The Value of Storage in Electricity Distribution: The Role of Markets

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Electricity distribution companies deploy battery storage to defer grid upgrades by reducing peak demand. In deregulated jurisdictions, such storage often sits idle because regulatory constraints bar participation in electricity markets. Here, we develop an optimization framework that, to our knowledge, provides the first formal model of market participation constraints within storage investment and operation planning. Applying the framework to a Massachusetts case study, we find that market participation could deliver similar savings as peak demand reduction. Under current conditions, market participation does not increase storage investment, but at very low storage costs, could incentivize deployment beyond local distribution needs. This might run contrary to the separation of distribution from generation in deregulated markets. Our framework can identify investment levels appropriate for local distribution needs.

1 Introduction

1.1 Background and motivation

In the 1980s and 1990s, deregulation was en vogue. By breaking up established monopolies, the hope was to increase market efficiency by stimulating competition across various industries, including electricity. Massachusetts hoped to remedy a situation in which "the existing regulatory system results in among the highest, residential and commercial electricity rates paid by customers throughout the United States" by separating electricity generation from distribution and transmission, which were to be kept as regulated monopolies (Massachusetts General Court, 1997, ch. 164, sec. 1(d)). The rationale for the separation was to increase competition in generation while avoiding any "cross-subsidization of competitive businesses from regulated businesses and discriminatory policies affecting access to distribution and transmission networks upon which all competitive suppliers depend" (Joskow, 2008, p. 12). Deregulation occurred at different rates in different jurisdictions (Borenstein and Bushnell, 2015). To our knowledge, 13 US states (CT, DE, IL, ME, MD, MA, NH, NJ, NY, OH, PA, RI, TX) and the District of Columbia restrict investor-owned utilities in owning both generation assets and transmission and distribution assets.

In the context of such separation between generation and distribution, storage investment and operations within electricity markets warrant a closer look. Storage is generally considered generation, but can be considered distribution if it serves grid reliability or defers grid investments such as substation or line upgrades. In the latter case, utilities have been allowed to own and operate storage for distribution needs. Such needs are generally infrequent, especially if they arise from reliability toward extreme events. Even in the European Union, distribution system operators are only allowed to own storage if they cannot contract it from third parties and may not use storage for market participation (European Parliament and the Council of the European Union, 2019, art. 36(2)(b)). Storage built to address grid reliability thus experiences low utilization, e.g., on the order of one discharge cycle per month (Orange and Rockland Utilities, 2024), and misses the economic opportunity of participating in electricity markets. Allowing for market participation would improve storage economics but risk incentivizing investments that go beyond serving local distribution needs, which would run contrary to the separation of distribution and generation.

Here, we search a policy that allows for utility-owned storage to participate in the wholesale electricity market while constraining the level of storage investment to local distribution needs, thus limiting market distortions. To identify permissible storage investments, we design a model that calculates optimal degrees of investment in different grid assets, such as substation and line upgrades, and non-grid assets such as storage and backup generation. Crucially, this investment model incorporates market participation constraints, which limit the generation from non-grid assets to serving local distribution needs. Next, we quantify the economic gains from participation in arbitrage and capacity markets and analyze if the gains may lead to storage investments that go beyond meeting local distribution needs.

Our study is timely as utilities plan to spend billions of dollars on distribution grid upgrades in the next five years (Eversource, 2024; National Grid, 2024) and some deregulated states, *i.e.*, Maryland (2019, p. 2) and New York (2021, p. 12), have recently allowed market participation, hoping to reduce costs and recognizing that current utility-owned distribution grid storage would likely not have much market power (State of New York Public Service Commission, 2021, p. 13). In fact, utility-owned distribution storage accounted for less than 1% of total US generation capacity as of June 2025. On the other side of the Atlantic, the European Commission recommends exploring the

¹Based on the US Energy Information Administration's Preliminary Monthly Electric Generator Inventory of June 2025, accessible at https://www.eia.gov/electricity/data/eia860m/.

full flexibility potential of energy storage in distribution grids (European Commission, 2023, § 5) and entertains proposals to create a market for local services that would help alleviate distribution grid constraints (European Union Agency for the Cooperation of Energy Regulators, 2025, Art. 29, 34, 40 41, 44). We aim to provide a tool that enables jurisdictions to assess whether proposed storage investments meet local distribution needs and to quantify economic gains from market participation.

1.2 Research questions and contributions

We contribute to the market participation discussion by answering three research questions:

- 1. How to model market participation constraints in storage operation and investment planning?
- 2. How do profits from market participation compare to savings from reducing peak demand?
- 3. Would market participation generate storage investments that go beyond distribution needs, and if so, how may this be detected?

In answer to question 1, we model market participation constraints mathematically by limiting the supply from non-grid resources, such as storage, to the shortfall of grid capacity relative to electricity demand. We integrate these constraints into an optimization problem that determines distribution grid investment and operating decisions. To our knowledge, we are the first to formulate such constraints. In answer to questions 2 and 3, we apply the formulation to a Massachusetts case study. Question 2 helps assess whether the profits from market participation are sufficient to justify policy changes, considering that regulators have been allowing distribution companies to own storage to reduce or defer grid investments. Question 3 examines the trade-off between market power and efficient storage utilization. While current distribution-grid storage is considered too small to yield much market power, allowing for market participation could incentivize storage investments that exceed local distribution needs and increase market power over time. Our optimization problem can guide investment planning by limiting storage capacity to local grid needs. Regulators can then navigate the trade-off by authorizing market participation, while limiting storage investment to local needs.

1.3 Prior work

In the electricity industry, investment planning is typically done by solving capacity expansion models. Current models adopt a social planner perspective, which assumes perfect resource coordination (MIT Energy Initiative and Princeton University ZERO Lab; Brown et al., 2025). Market participation constraints limit resource coordination and are thus not included in these models. In distribution grids specifically, research has focused on reducing peak demand (Martin et al., 2019; Martínez et al., 2024) and balancing intermittent generation (Yi et al., 2023), citing but not modeling market participation constraints. A survey among distribution companies confirms that, in practice, storage investments are mostly evaluated based on the deferral value of capital investments (Keen et al., 2022, p. 7).

In terms of operating strategies, storage control relies on heuristic decision rules that limit market participation if storage may be needed for grid support, for example, by limiting the time or state-of-charge available for market participation (Balducci et al., 2019; Orange and Rockland Utilities, 2024; Lumen Energy Strategy, 2024). Such heuristics may seem oververly restrictive, especially when market incentives and grid needs are aligned so that storage could fulfill both objectives without compromising one over the other. Our model shows that, sometimes, it is indeed possible to operate storage in this way.

1.4 Structure

The paper unfolds as follows. Section 2 formulates a mathematical optimization model for storage investment and operation problems with market participation constraints, answering research question 1. Section 3 performs numerical experiments to answer research questions 2 and 3. Section 4 concludes. Appendix A presents the data used in the experiments, Appendix B a mixed-integer linear reformulation of the optimization problem, and Appendix C lists detailed experimental results.

Notation. We show vectors in boldface and refer to exogenous electricity demand as electric load.

2 Problem description and optimization model

Consider a distribution company planning its capital investments. We model the investment decisions in an optimization problem that accounts for market participation constraints.

2.1 Investment cost

Over a horizon of N periods, think of years, the company decides how much capacity x_{rn} of resource $r \in \mathcal{R} = \{b, g, s\}$ to add at the beginning of period n. Investing in resource (g) means expanding the connection to the electricity grid, for example, by adding a distribution line or upgrading a substation. Resources (b) and (s) stand for backup generation and storage, respectively. We assume that the cost of investing in any resource $r \in \mathcal{R}$ for any period n in a set \mathcal{N} , $|\mathcal{N}| = N$, of planning periods is mixed-integer linear representable, e.g.,

$$c_{rn}(x_{rn}) := \begin{cases} p_{rn}x_{rn} + p_{rn}^{0} & \text{if } \underline{x}_{r} \leq x_{rn} \leq \overline{x}_{r}, \\ 0 & \text{if } x_{rn} = 0, \\ \infty & \text{otherwise,} \end{cases}$$

$$(1)$$

where \underline{x}_r and \bar{x}_r are lower and upper bounds on admissible investments, and p_{rn} and p_{rn}^0 are nonnegative coefficients. The installed capacity of any non-grid resource $r \in \mathcal{R} \setminus \{g\}$ at the beginning of period n is

$$\bar{x}_{rn}(\boldsymbol{x}_r) \coloneqq \sum_{i \in \mathcal{I}_r} x_{rni}^0 + \sum_{i=n(n,N_r)}^n x_{ri}, \tag{2}$$

where \mathcal{I}_r is an index set covering preinstalled units and \boldsymbol{x}_{rn}^0 is their power capacity, N_r is their lifetime, and $\underline{n}(n,N) := \max\{1, n-N+1\}$ is an auxiliary function. For grid resources, we distinguish regular operations (c=0) from contingencies (c=1). We define $\mathcal{C} := \{0,1\}$. In contingencies, we discount the total installed capacity by the largest individual unit, hence

$$\bar{x}_{gnc}(\boldsymbol{x}_{g}) \coloneqq \sum_{i \in \mathcal{I}_{g}} x_{gni}^{0} + \sum_{i=n(n,N_{g})}^{n} x_{gi} - c \cdot \max \left\{ \max_{i \in \mathcal{I}_{g}} \left\{ x_{gni}^{0} \right\}, \max_{i \in \left\{ \underline{n}(n,N_{g}),\dots,n\right\}} x_{gi} \right\}.$$
 (3)

Non-grid resources may participate in capacity markets and claim credits valued at price \bar{p} . The total net investment cost is thus

$$f(\boldsymbol{x}) := \sum_{n \in \mathcal{N}} \sum_{r \in \mathcal{R}} c_{rn}(x_{rn}) - \sum_{r \in \mathcal{R} \setminus \{g\}} \bar{p}_{rn} \bar{x}_{rn}. \tag{4}$$

Proposition 1. The capacity functions \bar{x}_{rn} and \bar{x}_{gnc} are nondecreasing concave piecewise linear for all $r \in \mathcal{R} \setminus \{g\}$, $n \in \mathcal{N}$, and $c \in \mathcal{C}$.

