Title

Market participation strategy of hybrid energy resources: A New York ISO case study

Journal

Electric Power Systems Research, 262

ISSN

0378-7796

Authors

Bansal, Rajni Kant

Singhal, Nikita

Kemp, Julie Mulvaney

et al.

Publication Date

2027

DOI

10.1016/j.epsr.2026.113571

Electric Power Systems Research 262 (2027) 113571

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Market participation strategy of hybrid energy resources: A New York ISO case study ⋆

Rajni Kant Bansal [a,*], Nikita Singhal [b], Julie Mulvaney Kemp [c], Erik Ela [b], Miguel Heleno [d]

[a] Operations and Decision Sciences Area, Indian Institute of Management Ahmedabad, Ahmedabad, India
[b] Electric Power Research Institute, Palo Alto, USA
[c] Energy Analysis Division, Lawrence Berkeley National Laboratory, Berkeley, USA
[d] Energy Technologies and Systems Division, Lawrence Berkeley National Laboratory, Berkeley, USA

ARTICLE INFO

Keywords:
Wholesale electricity markets
Production cost model
Hybrid energy resource
Energy storage

ABSTRACT

Drawing on existing market designs with independent resource participation in electricity markets, this study analyzes participation models for hybrid resources combining renewable generation and storage. Two models are considered: in the first, the components operate independently, with the Independent System Operator (ISO) managing the storage state of charge (SoC); in the second, the hybrid resource acts as an integrated unit, submitting offers as a "black box" and managing its SoC internally. Using a production cost model for the zonal New York Bulk Power System, we evaluate trade-offs in system reliability, market efficiency, and asset profitability. Our results provide several key insights for policymakers, showing that the ISO-managed granular model enhances social welfare through explicit SoC management, while the simpler integrated model is more computationally efficient, but may cause more real-time violations and lower overall profits.

1. Introduction

The traditional electric power system is based on a supply-follows-demand model, with electricity flowing in one direction from centralized power plants to consumers [1]. However, over the past decade, the grid has undergone major changes due to the rapid growth of variable renewable energy, ambitious decarbonization goals, rising electricity demand, and accelerated adoption of new technologies. These structural shifts have made it increasingly challenging for system operators to maintain the supply-demand balance [2,3]. Specifically, the limited adaptability of demand to cheaper but variable renewable generation, combined with the unpredictability and limited controllability of renewable supply, underscores the growing need for flexibility on both the demand and supply. Hybrid energy resources, as a mixture of multiple generating technologies in a single power plant, have the technical flexibility to provide essential grid services, support system reliability, and ensure the stability of the power system [4]. These capabilities, together with recent regulatory and policy developments that enable emerging technologies to participate in wholesale electricity markets on a level playing field with conventional generators - such as FERC Orders 841, 2222, and 2023 [5–7] - are further accelerating their participation in grid operations. In particular, FERC Order No. 2023 requires transmission providers to permit the co-location of multiple generation technologies behind a single point of interconnection. Moreover, recent studies indicate that hybrid plants made up 46% *of the total generation capacity in interconnection queues* in 2024, with photovoltaic (PV) and energy storage resources (ESR) being the most common configuration [8]. Despite their potential to increase system flexibility and reduce renewable energy curtailments, the operation and regulation of hybrid resources remain complex. Their integration poses unique challenges within existing market structures. As a result, several Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) are re-evaluating participation rules to enable efficient dispatch and accurate representation of these emerging technologies in the market-clearing structure.

Although the independent participation of variable renewable energy resources (VERs) and ESRs has been widely studied, the literature remains limited in its comparison of the regulatory landscape and participation models for combined hybrid resources, and in providing comprehensive analyses of the economic benefits of operating these systems under different rules. Among the few relevant studies, Ref. [9] is perhaps most closely aligned with our work, employing a stylized framework to

⋆ This work was supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy and the Office of Electricity under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

* Corresponding author.
E-mail addresses: rajnikantb@iima.ac.in (R.K. Bansal), nsinghal@epri.com (N. Singhal), jmulvaneykemp@lbl.gov (J.M. Kemp), eela@contractor.epri.com (E. Ela), miguelheleno@lbl.gov (M. Heleno).

https://doi.org/10.1016/j.epsr.2026.113571
Received 14 October 2025; Received in revised form 11 March 2026; Accepted 21 June 2026
Available online 29 June 2026

analyze the game-theoretic behavior of hybrid resources under alternative market participation models. While offering valuable conceptual insights, this approach does not incorporate key elements of state-of-the-art market clearing, such as a unit commitment stage, transmission network representation, realistic supply-demand mixes, or increasing VER penetration. As a result, its findings cannot be readily generalized to large-scale power systems for deriving regulatory insights.

This paper addresses these shortcomings by presenting a large-scale, multi-stage, multi-cycle case study of the zonal New York Bulk Power System. The objective is to assess the participation of hybrid energy resources and to quantify associated economic and reliability metrics. The analysis focuses on resource participation in day-ahead energy markets, incorporating a real-time balancing mechanism to ensure that the impacts of forecast errors from load and VERs are realistically reflected in the results. The main contributions of this work are as follows:

- *Participation model evaluation:* We compare hybrid energy resource participation under an ISO-managed co-located model with independent resource participation and a self-managed hybrid model with integrated resource participation, to assess their roles in a large-scale power system.
- *Modeling and software enhancements:* The work incorporates software adaptations to enable market simulations and represent hybrid resource participation in wholesale electricity markets using a commercial-grade production cost modeling tool.
- *Comprehensive scenario analysis:* We simulate the model across multiple dimensions, including existing and high VER penetration, varying hybrid resource deployment levels, low and high peak demand periods, operational restrictions on grid charging, sensitivity to hybrid resource parameters, and different participation models.
- *Multi-perspective performance assessment:* Scenario results are evaluated from both the system operator and resource owner perspectives. The analysis highlights that system reliability and economic efficiency are more closely linked to the ISO-managed model, while dynamic system performance is more associated with the self-managed model.

The rest of this paper is organized as follows. Section 2 discusses the two market participation models, while Section 3 describes the New York ISO grid representation. Case study and results are provided in Sections 4 and 5, respectively. Finally, Section 6 concludes the work.

2. Electricity market participation

2.1. Model formulation

This section models the market participation of hybrid energy resources and their individual components, including stand-alone VERs and ESRs. Understanding how these resources are currently integrated into electricity market clearing processes provides critical insight into the operational challenges of hybrid configurations and the modifications required in existing market models to support them. Participation models vary in complexity and operational responsibility, depending on hybrid configurations and external factors such as implementation costs, prioritization, and computational constraints. A range of participation models could therefore be supported by system operators, while asset owners may choose the model that best aligns with their objectives, subject to system requirements. Although this study outlines the qualitative and quantitative trade-offs among various modeling approaches, it does not endorse a specific option.

