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Dynamic Storage Operation Under Uncertainty and the Reliability Externality: Implications for Capacity Investments

Daniel Shen†, Marija Ilic†, John Parsons‡

***Abstract*—Energy storage is increasingly relied upon to meet short-term demand uncertainties from renewable variability and electrification. Unlike conventional generators, storage's contribution to reliability is policy-dependent and balances near-term arbitrage against future scarcity risk. We study how demand uncertainty alters such dynamic storage operation and how these operating decisions propagate into long-run investment outcomes. We formulate storage operation as an average-cost Markov decision process and embed the resulting stationary policies into a stylized capacity expansion framework. Demand uncertainty induces a precautionary storage policy which hedges against stochastic scarcity, leading to materially different post-storage demand distributions relative to perfect-foresight benchmarks. We additionally demonstrate that the reliability externality characteristic of electricity markets interacts with uncertainty in a manner that uniquely distorts both storage operation and investment.**

***Index Terms*—energy storage, Markov processes, power system economics, power system planning, power system reliability**

I. Introduction

Energy storage systems, and in particular grid-scale battery energy storage, are playing an increasing role in resource adequacy. Unlike conventional generators, the ability of storage to meet demand is dependent on the amount of stored energy available at that moment: effective operation depends on appropriately scheduling charge and discharge decisions in anticipation of future demand conditions. Planning a least-cost resource mix with storage as a central technology requires jointly accounting for the subsequent operational decisions of storage resources.

This coupling is increasingly relevant as short-term demand uncertainty grows with higher penetrations of variable renewable generation and the electrification of end uses. Under uncertainty, storage operation takes on a dynamic,[1] precautionary character whereby energy is reserved for a *potential* period of high-demand (or high-price) events in the future [1]. The expansion in installed battery capacity over the past decade has subsequently spurred a rich literature studying such dynamic scheduling of battery storage under uncertainties. Such approaches as in [2]–[7] adopt a stochastic programming perspective on operation, while a closely related strand of literature links such dynamic storage operation to long-term investment decisions to encompass the feedback between these two problems [8]–[12].

Much of the capacity expansion literature, however, is formulated from a system-planning perspective and does not analyze the reliability externality that besets investment incentives in liberalized electricity markets [13]. Grid reliability is a non-excludable public good and short-run prices are often capped to prevent the exercise of market power. Thus, energy prices do not fully reflect the value of installed capacity and revenues earned through energy markets may be insufficient to support adequate investment [14], [15].[2] Many electricity markets address this externality through uniform payments based on pre-calculated measures of firm capacity. [3] However, such capacity payment mechanisms were primarily designed around thermal generators and may insufficiently compensate resources with state-contingent supply such as storage and renewables [13]. While availability obligations such as PJM's Capacity Performance Mechanism can mitigate these shortcomings, they are also infrequently declared and subjective in their assessment of penalties [17].

In this work, we adopt a stochastic control framework to study how demand uncertainty a) shapes the operation and investment of energy storage in electricity systems, and b) interacts with the reliability externality. We model storage operation as an infinite-horizon average-cost Markov decision process and embed the resulting stationary operating policies within a capacity expansion model. This formulation allows us to propagate short-run operational uncertainty into long-run equilibrium investment decisions. In particular, our work addresses the following questions:

1) *How does short-term demand uncertainty alter the operating policy of energy storage, relative to when the demand is known with perfect foresight?*
2) *How do uncertainty-driven storage operating policies map into long-run equilibrium investment decisions for storage and conventional generation capacity?*
3) *How does the reliability externality in electricity markets distort storage operation and capacity investment under uncertainty, and why are conventional capacity mechanisms insufficient to correct these distortions?*

To this end, we develop a stylized capacity expansion model that embeds a dynamic storage operating model. Although our model is deliberately kept simple, it retains the structure needed to capture interactions between uncertainty, storage operation, and investment incentives. In particular, our contributions are as follows:

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[1] Throughout this paper, "dynamic" refers to operational optimization under short-term uncertainty in the energy market context, not sub-hourly fast frequency reserves or dynamic stability.

[2] Regulatory price caps are the most prominent contributor to this phenomenon. Even in the absence of explicit caps, however, prices may fail to reach levels commensurate with the value of lost load since there is a lack of individualized penalties for failing to procure capacity for reliability.

[3] Four U.S. markets (PJM, ISO-NE, NYISO, and MISO) utilize capacity markets to pay suppliers for commitments to meet future demand [16].

- We characterize how demand uncertainty induces a precautionary storage policy distinct from perfect-foresight operation. This "precautionary storage" reserves energy to hedge against stochastic scarcity events. We then embed the precautionary policy into a capacity expansion model to compare equilibrium investment outcomes with a setup with perfect foresight.
- We demonstrate the reliability externality distorts the operating policies in a manner that qualitatively differs from conventional generators due to the dynamic nature of storage operation. We additionally model how these operational distortions propagate to long-run planning outcomes. Although our results do not find a significant impact on storage investment, we posit the externality should still lead to suboptimal storage capacity that cannot be corrected by standard capacity payments.

The rest of the paper is organized as follows. Section II introduces our operation and investment model. Section III illustrates the operating and investment characteristics of storage under uncertain net demand. Section IV analyzes how the reliability externality in electricity markets uniquely distorts outcomes for storage. Finally, Section V concludes.

II. Electricity System Model

We utilize a mean-reverting model of inelastic electricity demand combined with a stylized capacity expansion model that embeds a storage operating model. Storage operation is based on a Markov decision process (MDP) with probabilistic foresight of future net demand conditions. While our model omits consideration of transmission constraints, ramp rates, and co-optimization of investments in variable renewable energy resources, we are primarily concerned with the basic interaction between storage operation and net demand uncertainty and so opt for this simplified framework.