Proof. For all $r \in \mathcal{R} \setminus \{g\}$ and $n \in \mathcal{N}$, the functions \bar{x}_{rn} are affine and thus concave. For c = 0, the function \bar{x}_{gnc} is affine as well. For c = 1, it is concave piecewise linear because the maximum

of affine functions is convex. The functions are nondecreasing because they can be expressed as a minimum of nondecreasing linear functions. \Box

2.2 Operating cost

Each planning period consists of J operating periods, think of days, which themselves consist of K subperiods, think of hours. We differentiate supply from demand. On the supply side, y_{rnjkc}^s denotes the power supplied by resource $r \in \mathcal{R}$ in subperiod k of operating period j of planning period n under contingency c. Similarly, y_{rnjkc}^d denotes the power consumed by resource $r \in \mathcal{D}$. The set $\mathcal{D} := \{g, \ell, s\}$ contains exogenous load (ℓ) , in addition to grid and storage demand. As we distinguish supply from demand, all operating decisions are nonnegative.

We assume linear operating costs in all periods $\mathcal{J}(|\mathcal{J}|=J)$ and subperiods $\mathcal{K}(|\mathcal{K}|=K)$,

$$g_{nc}(\boldsymbol{y}) := T_c \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} \left(\sum_{r \in \mathcal{R}} p_{rnjk}^{\text{s}} y_{rnjkc}^{\text{s}} - \sum_{r \in \mathcal{D}} p_{rnjk}^{\text{d}} y_{rnjkc}^{\text{d}} \right), \tag{5}$$

where T_c is a probability-weighted time duration and p_{rnjk}^{s} and p_{rnjk}^{d} are prices for supply and demand, respectively. The operating decisions must obey the following constraints. In every subperiod, supply must equal demand, *i.e.*,

$$\sum_{r \in \mathcal{R}} y_{rnjkc}^{s} = \sum_{r \in \mathcal{D}} y_{rnjkc}^{d} \ \forall (n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C}.$$
 (6)

Supply and demand must respect capacity limitations, i.e., for all (n, j, k, c) in $\mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C}$,

$$y_{\text{b}njkc}^{\text{s}} \leq \bar{x}_{\text{b}n}(\boldsymbol{x}_{\text{b}}), \quad y_{\text{g}njkc}^{\text{s}} \leq \bar{x}_{\text{g}nc}(\boldsymbol{x}_{\text{g}}), \quad y_{\text{s}njkc}^{\text{s}} \leq \bar{x}_{\text{s}n}(\boldsymbol{x}_{\text{s}}),$$
 (7a)

$$y_{\text{gnjkc}}^{\text{d}} \le \bar{x}_{\text{gnc}}(\boldsymbol{x}_{\text{g}}), y_{\ell njkc}^{\text{d}} \le \bar{y}_{\ell njk}, \quad y_{\text{snjkc}}^{\text{d}} \le \bar{x}_{\text{sn}}(\boldsymbol{x}_{\text{s}}),$$
 (7b)

where $\bar{y}_{\ell njk}$ is exogenous load. If load shedding is not permissible, we set

$$y_{\ell nikc}^{\mathbf{d}} = \bar{y}_{\ell nik}. \tag{8}$$

Storage must maintain a state-of-charge between zero and an upper bound given by the product of installed power capacity and storage duration T^{s} , *i.e.*,

$$0 \le y_n^0 + \Delta t \sum_{l=1}^k \eta^c y_{\text{snjlc}}^{\text{d}} - \frac{y_{\text{snjlc}}^{\text{s}}}{\eta^{\text{d}}} \le T^{\text{s}} \bar{x}_{\text{sn}}(\boldsymbol{x}_{\text{s}}) \quad \forall (n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \{0\} \cup \mathcal{K} \times \mathcal{C}, \tag{9}$$

where y_n^0 is an initial state-of-charge target for planning period n, Δt is the duration of a subperiod, and η^c and η^d are charging and discharging efficiencies, respectively.

Remark 1. We require the initial state-of-charge to be the same across operating periods and contingency scenarios to limit the use of perfect foresight and ensure smooth transitions from contingency to non-contingency operations.

The terminal state-of-charge in each operating period must equal the initial state-of-charge, i.e.,

$$\sum_{k \in \mathcal{K}} \eta^{c} y_{\text{snjkc}}^{d} - \frac{y_{\text{snjkc}}^{s}}{\eta^{d}} = 0 \quad \forall (n, j, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{C}.$$
 (10)

In order to maintain battery warranty, the energy throughput per planning period may not exceed a certain threshold, e.g., 150 discharge cycles per year for the Tesla Powerpack 2 in our case study, which gives rise to the constraint

$$\frac{\Delta t}{\eta^{\rm d}} \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{K}} y_{{\rm s}njkc}^{\rm s} \le C^{\rm s} T^{\rm s} \bar{x}_{{\rm s}n}(\boldsymbol{x}_{\rm s}) \quad \forall (n, c) \in \mathcal{N} \times \mathcal{C}, \tag{11}$$

where C^{s} is the admissible number of discharge cycles per planning period.

Proposition 2. For fixed investment decisions, all operational constraints can be represented as a set of linear constraints $\mathcal{Y}_{nc}(\mathbf{x})$ for all $n \in \mathcal{N}$ and $c \in \mathcal{C}$.

Proof. The only complicated constraints are the capacity limitations in equations (7), which require that operating decisions be smaller than the concave piecewise linear capacity functions \bar{x} . Because concave upper bounds are convex constraints, these conditions can be represented by linear constraints.

Proposition 2 implies that the operating cost for fixed investment decisions and fixed $(n, c) \in \mathcal{N} \times \mathcal{C}$ are given by the solution to the linear program

$$g_{nc}^{\star}(\boldsymbol{x}) = \min_{\boldsymbol{y} \in \mathcal{Y}_{nc}(\boldsymbol{x})} g_{nc}(\boldsymbol{y}). \tag{OC}$$

Proposition 3. The optimal value function g_{nc}^{\star} is nonincreasing convex piecewise linear.

Proof. The set \mathcal{Y}_{nc} is an intersection of halfspaces, each determined by linear inequalities of the form $a^{\top} y + b \leq \bar{x}(x)$. The capacity functions \bar{x} are nondecreasing concave piecewise linear by Proposition 1. The claim thus follows from linear programming sensitivity analysis (Bertsimas and Tsitsiklis, 1997, Theorem 5.1).

2.3 Total cost

The objective is to minimize capital and operating costs,

$$\min_{x} f(x) + \sum_{n \in \mathcal{N}} \sum_{c \in \mathcal{C}} g_{nc}^{\star}(x). \tag{TC}$$

As operating costs are convex and nonincreasing in the capacity investments x, problem (TC) models the trade-off between investment costs and operating costs. The computational difficulty in solving (TC) stems from the nonconvex noncontinuous extended real-valued function f, which models the limits on admissible investments and hence the tradeoff between lumpy investments with low per-unit costs (grid investments) and modular investments with high per-unit costs (backup generation and storage).

2.4 Market participation constraints

In deregulated markets, distribution companies may be allowed to use backup generation and storage as a last resort to meet electricity demand but not for market participation in general. If such restrictions apply, we limit the supply from non-grid resources to the shortfall of grid capacity relative to demand and impose the constraint

$$\sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^{s} \le \left[y_{\ell njkc}^{d} - \bar{x}_{gnc}(\boldsymbol{x}_{g}) \right]^{+} \quad \forall (n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C}.$$
 (12)

Proposition 4. For any $(n, c) \in \mathcal{N} \times \mathcal{C}$, the market participation constraints define a nonconvex feasible set $\mathcal{M}_{nc}(\mathbf{x}_g)$ that shrinks with \mathbf{x}_g .

Proof. The set is nonconvex because constraints (12) impose lower bounds on the functions

$$\left[y_{\ell njkc}^{d} - \bar{x}_{gnc}(\boldsymbol{x}_{g})\right]^{+} = \max\left\{0, y_{\ell njkc}^{d} - \bar{x}_{gnc}(\boldsymbol{x}_{g})\right\},\tag{13}$$

which are convex in \mathbf{x}_g by composition as \bar{x}_{gnc} is concave by Proposition 1 and the function $h(x) = \max\{0, -x\}$ is convex and nonincreasing (Boyd and Vandenberghe, 2004, eq. (3.10)). The set shrinks with \mathbf{x}_g as h is nonincreasing and \bar{x}_{gnc} nondecreasing.

The nonconvexities can be modeled by introducing binary variables for each subperiod, which drastically increases the number of binary variables in the overall problem.

Operating decisions that respect the market participation constraints can be found by intersecting the feasible set in problem OC with $\mathcal{M}_{nc}(\boldsymbol{x}_{g})$ for each $n \in \mathcal{N}$ and $c \in \mathcal{C}$. The constrained operating cost is thus

$$\bar{g}_{nc}^{\star}(\boldsymbol{x}) = \min_{\boldsymbol{y} \in \mathcal{Y}_{nc}(\boldsymbol{x}) \cap \mathcal{M}_{nc}(\boldsymbol{x}_{g})} g_{nc}(\boldsymbol{y}). \tag{COC}$$

As \mathcal{M}_{nc} shrinks with \boldsymbol{x}_{g} , imposing this constraint invalidates Proposition 3: We lose convexity and monotonicity in grid investments but retain monotonicity in backup and storage investments.

