Market Power Challenges and Solutions for Electric Power Storage Resources

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Abstract

Energy storage can enable low-carbon power and resilient power systems. However, market design is critical if a transition to renewables and storage is to result in low costs for customers. Pivotal suppliers with energy storage resources (ESRs) can achieve supernormal profits when allowed to fully participate and set clearing prices in wholesale electricity markets. Additional strategic profit from offers inconsistent with marginal costs can hurt competition and increase customer payments, hindering ongoing transitions to high shares of low marginal cost renewable generation and ESRs in electricity markets. We classify three strategies identified by our bi-level model for achieving additional strategic profits: (1) increased ESR discharge bids, (2) decreased ESR charge bids, and (3) cross-product manipulation to benefit other resources owned by the pivotal ESR supplier. We examine cases on a 25-bus test system with 67% average renewable energy generation where the ESR is commonly pivotal due to congestion. We observe under some circumstances the ESR owner can increase its energy market profits from $10-20/MWh discharged when competitive to $40-250/MWh discharged when strategic. Most increased profit comes from cross-product manipulation aimed at increasing prices to benefit a large co-located or hybridized zero marginal cost wind generator owned by the same entity. Marginal cost-based offer caps commonly applied to other resources could be extended to include ESRs' intertemporal opportunity costs limit, but these caps do not fully mitigate manipulative cross-product strategies. Relative inframarginal ESR offers over co-optimized time intervals with energy limits can be used to manipulate clearing quantities and prices and should be closely monitored when ESRs are pivotal suppliers. Requiring inframarginal offer uniformity over co-optimized time intervals shows promise as a policy remedy.

Abbreviations and acronyms

CAISO	California Independent System Operator
CC	Combined Cycle
CT	Combustion Turbine
DA	Day-Ahead
DCOPF	Direct Current Optimal Power Flow
EPEC	Equilibrium Program with Equilibrium Constraints
ERCOT	Electricity Reliability Council of Texas
ESR	Energy Storage Resource
FERC	Federal Energy Regulatory Commission
IMM	Independent Market Monitor
KKT	Karush-Kuhn-Tucker
MILP	Mixed Integer Linear Program
MPEC	Mathematical Program with Equilibrium Constraints
NREL	National Renewable Energy Laboratory
NYISO	New York Independent System Operator
RT	Real-Time
RTPV	Rooftop Photovoltaic
RTS-GMLC	Reliability Test System – Grid Modernization Lab Consortium
PHS	Pumped Hydroelectric Storage
SPP	Southwest Power Pool
VRE	Variable Renewable Energy

1. Introduction

Mid-century decarbonization pathways commonly increase the quantity and share of final energy demand supplied by electricity (Williams *et al* 2012, 2021). A highly decarbonized and expanded electricity sector requires rapid transition from current generation mixes, with most pathways relying heavily on declining costs of variable renewable energy (VRE) technologies (Bistline and Young 2019) and energy storage technologies (Kittner *et al* 2017) that enable better instantaneous matching of supply and demand (Mileva *et al* 2016). While standard electricity market designs are theoretically consistent with this transition (Hogan 2010), a key question is what reforms to existing electricity market designs are complementary with high penetrations of variable, low emission, and low marginal cost resources (Ela *et al* 2014, Joskow 2019, Spees *et al* 2019, Batlle *et al* 2021).

Consistent with integrating higher quantities of variable renewables in the electricity sector, standalone, stationary energy storage resources (ESRs) and ESRs sharing an interconnection with another generator ("hybrids") (CAISO 2019) make up an increasingly large portion of interconnection queues in competitive North American wholesale electricity markets and are expected to increase in coming years (Gorman *et al* 2020). ESRs and hybrids are energy-limited and shift load and generation in time rather than generating electricity. These differences, combined with low variable operating costs for lithium-ion technologies likely to dominate near-term ESR deployment (Beuse *et al* 2020), mean marginal cost based competitive ESR and hybrid bids generally reflect the intertemporal opportunity costs of ESR usage (He *et al* 2018). Existing North American competitive electricity markets have experience with a limited number of pumped hydroelectric storage (PHS) units sharing these general operational characteristics (Ela *et al* 2013). However, ESRs and hybrids are forecast to be more numerous, modular in sizing and deployment, and more readily dispatchable than PHS in coming years, enabling different use cases than PHS (Denholm *et al* 2021) and requiring modifications to existing rules to enable their full participation in competitive electricity markets (FERC 2018).

We contribute to this discussion by identifying profit-maximizing bidding strategies for ESR- or hybrid-owning entities in a realistic multi-node, two-settlement electricity market with high penetration of variable, renewable, low marginal cost resources. Methods for identifying bidding strategies are essential to maintaining competitive electricity markets and delivering customers low-cost, reliable electricity service with high shares of VRE and ESRs.

We develop a bi-level model with a profit-maximizing supplier in the upper level and the market operator minimizing the as-bid cost of serving load in the lower level. A bi-level model allows full participation of resources with the ability to endogenously set locational marginal prices (LMPs) in nodal wholesale electricity markets (Ruiz and Conejo 2009), and is commonly referred to as a type of "price-maker" model when applied to ESRs (Miletić *et al* 2020). This approach is consistent with previous approaches to modeling ESR market participation with ability to set clearing prices (Mohsenian-Rad 2016, Ye *et al* 2019). The model can be used to identify bidding strategies. The major contribution of our research is to extend the policy relevance of previous research focused on solving stylized cases of ESRs exercising market power as a pivotal supplier (Mohsenian-Rad 2016, Tómasson *et al* 2020, Ye *et al* 2019). We do this by classifying three market manipulation strategies on a high VRE nodal test system and suggesting directions for monitoring and mitigating these strategies.

2. Methods

We develop a bi-level optimization model reformulated as a mixed-integer linear program (MILP). This approach can be conceived as finding an equilibrium in a leader-follower Stackelberg game applied to electricity markets. In the upper level the leading generation- and ESR-owning entity submits bids to maximize the expected joint profits of its portfolio of resources. In the lower level the follower market operator minimizes the as-bid cost of serving electricity loads, subject to physical constraints on power flow and generator operational parameters. To focus on the properties of resource offers in one market we exclude security constraints, markets for ancillary services, and demand-side offers other than ESR charging loads (model formulation in Appendix A).

We increase the policy relevance of our cases compared to bi-level models on single-node test systems by modeling a congested high VRE nodal network, allowing us to observe congestion-related cross-product strategies of particular concern in electricity markets (Cardell *et al* 1997, Lo Prete *et al* 2019). We further extend previous work using bi-level models in electricity markets (Nasrolahpour *et al* 2016, Fang *et al* 2018, Ye *et al* 2019) by allowing hybridization of ESR and other generators located at the same bus as a single resource in bidding.

2.1 Multiple Settlement Functionality

North American wholesale markets commonly have two settlement intervals: a day-ahead (DA) forward market co-optimized for the subsequent day at hourly resolution and a higher temporal resolution (often five minutes) real-time (RT) market for settling deviations from the DA market with more limited look ahead temporal co-optimization. Our cases are commonly run DA with perfect foresight, but we include multiple settlement functionality in the model to allow sensitivity analysis under uncertainty with DA bids cleared against RT actual load and generation with limited bidding recourse (Appendix B).

2.2 Offer Constraints and Mitigation

In all cases unless otherwise noted generators are assumed to offer all available generation at marginal cost (Appendix B). For variable renewable generators with zero fuel cost, we additionally assume zero variable O&M and no effect of subsidies (e.g., wind Production Tax Credit (Brown 2012)) on marginal cost, so these resources offer at $0/MWh. Because ESR offers are largely opportunity cost-based, no constraints are placed on ESR offers in cases without ESR-specific offer mitigation constraints.

To investigate the efficacy of ESR offer mitigation we develop two approaches. First, we mitigate day-ahead offers based on an ex-ante price forecast, disallowing offers from exceeding the expected competitive clearing price. We show this approach does little to mitigate the most profitable strategic bidding by entities owning both ESRs and generation, which can use relative rather than absolute price offers for energy-limited resources. Second, we propose a mitigation framework based on uniform bidding for co-optimized temporal intervals. This framework is more effective in mitigating cross-product manipulation but requires careful consideration to avoid over-mitigation and allow ESRs to capture option value.

3. Data

To achieve germane results we implement our model on the National Renewable Energy Laboratory (NREL)-modified version of the IEEE RTS-96 test system: the Reliability Test System Grid Modernization Lab Consortium (RTS-GMLC) (Barrows *et al* 2020). The RTS-GMLC test system updates an older IEEE test system primarily by modernizing the generation fleet to include more gas-fired and renewable resources. Renewable and load profiles are based on three zonal locations in the United States southwest, though we retain only a single 25-bus zone for model cases in this paper (Fig. 1).

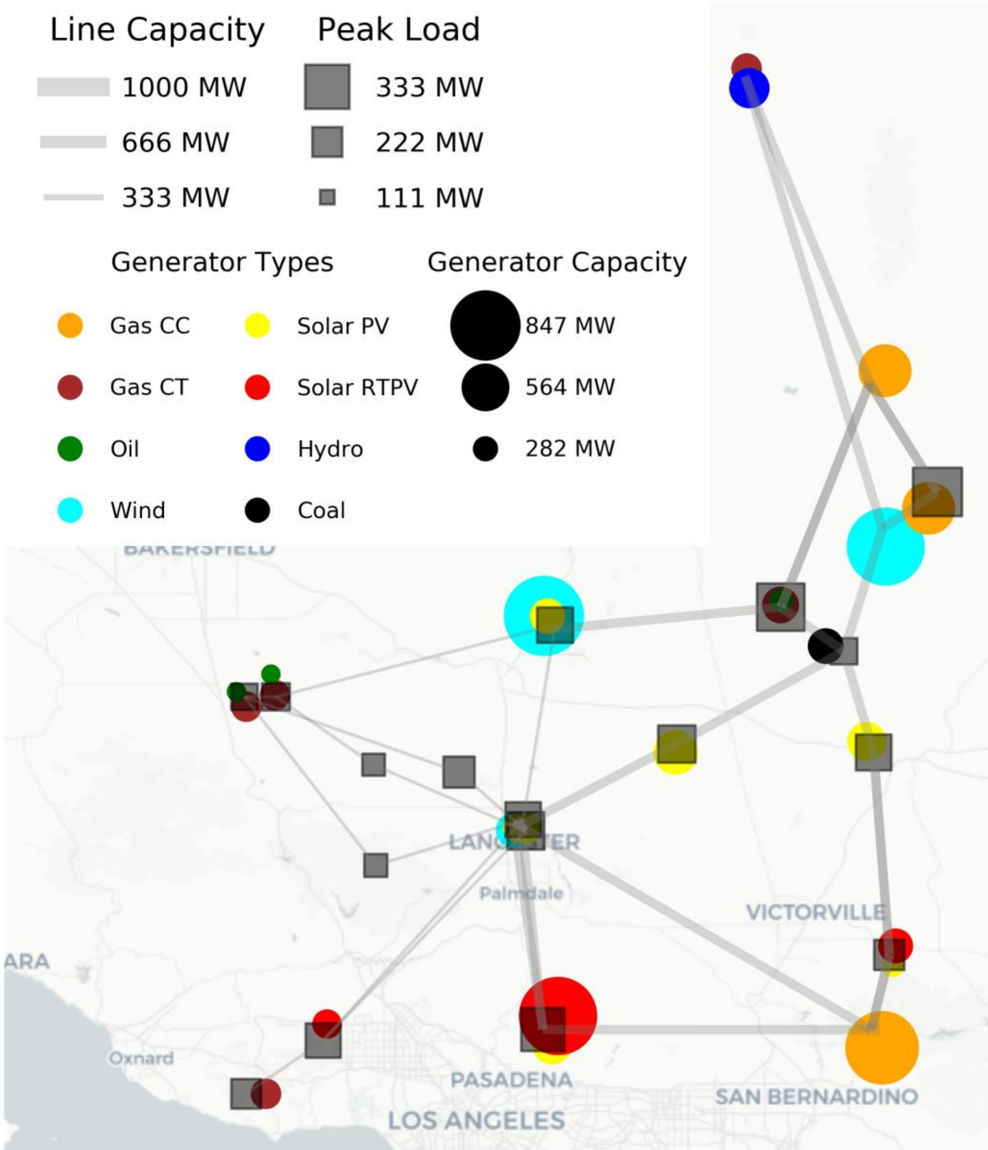

Fig. 1: Modified NREL RTS-GMLC case nodes, transmission lines, generation capacity, and peak loads. The three RTS-GMLC zones use geographic data based on Arizona Public Service Company (AZPS), Nevada Energy, and the Los Angeles Department of Water and Power (LADWP), though they are not intended to represent existing infrastructure. We retain only the displayed 25 buses in LADWP for cases to decrease runtime and because LADWP has the highest average (67%) and instantaneous renewables penetrations and the most congestion in the model year. RTPV is rooftop photovoltaic, CT combustion turbine, CC combined cycle.

We modify the RTS-GMLC source data to exclude native ESR and add ESRs with user-specified capacity, duration, and round-trip efficiency (assumed 85%) at select buses. These ESRs may also be hybridized with generators owned by the same entity at the same node. Day-ahead data are hourly resolution. Real-time data are 5-minute resolution, but are reformatted to equivalent hourly average load and renewable generation for the two-settlement model. The model is run as a sequence of co-optimized 24-hour resolution days to reduce solution time compared to co-optimization of a longer timeframe, and because this mimics DA markets. Constraints enforce a single daily cycle for ESR dispatch as a heuristic for degradation in the absence of more sophisticated degradation incorporation (He *et al* 2018). Initial and final ESR SOC are constrained to be zero to enforce continuity between days in sequential runs.

3.1 Summary of 25-bus Case Data

Fig. 2 shows January DA hourly average load, net load, and generation by resource for the reduced 25-bus version of the RTS-GMLC data without ESRs. A comparison to RT data used for multiple settlement functionality is included in Appendix B. The test system has high renewable generation compared to current United States averages (EIA 2021), but these renewable penetrations are commonly met or exceeded in forward looking decarbonization pathways (Williams *et al* 2021).

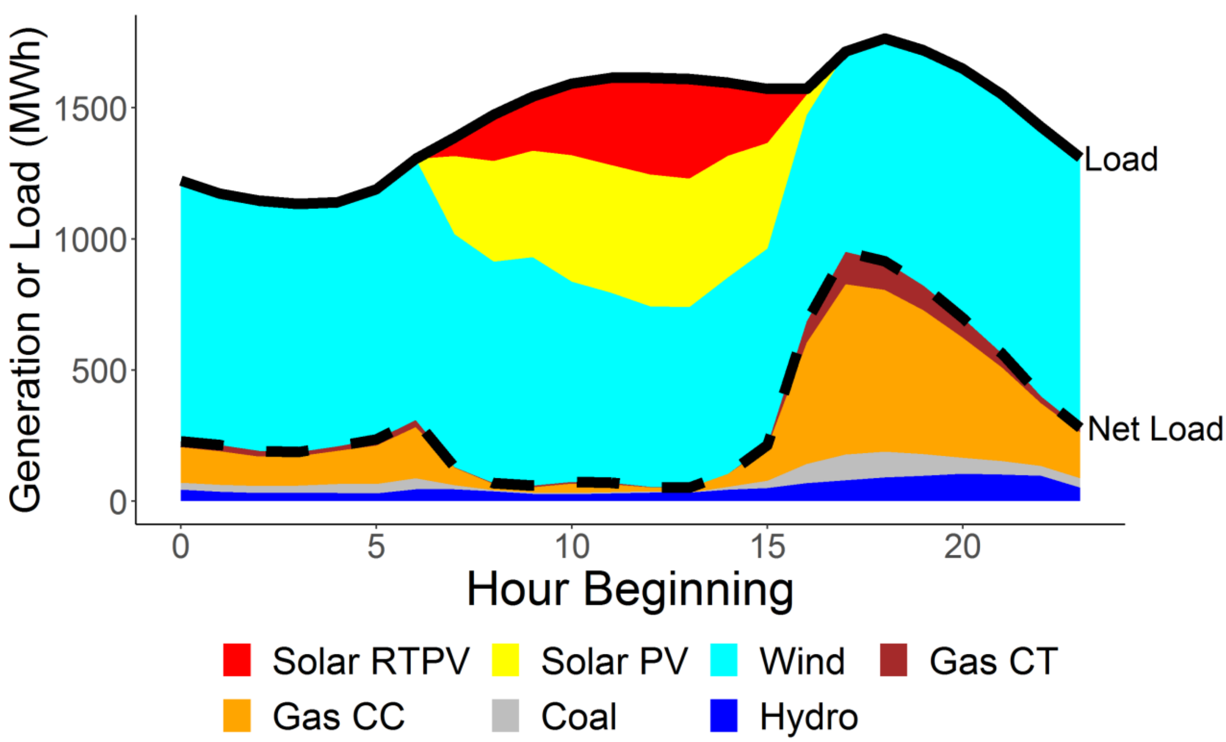

Fig. 2: Hourly day-ahead average load, net load, and generation by type for RTS-GMLC data without energy storage in Zone 3 for the modeled month, January. RTPV is rooftop photovoltaic, CT is combustion turbine, CC is combined cycle. Oil-fired generators are also included but not dispatched during the modeled month.