A. Demand Model

Let the net demand ℓ be a Markov chain where the transition probabilities $P_{\mathcal{L}}(\ell' \mid \ell)$ are calculated using an Ornstein-Uhlenbeck (OU) process. This treatment allows us to both capture the mean-reverting nature of net electricity demand and represent uncertainty in future demand. The OU process is a continuous-time stochastic process that exhibits mean-reverting behavior. The process is described by the stochastic differential equation:

$$dx_t = \theta(\mu - x_t)dt + \sigma dW_t, \tag{1}$$

where x is the state variable (in our case, the net demand ℓ), θ governs the drift speed of mean reversion toward the long-term mean μ, σ is the volatility parameter, and W_t is a standard Wiener process.

Given a time interval Δt and a starting state x_t, the conditional distribution of $x_{t+\Delta t}$ is normally distributed with mean and variance:

$$\mathbb{E}[x_{t+\Delta t} \mid x_t] = x_t e^{-\theta \Delta t} + \mu \left(1 - e^{-\theta \Delta t}\right) \tag{2}$$

$$\mathrm{Var}[x_{t+\Delta t} \mid x_t] = \frac{\sigma^2}{2\theta}\left(1 - e^{-2\theta\Delta t}\right). \tag{3}$$

Additionally, the long-term stationary distribution of the OU process is Gaussian with long-term mean μ and variance $\frac{\sigma^2}{2\theta}$.

For our discrete-time MDP framework, we discretize the demand into equally-spaced levels and calculate transition probabilities between levels by integrating the conditional distributions of (1).

B. Dynamic Storage Operating Model

Uncertainty of future net demand motivates reserving stored energy to hedge against potential demand states. Our broader analysis concerns the long-run equilibrium of operating and investment decisions; hence, we formulate the storage operating problem as an average-cost MDP where the system operator optimizes the dispatch to minimize expected costs over an infinite horizon.

The system has conventional generators $g \in G$, each with power capacity K_g and constant variable cost c_g. There is a single storage technology with power capacity K_s, stored energy capacity E, and round-trip efficiency η. If insufficient supply is available to fully meet net load, some load can be unserved / shed at the cost of the value of lost load c_{shed}. Finally, when the net demand is negative (*i.e.* excess renewable generation), surplus energy can be curtailed at no cost.

In each interval the system operator determines the dispatch based on the system state $S \in \mathcal{S} = \mathcal{E} \times \mathcal{L}$. This state is comprised of e, the stored energy available for use over the interval, and ℓ, the demand to be met during the interval. Based on the state, the operator subsequently chooses the mix of generation and storage dispatch which minimizes total costs in expectation. Let the dispatch decision affecting the interval be represented by the action $a = (p_s^{ch}, p_s^{dis}, p_g, p_{shed}, p_{curt})$. This vector captures the charge and discharge rates of storage, output of conventional generators, unserved energy, and curtailed surplus, respectively. [4]

Given fixed storage and generation capacities, the set of feasible actions $\mathcal{A}(S)$ includes all actions that satisfy the operating constraints given the current state. Specifically, $a \in \mathcal{A}(S)$ if a satisfies:

$$\sum_g p_g + p_s^{dis} + p_{shed} = \ell + \frac{1}{\eta} p_s^{ch} + p_{curt} \tag{4a}$$
$$0 \le p_g \le K_g \quad \forall g \tag{4b}$$
$$0 \le p_{shed} \tag{4c}$$
$$0 \le p_{curt} \tag{4d}$$
$$0 \le \frac{1}{\eta} p_s^{ch} \le K_s \tag{4e}$$
$$0 \le p_s^{dis} \le K_s \tag{4f}$$
$$p_s^{ch} p_s^{dis} = 0 \tag{4g}$$
$$e + p_s^{ch} - p_s^{dis} = e' \tag{4h}$$
$$0 \le e' \le E. \tag{4i}$$

Where (4a) is the power balance constraint, (4b) enforces generation capacity limits, (4c) enforces non-negativity of

[4] The injections $p_s^{(ch,dis)}$ capture the rate of change of stored energy; the charging load seen by the grid is adjusted by the efficiency factor η.

load shedding, (4d) enforces non-negativity of curtailment, (4e) and (4f) enforce grid-side storage power capacity limits, (4g) prevents simultaneous charging and discharging, (4h) describes the evolution of stored energy from state e to e' as a result of charging and discharging, and (4i) enforces stored energy capacity limits.[5]

Let $C(\ell, a)$ represent the system operating costs, which include both generation costs and load shedding costs:

$$C(\ell, a) = c_{shed} p_{shed} + \sum_{g \in \mathcal{G}} c_g p_g. \tag{5}$$

This infinite-horizon operational problem is commonly cast as a Bellman equation and solved with dynamic programming techniques. However, since our analysis is concerned with the long-run impact of storage operation on capacity investments *in equilibrium*, we instead opt to formulate the operating problem using the "average cost" criteria, [18] where the objective is to minimize the long-run expected average cost per time step. Specifically, given a fixed operating policy $\pi : \mathcal{S} \to \mathcal{A}$, the long-run average cost under the induced stationary distribution is given by:

$$J(\pi) = \limsup_{T \to \infty} \frac{1}{T} \mathbb{E}_\pi \left[\sum_{t=0}^{T-1} C(\ell_t, a_t) \right]. \tag{6}$$

We next establish the existence of a stationary distribution for the state process induced by the storage and load model:

Lemma II.1 (Existence of a stationary distribution)**.** *Under any stationary policy π, the controlled state process $S = (e, \ell)$ induced by the stored energy constraint* (4h) *admits a stationary distribution ρ which is unique on the recurrent class induced by π.*

Proof. The exogenous net-load process $\{\ell\}$ is obtained by discretizing a mean-reverting Ornstein–Uhlenbeck process on a finite grid; consequently, the net-load transition matrix $P_{\mathcal{L}}(\ell' \mid \ell)$ is irreducible and aperiodic. Under a stationary policy π, the joint process $S = (e, \ell)$ is a time-homogeneous Markov chain on the finite state space $\mathcal{S} = \mathcal{E} \times \mathcal{L}$, with transitions determined by the storage state update in (4h) and $P_{\mathcal{L}}$. The policy π may restrict the set of stored energy levels which are visited with positive probability. [6] Let $\mathcal{S}^\pi \subseteq \mathcal{S}$ denote the corresponding recurrent class. The induced chain is ergodic on its recurrent class $\mathcal{S}^\pi$, and therefore admits a unique stationary distribution ρ supported on $\mathcal{S}^\pi$. □

The stationary distribution and accompanying policy can be computed via dynamic programming methods (*e.g.*, value iteration), but our work's overall analysis focuses on the long-run equilibrium behavior of the system. Hence, we opt to directly find ρ and π using the occupancy measure formulation.