Proposition 5. The constrained optimal value function \bar{g}_{nc}^{\star} is piecewise linear and nondecreasing in \mathbf{x}_{b} and \mathbf{x}_{s} . For any $\mathbf{x} \in \text{dom } f$, we have $\bar{g}_{nc}^{\star}(\mathbf{x}) \geq g_{nc}^{\star}(\mathbf{x})$.

Proof. The function is piecewise linear because the case distinction underlying the max-term in constraint (12) can be expressed as a series of disjunctive inequalities with auxiliary binary variables, which results in a mixed-binary linear program. The function is monotone in \boldsymbol{x}_b and \boldsymbol{x}_s because \mathcal{Y}_{nc} expands with \boldsymbol{x} and \mathcal{M}_{nc} depends on \boldsymbol{x} only through \boldsymbol{x}_g . The inequality holds because the feasible set of problem (COC) is a restriction of the feasible set in problem (OC).

Remark 2. Under fixed grid investments and electricity demand decisions, *i.e.*, in the absence of load shedding, constraint (12) is linear and can be modeled without binary variables.

2.5 Theoretical takeaways

In summary, the theoretical analysis reveals that:

- 1. Operating costs are nonincreasing in backup and storage investments;
- 2. Maybe surprisingly, operating costs may *not* be nonincreasing in grid investments if market participation is constrained;
- 3. Constrained market participation increases operating costs;
- 4. There are two sources of computational complexity: market participation constraints and the trade-off between modular high-cost investments and lumpy low-cost investments. Both can be modeled with binary variables. The investment trade-off introduces $|\mathcal{R}|N$ binary variables, while the market participation constraints introduce NJK|C| binary variables.

Appendix B provides a mixed-integer linear reformulation of the total cost minimization problem.

3 Case study

3.1 Case study selection

We perform a case study for the island of Nantucket, Massachusetts, because it

- is located in a deregulated state that does not allow storage owned by distribution companies to participate in electricity markets;
- has publicly available data about the current energy system and its future evolution;
- is self-contained and of modest size, which facilitates analysis;
- already has a battery system owned by a distribution company.

The Nantucket Electric Company, a subsidiary of National Grid, serves the entire island and no other territory. In January 2024, the company filed a plan to proactively upgrade its distribution grid with the Massachusetts Department of Public Utilities as required by law (Massachusetts General Court, 2022, § 53). The plan describes the current energy system on the island and its projected future evolution through the year 2050 (National Grid, 2024). In addition to data from the distribution company, past electricity demand and price data are available from the grid operator serving Nantucket. Specifically, the Independent System Operator New England (ISO-NE) assigns the network node LD.CANDLE 13.2 with ID 16255 in load zone 4006 (Southeastern Massachusetts) to Nantucket.

In 2019, National Grid installed a 6MW/48MWh battery and a 13MW backup generator on the island to delay investments in an additional subsea cable that would have been needed to ensure supply if one of the two existing cables were to fail. Also in 2019, the Pacific Northwest National Laboratory (PNNL) released a study about the battery and the generator (Balducci et al., 2019).

3.2 Data

This section describes a few important problem parameters. A detailed list of all parameters with references, mostly pointing to National Grid, the ISO-NE, and PNNL, can be found in Appendix A. The left panel of Figure 1 shows the projected evolution of peak load and generation capacity in the absence of new investments from 2025 through 2050 with yearly resolution. In this study, we

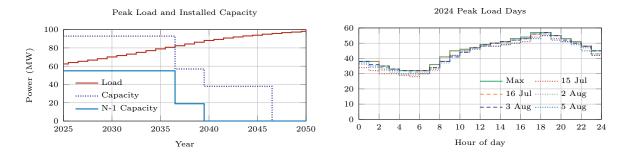


Figure 1. Electric load and generation capacity in the absence of new investments.

assume that peak load grows as in National Grid's highest load scenario, *i.e.*, from 62MW in 2025 to 98MW in 2050. In the absence of new investments, the installed capacity falls from 93MW in 2025 to zero by 2047, and N-1 capacity, *i.e.*, total installed capacity minus the largest installed unit, falls from 55MW in 2025 to zero in 2040. We match our case study planning horizon with the 2050 horizon used by National Grid. Over this horizon, it will be necessary to fully renew the existing energy infrastructure and almost double the N-1 capacity.

The right panel of Figure 1 shows load trajectories with hourly resolution for the 5 days with the highest peak load in the year 2024. These days are July 15 and 16, and August 2, 3, and 5. All days follow a similar pattern. Load is lowest at about 30MW in the early morning between 4–6am and highest at 57MW in the early evening between 5–7pm. The large load swings, near-doubling over a day, suggest opportunities for storage to reduce peak load by charging when load is low and discharging when load is high. Given that peak load days tend to follow each other, our modeling choice to impose a fixed state-of-charge target at the beginning of each day, see Remark 1, seems appropriate.

Figure 2 shows the load and electricity price for each hour in the year 2024, as reported by ISO-NE. Consistent with the observations about peak load days, load is high on summer afternoons and low throughout the rest of the year, which suggests that storage use for peak load reduction be concentrated in summer. Electricity price is high on summer afternoons and in winter. This suggests that storage operation for peak load reduction is at least partially aligned with storage operation for market participation. In summer, it is best to charge in the morning and discharge in the evening. During the rest of the year, no peak load reduction is needed, and storage could in principal be freely used for market participation if it were not for regulatory constraints.

Figure 3 shows all scarcity events in the year 2024, i.e., times at which the ISO-NE did not have

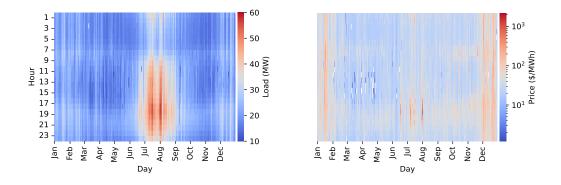


Figure 2. Nantucket electricity load and price in 2024.

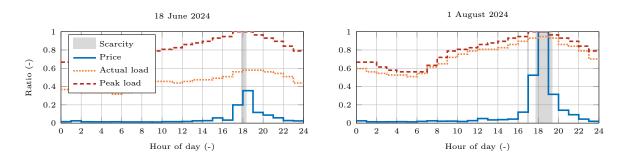


Figure 3. Scarcity events in the ISO-NE in 2024; locational marginal prices and load are normalized by their peak values in the year (\$2173.15/MWh and 57MW).

sufficient generation capacity to reliably meet demand. In these times, the ISO-NE calls on generation providers that had been awarded supply obligations in a forward capacity market. Supply obligation holders are remunerated at the capacity price shown in Figure A3, which varies on a yearly basis. The year 2024 had two scarcity events, both on summer evenings. This suggests that storage operation for peak load reduction is aligned with capacity market participation.

3.3 Assumptions

We make the following simplifying assumptions.

1. Constant resource parameters: The capacity and efficiency of all resources stay the same over their lifetimes. In practice, the resources will experience degradation. While the manufacturer of the Nantucket battery guaranteed the nominal capacity over a 20-year lifespan conditional on regular maintenance and respect of a yearly maximum number of discharge cycles, the roundtrip efficiency will degrade, which we account for by using a lifetime average

efficiency, similar to Balducci et al. (2019, p. 3.3). We assume that market participation does not cause any additional degradation as long as the yearly cycle limit is respected. In practice, Orange and Rockland Utilities (2024) report that market participation requires one maintenance day per month. Here, we neglect any downtime requirements. These assumptions can be relaxed by adapting problem parameters. For example, battery degradation could be considered more explicitly via positive charging and discharging costs p_s^d and p_s^s .

- 2. Simplified battery dynamics: The maximum charge and discharge power and charging and discharging efficiencies are independent of operational parameters. In reality, they would depend on the state-of-charge and temperature, among others. Such dependencies could be partly addressed by maintaining the state-of-charge within a limited range. In addition, we ignore the complementarity constraint between charging and discharging, and check *ex-post* for violations. While there were none in our experiments, they could happen, in principle, if electricity prices are negative.
- 3. Limited foresight: Prices, demand, and the occurrence of contingencies are used one day ahead of time for operating decisions. In addition, they are used one year ahead of time for the allocation of the annual battery discharge budget of 150 cycles and to decide on the fixed state-of-charge target for the beginning of each day. Finally, they are used up to 26 years ahead of time, the length of our planning horizon, for investment decisions. These assumptions can be relaxed by considering multiple scenarios, at the price of increased computational complexity. On an operational level, this may not be worthwhile because a near-optimal allocation of discharge cycles may be determined ex-ante. In fact, the data analysis in Section 3.2 reveals that summer is by far the most promising time of year for storage operations, suggesting that that most of the discharge budget be spent then. The analysis also shows that peak load days tend to be similar and follow each other, suggesting that the state-of-charge target can be based on a few select peak load days.

3.4 Numerical implementation

All numerical experiments are conducted on AMD EPYC 9474F CPUs with 48 cores, a 3.6GHz base clock, and 376GB of RAM. Simulations are implemented in Julia 1.11.2 using JuMP 1.23.5 with

Gurobi 12.0.2. All code and data are available at https://github.com/mit-shin-group/storage-value.