2.1.1. 2R ISO-Managed co-located model (ISO-M)

In this model, each component of the hybrid resource participates independently in the market using an existing participation framework that reflects its operational characteristics, as shown in Fig. 1(a). Moreover, the system operator is responsible for optimizing the market dispatch, including the SoC of the energy storage component, and ensuring

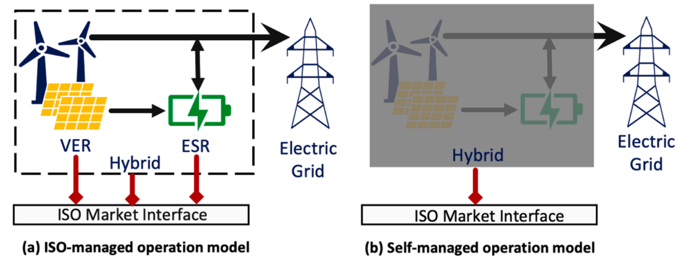

Fig. 1. Hybrid energy resource market participation models.

dispatch feasibility and overall system reliability. For each VER v, the power dispatch, upward reserve schedule, and downward reserve schedule at time t is denoted by $P_{v,t}, R^{r^+}_{v,t}, R^{r^-}_{v,t}$, subject to constraints, as:

$$P_{v,t} + \sum_{r^+\in R^+} R^{r^+}_{v,t} \le P^{forecast}_v, \; t\in\mathcal{T}, v\in\mathcal{V} \tag{1a}$$

$$P_{v,t} - \sum_{r^-\in R^-} R^{r^-}_{v,t} \ge 0, \; t\in\mathcal{T}, v\in\mathcal{V} \tag{1b}$$

$$R^{r^+}_{v,t} \ge R^{r^{\%,+}}_v P^{max}_v, \; t\in\mathcal{T}, v\in\mathcal{V}, r^+\in\mathcal{R}^+ \tag{1c}$$

$$R^{r^-}_{v,t} \ge R^{r^{\%,-}}_v P^{max}_v, \; t\in\mathcal{T}, v\in\mathcal{V}, r^-\in\mathcal{R}^- \tag{1d}$$

Here $\mathcal{R}^+, \mathcal{R}^-$ denotes the set of upward and downward reserve categories, e.g., spinning reserve, regulation reserve, etc., $\mathcal{V}$ denotes the VER set, and $\mathcal{T}$ denotes the set of time intervals. $R^{r^{\%,+}}_v, R^{r^{\%,-}}_v$ represents the reserve requirement as a fraction of the maximum power output limit denoted by $P^{\max}_v$. $P^{forecast}_v$ represents the power forecast for the VER. Eqs. (1a) and (1b) constrains the net power output, and Eqs. (1c) and (1d) restrict the reserve schedule of VERs.

Similarly, for each ESR e, we denote the discharge (charge) power at time t as $P^d_{e,t}(P^c_{e,t})$, respectively. $R^{r^+}_{e,t}, R^{r^-}_{e,t}$ represents the upward and downward reserve schedule at time t, such that,

$$P^d_{e,t} - P^c_{e,t} + \sum_{r^+\in R^+} R^{r^+}_{v,t} \le Max^d_e, \; t\in\mathcal{T}, e\in\mathcal{E} \tag{2a}$$

$$P^d_{e,t} - P^c_{e,t} - \sum_{r^-\in R^-} R^{r^-}_{v,t} \ge -Max^c_e, \; t\in\mathcal{T}, e\in\mathcal{E} \tag{2b}$$

$$P^d_{e,t} \ge 0, P^c_{e,t} \ge 0, R^{r^+}_{e,t} \ge 0, R^{r^-}_{e,t} \ge 0 \tag{2c}$$

Here Max^d_e, Max^c_e represents the maximum discharge and charge limit of energy storage $e\in\mathcal{E}$. Eqs. (2a) and (2b) constrain the maximum discharge and charge power dispatch of ESR, respectively. The initial stored energy level is:

$$SOC_{e,0} = SSOC_e, \; e\in\mathcal{E} \tag{3}$$

such that the SoC of each ESR e at the end of time $t\in\mathcal{T}$, denoted by $SOC_{e,t} \ge 0$, follows:

$$SOC_{e,t} = SOC_{e,t-1} - \frac{1}{\eta^d_e} P^d_{e,t} + \eta^c_e P^c_{e,t}, \; t\in\mathcal{T}, e\in\mathcal{E} \tag{4a}$$

$$SOC_{e,T} = TSOC_e, \; e\in\mathcal{E} \tag{4b}$$

where η^d_e, η^c_e denotes the discharge and charge efficiency, respectively. $SSOC_e$ and $TSOC_e$ represent the initial and target SoC, i.e., $SOC_{e,0}, SOC_{e,T}$ of an ESR, respectively. Finally, the SoC of ESR is subject to limits, given by:

$$SOC_{e,t} + \eta^c_e \sum_{r^-\in R^-} R^{r^-}_{esr,t} \le SOC^{max}_e, \; t\in\mathcal{T}, e\in\mathcal{E} \tag{5a}$$

$$SOC_{e,t} - \frac{1}{\eta^d_e} \sum_{r^+\in R^+} R^{r^+}_{esr,t} \ge SOC^{min}_e, \; t\in\mathcal{T}, e\in\mathcal{E} \tag{5b}$$

where $SOC^{\max}_{esr}$ and $SOC^{\min}_{esr}$ represent the maximum and minimum SoC limits, respectively. Eqs. (5a) and (5b) ensures that ESR has the capacity for any reserve requirements. However, the combined output is constrained by the interconnection limit or the capacity of the shared AC/DC inverter, such that

$$P_{v,t} + \sum_{r^+\in R^+} R^{r^+}_{v,t} + P^d_{e,t} - P^c_{e,t} + \sum_{r^+\in R^+} R^{r^+}_{e,t} \le \overline{F}_{l,t} \tag{6a}$$

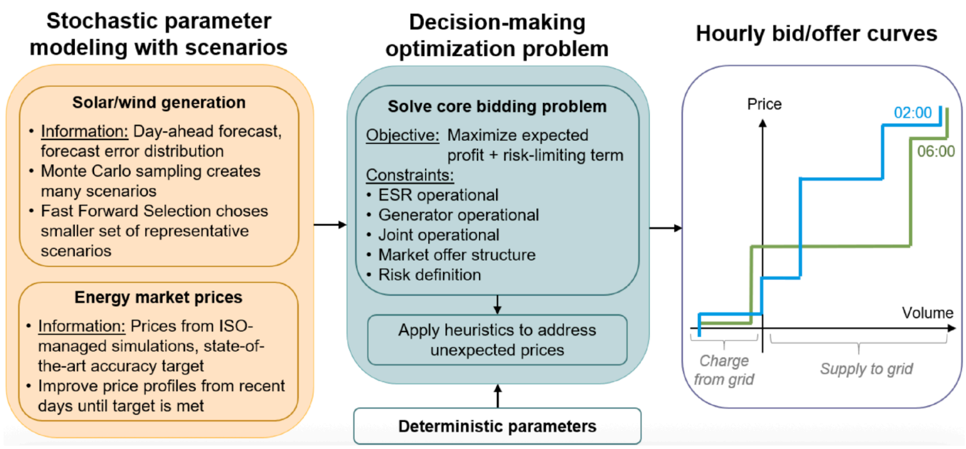

Fig. 2. Bid strategy methodology overview [10,11]. Stochastic optimization model representing hybrid resource participation in day-ahead markets, generating hourly price-quantity bids under uncertain renewable output and ISO-managed model prices. The price-taker formulation maximizes expected profit while managing risk through scenario-based uncertainty.

$$P_{v,t} - \sum_{r^- \in R^-} R^{r^-}_{v,t} + P^d_{e,t} - P^c_{e,t} - \sum_{r^- \in R^-} R^{r^-}_{e,t} \geq -\underline{F}_{l,t} \tag{6b}$$

where $\overline{F}_l$ and $\underline{F}_l$ represent the upper and lower interconnection (or inverter) limits, and $l \in \mathcal{L}$ denotes the set of transmission line constraints.

2.1.2. 1R Self-managed hybrid model (Self-M)

In this model, the hybrid energy resource participates as a single, integrated entity by submitting a set of bid or offer curves that reflect its willingness to buy and sell energy in the market, as shown in Fig. 1(b). Unlike conventional generation resources, the integrated hybrid resource can also draw power from the grid to charge its storage component. The SoC of the energy storage system is managed internally by the resource operator. The market operator does not model the internal constraints of the constituent resources nor receive real-time telemetry data, which can lead to infeasible dispatch schedules. In such cases, the resource owner is responsible for ensuring the feasibility of dispatch and maintaining operational reliability.