1) Occupancy Measure LP Formulation: To compute ρ, we can utilize the occupancy-measure formulation [19] which seeks ρ as part of the solutions to a linear program constructed around the *occupancy measure* that minimizes the expected average cost. The occupancy measure $q(S, a)$ represents the long-run fraction of time the system spends in each state-action pair; the occupancy which minimizes system operating costs can be found with the following linear program (LP):

$$\min_q \quad \sum_S \sum_{a \in \mathcal{A}(S)} q(S, a)\, C(\ell, a) \tag{7a}$$

$$\text{s.t.} \quad q(S, a) \geq 0, \quad \forall S \in \mathcal{S},\ \forall a \in \mathcal{A}(S), \tag{7b}$$

$$\sum_S \sum_a q(S, a) = 1, \tag{7c}$$

$$\sum_a q(S, a) = \sum_{S'} \sum_{a'} q(S', a')\, P(S \mid S', a') \quad \forall S \in \mathcal{S}. \tag{7d}$$

Here, the objective (7a) minimizes the expected average system cost per time step. The first two constraints (7b) and (7c) ensure that q is a valid probability distribution and the last constraint (7d) enforces flow conservation for each state S such that the probability of entering state S in any interval equals the probability of leaving it.

The optimal $q^\star$ induces a distribution of actions:

$$\mathbb{P}[a \mid S] = \frac{q^\star(S, a)}{\sum_{a'} q^\star(S, a')}, \quad a' \in \mathcal{A}(S) \tag{8}$$

on its support. Because the stored energy transition is deterministic conditional on the action (*i.e.* the next state of charge is uniquely determined by (S, a)), for each state S all mass is assigned to a single action and the action taken in state S is deterministic; thus the optimal policy π^* is also deterministic.

By marginalization, the state occupancy satisfies:

$$\rho^\star(S) = \sum_a q^\star(S, a), \tag{9}$$

thus recovering the stationary distribution.

Solving (7a) as a LP involves discretizing the load, stored energy, and action spaces. In particular, the discretization step of p_s^{ch} and p_s^{dis} must match the discretization step of stored energy levels so that conservation of energy is maintained.

C. Capacity Expansion Model under Dynamic Storage Operation

Storage operation and generation capacity choices are mutually dependent: the optimal storage policy depends on the cost spread of generators, while optimal generation capacities depend on the arbitrage provided by storage. Building on [8], we address this interaction via an iterative fixed-point algorithm that alternates between determining storage operation and adjusting generation capacities. We additionally extend the aforementioned approach by introducing a capacity update rule for storage based on a long-run zero-profit condition.

Let $\mathbf{K}$ denote the vector of installed capacities, consisting of generation capacities $\mathbf{K}_{\mathcal{G}}$ and storage power capacity K_s. Storage is assumed to have a fixed duration τ, so that its

[5] Constraints (4a)–(4i) are practically modeled by removing points from the discrete action set instead of encoding them as constraints in a solver, thus avoiding the nonlinearity of (4g).

[6] For example, if the stored energy capacity is much larger than the net load peaks, the upper bound on stored energy may be slack and the optimal policy may never utilize the upper levels of the storage.

energy capacity satisfies $E = \tau K_s$. For any fixed capacity vector $\mathbf{K}$, the storage operating problem (Section II-B1) admits an optimal policy $\pi^\star$ with associated occupancy measure $q^{\mathbf{K}}(S,a)$ and induced stationary state distribution $\rho^{\mathbf{K}}(S)$.

Finally, let $G(S,a)$ denote the *post-storage net demand* which must be balanced by conventional generation, curtailment, and load shedding:

$$G(S,a) = \ell + \frac{1}{\eta} p_s^{ch} - p_s^{dis}. \tag{10}$$

a) Generation Capacity Update Under Fixed Storage Policy: Given $\mathbf{K}$, the stationary distribution of the post-storage net demand $G = G(S,a)$ is given by:

$$\mathbb{P}\left[G = x\right] = \sum_{S\in\mathcal{S}} \sum_{a\in\mathcal{A}(S)} q^{\mathbf{K}}(S,a)\,\mathbf{1}\{G(S,a) = x\}\,. \tag{11}$$

Let $F_G(x) = \mathbb{P}\{G \le x\}$ denote the corresponding cumulative distribution function with an inverse function $F_G^{-1}(u) = \inf\{x : F_G(x) \ge u\}$. The associated post-storage load-duration curve is:

$$D_G(h) = F_G^{-1}(1-h), \qquad h \in [0,1]. \tag{12}$$

This curve is the direct analogy to the canonical load-duration curve, with post-storage net demand replacing net load. As a result, standard screening-curve methods can be applied to D_G to update $\mathbf{K}_{\mathcal{G}}$ based on each technology's corresponding fixed costs I_g.

