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U.S. DEPARTMENT OF ENERGY

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Abstract

Energy storage resources (ESRs) and other zero marginal cost (ZMC) resources have unique characteristics that are not fully captured in today's electricity planning and operations modeling tools. Because the modeling assumptions used in these tools are simplified approximations of how operations and investment decisions occur in the real-world, accurately representing cost and operational characteristics are key for determining how these resources impact price formation. Questions requiring accurate electricity prices, such as—Where should we build new transmission? Will a small modular reactor earn enough revenue to participate in the future electric grid? Is retrofitting a coal plant with carbon capture technology economically feasible?—aren't available from today's electricity planning and operations modeling tools.

As an example, production cost models (PCMs) are heavily utilized tools that determine the cost and reliability of the electric system. However, as PCMs were developed to help thermal generators manage their fuel inventories, production cost modeling is largely based on fuel prices. Because ESRs do not incur fuel costs, they are often modeled as ZMC resources. In reality, ESRs incur opportunity costs as well as technology-specific (degradation) costs that are non-trivial to calculate but are important for price formation.

In this research, we identify options to incorporate more realistic opportunity and degradation costs in ESR bidding algorithms. Expanding available bidding assumptions allows energy system modelers to develop more accurate economic valuations for ESRs, leading to more accurate price formation from leading energy system modeling tools.

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Acronyms and Abbreviations

DAM	day-ahead market
ESR	energy storage resource
ISO	independent system operator
PCM	production cost model
RTM	real-time market
RTO	regional transmission operator
SCED	security constrained economic dispatch
SCUD	security constrained unit commitment
SoC	state-of-charge
SoH	state-of-health
ZMC	zero marginal cost resource

Contents

Figures

Tables

1.0 Introduction

Energy system modeling tools are used for reasonable price and resource utilization projections in many grid planning activities. As the grid heads toward a high-renewable future, it is worth considering whether the costs of new technologies are adequately modeled using traditional methods that were developed for thermal resources. Production cost modeling with thermal resources is largely based on fuel prices. In contrast, many renewable and carbon-free resources bid into real-world electricity markets using opportunity costs or other technology-specific costs. For example, energy storage resources (ESRs) do not incur fuel costs and are therefore currently often modeled with zero marginal costs (ZMC). Although ESRs do not have fuel costs, ESRs may incur opportunity costs if decisions within a dispatch horizon prevent the ESR from selling energy in future periods, and they also incur technology-specific costs (such as degradation) that are nontrivial to calculate. These opportunity costs and degradation costs are often ignored in existing production cost models.

In this research, we identify options to incorporate more realistic costs in the bids for ESRs in leading energy system modeling tools. Expanding ESR bidding assumptions to include opportunity and degradation costs will enable energy system modelers to analyze price formation and develop more accurate economic valuations for investment and operations decisions in the future electric grid by reflecting a more accurate cost structure faced by market participants and more economic utilization of ESR resources. We investigate various methods to estimate these costs within existing energy system modeling tools, providing a step forward for future grid planning.

1.1 Motivation

ZMC resources (including wind and solar), and newer technologies (including many ESRs) have unique characteristics that are not always efficiently captured in today's electricity planning and operations modeling tools. As an example, production cost models (PCMs) were developed to help thermal generators manage their fuel inventories – an antiquated objective for an electricity grid made up of ZMC resources. Market optimization models – such as Security Constrained Unit Commitment (SCUC) and Security Constrained Economic Dispatch (SCED), used to plan for and dispatch the electricity system to meet electricity demand – were also designed around the scheduling needs of dispatchable, thermal resources.

While the modeling assumptions used in electricity planning and operations models are necessarily simplified approximations of how operations and investment decisions are made in the real-world energy system, representing resources' cost and operational characteristics are key determinants for how these resources interact within the power system model and impact price formation. Newer technologies, such as ESRs, require modeling enhancements to accurately capture their value (Levin et al. 2023a, 2023b, Mays 2021a, 2021b). These modeling enhancements include technology representation, temporal fidelity, spatial fidelity, uncertainty representation, and the need for new methodologies and metrics to measure ESR contributions to reliability.

Additionally, as current electricity planning and operations modeling tools focus on optimizing the centralized dispatch of generators, bidding strategies employed by individual generators or market participants outside of this centralized framework are often not represented. This omission stems from the complexity and diversity of strategies that vary significantly among participants, including tactics to manage risk, exploit market conditions, or optimize profit margins. Such strategies, often involving advanced algorithms and market insights, play a pivotal role in shaping market outcomes and system reliability.

1.2 Research Approach

In this research we develop a comprehensive approach to understand current limitations in electricity planning and operations models for ESRs and develop options and algorithms for incorporating more realistic cost approximations for ESR bidding assumptions in leading energy system modeling tools. We first perform a survey of existing modeling approaches to gain a comprehensive understanding of leading practices and assumptions which may impact the applicability of current modeling approaches for valuing ESR contributions. We then take a deep dive into real-world markets and empirical ESR bidding behavior to understand how ESR market participation rules and market design impact how ESRs bid in practice. Given this survey, we then develop a menu of options for incorporating more realistic bidding behavior in leading electricity planning and operations modeling tools. For our menu of potential options, we develop modeling approaches and recommended algorithms for improving ESR representation. We implement our algorithms in a wholesale electricity market simulation – leveraging PNNL's Wholesale Electricity Analysis via Simulation & Learning Experiments (WEASLE) platform (Eldridge et al., 2024) – to determine if and how our algorithms improve market surplus and ESR profits in a high-renewables power grid.

2.0 Survey of Existing Modeling Approaches

2.1 The Value Proposition of Energy Storage Resources

ESRs unique value proposition is driven by their ability to charge or discharge, allowing these resources to function as generation or load. ESRs can flexibly store electricity during periods of low net demand and discharge during periods of high net demand, allowing them to fulfill the important function of smoothing variability from intermittent renewable energy resources while providing stability and resilience to the grid. ESRs can also provide capacity and resource adequacy by dispatching during peak load, reducing the need for peaking resources. ESRs can be sited in geographically dispersed areas, allowing them to alleviate transmission congestion, and provide resilience and reliability either in front of, or behind the meter. However, enabling the value that ESRs can bring to the grid requires planning and operations modeling tools and market designs that enable their entire value stack of services.

2.2 Current Electricity Planning and Operations Models

In this review, we focus on needed improvements for current electricity planning and operations modeling tools—including PCMs, other market optimization models, and capacity expansion models—which were designed around the scheduling needs of dispatchable, thermal resources.

2.2.1 Planning and Operations Models

PCMs are a widely used planning tool for electricity market operators, regulators, and other stakeholders for their ability to provide detailed insight into electricity system operations over a various time horizons (e.g., from one day to multiple years). PCMs belong to a family of mathematical optimization problems, and most of their core decision variables control the chronological commitment status (i.e., on/off) and dispatch (i.e., amount of generation) of generators. These models simulate power system market operations with a goal to minimize power systems' operating costs of meeting electricity demand and reserve requirements while simultaneously satisfying a wide variety of operating constraints. These constraints consist of unit-specific constraints (e.g., minimum/maximum capacity limits, minimum up and down times, ramping limits) and system-wide constraints (e.g., transmission line capacity limits, interface capacity limits, operating reserves, emission constraints, hurdle rates). Operating costs largely consist of fuel costs, variable operating and maintenance costs, and start-up/shut-down costs. PCMs often leverage standardized datasets to represent the transmission topologies.

PCMs typically employ an hourly time step and optimization horizons that span a single day (24 hours), week (168 hours), or year (8760 hours) to represent day-ahead market operations. However, to better capture the variability in systems with a large share of renewable energy resources where ramping needs might exceed the capability of dispatchable thermal units, PCMs can also be formulated to model real-time operations which adjust the day-ahead dispatch in times ranging from five minutes to fifteen minutes depending on the real-time market paradigm. To this end, PCMs are utilized to minimize operating costs in both "day-ahead" and "real-time" decision-making processes: day-ahead energy and ancillary service markets open several days before the commitment period (e.g., a week) and close a day ahead. Day-ahead markets allow participants to buy or sell wholesale electricity before the operating day to minimize reliability issues and price volatility; real-time energy and ancillary markets operate on much shorter intervals, clearing every 15 or 5 minutes, and act as a balancing market where the day-ahead commitments are balanced against actual demand and system constraints, accounting in many cases for forecast errors.

All organized wholesale electricity market operators in the United States use modeling approaches similar to those used in production cost modeling to plan for and execute day-ahead and real-time market operations. In the day-ahead market, the market operator determines which generators should be committed to produce electricity the next day by solving a Security Constrained Unit Commitment (SCUC) optimization problem. The unit commitment problem determines the least cost production schedule to meet the next day's load forecast based on generator supply offers. The real-time market involves dispatching the system (unit dispatch) based on the day-ahead unit commitment. The day-ahead SCUC is a challenging optimization problem formulated for addressing the unique characteristics of conventional generators, including supply offers based on variable fuel costs, start-up costs, operating costs, as well as operating characteristics. As real-time conditions may differ from day-ahead projections, a Security Constrained Economic Dispatch (SCED) problem is run in the real-time market to adjust dispatch and address any real-time imbalances.

Capacity expansion models are used to simulate needed investment in generation or transmission capacity in the mid- to long-term. Capacity expansion models consider what the future resource portfolio may look like, including assumptions about demand, generation resources and policy or regulatory objectives. However, capacity expansion models tend to have less temporal fidelity and do not consider chronological unit commitment as in PCMs (Levin et al., 2023a, 2023b).

2.2.2 Recommended Modeling Improvements for Energy Storage Resources

Assumptions for electricity planning and operations models are necessarily simplified approximations the real-world energy system. However, ESRs and other new technologies have unique characteristics that are not represented well in current planning and operations modeling tools. ESRs and many other newer technologies require modeling enhancements to accurately capture their value. Levin et al. (2023a, 2023b) highlight the following areas for improvement:

1. **Technology representation:** ESRs have unique cost and performance characteristics, such as power or energy capacity, discharge duration, depth of discharge, state-of-charge, cycle life, round trip efficiency. Additionally, ESRs may incur opportunity costs from the potential profit lost if ESRs are unable to provide energy in the future, and they incur degradation costs when operational decisions affect temperatures or other factors that reduce the useful life of the resource.

2. **Temporal fidelity:** ESR state-of-charge decisions are dynamically linked through time, where the decision to charge or discharge in one period affects state-of-charge in the next. Modeling assumptions that use too coarsely-grained time intervals may ignore intertemporal variability and therefore undervalue ESRs.

3. **Spatial fidelity:** ESRs can be built at geographically dispersed locations to address grid conditions. This requires also including sufficient transmission detail to capture price and congestion impacts.

4. **Uncertainty:** ESRs can provide value by mitigating increased net load uncertainty in future power systems. From a modeling perspective, improving uncertainty representation may require improved stochastic optimization methods and computational

approaches or reasonable approximations. This could include modeling full distributions of weather outcomes to capture potential weather extremes and using stochastic methods or sensitivity analyses to examine the full distribution of potential outcomes.

5. **Reliability:** New methodologies and metrics to measure ESRs' contributions to reliability could include modeling ancillary services with more fidelity and developing new metrics to capture marginal reliability contributions of ESRs.

Further, current electricity planning and operations models are typically structured to assume perfectly competitive and risk-neutral market or utility operations. Market power is well-known to affect supply availability and prices in power markets (Gabriel et at., 2012). In practice, grid operators are often risk averse and try to avoid price volatility that may benefit ESRs (Mays 2021a). Future grid planners and operators could also move towards multi-criteria approaches that consider broader environmental impacts that are not included in existing grid planning tools (Hobbs and Meier, 2012). As the above factors become more influential, a new generation of market modeling tools may explore more broadly how profit incentives, risk management, and gaming opportunities affect market outcomes.

Pursuing these enhancements may provide grid planners, investors, regulators, and other interested parties with more accurate projections of future grid conditions. Addressing this gap in modeling strategic behavior could involve developing models that better capture the bidding strategies of market participants (i.e., energy suppliers, load consumers), considering factors such as generation costs, proxy costs of renewable resources, capacity constraints, reserve requirements, transmission availability, and market power exertion. Likewise, future gird operators may explicitly pursue risk aversion or environmental and other multi-criteria objectives that need to be reflected in grid modeling tools. While this paper focuses solely on improvements to ESR bidding assumptions, it is part of a more comprehensive set of future advancements in power system modeling that may be necessary to support more efficient market outcomes and resilient grid operations in the face of evolving zero marginal cost energy landscapes and regulatory frameworks.

2.3 Current Electricity Market Design

Electricity market design and detailed rules for resource participation fundamentally influence market efficiency. This is especially true when considering the time horizons over which market solutions are optimized as well as ESR participation rules. In this section, we consider existing market designs and market participation rules that facilitate the participation of ESRs, assessing current advancements and limitations for accurate ESR valuation.

2.3.1 Wholesale Market Design

The majority of electric power consumption in the U.S. is procured through organized wholesale markets, also known as Independent System Operators (ISOs) or Regional Transmission Operators (RTOs) (DOE, 2023). ISOs/RTOs schedule electric power generation and determine wholesale electricity prices through a multiparty auction mechanism. These auctions are cleared by solving a large, centralized commitment and dispatch problem that minimizes the cost to ensure a reliable supply of electricity. Competitive prices are calculated from the outcome of the least-cost solution and are generally set at the marginal cost to supply incremental demand. These prices may vary at each location in the ISO/RTO's service territory and are called locational marginal prices (LMPs).

All ISO/RTO markets use a two-settlement system which includes a day-ahead market that schedules resources in preparation for the following day and a real-time market that continually updates resource dispatch in response to load forecast error and other uncertainties. At a fundamental level, in each market run – day ahead or real time – electricity suppliers submit offers to sell electricity and load-serving resources submit bids to buy electricity. Electricity suppliers typically submit a price-based offer curve which details the price at which they are willing to sell a specific quantity of electricity (and may include bidding parameters such as start-up and shut-down costs, operating costs, variable fuel costs, and other operating characteristics such as minimum and maximum output). The ISO/RTO then determines the least-cost dispatch for all resources in the system. Resource offers are examined for non-competitive constraints by the ISO/RTO, and qualifying offers are accepted to meet load.