For each integrated hybrid resource h, we denote the discharge power, charge power, upward reserve schedule, and downward reserve schedule at time t as $P^d_{h,t}$, $P^c_{h,t}$, $R^{r^+}_{h,t}$, and $R^{r^-}_{h,t}$, respectively. The dispatch of integrated hybrid resources is subject to capacity constraints and interconnection limit or shared inverter capacity constraints, such that

$$P^d_{h,t} - P^c_{h,t} + \sum\nolimits_{r^+ \in R^+} R^{r^+}_{h,t} \leq Max^d_h, \; t \in \mathcal{T}, h \in \mathcal{H} \tag{7a}$$

$$P^d_{h,t} - P^c_{h,t} - \sum\nolimits_{r^- \in R^-} R^{r^-}_{h,t} \geq -Max^c_h, \; t \in \mathcal{T}, h \in \mathcal{H} \tag{7b}$$

$$-\underline{F}_{l,t} \leq P^d_{h,t} - P^c_{h,t} + \sum_{r^+ \in R^+} R^{r^+}_{h,t} - \sum_{r^- \in R^-} R^{r^-}_{h,t} \leq \overline{F}_{l,t}, \; t \in \mathcal{T}, h \in \mathcal{H}, l \in \mathcal{L} \tag{7c}$$

where $\mathcal{H}$ denote the set of the integrated hybrid resources. Max^d_h, Max^c_h represents the maximum discharge and charge limit of integrated resource $h \in \mathcal{H}$.

2.2. Offer curve strategy for Self-M participation model

In the Self-M model, hybrid energy resources submit integrated bids or offer curves without revealing internal constraints to the market operator. Unlike conventional generators (with fuel-based marginal costs) or VERs (typically bidding near zero), ESR bids depend on *expectations* of future prices-making them more complex to model. This study used a stochastic optimization model to generate day-ahead bids or offer curves that reflect hybrid operator behavior under uncertainty, as shown in Fig. 2.

The optimization model, described in [10] and implemented as an open-source tool in [12], generates hourly price-quantity bids or offer curves with a limited number of non-decreasing marginal price steps, which are then input to the production cost model (PCM). In the stochastic optimization model, the hybrid resource is modeled as a price-taker seeking to maximize expected operating profit while managing risk via scenario-based uncertainty in renewable generation and prices. The model uses a 48-hour horizon to better capture the opportunity cost of storage actions near the end of the day, even though only the first 24 hours of bids are submitted.

Uncertainty in hybrid resource bidding was modeled using paired scenarios for renewable generation and day-ahead prices. Generation scenarios were derived by sampling from empirical forecast error distributions around day-ahead forecasts and reduced to 20 representative cases using the Fast Forward Selection algorithm [13]. A probability of 0.8 was assigned to the forecast and 0.2 to the sampled scenarios.

Price scenarios for the hybrid resource's expected profit-maximization model were derived from a reference price signal obtained from prior ISO-M PCM simulations. These reference prices were simulated for an additional prior month to provide sufficient data for scenario generation. The prices served as a baseline around which statistical perturbations were applied to construct forecast scenarios. The scenarios are iteratively adjusted to achieve a weighted mean absolute error (WMAE) of approximately 5%, consistent with current forecasting standards [14,15]. A symmetric scenario tree paired each generation scenario with each price scenario, with joint probabilities determined by the generation scenario probabilities.

Within each scenario, the stochastic program co-optimizes renewable dispatch, storage charging and discharging, and state-of-charge evolution subject to efficiency losses, power limits, and intertemporal energy-balance constraints. The solution produces scenario-specific operating schedules that reflect how a profit-maximizing hybrid operator would respond to uncertain prices and renewable output over the 48-hour horizon. These schedules provide a high-resolution mapping between simulated market prices and optimal net injections (charge or discharge), but this raw output is not directly compatible with market bidding formats.

To construct implementable offers, the simulated operating points are post-processed into a limited number of bid segments using a Jenks natural-breaks clustering procedure. This method groups hours with similar behavior while minimizing within-segment variance, thereby reducing the stochastic solution to a small set of representative price-quantity blocks. The clustering step serves as a dimensionality-reduction bridge between the detailed optimization model and ISO bidding requirements, producing monotonic block offers that preserve the under-

Table 1
Values for selecting SoC-dependent bid or offer curve sets.

Initial SoC (%)	2.5	12.5	30	50	70	87.5	97.5
Band (%)	[0, 5]	(5, 20]	(20, 40]	(40, 60]	(60, 80]	(80, 95]	(95, 100]

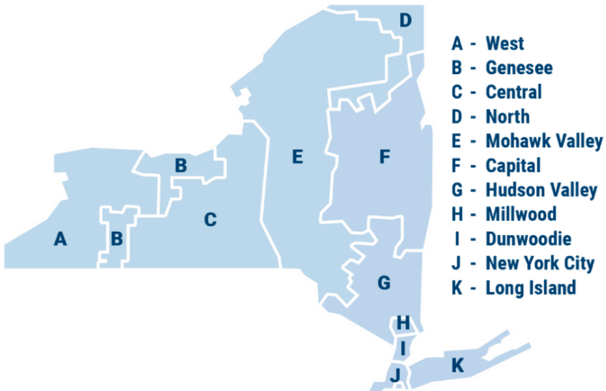

Fig. 3. New York control area load zones [16].

lying operational value signal while satisfying market rules for non-decreasing bid curves. The resulting hourly price-quantity blocks are submitted to the PCM as the hybrid resource's day-ahead bids or offer curves, as illustrated in Fig. 2.

Since the ESR's SoC is known or can be accurately estimated at the start of each day, but PCMs typically do not support multi-day co-simulation of SoC and bidding logic, this study precomputed bids or offer curves for a set of initial SoC levels. The PCM selects the appropriate bid or offer curve each day based on the previous day's simulated end of day SoC, with bands defined to cover the full SoC range and narrower intervals near the extremes to avoid infeasible dispatches, as shown in Table 1.

3. New York ISO grid representation

This study employs a zonal-level representation of the New York ISO system, rather than a nodal-level model. Transmission constraints are modeled through key interzonal interfaces, while intra-zonal network constraints are relaxed to reduce the complexity associated with nodal modeling. This approach helps prevent unintended infeasibilities or artificial congestion that could result from integrating hybrid resources without corresponding transmission upgrades. A visualization of the New York ISO zones can be seen in Fig. 3.

3.1. Market operation

The market operations simulations reflect state-of-the-art practices in NY ISO and incorporate two distinct market timelines. Specifically, the planned multi-cycle simulation approach includes a day-ahead market (DAM) and a real-time market (RTM), with forecast errors introduced between the two to capture uncertainty and operational variability.

3.1.1. Day-ahead market

The day-ahead market model includes both unit commitment (DASCUC) and economic dispatch (DASCED) functions. It commits long-lead-time resources, schedules hybrid resources based on submitted offer strategies (when applicable), and operates using day-ahead forecasts. The scheduling framework employs a three-day optimization horizon: a 24-h *binding* window and a 48-hour *advisory or look-ahead* window, all at a one-hour time resolution.

3.1.2. Real-time market

Market operations typically involve both a real-time unit commitment (RTSCUC) and a real-time economic dispatch (RTSCED) model. However, for the purposes of this study, a simplified real-time market structure is implemented using a single unit commitment and dispatch model with a one-hour optimization horizon and one-hour time resolution. This model enables the commitment of quick start resources and the re-dispatch of already committed units to address real-time imbalances.

(Real-Time) Operational plans. This study focuses on the impacts of hybrid resource participation models in the DAM, isolating these effects from real-time re-optimization and ancillary service interactions. Real-time *operation* is represented using two simplified plans derived from the day-ahead schedule:

- **Storage Follow (SF):** The storage component follows its DAM schedule when its state of charge permits.
- **Hybrid Balance (HB):** The storage component adjusts as needed to meet the DAM schedule in the presence of VER forecast errors.