b) Storage Capacity Update With Zero-Profit Condition: We update storage capacity using a long-run zero-profit condition computed under the stationary distribution induced by optimal operation. For each state–action pair (S,a) with positive occupancy, define the *statewise marginal price*:

$$\lambda(S,a) \triangleq \max\Big\{ \max_{g:\, p_g(S,a)>0} c_g,\ c_{\text{shed}} \cdot \mathbf{1}\{p_{\text{shed}}(S,a) > 0\} \Big\}, \tag{13}$$

i.e., the variable cost of the most expensive generator dispatched in that period, or VoLL if load shedding occurs. The corresponding storage operating surplus in state S is:

$$\phi_s(S,a) = \lambda(S,a)\left(p_s^{dis} - \frac{1}{\eta} p_s^{ch}\right). \tag{14}$$

The expected annual operating surplus of storage over the planning horizon is:

$$\Phi_s(\mathbf{K}) = T \sum_{S\in\mathcal{S}} \sum_{a\in\mathcal{A}(S)} q^{\mathbf{K}}(S,a)\,\phi_s(S,a), \tag{15}$$

where T is the number of operating intervals per year.

Let I_s^τ denote the annualized fixed cost of a storage technology with duration τ. Storage capacity is updated via a proportional stepsize rule until surplus and investment break even. Denote $\mathbf{K}_{\mathcal{G}}^{(m+1)}$ as the optimal generation capacities from the generation capacity update procedure based on the fixed storage capacity $K_s^{(m)}$. The storage update is:

$$K_s^{(m+1)} = \Big[K_s^{(m)} + \gamma_s\big(\Phi_s(\mathbf{K}_{\mathcal{G}}^{(m+1)}, K_s^{(m)}) - I_s^\tau K_s^{(m)}\big)\Big]_+, \tag{16}$$

where $\gamma_s > 0$ is a stepsize parameter and $[\cdot]_+$ enforces nonnegativity. At convergence, $\Phi_s(\mathbf{K}^\star) = I_s^\tau K_s^\star$.

c) Fixed-Point Capacity Expansion Algorithm: For a fixed storage duration τ, the equilibrium $\mathbf{K}$ is determined by the following fixed-point algorithm:

1) Initialize storage and generation capacities $\mathbf{K}^{(0)}$.
2) For outer iteration $m = 0, 1, 2, \ldots$:
   a) *Generation update:* Hold storage capacity $K_s^{(m)}$ fixed and update $\mathbf{K}_{\mathcal{G}}^{(m)}$ to new capacities $\mathbf{K}_{\mathcal{G}}^{(m+1)}$ by alternating between the operating LP and screening curve until a fixed point between storage operation and generation capacities is reached.
   b) *Storage update:* compute $\Phi_s(\mathbf{K}_{\mathcal{G}}^{(m+1)}, K_s^{(m)})$ and update $K_s^{(m+1)}$ using (16), $E^{(m+1)} = \tau K_s^{(m+1)}$.

The algorithm terminates when both storage and generation capacities converge within a prescribed tolerance ε:

$$|K_s^{(m+1)} - K_s^{(m)}| \le \varepsilon_s \quad \text{and} \quad \big\|\mathbf{K}_{\mathcal{G}}^{(m+1)} - \mathbf{K}_{\mathcal{G}}^{(m)}\big\| \le \varepsilon_{\mathcal{G}}.$$

III. Storage Operation and Investment

In this section, we study the operation and investment decisions in a stylized electricity system with uncertain net demand, two generation technologies, and a single storage technology. The analysis is intended to highlight the general implications of dynamic storage utilization for long-run planning, rather than to represent any specific real-world system.

A. Example Electricity System

We construct our system based on a hypothetical future of a high-renewable, highly electrified grid where there is significant net demand uncertainty and frequent periods of negative net demand. To this end, we utilize an Ornstein-Uhlenbeck process (Section II-A) whose drift and volatility are calibrated to 2024 net demand data from the California ISO (CAISO) balancing area. We exogenously set the long-term mean μ of the process to 6.5 GW, which creates a net demand that is negative approximately 15% of the time. [7]

The system planner may invest in three technologies: a baseload generator, a peaking generator, and an energy storage technology with a fixed four-hour duration. The operating problem is solved on an hourly basis. Numerical values for the demand process and technology cost parameters are provided in Appendix A.

B. Operating Policy and Investment Decisions under Demand Uncertainty

We first examine the operating policy of storage under demand uncertainty when the system capacities are fixed. Figure 1 shows the canonical (pre-storage) net load-duration curve of the system along with two post-storage load-duration curves. The post-storage curve represents the distribution of net demand which must be met by conventional generation or load shedding after the storage action is taken. Charging shifts the post-storage curve above the pre-storage curve and discharging vice-versa.

[7] See Table II in the Appendix for further discussion on the parameters.

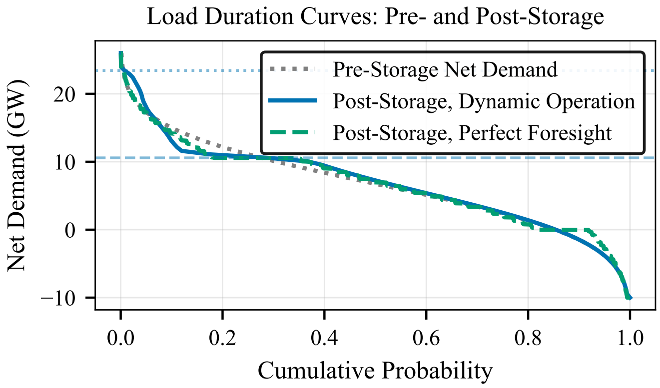

Fig. 1. Load duration curves for i) net demand, ii) post-storage demand under dynamic (imperfect-foresight) operation, and iii) post-storage demand under perfect-foresight operation. Post-storage demand is higher than net demand when storage is charging, see (10) for definition. System baseload and peaker capacity steps are denoted with horizontal dashed and dotted lines, respectively. Storage capacity is 4.0 GW.