Day ahead market optimizes over a 24-hour horizon and commits resources in one-hour interments. The resulting resource schedules are financially but not physically binding; this ensures that resources that follow their day-ahead schedule can be made whole regardless of what happens in real time. In the real-time market, resource dispatch is adjusted incrementally every 5 minutes to balance actual supply and demand. In practice, real time LMPs will be higher than the day ahead LMP to signal that more generation is needed, or real time LMPs will be lower to signal that less generation is needed. In addition to energy and LMPs, ISOs/RTOs also procure and price various ancillary service products (such as regulation, operating reserves, and ramp products) to ensure that the system has sufficient flexibility to maintain reliability and respond to variability and uncertainty.

It is worth considering whether the offers submitted to wholesale electricity markets reflect the actual resource costs. For example, Borenstein, Bushnell, and Wolak (2002) estimate significant use of market power during the 2000 California energy crisis Additional examples are provided in Section 2.4. Although there is evidence of market manipulation in some contexts, under typical conditions, it is reasonable to assume that the energy markets perform competitively. This assumption does not rest on competitive pressure alone (that is, that the market is composed of many small firms, none of which hold a significant portion of total market share). For example, virtual bidding helps improve market competition by allowing participation by entities that are neither physical load nor physical generation (Hogan, 2016). Forward contracting provides incentives for firms to either increase *or* decrease prices depending on wither they are long or short on contracted supply (Hortaçsu and Puller, 2008). And finally, market power mitigation also provides a mechanism for market monitors to perform various screens and tests to determine if market offers are competitive (Nicholson, 2014).

In the context of this work, the ISO and RTO market design generally incentivizes resources to run efficiently and offer their true costs into the market. However, ESRs face a substantially different cost structure than the start-up and shut-down costs, operating costs, variable fuel costs, and minimum and maximum output parameters often used to model thermal generators. Among other technical characteristics, ESRs require assumptions for maximum charging and discharging output, minimum and maximum state-of-charge limits, and charge/discharge efficiency. More detailed bidding parameters are provided in the following section. It is commonly assumed that these parameters do not include fuel costs, and so therefore the ESRs should bid (competitively) into the market at $0/MWh. However, it is worth considering whether broader economic and/or technical factors may affect ESR bidding behavior.

2.3.2 ESR Participation Rules

Actual rules for participation can vary, influencing how market participants earn revenues and incur costs. In practice, participation rules define how resources can offer supply or bid demand into the market as well as share any limitations on their participation with the market operator. To explore this issue in more depth, we reviewed the current and proposed ESR participation models in the wholesale markets in Table 1.

ESR participation rules (participation models) vary across ISOs/RTOs. Most markets allow ESRs to participate as a continuous resource with a single supply curve for charge and discharge capability, although participation models which require ESRs to participate as two distinct assets (for supply and demand capabilities) also exist. Importantly, markets also vary in their requirements over state-of-charge management, and whether state-of-charge is managed by the resource owner/operator or the market operator.

Whether bids are simple price-quantity pairs or more complex (providing technical constraints, such as state-of-charge that the market manages) are important for the strategic behavior that may be exercised by market participants as well as market power mitigation. As an example, resource owners that submit price-quantity bids can determine operating status (charge, discharge) based on the price component (if price bid is less than or greater than the market price) and strategically withhold capacity to maintain feasibility of the bid. Withholding capacity to maintain feasibility can result in overly conservative operations. With complex bids, resource owners provide more information to the market, likely lessening the autonomy of the storage owner to exercise strategic bids but potentially realizing higher utilization rates. However, market operators have different objectives than individual resource owners, which may result in conflicts of interest (Vivero-Serrano et al., 2019).

Emerging issues for integrating energy storage resources include developing participation models that reflect the various services these resources can provide, exemplified by markets moving toward participation models which allow a single bid curve which reflects charge and discharge capacity; accounting for an energy storage resource’s state-of-charge when optimizing over multiple services (such as energy and ancillary services); and optimizing the dispatch of an energy storage resource considering its duration and opportunity costs. For the latter two challenges, markets are developing rules which solicit more information from energy storage resource operators to provide more visibility into state-of-charge.

Table 1: Energy Storage Participation Rules in Wholesale Markets

ISO/ RTO	Storage Participation Model	Bid Parameters	State of Charge Management
CAISO[a]	ESRs participate in CAISO under the non-generator resource (NGR) model and can operate as either generation or load. NGRs bid a single supply curve with prices for negative capacity (charging) and positive capacity (discharging). ESRs can participate in energy, ancillary services, flexible ramping product, or as resource adequacy resources.	The ISO models minimum and maximum storage capability, upper and lower operating limits, and round-trip efficiency for each storage resource. Several bid parameters are available to NGRs to help manage their state of charge including upper and lower charge limits for each trading day to reflect the highest and lowest stored energy values (MWh) that must be maintained, as well as an end-of-hour state-of-charge parameter with an upper and lower state-of-charge limit to control how state-of-charges changes throughout the day. NGRs can also submit an initial state-of-charge value to indicate the energy available for the first participation interval. When providing ancillary services, resources also provide an ancillary service state-of-charge parameter which can bind in real-time to enable resources to fulfill ancillary service awards. When providing resource adequacy, an energy storage resource's net qualifying capacity is based on a test of its sustained output over a 4-hour period.	ISO generally manages state of charge. CAISO will try to follow non-binding constraints set by storage operators regarding minimum and maximum charge goals for an hour, and these goals can't be outside of state of charge limits.
ERCOT	Until late 2024, ESRs participated as both a generation resource (GR) and a controllable load resource (CLR) under ERCOT's combination model, where generation and load were modeled as separate and independent devices (NPRR1002). ERCOT transitioned to a single model structure in late 2024 (NPRR1014). The single model structure allows energy storage resources (ESRs) to bid a single price curve which includes both the charging and discharging MW range. Other improvements include better state-of-charge accounting in the reliability unit commitment process and real-time market (security constrained economic dispatch [SCED] process) (NPRR1204).	In the single model structure, ESRs provide a single incremental Energy Bid/Offer curve from charging (bid-to-buy) to discharging (offer-to-sell) that is monotonically non-decreasing from the ESR's negative MW (charging) to positive MW (discharging). Start up and minimum energy costs are zero (no commitment costs, resource is on-line and available for dispatch). Changes from NPRR1204 include adding three new state-of-charge (SOC) related fields to the current operating plan (MaxSOC, MinSOC, and Planned Hour Begin SOC) to increase awareness, accounting and monitoring of each energy storage resource's state-of-charge for RUC and SCED processes (in particular, for ancillary service awards), but managing the SOC is the responsibility of the qualified scheduling entity.	Managed by resource owner/operator

ISO-NE[b]	Continuous storage facilities (CSF) are modeled in the market as two distinct asset types: a dispatchable Generator Asset for supplying energy or a Dispatchable Asset-Related Demand (DARD) for consuming energy. A CSF can offer as a Generator or bid as a DARD in the energy and reserve markets. CSFs can also participate as an Alternative Technology Regulation Resource (ATRR) in the regulation market. CSFs are by default committed as on-line allowing the ISOs dispatch software to simultaneously consider the Generator Asset and the DARD. ATRRs receive a signal dispatch instruction for both positive and negative MWs based on its regulation dispatch signal and energy market dispatch signals.	Generators Assets and DARDs use the same offer parameters as other dispatchable Generator Assets and DARDs. In the day-ahead market, Maximum Daily Energy Limit and Maximum Daily Energy Consumption Limit offer parameters allow a CSF to manage its storage capacity. In the real-time market, the CSF operator may call the control room and provide hourly MW values it does not want to be dispatched above. When a CSF is not fully charged or discharged, dispatch is based on offer parameters, availability status, and dispatch limits (updated based on telemetered available energy and storage).	Managed by resource owner/operator. Owner must submit bids that result in the storage resource remaining between a minimum and maximum charge limit.
PJM[c]	ESRs are modeled as one continuous resource. ESRs can participate in energy, ancillary services, and capacity markets. ESRs have three modes of operation: continuous, charge, and discharge. PJM does not optimize an ESR's state-of-charge, market participants are responsible for managing real-time state-of-charge for honoring day-ahead market commitments. Market participants can modify economic max and min limits to signal availability.	Bid parameters account for ESR characteristics. In the day-ahead market, market participants provide economic minimum and maximum limits which reflect the capability to produce or consume energy for each hour of the day (in MWh). If there is a spread between min and max limits, the unit is economically dispatched based on a participant-provided incremental offer curve. ESRs are self-scheduled, i.e., startup costs and no-load costs are zero. In the real-time market, the ramp-limited security-constrained economic dispatch does not optimize total energy over future periods, market participants can modify economic max and min limits to represent charge and discharge abilities for a given interval.	Managed by resource owner/operator
NYISO[d]	ESRs are modeled as a single resource. ESRs can participate in energy, capacity, and ancillary services markets.	For economic offers, ESRs must submit their normal upper operating limit, emergency upper operating limit, lower operating limit, incremental bid curve, market choice, unit operation, beginning	Managed by ISO or resource owner/operator.

	NYISO has a technology neutral participation model for all storage types. ESRs have three operating states: injecting, withdrawing, and off/idle. Due to market software solution times, ESRs are currently only recognized as “on” and fully dispatchable within their offered operating range. Start-up costs are not allowed.	energy level (day-ahead market only), and energy level mode (NYISO or self). Optional parameters include fuel type, burdened fuel price, and opportunity cost. When NYISO manages the ESR the beginning energy level, roundtrip efficiency, lower and upper storage limits are used to ensure ESRs receive physically feasible schedules in the day-ahead market and real-time market. For self-managed ESRs beginning energy level, roundtrip efficiency, lower and upper storage limits are not considered in the market optimization. Instead ESRs are responsible for managing energy constraints through offers and telemetry is evaluated for schedule feasibility.	Owners can choose to manage state-of-charge, or state-of- charge/scheduling can be managed by NYISO optimization.
MISO[e]	ESRs can participate in the day-ahead, real-time, and operating reserves markets. An ESR determines how it is used the day-ahead and real-time markets by its commitment status. Commitment status options include charge, discharge, continuous, emergency charge, emergency discharge, available, outage, and not participating. The commitment status governs which operating limits are used by MISO to facilitate state of charge management (regulation, economic, emergency minimum and emergency maximum limits).	ESR owners/operators provide data for commitment and consideration in dispatch activities. Offer parameters include various economic data including an energy offer curve (in MW, $/MW, slope or block form), various reserve offers (regulating capacity and mileage, spinning, supplemental reserve offers), no-load offer, start-up offers (hot, intermediate, cold), as well as self-scheduled energy, regulation, and reserve offers. ESR owners also provide various commitment operating parameter data including start times and minimum/maximum charge/discharge times. ESR owners also provide dispatch operating parameter data which include dispatch limits and ramp rates.	Managed by resource owner/operator
SPP[f]	A market storage resource (MSR) can participate in SPP energy and operating reserve markets. They offer charging capacity, discharge capacity or a “continuous” classification where they can easily transition between charging and discharging. The MSR classifies itself as one of these options over each market interval. Commitment status, and maximum/ minimum discharge	Minimum/maximum charge and discharge limits as well as emergency charge/discharge limits are set by the owner. The resource communicates state-of-charge information, including current state-of-charge, and state-of-charge forecast. Ramp rates are required for determining “continuous” resource classification. Loss factor, and charge and discharge times are also included.	Managed by resource owner/operator

limits are parameters used by SPP to make a schedule.

[a]CAISO (2023).
[b]ISO New England Inc. and New England Power Pool; Enhanced Storage Participation Revisions (2018). Available at: https://www.iso-ne.com/static-assets/documents/2018/10/er19-84-000_enhanced_storage_revisions.pdf. https://www.iso-ne.com/static-assets/documents/2014/12/mr1_sec_1_12.pdf
[c]PJM Energy Storage Participation Model: Energy Market (2019) https://www.pjm.com/-/media/committees-groups/committees/mic/20190315-special-esrco/20190315-item-03a-electric-storage-resource-model.ashx
[d]ESR Participation Model: Energy Market Design (2019). Available at: https://www.nyiso.com/documents/20142/2686166/ESR%20Market%20Design%20MIWG%2009212018.pdf/ce0dccc8-f903-35b0-fbf9-74e8311a202e
[e]MISO Storage Participation – FERC Order 841 Compliance. Available at: https://www.misoenergy.org/engage/MISO-Dashboard/storage-participation--ferc-order-841-compliance/
[f]SPP Member Impacting Program Overview: FERC Order 841 – Stored Energy Version 1.8. Available at: https://www.spp.org/documents/65314/order%20841%20member%20impacting%20program%20overview%20-%20v1.8_clean.pdf

2.4 Evidence of and Potential for Exercising Strategic Behavior under Existing Electricity Market Design

The previous section reviewed the current bidding rules for ESRs across major markets in the U.S. There's a clear trend toward more sophisticated bidding mechanisms that can better capture the unique characteristics of ESRs. However, electricity market participants—such as investor-owned ESRs and renewables—may exhibit strategic behavior in managing risk, exploiting market conditions, or optimizing profit margins. Such strategies, often involving advanced algorithms and market insights, play a pivotal role in shaping market outcomes and system reliability. Recent studies on generation resources' interactions with existing market frameworks have provided insights into how bidding structures and market design might affect ESRs' bidding behaviors in shaping market outcomes. This section reviews key findings from notable papers that have contributed to our understanding of how generation resources bid in electricity markets and influence price formation and market outcomes.