Both plans include load and VER forecast deviations between day-ahead and real-time, providing a directional assessment of participation impacts. Full real-time bid updates and state-of-charge re-optimization are left for future work.

3.2. Market simulation software tool

The analysis employs a state-of-the-art commercial PCM tool – Power System Optimizer (PSO) – developed and licensed by Polaris Systems Optimization [17]. Built on the AIMMS platform, PSO interfaces with industry-standard optimization solvers such as GUROBI and CPLEX. It is a multi-cycle, multi-timescale, steady-state power system operations simulation tool that incorporates advanced unit commitment (UC) and economic dispatch (ED) models. The PCM is designed to replicate actual system operations at high temporal resolution and offers the flexibility to represent a range of market and operational structures.

PSO also includes advanced participation models for several specific technologies, including combined-cycle units and pumped storage hydropower. Its flexible modeling framework enables the simulation of both competitive electricity markets and vertically integrated systems. As a result, PSO is widely used for applications such as asset valuation under varying technology and resource mixes, operational and fuel price sensitivity analyses, renewable integration studies, profitability and ancillary service assessments, regional market design evaluation, and policy impact analysis.

In this study, PSO is used to evaluate the specific impacts of hybrid resource participation models from both system operator and market participant perspectives. Several modifications are made to the simulation software to enable accurate representation of hybrid operations and market behavior. First, a modeling feature is added to allow SoC-dependent bids or offer curves for hybrid plants in the day-ahead market under the self-managed participation model. The software selects the appropriate offer curve set based on the observed initial SoC of the storage component. This allows for daily bid or offer updates, which are not typically supported in conventional production cost simulations.

The model also incorporates logic to utilize the SoC from the end of one day-ahead binding window to the next, ensuring continuity across scheduling cycles. A preferred violation sequence is implemented to guide the dispatch model based on hybrid physical limitations, prioritizing the violation of storage real-time operational plan before curtailing renewables, relaxing power balance, or breaching inverter and SoC constraints. Additional features are introduced to prevent simultaneous charging and discharging and to reset SoC appropriately across simulation days.

4. Case study

This section evaluates the impact of hybrid resource participation in energy markets on overall production cost, steady-state reliability, and resource revenue, using various proposed participation modeling options. The primary objective is to investigate the key differences that alternative market designs for hybrid resources introduce across critical metrics through modeling, simulation, and analysis, with a focus on their effects in the day-ahead and real-time energy markets. Each scenario is simulated over two distinct one-month periods to represent different NYISO system operating conditions: April, typically characterized by minimum instantaneous demand, and July, which generally reflects peak instantaneous demand. Simulations used a realistic NYISO dataset and followed existing operational procedures, applied both with and without hybrid storage resources participating under the proposed models.

4.1. Base case description

We base our case study on the NYISO 2020 Load and Capacity Data Report (Gold Book) [18]. The system includes approximately 5433 MW of nuclear resources, 12,654 MW of combined cycle (CC) resources, 11,945 MW of steam turbine (ST) resources, 5702 MW of combustion turbine (CT) and internal combustion (IC) resources, 1409 MW of pumped storage hydropower (PSH), 4343 MW of conventional hydro, 1985 MW of wind, 57 MW of utility-scale solar, 315 MW of distributed PV, and 41 MW of storage resources.

Nuclear resources are modeled as must-run, operating continuously except during refueling, maintenance, or forced outages based on historical data. Conventional hydroelectric generators are treated as energy-constrained, with output limited by monthly water flow and optimized to minimize system production costs. Wind and solar resources are represented using hourly generation profiles. Fuel prices, including natural gas, are derived from historical data and assigned according to proximity to major trading hubs. Energy and ancillary services – regulation, 10-minute spinning and non-spinning reserves, and 30-minute reserves – are co-optimized within the market model.[1]

The load data for NYISO utilizes historical 2012 load shapes, adjusted to align with the 2019 historical peak demand and annual energy consumption for each NYISO zone. For the selected simulation months, April and July, the corresponding peak system loads are approximately 18,438 MW and 30,953 MW, respectively. Wind generation profiles are derived from NREL's Wind Toolkit Dataset [19], representing the 2012 weather year, and calibrated to match annual production levels reported in NYISO 2020 Load and Capacity Data Report [18]. Distributed PV generation in each NYISO zone is modeled using NREL's PVWatts Calculator [20], with input weather data based on the largest metropolitan area within each zone. The resulting hourly PV generation profiles are scaled according to NYISO's annual installed capacity forecast.

Behind-the-meter PV (BTMPV) nameplate capacity for each zone is obtained from the NYISO Load and Capacity Data Report [18], reflecting expected energy reductions from BTMPV installations. Conventional hydropower resources are modeled at the plant level using 2019 data from ABB's Velocity Suite. Interchange flows with neighboring regions are based on 2019 historical NYISO data. Greenhouse gas policies are incorporated via emission allowance prices. To capture the economic value of storage-based energy arbitrage, daily natural gas price forecasts are included, improving representation of inter-day price variability and enhancing peak price modeling under gas price volatility.

4.2. Case study scenario

The simulated case studies, developed in consultation with technical advisors and industry experts, are based on sensitivities most relevant to the impacts of hybrid resource participation models. The scenarios include various combinations of two levels of VER penetration (current and high), two levels of hybrid resource deployment (low and high), and two grid charging configurations (unrestricted storage charging from grid and storage charging limited to co-located VER only). They also incorporate two real-time hybrid operational strategies - storage follow and hybrid balance - and two different hybrid participation models: ISO-Managed and Self-Managed participation, as shown in Table 2. Table 3 provides an exhaustive summary of the study case scenarios.

4.2.1. VER Configuration

The resource mix for the low renewable penetration sensitivity is based on a historical NYISO base case benchmarked to 2019. In this scenario, approximately 473 MW of new battery storage is added to hybridize about 973 MW of existing VER, including 57 MW of utility-scale PV and 916 MW of wind generation. The high renewable penetration sensitivity assumes approximately 70% VER penetration, reflecting near-term targets in the New York region. This scenario includes around 9 GW of offshore wind and 6 GW of distributed PV solar generation, with the remainder supplied by land-based wind and utility-scale PV solar generation. Additionally, the high VER mix incorporates about 3000 MW of energy storage, of which approximately 1500 MW is hybridized with co-located VERs. This includes 2084 MW of utility-scale PV and 916 MW of wind in the high hybrid penetration scenario. While NYISO planning documents do not specify storage duration, this study assumes a four-hour duration and an 85% round-trip efficiency for all energy storage systems.

The modified renewable buildout and siting developed in this study to meet the high VER target mandated by the New York Climate Leadership and Community Protection Act (CLCPA) are presented in Table 4. Building on the NYISO Congestion Assessment and Resource Integration Study (CARIS) 70x30 scenario assumptions [21], this study refines the allocation of VER and storage resources to better reflect evolving trends in hybrid storage development-particularly solar hybrid storage, which shows greater penetration in ISO/RTO interconnection queues compared to wind hybrid storage. Additional onshore wind and utility-scale solar capacity were added in a 1:1 ratio as needed to reach the 70% renewable energy target. Resource placement was further adjusted to prioritize zones with larger regional loads and greater potential for energy arbitrage under the assumed system conditions. Table 4 details the resulting high VER sensitivity capacity buildout by resource type and NYISO zone, supporting a more targeted investigation of the study's key analytical objectives.