The combination of high quantities of available zero marginal cost renewable generation concentrated at a few buses with large wind generators and higher load hours often results in transmission congestion. The 175MW line connecting buses 03 and 09 is most often congested when large quantities of wind generation are available from the 847MW of installed wind capacity at bus 03. Bus 03 is the lowest LMP bus when there is congestion on the line connecting buses 03 and 09 (Fig. 3)**.**

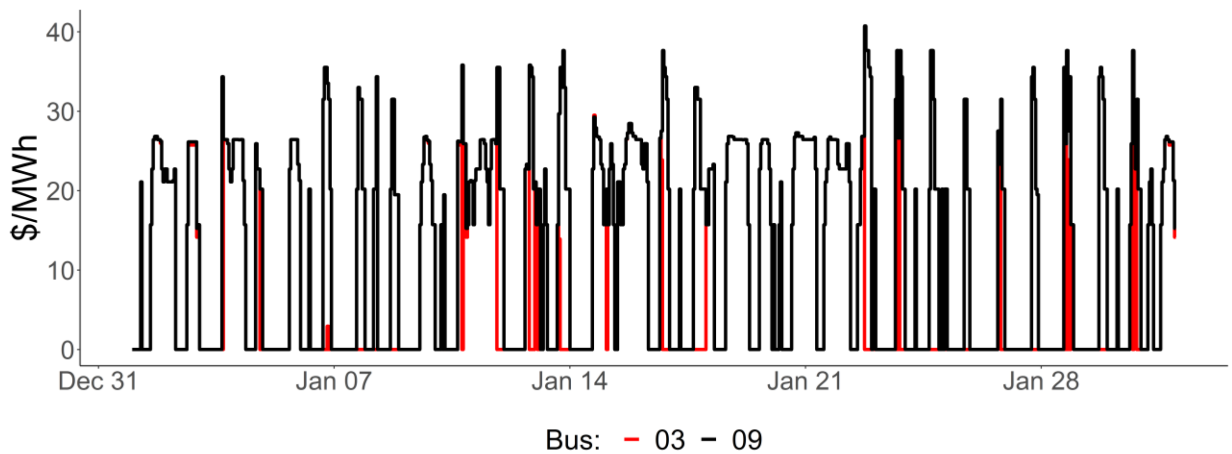

Fig. 3: Hourly LMPs without ESRs at the two buses in the test system linked by an often-congested line for the entire modeled month. LMPs for all buses are included in Appendix B.

4. Results

Three ESR bidding strategies increase the profit of a portfolio of resources owned by a strategic entity.

1) Increase discharge offers when pivotal to increase LMP at ESR bus when discharging;
2) Decrease charge offers when pivotal to decrease LMP at ESR bus when charging;
3) Increase ESR charge or discharge offers to increase LMP at buses where the strategic entity owns other generation.

Of these strategies the third, a cross-product strategy, is the most profitable when strategic ESRs are co-located or hybridized with a large renewable generator at a commonly congested bus. It is also the most difficult to mitigate against (Section 4.4).

To assess the additional profit associated with strategic ESR bids in a portfolio of resources we use two metrics: additional total portfolio profit $\Delta\pi^p$ over an applicable time interval and ESR incremental per-MWh discharged portfolio profit $\frac{\Delta\pi^p}{MWh}$. These metrics are defined:

$$\Delta\pi^p = \pi^{SS} - \pi^{NSS} \tag{1}$$

$$\frac{\Delta\pi^p}{MWh} = \frac{\pi^{SS} - \pi^G}{\sum sd^S} \tag{2}$$

Where π^{SS} is the profit of the strategic entity's portfolio p of generators with ability to bid its ESRs strategically (strategic storage is *SS*), π^{NSS} is the strategic entity's portfolio profit when it does not bid ESRs strategically (non-strategic storage is *NSS*), and π^G is the non-ESR generator profit in the non-strategic case. sd is total discharge over the applicable time interval of the ESR, S.

Assumptions include generators being mitigated to offer at marginal cost, but no offer mitigation applied to opportunity costs for ESRs, and the strategic entity has perfect foresight of load, renewable generation, and offers by other suppliers. Results in Section 4.1-4.2 using these assumptions set an upper bound on strategic profit of ESR bidding decisions for an assumed system and strategic ownership parameterization. Section 4.3 investigates relaxing some perfect foresight assumptions. Section 4.4 explores monitoring and mitigation frameworks for the most profitable perfect foresight strategies.

4.1 Demonstrating the Three Strategies

We parameterize two cases to demonstrate the applicability of the three strategies assuming perfect foresight of the market clearing problem (Table 1).

Table 0-1: Demonstration case parameterization. Differences between cases are in bold.

Case Label	Generators and Loads	Storage Sizing	Storage Location	Other Owned Generators	Time Period and Resolution
Case A: "ESR Only"	All NREL-RTS LADWP	300MW/900MWh	Bus 03	None	Hourly Day-Ahead, January 2020
Case B: "ESR+Wind"	All NREL-RTS LADWP	300MW/900MWh	Bus 03	**Wind (847MW), bus 03**	Hourly Day-Ahead, January 2020

In both cases the model is configured and run in two ways: "competitive" and "strategic." Competitive is equivalent to a cost-minimizing linear program under the assumption all resources offer at marginal cost. Competitive ESRs are dispatched to minimize production costs. Strategic assumes ESRs and other generators owned by the strategic entity[1] submit offers to maximize the strategic generation-owning entity's profit knowing the market operator will minimize as-bid costs of serving load. Strategic uses the full functionality of our model to find a profit-maximizing solution to within a pre-set MILP optimality gap (1% in these cases). Differences between the strategic and competitive solution in the profits accrued by the strategic entity are quantified as $\Delta\pi^p$. Figures show LMPs only at the bus where the ESR is installed unless otherwise noted.

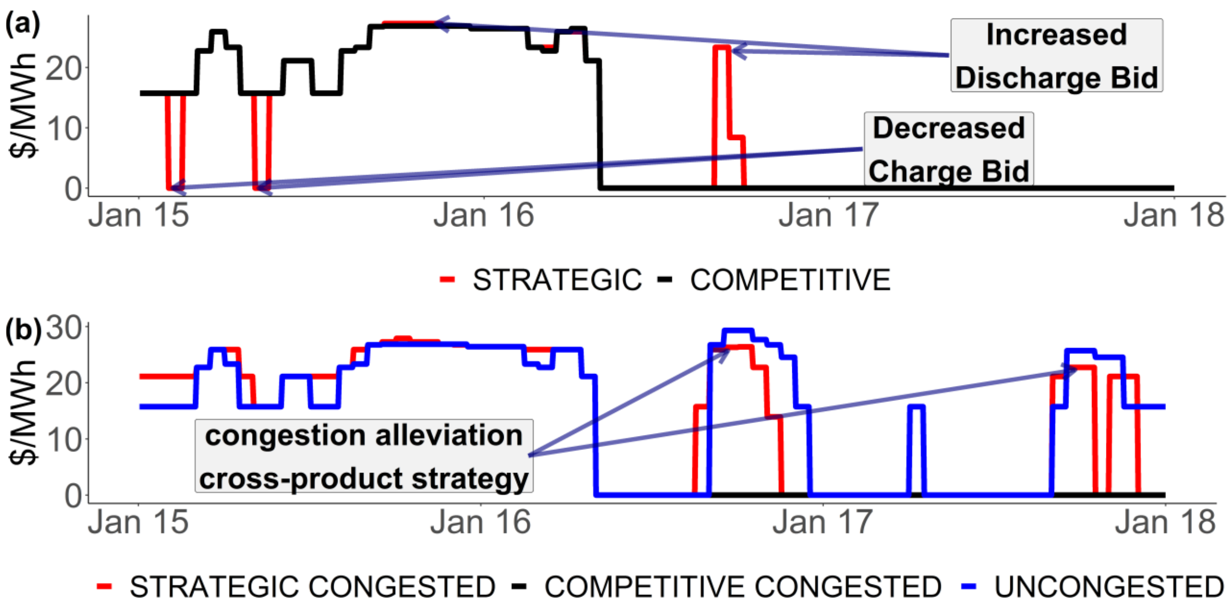

Fig. 4: Comparison of strategic and competitive LMPs at the bus (03) with ESR for an illustrative subset of modeled January days. In case A the ESR is able to set price and increase profits when pivotal through two strategies: increasing its discharge bid and decreasing its charge bid. In case B the strategic entity also owns a 847MW wind generator. Bus 03 is congested in many hours due to the wind generation and transmission limits, so prices are often below the system lambda (blue). Strategies used in case A still appear (though decreasing price for charging only makes sense when little wind is available), but the most profitable strategy is a cross-product strategy to alleviate congestion that results in the greatest increases in clearing price.

[1] As applicable in the case per Table 1, though recall generators are constrained to offer at marginal cost.

The total profits accrued in case A and B for the full month by the ESR and wind generator are compared in Fig. 5.

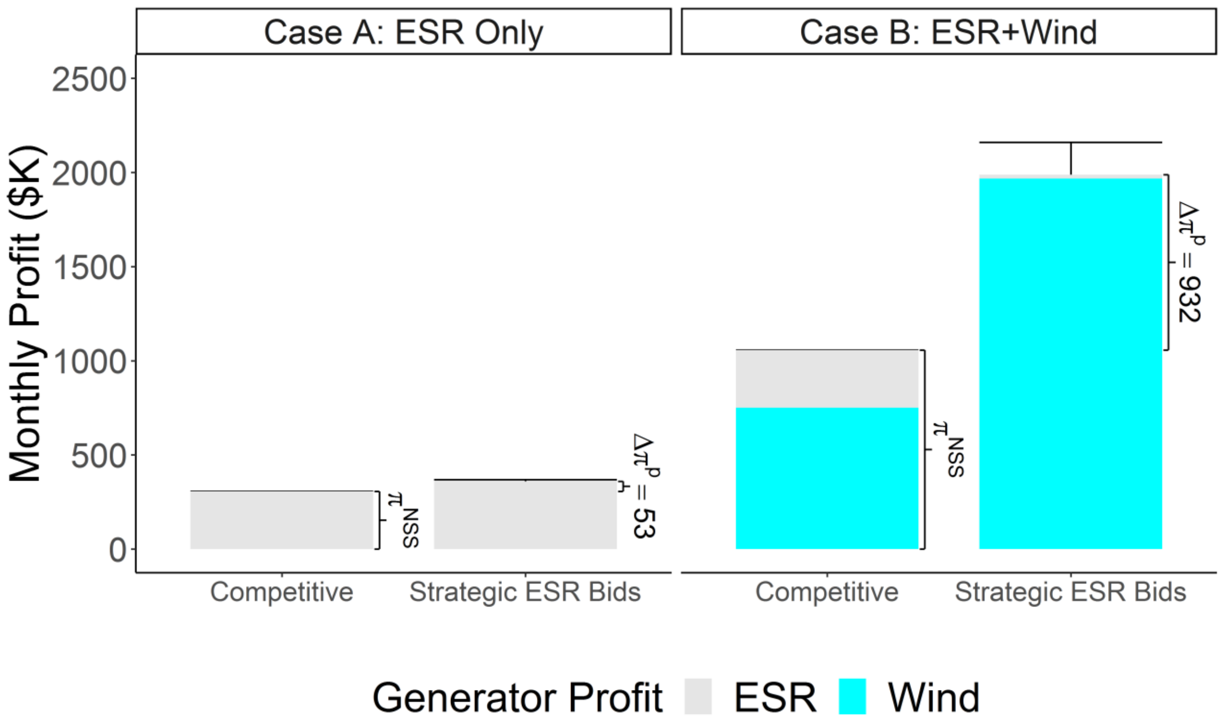

Fig. 5: Comparison of case profits for month of January when dispatched competitively vs. strategically. In case A the strategic entity only owns the ESR; in case B it also owns the wind generator and maximizes the joint profits by modifying ESR bids to increase revenues received by the wind generator. Uncertainty bars show the aggregate upper bound optimality gap for strategic MILP. Competitive cases are cost-minimizing LPs and have no optimality

4.2 Sensitivity to ESR parameterization and hybridization

This section adds sensitivity analysis on how ESR sizing and hybridization affects strategic profits. In these sensitivity cases we maintain the perfect foresight assumption, so results set an upper bound on portfolio profit from ESR bidding.

Fig. 6 shows ESR capacity and duration sensitivity analysis. The only changes to the case B parameterization are ESR capacity and duration. Because the cross-product strategy is profitable only when wind generation exceeds storage charging load, sensitivities consider ESR capacity installations up to 500 MW.[2] Per-MWh profits associated with storage ownership $\frac{\pi^{NSS}}{\sum sd^{S}}$

[2] the wind generator's capacity factor is 53% in the month; 448 MW average wind generation

are \$10-20/MWh ESR discharge in all competitive cases, while strategic incremental profits $\frac{\Delta\pi^p}{MWh}$ are \$40-250/MWh ESR discharge. Increased profits largely result from cross-product manipulation that decreases ESR revenues, but increases clearing price and thus wind revenues by more.

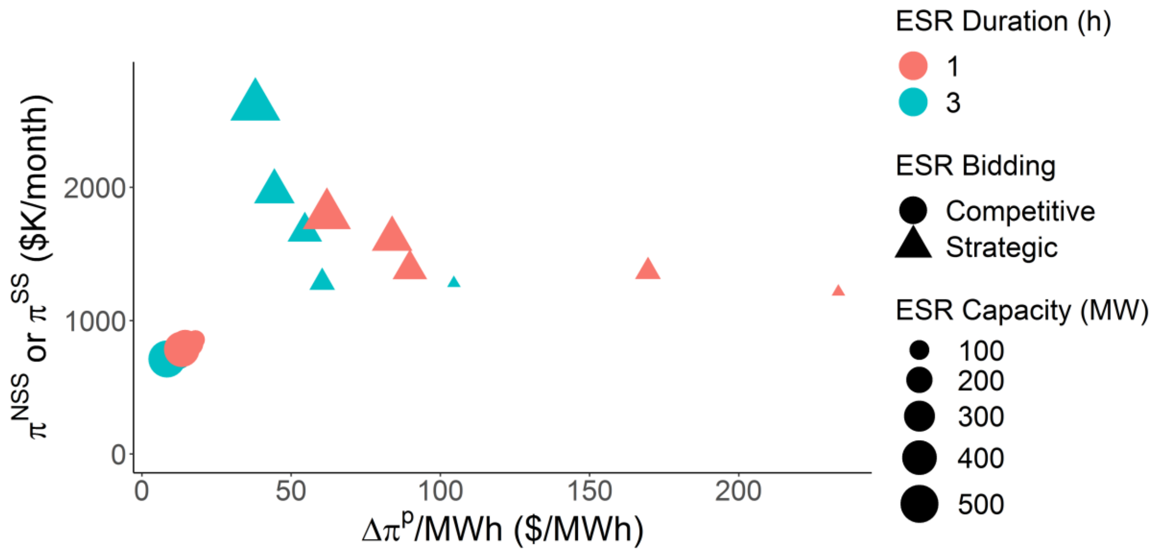

Fig. 6: Profit sensitivities show in all cases strategic bidding increases joint profits compared to the competitive outcome where the ESR is dispatched to minimize production costs. Increasing ESR capacity and duration generally exhibit decreasing marginal value (lower \$/MWh profits) under the perfect foresight assumption.