3.5 Numerical experiments

3.5.1 Experimental setup

We solve the investment problem (TC) formulated as problem (B1) for the case study over a 26 year planning horizon with hourly resolution. We perform nine experiments, varying market participation constraints, available resources for investments, storage costs, storage cycle limits, and forward capacity prices. Table A3 in Appendix C reports total cost, solve time, mixed-integer programming gaps, operating and capital costs, revenue from capacity payments, investment and operating decisions, yearly discharge cycles, and the minimum supply ratio during scarcity events, defined as the minimum power generation during the event divided by the installed generation capacity of backup generation or storage.

3.5.2 Experiments and results

We obtain the following results. All cost reductions are expressed in percent of the total cost of Experiment 1.

- 1. Relying only on grid investments yields the highest total cost. Experiment 1 allows only for investments in grid expansion, resulting in total costs of \$678.9 million.
- 2. Allowing for storage investments reduces total costs by 4.7%. Experiment 2 allows for grid and storage investments, which reduces total grid investments from 160MW to 120MW in exchange for a 19.3MW storage investment. Market participation is constrained in this experiment, modeling the status quo, which leads to storage experiencing 7.0 discharge cycles per year on average during contingencies and none during normal operations. Effectively, storage is thus kept sitting idle at a high state-of-charge for the vast majority of the time and discharged only when necessary to meet peak load.
- 3. Allowing for market participation reduces total costs by an additional 2.0–4.5% and does not trigger increased generation investment. Experiment 4 allows for arbitrage on wholesale markets and participation in the ISO-NE capacity market, which in-

creases storage utilization to 150 discharge cycles per year during both normal operations and contingencies, but does not trigger any additional storage investment. Importantly, storage operations are virtually *identical* in normal operations and contingencies. This suggests that there would be little value in adopting operations to contingencies.

Both backup generation and storage are operating at their maximum capacity during scarcity operations. Neither would thus pay any penalty for failing to meet their capacity supply obligations. While this may at first seem surprising as we did not use any information about scarcity events in the problem formulation, it can be explained by the high prices wholesale prices during the events. In principle, local demand reduction may limit the availability of storage to provide power during scarcity events. In this case, however, local needs align with larger system needs, *i.e.*, provide power on summer evenings, and thus we do not observe this effect. We conclude that under the 2024 load pattern an 8h duration is sufficient for storage to reliably meet its capacity supply obligations, which is consistent with ISO-NE assigning an effective load carrying capacity of 1 to 2h+ duration storage. However, as the year 2024 only had 2 scarcity events, there could be other scenarios in which the battery cannot fulfill its capacity supply obligation. We thus perform Experiment 3, which allows for arbitrage but not capacity market participation. In this case, total costs decrease by 2.0%, otherwise by 4.5%.

- 4. Evenly distributing the yearly storage cycle budget across each day reduces solve time and increases costs. Experiment 5 evenly splits the 150 yearly cycle budget across each day, which reduces intertemporal coupling and results in a total cost reduction of only 2.9% because almost twice as much storage is needed to reduce peak demand, compared to 6.7% under flexible discharge cycle allocation.
- 5. Allowing for backup generation investments reduces total costs by an additional 0.5–2.5%. Experiments 6 and 7 allow for backup generation investments and arbitrage without and with capacity markets, respectively. Compared to Experiments 3 and 4, backup generation investments increase from 0MW to 22.2MW, while storage investments decrease from 19.3MW to 11.6MW.
- 6. Cheaper storage increased deployment by 10.2% if market participation is not



Figure 4. Indicative cost savings from storage in distribution grids.

allowed and 2028.8% if arbitrage is allowed. Experiments 8 and 9 serve to model deployment if storage were virtually free, *i.e.*, have a capital cost of \$1/kWh. Without market participation, deployment increases from 19.3MW in Experiments 2–4 to 21.3MW. With arbitrage, storage deployment increases to 391.9MW, far greater than the needs for local demand reduction.

Figure 4 shows the cost savings from storage with and without market participation. Figure 5 shows the supply decisions for each resource type for the year 2025 for Experiments 2 and 3. The figure confirms that there is little difference between base case and contingency operations for storage and backup generation if market participation is allowed.

3.6 Practical takeaways

In summary, the numerical experiments reveal that:

- Arbitrage and capacity market participation each increase the cost savings from allowing for storage investment by about 50%;
- 2. Under current conditions, market participation generates no additional storage investment;
- 3. Under very low costs, market participation does generate additional storage investment. In this case, the market participation constraint (12) can be used to find the level of storage investment appropriate for addressing local distribution needs. As the constraint is nonconvex, it increases computation complexity. If that increase is judged excessive, the analytical model in Appendix A.1, currently used to determine big-M constants of the mixed-integer linear programming reformulation in Appendix B, can be used to determine an upper bound on appropriate storage investments.

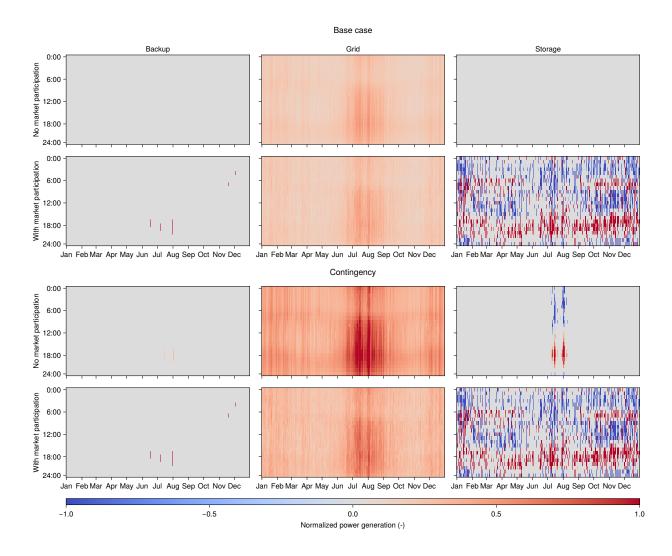


Figure 5. Supply decisions for the year 2025, normalized by installed capacity.

4 Conclusion

We addressed three questions about the value of storage in distribution grids:

- 1. How to model market participation constraints in storage operation and investment planning;
- 2. How profits from market participation compare to savings from reducing peak demand;
- 3. If market participation would generate storage investments that go beyond distribution needs, and if so, how this may be detected?

Equation (12) models market participation constraints by limiting the supply from non-grid re-

sources, such as storage, to the shortfall of grid capacity relative to electricity demand. We integrate these constraints into an optimization problem that determines distribution grid investment decisions. As the constraints are nonconvex, they increase the computational complexity of the problem, raising questions about tractability. In a Massachusetts case study, we find that problems with a 26 year horizon and hourly resolution can be solved within several hours on current compute servers.

The case study further reveals that arbitrage and capacity market participation each generate about 50% of the capital cost savings from reducing or deferring grid investments. We determine storage investment levels appropriate for serving local distribution needs by solving the planning problems with the market participation constraints. We find that under current technology costs, market participation does not generate any storage investment that go beyond distribution needs. In the past, the prospect of reduced or deferred grid investments was large enough to cast aside fears about market distortion, and regulators allowed storage investment for distribution needs. Given that allowing for market participation promises similar savings, we wonder if this may justify another policy change.

There is a risk that allowing for market participation would incentivize distribution companies to invest in storage solely for serving the market. Under current market conditions, we find that such investments are not profitable. Even if they were profitable, our model could be used to audit proposed investments and limit them to levels appropriate for addressing distribution needs.

In fine, jurisdictions that have already allowed market participation, e.g., New York and Maryland, may find our model useful to audit proposed storage investments. Jurisdictions that do not currently allow for market participation may use our model to inform discussions about market participation or contracting with third-party storage providers.

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A Data

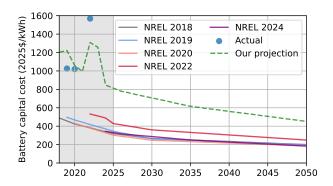


Figure A1. Projected and actual battery capital costs. Solid lines are NREL projections, blue dots are actual distribution grid battery projects in Provincetown and Nantucket, both MA, and Ponoma, NY. The dashed green line is our projection based on the average factor by which actual costs exceed NREL projections. The mean storage investment cost is \$604/kWh, *i.e.*, \$4832/kW for an 8h duration.

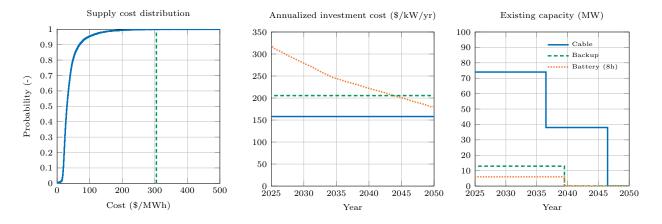


Figure A2. Case study generation cost, investment cost, and preexisting capacity.

