horizon into real-time dispatch. For example, a battery owner will have to determine its charge bid prices based on predictions of the price at which the charged energy will be sold later. Many studies have explored how different participation strategies could impact storage revenue and market efficiencies, including self-scheduling [18], [19] and bidding [20], [21], [22]. Some of these studies have concluded that considering SoC in bid designs is critical to the storage market revenue [12], [23], [24]. However, few studies have investigated alternative market designs to better manage SoC through bidding parameters, which is the problem targeted in this paper.

B. Storage Parameters State-of-Charge Dependency

In practice, energy storage parameters, including power rating, efficiency, and discharge cost, often have nonlinear relationships with storage SoC for various reasons based on the technology, such as the voltage dependency in electrochemical batteries [25] and storage pressure levels in compressed air energy storage [26]. Utility-scale energy storage systems in the US are primarily Li-ion batteries with a 4-hour duration (.25 C-rate). According to lab test data, operation power rating has a limited impact on energy storage parameters at a low C-rate [27], [28], and SoC has the highest influence in utility-scale Li-ion battery degradation [29]. Therefore, the dependencies of power rating are not in the scope of this paper, but we can incorporate piece-wise linear cost curves to model power rating influences.

SoC-dependent energy storage models have been widely investigated by experiments and implemented in energy storage control models. Previous works, [25], [30], [31] investigated the influence of SoC range and cycle depth on the aging of different Li-ion batteries and found that battery degradation strongly depends on SoC, especially cycling in high and low SoC ranges. Xu et al. [8], [32] incorporated Rainflow cycle depth models in power system optimizations and frequency controls but did not consider the dependency on SoC. Koller et al. [33] modeled high and low SoC as a stress factor of battery degradation in model predictive control. The high degradation rate jeopardizes the cycling life of the battery, which leads to higher production (discharge) costs in high and low SoC. Pandžić [9] obtained the dependency of battery power rating on SoC and formulated battery power rating using a piece-wise linear approximation in a battery operation model. Yang et al. [34] proposed a multi-state control strategy that determines power rating based on the states of the SoC and the system frequency to enhance the system frequency stability. Zheng et al. [35] examined the correlations between SoC and Coulombic efficiency due to voltage and resistance dependent on SoC. Jafari et al. [28] investigated a vanadium redox flow battery and modeled its dynamic efficiency and power limits as a function of SoC in a price arbitrage optimization problem. Motivated by previous studies, we use SoC-dependent energy storage physical models in market model comparisons, which is rarely studied in the literature.

C. State-of-Charge Management Using Market Design

Researchers and electricity market operators are actively seeking new market mechanisms to efficiently manage SoC to
better model storage’s opportunity cost and physical characteristics [36]. Bhattacharjee et al. [12] used a bi-level stochastic optimization model, investigated the implications of different energy storage SoC management entity settings, and found that energy storage SoC self-management could be inefficient under uncertainty. Fang et al. [10] proposed a bidding structure and a corresponding clearing model for energy storage integration in the day-ahead market. The proposed advanced Vicker-Clarke-Groves mechanism incentivizes energy storage participants to truthfully submit parameters and economically manage SoC by incorporating end-period SoC value. Chen and Tong [37] examined energy storage wholesale market participation using convexified bids under a multi-period economic dispatch setting.

Compared to previous works that seek to better manage storage SoC with existing market designs, we propose to directly incorporate SoC-dependency in market models in day-ahead and real-time markets to explore the impact of market models on energy storage arbitrage profits and market efficiencies.

III. FORMULATION

We first define an SoC-dependent energy storage model in which the power rating, efficiency, and discharge cost depend on storage SoC. We describe how to incorporate SoC-dependent energy storage model into multi-period optimizations, which we will use as a benchmark for comparison. We then present the single-period SoC segment market model, which dispatches storage using SoC-dependent charge and discharge bids and SoC-dependent energy storage model.

A. State-of-Charge Dependent Energy Storage Model

We consider a generalized piece-wise linear storage model in which the storage has $S$ segments of discharge cost, efficiency, and power rating parameters to model their dependency over SoC, as illustrated in Section II-B. Each segment $s \in S = \{1, \ldots, S\}$ is specified according to the following parameters:

- $E_s$ denotes the ending SoC range of segment $s$ in MWh. Segment $s$ has an SoC range between $E_{s-1}$ and $E_s$. $E_0$ is the lower SoC limit, and $E_S$ is the upper SoC limit. The sequence of the SoC segment index $s$ is monotonic with the SoC range, i.e., $E_s > E_i$ for all $i < s$.
- $C_s$ is the physical discharge cost of segment $s$, in $$/MWh; this cost includes prorated cost based on battery degradation and other maintenance costs, but does not cover the electricity cost of charging the storage.
- $D_s$ is the maximum discharge power output of segment $s$ standardized with the dispatch time step, in MWh.
- $P_s$ is the maximum charge power output of segment $s$ standardized with the dispatch time step, in MWh.
- $\eta_s^d$ is the discharge efficiency of segment $s$, $\eta_s^d \in [0, 1]$.
- $\eta_s^p$ is the charge efficiency of segment $s$, $\eta_s^p \in [0, 1]$.