4.2.2. Hybrid technical configuration

The hybrid systems were modeled using AC-coupled configurations, with battery power capacity set to 50% of the paired generation capacity [8]. The 0.5 storage-to-generation capacity ratio aligns with expectations reported by developers and utilities in MISO, where 67% of planned hybrid projects fall within a 0.25-0.75 range [22], and with the average ratio of approximately 0.65 across proposed hybrid resources in interconnection queues [23]. The four-hour duration is similarly well-supported: 86% of MISO survey respondents indicated plans for 2-4 hours of storage. As of the end of 2021, operational solar hybrids had a weighted average duration of 3.2 hours, compared to just

[1] While the market-clearing formulation co-optimizes energy and ancillary services for eligible resources, the hybrid resources in this study are modeled as energy-only participants and do not submit reserve offers. Accordingly, their reserve quantities are set to zero in the input data, and no reserve capability is enforced for these resources, even though reserve variables remain in the general system equations.

Table 2
Case study matrix.

Sensitivity Type	Sensitivity level	NYISO: Existing Resource Mix (Low VER)	NYISO: High VER Resource Mix: 70% VER with 9 GW offshore wind, 6 GW distributed PV, and the rest land-based wind and utility PV
Operational	*Unrestricted Grid Charging (**UnGC**)*	•	•
	*No Grid Charging (**NoGC**)*	•	
	*(Real-time) Operation: Storage Follow (**SF**)*	•	•
	*(Real-time) Operation: Hybrid Balance (**HB**)*	•	•
Hybrid Resource Penetration	*Low Hybrid Penetration*	•	
	High Hybrid Penetration		•
Hybrid Resource Participation Option	*2R ISO-Managed Co-located Model (**ISO-M**)*	•	•
	*1R Self-Managed Hybrid Model (**Self-M**)*	•	•

Table 3
Simulation case scenarios.

Case	Simulation Period	VER Level	Hybrid Resource Level	Participation Option	Grid Charging (GC)	Real-time Operation Strategy
1	April, July	Low	No Hybrid (Base)	–	–	Storage Follow
2	April, July	Low	Low	ISO-M	No	Storage Follow
3	April, July	Low	Low	Self-M	No	Storage Follow
4	April, July	Low	Low	ISO-M	Unconstrained	Storage Follow
5	April, July	Low	Low	Self-M	Unconstrained	Storage Follow
6	April, July	Low	Low	ISO-M	No	Hybrid Balance
7	April, July	Low	Low	Self-M	No	Hybrid Balance
8	April, July	Low	Low	ISO-M	Unconstrained	Hybrid Balance
9	April, July	Low	Low	Self-M	Unconstrained	Hybrid Balance
10	April, July	High	No Hybrid (Base)	–	–	–
11	April, July	High	High	ISO-M	Unconstrained	Storage Follow
12	April, July	High	High	Self-M	Unconstrained	Storage Follow
13	April, July	High	High	ISO-M	Unconstrained	Hybrid Balance
14	April, July	High	High	Self-M	Unconstrained	Hybrid Balance

Table 4
High VER sensitivity capacity buildouts by resource type and zone.

Resource Additions \ Zone	A	B	C	D	E	F	G	H	I	J	K	Total
Offshore Wind (MW)	460	•	450	•	•	•	460	•	•	5,390	2,240	9,000
Land Based Wind (MW)	1,470	1,282	1,568	821	985	•	•	•	•	•	•	6,126
Distributed PV (MW)	558	391	825	137	774	932	685	71	88	518	904	5,883
Utility PV (MW)	1,609	251	1,225	•	858	2,067	767	•	180	910	460	8,327
4-Hr Battery Storage (MW)	200	90	300	280	235	240	190	190	90	725	508	3,048

0.6 hours for wind hybrids [8]. However, since wind-plus-storage hybrids are still nascent, their observed durations were not used to inform forward-looking assumptions in this study.

Each hybrid system was assumed to have a point of interconnection equal to the nameplate capacity of the wind or solar generator. This reflects current design expectations, where batteries are dispatched only when the generator is operating below full output [8]. Battery cycle limits and degradation costs were not included in this study. All hybrid batteries were initialized at a 50% SoC at the beginning of the simulation horizon. To assess the system-level impacts of different hybrid participation models, simulation scenarios were developed using current and projected hybrid resource deployment.

5. Results

This section presents the results of participation models across different cases, evaluated using key metrics from the perspectives of both the market operator – such as economic efficiency and reliability, and the individual resource owner, such as resource profitability. The analysis supports a deeper understanding of the implications for various power systems with differing resource mixes. In all scenarios, the DASCUC and RTSCUC models were solved using a MIP gap of 0.01%.

5.1. Economic and system efficiency

Efficiency is assessed using real-time operating costs, including fuel, no-load, startup, and shutdown expenses. The analysis focuses on incremental delta operating cost – the difference in real-time costs between a participation model and its corresponding base case (e.g., comparing cases 2-9 with case 1, or cases 11-14 with case 10 in Table 5). Day-ahead costs are excluded, as they are not always realized and are less relevant for comparative evaluation.

For low VER penetration, delta operating cost represents the percentage change in real-time system costs between a low VER, low hybrid scenario and the base-case low VER scenario without hybrid resources (Case 1). For high VER penetration, it represents percentage change between a high VER, high hybrid scenario and the base-case high VER scenario without hybrid resources (Case 10).

Operating cost comparisons indicate that the ISO-M participation model consistently outperforms the Self-M model, particularly under the SF (real-time) operational plan, across both low and high VER penetration scenarios, e.g., case 4 vs. 5 and case 11 vs. 12 in Table 5. The ISO-M model often yields operating cost savings relative to the Self-M formulation, while the Self-M model may increase costs relative to the base case (cases 1 and 10, respectively). This is primarily due to infeasible real-time dispatch of energy storage and increased reliance on expensive quick-start units. In Self-M, the day-ahead dispatch is based on bids or offer curves that often produce unrealistic schedules for storage, resulting in real-time imbalances. In contrast, ISO-M explicitly accounts for storage constraints during scheduling, allowing for more reliable and cost-effective commitment of thermal resources. Moreover, by enabling operator control of storage SoC, ISO-M improves real-time flexibility and reduces dependence on high-cost generation.

In the no grid charging sensitivity (Case 2 vs. 3 in Table 5), ISO-M again achieves greater cost savings than Self-M, driven by reduced use of high-cost resources. Under unconstrained grid charging, Self-M exhibits higher costs due to frequent maximum charging and discharging in day-ahead schedules, which are often infeasible in real time.

Table 5
Production cost and delta operating cost (production cost difference w.r.t to the base case) for different case scenarios; NoGC: no grid charging, UnGC: unconstrained grid charging.

Case No.	VER and Hybrid Penetration	Real-time Operation Strategy	Participation Model, Grid Charging	April		July	
				Operating Cost ($M)	Delta Operating Cost (%)	Operating Cost ($M)	Delta Operating Cost (%)
1	Low VER, No Hybrid	–	Base	131.37	–	271.66	–
2	Low VER, Low Hybrid	Storage Follow	ISO-M, NoGC	131.30	-0.05	271.49	-0.06
3			Self-M, NoGC	131.45	0.06	271.63	-0.01
4			ISO-M, UnGC	131.25	-0.10	271.38	-0.11
5			Self-M, UnGC	131.52	0.11	271.67	0.00
6		Hybrid Balance	ISO-M, NoGC	131.40	0.02	271.60	-0.02
7			Self-M, NoGC	131.41	0.03	271.69	0.01
8			ISO-M, UnGC	131.47	0.07	271.52	-0.05
9			Self-M, UnGC	131.58	0.15	271.72	0.02
10	High VER, No Hybrid	–	Base	90.41	–	242.67	–
11	High VER, High Hybrid	Storage Follow	ISO-M, UnGC	90.32	-0.10	242.33	-0.14
12			Self-M, UnGC	90.34	-0.08	242.73	0.02
13		Hybrid Balance	ISO-M, UnGC	90.30	-0.13	242.45	-0.09
14			Self-M, UnGC	90.28	-0.14	242.45	-0.09

Table 6
Aggregate hybrid energy resource day-ahead revenue, real-time (adjusted) revenue, two-stage settlement profit, and delta profit for ISO-M w.r.t Self-M participation option for different case scenarios; NoGC: no grid charging, UnGC: unconstrained grid charging.