2.4.1 Empirical Evidence of Strategic Behavior in Electricity Markets

Wolak (2003) analyzed bidding behavior in the California electricity market during the 2000-2001 electricity crisis. Using detailed bid data, he found evidence of market power being exercised through economic and physical withholding of capacity by suppliers. Actual bids departed significantly from competitive benchmark bids which were estimated based on marginal costs. Examining the California electricity market during the same timeframe, Kamat and Oren (2004) developed a multi-stage stochastic optimization model to analyze generator bidding behavior. Their findings underscored the strategic nature of bidding, with generators considering factors such as market demand and transmission constraints to maximize profits. Hortaçsu and Puller (2008) compared actual bids to theoretical benchmarks derived from optimal bidding models in the Texas (ERCOT) electricity market, revealing departures from theoretical optima, especially during peak demand periods. These papers contribute to a well-established literature that conventional generators can exercise strategic bidding behavior (that is, they exercise market power by bidding price above marginal cost) in electricity markets.[1]

However, increasing levels of ZMC renewable resources and financial traders are changing market dynamics as well as the potential for exercising market power or other strategic behavior. More recent research has focused on the impacts of these market participants on price formation. Ketterer (2014) investigated strategic behaviors of wind power producers on the German electricity market, focusing on their risk-averse portfolio optimization, bidding above marginal cost, and adapting to auction designs. Furthermore, Ketterer (2014) discusses how geographic dispersion of renewable generators can reduce market power and increase social welfare.[2] Ito and Reguant (2016) examined strategic behavior in the Iberian sequential electricity markets, finding that dominant firms undersell or withhold production in forward markets to exercise market power, while fringe producers (including some renewables) systematically oversell in the day-ahead market and buy back at lower prices later. The study demonstrates that limited arbitrage and market power can create a systematic day-ahead price premium, with implications for market efficiency and the impact of renewable energy integration on market

[1] Borenstein et al. (1999), Chen and Hobbs (2005), Puller (2007) also find evidence of strategic behavior in electricity markets.

[2] See Tarufelli et al. (2022) for a recent survey of the literature on the impacts of variable renewable energy resources on price formation.

dynamics. Mercadal (2022) examined the effects of financial traders in electricity markets, finding that increased financial trading reduced generators' market power and increased consumer surplus. The study demonstrates that financial traders engage in arbitrage, which restricts producers' ability to strategically exert market power through intertemporal price discrimination, leading to lower prices and improved market efficiency.

2.4.2 Strategic Behavior from Energy Storage Resources

Due to the limited deployment of ESRs in today's electricity markets, there is sparse ex-post empirical analyses of strategic behavior from these resources. A more common approach in the literature is to develop an ex-ante model that examines the potential for ESRs to exercise strategic behavior and influence market outcomes.

Models for strategic behavior in ESRs have a wide array of structural features due to the various services they can provide, with most models focusing on strategic behavior in energy arbitrage. As electricity market participants' strategic behavior can differ based on the market setting, a tailored model is needed to tractably represent the system and market details for each case. It is common for strategic behavior models to compute an equilibrium, for instance, partial, Nash, or generalized Nash, using either stylized or multi-level formulation to capture both strategic decision-making and key market details.

Sioshansi (2010) used a stylized approach to study the effects of ESR ownership (generator-, load-, and standalone-ownership) on storage use and welfare; finding that strategic behavior leads to fewer social welfare gains (compared to the socially optimal solution), regardless of ownership. In some cases, adding storage may even lead to social welfare losses (compared to case where no storage was added). Furthermore, Hartwig and Kockar (2016) investigated the impact of ESR ownership by introducing a price of anarchy (PoA) to quantify the efficiency loss caused by ESR's selfish behaviors, finding that strategic bidding has a nuanced impact on welfare, but can cause sub-optimal results if strategic bidding leads to underuse of ESRs. Mohsenian-Rad (2016) formulated a Stackelberg game to coordinate the operation of large, price-making, and geographically dispersed energy storage/battery systems in a nodal transmission-constrained energy market. Mohsenian-Rad found that line congestion yields more arbitrage (and profit) opportunities through creating more price differentials across time slots. However, results were sensitive to locational diversity (critical for ensuring ESR profit in transmission-constrained networks) as well as ESR roundtrip efficiency. Shahmohammadi et al. (2018) also studied the impacts of asset ownership and market-participation structures but assumed that all market participants (including conventional, variable, and energy storage resources) behave strategically. They found that ESRs could mitigate the inefficiencies of wind energy regardless of ESR ownership; however, co-ownership and co-operation of ESRs by the wind generator yielded the best results in terms of minimizing generation costs, maximizing wind-generation profits, minimizing wind curtailment, and minimizing the use of the high-cost peaking generator.

Although empirical research on ESRs is limited, Sioshansi (2011) utilized a Stackelberg game to explore the impacts of strategic ESR behavior in electricity markets using historical data from the Texas electricity market (with no network constraints). The case study results showed that when wind generator-owned ESRs co-optimized operations to increase its own profits, it also decreased the profits of competing generators and overall consumer surplus. Further, strategic ESR dispatch always resulted in suboptimal welfare regardless of ownership (stand-alone or owned by wind-generators). The suboptimal welfare results were due to incentives for generators and energy traders to underuse the ESR (increasing price volatility and arbitrage opportunities). Similar conclusions were drawn from the game-theoretic electricity market model by Schill and Kemfert (2011) who examined strategic utilization of pumped hydro storage in the German electricity market, finding that storage operators generally under-utilize their capacity to maximize profits. The study demonstrated that while storage increases overall welfare by smoothing prices, it also decreases total producer surplus (as generators' losses outweigh arbitrage profits earned by storage resources). Consumer surplus, on the other hand, increases as lower peak prices outweigh the effect of higher off-peak prices.

2.5 Future Considerations

ESRs—with their ability to act as generation and demand—are vital for addressing the increased uncertainty, driven by high penetrations of VRE resources, expected in the decarbonization future. The full services ESRs can provide include energy arbitrage, ancillary services, capacity contributions, transmission and distribution services, customer services, and more. Although current ESR installations are relatively a small portion of total generation capacity, utility-scale battery energy storage systems (BESS) capacity is expected to increase significantly by 2025, reaching 30 GW (from 1.5 GW in 2020) in the U.S. alone—a 20-fold increase that is expected to change the electricity generating portfolio and electricity market dynamics. However, to capture the full value stack of ESRs in future electricity markets, improvements are needed for electricity planning and operations tools; including better technology representation, more robust uncertainty representation, and new metrics for capturing ESR contributions to resource adequacy and system reliability.

Although current ESR market participation models improve ESR technology representation through capturing more of their technical characteristics, an important need remains for better representation of ESR operating costs (opportunity costs and degradation costs). Accurate representation of ESR operating costs is important for the future electricity system, as ESRs may frequently be the marginal resource, setting prices for all resources based on these costs. Furthermore, current PCM and capacity expansion tools both assume market participants behave perfectly competitively. As summarized in the previous section, monitoring and mitigating the exercise of market power is an important consideration for ensuring competitive prices and system reliability. In the future electricity system, when the need for flexibility is increased by short and steep ramps from VREs to balance supply and demand, understanding the opportunity costs of ESRs becomes more important for mitigating their potential exercise of market power (Zhou et al., 2021).

Traditional modeling approaches also underestimate system uncertainties and focus mostly on the short run time horizon. In the future, long duration ESRs are a key option to ensure supply and demand balance in the multi-day/week and seasonal market segments (Chad et al., 2021). New capacity market design may be needed to address duration-dependent qualifying capacity as well as longer time horizons for resource adequacy analysis.

Last, new value streams for ESRs need to be evaluated due to the dynamics of the future resource mix. Reduced energy arbitrage opportunities from a high penetration of ESRs and reduced average wholesale energy prices from a high penetration of variable renewable energy resources means ESR revenues may shift from energy arbitrage to other services for addressing increased volatility. While it remains to be seen how the ESR value stack will evolve in the long term, enabling the value of ESRs may require interconnection queue reform as well as classification of ESRs as “dual use” transmission and market assets (Twitchell et al., 2022).

3.0 Enhancing Energy Storage Representation through a Bid-Based Modeling Approach

Based on our survey of existing modeling approaches, current market designs and market participation models, as well as how ESRs may bid in practice (based on our survey of available literature) we developed a menu of options for incorporating more realistic bidding behavior for ESRs in leading electricity planning and operations modeling tools. We incorporate our bidding algorithms using an enhanced ESR model which we describe in Section 3.1, followed by our bidding algorithms in Section 3.2.

3.1 Enhanced Energy Storage Resource Model

In this section we describe our enhanced representation for our ESRs. Our enhanced physical battery model is Lithium-ion battery with available state-of-charge, power conversion efficiency, operating temperature, and degradation costs based on an equivalent circuit model (the Thevenin model) which considers thermal dynamics to value battery degradation. As our research focus is on the impact of more representative bidding algorithms, we provide a brief overview of our physical battery model. Full model details are available in Eldridge et al. (2024).

3.1.1 Physical Battery Model

We selected a 0^{th} order Thevenin equivalent battery model (as described in the Appendix, Section **Error! Reference source not found.**) of an open circuit voltage with internal resistance. Our physical battery model also includes coupling to the environment to allow thermal transfer of resistive heating, making this a version of an electrical-thermal model (Appendix Section **Error! Reference source not found.**). We track the battery state-of-charge (SoC) and temperature as well as internal variables like DC power, voltage, current, and inverter losses (similar to Rosewater et al., 2019). We size our batteries to be large grid-scale ESRs, which can also be considered as aggregations of ESRs. ESR characteristics are shown in Table 2.

Characteristic	Parameter	Value
State of Charge Capacity	A^{Tcap}	640 MWh
Maximum State of Charge (95%)	SoC^{max}	608 MWh
Minimum State of Charge (20%)	SoC^{min}	128 MWh
Maximum Charge Rate	$P^{\mathrm{ch,max}}$	125 MW
Maximum Discharge Rate	$P^{\mathrm{dc,max}}$	125 MW
Charging Efficiency	θ	0.892
Capital Cost	C^{EoL}	$208 million

Table 2: Selected characteristics and values for the battery model

Note that the efficiency parameter is only applied to charging, so the round-trip efficiency, θ, is 94.6%. We determine the capital cost based on the ESR capacity. Using the projections in Cole and Karmakar (2023), we adopt the medium-case energy storage cost for the year 2030 of

$325/kWh for installed capacity[1]. Given the State of Charge (SoC) capacity (A^{Ccap}) of these storage units equals $640\ \mathrm{MWh}$, capital costs (C^{EoL}) equal $\$208$ million dollars.

3.1.2 Battery Degradation Model

While batteries are considered ZMC resources, batteries are subject to performance degradation. This degradation varies depending on how the battery is operated. Batteries can lengthen or shorten their expected lifetimes depending on the frequency, duration, and depth of their charging and discharging cycles. In this section we describe our adaptation of the degradation model proposed in Rosewater et al. (2019), which computes degradation and converts it to a dollar-valued cost. We assume a generic Lithium-ion type battery.

The overall degradation cost in any interval is given by

$$c^{\mathrm{deg}} = C^{\mathrm{EoL}} \Delta \mathrm{SoH} \tag{1}$$

Where c^{deg} is the degradation cost, C^{EoL} is the end-of-life cost and $\Delta \mathrm{SoH}$ is the change in battery state of health (SoH) in a given interval. We use the end-of-life cost from Table 2. The SoH is a complex quantity affected primarily by four values:

- Clock time since the battery installation.
- Average battery SoC
- Average battery temperature
- Average depth of discharge (DoD)

In general, degradation rates increase with higher SoC, hotter temperatures, and deeper cycles (higher DoD).

Battery degradation is calculated periodically, at an interval of Δt, based on the regularization method presented in Rosewater, et al. (2019). The degradation cost in each interval, c^{deg}, is the product of the battery's end-of-life (EoL) cost, C^{EoL}, times the device's incremental loss in state-of-health (SoH), d^{SoH} shown in eq. (1).

Alternatively, degradation cost can be written as:

$$c^{\mathrm{deg}} = c^{\mathrm{cyc}} + c^{\mathrm{therm}} + c^{\mathrm{SoC}} + c^{\mathrm{DoD}} \tag{2}$$

Where $c^{\mathrm{cyc}}, c^{\mathrm{therm}}, c^{\mathrm{SoC}}, c^{\mathrm{DoD}}$ denotes four separate degradation components for the effects of cycling, thermal stress, state-of-charge, and depth-of-discharge on the battery's state-of-health, the detailed calculation of which is shown Eldridge et al. (2024).

Each component of the degradation cost can be represented by eq. (3) for the cycling degradation cost, eq. (4) for thermal degradation cost, eq. (5) for SoC degradation cost, and eq. **Error! Reference source not found.** for the depth-of-discharge (DoD) degradation cost.

[1] This is equivalent to $1300/kW for installed capacity.

$$c^{\text{cyc}} = \frac{\Delta t\, C^{\text{EoL}}}{\left(1 + \frac{1}{A^{\text{eff}}}\right) A^{\text{life}} A^{\text{Ccap}}} \left\| i^{\text{bat}} \right\|_1 \tag{3}$$

$$c^{\text{therm}} = \frac{\Delta t^2\, C^{\text{EoL}} K^T A^{\text{resis}}}{A^{\text{Tcap}}} \left\| i^{\text{bat}} \right\|_2^2 \tag{4}$$

$$c^{\text{SoC}} = \Delta t\, C^{\text{EoL}} K^{\text{S}} \bar{\sigma} \tag{5}$$

$$c^{\text{DoD}} = C^{\text{EoL}} K^{\text{D}} \bar{\delta} \tag{6}$$

Where Δt denotes time interval, end-of-life cost C^{EoL}, coulombic efficiency A^{eff}, rated cycle life A^{life}, and charge capacity A^{cap}, the L-1 norm and L-2 norm of the battery's charge profile $\left\| i^{\text{bat}} \right\|_1$ and $\left\| i^{\text{bat}} \right\|_2^2$, SoC degradation factor K^{S}, average of SoC $\bar{\sigma}$, DoD degradation factor K^{D}, and the average DoD variable.