Fig. 1 shows a 5-segment example of the storage model parameters, where charge and discharge efficiency are simplified to be identical but we can model them as different parameters.

We present a multi-period model that dispatches storage directly using SoC-dependent parameters. Although in theory power system operators can use multi-period models to dispatch energy storage in real-time using a look-ahead dispatch setting, this only applies to dispatch decisions from the first time period and repeats the dispatch optimization with updated system states and prediction horizon. As discussed in Section II-A, the multi-period dispatch may not be practical due to computation and prediction complexities. Therefore, the primary motivation for using the multi-period dispatch model is to provide a benchmark for comparison with the single-period dispatch model.

We consider a generalized multi-period energy storage dispatch model with a time-varying operating cost function $J_t(\cdot)$ over a time horizon of $t \in T = \{1, 2, \ldots, T\}$. We introduce binary variables to enforce the SoC segment transition logic. We formulate the dispatch problem as

$$\min_{p_{t,s}, d_{t,s}} \sum_{t \in T} J_t \left( \sum_{s \in S} (p_{t,s} - d_{t,s}) \right) + \sum_{s \in S} C_s d_{t,s} \quad (1a)$$

s.t. $\sum_{s \in S} (p_{t,s} / P_s) \leq \nu_t \sum_{s \in S} (d_{t,s} / D_s) \leq 1 - \nu_t, \forall t \in T \quad (1b)$

$e_{t,s} - e_{t-1,s} = -d_{t,s} / \eta_s^d + p_{t,s} \eta_s^p, \forall t \in T, s \in S \quad (1c)$

$(E_s - E_{s-1}) u_{t,s} \leq e_{t,s} \leq (E_s - E_{s-1}) u_{t,s-1}, \forall t \in T, s \in S. \quad (1d)$

The decision variables in (1) include non-negative continuous variables $p_{t,s}, d_{t,s}, e_{t,s}$ and binary variables $\nu_t$ and $u_{t,s}, p_{t,s}, d_{t,s}$ are the battery charging/discharging power output over time period $t$ from SoC segment $s$, and $e_{t,s}$ is the state of energy stored in segment $s$ at the end of period $t$. (1b) enforces the segment-wise power rating for charge and discharge power; the binary variable ensures that the storage cannot charge and discharge simultaneously. (1c) models the segment energy evolution subject to the segment charge and discharge efficiency. Finally, (1d) models the SoC segment logic, that a segment of higher SoC levels must be empty if the lower SoC segment
is not full; this logic is achieved using binary variables \( u_{t,s} \). \( u_{t,s} = 1 \) indicates SoC segment \( s \) is full during time period \( t \) \((e_{t,s} = E_s - E_{s-1})\), and \( u_{t,s} = 0 \) indicates the segment is not full. The upper energy limit of SoC segment \( s \) is limited by \( u_{t,s-1} \), forcing \( e_{t,s} \) to be zero if the lower SoC segment \( s - 1 \) is not full, i.e., \( u_{t,s-1} = 0 \).

Total power output and storage SoC is simply the sum of each segment, i.e.,

\[
 p_t = \sum_s p_{t,s} , \quad d_t = \sum_s d_{t,s} , \quad e_t = \sum_s e_{t,s} \tag{1e}
\]

where \( p_{t,s} \) is the storage charge power output over time period \( t \), \( d_{t,s} \) is the discharge power output, and \( e_{t,s} \) is the storage SoC.

**Remark 1:** Binary variables in multi-period dispatch: We employ binary variables \( u_{t,s} \) to enforce the SoC segment transition logic because if we relax \( u_{t,s} \), the SoC segment transition may not follow the correct charging or discharging order. For example, assume we have a 2-segment SoC model. The model should always discharge the upper segment first or charge the lower segment first. Now assume the lower segment has a lower discharge cost and the battery is fully charged. The optimization will discharge the lower SoC segment first due to the lower discharge cost, which is against the SoC transition logic. On the other hand, assume a 2-segment empty battery where the upper segment has a cheaper discharge cost. In this case, the optimization will first charge the upper segment because it can discharge later at a lower cost, which also violates the SoC transition logic. Therefore, we use binary variables to enforce the SoC transition logic in this generalized storage SoC market segment model.

**Remark 2:** SoC-independent storage model: If the storage has constant parameters, i.e., a linear SoC independent storage model, it is equivalent to a 1-segment model in which \( s \in \{1\} \).

### B. Single-Period Bid-Based SoC Segment Market Model

We now formulate the single-period economic dispatch problem in which the system operator dispatches energy storage based on their submitted bids with physical parameters instead of physical parameters only. We assume the storage submits two sets of time-variant bids, each with \( S \) segments. Same as the multi-period model, each bid and parameter segment is associated with an SoC range \( E_{s-1} \) to \( E_s \).