Motivated by increasing prominence of wind-ESR and solar-ESR hybrid generators in North American interconnection queues (Gorman *et al* 2020), Fig. 7 compares case B with a hybrid made up of the same wind and ESR. The hybrid differs from co-located in two ways: (1) it makes a single, unconstrained offer, and (2) the hybrid cannot dispatch more than the rated capacity (847MW) of its wind generator as an assumed interconnection limit, whereas the co-located resources can both dispatch at their full rated capacity.

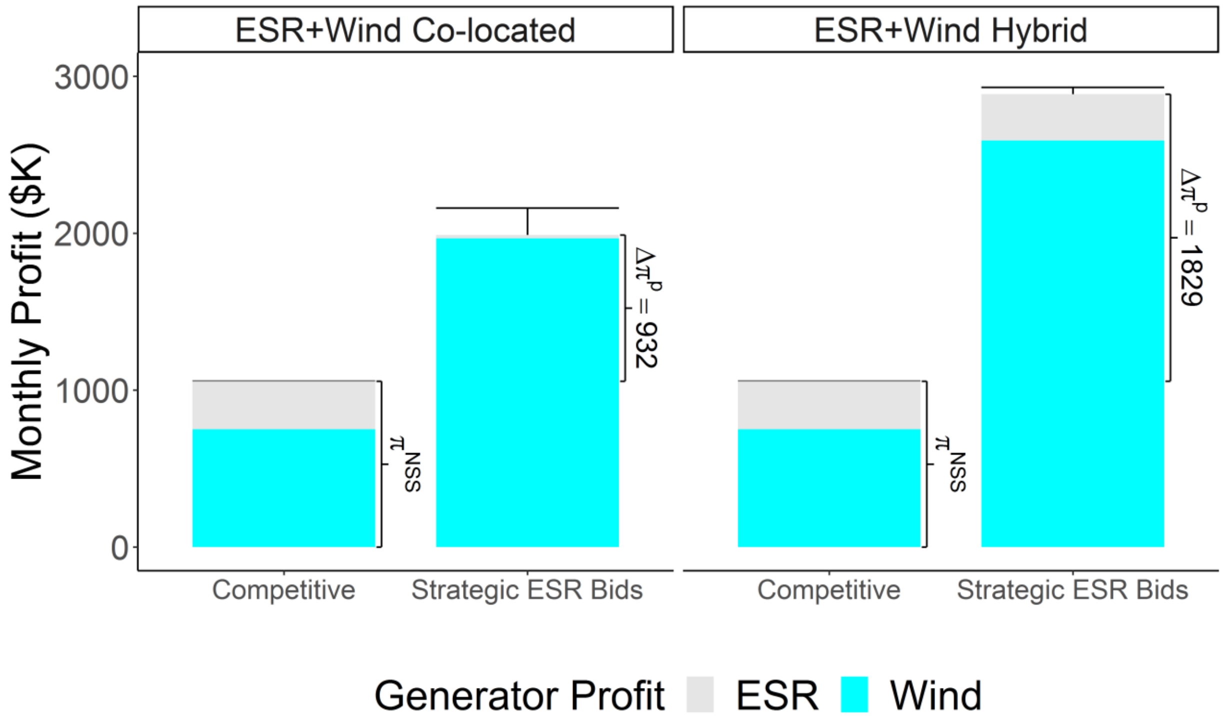

Fig. 7: Comparison of co-located and hybrid strategic profits with the competitive solution. Co-located case is the same as Case B in Section 4.1.

The hybrid achieves more profit than the co-location because of the removal of offer constraints on the wind generator, previously offered at its marginal cost of $0/MWh even when owned by the strategic entity. The new, larger hybrid generator can exercise additional ability to alleviate congestion affecting the LMP at bus 03 and set a higher price. The results illustrate how hybridization could be used to enable additional bidding latitude not afforded to a generator or ESR if hybridization allows the resource a new classification with fewer bidding restrictions.

4.3 Incorporating Uncertainty

Previous cases were day-ahead, hourly resolution under the assumption the strategic entity has perfect foresight of bus-level system loads, price-quantity bids by other generators, and knowledge how the market operator will minimize production costs and set prices. This section considers whether the strategic entity could achieve some of the perfect information profit when uncertainties in available generation and loads are incorporated. When fixing its profitable pivotal supply bid quantities in DA prior to realization of actual load and generation in

RT, the strategic entity can maintain some profit (Fig. 8, Appendix B for detail on strategy under uncertainty).

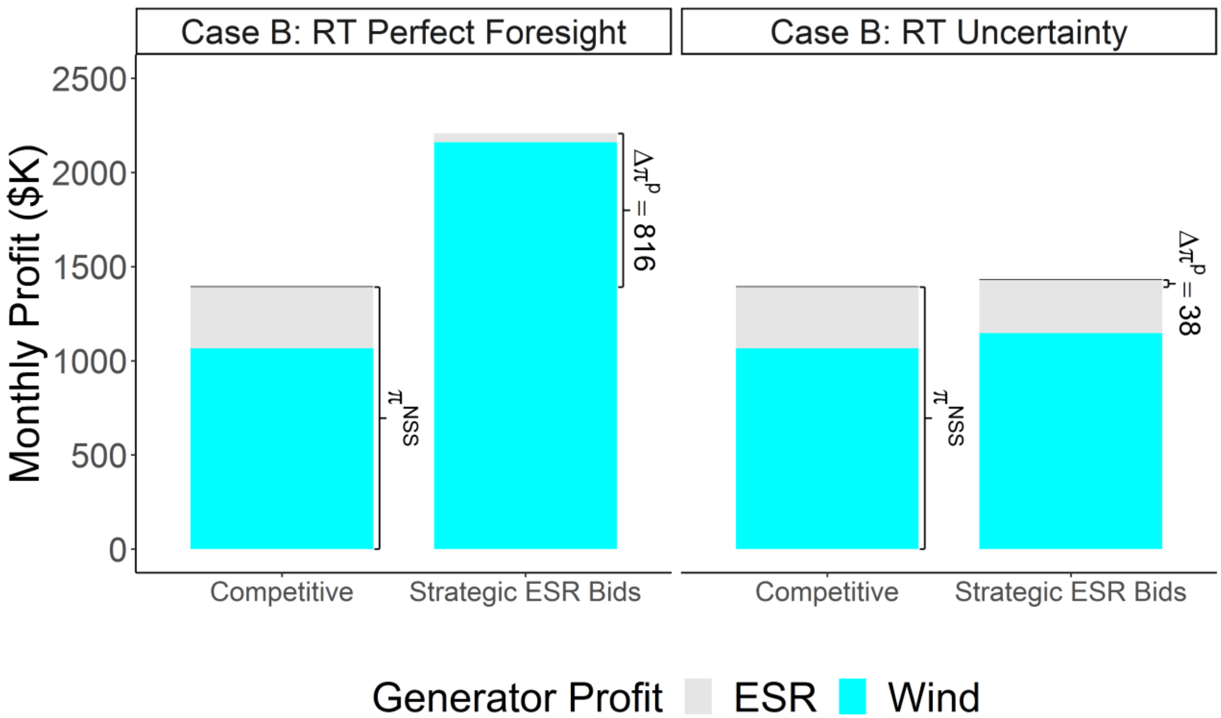

Fig. 8: Strategic profits are reduced under uncertainty. Implemented bidding strategy under uncertainty is explained in Appendix B.

Fig. 8 is only an existence proof for potential market manipulation, and real traders have in markets have developed profitable strategies under uncertainty. Market monitoring can still benefit from considering the profit maximizing strategy assuming perfect foresight, since tools for mitigating the three strategies identified in Section 4.1 will still be applicable under uncertainty.

4.4 Analytical Considerations for ESR Market Monitoring and Offer Mitigation

In this section we extend results to a discussion of detection and mitigation of ESR offers intended to manipulate market prices.

A common tool for mitigating offers in existing wholesale electricity markets are offer caps. North American electricity markets generally have both a market-wide offer cap and resource level offer mitigation using estimation and verification of marginal costs. Extending offer mitigation to ESRs and hybrids often proceeds from this framework, assuming adding intertemporal opportunity costs[3] to the marginal cost framework will account for the energy-limits of ESRs. Results in this section suggest an absolute offer cap for ESRs, even assuming an agreeable framework for estimation of ex-ante opportunity costs, misses important aspects of the ability of ESRs to exercise market power.

Over co-optimized temporal intervals with market operator incorporation of ESR energy limit constraints time-varying relative ESR offers can be used to manipulate market clearing prices and quantities, even with a stringent absolute offer cap. The critical mathematical insight is the effect of energy-limited ESR offers on clearing prices in all co-optimized time periods depends on the relative storage offers in each time period. When pivotal the ESR can make use of this fact to change its dispatch, and thus pricing, based on its relative offers, even when its absolute offers are constrained to be inframarginal in all time periods. A mathematical derivation of this result and parameterized example are in Appendix C.

To demonstrate the efficacy of an absolute offer cap the case B parameterization is run for a single day (1 January) with DA data. An ex-ante bus 03 LMP-based offer cap is developed as the market clearing price from the fully competitive solution. The model is then re-run with an additional set of constraints requiring ESR discharge offers to be less than or equal to the ex-ante LMP offer cap. This approach is similar to marginal cost-based mitigation for generator offers, and more stringent than mitigation using a uniform estimate of daily opportunity costs equivalent to the Nth (N=ESR duration) highest price hour, as would be suggested by optimal price-taker dispatch of a single daily ESR cycle. Perfect information profits remain well above the competitive solution (Fig. 9).

[3] Generator bids commonly account for lost opportunity costs (LOC) for co-optimized products in electricity markets. For example, a generator required to provide upward reserves for security reasons cannot simultaneously clear that capacity in an energy market and, if it would be more profitable to provide energy, incurs a LOC, which will then be reflected in its competitive reserve bid to make the generator at minimum indifferent between providing upward reserve and energy. This is distinct from *intertemporal* opportunity costs considered for energy-limited resources like ESRs.

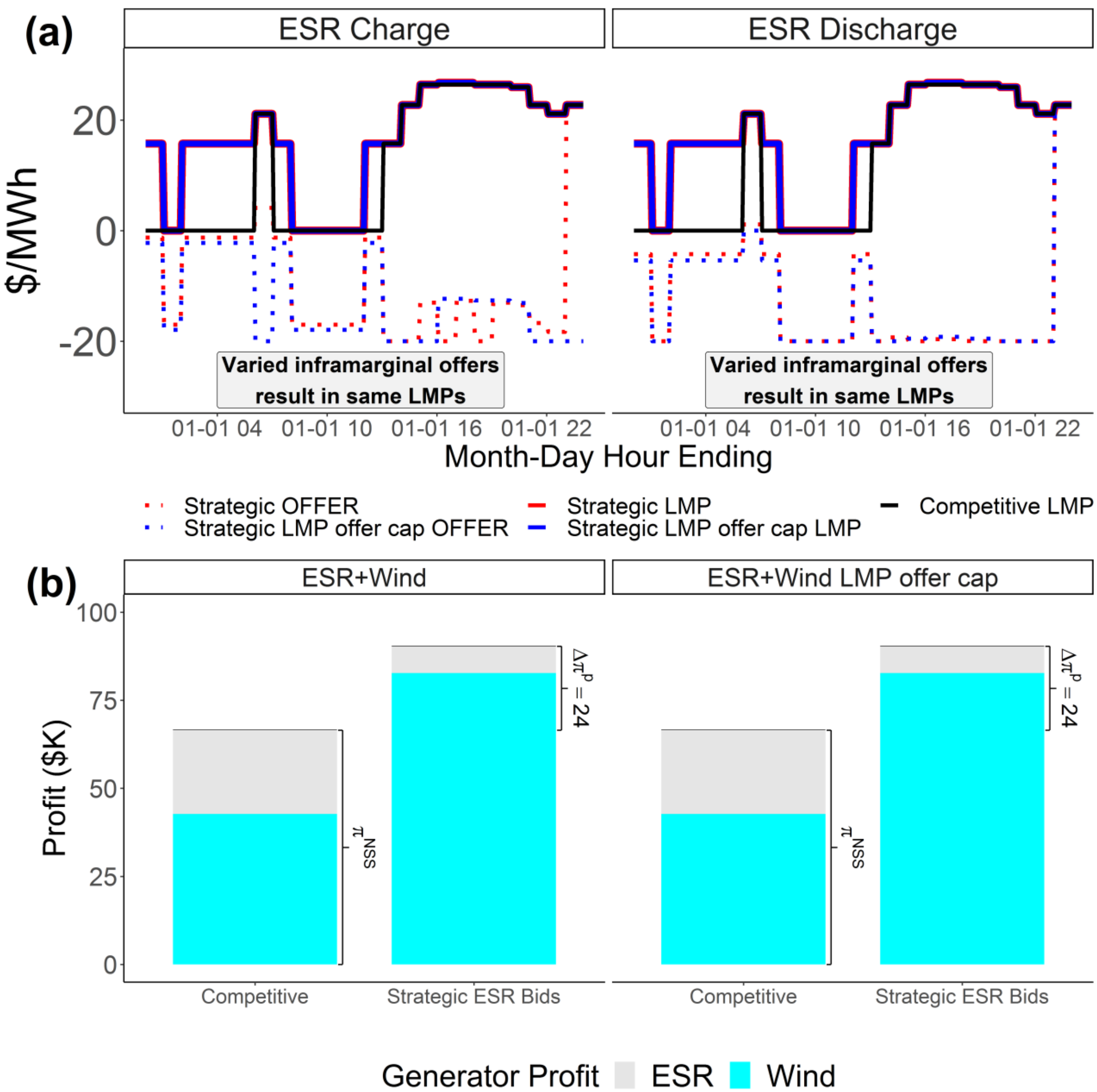

Fig. 9: ESR and wind owning strategic entity offers for a single day (1 January) at hourly resolution (a). In the “offer cap LMP” case offers are constrained to be no greater than the ex-ante competitive LMP, but are allowed to be negative. Reduced ability of the ESR to set price does not eliminate strategic profit (b).

Notably, the ESR’s ability to maintain strategic profits with inframarginal offers is different than for an inframarginal generator offer, which would not affect clearing prices. This occurs because energy-limited resources incorporate an additional energy-limit constraint in temporally co-optimized dispatch that generators do not, and can make use of this constraint to affect clearing prices and quantities based on relative offers (Appendix C).

That ESRs' ability to manipulate dispatch and pricing depends on relative offers over temporally co-optimized intervals suggests a direction for monitoring and mitigation: focus on relative offers. A simple, restrictive mitigation technique could involve requiring a temporally uniform ESR offer for all co-optimized time periods. Running an additional case where the ESR is constrained to a single offer for charge and discharge over co-optimized intervals on the same example day as Fig. 9 produces Fig. 10.