We model a 5-year-old battery as it provides a reasonable approximation of the lifetime average degradation cost. Average SoC and temperature are computed based on the physical battery model in Section 3.1.1. The depth of discharge is calculated from the battery SoC profile using a rainflow counting algorithm (Downing and Socie, 1982). These four attributes are used to compute the battery SoH at the start and end of an interval following the methodology outlined in Eldridge et al. (2024). Because the rainflow counting algorithm requires a moderate time baseline, we assess overall degradation costs on a daily basis.

3.2 Energy Storage Bidding Algorithms

In this section, we describe the underlying market design assumptions and energy storage bidding algorithms explored in this work. We also suggest additional algorithms to explore in future work.

3.2.1 Market Design Assumptions

We assume that the ESRs participate in a conventional two-settlement market with day-ahead and real-time market clearing where the general market clearing optimization model is a security constrained unit commitment (SCUC) model. We assume the day-ahead market clears at hourly intervals and the real-time market clears at 15-minute intervals. For both markets, we assume that ESRs have knowledge of renewable and load forecasts. We also assume that SoC management is by the market operator. We assume the market operator has the objective to maximize total market surplus subject to resource and system constraints.

The underlying market structure for the simulation is similar to real-world electricity markets which typically employ a sealed bid auction with a uniform price rule. Under this market structure, power suppliers and consumers offer price and quantity bids to the market operator, who then determines the market clearing price via merit order dispatch. In a perfectly competitive market, power suppliers would be incentivized to bid at their marginal cost and are considered "price takers".

The goal of the present work is to determine a reasonable approximation for an ESR price taker that submits its marginal costs to the market operator. This task is non-trivial due to the complexity of the battery model presented in Section 3.1 and the simplified bidding structures discussed in Section 2.3.2. The following sections describe various methods or bidding formats that ESRs might use to approximate their complex cost structure.

3.2.2 Selected Bidding Methods

We develop a menu of options for incorporating more realistic bidding behavior in open-source modeling tools. These options range from a baseline bidding algorithm which assumes storage units bid with zero marginal costs ($0/MWh) for both charging and discharging to algorithms that include analytically and empirically derived price deltas for discharge bids to better represent opportunity costs. We also examine the impacts of maintaining a soft or hard limit on state-of-charge values to better link energy storage bids to degradation costs. The soft limit requires end-of-interval state-of-charge levels be kept at or above a minimum value and the hard limit requires end-of-interval state-of-charge levels be kept at or above a maximum value. We also consider the impact of self-scheduling behavior based on profit-maximizing expectations of price forecasts.

Our main algorithms are summarized in Table 3 and described in more detail in this section.

Table 3: Overview of Selected Bidding Algorithms

Algorithm	Summary
Baseline	The baseline algorithm follows a standard PCM assumption. The algorithm has the following characteristics: Day-Ahead Market (DAM): Storage units bid with zero marginal cost ($0/MWh) for charging and discharging. Real-Time Market (RTM): Same as DAM.
Analytical Price Delta	We analytically derive an optimal discharge price of $X based on reasonably assumed dispatch schedule and degradation cost.
Empirical Price Delta	As it is computationally difficult to derive an analytical price delta, we calculate storage profit for a selection of price deltas (X) and pick the best option based on our numerical simulation. The algorithm has the following characteristics: DAM/RTM charging: $0/MWh. DAM/RTM discharge: $X/MWh, X > 0. No DAM SoC value. No RTM SoC value.
Price Delta with a Hard SoC Limit	With this algorithm we incorporate a SoC target, which is a hard SoC limit, to approximately link the DAM and RTM. The hard SoC limit also approximately links ESR bids to degradation costs. The algorithm has the following characteristics: DAM/RTM charging: $0/MWh.

	DAM/RTM discharge: \$X/MWh, X > 0. No DAM SoC value. RTM ending SoC hard limit > 0.
Price Delta with a Soft SoC Limit	With this algorithm we incorporate a SoC valuation, which is a soft SoC limit, to better link the DAM and RTM. The soft SoC limit also better links ESR bids to degradation costs. The algorithm has the following characteristics: DAM/RTM charging: \$0/MWh. DAM/RTM discharge: \$X/MWh, X > 0. No DAM SoC value. RTM ending SoC soft limit with value > 0.
Self-Schedule	To understand the impact of self-scheduling behaviors, we develop a price forecast and schedule the ESR to maximize profit over expected prices. The market follows ESR's self-schedule.

3.2.2.1 Baseline

The baseline algorithm follows a standard PCM assumption. Storage units bid with zero marginal cost (\$0/MWh) for charging and discharging in both the day-ahead market and real-time market. In the real-time market, storage units bid an end-of-interval state-of-charge (SoC) value using espa_bandit algorithm (https://github.com/breldridge/espa-bandit) developed for the energy storage participation algorithm competition (ESPA-COMP; Tarufelli, et al. 2024). In the baseline scenario, the espa-bandit algorithm sets a hard price limit on end-of-interval SoC (see Section 3.2.2.3).

3.2.2.2 Price Delta

The price spread between charging and discharging prices is crucial for an ESR's operational and bidding strategy because it determines its profitability. With only round-trip efficiency considered, the minimum profitable price spread for ESR needs to satisfy the condition that the price differential (price spread) between the discharge price and charge price (taking into account round trip efficiency losses) is positive ($\lambda^{\text{dis}} - \theta\lambda^{\text{ch}} > 0$). If degradation or operational costs are considered, a higher price spread is needed for the ESR to be profitable. To maximize the profit in the market, we assume the ESR adds a constant cost (i.e., price delta, Δ_p) for discharge offers to cover the degradation costs.

The resulting ESR cost equation is as follows:

$$z(\Delta_p) = \sum\nolimits_t \left(p_t^{\text{dis}} * \Delta_p - p_t^{\text{ch}} * 0\right) \tag{7}$$

Letting $p_t^{\mathrm{dis}(\Delta)}$, $p_t^{\mathrm{ch}(\Delta)}$, $c^{\deg(\Delta_p)}$ and λ_t be ESR's the discharge, charge, degradation cost, and LMP after submitting a dispatch cost of Δ_p, the ESR's profit is as follows:

$$\pi = \sum\nolimits_t \lambda_t\left(p_t^{\mathrm{dis}(\Delta)} - p_t^{\mathrm{ch}(\Delta)}\right) - c^{\deg(\Delta_p)} \tag{8}$$

Which is subject its constraints on charge and discharge rate and SoC level. Although this price delta Δ_p term may help improve the ESR's profit margin, it is important to note that its inclusion is not necessarily an indication of strategic bidding or market power exertion. Rather, this cost term is a proxy for degradation costs (Section 3.1.2) that are not trivially part of the EST's standard bidding parameters. Section 4.1 explores two methods, analytical and numerical, to determine an appropriate price.

It's crucial for market operators to understand the impacts of ESR's bidding in terms of price deltas on market efficiency, system reliability, and market bidding rules. A higher price delta leads to underutilization of ESRs while lower price deltas can lead to ESRs incurring excessive degradation costs. Also, the price delta affects the available storage capacity for system flexibility as well as price formation. We study the price delta patterns and identify the impacts of ESR price delta bidding strategies by assessing both the market outcomes and ESR performance.

3.2.2.3 SoC Limit Options

For the real-time market, all ESRs can offer additional constraints on their SoC. These options allow the resource to better manage SoC, for example ensuring sufficient charge is available to meet their day-ahead schedule. The espa-bandit algorithm offers two options: a hard SoC limit and a soft SoC limit.

The hard SoC limit provides a minimum acceptable SoC value for the ESR at the end of the real-time market horizon (which is 3 hours in our simulation). This is included as a constraint in the SCUC algorithm. The hard SoC limit is computed from the day-ahead schedule. The algorithm looks ahead to the scheduled charge or discharge values and ensures that the enough SoC will be available to meet the schedule. For example, if the unit is scheduled to discharge at 125MW from hours 17:00 to 20:00, the hard limit will ensure that at least 375MWh of capacity are available at 17:00.

Mathematically, the hard limit constraint of S is shown below for an assumed state-of-charge variable σ_t and end-of-horizon $t = T$:

$$\sigma_T \geq S \tag{9}$$

The soft SoC limit does not include an ending SoC constraint. Instead, the end-of-interval SoC is bid into the market. Our simulation platform is specifically designed to accept SoC valuation bids. The SCED solution will then be computed, accounting for the ESR preference to retain SoC. In the example above where the unit is scheduled to discharge at 125MW from 17:00 to 20:00, the SoC bid value would be low before ~14:00, but will progressively rise as the time nears 17:00. This increases the likelihood that the ESR will have sufficient SoC capacity to meet the day-ahead schedule.

Mathematically, the soft limit is implemented below, assuming a multi-step cost curve with costs C_j and state-of-charge quantities S_j:

$$z = \sum_{b} C_j \sigma_{j,T} \tag{10}$$

$$\sigma_{jT} \leq S_j \tag{11}$$

$$\sum_{j} \sigma_{jT} = \sigma_T \tag{12}$$

Both offer types have the same purpose, but different benefits and risks. The hard SoC limit option is best at ensuring the unit will have enough SoC, since it is used as a constraint in the SCUC solution. However, the soft SoC limit option is more flexible and can better adapt to changing market conditions since SoC bids are included in the real-time market. Economically, the hard limit constraint is equivalent to setting $C_j = \infty$ and $S_j = S$ for one block step j, and $C_{j'} = 0$ for all other quantities.

3.2.2.4 Self-Scheduled

Self-scheduling is currently employed in markets and allows resources to state their preferred schedule explicitly to the market operator. For example, this bidding method is often used by nuclear or coal power plants that are relatively inflexible or otherwise cannot be economically committed and dispatched by the market operator. In this section, we develop a method for self-scheduling ESRs. In this case, the ESR determines its preferred schedule, then submits this schedule as fixed to the market. The market includes this fixed schedule as part of the SCUC or SCED problem.

Typically, an ESR uses price forecasts to determine its profit-maximizing charge and discharge schedule (Mohsenian-Rad, 2015). These can be further modified by accounting for degradation or renewable uncertainty, although we do not currently include these factors in this bidding algorithm. However, this strategy assumes that the ESR’s price forecast is accurate. As this assumption does not hold in our simulation, nor in real life, self-scheduled ESR bids may result in suboptimal scheduling decisions even though degradation costs may be estimated accurately.

We modify the profit maximization framework by dynamically estimating the future prices based on the excess load, including storage unit charging and discharging. To calibrate these estimates, we use 30 days of demand, renewable power, and ESR power outcomes from the baseline simulation. From this we compute the net demand, D_{net}, in MW defined as

$$D_{\mathrm{net}} = p_{\mathrm{demand}} - p_{renewable} - p_{storage} \tag{13}$$

Here p_{demand} is the total system demand (MW), $p_{renewable}$ is the total renewable power (MW), and $p_{storage}$ is the total ESR power (MW). The net demand roughly tracks the price/quantity curve of the conventional generators.

We plot the net demand vs. prices in Figure 1. From these points, we determine a best fit curve for the expected LMP $\lambda(D_{\mathrm{net}})$ using a mixed exponential function

$$\lambda(D_{\mathrm{net}}) = (a_0 + a_1 D_{\mathrm{net}}) e^{\left(\frac{D_{\mathrm{net}}}{a_2 + a_3 D_{\mathrm{net}}}\right)} \tag{14}$$

The coefficients a_0 to a_3 are determined using a minimization algorithm. We put a lower bound of $0/MWh on the price to avoid potential negative price estimates.

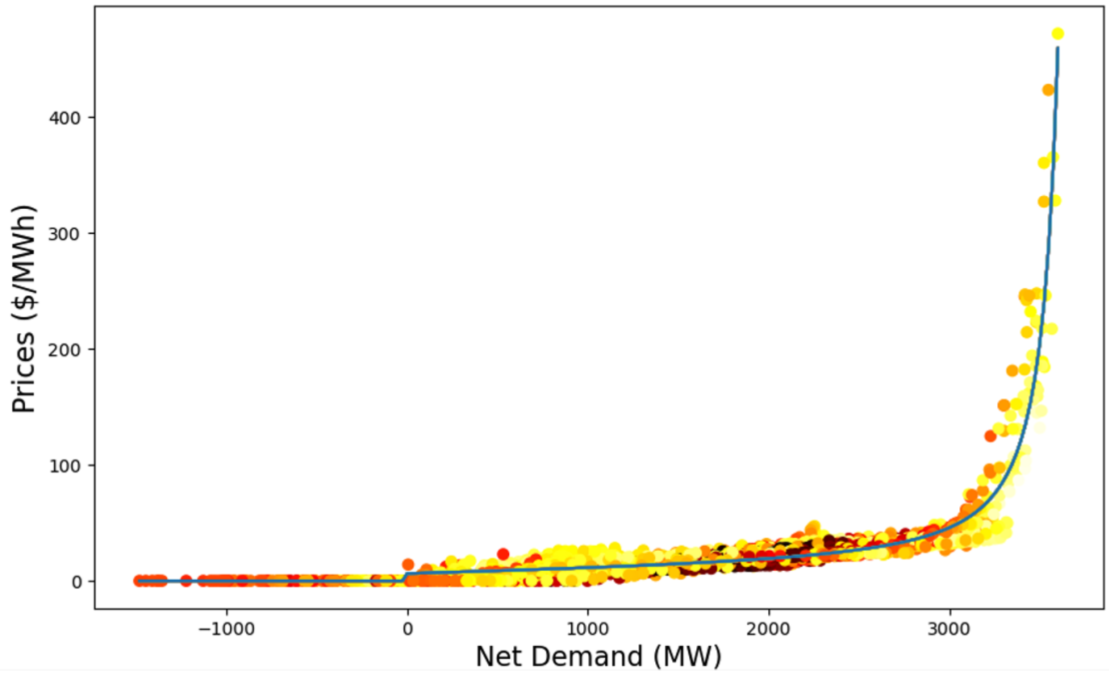


Figure 1: Net Demand (Net Demand = Demand – Renewable – Storage) vs. LMP from 30 days of baseline simulation. Values are plotted as colored dots where color indicates the demand (red=low demand, yellow=high demand). The best-fit curve using our mixed exponential function is shown in blue.