A.1 Maximum peak shaving potential

To assess the maximum potential of storage to reduce peak load, we introduce a simplified linear program. This will be used to determine the upper bound on storage investments \bar{x}_s and big-M constants for the mixed-integer linear programming reformulation of problem (TC) in Section B. Consider a storage device with infinite power and energy capacity and an infinite grid connection

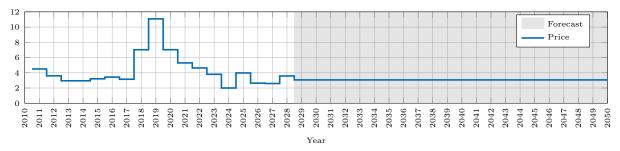


Figure A3. Forward price for existing capacity in Southeastern Massachusetts.

used to fully flatten electric load. The flattened load in any operating period $j \in \mathcal{J}$ of planning period $n \in \mathcal{N}$ is given by

$$y_{\ell nj}^{\star}(\boldsymbol{\eta}^{\mathrm{c}}\boldsymbol{\eta}^{\mathrm{d}}) = \min \max_{k \in \mathcal{K}} \bar{y}_{\ell njk} - y_{\mathrm{s}njk}^{\mathrm{s}} + y_{\mathrm{s}njk}^{\mathrm{d}} \quad \text{s.t.} \quad \sum_{k \in \mathcal{K}} \boldsymbol{\eta}^{\mathrm{c}}\boldsymbol{\eta}^{\mathrm{d}}y_{\mathrm{s}njk}^{\mathrm{d}} - y_{\mathrm{s}njk}^{\mathrm{s}} \ge 0, \ \boldsymbol{y}_{\mathrm{s}nj}^{\mathrm{d}}, \boldsymbol{y}_{\mathrm{s}nj}^{\mathrm{s}} \ge 0, \quad (\mathrm{FL})$$

which can be formulated as a linear program that only depends on roundtrip efficiency and load.

Proposition A1. The flattened demand function is convex noninreasing and ranges from $\max_{k \in \mathcal{K}} \bar{y}_{\ell n j k}$ for $\eta^c \eta^d = 0$ to $\frac{1}{K} \sum_{k \in \mathcal{K}} \bar{y}_{\ell n j k}$ for $\eta^c \eta^d = 1$.

Proof. Problem (FL) admits the dual formulation

$$\max_{\lambda, \mu} \sum_{k \in \mathcal{K}} \bar{y}_{\ell n j k} \mu_k \quad \text{s.t.} \quad \sum_{k \in \mathcal{K}} \mu_k = 1, \, \eta^{\text{c}} \eta^{\text{d}} \lambda \leq \mu_k \leq \lambda \quad \forall k \in \mathcal{K}, \, \lambda \geq 0.$$

Since the objective function is linear and the feasible set a polyhedron, there exists an optimal solution at a vertex of the polyhedron. Let \bar{y} be ordered such that $\bar{y}_{\ell n j 1} \geq \ldots \geq \bar{y}_{\ell n j K}$. Then, there exists an optimal solution of the form $\mu_{1,\ldots,m} = \lambda$, $\mu_{m+1,\ldots,K} = \eta^c \eta^d \lambda$, and $\lambda = \frac{1}{m+(K-m)\eta^c \eta^d}$, i.e., at a vertex of the box constraints that satisfies the sum constraint, for some $m \in [0, K] \cap \mathbb{Z}$. Let

$$\varphi_m(\eta^{\mathrm{c}}\eta^{\mathrm{d}}) := \frac{\sum_{i=1}^m \bar{y}_{\ell n j i} + \eta^{\mathrm{c}} \eta^{\mathrm{d}} \sum_{i=m+1}^K \bar{y}_{\ell n j i}}{m + (K - m) \eta^{\mathrm{c}} \eta^{\mathrm{d}}}.$$

The optimal value of the dual problem as a function of $\eta^c \eta^d$ is thus

$$\varphi(\eta^{c}\eta^{d}) := \max_{m} \varphi_{m}(\eta^{c}\eta^{d}) \text{ s.t. } m \in [\eta^{c}\eta^{d}K, K] \cap \mathbb{Z}.$$

Evaluating first derivatives, we find

$$\varphi_m(\eta^{c}\eta^{d})' = \frac{m \sum_{i=m+1}^{K} \bar{y}_{\ell n j i} - (K-m) \sum_{i=1}^{m} \bar{y}_{\ell n j i}}{(m + (K-m)\eta^{c}\eta^{d})^{2}},$$

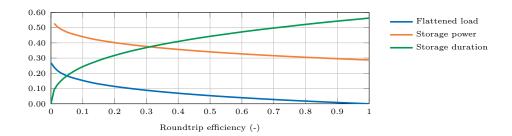


Figure A4. Flattened load (normalized by the deviation from average load), storage power (normalized by average load), and storage duration (normalized by 12 hours).

which is nonpositive because

$$\frac{\sum_{i=m+1}^{K} \bar{y}_{\ell n j i}}{K-m} \le \frac{\sum_{i=1}^{m} \bar{y}_{\ell n j i}}{m},$$

as $\bar{y}_{\ell nj1} \geq \ldots \geq \bar{y}_{\ell njK}$, and thus increasing in $\eta^c \eta^d$. The functions φ_m are therefore convex nonincreasing and so is their pointwise maximum φ . In addition, $\varphi(0) = \max_{k \in \mathcal{K}} \bar{y}_{\ell njk}$ and $\varphi(1) = \frac{1}{K} \sum_{k \in \mathcal{K}} \bar{y}_{\ell njk}$. The dual problem thus admits finite optimal values and strong linear programming duality holds. Therefore, the optimal value functions of the primal and dual problems coincide. \square

For any given roundtrip efficiency and load profile, we can compute the power and energy capacity required to fully flatten load based on the optimizers to problem (FL) as

- 1. $\max_{k \in \mathcal{K}} \left\{ y_{\text{s}njk}^{\text{s}\star}, y_{\text{s}njk}^{\text{d}\star} \right\}$ for power capacity and
- 2. $\max_{k \in \mathcal{K}} \Delta t \sum_{l=1}^{k} \left(\eta^{c} y_{\text{s}njk}^{\text{d}\star} \frac{y_{\text{s}njk}^{\text{s}\star}}{\eta^{\text{d}}} \right) \min_{k \in \mathcal{K}} \sum_{l=1}^{k} \left(\eta^{c} y_{\text{s}njk}^{\text{d}\star} \frac{y_{\text{s}njk}^{\text{s}\star}}{\eta^{\text{d}}} \right)$ for energy capacity.

Figure A4 shows the peak-shaving potential for the load profile in Figure 1. For typical battery roundtrip efficiencies of 85% to 95%, the flattened load will be about 1% higher than the average load and require a power capacity of 30% of the average load and a storage duration of 6.5 hours.

A.2 Sources and assumptions

We source data from

- NREL's cost projections for utility-scale battery storage (Cole and Frazier, 2019, 2020; Cole et al., 2021, 2025; Cole and Karmakar, 2023);
- A consumer price index (https://www.rateinflation.com/consumer-price-index/usa-historical-cpi/) to adjust price data from different years;

- existing distribution-grid batteries in the Northeastern US, specifically from
 - Nantucket, MA, with an estimated investment cost of \$33 million for the 6MW/48MWh battery commissioned in 2019, \$35.6 million for the combustion turbine generator (Balducci et al., 2019, p. 3.3), and total actual costs of \$81 million (Gheorghiu, 2019);
 - Provincetown, MA, with a reported investment cost of \$54.8 million for a 25MVA/38MWh
 battery commissioned in 2022 (Eversource Energy, 2024, Fig. 34);
 - Ponoma, NY, with a reported cost of \$9.2 million for a 3MW/12MWh battery commissioned in 2020 (Orange and Rockland Utilities, 2021, p. 3).
- The ISO-NE's webportal (https://www.iso-ne.com/isoexpress/web/reports/load-and-demand/-/tree/nodal-load-weights) from network node LD.CANDLE 13.2 with ID 16255 in load zone 4006 for hourly load and price profiles for the year 2024. We assume that the price profile is identical in each planning period. In reality, it will be different and efforts are made to project future price patters, e.g., via NREL Cambium. We do not use these because they currently underestimate price variability (Seel and Mills, 2021, p. 5), an important determinant of arbitrage profitability. In addition, we assume that future load follows the same pattern as in 2024 and is linearly scaled by the increase in peak load. This is unrealistic because we expect shifts in electricity usage patterns. While distribution companies project these shifts, the underlying data was not included in National Grid's electric sector modernization plan;
- National Grid's electric sector modernization plan for yearly peak load projections through 2050 (National Grid, 2024, 2023 to 2050 Electric Peak (MW) Forecast, p. 62);
- Caterpillar (https://s7d2.scene7.com/is/content/Caterpillar/CM20150703-52095-43744) for the technical parameters of combustion turbine generators, namely, a heat rate of 10.4 MJ/kW-hr for temperatures around 30°C. This heat rate is accurate during hot summer afternoons, *i.e.*, when backup generation is needed most;
- The Energy Information Administration for diesel fuel costs, \$4 per gallon, *i.e.*, about \$1.057 per liter as of 9 September 2025 (https://www.eia.gov/petroleum/gasdiesel/);
- An online engineering manual for the lower heating value of diesel fuel, i.e., 36MJ/l (https://www.engineeringtoolbox.com/fuels-higher-calorific-values-d_169.html);

- The ISO-NE webportal for capacity prices (https://www.iso-ne.com/about/key-stats/markets#fcaresults) and supply scarcity events (https://www.iso-ne.com/isoexpress/web/reports/auctions/-/tree/fcm-hist-csc);
- ISO-NE's market monitor report for information about effective load carrying capacities, *i.e.*, discount factors applied to resources particing in capacity markets. We find an effective load carrying capacity of 1 for storage with a duration of 2h or longer and for combustine turbine backup generation (Potomac Economics, 2022, p. 64), which means that these resources can bid their nominal power supply capacity.

Table A1 lists all case study parameters with references.

Table A1. Case study parameters.