- \( G_{t,s} \) is the discharge bid over segment \( s \), above which the storage is willing to discharge over segment \( s \).
- \( B_{t,s} \) is the charge bid over segment \( s \), below which the storage is willing to charge up over segment \( s \).

The single-period dispatch model with storage charge and discharge bids is

\[
\begin{align*}
\min_{p_{t,s},d_{t,s}} & \quad J_t \left( \sum_s (p_{t,s} - d_{t,s}) \right) + \sum_s (G_{t,s}d_{t,s} - B_{t,s}p_{t,s}) \\
\text{s.t.} & \quad (1b) - (1d) \tag{2a}
\end{align*}
\]

which is subject to the same storage constraints as in the multi-period optimization case, but covers only one time period. We illustrate the proposed SoC segment market model in Fig. 2, where energy storage participants can submit multiple charge and discharge bids between usable SoC (USOC) and lowest SoC (LSOC), depending on SoC segments. We can adjust USOC and LSOC according to the ancillary service award when considering the ancillary services market. The single-period charge and discharge revenues are shown by blue and red shadow areas, respectively. If \( G_{t,s} \) and \( B_{t,s} \) are strictly decreasing within time step \( t \), we can relax the problem to linear programming by omitting binary variables.

**Remark 3:** Binary variables in single-period dispatch: In single-period dispatch, we can remove the binary variable \( u_{t,s} \) if \( G_{t,s} \) and \( B_{t,s} \) monotonically decrease with storage SoC increases. The major difference here is that the optimization considers only a single time period at a time. If we relax binary variables, the single-period dispatch will always try to discharge the segment with the lowest \( G_{t,s} \) or charge segments with the highest \( B_{t,s} \). If bids monotonically decrease with SoC increases, this becomes equivalent to always discharging SoC segments in descending order and charging in ascending order, which follows the SoC transition logic.

### IV. BIDDING WITH SOC SEGMENT MARKET MODEL

We include a bidding model in this paper with a focus on benchmarking the performance of the proposed and existing storage market models in terms of system cost savings, price volatilities, and revenues. While market participants are free to use any approaches to design bids following the proposed model, the bidding algorithm adopted in this paper is derived theoretically based on dynamic programming and is proven to provide optimal arbitrage decisions [7], [38]. Thus, the comparison reasonably represents results in a competitive electricity market.

We consider storage participants who design their bids using a profit-maximization price arbitrage model based on a set of price predictions \( \lambda_t \). To handle the SoC dependencies in the storage model, we approximate all storage parameters to depend on the storage SoC at the beginning of the time period. The resulting dynamic programming arbitrage problem becomes

\[
Q_{t-1}(e_{t-1}) = \max_{p_t, d_t} \lambda_t (d_t - p_t) - c(e_{t-1})d_t + Q_t(e_t) \tag{3a}
\]
subjects to the following constraints

\[
0 \leq d_t \leq D(e_{t-1}), \quad 0 \leq p_t \leq P(e_{t-1}) 
\]

\[
d_t = 0 \text{ if } \lambda_t < 0 
\]

\[
e_t - e_{t-1} = -d_t/\eta^d(e_{t-1}) + p_t\eta^p(e_{t-1}) 
\]

\[
0 \leq e_t \leq E 
\]

where \(Q_{t-1}\) is the maximized energy storage arbitrage profit dependent on the energy storage SoC at the end of the previous time period \(e_{t-1}\). \(Q_t\) represents the opportunity value of the energy storage SoC \(e_t\) at the end of time period \(t\), hence the value-to-go function in dynamic programming. Note that to model the dependencies of the physical parameters illustrated in Section II-B, here the storage discharge cost \(c\), power ratings \(D\) and \(P\), and efficiencies \(\eta^d\) and \(\eta^p\) are all functions of \(e_{t-1}\). Hence, in this dynamic programming formulation, we apply local linearization to assume the storage parameters are constant within a single time step. In this case, we can up-sample the time step; for example, instead of solving the problem using a market-clearing time frequency such as 5 minutes, we solve the problem at a 1-minute resolution to obtain a more accurate local linearization to the nonlinear storage model.

We now design bids based on factoring the marginal discharge cost and charge value counting in both physical and opportunity costs

\[
\partial c(e_{t-1})/\partial d_t - Q_t(e_t) = c(e_{t-1}) + 1/\eta^d q_t(e_t) 
\]

\[
\partial c(e_{t-1})/\partial p_t = -\eta^p q_t(e_t) 
\]

where \(q_t\) is the derivative of \(Q_t\). To generate bids for each \(G_{t,s}\) and \(B_{t,s}\) segment, we replace the discharge cost \(c\) with the segment discharge cost \(c_s\). For \(q_t\), we take its average value between the SoC range \(E_{s-1}\) to \(E_s\) by sampling SoC

\[
G_{t,s} \approx c_s + 1/\eta^d \sum_i q_t(e_{i,s})/N_s \]

\[
B_{t,s} \approx \eta^p \sum_i q_t(e_{i,s})/N_s \]

where \(e_{i,s} \in [E_{s-1}, E_s]\) is the SoC samples and \(N_s\) is the number of samples.