To estimate future prices, the ESR takes market forecast for demand and subtracts the forecast for renewable power. These forecasts are created during the simulation so they are up-to-date based on the ESR behavior. The ESR bidding algorithm then subtracts off the total ESR power (discharging – charging) to determine the expected excess.

The ESR power is scaled by a factor of 12, since there are 12 ESRs (Section 4.1) each with nearly identical bidding behavior. From the best-fit curve, the ESR computes the expected price (which is now a function of battery power) and uses this to determine its optimal charge and discharge schedule. This is a convex but nonlinear optimization problem.

To submit the ESR schedule as ‘fixed’ the ESR provides extreme bid values for its optimal schedule. For discharge bids, the ESR submits an offer at the lowest system offer value, which in our case is -$25/MWh. For charging bids, the ESR submits bids above the system penalty price of $2000/MWh. This ensures that the desired charge and discharge schedules are always met. These extreme bids are equivalent to submitting fixed power limits based on charge and discharge schedules.

3.2.3 Bidding Algorithms to Explore in Future Work

ESR bidding is expected to vary between storage units and these different bidding algorithms are expected to have different impacts on the market. Because of these two factors, it will be important to further explore ESR bidding algorithms in future work. We propose several promising methods in this section.

3.2.3.1 Self-Management

Currently, ISOs/RTOs (market operators) vary in their participation rules for SoC management, where existing rules range from an ESR operator being responsible for SoC management to the market operator being responsible for SoC management. To model the impacts of ESR operator's being responsible for SoC management, in future research we recommend developing a bidding algorithm in which the ESR operator manages their SoC. This requires the operator to ensure that the resource has sufficient energy available to charge or discharge during the intervals scheduled by the market operator. The resource owner will need to pay any unmet schedule at the LMP. In a self-management scheme, the market would not include constraints on storage SoC.

3.2.3.2 Deep Reinforcement Learning

Deep reinforcement learning (DRL) offers a way to leverage artificial intelligence and machine learning to maximize storage unit profits. DRL can be built atop the price delta formulation to dynamically find the optimal price delta. Alternatively, DRL can be used to create a more flexible bidding structure in which charge and discharge bids vary in each interval throughout the day. While DRL is a powerful tool, it requires significant training data and can be more difficult to implement in a bi-level problem (where the first level is the day-ahead and the second level is the real-time market).

3.2.3.3 Stochastic

Renewable forecast uncertainty can have a significant impact on prices. ESRs that incorporate this stochastic variability into their bidding algorithm outperform those that employ deterministic bidding (Krishnamurty et al. 2017). In this scenario, the ESR would need to estimate the forecast uncertainty and generate bids that maximize profits over the range of potential prices.

3.2.3.4 Monte Carlo

One limitation of this simulation is that it the results represent a particular realization of the demand and renewable forecast. By running multiple instances of the simulation in a Monte Carlo style, we could assess the sensitivity of these results to changes in demand and renewable generation. This approach is also of value in determining the impact on the market under uncommon operating conditions, such as unusually low renewable generation paired with unusually high load. For the Monte Carlo simulation, any of the bidding algorithms could be adopted, showing the market sensitivity under a particular ESR bidding strategy.

4.0 Simulation Results

In this section we first describe our simulation details. We then present results exploring the optimal price delta, followed by our key findings from different bidding algorithms.

4.1 Simulation Details

To perform our modeling simulation, we leverage PNNL's Wholesale Electricity Analysis via Simulation & Learning Experiments (WEASLE) platform (Eldridge et al., 2024). The topology of the WEASLE platform is an aggregated zonal topology from the 2030 WECC Common Case database that consists of 38 nodes created from the 38 balancing authorities (load areas, BA) of the Western Interconnection (WECC, 2021). In the WEASLE platform generation capacity at each node is created by aggregating values from each BA. Transmission topology, line ratings, and path limits are modified from the 2030 WECC Common Case database. Hourly load profiles for each BA are adjusted as needed to ensure deliverability. Wind and solar generation shapes are based on the 2009 NREL wind data and 2009 NREL irradiance and weather data, respectively. Hydro resources are modeled based on EIA Form 906/920 monthly average generation values for the year 2009 – a typical hydrologic year. Endogenous parameters within the market clearing model determine ancillary services including regulation up, regulation down, spinning reserve, and non-spinning reserve.

The baseline simulation has three high renewables scenarios designed to reflect summer, shoulder (spring/fall) and winter seasons. Baseline resource capacities are shown in Table 4. Baseline battery (15%), wind (15%), and solar (25%) capacities are designed to be higher than currently planned for in the 2030 WECC Common Case database. The baseline also has lower amounts of coal (2%), and natural gas (20%) capacity as compared to the 2030 WECC Common Case database. Demand response (3%) capacity is similar to the 2030 WECC Common Case database.

Table 4: Simulation Resource Portfolio Capacity Compared to 2030 WECC Common Case

Resource	WECC ADS 2030[a]	Baseline Scenario
	Percentage of Total Capacity	
Battery Storage	1%	15%
Wind	12%	15%
Solar	13%	25%
NG-Steam/Combined Cycle	31%	20%
Coal	5%	2%
Demand Response	3%	3%
Other Renewables	35%	20%

[a]The 2030 WECC Common Case is available at: https://www.wecc.org/program-areas/reliability-planning-performance-analysis/reliability-modeling/anchor-data-set-ads

Our market follows a conventional two-settlement market with day-ahead (SCUC) and real-time (SCED) components. We model the real-time market on 15-minute intervals. For both markets, renewable and load forecasts are provided to the storage unit resources. The forecasts are drawn from a set of actual values with correlated noise added following the prescription in

(Ghosal et al., 2023). As the time approaches the real-time interval, the forecast converges on the actual value, reflecting an improved forecast with a short lookahead window. The WEASLE platform includes a storage resource offer type, enabling SoC management by the market operator. This is representative of CAISO or NYISO under current ISO tariffs (Table 1).

We run the simulation for 30 days starting on October 1st. Our preliminary results showed that the fall season has high battery storage income, comparable to July performance, with a more modest load requirement. Our network includes 12 storage units with 640MWh capacity and a maximum charge and discharge rate of 125MW.

We repeat the simulation for each of the bidding algorithms described in 3.2.2. All 12 units use the same bidding algorithm in each scenario, but their profits, physical characteristics (SoC, temperature), and degradation costs are tracked individually.

4.2 Price Delta

In this section, we obtain an approximately optimal price delta for the ESR discharge offer (both analytically and numerically).

4.2.1 Analytical Price Delta

Further assumptions are made to derive the analytical optimal discharge offer markup Δ_p. That is, we assume a perfect forecast of the day ahead price is available, and that ESRs discharge all of their charged energy at the end of simulation time horizon. Note that the profit maximization objective function in eq. (8) is calculated with discrete prices at each time interval. According to the profit formulation, the revenue of an ESR from discharging should cover the charging and degradation costs. The price delta bids for discharging affect the charge profile, average SoC level, and the depth of discharge. To simplify the derivation, we assume all degradation cost factors ($C^{\mathrm{EoL}}, A^{\mathrm{eff}}, A^{\mathrm{life}}, K^{\mathrm{T}}, A^{\mathrm{cap}}, A^{\mathrm{T_{cap}}}, K^{\mathrm{D}}, K^{\mathrm{S}}$) are constants, and then each cost component can be rewritten with constant factor parameters ($A^{\mathrm{cyc}}, A^{\mathrm{thermal}}, A^{\mathrm{SoC}}, A^{\mathrm{DoD}}$) and variables ($\|i^{\mathrm{bat}}\|_1, \|i^{\mathrm{bat}}\|_2^2, \bar{\sigma}, \bar{\delta}$). By assuming all the variables in eq. (3)-(7) are continuous and differentiable, the first-order derivative of the profit objective function with respect to the price delta is:

$$\frac{\partial \pi}{\partial \Delta_p} = \Lambda \left[\lambda_t^{\mathrm{dis}} \frac{\partial p_t^{\mathrm{dis}}}{\partial \Delta_p} - \lambda_t^{ch} \frac{\partial p_t^{ch}}{\partial \Delta_p} - A^{\mathrm{cyc}} \frac{\partial \|i^{\mathrm{bat}}\|_1}{\partial \Delta_p} - A^{\mathrm{thermal}} \frac{\partial \left(\|i^{\mathrm{bat}}\|_2^2 \right)}{\partial \Delta_p} - A^{\mathrm{SoC}} \frac{\partial \bar{\sigma}}{\partial \Delta_p} - A^{\mathrm{DoD}} \frac{\partial \bar{\delta}}{\partial \Delta_p} \right] \tag{15}$$

Where $\Lambda = \sum_t \Delta t$. As shown in eq. (15)**Error! Reference source not found.**, the analytical determination of the relationship between the variables and the price delta is difficult. For example, the L-2 norm of the charge profile is nonlinear to the change of charging behaviors. For a given price forecast $\{\lambda_t, t = 1,2, \dots, T\}$, with a higher price delta, overall discharge energy decreases since discharge only occurs when $\lambda_t > \Delta_p$ and charge only occurs when prices are in a lower range. Thus, L1 and L2 norms decrease too because ESRs are more likely to have less trading activity/volume when the price delta is higher. Changes in average SoC level and DoD depth with increased Δ_p are ambiguous; initially (within some lower ranges, $[\bar{\sigma}, \bar{\delta}]$), SoC level and DoD depth will increase as the price delta increases, but the SoC level and DoD depth will decrease when price delta becomes too high as there are fewer opportunities to participate in the market. By setting eq. (15) equal to 0, we can obtain the approximately optimal Δ_p^* in the day-ahead market.

For each ESR in the system, we can estimate a constant factor for each cost component. For example, if each unit is assumed to have 5000 cycles during its lifespan ($A^{\text{life}} = 5000$), the cycling cost parameter A^{cyc} can be computed using eq. (3). By assuming each unit has a thermal constant of $K^T = 0.1$ and a normalized resistance constant of $A^{\text{resis}} = 1$, the thermal stress cost parameter c^{therm} can be computed. The two remaining cost parameters are obtained based on the assumptions that $K^{\text{S}} = 0.0005$ and $K^{\text{D}} = 0.001$ for the SoC and DoD cost component respectively (that is, c^{SoC} for each unit of fractional SoC and c^{DoD} for each unit of DoD). For a given price forecast of one day, we further assume $\left\|i^{\text{bat}}\right\|_1$, $\overline{\sigma}$, $\overline{\delta}$ have linear relationships with Δ_p while $\left\|i^{\text{bat}}\right\|_2$ has a quadratic relationship with Δ_p . By using C^{deg} as the total degradation and setting the first derivative in eq. (15), to 0, the following equation can be obtained

$$\sum_{\lambda_t > \Delta_p} \Delta t \frac{\partial(\lambda_t p_t^{\text{dis}})}{\partial \Delta_p} = \sum_{\lambda_t < \Delta_p} \Delta t \frac{\partial(\lambda_t p_t^{\text{ch}})}{\partial \Delta_p} + \frac{\partial C^{\text{deg}}}{\partial \Delta_p} \tag{16}$$

Where $\frac{\partial C^{\text{deg}}}{\partial \Delta_p} = -A^{\text{cyc}} \cdot \alpha - A^{\text{thermal}}(2\beta \cdot \Delta_p) - A^{\text{SoC}} \cdot \gamma - A^{\text{DoD}}\varphi$. The optimal price delta can be computed as:

$$\Delta_p^* = \frac{A^{\text{cyc}} \cdot \alpha + A^{\text{SoC}} \cdot \gamma + A^{\text{DoD}}\varphi}{\bar{\lambda} - \theta - 2A^{\text{thermal}} \cdot \beta} \tag{17}$$

Where $\bar{\lambda}$ denotes the average price spread between discharging and charging. By setting marginal revenue from discharge equal to marginal cost, and by setting parameters $\alpha = \$3\ \text{Ah/MWh}$, $\beta = \$0.007 \frac{\text{Ah}^2}{\text{MWh}^2}$, $\gamma = \$\ 0.0002/\text{MWh}$, and $\varphi = \$\ 0.0006/\text{MWh}$, we can approximate the analytical solution for an optimal price delta discharge offer based on price forecast. For example, $\Delta_p^* = \$20.03/\text{MWh}$ given the price forecast, as shown in Figure 2.