Parameter	Resource	Symbol	Value	Reference/Note		
Supply resources		\mathcal{R}	{b, g, s}	b: backup, g: grid, s: storage.		
Demand resources		\mathcal{D}	$\{g,\ell,s\}$	g: grid, ℓ : electric load, s: storage.		
Planning periods		\mathcal{N}	$\{2025, \dots, 2050\}$	Yearly resolution.		
# of planning periods		N	$ \mathcal{N} $			
Contingency cases		$\mathcal C$	$\{0, 1\}$	0: no contingency, 1: largest installed cable fails.		
# of contingencies		C	C			
Operating periods		$\mathcal J$	$\{1, \dots, 365\}$	Days per planning period.		
# of operating periods		J	$ \mathcal{J} $			
Operating subperiods		κ	$\{1,\ldots,24\}$	Hours per operation period.		
# of subperiods		K	$ \mathcal{K} $			
Time discretization		Δt	1h	Resolution of available ISO-NE load and price data.		
Time without contingency		T_0	0.8h	Per subperiod.		
Time with contingeny		T_1	0.2h	Per subperiod.		
Discount rate			0			
Maximum demand	Load	$ar{y}_\ell$	Fig.2	Hourly load (Fig.2) is scaled linearly.		
				with yearly peak load evolution (Fig.1).		
Charging efficiency	Storage	η^{c}	0.913	(Balducci et al., 2019, p.3.3)		
Discharging efficiency	Storage	$\eta^{ m d}$	0.913	(Balducci et al., 2019, p.3.3)		
Maximum discharge cycles	Storage	C^{s}	150 cycles/yr	(Balducci et al., 2019, p.3.2)		
Duration	Storage	T^{s}	8h	Same as existing battery (Balducci et al., 2019, p.3.2).		
Minimum investment	Backup	x_{b}	$_{ m 2MW}$	Assumed similar threshold to storage.		
	Grid	x_{g}	$40\mathrm{MW}$	Existing cables are 36MW and 38MW installed in 1996 and 2006		
		_		(Bluedot Living, 2024).		
	Storage	x_{s}	$_{ m 2MW}$	Orange and Rockland Utilities (2021) installed a 3MW battery.		
Maximum investment	Backup	$ar{x}_{ m b}$	$30 \mathrm{MW}$	Assumed to be twice the currently installed backup capacity.		
	Grid	$ar{x}_{ ext{g}}$	$40\mathrm{MW}$	Assumed to be the same as the minimum investment.		
	Storage	$ar{x}_{ ext{s}}$	$24\mathrm{MW}$	Maximum peak shaving potential (Sec.A.1).		
Existing units	Backup	\mathcal{I}_{b}	{1}	(Balducci et al., 2019, p.3.4)		
	Grid	\mathcal{I}_{g}	$\{1, 2\}$	(Bluedot Living, 2024)		
	Storage	\mathcal{I}_{s}	{1}	(Balducci et al., 2019, p.3.2)		
Lifetime	Backup	$N_{ m b}$	20yr	(Balducci et al., 2019, p.3.5)		
	Grid	$N_{ m g}$	$40 \mathrm{yr}$	(The Martha's Vineyard Times, 2023)		
	Storage	$N_{ m s}$	$20 \mathrm{yr}$	(Balducci et al., 2019, p.3.2)		
Existing capacity	Backup	$oldsymbol{x}_{\mathrm{b}}^{0}$	Fig.A2	(Balducci et al., 2019, p.3.4) + lifetime assumption.		
	Grid	$oldsymbol{x}_{ m g}^0$	Fig.A2	(Bluedot Living, 2024) + lifetime assumption.		
	Storage	\boldsymbol{x}_{0}^{0}	Fig.A2	(Balducci et al., 2019, p.3.2) + lifetime assumption.		

Table A1. Case study parameters.

Parameter	Resource	Symbol	Value	Reference/Note
Investment costs	Backup	$m{p}_{ m b}$	Fig.A2	PNNL and actual project costs (Sec.A.2).
	Grid	$oldsymbol{p}_{\mathrm{g}}$	Fig.A2	40MW cable would have cost \$200 million in 2019 (Gheorghiu, 2019).
	Storage	$oldsymbol{p}_{ ext{ iny S}}$	Fig.A2	PNNL and actual project costs (Sec.A.2).
Investment fix costs	Backup	$m{p}_{ m b}^0$	0	Considered through minimum investment threshold.
	Grid	$m{p}_{ m g}^0$	0	Considered through minimum investment threshold.
	Storage	$oldsymbol{p}_{ ext{s}}^{\ddot{0}}$	0	Considered through minimum investment threshold.
Capacity prices	Backup	$ar{m{p}}_{ m b}$	Fig.A3	https://www.iso-ne.com/about/key-stats/markets#fcaresults.
	Grid	$ar{m{p}}_{ m g}$	0	Capacity payment applies only to generation.
	Storage	$ar{m{p}}_{ ext{ iny S}}$	Fig.A3	https://www.iso-ne.com/about/key-stats/markets#fcaresults.
Supply cost	Backup	$m{p}_{ m b}^{ m s}$	305/MWh	See Sec.A.2 and Fig.A2
	Grid	$oldsymbol{p}_{ m g}^{ m s}$	${\bf Figs. 2\&A2}$	Same as the 2024 cost, available from ISO-NE (Sec.A.2).
	Storage	$oldsymbol{p}_{ ext{ iny S}}^{ ext{ iny S}}$	0	Could be set to nonzero to account for degradation.
Demand revenue	Grid	$m{p}_{ m g}^{ m d}$	Fig.2	Same as supply cost.
	Load	$\boldsymbol{p}_{\ell}^{\mathrm{d}}$	0	if load shedding is not allowed,
			9,337/MWh	if load shedding is allowed (Potomac Economics, 2025, p.70).
	Storage	$m{p}_{ m s}^{ m d}$	0	Could be set to nonzero to account for degradation.
Maximum solution time			14,400s	docs.gurobi.com/projects/,
				optimizer/en/current/reference/parameters.html#timelimit.
Maximum MIPGap			10-5	Relative mixed-integer optimality gap: docs.gurobi.com/projects/,
				optimizer/en/current/reference/parameters.html#mipgap.

B Optimization problem

B.1 Decision variables

Table A2. Decision variables.

Variable	Symbol	Space	Dimension	Note
Supply investment	x	$\mathbb{R}_{+}^{ \mathcal{R} N}$	Power	Capacity of type $r \in \mathcal{R}$ becoming available at the start of planning period $n \in \mathcal{N}$.
Largest investment	$oldsymbol{x}^{\max}$	\mathbb{R}^N_+	Power	Largest grid investment that is still live during planning period $n \in \mathcal{N}$.
Investment indicator	\boldsymbol{z}	$\{0,1\}^{ \mathcal{R} N}$	None	= 1 if $x_{rn} > 0$ for $r \in \mathcal{R}$ and $n \in \mathcal{N}$, = 0 otherwise.
Supply capacity	$oldsymbol{x}^{ ext{tot}}$	$\mathbb{R}_{+}^{ \mathcal{R} N}$ $\mathbb{R}_{\perp}^{ \mathcal{R} NJKC}$	Power	Installed capacity of type $r \in \mathcal{R}$ available during planning period $n \in \mathcal{N}$.
Supply operation	$oldsymbol{y}^{\scriptscriptstyle{\mathrm{S}}}$	$\mathbb{R}_{+}^{ \mathcal{R} NJKC}$	Power	Supply of type $r \in \mathcal{R}$ during subperiod $k \in \mathcal{K}$, in operating
		·		period $j \in \mathcal{J}$, in planning period $n \in \mathcal{N}$, in contingency case $c \in \mathcal{C}$.
Demand operation	$\boldsymbol{y}^{\mathrm{d}}$	$\mathbb{R}_{+}^{ \mathcal{D} NJKC}$	Power	Same as above for demand.
State-of-charge	\boldsymbol{y}	\mathbb{R}_{+}^{NJKC}	Energy	State-of-charge at the beginning of subperiod $k \in \mathcal{K}$, in operating
				period $j \in \mathcal{J}$, in planning period $n \in \mathcal{N}$, in contingency case $c \in \mathcal{C}$.
State-of-charge target	$oldsymbol{y}^0$	\mathbb{R}^N_+	Energy	State-of-charge target in planning period $n \in \mathcal{N}$.
Operating indicator	$oldsymbol{z}^{ ext{M}}$	\mathbb{R}^{NJKC}	None	= 1 if $y_{\ell njkc}^{d} > x_{gnc}^{tot}$ in subperiod $k \in \mathcal{K}$, in operating period $j \in \mathcal{J}$,
				in planning period $n \in \mathcal{N}$, in contingency case $c \in \mathcal{C}$; = 0 otherwise.

B.2 Auxiliary functions

$$\underline{n}(n,N) = \max\{1, n-N+1\}$$

B.3 Full formulation

We introduce epigraphical variables for the capacity functions $\bar{x}(\cdot)$ and state-of-charge variables to increase sparsity at the expense of a greater number of decision variables and constraints.