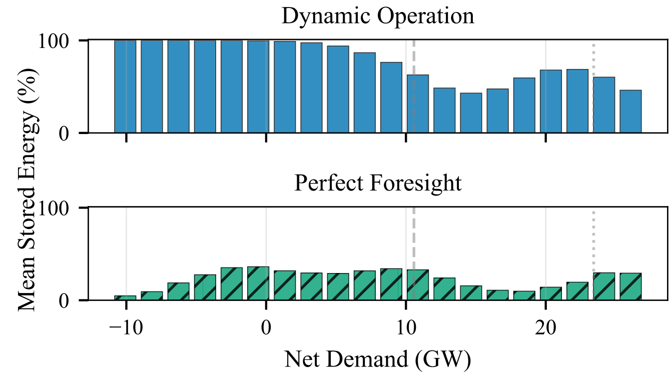

Fig. 2. Expected level of stored energy conditioned on net demand state. Values for the perfect-foresight panel are constructed by sampling 10 years of hourly data from the net load process, computing the optimal dispatch, and then binning the state of charge by net demand level. Baseload and peaker capacity steps are denoted with vertical dashed and dotted lines, respectively. Capacities correspond to the first row of Table I.

Under dynamic operation, the storage unit primarily charges during two regions: i) when net demand is below 10 GW and baseload generation is marginal, and ii) when net demand is within 15–23 GW and peaker generation is marginal. The second condition corresponds to a "precautionary storage" operation whereby demand uncertainty induces banking energy for the *potential* of a period of high demand.

In contrast, storage under perfect-foresight exhibits the same operating behavior in the first region, but not in the second region. With full information, it is possible to almost exclusively charge during baseload and curtailment conditions to meet peaks where net demand exceeds peaker capacity, hence the post-storage curve overlaps with the pre-storage in the 15–23 GW region.

Overall, the "precautionary storage" behavior under uncertainty results in a more conservative operating policy that reserves a portion of energy for future scarcity events rather than fully exploiting arbitrage opportunities. Figure 2 demonstrates this outcome: the average stored energy levels at the beginning of each operating interval (conditioned on the net demand) are everywhere higher in the dynamic operating case than the perfect-foresight case. In the latter case, the operator can more economically utilize stored energy by precisely timing discharges to meet high-demand events.

Demand uncertainty induces a more conservative storage operating policy, which substantially reduces the system value of storage. At equilibrium, the perfect-foresight capacity mix includes 7.2 GW of storage, whereas under demand uncertainty the mix only includes 4.0 GW (Table I).

The inability of storage to fully arbitrage scarcity events under uncertainty shifts investment toward peaker generation which has a greater availability to meet demand: peaker capacity increases from 10.7 GW in the perfect-foresight case to 12.9 GW under uncertainty, and baseload capacity decreases from 11.1 GW to 10.6 GW. Demand uncertainty biases the equilibrium capacity mix away from storage and towards a greater total amount of conventional generation, whose availability is less contingent on future state information.

TABLE I
CAPACITY INVESTMENTS (GW) UNDER VARYING PRICE CAPS

Technology	**VoLL ($/MWh)**	**Price Cap ($/MWh)**		
	10,000	5,000	2,500	1,000
Dynamic Operation				
Storage	4.0	3.9	4.0	3.9
Baseload	10.6	11.1	10.6	11.1
Peaker	12.9	11.3	10.8	9.3
Total	**27.5**	**26.3**	**25.4**	**24.3**
Perfect-Foresight Operation				
Storage	7.2	6.8	6.6	6.2
Baseload	11.1	11.2	11.2	11.2
Peaker	10.7	10.2	8.8	7.0
Total	**29.0**	**28.2**	**24.6**	**24.4**

Capacities for *Dynamic Operation* are determined based on Section II-C, while capacities for *Perfect-Foresight Operation* are determined by solving a deterministic capacity expansion over a 10-year hourly sample drawn from the demand transition matrix.

IV. CAPACITY INVESTMENTS AND THE "MISSING MONEY" PROBLEM UNIQUE TO STORAGE

A. Missing Money Impacts on Capacity and Operation

Grid reliability is a non-excludable public good: during rotating blackouts, service interruptions cannot be targeted to individual customers and are instead imposed broadly or along shared feeders. This reliability externality, in conjunction with the regulatory price caps present in many markets, results in an effective cap on short-run electricity prices below the social value of lost load (VoLL). As a result, there is a disincentive for markets to invest in the socially optimal level of capacity.

These distortions give rise to a "missing money" problem, whereby energy market revenues alone cannot cover the fixed costs of resources needed to maintain adequate reliability. Table I illustrates the impact of this phenomenon on capacity investments by way of price cap which truncates prices below the VoLL of $10k/MWh. In both the dynamic and perfect-foresight cases, peaker investment decreases in the presence of a price cap, since the cap reduces revenues during scarcity events.

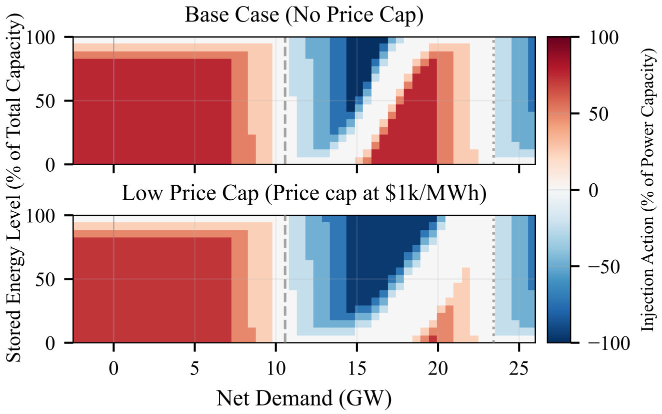

Fig. 3. Impact of price cap on dynamic storage operation. Resource capacities are held constant at the VoLL capacities for *Dynamic Operation* (first column, upper panel in Table I). Red = optimal to charge, blue = optimal to discharge, white = optimal to idle. System baseload and peaker steps are denoted with vertical dashed and dotted lines, respectively.