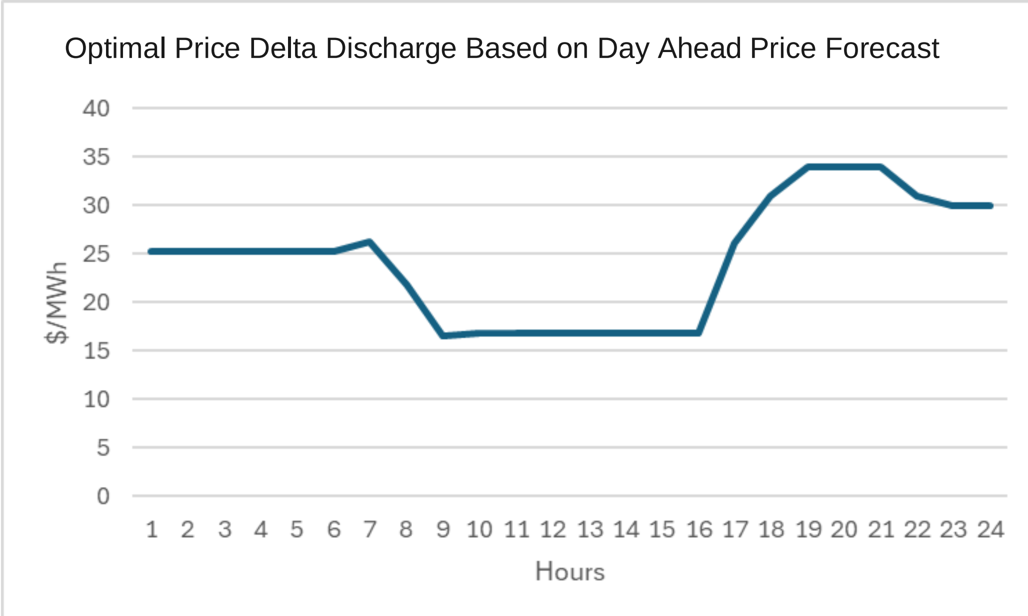


Figure 2: Analytical solution for an optimal price delta discharge based on a sample day ahead price forecast

While the analytical derivation for the optimal price delta (Δ_p^*) provides valuable theoretical insights, it is subject to significant limitations when applied to real-world electricity markets. In practice, electricity markets operate with two interdependent marketplaces—day-ahead and real-time markets—where price deviations between the two markets introduce additional complexity. These deviations are driven by unforeseen changes in supply, demand, and grid constraints, which cannot be captured analytically without simplifying assumptions. This analytical process also assumes static price forecasts and does not account for dynamic impacts from energy storage on the market clearing process. In reality, ESR's charging and discharging decisions impact market clearing prices, especially in the real-time market. The absence of this feedback effect limits the applicability of the derived results in markets where storage acts as a price maker rather than a price taker. Last, the analytical result relies on functional forms (e.g., linear, quadratic) to approximate degradation cost sensitivities, which may not fully capture the actual behavior of ESRs due to diverse storage technologies, the interdependence of cost components, and other nonlinear, system-specific cost relations.

4.2.2 Numerical Price Delta

To determine a more realistic Δ_p^* for ESRs, we perform simulations for a 30 day time horizon by choosing price deltas from the set $\Delta_p \in \{0, \$10, \$20, \$30, \$40, \$50, \$60\}/\mathrm{MWh}$ for discharge offer and $0/MWh for charging in the day-ahead market based on a hard SoC limit bidding rules. The baseline case is when $\Delta_p = 0$, meaning that there is a zero marginal cost for both charging and discharge offers.

4.2.3 Market Performance

First, the impact of changing the price delta on total surplus (sum of consumer and producer surplus) is analyzed. We computed the physical market surplus at each interval, including consumer (demand) surplus, generation surplus, and battery surplus. For battery surplus, the bid values (opportunity cost) are a proxy for the true degradation cost. We subtracted the bid surplus and added the degradation cost to capture the true physical surplus.

In Figure 3, we plot the percent difference from each of the price deltas relative to the baseline. This plot shows the spread of daily differences, with the median values displayed. Compared to the baseline case (with default zero marginal cost bid), the price delta has slightly positive impacts on total surplus, as shown in Figure 3. For all simulated price deltas, the surplus increases from the baseline case by ~0.01 to ~0.04% due to discharging the stored energy at a higher price discharge offer delta than the baseline (zero price delta). Market surplus tends to increase with higher price deltas, however changes in surplus are also more widely dispersed. A price delta of $40/MWh ($\Delta_p = \$40/\mathrm{MWh}$) yields the highest market surplus. Although the market surpluses for price deltas of $ 20/MWh, $50/MWh, and $60/MWh yield the same median increases in market surplus, the higher price deltas have more dispersion; meaning that higher price deltas could result in a more significant market surplus with longer simulation time horizon.

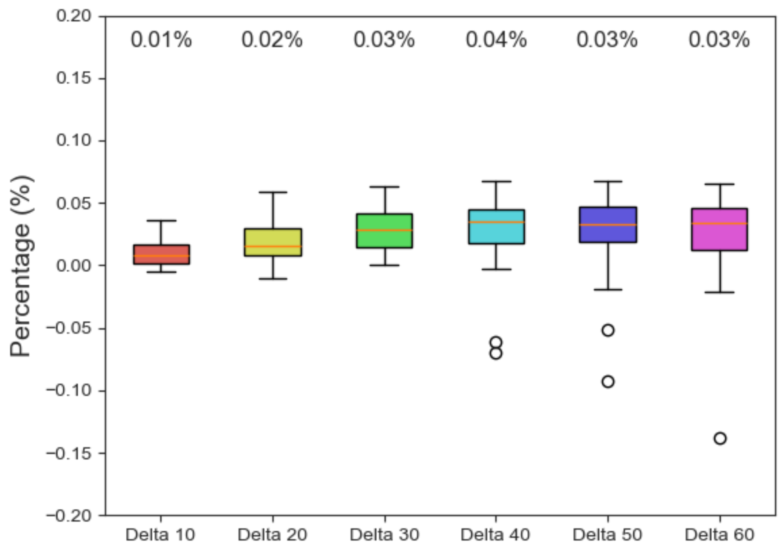


Figure 3: Market surplus changes (in percentage) between price deltas and baseline

As shown in Figure 3, more consistent LMPs are obtained throughout the day with lower price deltas ($0/MWh for the baseline and $10/MWh, Delta 10) while the biggest price delta ($60/MWh, Delta 60) leads to an extreme price spike of $2000/MWh due to an energy shortage. For the price delta between $30/MWh (Delta 30) and $50/MWh (Delta 50), there are some price spikes at around $500/MWh. The price spread between discharge and charge price shows the same trend. Stable prices in the baseline and $10/MWh price delta scenarios yield a very small price spread while the largest price delta (Delta 60) leads to a larger price spread. The higher the price delta, the fewer ESRs are utilized. Consequently, a higher price delta reduces the capability of ESRs to provide flexibility in the system to balance supply and demand, leading to higher price volatility in the real time market. Note that the battery has a duration of less than 5 hours, so it mainly takes the advantage of the price spread in an intraday horizon.

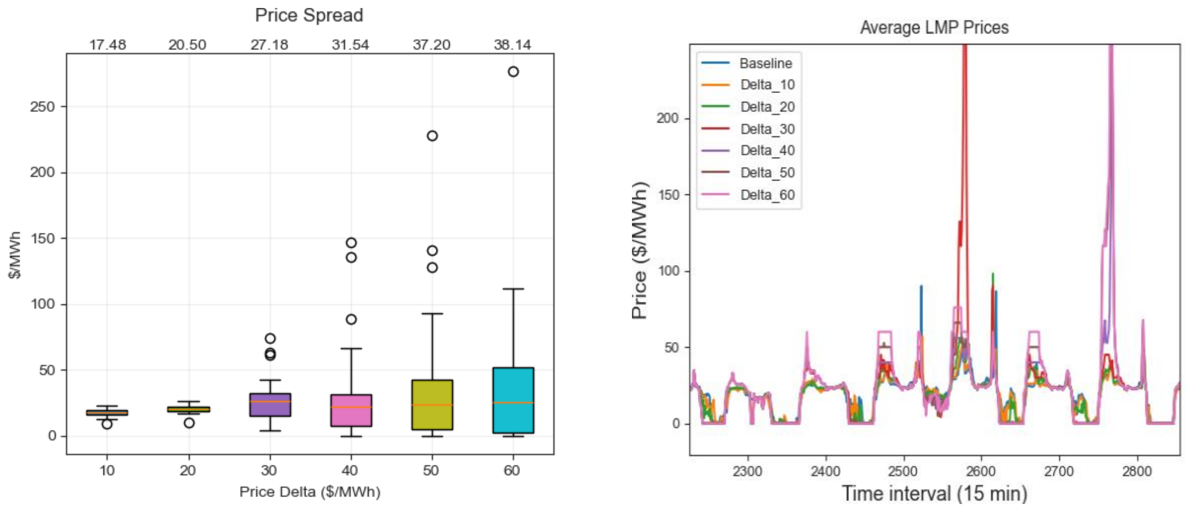


Figure 4: Price spread and load-weighted locational marginal prices in RTM.

4.2.4 Energy Storage Resource Performance

This section summarizes the performance of ESRs under different price deltas for discharge offers. As stated in section **Error! Reference source not found.**, it is difficult to have an explicit analytical solution to the optimal price delta under the two-settlement market design due to the dynamic and uncertain nature of the market. However, we obtained an approximate solution by numerically simulating different scenarios.

We summed the LMP-based revenue for all storage units across each day of the 30-day simulation. This includes both income from discharging and regulation services and subtracts expenses from charging. Both DAM and RTM revenue is included in the calculation. Figure 5 shows the average daily revenue from discharging and reserve services (panel a), the average daily degradation cost (panel b) and the average daily net profit (panel c) across all 12 ESRs. Compared to our analytical results, which only include revenue from energy arbitrage as a simplifying assumption, in the numerical simulation, a small portion of revenue (less than 10% of total revenue) is earned in the reserve market. The average daily revenue for ESRs shows a decreasing trend as the price delta increases from $10/MWh to $40/MWh which levels off from $50/MWh to $60/MWh. As higher price deltas result in lower ESR participation and higher price volatility; the revenues earned with the lowest price delta of $10/MWh has the widest range.

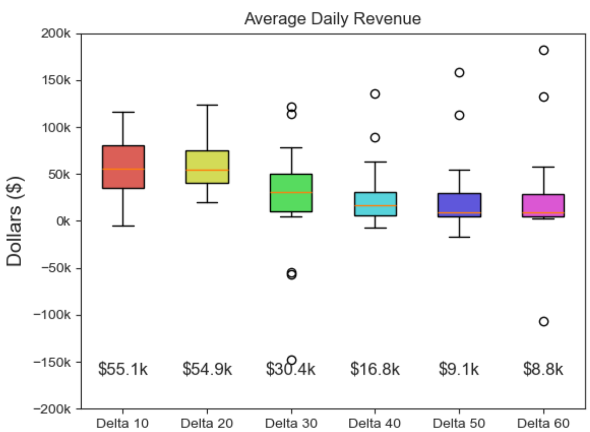
Average degradation costs, as shown in Figure 5 panel b display a similar trend, decreasing as the price delta increases from $10/MWh to $40/MWh and then leveling off from $50/MWh to $60/MWh. The baseline scenario ($0/MWh price delta) has a significantly higher degradation cost than the other cases.

Net profits are obtained by subtracting average daily degradation costs from average daily revenues, as shown in Figure 5 panel c. For all price deltas, average daily net profits are negative, indicating the costs associated with efficiency loss and battery degradation are not fully covered by ESRs' revenues. Due to the high degradation costs[1], the baseline case (zero

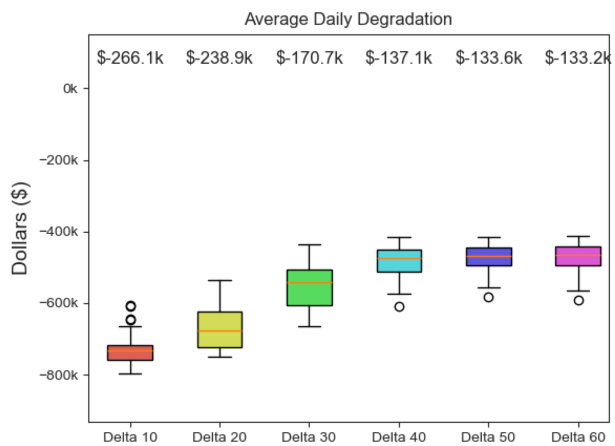
[1] We benchmarked degradation costs to values reported in the literature. For instance, a mid-case projection for 2030 indicates a capital cost of approximately $326/kWh for a 4-hour lithium-ion battery

marginal cost for both charging and discharging) has the lowest net profit. As price deltas increase, net profits improve. At a $60/MWh price delta, the median ESR gains a 40% increase in net profits (40% reduction in net losses) compared to that of the baseline case.

To conclude, based on our simulations, there exists a threshold (optimal) price delta (Δ_p^*) at which an ESR earns their maximum profit by balancing their potential revenue with degradation cost, given existing market conditions. When the price delta (markup for discharging) is above that optimal value $(\Delta_p > \Delta_p^*)$, net profits no longer increase as the price delta increases because higher price deltas lead to fewer dispatch opportunities (despite stable degradation costs). On the other hand, when the price delta is below the optimal value $(\Delta_p < \Delta_p^*)$, net profits no longer decrease as the price delta decreases because lower price deltas lead to higher degradation costs, although the ESR has more discharge opportunities.



(a) Average daily revenue



(b) Average daily degradation cost

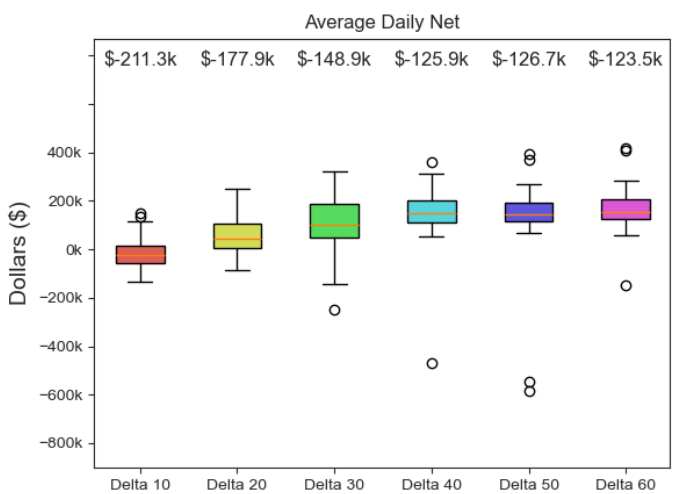


Figure 5: Average daily revenue (a), average daily degradation cost (b), and average daily net profits (c) of all 12 storage units. Median values are shown for each scenario.

system. With an expected charge-discharge cycles of 4000, a degradation cost of $81.5/MWh is estimated.