Case No.	VER and Hybrid Penetration	Real-time Operation Strategy	Participation Model, Grid Charging	April				July			
				Day-ahead Revenue ($k)	Real-time Revenue Only ($k)	Two-settlement Profit ($k)	Delta Profit (%)	Day-ahead Revenue ($k)	Real-time Revenue Only ($k)	Two-settlement Profit ($k)	Delta Profit (%)
2	Low VER, Low Hybrid	Storage Follow	ISO-M, NoGC	2,932.58	-113.59	2,818.99	5.64	2,671.95	-198.66	2,473.30	6.65
3			Self-M, NoGC	3,228.42	-559.88	2,668.54	-	2657.21	-338.23	2,318.98	-
4			ISO-M, UnGC	2,939.02	-119.99	2,819.04	9.00	2,721.60	-145.67	2,575.94	10.61
5			Self-M, UnGC	3,245.51	-659.13	2,586.38	-	2,566.81	-237.95	2,328.86	-
6		Hybrid Balance	ISO-M, NoGC	2,933.04	-197.75	2,735.29	4.29	2,676.81	-296.03	2,380.78	4.46
7			Self-M, NoGC	3,223.37	-600.60	2,622.77	-	2,641.98	-362.76	2,279.22	-
8			ISO-M, UnGC	2,942.13	-204.94	2,737.20	7.27	2,725.38	-336.82	2,388.56	3.82
9			Self-M, UnGC	3,270.86	-719.27	2,551.59	-	2,569.35	-268.67	2,300.68	-
11	High VER, High Hybrid	Storage Follow	ISO-M, UnGC	1,546.85	-143.92	1,402.93	5.27	13,238.44	-247.71	12,991.14	3.72
12			Self-M, UnGC	1,836.70	-503.97	1,332.73	-	13,019.23	-493.81	12,525.42	-
13		Hybrid Balance	ISO-M, UnGC	1,545.26	-137.77	1,407.49	-0.77	13,247.32	-539.36	12,707.96	1.69
14			Self-M, UnGC	1,835.05	-416.65	1,418.41	-	12,990.87	-494	12,496.88	-

Conversely, ISO-M benefit from increased arbitrage opportunities, leading to improved economic performance. Under the HB (real-time) operational plan, similar trends are observed. However, in April (low VER), both ISO-M and Self-M increase operating costs compared to the base case (0.07% in case 8 and 0.15% in case 9, respectively), largely due to inflexible scheduling in response to forecast errors. In July, while cost reductions for ISO-M are smaller than under SF (-0.05% in case 8 vs. -0.11% in case 4), it still performs better than Self-M by effectively utilizing combined cycle units and limiting steam turbine dispatch. At high VER levels in HB, the ISO-M and Self-M models yield comparable operating costs within the MIP gap, indicating minimal differences in performance under those conditions.

5.2. Profits and incentives

This subsection evaluateshybrid resource owners' short-run profits in a two-stage market, combining day-ahead revenue – based on scheduled dispatch and clearing price – with real-time revenue from deviations, excluding amounts already settled in the day-ahead market.

Two-stage settlement profits are used to evaluate participant economic performance, while the separation of day-ahead and real-time revenues enables comparison of behavior across market stages (Table 6). The delta profit measures the difference between the ISO-M and Self-M option in each scenario. These calculations exclude investment tax credits, maintenance, degradation, or other operational costs, and are based solely on dispatch and market clearing prices.

In April, under both the SF and HB real-time operation plans, the Self-M participation option exhibited higher day-ahead market revenues compared to the ISO-M option across both low and high VER penetration scenarios (April cases 2-9 and 11-14 in Table 6). This is primarily due to the internal SoC management in the Self-M model, which allows hybrid resources to submit more aggressive bids or offer curves and secure higher day-ahead dispatch levels than the ISO-M model, which explicitly enforces SoC constraints.

However, in the real-time market – where SoC constraints apply to all participation models – the Self-M option incurs higher repurchases due to infeasible energy storage dispatch. These buybacks often occur at real-time clearing prices that exceed day-ahead prices, leading to negative real-time revenue. This effect is amplified by the Self-M model's aggressive day-ahead bidding strategy and the absence of day-ahead SoC management, combined with forecast errors in real-time. As a result, the Self-M option typically yields lower two-stage settlement profits than the ISO-M model, as shown in the two-settlement profit column for April cases in Table 6.

In July, under both real-time operation plans, the Self-M option shows lower day-ahead revenues compared to the ISO-M option. This is attributed to peak load conditions in July, which increase reliance on conventional generators with long start-up times and reduce the day-ahead dispatch of hybrid resources. Despite this, the Self-M model continues to exhibit higher real-time repurchases due to infeasible storage dispatch, except in the HB plan under unconstrained grid charging. Consequently, the Self-M option generally achieves lower two-stage settlement profits in July as well (July cases 2-9 and 11-14 in Table 6).

Across all scenarios, real-time revenues are consistently negative, indicating that all participation models adjust their day-ahead commitments. In the SF plan, this reflects forecast errors that cause deviations in dispatch from the day-ahead schedule. In the HB plan, such errors can cause SoC imbalances in early intervals, reducing energy storage availability in later periods and requiring further dispatch adjustments. The

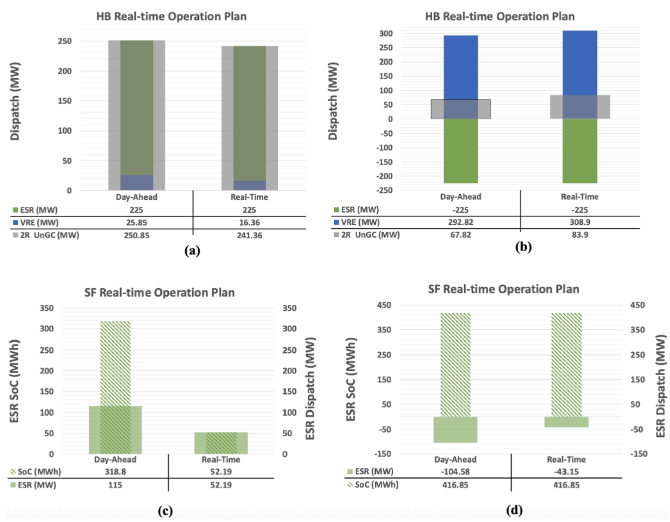

Fig. 4. Illustration of violation of real-time operation plans; constituent ESR resource of hybrid energy resource in (a) Area J has insufficient discharge capacity under ISO-M/HB option, (b) Area J has insufficient charge capacity under ISO-M/HB option, (c) Area E has insufficient SoC capacity under Self-M/SF option, (d) Area E has maxed out SoC capacity under Self-M/SF option.

Self-M model, in particular, is more susceptible to infeasible real-time storage dispatch, leading to imbalance payments.