Our prior work [7] proposed an analytical algorithm that calculates \(q_t\) recursively in reverse order. This algorithm uses the following equation to calculate the value \(q_{t-1}\) to an SoC input \(e\) based on the opportunity function from the next time period \(q_t\) as

\[
q_{t-1}(e) = \begin{cases} 
q_t(e + P\eta^p) & \text{if } \lambda_t \leq q_t(e + P\eta^p)\eta^p \\
\lambda_t/\eta^p & \text{if } q_t(e + P\eta^p)\eta^p < \lambda_t \leq q_t(e)\eta^p \\
q_t(e) & \text{if } q_t(e)\eta^p < \lambda_t \leq \{q_t(e)/\eta^d + c]\}^+ \\
(\lambda_t - c)\eta^d & \text{if } \{q_t(e)/\eta^d + c\}^+ \leq \lambda_t \leq \{q_t(e - D/\eta^d)/\eta^d + c\}^+ \\
q_t(e - D/\eta^p) & \text{if } \lambda_t > \{q_t(e - D/\eta^p)/\eta^p + c\}^+. 
\end{cases}
\]

Note that in (5), \(c\), \(\eta^p\), \(\eta^d\), \(P\), \(D\) are all functions of \(e\), but we omitted the function form for simpler presentation. Since \(c\) is input to (5), the algorithm simply looks up the value of storage parameters based on the input \(e\) and finishes the calculation. Thus, we solve the dynamic programming by initializing the final value function \(q_T\) as all zeros indicating no more opportunity value at the end of operation horizon, then we perform (5) in reverse order to calculate \(q_t\) over the entire time horizon.

We further discretize \(q_t\) by equally dividing energy storage SoC level \(e\) into small segments, which is finer than the power rating \(P\). For any SoC level \(e_t\), we can find the nearest segment and return the corresponding value. Note that \(Q_t\) in the objective function is the integral of \(q_t\). Therefore, discretizing the derivative \(q_t\) is equivalent to approximating \(Q_t\) using piece-wise linear functions.

V. PRICE-TAKER CASE STUDY

In the first case study, we consider an energy arbitrage problem assuming energy storage is a price-taker with no power to influence market prices. The objective of the price-taker case study is to simulate real-time market clearing with various storage market models while assuming the storage would not impact the market price. In this case, the market clearing problem - in which the system operator minimizes the total system operating cost, can be equivalently modeled as an arbitrage profit-maximizing problem [39]. However, the key difference between our considered price-taker market clearing model and a price-response/self-schedule model is that the storage’s action is constrained by its bids, which must be submitted one hour ahead of time and the bid must stay the same for each hour which contains twelve market clearing time periods. Storage charge and discharge decisions in our study have to be a result of comparing the submitted bids and the market clearing price.

To focus on the comparison of market models, we assume the storage can predict price perfectly but must obey the market rule to design bids and be cleared. This case study aims to demonstrate how different storage market models would impact storage arbitrage profit potential. In terms of market design, we consider three market models:

1) Multi: the energy storage is not constrained by the market bidding model and can freely make charge and discharge decisions to arbitrage price differences. This case represents the best possible arbitrage results and adopts the optimization multi-period dispatch model (1).

2) RTD-1: the storage submits one charge bid and one discharge bid for each hour, and the system operator clears
the storage bids in single-period real-time dispatches. This model represents existing storage participation models being used now in most ISOs. This case uses optimization model (2) and sets $S = 1$ as it assumes a 1-segment model.

3) RTD-5: similar to RTD-1 except the storage submits 5-segment bids as proposed in this paper. We use an equally spaced 20% SoC segment range; this case uses optimization model (2) and sets $S = 5$.

All three cases use a price arbitrage objective function; the $J_t$ function in the objectives (1a) and (2a) becomes the product between price and storage total power:

$$J_t\left(\sum_s (p_{t,s} - d_{t,s})\right) = \lambda_t \left(\sum_s (p_{t,s} - d_{t,s})\right)$$

(6)

where $\lambda_t$ is the market price.

We use the 2016 CAISO real-time locational marginal prices of one node (WALNUT_6_N011) with 5-minute resolution. The energy storage submits hourly charge/discharge bids, and the real-time market clears every 5 minutes. Hence, in Multi, the storage optimizes charge and discharge decisions every 5 minutes, while in RTD-1 and RTD-5, the storage bids are the same through 1 h, and will be cleared every 5 minutes.