Figure 6 shows the degradation cost metrics associated with the cycling, thermal, average SoC, and DoD degradation costs, which include the changes of L1, L2 norm for charge profile, average SoC level and the depth of discharge for all 12 storage units and across all 30 days. The results indicate complex interactions between the four degradation cost components and the price deltas. As price delta increases, both L1 and L2 norms show consistent decreases, reflecting reduced battery utilization and power intensity. The average SoC level and DoD exhibit similar patterns, decreasing until price delta reaches $40/MWh and then stabilizing slightly above the minimum level. The degradation cost metrics show consistent conclusion with average degradation cost shown in Figure 5, panel b, degradation costs decrease when price delta increases within some range.

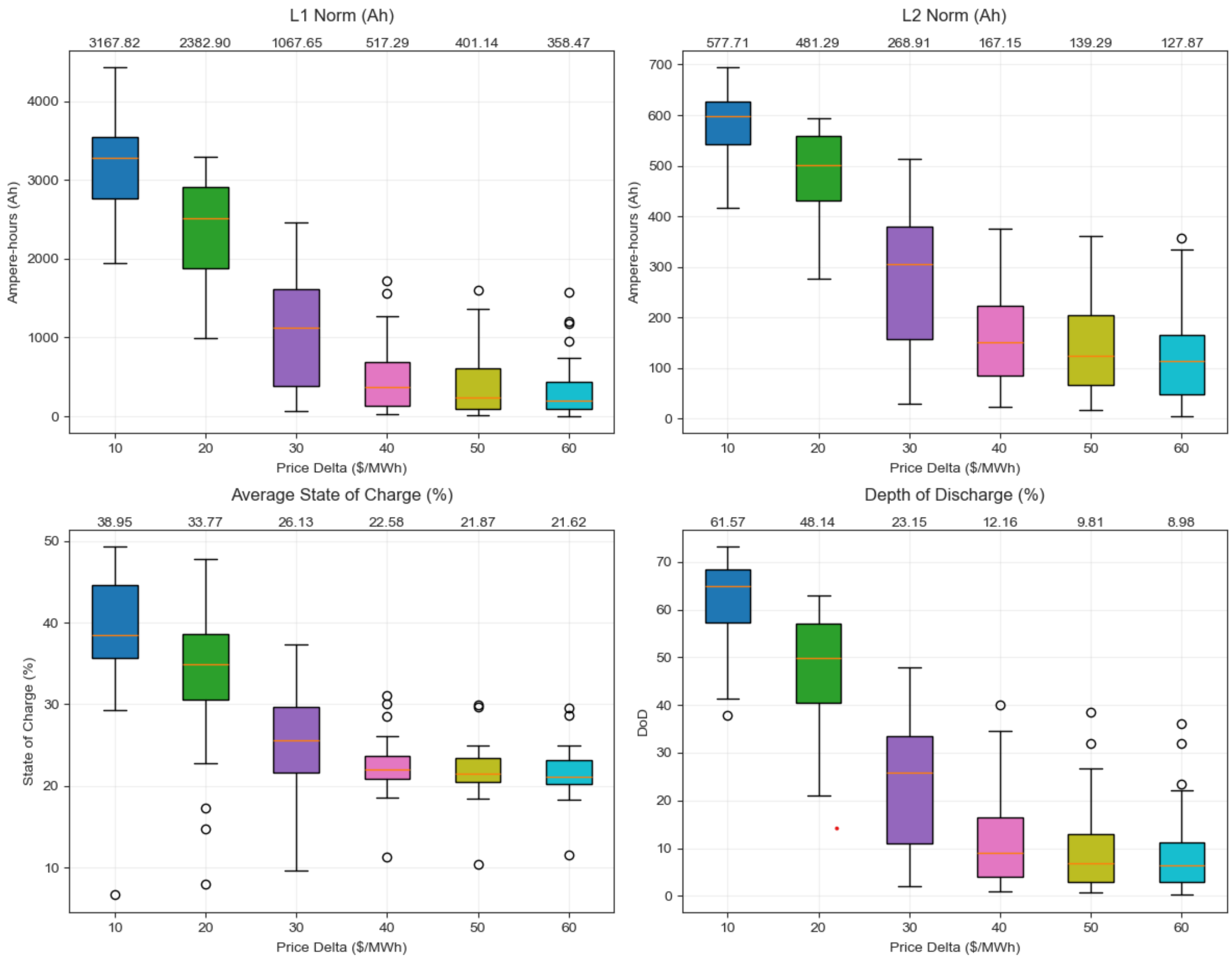


Figure 6: L1 norm, L2 norm, average SoC (in percentage), and DoD (in percentage) of all 12 storage units. Median values are shown at the top of each figure.

4.3 Price Delta with State of Charge Limits Compared to Baseline and Self-Schedule Algorithms

In this section we compare the performance of both the price delta with the inclusion of a hard SoC limit which we posit should crudely link the day-ahead and real-time market through SoC management and approximately represent degradation costs; as well as the price delta with the inclusion of a soft SoC limit to better link the day-ahead and real-time markets while approximately representing degradation costs. We compare the performance of both algorithms to the baseline algorithm ($0 price delta with hard SoC Limit) as well as a self-scheduling algorithm which is based on a schedule to maximize profits over *expected* prices.

The algorithms analyzed in this section are as follows:

- Baseline ($0 price delta with hard SoC Limit)
- Hard SoC Limit ($30 price delta[1])
- Soft SoC Limit ($25 price delta[1])
- Self-Scheduled

We first examine the impact on the overall market behavior, including the market surplus and the real-time locational marginal price (LMP). Then we explore the impact on storage operation and compare ESR profitability and degradation between scenarios.

4.3.1 Market Performance

ESR bidding behavior can have multiple impacts on the market, including a change in the overall surplus and adjustments to the LMP. In Figure 7 we show the LMP over the first two days of the horizon. While prices fluctuate, for much of the day the overall LMPs are comparable between scenarios. In all scenarios, the LMP is lowest during the middle of the day (when there is high solar availability) and highest in the evening hours. LMP remains high overnight, with a small peak in the morning.

We notice that with the baseline ESR bidding algorithm, LMPs vary the least during the day. Baseline LMPs remain higher during the day and are slightly lower during the evening peak relative to the other bidding algorithms. The soft SoC algorithm most closely tracks the baseline. The hard SoC algorithm is similar but does contain several modest LMP price spikes. The self-scheduled algorithm is the only algorithm that leads to extreme price spikes, reaching the energy shortage penalty ($2000/MWh) during the peaks. Although extreme price spikes do not occur consistently over the entire 30 days, the self-scheduled algorithm does consistently result in the highest average SoC levels. This may indicate the exercise of market power by the ESR algorithm, which can increase profits by limiting discharge during peak hours.

Over the entire 30-day simulation, the average baseline LMPs are very close to those of the soft SoC limit. The hard SoC limit average LMP is only slightly larger than the baseline. Only the self-scheduled algorithm has a significantly larger average LMP.

[1] In future work price deltas would be consistent for both the hard and soft SoC limits. Currently, these have different limits due to time and budget constraints. The $5 price delta does not make a significant difference in overall profit (see Section 4.2), nor does it affect the conclusions of this report.

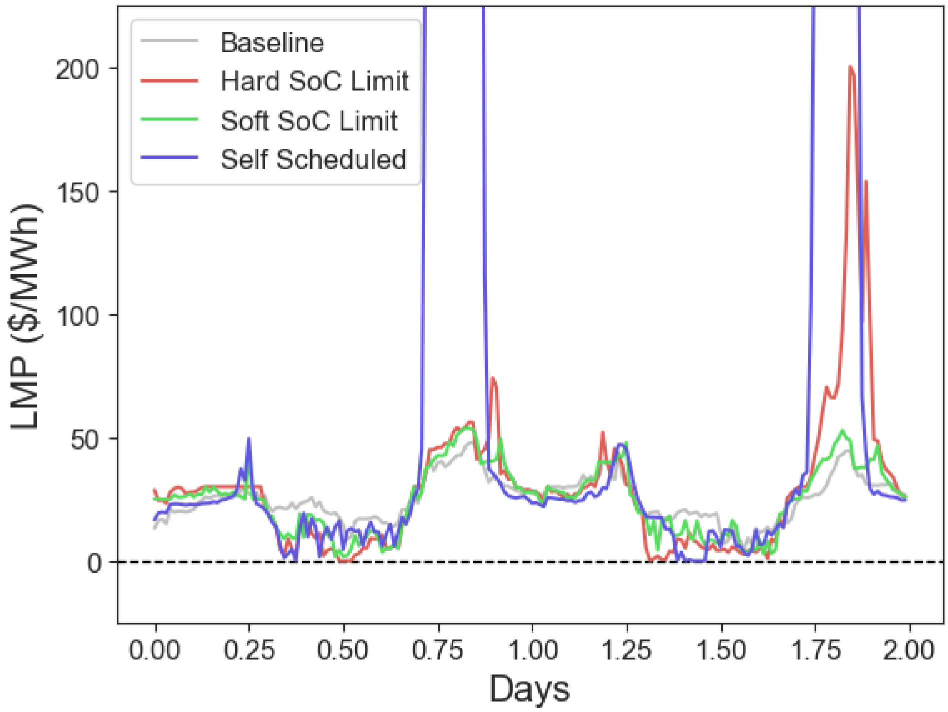


Figure 7: Real-time average (load-weighted) locational marginal prices for the first two simulation days. Prices are shown for four ESR bidding strategies.

We also examine the impact of bidding algorithms on the market surplus. Here we define surplus as the value of load served minus the cost of generation. However, storage unit bids are not necessarily representative of the true costs of ESR delivery. The cost incurred through degradation is a better representation of the cost to operate the battery. We therefore subtract the storage unit bid cost from the overall market surplus, then replace it with our computed degradation cost.

The surplus is shown in Figure 8. This compares the percentage change of each bidding algorithm to the baseline. In all cases, the surplus decreases by ~0.01 to 0.02%. In all three scenarios, this difference is not statistically significant as the 0% change value is within, or nearly within one quartile from the median. The self-scheduled case shows the most deviation, which could become statistically significant under a longer simulation. While this is a small percentage, it can still lead to a non-trivial dollar value due to high overall surplus (~$150 million loss in total surplus in this simulation).

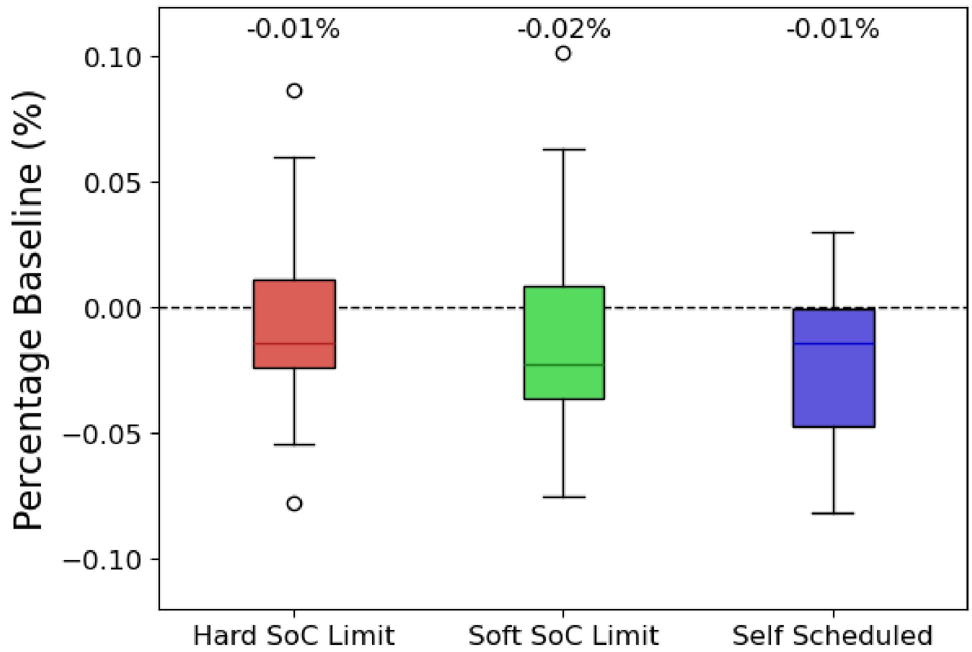


Figure 8: Market surplus as a percentage of the baseline surplus showing the distribution across each of the 30 days of the simulation. Median values are shown for each scenario.

4.3.2 Energy Storage Resource Performance

Operators of ESR will seek algorithms that maximize the storage unit profit. In this section, we examine how the storage units are physically dispatched and the corresponding profitability.

Figure 9 shows the average state-of-charge profile across a day. These profiles are averaged across all 12 storage units and across all 30 days. A dotted line is shown at 128MWh, demonstrating the minimum SoC capacity allowed in our simulation. All the algorithms have the same general behavior. Some charge is reserved overnight then the storage unit discharges a little during the morning peak in price (see Figure 7). During the middle of the day, when solar output is significant, the storage units charge. Finally, they discharge to a low level over the evening hours, approximately 4:00pm to 10:00pm, when prices are typically high.

The primary difference between the scenarios is the maximum state of charge. The baseline case reaches a high maximum, roughly 550MWh (out of 608MWh capacity), and discharges to the lowest level in the morning around hour 7. Both the self-scheduled and the soft SoC limit reach a peak of ~375MWh, while the hard SoC limit stops around 300MWh.