5.3. SoC Feasibility and system reliability

This metric assesses the ability of hybrid resources to follow either the *Storage-Follow* or *Hybrid-Balance* (real-time) operational strategies. It indicates how feasible day-ahead dispatch schedules are in real time, considering forecast errors and physical constraints of the storage, renewable, and overall hybrid systems. Under the SF strategy, storage must follow its day-ahead schedule regardless of renewable output. Under the HB strategy, the hybrid resource must follow its day-ahead schedule using storage to offset renewable variability. Real-time feasibility may be limited by component constraints (e.g., SoC, charge or discharge rates, efficiency, generation limits) and hybrid-level limits (e.g., inverter capacity). Hence, feasibility is observed through whether a violation of the (real-time) operational plan under consideration occurs due to any of the following reasons:

- Insufficient discharge capacity: This occurs when the storage component reaches its maximum discharge limit and cannot increase output. For example, at hour 29 in July (Fig. 4a), a hybrid facility in Area J required 234.49 MW from storage to offset a VER shortfall, but was limited to 225 MW, violating the HB strategy.
- Insufficient charge capacity: This occurs when the storage reaches its maximum charging rate and cannot further reduce output. At hour 11 in July (Fig. 4b), a facility needed -241.08 MW of charging to offset excess VER generation, but was capped at -225 MW, again resulting in a violation of the HB strategy.
- Insufficient SoC: This arises when storage lacks sufficient energy to discharge as required. At hour 39 in July (Fig. 4c), a facility scheduled to discharge 115 MW had only 52.19 MWh available, preventing compliance with the SF strategy.
- Maximum SoC limit: This occurs when the storage is full and cannot absorb additional energy. At hour 3 in July (Fig. 4d), a facility scheduled to charge at -104.58 MW could only manage -50.76 MW due to limited remaining capacity, violating the SF strategy.

These four metrics help assess how well hybrid resources can meet real-time system needs under the SF and HB strategies. Table 7 summarizes simulation results illustrating adherence to these strategies. Although the results do not explicitly show violations of physical limits (e.g., SoC bounds or interconnection limits), such constraints can prevent full compliance with day-ahead schedules. For example, under the SF strategy, a combination of VER forecast error and interconnection constraints may render the storage schedule infeasible. In such cases, the market software prioritizes enforcing interconnection limits, adjusting storage dispatch as needed.

SoC constraints can also introduce temporal coupling, especially under the Self-M model, which ignores SoC in day-ahead scheduling. This may lead to repeated charging instructions that become infeasible in real time once SoC reaches its maximum. Some intervals may involve overlapping constraints. For instance, storage needed to charge at -133.96 MW to follow the HB strategy but was limited by both a -115 MW charge cap and a near-full SoC (431.72 MWh out of 460 MWh), reducing feasible charging to -33.27 MW. Such intervals are categorized under a single primary constraint to avoid double-counting.

In both April and July simulations, and under both low and high VER scenarios, the SF strategy resulted in no intervals limited by insufficient charge or discharge capacity for either the Self-M or ISO-M participation models. This is expected for the ISO-M model, which enforces physical limits in both the DAM and RTM. For the Self-M model, similar results stem from conservative bidding strategies and a pseudo-2R implementation that indirectly respects charge/discharge limits.

However, violations due to SoC limits (insufficient or maximum SoC) still occur under the Self-M model, which does not consider SoC explicitly in the DAM. For example, repeated charging in early morning hours can lead to maxed-out SoC, preventing further charging and causing SF violations in later intervals. Similarly, discharging may become infeasible due to insufficient SoC. In contrast, ISO-M models perform significantly better, as they incorporate SoC constraints in the DAM. For instance, in April under low VER penetration, the ISO-M model recorded just 39 intervals with insufficient SoC compared to 865 for the Self-M model.

Even in ISO-M models, forecast errors can cause storage to deviate from its day-ahead schedule to respect hybrid-level constraints (e.g., inverter limits), leading to downstream SoC issues. At hour 421 in July, a hybrid resource in Area E discharged only 85.13 MW (vs. 115 MW scheduled), resulting in max SoC by hour 438 and reduced charging capability. Overall, the Self-M model consistently exhibits more SoC-related violations under the SF strategy due to its lack of SoC tracking and reliance on bidding strategies.

Further, under the SF strategy and low VER scenarios, the ISO-M UnGC model outperforms ISO-M NoGC, with fewer intervals limited by insufficient SoC, 73 vs. 235 in July. This is due to NoGC's reliance on VER-only charging, making it more vulnerable to forecast errors. For example, in Area E, lower-than-expected VER output between hours 45-78 in July led to insufficient storage energy, limiting discharge to 62.5 MW (vs. 115 MW scheduled) at hour 86. In contrast, the Self-M model shows the opposite trend. The Self-M UnGC case records more SoC violations than Self-M NoGC, as grid-charging flexibility enables more aggressive DAM schedules, which may become infeasible in real time due to SoC constraints. The NoGC case, relying on VER-only charging, results in more conservative schedules and fewer violations.

Lastly, unlike SF, the HB strategy results in intervals limited by charge or discharge capacity across all models and scenarios. These arise when VER forecast errors require storage to deviate from its day-ahead schedule. For instance, at hour 29 in July, a facility in Area J needed 234.49 MW from storage to offset low VER output but was limited to 225 MW, causing a violation due to insufficient discharge capacity.

5.4. Computational complexity

This subsection summarizes total solve times (in seconds) for day-ahead and real-time stages across case scenarios, as shown in Table 8. As expected, ISO-M model, which explicitly model hour-to-hour storage chronology, exhibit higher day-ahead solve times than the Self-M option. This trend holds across most cases, due to added SoC constraints.

Table 7
Interval count for hybrid energy resource capability to follow real-time operation plan.

Case No.	VER and Hybrid Penetration	Real-time Operation Strategy	Participation Model, Grid Charging	April (Count of violation Intervals)				July (Count of violation Intervals)			
				Insufficient discharge capacity	Insufficient charge capacity	Insufficient SoC	Max SoC	Insufficient discharge capacity	Insufficient charge capacity	Insufficient SoC	Max SoC
1	Low VER, No Hybrid	–	Base	-	-	-	-	-	-	-	-
2	Low VER, Low Hybrid	Storage Follow	ISO-M, NoGC	-	-	39	-	-	-	235	2
3			Self-M, NoGC	-	-	865	102	-	-	684	573
4			ISO-M, UnGC	-	-	28	3	-	-	73	48
5			Self-M, UnGC	-	-	999	64	-	-	733	1044
6		Hybrid Balance	ISO-M, NoGC	37	38	757	327	149	75	652	434
7			Self-M, NoGC	22	11	930	262	93	60	741	742
8			ISO-M, UnGC	33	66	880	311	241	252	908	397
9			Self-M, UnGC	41	23	1224	171	170	203	920	809
10	High VER, No Hybrid	-	Base	-	-	-	-	-	-	-	-
11	High VER, High Hybrid	Storage Follow	ISO-M, UnGC	-	-	130	31	-	-	155	22
12			Self-M, UnGC	-	-	690	3347	-	-	600	623
13		Hybrid Balance	ISO-M, UnGC	150	314	1270	320	166	240	1082	571
14			Self-M, UnGC	58	128	564	3110	125	129	871	724

Table 8
Computational complexity for all case scenarios.

Case No.	VER and Hybrid Penetration	Real-time Operation Strategy	Participation Model, Grid Charging	April (Solve Time in seconds)		July (Solve Time in seconds)	
				Day-ahead	Real-time	Day-ahead	Real-time
1	Low VER, No Hybrid	–	Base	164.70	32.34	242.79	37.12
2	Low VER, Low Hybrid	Storage Follow	ISO-M, NoGC	184.94	34.26	304.28	44.73
3			Self-M, NoGC	171.25	31.48	273.86	40.04
4			ISO-M, UnGC	185.41	35.25	292.40	41.56
5			Self-M, UnGC	162.96	31.78	261.84	42.68
6		Hybrid Balance	ISO-M, NoGC	192.32	36.70	302.59	43.44
7			Self-M, NoGC	179.32	34.74	283.41	43.06
8			ISO-M, UnGC	181.56	31.77	278.91	40.42
9			Self-M, UnGC	172.59	36.33	264.12	39.99
10	High VER, No Hybrid	–	Base	70.67	30.85	596.73	37.70
11	High VER, High Hybrid	Storage Follow	ISO-M, UnGC	89.67	32.32	516.83	45.44
12			Self-M, UnGC	87.32	32.43	488.11	46.84
13		Hybrid Balance	ISO-M, UnGC	94.99	41.43	523.08	50.29
14			Self-M, UnGC	87.94	34.37	531.84	47.09

An exception occurs during July's peak load under high VER and hybrid penetration with the HB strategy, where the Self-M option unexpectedly incurs a longer solve time than ISO-M. This anomaly likely stems from tight feasibility conditions due to resource scarcity, unit commitment constraints, and ramp limits. In general, July simulations have higher solve times than April, and NoGC cases show longer solve times than UnGC ones under low VER conditions due to tighter constraints. As all RTM models are aligned for fairness, real-time solve times remain largely comparable across options.