We consider an SoC-independent storage model and several SoC-dependent storage models in this case study to demonstrate the effectiveness of the proposed SoC market model as shown in Table I. In both case we apply multi-period dispatch model (Multi) and single-period dispatch model with SoC segment market model (RTD-1 and RTD-5). We assume a 4-hour battery energy storage with 1 MWh capacity in all models. In the SoC-independent storage model, we use constant parameters assume the charge/discharge power rating of 0.25 MW (normalized according to 4-hour energy storage with 1 MWh capacity), one-way charge/discharge efficiency of 90%, and marginal discharge cost of $20/MWh for all segments. In contrast, SoC-dependent storage model parameters are approximated to 5 segments of step-wise linear functions as shown in Fig. 1. We write our code implementation in Julia with JuMP and Gurobi solver, which is available on GitHub. We run all numerical simulations on a laptop with an Apple M1 Pro chip and 16 GB memory.

### A. SoC-Independent Storage Model

We first compare the three market models using an SoC-independent storage model in which the storage power ratings, efficiencies, and discharge costs are constant. The year-round result of 2016 is shown in Table II. The single-period model with SoC segment bids (RTD-5) only loses 2.7% of profit compared to the multi-period model (Multi) due to hourly bidding limitations. The energy storage cannot change bids according to price/opportunity cost variation within hours and submits averaged bids to the system operator instead. The single-period model with 1-segment bids (RTD-1) loses 9.6% more profit than RTD-5. The result shows that RTD-5 improves storage profit in the market even energy storage parameters are SoC-independent because RTD-5 incorporates SoC-dependent opportunity value. The single-period dispatch decouples intertemporal decision variables, which reduces problem complexity. Therefore, the solution times for single-period models are lower than for the multi-period model.

### B. SoC-Dependent Storage Model

We now compare market designs using SoC-dependent storage models, in which the storage power ratings, efficiencies, and discharge costs depend on the SoC range. To bound energy storage dispatch within the physically feasible region of the storage in RTD-1, we project the dispatch instruction to the storage feasible operation region as in (2b) by minimizing the square error, i.e.:

$$\min_{p_{t,s}, d_{t,s}} \left\| \sum_s p_{t,s} - \hat{p}_t \right\|^2 + \left\| \sum_s d_{t,s} - \hat{d}_t \right\|^2$$

(7)

subject to (2b) (8)

where $\hat{p}_t$ and $\hat{d}_t$ are the dispatch instructions cleared by the system operator. In this setting, we simulate the process of SoC-dependent energy storage submitting bids to the system operator and trying their best to follow the received dispatch signals from the system operator.

We design five SoC-dependent storage models with different power ratings, motivated by our observation that SoC-dependent storage power ratings are the primary factor affecting storage profit potentials:

1) DPA: the storage has SoC-dependent segment-wise charge and discharge power ratings as shown in Fig. 1.

2) DPB: same as DPA except the storage has a constant discharge power rating.

3) DPC: same as DPA except the storage has constant charge and discharge ratings.
The performances of single-period models are better than the DPA case, especially in DPF, which only has reduced power rating at lowest SoC segment. The charge power rating has little effect on the profit ratio, as shown in the DPC case.

Table III shows the result for the entire year of 2016. In DPA, RTD-5 gets a lower profit ratio than the SoC-independent storage model case, and RTD-1 only captures 57.3% of the highest power rating among the model cases. This is because the storage has a constant charge power rating, but the discharge power ratings decrease in the last two segments. The segment-wise discharge power ratings are [100%, 100%, 100%, 90%, 50%] of the highest power rating; otherwise, the model is the same as DPA.

Table III shows the result for the entire year of 2016. In DPA, RTD-5 gets a lower profit ratio than the SoC-independent storage model case, and RTD-1 only captures 57.3% of the highest power rating among the model cases. This is because the storage has a constant charge power rating, but the discharge power ratings decrease in the last two segments. The segment-wise discharge power ratings are [100%, 100%, 100%, 90%, 50%] of the highest power rating; otherwise, the model is the same as DPA.

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We further investigate two SoC-dependent energy storage models with different discharge power rating curves (DPL and DPF). The performances of single-period models are better than the DPA case, especially in DPF, which only has reduced power rating at lowest SoC segment. The charge power rating has little effect on the profit ratio, as shown in the DPC case.

RTD-5 provides a lower profit, primarily because the storage has to discharge at a lower power rating when price spikes occur, and the SoC is not positioned at the 20% to 60% range with the highest power rating. In the single-period dispatch, the storage is more likely to charge up to high SoC values or discharge to low SoC values based on the submitted bids, while the multi-period optimization better optimizes operation based on SoC segments. Fig. 3 shows a histogram comparing SoC distribution in the DPA model with the Multi and RTD-5 cases. The energy storage stays between 20% to 60% more often in the Multi case, so the storage can discharge at a higher power rating more frequently than the RTD-5 case.