Storage investment decreases slightly in the dynamic setting over the modeled range, from 4.0 GW at full VoLL to 3.9 GW at a \$1k/MWh cap. This pattern should be interpreted with caution. The dynamic investment problem is nonconvex, and the fixed-point algorithm used here does not guarantee convergence to a global optimum. While the qualitative interactions between uncertainty, operating policy, and investment incentives are robust, the direction and magnitude of storage investment responses to price caps may change under alternative solution methods or improved global search.

In addition to impacts on capacity, the price cap also biases the operating behavior of storage under uncertainty. The operating policy is shifted away from charge and towards discharge as the cap is lowered. Figure 3 illustrates this effect by comparing the optimal dynamic storage policy under VoLL pricing and under a binding price cap. As the cap is lowered, the state space in which charging is optimal contracts, while the region in which discharging is optimal expands.

This distortion arises because the price cap reduces the continuation value of stored energy and weakens the incentive to charge in anticipation of future scarcity events. The distortion is similar to the problem identified in [15], whereby a price cap in combination with storage's need to break even on round-trip efficiency losses can, under certain net load sequences, remove the incentive to store energy for load shed events. [8] While [15] focuses on this phenomenon in a perfect-foresight setting, we identify here an additional mechanism which is not dependent on the round-trip efficiency and is unique to the dynamic operation. As Table IV in the Appendix illustrates, it is possible for the price cap to have no impact on unserved energy under perfect-foresight operation while having a significant impact in the dynamic operation by shifting the optimal policy towards earlier discharge in moderately high-demand states (Fig. 3).

Capacity payments are a common mechanism used to address this problem by providing additional payments to resources based on an *ex ante* calculation of their firm capacity contribution. However, the fact that storage's preferred operating states are affected by the missing money problem implies that state-independent capacity payments alone are insufficient to fully remedy underinvestment in storage capacity. While a fixed capacity payment will incentivize additional storage investment by offsetting fixed costs, it cannot address the reduction of the incentives for storage to hold energy in reserve. Thus, without a state-contingent contract structure that compensates reserving energy for possible scarcity events, the distortion to storage operation will create lower revenues and lead to less investment than would be socially optimal.

V. Conclusions

This paper examined how demand uncertainty alters the operation and investment incentives of energy storage in electricity systems. By modeling storage operation as an infinite-horizon stochastic control problem and embedding the resulting stationary policies into a capacity expansion framework, we showed that uncertainty induces a precautionary operating policy where storage reserves energy to hedge against potential future scarcity events. This behavior reshapes post-storage net demand distributions and affects the equilibrium capacity mix relative to a perfect-foresight benchmark, with storage becoming significantly less attractive under uncertainty.

A key limitation of our work is that the capacity outcomes are obtained using a fixed-point algorithm that cycles between dynamic storage operation and investment, but the algorithm does not guarantee convergence to a globally optimal solution in the presence of nonconvexities. However, the qualitative mechanisms identified in this work arise from the structure of the underlying stochastic control problem and as such are robust to any numerical approximations or optimality gaps. Developing algorithmic approaches with stronger optimality guarantees remains an important direction for future research.

Finally, the reliability externality inherent to electricity markets interacts with demand uncertainty to uniquely distort storage outcomes when compared to conventional generators. Price caps and the "missing money" problem affect not only the revenues during scarcity events, but also the structure of the optimal operating policy by reducing the continuation value of holding energy for uncertain future scarcity states. These operational distortions impact long-run planning outcomes, leading to underinvestment in storage capacity that cannot be corrected by uniform, state-independent capacity payments alone. Our work highlights the need for capacity contracting mechanisms for resource adequacy that account for the state-contingent value of stored energy in systems with high uncertainty and a growing reliance on storage.

VI. AI Usage Disclosure

ChatGPT was used to assist with grammar, phrasing, and formatting in all sections of this paper. Code was written with Github Copilot and Claude Code. All AI-generated content was reviewed and edited for accuracy and clarity.

[8] For example, assume there is a high-price hour immediately followed by a scarcity hour where the price cap is binding. If the first hour has a price equal to \$500/MWh, and the storage has $\eta = 25\%$, a cap below \$2,000/MWh removes the incentive to charge in the first hour and creates more load shedding.

Appendix

A. System Parameters

TABLE II
Stochastic Process Parameters and Demand Discretization

Category	Parameter	Value
OU Process*	Long-run mean μ (GW)	6.5
	Volatility σ (GW)	2.29
	Drift speed θ (h^{-1})	0.0637
Demand Discretization	Minimum load (GW)	-10
	Maximum load (GW)	26
	Discrete demand states	71

* The volatility and drift match the autocorrelation and standard deviation of the 2024 CAISO net load data; the resulting OU process has a standard deviation of 6.4 GW. Independently of the CAISO data, the process mean μ is set to 6.5 GW. This places a zero-value of net demand approximately one standard deviation below the mean such that the process includes a significant amount of negative net-demand states.

TABLE III
Generation and Storage Cost Assumptions

Technology	Fixed Cost* ($/MW-yr)	Variable Cost ($/MWh)	Efficiency
Baseload	400,000	12	–
Peaker	110,000	180†	–
Battery Storage (4h)	65,000	–	0.85

* Fixed cost values are loosely based on the NREL Annual Technology Baseline for 2050.
† The variable cost of the peaker is deliberately set at a relatively high level to induce storage investment in our examples.