While ISO-M models improve market efficiency through more accurate representation of storage behavior, they increase computational burden, potentially limiting scalability.

6. Conclusions

This study evaluated two participation frameworks for hybrid resources - 1R Self-Managed (Self-M) and 2R ISO-Managed (ISO-M)- within a two-stage market setting. The model developed: (i) a production-cost-modeling framework that explicitly accounts for hybrid operational flexibility, (ii) a comparative assessment of decentralized versus centralized management of SoC constraints, and (iii) an evaluation of resulting system- and participant-level economic impacts under uncertainty.

The results show that embedding hybrid operational constrains directly within the market clearing (ISO-M) leads to more reliable schedules, reduced real-time corrections, and system cost savings relative to the Self-M formulation. In contrast, when resource dispatch and constraints feasibility is managed externally through offers (Self-M), hybrid resources tend to submit more aggressive day-ahead schedules that increase deviations and redispatch in real time, particularly under forecast error. The efficiency gains observed under ISO-M arise primarily from structural coordination of storage constraints rather than differences in forecasting assumptions.

From a market design perspective, our results highlight the need to represent hybrid operational limits directly within dispatch and pricing. In particular, the risks associated with day-ahead renewable generation uncertainty are more effectively managed in a centralized framework by the ISO than by individual hybrid assets, resulting in lower system costs and higher revenues for hybrid participants. The ISO-M model, however, introduces additional complexity into market-clearing software and may pose implementation challenges for system operators as the penetration of a diverse portfolio of hybrid resources increases. Future work should examine full real-time re-optimization and assess the trade-off between improved modeling accuracy and computational complexity as more data-driven bidding strategies become feasible.

CRediT authorship contribution statement

Rajni Kant Bansal: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization; **Nikita Singhal:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization; **Julie Mulvaney Kemp:** Writing – review & editing, Validation, Software, Investigation, Formal analysis, Data curation; **Erik Ela:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Investigation, Funding acquisition, Formal analysis; **Miguel Heleno:** Writing – review & editing, Visualization, Validation, Resources, Project administration, Investigation, Funding acquisition, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

[1] D.P. Zhou, M. Roozbehani, M.A. Dahleh, C.J. Tomlin, Stability analysis of wholesale electricity markets under dynamic consumption models and real-time pricing, in: 2017 American Control Conference (ACC), IEEE, 2017, pp. 2048–2053.

[2] T. Levin, A. Botterud, J. Kwon, et al., Planning and Operations in Electricity Markets Under System Tansformation: Key Findings, Technical Report, National Renewable Energy Laboratory (NREL), Golden, CO, 2024.

[3] T. Levin, B. Frew, A. Moreira, et al., Research Priorities and Opportunities in U.S. Wholesale Electricity Markets: Market Design under Deep Decarbonization, Technical Report, Argonne National Laboratory (ANL), Argonne, IL (United States), 2024.

[4] K. Dykes, J. King, N. DiOrio, et al., Opportunities for Research and Development of Hybrid Power Plants, Technical Report, National Renewable Energy Lab.(NREL), Golden, CO (United States), 2020.

[5] FERC, Electric Storage Participation in Markets Operated by Regional Transmission Organizations and Independent System Operators - Docket No. RM16-23-000; Order No. 841, Technical Report, Federal Energy Regulatory Commission, 2018.

[6] FERC, Participation of Distributed Energy Resource Aggregations in Markets Operated by Regional Transmission Organizations and Independent System Operators - Docket No. RM18-9-000; Order No. 2222, Technical Report, Federal Energy Regulatory Commission, 2020.

[7] FERC, Improvements to Generator Interconnection Procedures and Agreements - Docket No. RM22-14-000; Order No. 2023, Technical Report, Federal Energy Regulatory Commission, 2023.

[8] M. Bolinger, W. Gorman, et al., Hybrid Power Plants: Status of Operating and Proposed Plants 2022 edition, Technical Report, Berkeley Laboratories Energy Markets & Policy, LBNL, 2022.

[9] S. Bhattacharjee, R. Sioshansi, H. Zareipour, Comparing participation models in electricity markets for hybrid energy-storage resources, IEEE Trans. Power Syst. 40 (1) (2024) 650–661.

[10] J.M. Kemp, M. Heleno, A.D. Mills, Hybrid power plant bidding in models of future electricity systems, in: 2023 IEEE Power & Energy Society General Meeting (PESGM), 2023, pp. 1–5. https://doi.org/10.1109/PESGM52003.2023.10252335

[11] N. Singhal, R. Bansal, J. Kemp, E. Ela, M. Heleno, Integration of hybrids into wholesale power markets (2023). LBL Publications [Online]. https://escholarship.org/content/qt8nv6j94c/qt8nv6j94c.pdf

[12] LBNLgrid, Hybrid Energy Resources Bidding Model (HERB), 2025 (https://github.com/LBNLgrid/Hybrid-Energy-Resources-Bidding-Model). GitHub repository, accessed Feb. 2026.

[13] N. Growe-Kuska, H. Heitsch, W. Romisch, Scenario reduction and scenario tree construction for power management problems, in: 2003 IEEE Bologna Power Tech Conference Proceedings,, Vol. 3, IEEE, 2003, pp. 7–pp.

[14] R. Weron, Electricity price forecasting: a review of the state-of-the-art with a look into the future, Int. J. Forecast. 30 (4) (2014) 1030–1081.

[15] Z. Yang, L. Ce, L. Lian, Electricity price forecasting by a hybrid model, combining wavelet transform, ARMA and kernel-based extreme learning machine methods, Appl. Energy (2017) 291–305.

[16] xsnm[New York ISO], Reliability Needs Assessment (RNA), Technical Report, The New York Independent System Operator (NYISO), NY (United States), 2024. Accessed: 2025-07-12.

[17] Polaris Systems Optimization, Inc., PSO - Power System Optimizer (PSO), Polaris Systems Optimization, 2025 Accessed: 2025-07-12, https://psopt.com/pso/.

[18] New York ISO, 2020 Load & Capacity Data Report, Technical Report, The New York Independent System Operator (NYISO), NY (United States), 2020. Accessed: 2025-07-12.

[19] National Renewable Energy Laboratory (NREL), Wind Integration National Dataset (WIND) Toolkit, 2015 (https://www.nrel.gov/grid/wind-toolkit.html). Accessed: 2025-07-12.

[20] National Renewable Energy Laboratory (NREL), PVWatts Calculator, 2025, (https://pvwatts.nrel.gov/). Accessed: 2025-07-12.

[21] New York Independent System Operator (NYISO), Congestion Assessment and Resource Integration Study (CARIS), Technical Report, NYISO, 2019. Accessed: 2025-07-12.

[22] M. Kristian, M. Prorok, "Survey on Hybrid Resources Says They" Coming, and Fast, Technical Report, Great Plains Institute, 2021. Accessed: 2025-07-12.

[23] J. Rand, R. Strauss, et al., Queued Up: Characteristics of Power Plants Seeking Transmission Interconnection as of the End of 2022, Technical Report, Lawrence Berkeley National Laboratory, 2022.