VI. PRICE-INFLUENCER CASE STUDY

In the second case study, we consider energy storage as a price-influencer, meaning its charge and discharge will affect the price. We assume a competitive market in which the storage participant will not try to exercise market power, but its action will still impact the market prices and other outcomes. Since the focus of the study is to compare different storage market models, we assume the storage only participates in real-time markets and has a perfect prediction of the day-ahead market prices cleared without energy storage participation, but cannot predict how its market actions will impact the real-time price clearing. To do this, we first perform a day-ahead 24-hour unit commitment in Appendix A without storage and record the dispatch cost, commitment status, and prices. The storage will use the price results from the unit commitment and design bids using the considered market rule, and then we perform both a multi-period dispatch and a sequential single-period dispatch using the same demand and wind profile, and the commitment results from unit commitment.

Two types of dispatch settings are compared:

1) Multi-period dispatch (Multi): The system operator solves a 24-hour period economic dispatch with storage’s physical cost as in Appendix B (10a). The Multi-period case also serves as a benchmark as it provides the optimal dispatch result if assuming the same storage model and forecast accuracy.

2) Single-period dispatch (RTD): The system operator solves sequential real-time dispatch problems with storage bids as in Appendix B (10c). These bids cover both the physical and opportunity cost of the storage.

We do not consider ramp limits so that the multi-period and single-period dispatch yield the same dispatch and price results without storage, as there are no more intertemporal constraints. We perform simulations on an Independent System Operator New England (ISO-NE) 8-zone test system [40]. The system demand varies between 9 GW to 17 GW, with an average of 13 GW. The wind capacity is 6.5 GW with an average wind capacity factor (average power output divided by its maximum power capacity) of 0.4. We pick five representative demand and wind profiles for our study using a K-means approach. In all cases, we observe the market clearing results with storage capacity increasing from 1 MW to 1000 MW with a 4-hour duration, simulating increasing storage participation in markets. We assume multiple storage have the same action. The code implementation is written in Matlab 2021b with YALMIP as a solver.

We run the numerical simulations on a desktop PC computer with an Intel i7-11700 chip and 64 GB memory.

A. SoC-Independent Storage Model

We first consider an SoC-independent storage model to show the benefit of implementing SoC-segment market models even

| Storage Model | Market Model | Revenue ($) | Cost ($) | Profit ($) | Profit Ratio (%) | Solution Time (s) |
|---------------|-------------|-------------|---------|------------|-----------------|-----------------|
| DPA           | Multi       | 20903       | 3228    | 17775      | 100             | 283             |
|               | RTD-5       | 17328       | 2707    | 14621      | 83.2            | 22              |
|               | RTD-1       | 12468       | 2389    | 10079      | 57.3            | 16              |
| DPB           | Multi       | 22123       | 3148    | 18085      | 100             | 193             |
|               | RTD-5       | 20372       | 2995    | 17377      | 96.1            | 19              |
|               | RTD-1       | 17564       | 2834    | 14710      | 81.3            | 11              |
| DPC           | Multi       | 22081       | 3310    | 18772      | 100             | 97              |
|               | RTD-5       | 21450       | 3382    | 18068      | 96.2            | 18              |
|               | RTD-1       | 18529       | 3056    | 15472      | 82.4            | 11              |
| DPF           | Multi       | 21905       | 3470    | 18435      | 100             | 170             |
|               | RTD-5       | 20174       | 3299    | 16675      | 91.5            | 18              |
|               | RTD-1       | 17261       | 2851    | 14410      | 78.2            | 11              |
| DPL           | Multi       | 21833       | 3236    | 18598      | 100             | 172             |
|               | RTD-5       | 19898       | 3282    | 16616      | 89.3            | 18              |
|               | RTD-1       | 14462       | 2853    | 11569      | 62.2            | 11              |
if the storage physical parameters are independent of SoC. In this case, the system operator can dispatch the storage optimally in multi-period dispatch without implementing SoC-segment models. Yet, the SoC-segment model still provides benefits in real-time dispatch as the storage opportunity cost depends on the SoC. In this case study, we have storage with a one-way efficiency of 90%, total charging/discharging power ratings are normalized according to installed 4-hour energy storage capacity, and marginal discharging cost at $20/MWh.

Fig. 4 shows the simulation results with different installed energy storage capacities over multi-period and single-period dispatch using different market models. Fig. 4(a) shows the averaged total system operating cost comparison, and 4(b) shows the normalized cost comparison based on the single-period dispatch 1-segment (RTD-1) market model results. These results conclude that the multi-segment (RTD-2, 5, 10) market model is better at reducing system operating costs, hence improving social welfare. A higher number of segments can further narrow the gap to optimal social welfare. In Fig. 4(b), we observe that RTD-2 provides a significant improvement compared to RTD-1, while RTD-5 and RTD-10 produce similar results to RTD-2. RTD-2 further reduces the system operating cost by an additional 0.1% of the total system cost, or 5% more cost reduction led by energy storage (compare cost without energy storage to with 1000 MW energy storage) compared to RTD-1. This equals an annual cost savings of around $2 million in our tested ISO-NE system.