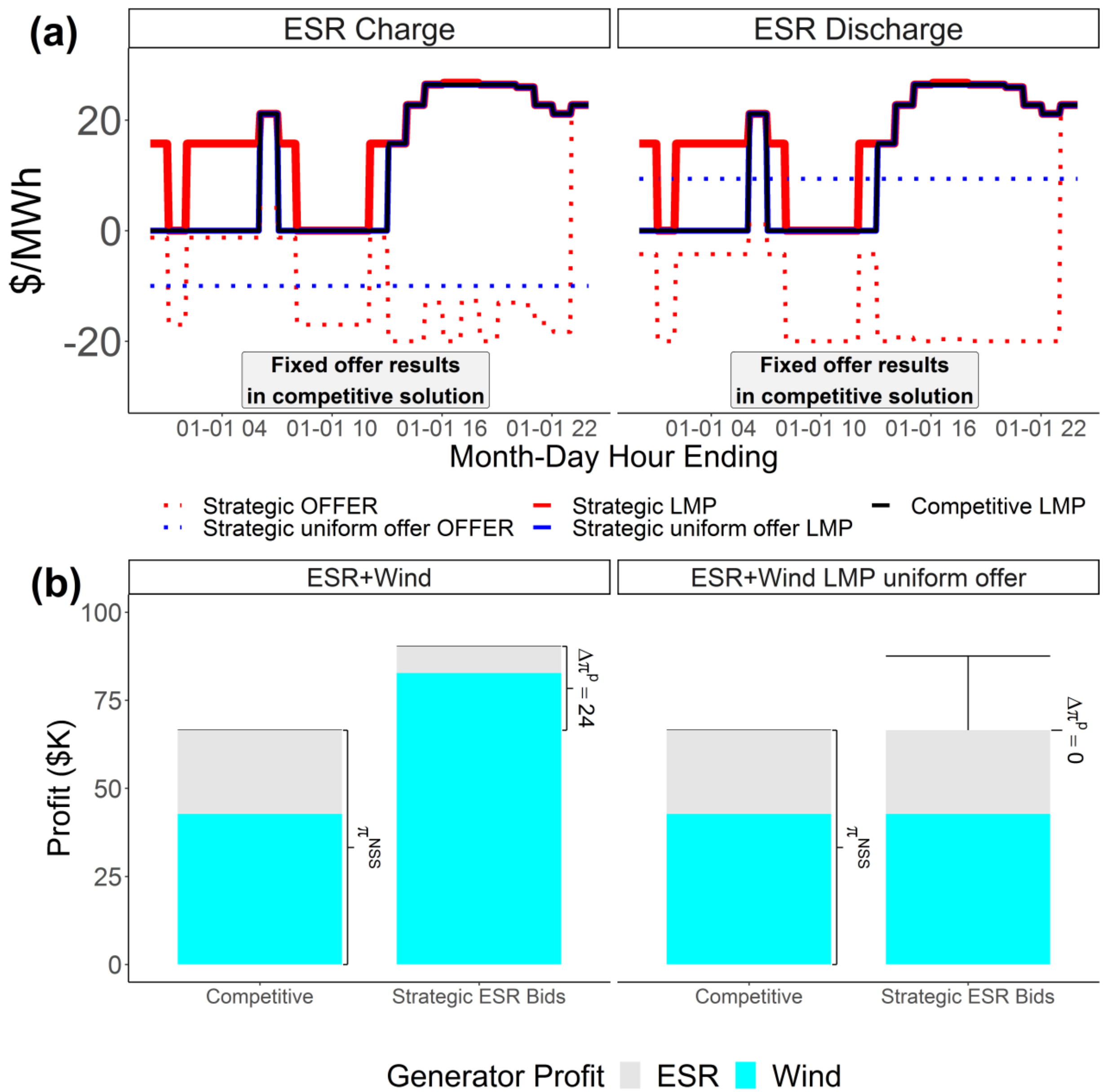

Fig. 10: ESR and wind owning strategic entity offers for a single day (1 January) at hourly resolution (a). In the "uniform offer" case offers are constrained to a single value for charge and discharge, respectively. The uniform offer LMP is the same as the competitive LMP and is overplotted. The uniform offer reduces strategic profits to be equivalent to the competitive solution for this day (b).

The requirement of uniform ESR charge and discharge offers results in the competitive solution. This occurs because a uniform offer disallows the ESR modifying the perceived social welfare gain of its limited dispatch with different bids in different hours. With a uniform offer, the perceived social welfare gain is the difference between the offer and the production costs it replaces, resulting in discharge replacing generation the highest production cost time periods and charge increasing generation the lowest production cost time periods, as in the competitive case.

Requiring a uniform offer has potential drawbacks of over-mitigation if not properly applied, and does not mitigate all strategies for exercising market power in bidding. A pivotal ESR could still set price in a time interval or intervals with a uniform bid above marginal cost or bid above expected market clearing prices to withhold its capacity. A very high bid could be justified by opportunity costs realized beyond the co-optimized time horizon. Limiting the ability of ESRs to update a uniform DA offer in shorter time horizon balancing or RT markets also risks over mitigation by reducing ESR option value if prices are higher (or lower) than expected. However, uniform offers mitigate the modeled optimal strategy of a profit-maximizing strategic entity with perfect foresight to increase its portfolio's profits and suggest a direction for ESR market monitoring and design considerations.

5. Discussion

Energy storage resources can facilitate integration of high levels of variable renewable energy, and market design must recognize their unique characteristics to prevent storage from manipulating high VRE, low marginal cost markets. This work highlights how price-making ESRs' ability to increase load and state of charge limitations enables additional latitude in bidding to manipulate dispatch and pricing and suggests ways that market monitors can avoid manipulation.

Modeling on a high VRE test system under perfect foresight suggests the most profitable strategy involves cross-product manipulation by bidding an ESR to raise prices and thus revenues received by other generators in the strategic entity's portfolio. ESRs can more commonly be pivotal at or near buses with high VRE generation and congestion than system-wide – exactly where ESRs would be installed to reduce transmission related renewable energy curtailments (Denholm and Mai 2019) – suggesting those generation pockets deserve additional attention. While we model only energy markets, identified strategies could be extended to ancillary service markets providing nearer term profit opportunities for ESR participation (Denholm *et al* 2021, Lee 2017, Xu *et al* 2018). Hybridization of ESRs with generators otherwise constrained to offer at low or zero marginal cost is another potential avenue for manipulating prices upward if bidding rules allow. Hybrid bidding rules are highly policy relevant given large quantities of renewable-ESR hybrid generators entering North American interconnection queues (Gorman *et al* 2020).

Strategic profits are limited with a deterministic bidding strategy under uncertainty about future loads and generation, but may be increased with more targeted or sophisticated strategies. Incorporating methods for predicting future market prices under uncertainty (Xu *et al* 2019) and stochastic optimization (Morales 2010) with a bi-level or other price-making model for ESRs suggest directions for future research. We assume fixed capacity and perfect information about the market operator's algorithm; both assumptions could be relaxed or extended to incorporate aspects of investment decision-making (Fernández-Blanco *et al* 2017, Nasrolahpour *et al* 2020) and algorithmic differences between forward and real-time markets, such as treatment of nonconvexities (Ye *et al* 2020) and effects of financial products (Jha and Wolak 2019, Lo Prete *et al* 2019).

We show ESRs can use their intertemporal energy limit constraint to change pricing and dispatch even with exclusively inframarginal offers. If the market operator respects ESRs' energy limits in optimizing its schedule and setting prices over multiple time intervals monitoring should look closely at relative inframarginal offers when ESRs are pivotal suppliers. We suggest uniform offer requirements as one approach. However, the assumption that market operators will respect energy limits through a SOC parameter or penalty is itself not a policy guarantee. The Electric Power Research Institute (EPRI) outlines four approaches for ESR participation in US wholesale markets under Federal Energy Regulatory Commission Order 841, including a self-SOC management option where the market operator considers only whether ESR offers are part of least-cost security constrained economic dispatch and ESRs are expected to self-update offers to maintain sufficient SOC to meet their schedules (Singhal and Ela 2020). EPRI's modeling shows self-SOC management can have severe reliability implications if ESRs cannot meet their dispatch schedule due to SOC infeasibility in real-time (Singhal 2019).

Weighing reliability and market participation objectives highlights the broader point: market design reforms to accommodate the technical characteristics of ESRs must carefully consider objectives including competition, reliability, and rapid decarbonization. If updated monitoring and mitigation for ESRs and hybrids is not included alongside these objectives, ossified market design can undermine the benefits of competition and hinder rapid decarbonization using high shares of low marginal cost VRE and ESRs.

6. CRediT authorship contribution statement

Luke Lavin: Conceptualization, Method, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Writing – review & editing, Visualization, Project administration. **Ningkun Zheng**: Software, Data curation. **Jay Apt**: Resources, Writing - review & editing, Supervision, Funding acquisition.

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A Model Explanation and Formulation

A.1 Additional Model Explanation

The full formulation of the model includes ramping and an implementation of linearized unit commitment but excludes security constraints. Generally additional security constraints and markets make pivotal supplier conditions more common and increase opportunities for strategic bidding, while demand side offers reduce supply side market power. Minimizing as-bid cost of serving load ignoring ancillary service utility is equivalent to maximizing social welfare assuming a uniform value of marginal electricity demand at or above the market clearing price cap. By anticipating the market operator's decisions, the strategic leading entity can submit bids to increase profits from its portfolio of assets.

Configurable options in running cases allow implementation of offer mitigation constraints based on ex-ante price forecasts, similar to an approach proposed by Southwest Power Pool's (SPP) Market Monitoring Unit (SPP 2018). Other configurable options allow changes to temporal indexing of ESR offers in the upper level and running the model as a single level linear program with fixed cost-based bids to compare results to the fully competitive solution for a given parameterized case.

Configurable options in the model explored in the paper include:

- Reformulation as a single level linear program for market clearing assuming fixed bids. Produces competitive solution when all resources are assumed to offer at marginal cost. (all results sections)
- Hybridization of co-located ESR and generation resources owned by strategic bidder. (Section 4.2)
- Multiple market settlements with reduced bidding and dispatch recourse in real-time. (Section 4.3)
- Offer mitigation constraints including requiring ESR discharge offers not exceed an offer cap based on ex-ante expected market clearing prices, or requiring a single, uniform discharge or charge ESR offer over co-optimized temporal intervals. (Section 4.4)

A full formulation of the model follows.

A.2 Notation

A.2.1 Sets

G	generators, indexed by g
GC	subset of generators owned by strategic entity, indexed by gc
GNC	subset of generators not owned by strategic entity, indexed by gnc
GS	linearized segments of generator heat rate curves, indexed by gs
GUC	subset of unit commitment generators, indexed by guc
$GNUC$	subset of non-unit commitment generators, indexed by $gnuc$
L	transmission lines connecting nodes, indexed by l
S	Energy storage resources, indexed by s
SS	subset of storage owned by strategic entity, indexed by ss
NSS	subset of storage not owned by strategic entity, indexed by nss
T	timepoints, indexed by t
Z	buses in power system, indexed by z

A.2.2 Decision Variables

$gd_{t,g}$	Generator dispatch [MWh]

$gdn_{t,g}$	Shutdown status of generator with unit commitment [0,1]
$gsd_{t,g,gs}$	dispatch on generator segment [MWh]
$gso_{t,g,gs}$	offer on generator segment for generators with unit commitment [$/MWh]
$go_{t,g,gs}$	offer for generators without unit commitment [$/MWh]
$gopstat_{t,g}$	Online operating status of generator with unit commitment [0,1]
$gup_{t,g}$	Startup status of generator with unit commitment [0,1]
$nucgd_{t,g}$	non unit commitment generator dispatch [MWh]
$sc_{t,s}$	Charging of energy storage resource [MWh]
$sd_{t,s}$	Discharging of energy storage resource [MWh]
$soc_{t,s}$	State-of charge (SOC) of energy storage resource [MWh]. SOC is definitionally determined by discharge and charge, so SOC-related terms are written as a summation of charge and discharge in subsequent equations.
$sofc_{t,s}$	Energy storage resource charge offer [$/MWh]
$sofd_{t,s}$	Energy storage resource discharge offer [$/MWh]
$txmwh_{t,l}$	real power flow on transmission line [MWh]
$va_{t,z}$	Bus voltage angle
$\alpha_{t,s}$	Energy storage resource charge lower bound dual variable
$\beta_{t,s}$	Energy storage resource discharge lower bound dual variable
$\gamma_{t,s}$	Tight energy storage resource operation constraint dual variable
$\nu_{t,s}^{max/min}$	State of Charge (SOC) constraint dual variable
χ_s	Final SOC dual variable
ξ_s	Energy storage resource cycle constraint dual variable
$\mu_{t,l}^{max/min}$	transmission flow dual variables
$\psi_{t,z}^{max/min}$	Voltage angle dual variables
$\lambda_{t,z}$	Power balance equation dual variable; interpreted as locational marginal price (LMP)
$\eta_{t,s}$	SOC balance equation dual variable
$\phi_{t,g}^{max/min}$	generator dispatch dual variables
$\varphi_{t,g,gs}^{max/min}$	generator segment dispatch dual variables
$\omega_{t,g}^{max/min}$	non-unit commitment generator dispatch dual variables
$\pi_{t,g}$	Unit commitment generator operating status change dual variable
$\sigma_{t,g}^{up/down}$	Generator ramp up/down dual variables

A.2.3 Parameters

$CAP_{t,g}$	generator capacity [MW]
$CAPA_{t,g}^{RT}$	Real-time available generation capacity of strategic entity [MW]
CE_s	energy storage resource charge efficiency, unitless
$CMAX_s$	maximum charge rate of energy storage resource [MW]
$CMAXO_s$	Maximum energy storage resource charge offer with offer mitigation [$/MWh]
$CDA_{t,s}$	Day-ahead energy storage resource charge for use in real-time [$/MWh]
DE_s	energy storage resource discharge efficiency, unitless
$DMAX_s$	maximum discharge rate of energy storage resource [MW]

$DMAXO_s$	Maximum energy storage resource discharge offer with offer mitigation [$/MWh]
$DDA_{t,s}$	Day-ahead energy storage resource discharge for use in real-time [$/MWh]
$GMC_{g,gs}$	marginal cost of generation on segment [$/MWh]
$GSL_{g,gs}$	fraction of generator capacity on marginal segment
$\Delta\lambda^{DA}_{t,z==SZL_s}$	Observed change in ESR bus clearing price in DA case when strategic vs. competitive (used only in RT cases)
$L_{t,z}$	gross load at bus [MWh]
NLC_g	No-load costs of committed generator ($/timepoint)
$PMIN_g$	Minimum online generation of committed unit commitment generator
$RBUS_t$	label of reference bus
RR_g	Generator ramp rate (MW/timepoint)
S_l	susceptance of transmission line [Siemens]
$SA_{t,g}$	fraction of generator capacity scheduled to be available
SC_g	Generator start-up costs [$/start]
$SMAX_s$	maximum state of charge of energy storage resource [MWh]
$TXFL_l$	zone or node from which transmission line originates
$TXTL_l$	zone or node to which transmission line goes
$TFCAP_l$	capacity of transmission line from zone or bus [MW]
$TTCAP_l$	capacity of transmission line to zone or bus [MW]
UE	Cost of unserved energy or offer cap [$/MWh]
$VMAX_z$	maximum voltage angle of bus (positive)
$VMIN_z$	minimum voltage angle of bus (negative)
ZL_g	Generator zone or bus label (assignment)
ZLS_s	Energy storage resource zone or bus label (assignment)

A.3 Model Formulation

A.3.1 Upper-level Objective Function

The upper-level objective function maximizes the profit of a single entity's competitively owned generators and ESRs.

$$MAX\ [\sum_{t,g\in guc,z==ZL_g}^{T,GC} gd_{t,g} + \sum_{t,g\in GNC,z==ZL_g}^{T,GC} nucgd_{t,g} + \sum_{t,s,z==ZLS_s}^{T,SS}(sd_{t,s} - sc_{t,s})] * \lambda_{t,z} - \sum_{t,g\in GUC,gs}^{T,GC,GS} GMC_{g,gs} * gsd_{t,g,gs} \tag{A.1A}$$

The upper-level objective function can optionally be configured to include no-load and startup costs when the model is configured to include tight relaxed unit commitment (TRUC) (Kasina 2017).

$$MAX\ [\sum_{t,g\in guc,z==ZL_g}^{T,GC} gd_{t,g} + \sum_{t,g\in GNC,z==ZL_g}^{T,GC} nucgd_{t,g} + \sum_{t,s,z==ZLS_s}^{T,SS}(sd_{t,s} - sc_{t,s})] * \lambda_{t,z} - \sum_{t,g\in GUC,gs}^{T,GC,GS} GMC_{g,gs} * gsd_{t,g,gs} - \sum_{t,g\in GUC}^{T,GC} SC_g * gup_{t,g} - \sum_{t,g\in GUC}^{T,GC} NLC_g * gopstat_{t,g} \tag{A.1B}$$

A.3.2 Upper-level Offer Constraints

Generator offer constraints are either optional constraints implemented to reduce solution time or based on common market rules in North American wholesale electricity markets. Implemented offer constraints also prevent physical withholding of unit commitment generators, a common market rule.