B. Reliability Statistics Comparison

TABLE IV
Reliability Indices Under Varying Price Caps*

Reliability Index †	VoLL ($/MWh)	Price Cap ($/MWh)		
	10,000	5,000	2,500	1,000
Dynamic Operation				
LOLE ‡	33.3	36.0	34.3	33.8
EUE	39.4	43.9	49.2	58.7
Perfect-Foresight Operation				
LOLE	11	11	11	11
EUE	28.5	28.5	28.5	28.5

* All operations are determined with the *Dynamic Operation* + VoLL capacities in Table I. Reliability indices are evaluated over a 10-year sample from the OU process at hourly resolution.
† Loss of load expectation (LOLE) is in hours / year; expected unserved energy (EUE) is in GWh / year.
‡ LOLE for the *Dynamic Operation* case does not change monotonically; we hypothesize that this is due to degeneracy in how load can be shed, *e.g.* shedding 1 MW of load for 1 hour has an equivalent system cost as shedding 0.5 MW of load for 2 hours.

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I. Review #12A

A. Paper summary

The paper studies how demand uncertainty impacts energy storage operation and how operating decisions propagate into long-run investment outcomes. The authors formulate storage operation as an average-cost Markov decision process and embed the resulting stationary policies into a stylized capacity expansion framework.

B. Comments for authors

The paper is well written and mathematically rigorous. Maybe even too rigorous as the problem at hand is a system adequacy problem, commonly addressed by the system operator by administrating capacity auctions. The assets receiving subsidies through these auctions need to be available at specific time periods, commonly announced one or more days before, depending on the expected system loading. I would like the authors to address this in the introduction and put it in the paper perspective. I didn't quite understand the concept of "post-storage net demand". Is it the demand after depleting a storage unit? How long should the storage last and how long would a high-demand event last? Shouldn't storage be dimensioned for such events? If a problematic event lasts for 4 hours, then the demand would reduce after that. I find the paper title slightly misleading as the term "dynamic" usually involves short-term actions, i.e. fast reserve activation, which is not considered in this paper.

C. Summarize your recommendation in one to two sentences

This is a good paper, mathematically strong and convincing, very well written, however, lacks relationship with reality.

— Hrvoje Pandzic

II. Review #12B

A. Paper summary

The paper proposes a methodology to analyze the impact of demand uncertainty on storage operation and investment.

B. Comments for authors

The paper addresses an important topic, and the role of storage becomes more important in highly renewable power systems. In that respect, analyzing optimal investments and operations of storage assets is relevant in the face of uncertainty (demand uncertainty here) that stems from renewable power output (implicit in the net demand). Moreover, the methodology is well-described and easy to follow.

With respect to the weaknesses, the authors point out themselves, that their methodology does not guarantee to provide globally optimal solutions. Hence, the results, and solutions that we are discussing might be locally optimal (far away from global solutions). On the other hand, the way that the methodology is set up, there is just one technology that faces uncertainty here, and that is storage. Since all other technologies are thermal, they are not affected by the demand uncertainty in this matter because they do not have any temporal linking constraints (no memory etc.). Since storage is the only technology that does, it is clear - even before formulating the model and solving it - that it will be negatively affected by the uncertainty.

What would make this more interesting, would be to analyze such a setup in a power system with renewable goals, enforced by quotas, or even penalties for emitting CO_2. In other words, there has to be some kind of penalty for thermal technologies, because otherwise, uncertainty will always only affect negatively storage and nothing else.

Some minor comments/questions. Essentially you have a cost minimzation model. However, in markets, assets often maximize profits, rather than minimize system costs. You could have equilibrium models that are not perfectly competitive (and have market power), e.g. an oligopoly, and then assess this issue. Letting storage operate strategically might give it an opportunity to take advantage of uncertainty.

Your stochastic process (1) is very simplistic. How do you account for long-term trends in power systems. Seasonal variations on top of daily variations.

(4g) is nonconvex. Is it even necessary to include this constraint. In optimization problems (economically driven), often, this constraint is not active anyways. When would it be active in your setting? It could be linearized using binaries.

Regarding your case study, as you point out, it is very simple. A 4-hour Battery is a very limited asset. How would this change if you had long-term storage, such as a hydro reservoir with the option of pumping, or even several hydro assets at the same time.

C. Summarize your recommendation in one to two sentences

I would accept the paper for the conference, but for a journal submission I would suggest to address some of the issues raised previously.

— Sonja Wogrin

III. Review #12C

A. Paper summary

This paper uses an Ornstein-Uhlenbeck process to describe net load. Using this representation of net load, the paper finds a strategy for operating storage that is different from the strategy under perfect foresight. This analysis is similar to the analysis performed by Geske and Green (Ref. [7]). The results show (a) how net load uncertainty can result in precautionary operation of storage and alter investment results; and (b) how the price of lost load in the market affects investments and operations. Results are presented for a case study with parameters loosely based on California.

B. Comments for authors

Strengths:

(+) The article is well-written with a good structure and clear messages.

(+) In terms of potential impact, the qualitative insights of the analysis are relevant for system operators and policymakers.

(+) In terms of rigour, simulations are performed for 10 sampled years.

Questions/Suggestions:

(-) The relationship between this article and Ref. 7 (Jeske and Green, 2020) could be articulated more clearly. In particular, it would be helpful for the authors to explicitly state which methodological or conceptual contributions are new beyond that earlier work.

(-) In Section III.B, results for mean stored energy and capacity investment at equilibrium are discussed. It would also be useful to discuss the differences in system costs and unserved energy between the two cases (dynamic operation and perfect foresight operation).

(-) In Section III.B, footnote 5 mentions that the Ornstein-Uhlenbeck process cannot capture diurnal or seasonal patterns. Could the authors provide additional information that shows how well the OU process approximates storage arbitrage profits? For instance, how different are the average arbitrage profits of storage under perfect foresight between two cases: (a)one with net demand trajectories generated with the OU process vs. (b) another with the actual 2024 time series?

(-) In Section IV.A, a sentence states, "this distortion arises only under dynamic operation: by reducing the continuation value of stored energy, the price cap weakens the incentive to charge in anticipation of future scarcity events." This seems to differ from the findings of Suski et al., who show that reductions in the price cap also affect charging incentives under perfect foresight. Can the authors elaborate on the sentence from Section IV.A?