Fig. 4(c) and (d) show the average price and scenario-averaged price standard deviations. The multi-segment model provides significant improvements in reducing market prices and their volatilities, especially with RTD-10 which achieves price results similar to those of Multi. RTD-10 reduced the average price by around 10% and the price standard deviation by around 30% compared to the RTD-1 in the range between 200 and 1000 MW storage capacity. On the other hand, the number of segments did not provide much difference in storage profitability, and per-MW profit decreases as the storage capacity increases, as shown in Fig. 4(e) and (f). Notably, at a low storage capacity (below 500 MW), RTD-1 provides the highest profit. This is because RTD-1 kept price volatilities as shown in Fig. 4(c), maintaining higher profit than all other cases. Yet as storage capacity increases, storage starts to have more potent influences on market price patterns, and the storage profit stops increasing in single-period cases after 600 MW storage capacity.
B. SoC-Dependent Storage Model

We now consider an SoC-dependent model, in which storage physical parameters depend on SoC, to demonstrate the benefit of dispatch storage using SoC-segment models. In this case, modeling SoC segments will improve the dispatch accuracy in both multi-period and single-period dispatch, as an SoC-segment model provides a closer approximation to the true storage model. In the case study, we consider a storage segment model the same as Fig. 1, prorated to 1, 5, or 10 segments depending on the case study setting. Note that the dispatch may not be feasible in the case of the 1-segment model as we assume the real storage model is 5-segment. Thus, we will again use norm-2 projection as in (7), while the mismatch between the instruction and the actual dispatch is penalized with a $50/MWh penalty cost.

We first compare storage market models in RTD. Fig. 5 shows a similar trend as in the SoC-independent case study that a higher number of SoC segments achieves lower system costs, average price, and price volatility. Yet, the improvement is more significant than the SoC-independent cases because now both the storage physical parameters and opportunity costs depend on SoC. Notably, the 1-segment storage model increased the system cost at high storage capacity cases, which primarily contributed to the $50/MWh infeasibility penalty cost. On the other hand, the profit result for storage is mixed, but RTD-1 still provides higher profit at low storage capacity. This result also agrees with the SoC-independent case, which is due to that the one-segment model is not effective in reducing price volatility which in turn increases storage profits.

Furthermore, we also include a comparison of adopting SoC-segment models in multi-period dispatch with 1-segment model (Multi-1) and 10-segment model (Multi-10). The result shows that model SoC segments also improve in the system cost savings as the Multi-10 is a more accurate representation of the storage model. The price results from Multi-1 and Multi-10 are similar, while Multi-1 earned more profits as we did not consider the mismatch penalty in profit calculation.

Finally, we compare the impact of the SoC-segment model over the solution time. As shown in Fig. 6, in the case of SoC-independent storage models, the SoC-segment model is a linear programming model and the number of segments has negligible impacts over the computation time. However, in the case of SoC-dependent storage models, we have to introduce
binary variables to enforce the segment transition logic as the underlying storage model is inherently non-convex. Thus the use of binary variables increased the solution time significantly. Overall, our result suggests the SoC-segment model improves the market efficiency and has negligible computation impact with SoC-independent storage models that are most often used in power system studies [41]. On the other hand, while the SoC-segment market model can further improve market efficiency when extended to the more sophisticated SoC-dependent storage models, it introduces computation challenges that require careful attention when implemented in practice.

VII. CONCLUSION

In this paper, we propose a new wholesale market model for energy storage that allows energy storage to submit charge and discharge bid segments according to the storage SoC ranges. Combining this model with an optimal bid generation algorithm, we show that the SoC segment market model improves storage utilization in markets from several perspectives. In the price-influencer case study, the SoC segment market model is most effective in reducing real-time prices (\(\sim 10\%\)) and their volatilities (\(\sim 30\%\)) compared to the existing storage model, as the segment model provides finer granularity for storage to respond to different prices. Using SoC segment market models can also further reduce total system cost by around 0.5%, which is 5% more compared to the current storage model. The impact of the SoC segment market model on storage profit potential is mixed: When ignoring the influence of storage over market prices, the SoC segment market model provides 10% to 56% more profit to storage than the 1-segment model, especially if the storage parameters are sensitive to SoC; yet when considering the influence of storage on price, the SoC segment market model reduces storage profits because it is more effective at reducing system price volatilities.