$2 * GMC_{g,gs} \geq gso_{t,g,gs} \geq GMC_{g,gs}$	$\forall g \in GC \cap GUC$	Generators may offer only up to two times their marginal cost and must offer at least their marginal costs. Helps reduce solution time.	(A.2)
$gso_{t,g,gs} \geq gso_{t,g,gs-1}$	$\forall g \in GC \cap GUC$	Each generator segment must offer at least the offer on the previous segment. Common wholesale market rule.	(A.3)
$UE \geq gso_{t,g,gs}$	$\forall g \in GC \cap GUC$	Generators may offer only up to the market cap, assumed \$2000/MWh in paper cases. Common wholesale market rule.	(A.4)
$0 == go_{t,g}$	$\forall g \in GC \cap GNUC$	Variable renewable generators (non-unit commitment) are assumed to have zero marginal cost and offer. Helps reduce solution time and refects low marginal cost of VRE.	(A.5)

A.3.3 Lower-level Objective Function

The lower-level objective function minimizes the as-bid cost of serving firm load

$$\forall \lambda \in \arg[\text{MIN} \sum_{t,g,gs}^{T,GUC,GS} gso_{t,g,gs} * gsd_{t,g,gs} + \sum_{t,g}^{T,GNUC} go_{t,g} * nucgd_{t,g} + \sum_{t,s}^{T,SS}(sofd_{t,s} * sd_{t,s} - sofc_{t,s} * sc_{t,s})] \tag{A.6A}$$

As with the upper level objective, the lower level objective may be optionally configured to include TRUC terms.

$$\forall \lambda \in \arg[\text{MIN} \sum_{t,g,gs}^{T,GUC,GS} gso_{t,g,gs} * gsd_{t,g,gs} + \sum_{t,g}^{T,GNUC} go_{t,g} * nucgd_{t,g} + \sum_{t,s}^{T,SS}\left(sofd_{t,s} * sd_{t,s} - sofc_{t,s} * sc_{t,s}\right) + \sum_{t,g \in GUC}^{T,GC} SC_g * gup_{t,g} + \sum_{t,g \in GUC}^{T,GC} NLC_g * gopstat_{t,g}] \tag{A.6B}$$

A.3.4 Lower-level Constraints

$L_{t,z} == \sum_{t,g,gs,z==ZL_g}^{T,GUC.GS} gsd_{t,g,gs} + \sum_{t,g,z==ZL_g}^{T,GNUC} nucgd_{t,g} + \sum_{t,s,z==ZLS_s}^{T,S} (sd_{t,s} - sc_{t,s}) + \sum_{t,l}^{T,L} (txmw_{t,l,TXTL_l==z} - txmw_{t,l,TXFL_l==z}) : \lambda_{t,z}$	Load-balance constraint	(A.7)
$va_{t,z==RBUS_t} = 0$	voltage angle at reference bus	(A.8)
$DMAX_s * CMAX_s \geq DMAX_s * sc_{t,s} + CMAX_s * sd_{t,s} : \gamma_{t,s}$	Tight storage dispatch	(A.9)
$sc_{t,s} \geq 0 : \alpha_{t,s} ; sd_{t,s} \geq 0 : \beta_{t,s}$	Non-negative storage charge and discharge	(A.10)
$SMAX_s \geq \sum_{t}^{1,\dots,t} (CE_s * sc_{t,s} - DE_s * sd_{t,s}) \geq 0 : \nu_{t,s}^{max}, \nu_{t,s}^{min}$	Sum of storage charge and discharge in previous timepoints stays below max SOC	(A.11)
$SMAX_s \geq \sum_{t}^{T} sd_{t,s} \geq 0 : \xi_s$	Limits storage discharge during a day to a single cycle	(A.12)
$\sum_{t}^{T} (CE_s * sc_{t,s} - DE_s * sd_{t,s}) == 0 : \chi_s$	Final storage SOC balance	(A.13)
$CAP_{t,g} * SA_{t,g} * gopstat_{t,g} \geq gd_{t,g} \geq gmin_{t,g} : \phi_{t,g}^{max}, \phi_{t,g}^{min} \ \forall g \in GUC$	Generator dispatch limited by maximum available capacity	(A.14)
$CAP_{tg} * SA_{t,g} * GSL_{g,gs} \geq gsd_{t,g,gs} \geq 0 : \varphi_{t,g,gs}^{max}, \varphi_{t,g,gs}^{min} \forall g \in GUC$	Generator piecewise segment dispatch limited by maximum available capacity	(A.15)
$gd_{t,g} == \sum_{gs}^{GS} gsd_{t,g,gs} \ \forall g \in GUC$	Sum of generator segment dispatch equivalent to total generator dispatch	(A.16)
$CAP_{t,g} * SA_{t,g} \geq nucgd_{t,g} \geq 0 : \omega_{t,g}^{max}, \omega_{t,g}^{min} \ \forall g \in GNUC$	Generator dispatch limited by maximum available capacity	(A.17)

$TTCAP_l \geq txmwh_{t,l} \geq TFCAP_l : \mu_{t,l}^{max}, \mu_{t,l}^{min}$	Transmission flows bounded by maxima in positive and negative direction	(A.18)
$VMAX_z \geq va_{t,z} \geq VMIN_z : \psi_{t,z}^{max}, \psi_{t,z}^{min}$	Voltage angle limits	(A.19)
$txmwh_{t,l} == S_l * (va_{t,z==TXTL==z} - va_{t,z==TXFL_l})$	DCOPF constraint	(A.20)

A set of additional optional constraints implement TRUC, associated minimum generation levels for online generators, and ramping limits.

$gmin_{t,g} == PMIN_g * SA_{t,g} * CAP_{t,g} * gopstat_{t,g}\ \forall g \in GUC$	Minimum generation scales with online capacity in TRUC	(A.21)
$gopstat_{t,g} - gopstat_{t-1,g} == gup_{t,g} - gdn_{t,g} : \pi_{t,g}\ \forall g \in GUC$	Unit commitment status changes only with startups and shutdowns	(A.22)
$gd_{t-1,g} - gmin_{t-1,g} + RR_g * gopstat_{t,g} \geq gd_{t,g} - gmin_{t,g} : \sigma_{t,g}^{up}\ \forall g \in GUC$	In TRUC upward operating status changes are bound by ramp rate	(A.23)
$gd_{t,g} - gmin_{t,g} + RR_g * gopstat_{t,g} \geq gd_{t-1,g} - gmin_{t-1,g} : \sigma_{t,g}^{down}\ \forall g \in GUC$	In TRUC downward operating status changes are bound by ramp rate	(A.24)

A.3.5 Optional constraints for implementing offer mitigation and binding day-ahead offers

The model may be configured to optionally include additional constraints for two settlement functionality or offer mitigation, and may also be configured to run as a cost-minimizing linear program.

Our approach to implementing offer mitigation requires developing an ex-ante price forecast to parametrize and mitigate against maximum offers, similar to an approach suggested by SPP's market monitor (SPP 2018). To achieve this we run a preliminary cost-minimizing dispatch of all resources as a linear program and extract the resulting bus LMPs. Offers are then mitigated against this price stream in each timepoint.

As one way of investigating the effect of uncertainty in loads and other offers when submitting strategic offers, we also allow the model to be configured to first optimize a DA run, then run a RT case where storage offers or quantities can be fixed to some of their DA values.

$DMAXO_{t,s} \geq sofd_{t,s}$	Storage discharge offer mitigated to ex-ante maximum (set equivalent to LMP in Section 4.4)	(A.25)
$CMAXO_{t,s} \geq sofc_{t,s}$	Storage charge offer mitigated to ex-ante maximum	(A.26)
$sd_{t,s} == DDA_{t,s}, (\forall t \mid DDA_{t,s} > 0, CAPA^{RT}_{t,g} \geq DMAX_s, \Delta\lambda^{DA}_{t,z==SZL_s} > 0)$	Real-time storage discharge is equivalent to DA discharge in time periods with pivotal DA dispatch and sufficient RT strategic wind generation	(A.27)
$sc_{t,s} == CDA_{t,s}, (\forall t \mid CDA_{t,s} > 0, CAPA^{RT}_{t,g} \geq CMAX_s, \Delta\lambda^{DA}_{t,z==SZL_s} > 0)$	Real-time storage charge is equivalent to DA charge in time periods with pivotal DA dispatch and sufficient RT strategic wind generation	(A.28)

A.3.6 Derivation of KKT conditions and MPEC reformulation

Since the lower level problem is a linear program, it can be reformulated using its Karush-Kuhn-Tucker (KKT) conditions as an equivalent Mathematical Program with Equilibrium Constraints (MPEC). The four KKT conditions are stationarity, complementary slackness, primal feasibility, and dual feasibility. The lower-level LP is primal and dual feasible, so the two tasks for MPEC reformulation are to write and the stationarity and complementary conditions of the lower-level problem and add them as constraints. Pyomo allows for representation of complementarity constraints in the formulation of optimization problems. The lower level objective and pre-existing constraints are unchanged.

A.3.7 Stationarity Conditions

Stationarity conditions are derived by taking partial derivatives of the problem's Lagrangian function with respect to the decision variables, then constraining the resulting equations to be zero to ensure stationarity. These equations are written below.

$$gso_{t,g,gs} - \lambda_{t,z==ZL_g} + \phi^{max}_{t,g} - \phi^{min}_{t,g} + \varphi^{max}_{t,g,gs} - \varphi^{min}_{t,g,gs} = 0 \qquad \forall g \in GUC \qquad (A.29)$$

$$SC_g - \pi_{t,g} = 0 \qquad \forall g \in GUC \qquad (A.30)$$

$$NLC_g - SA_{t.g} * CAP_{t,g} * \phi^{max}_{t,g} + PMIN_g * SA_{t.g} * CAP_{t,g} * \phi^{min}_{t,g} + \pi_{t,g} = 0 \qquad \forall g \in GUC \qquad (A.31)$$ [4]

[4] This equation is extended to include ramp rate-related terms when TRUC is implemented

$$sofd_{t,s} + CMAX_s * \gamma_{t,s} - \beta_{t,s} - DE_s * \eta_{t,s} + \xi_s - \lambda_{t,z==SZL_s} = 0 \qquad \forall s \in SS \qquad (A.32)$$

$$-sofc_{t,s} + DMAX_s * \gamma_{t,s} - \alpha_{t,s} + CE_s * \eta_{t,s} + \lambda_{t,z==SZL_s} = 0 \qquad \forall s \in SS \qquad (A.33)$$

$$CMAX_s * \gamma_{t,s} - \beta_{t,s} + DE_s * (\chi_s - \sum_{t}^{t,\dots N_T} \nu_{t,s}^{max} - \nu_{t,s}^{min}) + \xi_s - \lambda_{t,z==SZL_s} = 0 \qquad \forall s \in NSS \qquad (A.34)$$

$$DMAX_s * \gamma_{t,s} - \alpha_{t,s} - CE_s * (\chi_s - \sum_{t}^{t,\dots N_T} \nu_{t,s}^{max} - \nu_{t,s}^{min}) + \lambda_{t,z==SZL_s} = 0 \qquad \forall s \in NSS \qquad (A.35)$$

$$\eta_{t,s} - \eta_{t+1,s} + \nu_{t,s}^{max} - \nu_{t,s}^{min} = 0 \qquad \forall t \leq N_t \qquad (A.36)$$

$$\eta_{N_t,s} + \nu_{N_t,s}^{max} - \nu_{N_t,s}^{min} = 0 \qquad (A.37)$$

$$\mu_{t,l}^{max} - \mu_{t,l}^{min} + \psi_{t,z}^{max} - \psi_{t,z}^{min} = 0 \qquad (A.38)$$

$$-\lambda_{t,z==ZL_g} + \omega_{t,g}^{max} - \omega_{t,g}^{min} = 0 \qquad (A.39)$$

A.3.8 Complementarity Constraints

Complementary slackness conditions take the form $u_i * h_i(x) = 0, \forall i$. Such an equation is nonlinear as both terms contain decision variables. However, it may be rewritten as a complementarity constraint $0 \leq u_i \perp h_i(x) \geq 0$, which says either $u_i = 0$, or $h_i(x) = 0$, or both. These coupled constraints are then each themselves linear. The complementarity constraints used in the model are shown below.

$$0 \leq \gamma_{t,s} \perp DMAX_s * CMAX_s - DMAX_s * sc_{t,z} - CMAX_s * sd_{t,z} \geq 0 \qquad (A.40)$$

$$0 \leq \alpha_{t,s} \perp sc_{t,z} \geq 0 \qquad (A.41)$$

$$0 \leq \beta_{t,s} \perp sd_{t,z} \geq 0 \qquad (A.42)$$

$$0 \leq \nu_{t,s}^{max} \perp SMAX_s - \sum_{t}^{1,\dots,t} \left(CE_s * sc_{t,s} - DE_s * sd_{t,s}\right) \geq 0 \qquad (A.43)$$

$$0 \leq \nu_{t,s}^{min} \perp \sum_{t}^{1,\dots,t} \left(CE_s * sc_{t,s} - DE_s * sd_{t,s}\right) \geq 0 \qquad (A.44)$$

$$0 \leq \xi_s \perp SMAX_s - \sum_{t}^{T} sd_{t,s} \geq 0 \qquad (A.45)$$

$$0 \leq \mu_{t,l}^{max} \perp TTCAP_l - txmw_{t,l} \geq 0 \qquad (A.46)$$

$$0 \leq \mu_{t,l}^{min} \perp txmw_{t,l} - TFCAP_l \geq 0 \qquad (A.47)$$

$$0 \leq \psi_{t,z}^{max} \perp VMAX_z - va_{t,z} \geq 0 \qquad (A.48)$$

$$0 \leq \psi_{t,z}^{min} \perp va_{t,z} - VMIN_z \geq 0 \qquad (A.49)$$

$$0 \leq \phi_{t,g}^{max} \perp SA_{t.g} * CAP_{t,g} * gopstat_{t,g} - gd_{t,g} \geq 0 \qquad (A.50)$$

$$0 \leq \phi_{t,g}^{min} \perp gd_{t,g} - gmin_{t,g} \geq 0 \qquad (A.51)$$

$$0 \le \varphi_{t,g,gs}^{max} \perp SA_{t.g} * CAP_{t,g} * GSL_{g,gs} - gsd_{t,g,gs} \ge 0 \tag{A.52}$$
$$0 \le \varphi_{t,g,gs}^{min} \perp gsd_{t,g,gs} \ge 0 \tag{A.53}$$
$$0 \le \sigma_{t,g}^{up} \perp gd_{t-1,g} - gmin_{t-1,g} + RR_g * gopstat_{t,g} - (gd_{t,g} - gmin_{t,g}) \ge 0 \tag{A.54}$$
$$0 \le \sigma_{t,g}^{down} \perp gd_{t,g} - gmin_{t,g} * H + RR_g * gopstat_{t,g} - (gd_{t-1,g} - gmin_{t-1,g}) \ge 0 \tag{A.55}$$
$$0 \le \omega_{t,g}^{max} \perp SA_{t,g} * CAP_{t,g} - nucgd_{t,g} \ge 0 \tag{A.56}$$
$$0 \le \omega_{t,g}^{min} \perp nucgd_{t,g} \ge 0 \tag{A.57}$$

A.3.9 MILP reformulation using Big-M and Strong Duality

The objective function of the MPEC is still (A.1B) and remains non-linear because terms such as $\lambda_{t,z} * gd_{t,g}$ contain multiple decision variables (in the example, the LMP and generator dispatch are both decision variables). The following steps linearize the objective with an equivalent formulation by making use of the lower-level objective and complementarity conditions.