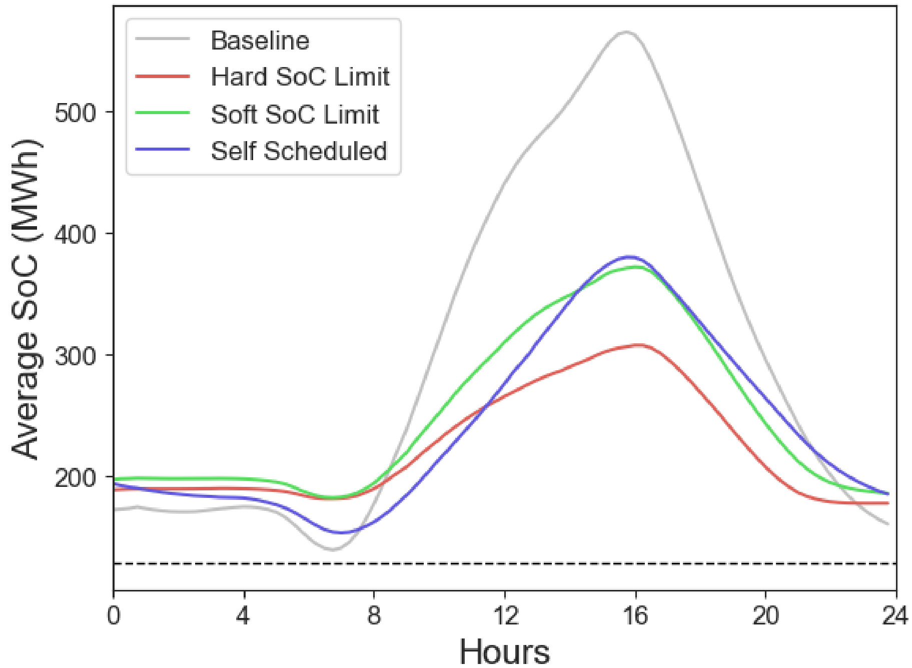


Figure 9: Average 1-day storage unit state of charge across all days and storage units. Curves are shown for four bidding algorithms.

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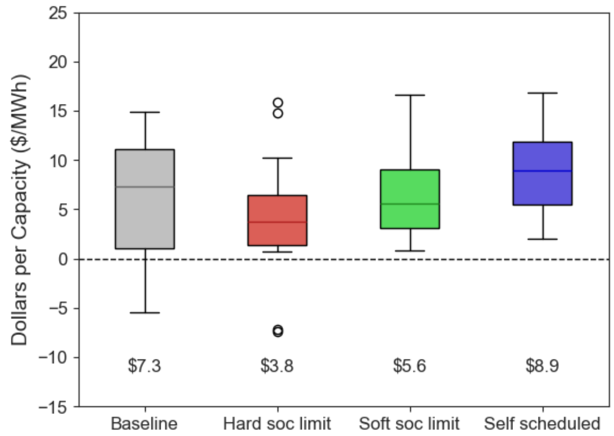
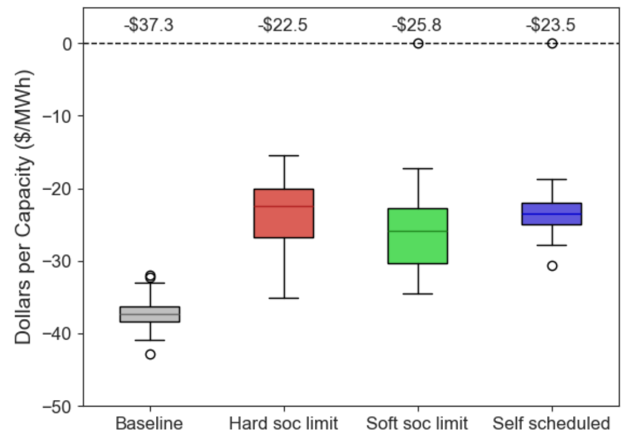
The profits are shown in Figure 10. In Figure 10, panel a) we see the revenue earned by the storage unit in the market. Values are scaled by the MWh capacity, showing the expected daily profit for an ESR per MWh of installed capacity. This includes profits from providing both energy and reserve services less expenses from charging. While reserves are included, in our simulation, arbitrage is responsible for most of the profits with >90% of revenue attributed to arbitrage. While there is a lot of overlap between scenarios, we see that the hard SoC limit returns the lowest median profit and the self-scheduled algorithm returns the highest median profit. The baseline case covers the widest range, including some days with high profits and other days with negative profits (losses).

While the storage units tend to earn a reasonable profit in the market, this must be weighed against the degradation cost incurred by the storage unit (see 3.2.2.2). Figure 10 b) shows the range of degradation cost by scenario. Here the baseline has a significantly higher degradation cost than other cases. All the bidding algorithms have comparable degradation cost with the lowest median value found with the hard SoC limit.

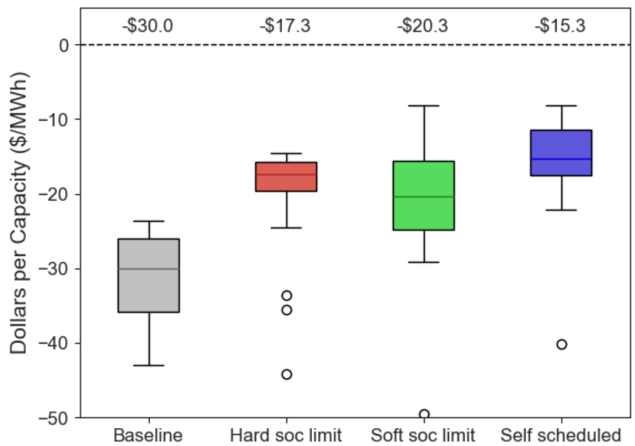
The net revenue, market profits less degradation cost, is shown in Figure 10, panel c). We can immediately see that regardless of the scenario, the storage unit reports a loss. Due to the high degradation, the baseline case (standard ZMC) has the lowest net profit. The self-scheduled shows the smallest loss, although it is very similar to the hard SoC limit. The soft SoC limit tends to slightly larger losses.



a) Average Daily Market Revenue



b) Average Daily Degradation Cost



c) Average Daily Net Revenue

Figure 10: Average profits of all 12 storage ($/MWh of capacity). This includes in panel a) the revenue earned by storage units in the market, panel b) the estimated degradation cost incurred, and panel c) the net revenue (sum of (a) and (b)). Median values are shown for each scenario.

5.0 Discussion

Based on our results, we can draw several conclusions. The first is that the inclusion of ESR bidding behavior has a small impact on overall market surplus. Though all scenarios have either a negative median surplus or positive median surplus relative to the baseline, the shift is too small to consider significant. However, we can clearly see that the ESR's bidding assumptions affect LMPs. In particular, the self-scheduling algorithm leads to several cases of extreme LMP, behavior which is not desirable from a market operator perspective. This suggests that enabling ESR participation in the market by allowing ESRs to submit bids and offers based on prevailing prices is advantageous for the market operator. Furthermore, our results show that ESR bidding can affect price formation and market outcomes.

Although ESR bidding did not significantly impact market surplus, it did impact LMPs as well as individual storage unit profitability. We found that both self-scheduling as well as incorporating a price delta with an end-of-interval maximum state-of-charge (hard) limit resulted in comparable net revenue, and either self-scheduling to maximize profits based on expected prices or allowing for a price delta with some form of state-of-charge management also significantly outperformed the baseline when degradation costs were considered. ESRs are both less profitable and poorly utilized when they are dispatched as ZMC resources; this is clear evidence that storage unit operators should not bid into the market as ZMC resources. Our algorithms can be considered as a starting point for developing more accurate economic valuations for ESRs, as financially motivated ESR operators would likely develop even more sophisticated and profitable bidding algorithms.

A more pressing concern is that, in this high-renewables simulation, ESR were not able to make a net profit when accounting for degradation cost. We note that our simulation is not calibrated to current reserve prices, meaning that ESR units could earn more in reserves. We also have not modeled capacity markets or federal and state subsidies which, in many cases, ESR units utilize to increase revenue. Nevertheless, under the structure of this simulation, there is no incentive to invest in ESR, despite potential benefits to the grid. Furthermore, we have not included any operations and maintenance costs, which would lead to even greater losses.

We can quickly estimate the average charge and discharge price differential needed for an ESR to profit in the market. We will adopt a typical ESR with a 16-year lifespan, a $208 million capital cost (see Table 2), and a discharge of 125MW for four hours per day. We will assume 90% of ESR revenue comes from arbitrage, as it did in this simulation. Under these circumstances, the ESR will annually discharge a total of

$$182{,}500\ \mathrm{MWh} = 125\mathrm{MW} \times \frac{4\mathrm{h}}{\mathrm{d}} \times \frac{365\mathrm{d}}{\mathrm{yr}}$$

For the profits to equal the capital cost we require an average LMP gain (the difference between the charging and discharging LMP) based on a simplified approximation to the levelized cost of storage (LCOS):

$$LCOS = \frac{Capital}{\sum_t MWh_t * (1+r)^{-t}}$$

Assuming a discount rate of 3% and that revenues from arbitrage will need to cover 90% of capital costs (and 10% will come from other services, such as reserves).

$$\$82/\mathrm{MWh} = \frac{\$208{,}000{,}000 * .9}{\left\{\frac{182{,}500}{(1+.03)^1} + \frac{182{,}500}{(1+.03)^2} \cdots \frac{182{,}500}{(1+.03)^{16}}\right\}}$$

This shows the ESR would need an average price differential of $82/MWh for its entire lifetime to cover its capital cost. While this neglects a number of considerations (for example, operating and maintenance costs as well as the capital charge rate), it sets an approximate value for the price at which ESR becomes profitable.

Based on Figure 7, we can see that in most scenarios, the high and low prices differ by roughly $40/MWh, excluding price spikes. This is well below the $82/MWh target. Furthermore, from the state-of-charge shown in Figure 9, we can see that, except for the baseline, these units are not fully charging and discharging in a single day. At most, they are discharging for the equivalent of ~2 hours at max discharge. If we instead assume that the ESR discharges 2 hours per day, we can use the same logic to compute the LCOS at which the storage unit can break even.

$$\$163/MWh = \frac{\$208{,}000{,}000 * .9}{\left\{\frac{91{,}250}{(1+.03)^1} + \frac{91{,}250}{(1+.03)^2} \cdots \frac{91{,}250}{(1+.03)^{16}}\right\}}$$

This means that for our scenario, the storage unit would need to earn $163/MWh for its entire operational life to cover its capital cost. The need for additional revenue is even more significant if we require the storage unit to earn a positive return over its lifetime.

While these are approximate figures, they highlight the need for an alternative market structure to enable effective ESR participation. First, increasing profits from reserve products would help reduce the percentage of income from arbitrage. Arbitrage revenue may also increase under alternative settlement structures like a multi-settlement or a rolling-horizon market (Eldridge et al. 2024). Other revenue could come in the form of capacity payments or markets rewarding the flexibility provided by ESR (Anuta et al. 2014). Regulatory tax incentives could also help enable ESR to function as a profitable grid resource.

Future work can include the addition of new market structures to gauge their impact. This can include modeling ESR revenue under forecast errors to assess the impact of uncertainty on the robustness of market behavior. This could help determine the contribution of ESRs to system reliability in the face of uncertainty.

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Appendix A – Potential Energy Storage Resource Models

A.1 Energy Storage Resource Representation Background

Improving battery energy storage models for electricity planning tools is a key consideration. In the literature, many battery equivalent modeling approaches are available to simulate battery performance, predict lifecycle behavior, and optimize grid integration, thereby enhancing the reliability and efficiency of energy systems. Battery equivalent models are used to understand and optimize the behavior of batteries when providing grid services (Pratt et al. 2020). Five battery equivalent models are summarized, which include electrical equivalent circuit models, electrochemical models, empirical models, data-driven models, and hybrid models.

A.1.1 Electrical Equivalent Circuit Models

Electrical equivalent circuit models are widely used due to their simplicity and effectiveness in representing battery dynamics. These models typically consist of resistors, capacitors, and voltage sources.

- Thevenin Model: Comprises a voltage source in series with an internal resistance and one or more RC (resistor-capacitor) networks to capture transient behavior. This model is effective for simulating the immediate voltage response of batteries under load conditions.
- Randles Model: Extends the Thevenin model by including elements like charge transfer resistance and Warburg impedance to account for electrochemical processes, making it suitable for more detailed analysis.
- Dual Polarization Model: Incorporates additional RC networks to represent more complex transient behaviors and provide a more accurate representation of the battery's dynamic response.

A.1.2 Electrochemical Models

Electrochemical models provide a detailed understanding of the internal processes within batteries, offering insights into both the electrode and electrolyte phases.

- Pseudo Two-Dimensional (P2D) Model: This model captures the electrochemical processes in two dimensions, accounting for spatial variations within the electrodes and the electrolyte. It is highly accurate but computationally intensive.
- Single Particle Model (SPM): Simplifies the P2D model by representing each electrode with a single particle, reducing computational requirements while still capturing essential dynamics.

A.1.3 Empirical Models

Empirical models are based on fitting experimental data to mathematical equations, providing straightforward predictions without detailed insights into the underlying processes.

- Equivalent Full Order Model (EFOM): Uses comprehensive parameter sets derived from experimental data to predict battery behavior under various load conditions.
- Equivalent Reduced Order Model (EROM): Streamlines the EFOM by reducing the number of parameters, enhancing computational efficiency while retaining reasonable accuracy.

A.1.4 Data-Driven Models

Data-driven models leverage historical data and machine learning techniques to predict battery performance, offering high adaptability and accuracy.

- Regression Models: Utilize statistical methods to fit historical data and predict future performance. These models are relatively simple but can be limited by the quality of the data.
- Neural Networks: Employ deep learning algorithms to capture complex, nonlinear relationships within the data, providing high predictive accuracy at the cost of increased computational complexity.
- Kalman Filter-Based Models: Use recursive algorithms to estimate battery state of charge (SoC) and state of health (SoH) in real-time, combining model-based and data-driven approaches for robust performance.

A.1.5 Hybrid Models

Hybrid models integrate elements from different modeling approaches to leverage their respective strengths and mitigate their weaknesses.

- Electrochemical-Mechanical Models: Combine electrochemical processes with mechanical effects such as stress and strain, offering a comprehensive view of battery behavior under various conditions.
- Electrical-Thermal Models: Couple electrical circuit models with thermal models to account for the influence of temperature on battery performance, critical for applications in varying environmental conditions.

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