The SoC segment market model provides a more accurate representation of the physical parameters and opportunity costs of energy storage. It also allows storage participants to economically manage their SoC through bid parameters. This market model opens up many new interesting research directions. The first is to incorporate the SoC segment market model into more realistic production cost models to observe the corresponding system cost, price, and storage profit estimates. Second, investigating two-stage settlement bidding strategies will be a future direction to help energy storage participants incorporate strategic bids in the day-ahead market. Besides, better reflecting SoC-dependent parameters, especially power ratings, in economic bids will be essential to narrow down the gap between SoC-independent and SoC-dependent storage models. Price uncertainty in storage bid design is another critical aspect of future research. Most storage participants design bids based on their private price predictions; their bids will set market prices and in turn impact their future price predictions. Quantifying the relationship between market price and storage participants’ price prediction strategy is crucial for analyzing future market efficiency and market power monitoring.

APPENDIX A

A. Unit Commitment Formulation

The objective function of unit commitment minimizes daily generation costs of thermal generators:

\[
\min \sum_{t=1}^{T} \sum_{i=1}^{N_g} C_i^1 g_{i,t} + C_i^2 g_{i,t}^2 + C_i^3 u_{i,t} + C_i^4 v_{i,t} \tag{9a}
\]

Decision variables include continuous variables \(g_{i,t}, r_{i,t}, \) and \(u_{i,t};\) binary variables \(u_{i,t}, v_{i,t}, z_{i,t}. \) \(g_{i,t}\) are the electric power generation of thermal generator \(i\) at period \(t, u_{i,t}\) is a binary variable indicating whether generator \(i\) is on at period \(t, \) and \(z_{i,t}\) is a binary variable indicating whether generator \(i\) turns off at period \(t. \) \(C_i^1\) and \(C_i^2\) are the first and second order terms for the marginal production cost of generator \(i, \) \(C_i^3\) is the no load cost, and \(C_i^4\) is the startup cost. \(N_g\) is the number of thermal generators and \(T\) is the number of steps.

The power generation of thermal generators should satisfy generation limits:

\[
G_{\min_i} \cdot u_{i,t} \leq g_{i,t} \leq G_{\max_i} \cdot u_{i,t} \tag{9b}
\]

where \(G_{\min_i}\) and \(G_{\max_i}\) denotes the minimum and maximum generation of thermal generator \(i.\)

Startup and shutdown logic constraints:

\[
y_{i,t} - z_{i,t} = u_{i,t} - u_{i,t-1} \tag{9c}
\]

\[
y_{i,t} + z_{i,t} \leq 1 \tag{9d}
\]

Generator minimum up and down time constraints:

\[
\sum_{\tau = \max(t-T_{up_i}+1,1)}^{t} y_{i,\tau} \leq u_{i,t} \tag{9e}
\]

\[
\sum_{\tau = \max(t-T_{dn_i}+1,1)}^{t} z_{i,\tau} \leq 1 - u_{i,t} \tag{9f}
\]

where \(T_{up_i}\) and \(T_{dn_i}\) are maximum up time and minimum down time of generator \(i,\) respectively.
Reserve constraints following the 5+3 rule (5% renewables and 3% demand):

\[
N_w \sum_{i=1}^{N_i} r_{i,t} \geq (5\%)w_t + (3\%)D_t \tag{9g}
\]

\[
r_{i,t} \leq G_{\text{max}} u_{i,t} - g_{i,t} \tag{9h}
\]

where \(w_t\) is accommodated wind generation during time period \(t\). The wind generation should satisfy:

\[
w_t \leq \tilde{W}_t \tag{9i}
\]

where \(\tilde{W}_t\) denotes the day-ahead wind generation forecast at period \(t\).

The electric power balance constraint and price:

\[
N_w \sum_{i=1}^{N_i} g_{i,t} + w_t = D_t : \lambda^\text{DA}_t \tag{9j}
\]

where the dual variable associated with constraint (9) is the day-ahead price \(\lambda^\text{DA}_t\) at period \(t\).

**B. Economic Dispatch**

The multi-period economic dispatch problem has the following objective function:

\[
\min \sum_{t=1}^{T} \sum_{i=1}^{N_i} C_i^l g_{i,t} + C_i^q g_{i,t}^2 + \sum_{s=1}^{S} c_s d_{s,t} \tag{10a}
\]

subject to the power balance constraint:

\[
\sum_{i=1}^{N_i} g_{i,t} + w_t + \sum_{s=1}^{S} d_{s,t} = D_t + \sum_{s=1}^{S} p_{s,t} + \lambda^\text{RT}_t \tag{10b}
\]

which now includes storage charge and discharge power from all segments. Other constraints include generator ratings (9b), wind limits (9i), and storage unit constraints (1b)–(1d).

The single period economic dispatch problem is:

\[
\min \sum_{i=1}^{N_i} C_i^l g_{i,t} + C_i^q g_{i,t}^2 + \sum_{s} (G_{i,s} d_{s,t} - B_{i,s} p_{s,t}) \tag{10c}
\]

subject to same constraints as the multi-period dispatch problem (10b), (9b), (9i), (1b)–(1d). Decision variables in both problems include \(g_{i,t}, w_t, p_{s,t}, d_{s,t}\). Note that the commitment status \(u_{i,t}\) is from the unit commitment results.

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