B.3.1 With full market participation

$$\min \sum_{n \in \mathcal{N}} \left(\sum_{r \in \mathcal{R}} p_{rn} x_{rn} + p_{rn}^{0} z_{rn} - \bar{p}_{rn} x_{rn}^{\text{tot}} \right) + \sum_{c \in \mathcal{C}} T_{c} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} \left(\sum_{r \in \mathcal{R}} p_{rnjk}^{\text{s}} y_{rnjkc}^{\text{s}} - \sum_{r \in \mathcal{D}} p_{rnjk}^{\text{d}} y_{rnjkc}^{\text{d}} \right)$$
(B1a)

s.t.
$$\boldsymbol{x}_r, \boldsymbol{x}_r^{\text{tot}} \in \mathbb{R}^N_+, \boldsymbol{y}_r^{\text{s}} \in \mathbb{R}^{NJKC}_+, \boldsymbol{z}_r \in \{0,1\}^N, \ \forall r \in \mathcal{R},$$
 (B1b)

$$\mathbf{y}_r^{\mathrm{d}} \in \mathbb{R}_+^{NJKC},$$
 $\forall r \in \mathcal{D},$ (B1c)

$$\boldsymbol{x}^{\max} \in \mathbb{R}_{+}^{N}, \, \boldsymbol{y} \in \mathbb{R}_{+}^{NJKC}, \, \boldsymbol{y}^{0} \in \mathbb{R}_{+}^{N},$$
 (B1d)

$$\underline{x}_r z_{rn} \le x_{rn} \le \bar{x}_r z_{rn}, \qquad \forall (r, n) \in \mathcal{R} \times \mathcal{N},$$
 (B1e)

$$x_{rn}^{\text{tot}} = \sum_{i \in \mathcal{I}_r} x_{rni}^0 + \sum_{i=n(n,N_r)}^n x_{ri}, \qquad \forall (r,n) \in \mathcal{R} \setminus \{g\} \times \mathcal{N},$$
 (B1f)

$$x_{\text{g}nc}^{\text{tot}} = \sum_{i \in \mathcal{I}_{g}} x_{\text{g}ni}^{0} + \sum_{i=n(n,N_{g})}^{n} x_{\text{g}i} - cx_{n}^{\text{max}}, \quad \forall \{n,c\} \in \mathcal{N} \times \mathcal{C},$$
 (B1g)

$$x_n^{\text{max}} \ge x_{\text{g}i},$$
 $\forall n \in \mathcal{N}, \forall i \in \{\underline{n}(n, N_{\text{g}}), \dots, n\},$ (B1h)

$$x_n^{\max} \ge x_{gni}^0,$$
 $\forall (n, i) \in \mathcal{N} \times \mathcal{I}_a,$ (B1i)

$$\sum_{r \in \mathcal{P}} y_{rnjkc}^{s} = \sum_{r \in \mathcal{D}} y_{rnjkc}^{d}, \qquad \forall (n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C},$$
(B1j)

$$y_{rnjkc}^{\rm s} \le x_{rn}^{\rm tot},$$
 $\forall (r, n, j, k, c) \in \mathcal{R} \setminus \{g\} \times \mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C},$ (B1k)

$$y_{gnjkc}^{d} \le x_{gnc}^{tot}, \ y_{gnjkc}^{s} \le x_{gnc}^{tot},$$
 $\forall (n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C},$ (B11)

$$y_{\ell njkc}^{\rm d} \le \bar{y}_{\ell njk}, \ y_{\rm snjkc}^{\rm d} \le x_{\rm sn}^{\rm tot},$$
 $\forall (n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C},$ (B1m)

$$0 \le y_n^0 \le T^s x_{sn}^{\text{tot}}, \ 0 \le y_{njkc} \le T^s x_{sn}^{\text{tot}}, \qquad \forall (n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C},$$
 (B1n)

$$y_{nj1c} = y_n^0 + \Delta t \left(\eta^c y_{\text{s}nj1c}^{\text{d}} - \frac{y_{\text{s}nj1c}^{\text{s}}}{\eta^{\text{d}}} \right), \qquad \forall (n, j, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{C},$$
 (B1o)

$$y_{njkc} = y_{nj(k-1)c} + \Delta t \left(\eta^c y_{\text{snjkc}}^{\text{d}} - \frac{y_{\text{snjkc}}^{\text{s}}}{n^{\text{d}}} \right), \, \forall (n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{K} \setminus \{1\} \times \mathcal{C},$$
 (B1p)

$$y_{njKc} = y_n^0,$$
 $\forall (n, j, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{C},$ (B1q)

$$\frac{\Delta t}{\eta^{\rm d}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} y_{\rm snjkc}^{\rm s} \le C^{\rm s} T^{\rm s} x_{\rm sn}^{\rm tot}, \qquad \forall (n, c) \in \mathcal{N} \times \mathcal{C}.$$
(B1r)

B.3.2 Without load shedding

Replace constraint (B1m) by

$$y_{\ell njkc}^{\mathrm{d}} = \bar{y}_{\ell njk}^{\mathrm{d}}, \quad \forall (n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C}.$$

B.3.3 With market participation constraints

For any $(n, j, k, c) \in \mathcal{N} \times \mathcal{J} \times \mathcal{K} \times \mathcal{C}$, we limit the supply from non-grid resources to the shortfall of grid capacity from load, *i.e.*,

$$\sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^{s} \le [y_{\ell njkc}^{d} - x_{gnc}^{tot}]^{+}.$$
(B2)

The difference to the original market participation constraint (12) is that we have replaced $\bar{x}_{gnc}(x_g)$ by the auxiliary variable x_{gnc}^{tot} . The case distinction in the $[\cdot]^+$ term can be handled with disjunctive constraints. We will determine the big-M parameters for these constraints under the following assumption.

Assumption 1. The build out of any supply resource is limited by local electricity demand.

Assumption 1 is in line with the spirit of market participation constraints, separating electricity generation from distribution. To apply Assumption 1, we introduce the following lemma.

Lemma 1. For any optimization problem of the form

$$\min f_0(\boldsymbol{x}) \text{ s.t. } \sum_{j \in \mathcal{J}} x_j \ge x_0, \ \boldsymbol{x} \in \{\boldsymbol{0}\} \cup [\underline{x}, \overline{x}]^J,$$

where f_0 is an increasing function and $\mathcal{J} \subseteq \{1, \ldots, J\}$, all optimal solutions satisfy

$$\sum_{j \in \mathcal{J}} x_j^* < x_0 + \bar{x}.$$

Proof. We prove the claim by contradiction. Assume that there was an optimal solution x' such that $\sum_{j\in\mathcal{J}} x'_j \geq x_0 + \bar{x}$. Set any nonzero component of x' to zero. The modified solution is feasible because $x' \leq \bar{x}$, and has a better objective value because f_0 is increasing. Thus, the original solution cannot be optimal.

Remark 3. Under Assumption 1, the installed capacity of any resource is limited by $\max\{\bar{y}_\ell\} + \bar{x}_b$ for backup generation via Lemma 1, by $\bar{x}_s^{\text{tot}} + \bar{x}_s$ for storage via Proposition A1 and Lemma 1, and by $\max\{\bar{y}_\ell\} + 2\bar{x}_g$ for grid build out via Lemma 1. The factor 2 accounts for contingencies.

We now state a mixed-integer linear reformulation of the market participation constraints.

Proposition A2. The supply limit can be modeled with auxiliary binary variables, i.e.,

$$\sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^{s} \le [y_{\ell njkc}^{d} - x_{gnc}^{tot}]^{+}$$

$$\iff \exists \, z_{njkc}^{\mathrm{M}} \in \{0,1\} : \begin{cases} (1-z_{njkc}^{\mathrm{M}})\underline{M}_{1} \leq y_{\ell njkc}^{\mathrm{d}} - x_{\mathrm{g}nc}^{\mathrm{tot}} \leq z_{njkc}^{\mathrm{M}} \overline{M}_{1njkc} \\ \sum_{r \in \mathcal{R} \backslash \{\mathrm{g}\}} y_{rnjkc}^{\mathrm{s}} \leq y_{\ell njkc}^{\mathrm{d}} - x_{\mathrm{g}nc}^{\mathrm{tot}} - (1-z_{njkc}^{\mathrm{M}})\underline{M}_{2} \\ \sum_{r \in \mathcal{R} \backslash \{\mathrm{g}\}} y_{rnjkc}^{\mathrm{s}} \leq z_{njkc}^{\mathrm{M}} \overline{M}_{2njk}, \end{cases}$$

where $-\underline{M}_1 = -\underline{M}_2 = \max\{\bar{y}_\ell\} + 2\bar{x}_g$, $\overline{M}_{1njkc} = \bar{y}_{\ell njk} - \bar{x}_{gnc}(\mathbf{0})$, and $\overline{M}_{2njk} = \bar{y}_{\ell njk}$. Here, \bar{x}_s^{tot} is the amount of installed storage capacity needed to fully flatten load, which can be computed ex-ante via a linear program (Proposition A1). The term $\max\{\bar{y}_\ell\}$ returns the maximum electricity demand over all planning and operating periods.

Proof of Proposition A2. We first show the (\Longrightarrow) and then the (\Longleftrightarrow) direction.