First, strong duality theory holds the objective of the primal problem is equivalent to the objective of the corresponding dual problem. The equivalence between the primal and dual objectives for the lower level problem (recall the primal objective is eq. (A.6B)) at the optimum is

$$\begin{aligned}
&\sum_{t,g,gs}^{T,GUC,GS} gso_{t,g,gs} * gsd_{t,g,gs} + \sum_{t,g}^{T,GNUC} go_{t,g} * nucgd_{t,g} + \sum_{t,s}^{T,SS} (sofd_{t,s} * sd_{t,s} - sofc_{t,s} * sc_{t,s}) \\
&\quad + \sum_{t,g \in GUC}^{T,GC} SC_g * gup_{t,g} + \sum_{t,g \in GUC}^{T,GC} NLC_g * gopstat_{t,g} \\
&\quad = \sum_{t,s}^{T,S} DMAX_s * CMAX_s * (-\gamma_{t,s}) + \sum_{t,s}^{T,S} SMAX_s * (-\nu_{t,s}) \\
&\quad + \sum_{s}^{S} SMAX_s * (-\xi_{t,s}) + \sum_{t,l}^{T,L} TTCAP_{t,l} * (-\mu_{t,l}^{max}) + \sum_{t,l}^{T,L} TFCAP_{t,l} * \mu_{t,l}^{min} \\
&\quad + \sum_{t,z}^{T,Z} VMAX_z * (-\psi_{t,z}^{max}) + \sum_{t,z}^{T,Z} VMIN_z * \psi_{t,z}^{min} + \sum_{t,z}^{T,Z} L_{t,z} * \lambda_{t,z} \\
&\quad + \sum_{t,g,gs}^{T,G,GS} CAP_{t,g} * SA_{t,g} * GSL_{g,gs} * (-\varphi_{t,g,gs}^{max}) \\
&\quad + \sum_{t,g}^{T,G} CAP_{t,g} * SA_{t,g} * (-\omega_{t,g,gs}^{max})
\end{aligned} \tag{A.58}$$

Using eq. (A.29), (A.32), and (A.33) to substitute for generator and storage offer-related decision variables and reformulate the primal objective in (A.58), as well as (A.5) to set $go_{t,g} = 0 \; \forall g \in GC \cap GNUC$, the dual and primal objectives are equivalent to

$$\begin{aligned}
&\sum_{t,g,gs}^{T,GUC,GS} \left(\lambda_{t,z==ZL_g} - \phi_{t,g}^{max} + \phi_{t,g}^{min} - \varphi_{t,g,gs}^{max} + \varphi_{t,g,gs}^{min} - \sigma_{t,g}^{up} + \sigma_{t,g}^{down}\right) * gsd_{t,g,gs} \\
&\quad + \sum_{t,g}^{T,GNUC} (\lambda_{t,z==ZL_g} - \omega_{t,g}^{max} + \omega_{t,g}^{min}) * nucgd_{t,g} + \sum_{t,g \in GUC}^{T,GC} SC_g * gup_{t,g} \\
&\quad + \sum_{t,g \in GUC}^{T,GC} NLC_g * gopstat_{t,g} \\
&\quad + \sum_{t,s \in SS}^{T,S} \left(\lambda_{t,z==SZL_s} - CMAX_s * \gamma_{t,s} + \beta_{t,s} - DE_s * (\chi_s - \sum_{t}^{t,\dots N_T} \nu_{t,s}^{max} - \nu_{t,s}^{min}) \right. \\
&\quad \left. - \xi_s \right) * sd_{t,s} \\
&\quad + \sum_{t,s \in SS}^{T,S} \left(-\lambda_{t,z==SZL_s} - DMAX_s * \gamma_{t,s} + \alpha_{t,s} + CE_s * (\chi_s \right. \\
&\quad \left. - \sum_{t}^{t,\dots N_T} \nu_{t,s}^{max} - \nu_{t,s}^{min}) \right) * sc_{t,s}
\end{aligned} \tag{A.59}$$

This allows us to set the dual objective from (A.58) equal to (A.59). Then, rearrange by moving all linear terms to the left hand (dual objective) side of the equation.

$$\sum_{t,s}^{T,S} DMAX_s * CMAX_s * (-\gamma_{t,s}) + \sum_{t,s}^{T,S} SMAX_s * (-\nu_{t,s}) + \sum_{s}^{S} SMAX_s * (-\xi_{t,s})$$
$$+ \sum_{t,l}^{T,L} TTCAP_{t,l} * (-\mu_{t,l}^{max}) + \sum_{t,l}^{T,L} TFCAP_{t,l} * \mu_{t,l}^{min}$$
$$+ \sum_{t,z}^{T,Z} VMAX_z * (-\psi_{t,z}^{max}) + \sum_{t,z}^{T,Z} VMIN_z * \psi_{t,z}^{min} + \sum_{t,z}^{T,Z} L_{t,z} * \lambda_{t,z}$$
$$+ \sum_{t,g,gs}^{T,G,GS} CAP_{t,g} * SA_{t,g} * GSL_{g,gs} * (-\varphi_{t,g,gs}^{max})$$
$$+ \sum_{t,g}^{T,G} CAP_{t,g} * SA_{t,g} * (-\omega_{t,g,gs}^{max}) - \sum_{t,g\in GUC}^{T,GC} SC_g * gup_{t,g}$$
$$- \sum_{t,g\in GUC}^{T,GC} NLC_g * gopstat_{t,g}$$
$$= \sum_{t,g,gs}^{T,GUC,GS} \left(\lambda_{t,z==ZL_g} - \phi_{t,g}^{max} + \phi_{t,g}^{min} - \varphi_{t,g,gs}^{max} + \varphi_{t,g,gs}^{min} - \sigma_{t,g}^{up} + \sigma_{t,g}^{down}\right) \tag{A.60}$$
$$* gsd_{t,g,gs} + \sum_{t,g}^{T,GNUC} (\lambda_{t,z==ZL_g} - \omega_{t,g}^{max} + \omega_{t,g}^{min}) * nucgd_{t,g}$$
$$+ \sum_{t,s\in SS}^{T,S} \Bigg(\lambda_{t,z==SZL_s} - CMAX_s * \gamma_{t,s} + \beta_{t,s} + DE_s * (\chi_s$$
$$- \sum_{t}^{t,\ldots N_T} \nu_{t,s}^{max} - \nu_{t,s}^{min}) - \xi_s\Bigg) * sd_{t,s}$$
$$+ \sum_{t,s\in SS}^{T,S} \Bigg(-\lambda_{t,z==SZL_s} - DMAX_s * \gamma_{t,s} + \alpha_{t,s} + CE_s * (\chi_s$$
$$- \sum_{t}^{t,\ldots N_T} \nu_{t,s}^{max} - \nu_{t,s}^{min})\Bigg) * sc_{t,s}$$

The relationship between the right hand side of (A.60) and the upper level objective (A.1B) can then be more straightfowardly seen after grouping the right hand side LMP-related terms, though showing this step is omitted. The remaining task is to substitute for the nonlinear, non-LMP related terms on the right hand side (e.g., $\phi_{t,g}^{min} * gsd_{t,g,gs}$) using complementarity relationships for the decision variables in (A.40)-(A.57), removing terms equal to zero, and cancelling resulting non-zero terms with left hand side terms where equivalent. The indexing of the right hand side across only strategic generators means, generally, strategic terms cancel and non-strategic generator and storage terms remain in the resulting objective. Finally, the generator marginal cost-related term is subtracted from both sides of the equation so the right hand side reproduces eq. (A.1B).

$$\begin{aligned}
&\sum_{t,z}^{T,Z} L_{t,z} * \lambda_{t,z} - \sum_{t,g\in GUC,gs}^{T,GNC,GS} CAP_{t,g} * SA_{t,g} * GSL_{g,gs} * \varphi_{t,g,gs}^{max} \\
&\quad - \sum_{t,g\in GUC}^{T,GNC} CAP_{t,g} * SA_{t,g} * \phi_{t,g}^{max} - \sum_{t,g\in GNUC}^{T,GNC} CAP_{t,g} * SA_{t,g} * (\omega_{t,g,gs}^{max}) \\
&\quad - \sum_{t,g\in GUC,gs}^{T,G,GS} GMC_{g,gs} * gsd_{t,g,gs} - \sum_{t,g\in GUC}^{T,G} SC_g * gup_{t,g} \\
&\quad - \sum_{t,g\in GUC}^{T,G} NLC_g * gopstat_{t,g} \\
&\quad + \sum_{t,s\in NSS}^{T,S} (-\gamma_{t,s} * DMAX_s * CMAX_s - \nu_{t,s}^{max} * SMAX_s) - \sum_{s\in NSS}^{S} (\xi_t * SMAX_s) \\
&\quad = [\sum_{t,g\in guc,z==ZL_g}^{T,GC} gd_{t,g} + \sum_{t,g\in GNC,z==ZL_g}^{T,GC} nucgd_{t,g} + \sum_{t,s,z==ZLS_s}^{T,SS} (sd_{t,s} - sc_{t,s})] \\
&\quad * \lambda_{t,z} - \sum_{t,g\in GUC,gs}^{T,GC,GS} GMC_{g,gs} * gsd_{t,g,gs} - \sum_{t,g\in GUC}^{T,GC} SC_g * gup_{t,g} \\
&\quad - \sum_{t,g\in GUC}^{T,GC} NLC_g * gopstat_{t,g}
\end{aligned} \tag{A.61}$$

The result is a linear left hand side of the equation equivalent to the original nonlinear objective. The left hand side of eq. (A.61) may now be used as a linear objective for solving the MILP.

Last, the complementarity constraints must be linearized. This can be done using the so-called “Big-M“ method first described by Fortuny-Amat and McCarl (Fortuny-Amat and McCarl 1981). This approach rewrites a complementarity constraint of the form $0 \leq u_i \perp h_i(x) \geq 0$ as a set of two constraints, $0 \leq u_i \leq M(1 - \nu_i)$ and $0 \leq h_i(x) \leq M * \nu_i$, where *M* is a large enough constant to balance not limiting the feasible space of the problem[5] and ν_i is an auxiliary binary variable. Note the use of the binary variable linking the constraints means at least one of the two constraints must be equivalent to zero, thus satisfying the original complementary slackness condition. The rewritten transformations of each complementarity constraint are not included but can be provided on request. These transformations are automatically undertaken in the model code by use of the big-M implementation in Pyomo's generalized disjunctive programming library.

The creation of a set of auxiliary binary variables for each constraint reformulation, along with the linearization of the objective, means the problem is now a MILP and can be readily solved by commercial solvers like CPLEX.

B Additional Data Description

B.1 Two-settlement functionality

We simplify two common aspects of two-settlement markets due to computational and data limitations and to better compare DA and RT results in cases incorporating uncertainty. First, DA and RT dispatch are commonly optimized using different algorithms; in particular, DA includes binary variables for unit commitment while RT is a linear program with fixed unit commitment. In the bi-level model the market operator's problem must be convex, so both settlements are cleared with the same lower level problem formulation and exclude or linearize (Appendix A) unit commitment. Second, we maintain the same temporal co-optimization across the entire day in both DA and RT, while market operators more commonly limit co-optimized look ahead to a single five-minute RT interval. Maintaining the same temporal co-optimization allows us to better compare the optimality of fixed DA ESR dispatch quantities when settled without recourse against RT deviations in load and generation. Because of the additional computational burden of co-optimizing 288 five-minute intervals instead of 24 hourly ones we reformat five-minute RT VRE generation and load data to hourly average equivalents and clear the RT market at hourly resolution. The primary purpose of these simplifications is to make DA

[5] If M is too large this can unnecessarily extend the feasible space and increase solution time, so choosing a value for M is something of an art; most values are 5000 in our implementation, reflecting upward limits on generator offers well in excess of the assumed $2000/MWh bid cap.

and RT settlements more comparable for incorporating uncertainty in load, wind, and solar generation in sensitivity analysis.

B.2 RTS-GMLC Generator Offer Data

Table B-1: Generator location, capacity, and offer data used in all cases

BusID	Group	Capacity (MW)	Type	Units	Bid Segments	Bid Capacities (MW)	Marginal Costs ($/MWh)
301	U20	20	Oil CT	2	4	8, 4, 4, 4	$87.26, $87.26, $99.7, $105.37
301	U55	55	Gas CT	2	4	22, 11, 11, 11	$28.47, $28.47, $29.29, $43.74
302	U20	20	Oil CT	2	4	8, 4, 4, 4	$87.26, $87.26, $99.7, $105.37
302	U55	55	Gas CT	2	4	22, 11, 11, 11	$33.79, $33.79, $38.38, $38.64
307	U55	55	Gas CT	2	4	22, 11, 11, 11	$27.89, $27.89, $29.22, $35.47
313	U355	355	Gas CC	1	4	170, 61.67, 61.67, 61.67	$15.73, $15.73, $26.76, $33.75
315	U12	12	Oil ST	5	4	5, 2.33, 2.33, 2.33	$75.44, $75.44, $100.4, $124.1
315	U55	55	Gas CT	3	4	22, 11, 11, 11	$26.4, $26.4, $26.9, $31.86
316	U155	155	Coal	1	4	62, 31, 31, 31	$21.12, $21.12, $21.29, $27.27
318	U355	355	Gas CC	1	4	170, 61.67, 61.67, 61.67	$26.85, $26.85, $27.28, $31.53
321	U355	355	Gas CC	1	4	170, 61.67, 61.67, 61.67	$22.73, $22.73, $25.91, $33.95
322	U55	55	Gas CT	2	4	22, 11, 11, 11	$23.33, $23.33, $26.5, $27.89
323	U355	355	Gas CC	2	4	170, 61.67, 61.67, 61.67	$26.43, $26.43, $30.28, $31.73
303	WIND	847	Solar RTPV	1	1	As available	$0
308	RTPV	100.9	Solar RTPV	1	1	As available	$0
309	WIND	148.3	Wind	1	1	As available	$0
310	PV	103.3	Solar PV	1	1	As available	$0
312	PV	189.2	Solar PV	1	1	As available	$0
313	PV	93.3	Solar PV	1	1	As available	$0
313	RTPV	806	Solar RTPV	1	1	As available	$0
314	PV	144.3	Solar PV	1	1	As available	$0
317	WIND	799.1	Wind	1	1	As available	$0
319	PV	188.2	Solar PV	1	1	As available	$0
320	PV	51.6	Solar PV	1	1	As available	$0
320	RTPV	120.2	Solar RTPV	1	1	As available	$0
322	U50	50	Hydro	1	1	As available	$0
324	PV	152.3	Solar PV	1	1	As available	$0

While the supply curve will change based on generation availability even when all generators offer at marginal cost, and congestion may result in different online generators and marginal cost than suggested by intersecting a single supply and demand curve, Fig. B-1 constructs an average supply curve for the modeled month and compares to average and peak demand.