A. Suski et al., 'Missing Money and Market-Based Adequacy in Deeply Decarbonized Power Systems with Long-Duration Energy Storage', forthcoming, IEEE Transactions on Energy Markets, Policy and Regulation, doi: 10.1109/TEMPR.2025.3648914

(-) I have a similar question about the sentence related to the deterministic setting: "In a deterministic setting, a cap above ... their timing and magnitude are known with certainty." I wonder if this sentence is valid for this specific case, and if it is not generalizable, as Suski et al. observe distortions for incentives to charge in a deterministic setting for storage dispatch.

(-) Fig. 4 shows an expansion in discharging, but a contraction in charging. How is the energy conserved? Is the initial state of charge different between the top and bottom figures? In addition to this figure, a table with the total energy charged/discharged per level of net demand might be helpful.

(-) The caption of Fig.4 states that "the generation and storage capacities are held constant in both cases." However, the capacities in Table III are different between the VOLL and price cap cases. Could you specify at what level the generation and storage capacities are held (VOLL, price cap, or other)? What is the rationale for choosing this level? The answer to this question is important because the conclusion about "state-contingent contracts" is based on this Figure. Considering that the capacities are constant but the operational strategy changes, the storage profits and their ability to break even should be different. Can you provide additional information on storage gross margins?

(-) The literature review could be expanded to better position the contribution within recent work on energy storage. For example, Guerra et al. have analysed different strategies for the dispatch of long-duration energy storage under imperfect foresight.

Guerra et al., Towards robust and scalable dispatch modeling of long-duration energy storage', Renewable and Sustainable Energy Reviews, vol. 207, p. 114940, Jan. 2025, doi: 10.1016/j.rser.2024.114940.

Minor comments:

(1) Table II. Are the units for the fixed costs correct, or should they be in $/kW-year?

(2) In Section IV.A, Figure 3 is hard to read since changes in capacity are minimal for different levels of price caps. The Figure has the same information as Table III. Hence, for brevity, my suggestion is to replace Fig. 3 with Table III.

(3) Figure 4 caption should specify that the graph is for the dynamic storage policy. In the current version, the reader can find this information in the 4th paragraph of Section IV.A.

C. Summarize your recommendation in one to two sentences

The paper analyses a timely topic and offers useful insights. Minor revisions would help future readers fully appreciate the results presented.

— Elina Spyrou

IV. Brief response to reviewers (optional)

We thank the reviewers for their constructive comments which improved the paper. Although we were unable to incorporate all of the suggestions into our edits, they are fruitful avenues for future work.

Some key responses follow (organized by reviewer).

Reviewer 1:

- ”The assets receiving subsidies...”: We agree and added a comment on it in the introduction.
- ”post-storage net demand”: Added a clarification to the caption of Fig. 1
- Added a clarification on our use of the term ”dynamic”.

Reviewer 2:

- Constraint (4g). We added a footnote explaining that the constraints are enforced by restricting the discrete action set, which avoids the nonconvexity entirely.
- ”Since storage is the only technology that does, it is clear... that it will be negatively affected by the uncertainty.”: We agree.

Reviewer 3:

- Geske and Green fix storage capacity and only optimize thermal generation, we also allow the storage capacity to vary.
- We included reliability stats in the revision; we leave discussion of costs for future work.
- ”Could the authors provide additional information that shows how well the OU process approximates...”: We added a note to Table II describing how we use the OU process; it is not intended to be an approximation of CAISO per se.
- Suski et al.: Thank you for pointing this out; we added discussion on the similarities and differences.
- ”How is the energy conserved? Is the initial state of charge different between the top and bottom figures?”: The probability of being in certain states also shifts between the two figures, so energy is still conserved.
- ”Could you specify at what level the generation and storage capacities are held”: added clarifications to the tables/figures.
- ”What is the rationale for choosing this level?”: We fix them at the dynamic + VoLL values since, in theory, this is the optimal value if one considers uncertainty.
- ”Can you provide additional information on storage gross margins?”: We plan to address this in a more extended followup work.
- Guerra et al.: Thank you for this reference, it is added.
- ”Are the units for the fixed costs correct”: Thank you for catching this mistake.
- ”Figure 3 is hard to read... replace Fig. 3 with Table III”: Agreed, made change.
- ”Figure 4 caption”: Agreed, made change.

V. Brief summary of changes made to the final paper

The model formulation, the fixed-point solution algorithm, and all dynamic (MDP) operation and investment results are unchanged from the reviewed version. The revisions correct one implementation error and add a reliability comparison.

Corrected storage capital cost (primary change). We corrected the annualized storage energy-capacity cost, which through a bug was input as $25,000/MW-yr rather than the $65,000/MW-yr assumed in our cost parameters. The error affected only the perfect-foresight capacity-expansion results; the dynamic operation and investment outcomes do not depend on it. Under the corrected cost, the perfect-foresight equilibrium storage capacity falls from the previously reported 66.4GW to 6 – 7GW, with baseload and peaker capacities adjusted accordingly. The correction does not alter our central finding All affected values in the capacity table and discussion in text were updated.

Added reliability statistics. We now report reliability indices (LOLE and EUE) for both operating regimes across the four price caps, evaluated on the fixed VoLL capacity mix.

Presentation of capacity results. We moved the capacity-investment table from the appendix into the main text and removed a bar-chart figure that conveyed the same information but in a less useful way.

Expanded discussion and literature. We expanded the treatment of the “missing money” problem to distinguish our mechanism from the round-trip-efficiency channel of Suski et al.,

Appendix. The appendix now documents the Ornstein–Uhlenbeck calibration to 2024 CAISO net load, and the units for annual investment cost were corrected from GW to MW.

Other. Remaining edits standardize equation punctuation and language style.