Let $y_{\ell njkc}^{\rm d} - x_{{\rm g}nc}^{\rm tot} \geq 0$, then the inequalities $(1-z_{njkc}^{\rm M})\underline{M}_1 \leq y_{\ell njkc}^{\rm d} - x_{{\rm g}nc}^{\rm tot} \leq \overline{M}_{1njkc}z_{njkc}^{\rm M}$ are valid if $z_{njkc}^{\rm M} = 1$ and $\overline{M}_{1njkc} \geq y_{\ell njkc}^{\rm d} - x_{{\rm g}nc}^{\rm tot}$ for all feasible $y_{\ell njkc}^{\rm d}$ and $x_{{\rm g}nc}^{\rm tot}$. Thus,

$$\max y_{\ell njkc}^{\rm d} - x_{\rm gnc}^{\rm tot} \quad \text{s.t.} \quad (y_{\ell njkc}^{\rm d}, x_{\rm gnc}^{\rm tot}) \quad \text{feasible in (B1)}$$

$$\leq \max \left\{ y_{\ell njkc}^{\rm d} \quad \text{s.t.} \quad y_{\ell njkc}^{\rm d} \quad \text{feasible in (B1d), (B1m)} \right\}$$

$$-\min \left\{ x_{\rm gnc}^{\rm tot} \quad \text{s.t.} \quad x_{\rm gnc}^{\rm tot} \quad \text{feasible in (B1b), (B1e), (B1g)} \right\}$$

$$\leq \bar{y}_{\ell njk} - \bar{x}_{\rm gnc}(\mathbf{0}) = \overline{M}_{1njkc},$$

where the first inequality holds because we split the initial problem into two relaxed subproblems and the second inequality holds because \bar{x}_{gnc} is nondecreasing in x_g and $x_g \ge 0$. For the remaining inequalities,

$$\sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^{s} \leq y_{\ell njkc}^{d} - x_{gnc}^{tot} - (1 - z_{njkc}^{M})\underline{M}_{2}$$

is implied by $\sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^{s} \leq [y_{\ell njkc}^{d} - x_{gnc}^{tot}]^{+}$ for $z_{njkc}^{M} = 1$, and

$$\sum_{r \in \mathcal{R} \backslash \{\mathbf{g}\}} y^{\mathbf{s}}_{rnjkc} \leq z^{\mathbf{M}}_{njkc} \overline{M}_{2njk},$$

holds for $z_{njkc}^{\mathrm{M}} = 1$ because

$$\sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^{s} \le \left[y_{\ell njkc}^{d} - x_{gnc}^{tot} \right]^{+} \le \bar{y}_{\ell njk} = \overline{M}_{2njk}.$$

The second inequality holds thanks to the constraints (B1d) and (B1m).

If $y_{\ell njkc}^{\rm d} - x_{\rm gnc}^{\rm tot} < 0$, the inequalities $(1 - z_{njkc}^{\rm M})\underline{M}_1 \le y_{\ell njkc}^{\rm d} - x_{\rm gnc}^{\rm tot} \le \overline{M}_{1njkc}z_{njkc}^{\rm M}$ are valid for $z_{njkc}^{\rm M} = 0$ and

where the inequality holds again because we split the initial problem into two relaxed subproblems and the second inequality follows from Lemma 1, which applies with constant $x_0 = \max\{\bar{y}_\ell\} + \bar{x}_g$ thanks to Assumption 1. For the remaining inequalities,

$$\sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^{s} \le z_{njkc}^{M} \overline{M}_{2njk},$$

is implied by $\sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^s \leq [y_{\ell njkc}^d - x_{gnc}^{tot}]^+$ for $z_{njkc}^M = 0$, and

$$\sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^{s} \leq y_{\ell njkc}^{d} - x_{gnc}^{tot} - (1 - z_{njkc}^{M})\underline{M}_{2}$$

holds for $z_{njkc}^{\mathrm{M}} = 0$ because

$$\begin{aligned} & \min \, y_{\ell njkc}^{\rm d} - x_{\rm gnc}^{\rm tot} - \sum_{r \in \mathcal{R} \backslash \{\rm g\}} y_{rnjkc}^{\rm s} \ \text{s.t.} \ (x_{\rm gnc}^{\rm tot}, y_{\ell njkc}^{\rm d}, y_{\rm bnjkc}^{\rm s}, y_{\rm snjkc}^{\rm s}) \ \text{ feasible in (B1)} \\ & = \min \, y_{\ell njkc}^{\rm d} - x_{\rm gnc}^{\rm tot} \ \text{s.t.} \ (y_{\ell njkc}^{\rm d}, x_{\rm gnc}^{\rm tot}) \ \text{ feasible in (B1)} \\ & \geq - \max \{\bar{y}_{\ell}\} - 2\bar{x}_{\rm g} = \underline{M}_{2}, \end{aligned}$$

where the first equality holds because $0 \leq \sum_{r \in \mathcal{R} \setminus \{g\}} y_{rnjkc}^s \leq [y_{\ell njkc}^d - x_{gnc}^{tot}]^+ = 0$ and the inequality follows from the same reasoning as in the derivation for \underline{M}_2 .

We now prove the reverse implication. Let $z_{njkc}^{M} = 1$, then the following constraints apply

$$0 \le y_{\ell njkc}^{\mathrm{d}} - x_{\mathrm{g}nc}^{\mathrm{tot}} \le \overline{M}_{1njkc}, \sum_{r \in \mathcal{R} \setminus \{\mathrm{g}\}} y_{rnjkc}^{\mathrm{s}} \le \min \left\{ y_{\ell njkc}^{\mathrm{d}} - x_{\mathrm{g}nc}^{\mathrm{tot}}, \, \overline{M}_{2njk} \right\}.$$

Following the same steps as in the first part of the proof, we see that the constraints involving \overline{M}_{1njkc} and \overline{M}_{2njk} are redundant. Thus,

$$z_{njkc}^{\mathrm{M}} = 1 \implies y_{\ell njkc}^{\mathrm{d}} - x_{\mathrm{g}nc}^{\mathrm{tot}} \ge 0, \sum_{r \in \mathcal{R} \setminus \{\mathrm{g}\}} y_{rnjkc}^{\mathrm{s}} \le y_{\ell njkc}^{\mathrm{d}} - x_{\mathrm{g}nc}^{\mathrm{tot}}.$$

Similarly, one can show that

$$z_{njkc}^{\mathrm{M}} = 0 \implies y_{\ell njkc}^{\mathrm{d}} - x_{\mathrm{g}nc}^{\mathrm{tot}} \le 0, \sum_{r \in \mathcal{R} \setminus \{\mathrm{g}\}} y_{rnjkc}^{\mathrm{s}} \le 0.$$

C Results

Table A3. Case study results.

				Experiments					
Number	1	2	3	4	5	6	7	8	9
		Param	eters						
Market participation	Peak		Full					Peak	Full
Available investments	g	$_{\mathrm{g+s}}$				$_{\mathrm{b+g+s}}$		$_{\mathrm{g+s}}$	
Storage cost ($\$/kWh$)	na	604						1	
Cycle limit	yearly				daily	yearly			
Cap. price (\$/kW-month)	na		0.000	3.064	0.000		3.064	na	0.000
			So	olution qualit	у				
Total cost (M\$)	678.874	647.026	633.441	616.688	659.310	629.823	599.411	609.227	432.174
Solve time (s)	52.848	4,211.116	4,083.086	2,374.322	886.687	17,631.037	$20,\!510.171$	14,402.060	651.564
Maximum MIP gap (%)	0.001		0.000					0.004	0.000
				Costs (M\$)					
Total operating	331.384	331.245	317.661		313.509	331.632	331.633	331.065	151.047
- base case	331.465		317.635		313.446	319.105		331.465	137.308
- contingeny	331.064	330.367	317.763		313.762	381.742		329.466	205.999
Total capital	347.490	315.781			345.801	298.191		278.162	281.127
- backup	na					89.451		na	
- grid	347.490	277.992				183.222		277.992	
- storage	na	37.789			67.809	25.518		0.170	3.135
Total capacity payment	na		0.000	-16.753	0.000		-30.413	na	0.000
- backup	na		0.000	-7.126	0.000		-23.138	na	0.000
- grid	na								
- storage	na		0.000	-9.627	0.000		-7.275	na	0.000
			Investm	ent decisions	(MW)				
Terminal capacity	160.000	139.318			157.900	138.084		139.289	367.921
- backup	0.000					6.513		0.000	
- grid	160.000	120.000							
- storage	0.000	19.318			37.900	11.571		19.289	247.921
Total investment	160.000	139.318			157.900	153.832		141.290	511.921
- backup	na					22.261		na	
- grid	160.000	120.000							
- storage	na	19.318			37.900	11.571		21.290	391.921

Table A3. Case study results.

			Ex	periments					
Number	1	2	3	4	5	6	7	8	9
		О	perating decisio	ns: Base ca	ase (GWh/yr))			
Demand (w/o storage)	295.000				295.249	295.012		295.000	483.825
- grid	0.000				0.248	0.012		0.000	188.825
- load	295.000								
- storage	0.000		13.237		20.358	10.003		0.000	307.816
Supply (w/o storage)	295.000		297.203		298.637	296.677		295.000	535.026
- backup	0.000		0.075			0.242		0.000	0.029
- grid	295.000		297.129		298.562	296.435		295.000	535.026
- storage	0.000		11.034		16.970	8.338		0.000	256.586
		Op	erating decisions	s: Continge	ency (GWh/y	r)			
Demand (w/o storage)	295.000				295.249	295.012		295.000	405.713
- grid	0.000				0.248	0.012		0.000	110.713
- load	295.000								
- storage	0.239	0.597	13.237		20.351	10.003		1.256	202.620
Supply (w/o storage)	295.040	295.100	297.203		298.636	296.677		295.209	439.435
- backup	0.028		0.075			9.431		0.010	0.068
- grid	295.012	295.072	297.128		298.560	287.246		295.200	439.367
- storage	0.199	0.498	11.034		16.964	8.338		1.047	168.897
			Yearly dis	charge cycl	es (#)				
Average (base case)	0.000		150.000					0.000	145.295
Maximum (base case)	0.000		150.000					0.000	150.000
Average (contingency)	4.551	7.051	150.000					7.622	105.870
Maximum (contingency)	8.656		150.000					9.057	150.000
			Minimum sca	rcity supply	y ratio (-)				
Backup (base case)	0.000		1.000					0.000	
Storage (base case)	0.000		1.000					0.000	0.483
Backup (contingency)	0.000		1.000					0.000	
Storage (contingency)	0.000		1.000		0.477	1.000		0.000	0.012

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