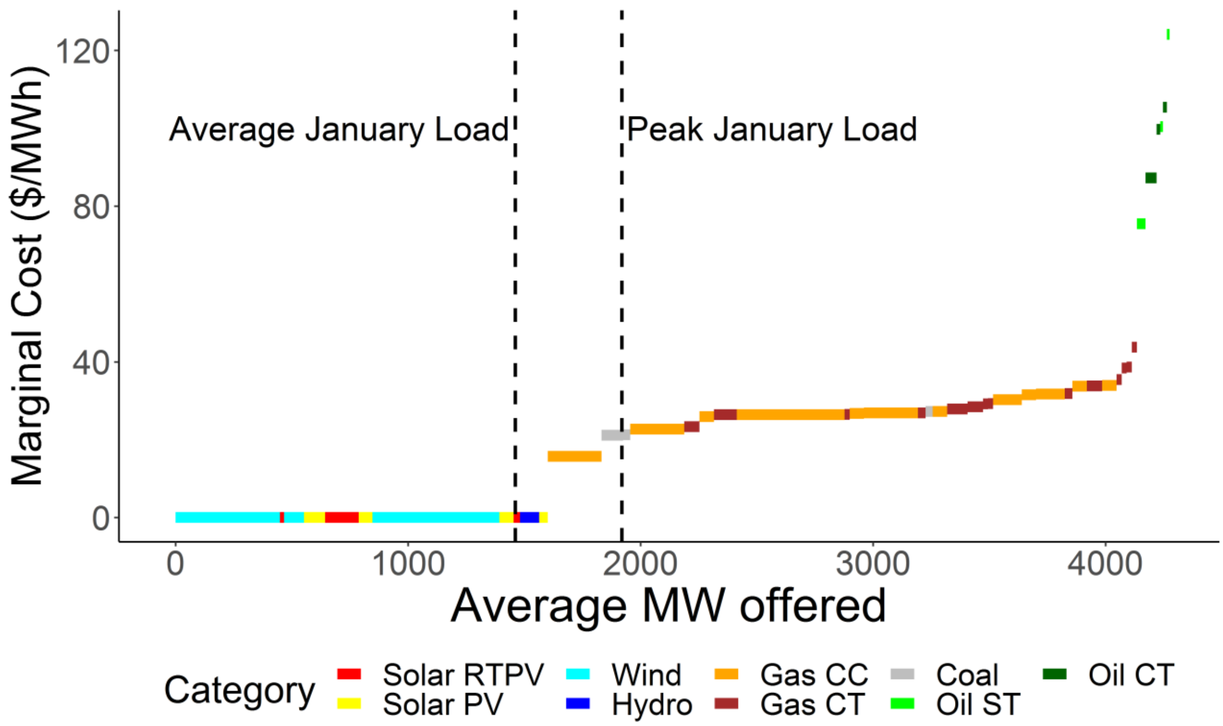

Fig. B-1: January supply curve. Variable renewable energy resources displayed at average hourly generation for the month. Supply curve ignores congestion and curtailment.

B.3 LMPs for all 25 buses in case without storage

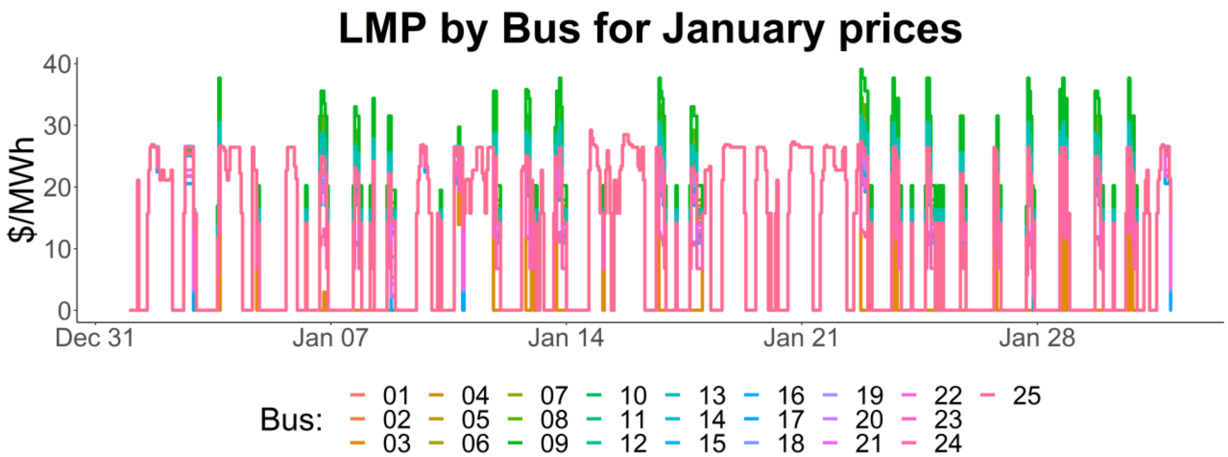

Fig. B-2: LMP at all 25 buses.

B.4 Load and Renewable Generation Day-Ahead Forecast Error Empirical Distributions

The model uses DA RTS-GMLC data to settle the forward market and RT RTS-GMLC data to settle the operational balancing market. Changes in dispatch and pricing result from deviations in RT data from DA expectations, termed forecast error, for load, solar PV, solar rooftop PV (RTPV), and wind resources. As a result, load net of PV and wind, defined as net load, shows the summed deviation of all forecast errors and is also included in the empirical distribution of forecast errors for the modeled month shown in Fig. B-3.

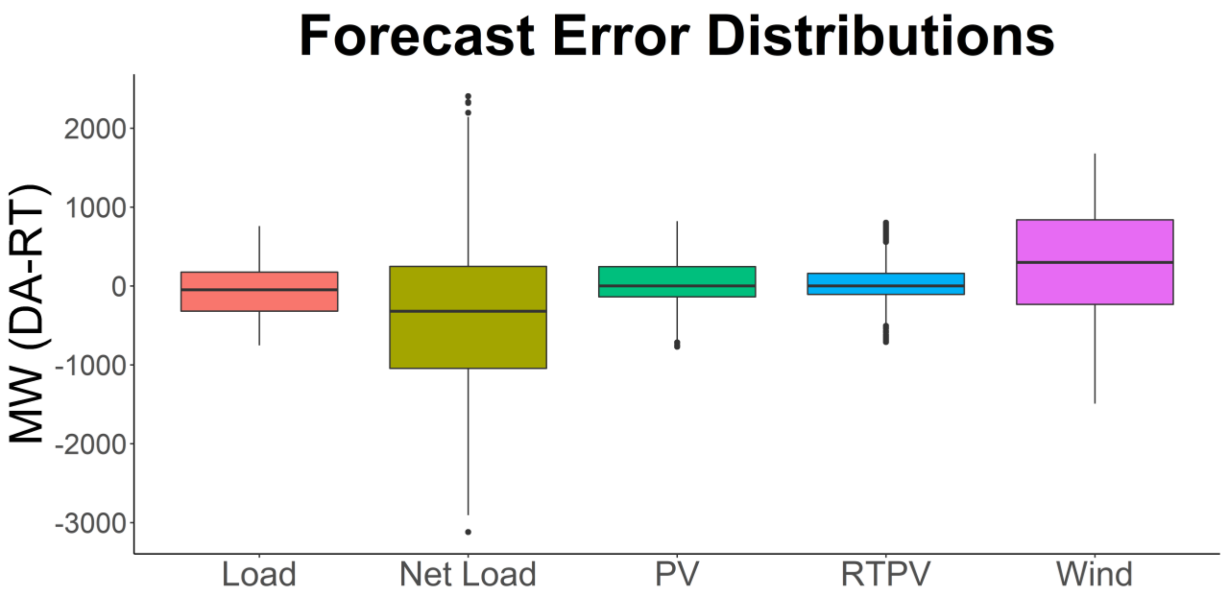

Fig. B-3: Distribution of differences between hourly DA forecast and RT actuals of renewable generation by type (solar PV, solar rooftop PV, Wind) and load in MW for the Zone 3 RTS-GMLC test system. Net load is load net of VRE (i.e., wind and solar PV, including rooftop PV).

B.5 Additional information on Results Section 4.1 Demonstrating the Three Strategies

In case A (ESR only,

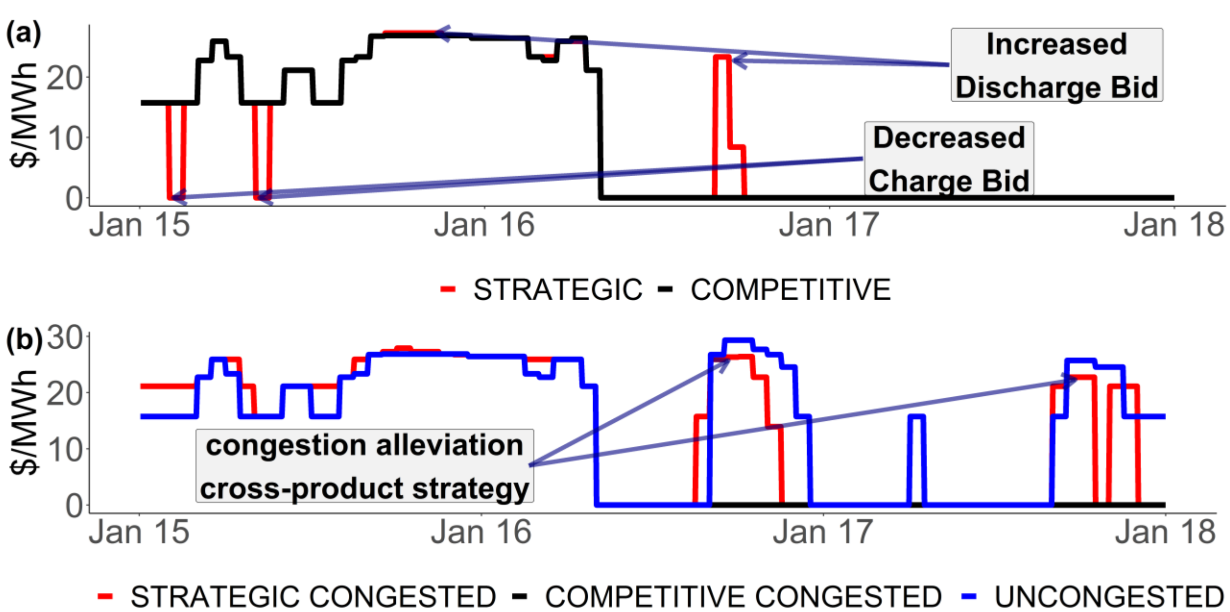

Fig. **4**) the strategic entity owns only the 300MW/900MWh ESR. It implements two strategies to increase its profit: increasing the applicable LMP at its bus when discharging, and decreasing the

LMP at its bus when charging. Full results are shown in Table B-2 to break out additional profits earned by the strategic entity and its effect on payments for serving firm load compared to the competitive case.

Table B-2: Case A (ESR Only) results for month of January. Changes are shown in red to indicate increased costs to consumers and in green to indicate increased profit for the strategic entity

A: Category	B: Competitive	C: Strategic	D: Change
1: Load Payments[6] ($M)	$5.223	$5.259	**+0.7%**
2: Storage Charging Cost ($M)	-$.048	-$.039	**-18.8%**
3: Storage Discharging Revenue ($M)	$.355	$.399	**+12.4%**
4: Storage Profit ($M)	$\pi^{p,NSS} = \$.306$	$\pi^{p,SS} = \$.360$	$\Delta\pi^p = \$.056$, **+17.6%**
5: Storage Profit ($/MWh discharged)	$\frac{\pi^{p,NSS}}{\sum sd^S}$=$9.9	$\frac{\pi^{p,SS}}{\sum sd^S}$=$11.6	$\frac{\Delta\pi^p}{MWh}$=$1.7, **+17.6%**

The strategies employed in case A (ESR Only) achieve additional profit when the ESR is pivotal: the inclusion of its charging load or discharging generation changes which generator(s) is/are[7] marginal and set price at bus 03. By adjusting its ESR bid the strategic entity can increase or decrease the cost of marginal supply at the cleared quantity of generation.

Case B extends case A by including the large (847 MW) wind generator at bus 03 in the strategic entity's portfolio ("ESR+Wind"). The strategic objective is to maximize the joint profits of the wind and ESR by modifying ESR bids; wind is constrained to offer at no more than its $0/MWh marginal cost. There is often congestion on a transmission line interconnecting bus 03 to the rest of the system (Fig. 3) due to the large amount of zero marginal cost wind generation in many hours relative to available transmission capacity. Because of the prevalent congestion, the ESR can be used by a strategic entity when pivotal to alleviate congestion and increase price at bus 03. When wind generation exceeds additional ESR charging load the ability to increase price

[6] Load payments are calculated as the inner product of bus clearing price and bus load

[7] When the system is congested there may be more than one marginal generator; equivalently, how clearing prices change depends on where load is added to the system.

is a profitable cross-product strategy. Notably, since co-locating of ESRs with VRE is often suggested as a welfare-improving strategy due to reduction in curtailment and increased deliverability of low-cost and low-emission VRE (Root *et al* 2017, Denholm and Mai 2019, Alanazi and Khodaei 2018) or to take advantage of incentives for ESR charging from VRE like the Investment Tax Credit (Gorman *et al* 2020), Table B-3 shows that at least some of this welfare for a given co-located ESR installation[8] could be absorbed by strategic bidding.

Table B-3: Case B (ESR+Wind) profits for month of January.

A: Category	B: Competitive	C: Strategic	D: Change
1: Load Payments ($M)	$5.223	$5.369	**+2.8%**
2: Storage Profit ($M)	$.306	$.040	**-86.9%**
3: Storage Profit ($/MWh discharged)	$9.9	$1.4	**-86.9%**
4: Wind Profit ($M)	$0.751	$2.002	**+166.6%**
5: Incremental Profit Associated with Storage Ownership ($M)	$\pi^{p,NSS}$ =$.306	$\Delta\pi^{p}$=$1.292	**+368.7%**
6: Incremental Profit Associated with Storage Ownership ($/MWh discharged)	$\frac{\pi^{p,NSS}}{\sum sd^{S}}$=$9.9	$\frac{\pi^{p,SS}}{\sum sd^{S}}$=$46.3	**+368.7%**

B.6 Additional information on Results Section 4.2

The sensitivity analysis in Fig. 6 shows that under the perfect foresight assumption additional ESR capacity and duration have declining marginal value, as seen in the decreasing monthly incremental profit. Increased capacity has more effect than increased duration on total profits, suggesting the ability to offer more capacity in a single time period is a larger contributor to perfect foresight ESR profits than how often an offered quantity can be accepted and dispatched. Profits do not scale linearly with capacity as the quantity offer need to be pivotal and change clearing price in a given time period will be system dependent, particularly in the presence of congestion.

Fig. 7 compares hybrid and co-located profits. Hybrid profits are higher because of additional assumed ability to submit a higher bid incorporating the wind with the ESR offer as a hybrid. Importantly, in practice different bidding rules can be applied to different types of

[8] The installation of the ESR may still be welfare improving compared to a no-ESR system even with strategic bidding, but we do not investigate investment decision-making.

resources. For example, section 4.4.9.3 of the Electricity Reliability Council of Texas' (ERCOT) December 2020 nodal protocols (ERCOT 2020) only allows generators to update energy offer curves prior to an operating hour, but specifically provides a carve out for ESRs to update offers until any time prior to intra-hourly RT Security Constrained Economic Dispatch (SCED), giving ESRs additional offering latitude.[9] Market operators and monitors should think carefully about whether hybridization allows additional bidding latitude not usually afforded to one of the hybridized resources individually.

B.7 Additional information on Results Section 4.3

To investigate incorporation of uncertainty the model is configured to run as two temporally sequential settlements. The settlements can be conceived as a financial forward market where entities submit bids, and real-time operational market where bids are fixed and any deviations from the forward market are settled. The setup is similar to two-settlement day-ahead and real-time wholesale market settlement periods in North American markets, with the additional assumptions that the market operator clears the market using the same algorithm for the same temporal resolution at each settlement interval[10] and ignoring financial products (e.g., virtual bidding).

Maintaining strategic profits under uncertainty is a delicate balance. If an offer expected to change the clearing price does not, the strategic entity makes no additional profit and may lose profit compared to market operator dispatch if the ESR is charged or discharged with non-zero opportunity cost compared to dispatch in alternative time periods. Because of this reality and fact that the congestion alleviation strategy depends on supplying an appropriate quantity of ESR charge or discharge to the market to change clearing price and increase wind revenue, we implement the following assumptions and strategy:

1. The strategic entity is assumed to have perfect foresight of the forward DA market (equivalently, it could update its forward offers prior to real-time based on full knowledge of how changing offers would change the forward market clearing).

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[9] Nodal Protocol Revision Request 1058 would update language to allow all generators to update energy offer curves at any time prior to RT SCED, and is available online at http://www.ercot.com/mktrules/issues/NPRR1058#keydocs

[10] Day-ahead markets are commonly cleared for the full day at hourly resolution and incorporate unit commitment, while real-time markets are cleared at 5-minute resolution with more limited forward temporal co-optimization and assume fixed unit commitment, eliminating binary decision variables.

2. The strategic entity has perfect foresight of its own wind generation in RT, but otherwise does not update its DA expectation of other loads and generation.
3. The strategic entity knows which of its DA offers changed prices. It self-dispatches exactly that DA optimal quantity in the RT market if it has sufficient wind generation (>300 MW ESR installed capacity in modeled case case) to ensure a price-setting offer will still increase joint profits.
4. The market operator dispatches any ESR capacity not self-dispatched to minimize production costs, subject to cycling constraints.

Taken together, this heuristic enables increased focus on pivotal hours under uncertainty, but is not an upper bound on strategic profits under uncertainty. A strategic entity with a more accurate updated forecast for load and generation in RT than simply maintaining its DA forecast would do better in our model. This strategy is reflected mathematically in the implemented constraints in Appendix A reproduced below.

$sd_{t,s} == DDA_{t,s}, (\forall t \vert DDA_{t,s} > 0, CAPA_{t,g}^{RT} \geq DMAX_s, \Delta\lambda_{t,z==SZL_s}^{DA} > 0)$	Real-time storage discharge is equivalent to DA discharge in time periods with pivotal DA dispatch and sufficient RT strategic wind generation	(B.1)
$sc_{t,s} == CDA_{t,s}, (\forall t \vert CDA_{t,s} > 0, CAPA_{t,g}^{RT} \geq CMAX_s, \Delta\lambda_{t,z==SZL_s}^{DA} > 0)$	Real-time storage charge is equivalent to DA charge in time periods with pivotal DA dispatch and sufficient RT strategic wind generation	(B.2)

Results compare the profit earned by the DA optimized bids fixed in the real-time balancing market to the perfect information real-time strategy as well as a fully competitive approach where the strategic entity offers at marginal cost. Results comparing these three strategies for Section 4.1's Case B parameterization for the same month of data are shown in Fig. 8.

C Mathematical exposition on ESR offers

C.1 Example derivation

To show ESRs face different constraints relevant to offer mitigation, consider the two time period (indexed by $t\epsilon\{1,2\}$) dispatch cost minimization problem in eq. (C.1-C.8). The market operator's objective in this problem is to minimize the costs of serving residual demands D_t using a generator *G* and an ESR *S*. For simplicity assume the ESR enters the two time periods fully charged at state of charge *SOC* and has sufficient capacity to fully discharge in either time period. To reduce constraints in the problem assume non-negative output from *G* is unbounded but comes at constant costs C_1 and C_2 per unit of output in each of the two time periods. Generation from *G* is denoted g_t, from *S* by sd_t, offers from *S* are denoted sd_t, and applicable dual variables for each constraint follow the colon in eq. (C.3-C.8). The two time period problem is formulated:

$$\min_{g_1, g_2, sd_1, sd_1} C_1 g_1 + C_2 g_2 + SO_1 sd_1 + SO_2 sd_2 \tag{C.1}$$

$$\text{Such that } D_1 = g_1 + sd_1 : \lambda_1 \tag{C.2}$$

$$D_2 = g_2 + sd_2 : \lambda_2 \tag{C.3}$$

$$g_1 \geq 0 : \phi_1 \tag{C.4}$$

$$g_2 \geq 0 : \phi_2 \tag{C.5}$$

$$sd_1 \geq 0 : \alpha_1 \tag{C.6}$$

$$sd_2 \geq 0 : \alpha_2 \tag{C.7}$$

$$SOC \geq sd_1 + sd_2 : \eta \tag{C.8}$$

Note that eq. (C.8) assumes the market operator will monitor SOC in formulating its problem. The monitored SOC assumption may not hold in frameworks allowing self-monitoring SOC for ESR and hybrid market participation (Gorman *et al* 2020). The Lagrangian for the two time period problem is:

$$\begin{gathered} L(\boldsymbol{g}, \boldsymbol{sd}, \boldsymbol{\lambda}, \boldsymbol{\alpha}, \boldsymbol{\phi}, \eta) = C_1 g_1 + C_2 g_2 + SO_1 sd_1 + SO_2 sd_2 \\ -\lambda_1(g_1 + sd_1 - D_1) - \lambda_2(g_2 + sd_2 - D_2) - \phi_1 g_1 - \phi_2 g_2 \\ -\alpha_1 sd_1 - \alpha_2 sd_2 - \eta(SOC - sd_1 - sd_2) \end{gathered} \tag{C.9}$$

At the optimum the Karush-Kuhn-Tucker (KKT) conditions will hold. The KKT conditions include stationarity for primal variables in the objective, which are the generator (g_t) and storage dispatch (sd_t) in each time period. These stationarity conditions are written

$$\frac{\partial L(\boldsymbol{g}, \boldsymbol{sd}, \boldsymbol{\lambda}, \boldsymbol{\alpha}, \boldsymbol{\phi}, \eta)}{\partial g_1} = C_1 - \lambda_1 - \phi_1 = 0 \tag{C.10}$$

$$\frac{\partial L(\boldsymbol{g}, \boldsymbol{sd}, \boldsymbol{\lambda}, \boldsymbol{\alpha}, \boldsymbol{\phi}, \eta)}{\partial g_2} = C_2 - \lambda_2 - \phi_2 = 0 \tag{C.11}$$

$$\frac{\partial L(\boldsymbol{g}, \boldsymbol{sd}, \boldsymbol{\lambda}, \boldsymbol{\alpha}, \boldsymbol{\phi}, \eta)}{\partial sd_1} = SO_1 - \lambda_1 - \alpha_1 + \eta = 0 \tag{C.12}$$

$$\frac{\partial L(\boldsymbol{g}, \boldsymbol{sd}, \boldsymbol{\lambda}, \boldsymbol{\alpha}, \boldsymbol{\phi}, \eta)}{\partial sd_2} = SO_2 - \lambda_2 - \alpha_2 + \eta = 0 \tag{C.13}$$

The two generator-related stationarity conditions have no shared decision variables, and, when combined with the complementary slackness conditions for the inequalities (C.4) and

(C.5), can be used to show G will set a non-zero price $C_t = \lambda_t$ in either time period if dispatched. However, the same does not hold for the ESR stationarity conditions, which both contain the SOC dual variable η and can be substituted and rewritten

$$SO_2 - SO_1 - \lambda_2 + \lambda_1 - \alpha_2 + \alpha_1 = 0 \tag{C.14}$$

Eq. (C.14) itself provides the critical insight: the effect of ESR offers on clearing prices λ_t in all time periods is a function of the relative storage offers SO_t in each time period. When pivotal the ESR can make use of this fact to change its dispatch, and thus pricing, based on its relative offers, even when its absolute offers are constrained to be inframarginal ($C_t > SO_t$) in all time periods.

Under the additional assumptions the ESR is a pivotal supplier in each hour individually ($D_t < SOC$) but not both hours jointly ($\sum D_t > SOC$), we can show the minimum revenues π^{ESR} accrued assuming an inframarginal non-negative ESR offer ($C_t > SO_t \geq 0$) in both hours are:

$$\min \pi^{ESR} = \begin{cases} (SOC - D_1)C_2, & SO_2 - SO_1 > C_2 - C_1 \\ (SOC - D_2)C_1, & SO_2 - SO_1 < C_2 - C_1 \end{cases} \tag{C.15}$$

The proof of this result using the above assumptions and problem defined in Eq. (C.1)-(C.8) as well as an explanation of the solution(s) when $SO_2 - SO_1 = C_2 - C_1$ is in Appendix C.2. An example suffices to show there exists practical relevance. Assume $SOC = 50, D_1 = 10, D_2 = 45, C_1 = 20, C_2 = 25$. Under these conditions if the ESR offers its full quantity $SOC = 50$ to the market without a price offer (equivalently, $SO_2 = SO_1 = 0$), the market operator will minimize dispatch costs by using as much of the ESR as feasible in the higher cost time period 2, and use the remainder in time period 1, so $\{sd_1^*, sd_2^*, g_1^*, g_2^*\} = \{5, 45, 5, 0\}$ and the objective value using Eq. (3) is 100. Price is set by G at 20 in time period 1, so ESR revenues are at least $\lambda_1^* sd_1^* = 20 * 5 = 100$. However, by filling in eq. (C.15) for the assumed parameterization:

$$\min \pi^{ESR} = \begin{cases} 1000, & SO_2 - SO_1 > 5 \\ \ \ 100, & SO_2 - SO_1 < 5 \end{cases} \tag{C.16}$$

1000 is greater than 100, so the ESR can guarantee a greater minimum profit by offering $SO_2 - SO_1 > 5$. Because achieving this profit depends on the relative ESR offers, whether ESR offers are capped based on an ex-ante maximum is irrelevant to the profits in eq. (C.16): so long as the range of allowable offers exceeds 5 the ESR can guarantee the higher minimum revenue by offering $SO_2 - SO_1 > 5$. The dispatch assuming this offer is $\{sd_1^*, sd_2^*, g_1^*, g_2^*\} = \{10, 40, 0,5\}$, with the minimum payments for dispatching *G* now being 5*25=125, greater than the optimal value of 100 when the ESR did not make a price offer.[11] The difference $SO_2 - SO_1 > 5$ in the offers makes the market operator perceive ESR dispatch is more valuable in time period 1 than time period 2, so using as much ESR as feasible under SOC and demand constraints in time period 1 minimizes the perceived total dispatch cost objective. Assuming perfect information a pivotal ESR supplier can exploit this fact by submitting appropriate temporally differentiated offers to change optimal dispatch and pricing.

C.2 Derivation with additional assumptions

Assume as in Appendix B that a ESR enters a two time period model with full state of charge *SOC* and can be discharge fully in either time period. Assume this state of charge SOC is sufficient to serve residual demand D_t in either time period individually, but not both; $SOC > D_t, SOC < \sum D_t$. Additionally, assume the ESR must offer its available discharge capability into the market at a price less than the offer of the generator *G* in either time period; $SO_t < C_t$. This last assumption guarantees the market operator will discharge the ESR within the two time period window, so Eq. (C.8) can be rewritten as the equality Eq. (C.1.9) and we have the below modifications of the model presented in Section 4.4:

Assume $SO_t < C_t, SOC > D_t, SOC < \sum D_t$	(C.1.1)
$\min\ C_1 g_1 + C_2 g_2 + SO_1 sd_1 + SO_2 sd_2$	(C.1.2)
S.T. $D_1 = g_1 + sd_1 : \lambda_1$	(C.1.3)
$D_2 = g_2 + sd_2 : \lambda_2$	(C.1.4)
$g_1 \geq 0 : \phi_1$	(C.1.5)
$g_2 \geq 0 : \phi_2$	(C.1.6)
$sd_1 \geq 0 : \alpha_2$	(C.1.7)
$sd_2 \geq 0 : \alpha_2$	(C.1.8)
$SOC = sd_1 + sd_2 : \eta$	(C.1.9)

Deriving the KKT conditions for this problem and substituting yields

$C_1 - \lambda_1 - \phi_1 = 0$	(C.1.10)
$C_2 - \lambda_2 - \phi_2 = 0$	(C.1.11)

[11] The value of the objective when $SO_2 - SO_1 > 5$ will also change based on the change in perceived costs of discharging the ESR, but for simplicity assume the actual costs of the ESR do not change, just the offer. Then the only change in actual production costs comes from the changing dispatch of the generator.

$SO_2 - SO_1 - \lambda_2 + \lambda_1 - \alpha_2 + \alpha_1 = 0$	(C.1.12)
$g_1\phi_1 = 0$	(C.1.13)
$g_2\phi_2 = 0$	(C.1.14)
$sd_1\alpha_1 = 0$	(C.1.15)
$sd_2\alpha_2 = 0$	(C.1.16)
$g_t, sd_t, \phi_t, \alpha_t \geq 0$	(C.1.17)

Using the assumptions and Eq. (C.1.3-C.1.4) offers only three feasible solutions: either $sd_1 = D_1, sd_2 = D_2$, or $sd_t < D_t$. The ESR cannot fully serve residual demand in both time periods because $SOC < \sum D_t$ and must fully discharge per eq. (C.1.9), so no other option remains. We can then proceed to solve these three cases (1)-(3) in parallel, below:

(1) $sd_1 = D_1$	(2) $sd_2 = D_2$	(3) $sd_t < D_t$	
$g_1 = 0;\ g_2 = SOC - D_1 > 0$	$g_1 = SOC - D_2 > 0;\ g_2 = 0$	$g_1 = SOC - D_2 > 0; g_2 = SOC - D_1 > 0$	(C.1.18)
$\phi_2 = 0;\ \lambda_2 = C_2$	$\phi_1 = 0;\ \lambda_1 = C_1$	$\phi_1 = 0;\ \lambda_1 = C_1$ $\phi_2 = 0;\ \lambda_2 = C_2$	(C.1.19)
$sd_t > 0;\ \alpha_t = 0$	$sd_t > 0;\ \alpha_t = 0$	$sd_t > 0;\ \alpha_t = 0$	(C.1.20)
$SO_2 - SO_1 + \lambda_1 = C_2$	$SO_2 - SO_1 - \lambda_2 = -C_1$	$SO_2 - SO_1 = C_2 - C_1$	(C.1.21)
$SO_2 - SO_1 = C_2 - C_1 + \phi_1$	$SO_2 - SO_1 = C_2 - C_1 - \phi_2$		(C.1.22)
$SO_2 - SO_1 = C_2 - C_1 + \phi_1 \geq C_2 - C_1$	$SO_2 - SO_1 = C_2 - C_1 - \phi_2 \leq C_2 - C_1$		(C.1.23)
(1)$SO_2 - SO_1 \geq C_2 - C_1$	(2)$SO_2 - SO_1 \leq C_2 - C_1$	(3)$SO_2 - SO_1 = C_2 - C_1$	(C.1.24)

As suggested by case (3) ($sd_t < D_t$), the cost-minimizing system operator will be indifferent between the dispatch solutions when $SO_2 - SO_1 = C_2 - C_1$, as they will produce equivalent as-bid total costs. We are thus left with optimal solutions for $\{sd_1^*, sd_2^*, g_1^*, g_2^*, \lambda_1^*, \lambda_2^*\}$ of:

(1) $SO_2 - SO_1 > C_2 - C_1$	(2) $SO_2 - SO_1 > C_2 - C_1$	(3) $SO_2 - SO_1 = C_2 - C_1$	
$\{sd_1^*, sd_2^*, g_1^*, g_2^*, \lambda_1^*, \lambda_2^*\} = \{D_1, SOC - D_1, 0, D_2 - SOC + D_1, SO_1, C_2\}$	$\{sd_1^*, sd_2^*, g_1^*, g_2^*, \lambda_1^*, \lambda_2^*\} = \{SOC - D_2, D_2, D_1 - SOC + D_2, 0, C_1, SO_2\}$	$\{sd_1^*, sd_2^*, g_1^*, g_2^*, \lambda_1^*, \lambda_2^*\} = \{D_1 - g_1^*, D_2 - g_2^*, D_1 - sd_1^*, D_2 - sd_2^*, C_1, C_2\}$	(C.1.25)

The profits accrued by the ESR are the dot product of the clearing price and ESR discharge in each time period; $\pi^{ESR} = \sum \lambda_t \, sd_t$. Substituting values for each of the optimal solutions from eq. (C.1.25) we have

(1) $SO_2 - SO_1 > C_2 - C_1$	(2) $SO_2 - SO_1 > C_2 - C_1$	(3) $SO_2 - SO_1 = C_2 - C_1$	
$\pi^{ESR} = \lambda_1^* sd_1^* + \lambda_2^* sd_2^*$	$\pi^{ESR} = \lambda_1^* sd_1^* + \lambda_2^* sd_2^*$	$\pi^{ESR} = \lambda_1^* sd_1^* + \lambda_2^* sd_2^*$	(C.1.26)
$\pi^{ESR} = SO_1 D_1 + (SOC - D_1) C_2$	$\pi^{ESR} = (SOC - D_2) C_1 + SO_2 D_2$	$\pi^{ESR} = C_1 sd_1^* + C_2 sd_2^*$	(C.1.27)

If we further assume for simplicity the ESR offers SO_t will not be lower than 0 and exclude the third case, we get Eq. (C.17):

$\min \pi^{ESR} = \begin{cases} (SOC - D_1) C_2, & SO_2 - SO_1 > C_2 - C_1 \\ (SOC - D_2) C_1, & SO_2 - SO_1 < C_2 - C_1 \end{cases}$	(C.1.28)