Valuation of Flexible Energy Resources in a Nonbinding Commitment Transactive Energy Market

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BIRS WORKSHOP

NEW CHALLENGES IN ENERGY MARKETS - DATA ANALYTICS, MODELLING AND NUMERICS

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Transactive Energy Markets

- Distributed flexible energy resources can provide numerous grid services.
- Transactive Energy Markets enable resources without direct access to wholesale markets to participate in energy transactions.
- Energy Storage:
  - ◇ unique capabilities
  - ◇ technological advances
- Market and regulatory barriers to energy storage deployment:
  - ◇ encouraging small distribution-level participants
  - ◇ revenue compensation mechanisms
  - ◇ maintaining grid operability and reliability

Transactive Energy Markets

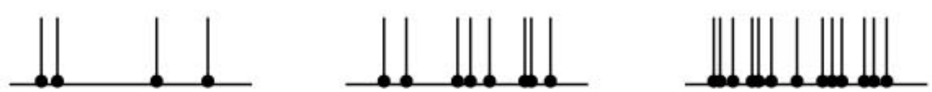
- Power injections from storage resources cannot be completely unsupervised and ad hoc.
- Otherwise, there will be times when a large number of storage owners discharge simultaneously.
- Restricting transactions to only those times that are specified in real time by a distribution system operator can alleviate this risk.

Outline

- Market Model: Nonbinding Commitment Market
- Discharge Time Optimization Problem
  - Structure of the Value Function and Optimal Policy
  - Computational Scheme
- Energy Storage with Stacked Services
  - Structure of the Value Function and Optimal Policy
  - Computational Scheme
- Conclusion and Discussion

Nonbinding Commitment Market Framework

- **Agents**:
  - ◇ utility company or a load serving entity
  - ◇ flexible capacity unable to participate in the wholesale market
- **Agreement**:
  - ◇ Action times are the utility company's discretion



  - ◇ Upon receiving a permission, an energy storage unit has the option to discharge in real time and receive a payment.
  - ◇ a time-varying payoff structure

Nonbinding Commitment Market Framework

- **Benefit for Storage Owners:**
  - ◇ Storage owners do not have to commit in advance to providing electricity, and do not need to get involved in a bidding process.
- **Benefit for the Utility:**
  - ◇ The utility company gets access to installed storage capacity without having to invest itself in those assets.
  - ◇ The utility does not commit in advance to buy electricity.
  - ◇ Constraining discharge times enables to indirectly supervise these participants and their interference in the grid.
- **Broader Benefit:**
  - ◇ It promotes deployment of available flexible capacities.
  - ◇ Presence of storage units can enable other services to smoothing out variability, and firming transactions by wind and solar agents.

Stochastic Model

- K: energy storage capacity
- T: contract duration (terminal time)
- Nonlinear Pricing Scheme:
  - ◇ $R_t(a)$: payoff for discharging a units at time $t \in [0, T)$
  - ◇ $R_t(a)$: concave and increasing in a, continuous in t.
  - ◇ log-utility function $R_t(a) = \log(1 + p_t a)$
  - ◇ $R_T(a)$: terminal reward
- Discharge permissions are generated by a Markovian self-exciting point process $\{N_t\}_{t \geq 0}$ with arrival rate $\{\lambda_t\}_t$.
- Self-exciting processes are well-suited to the modeling of permissions arriving in clusters.

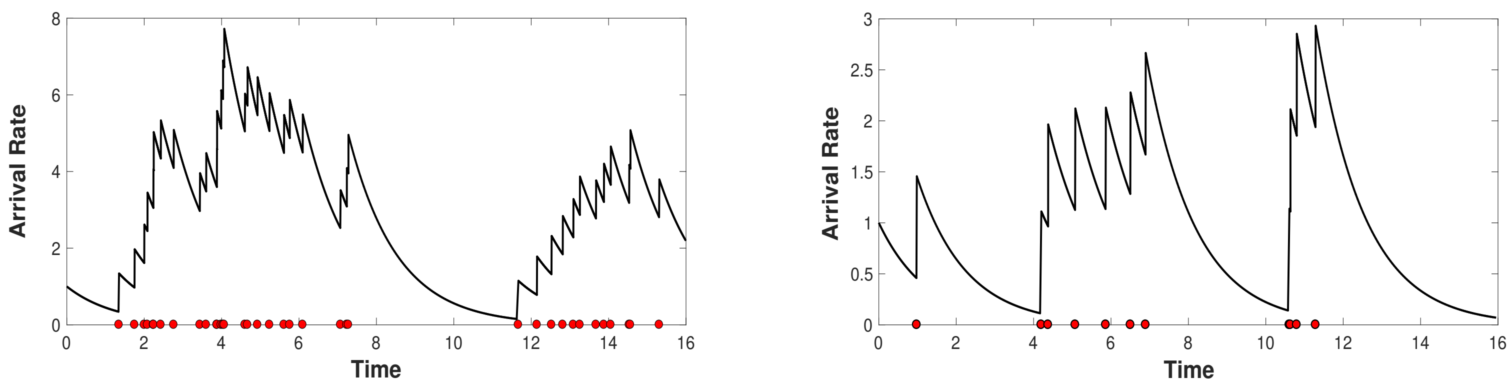
Uncertain Arrival Rates

- **Self-exciting Shot Process**:

$$\lambda_t = \lambda_0 e^{-\beta t} + \int_0^t \alpha e^{-\beta(t-s)} dN_s$$

$$N_t = \int_{[0,t]\times\mathbb{R}_+} M(ds, dz)\mathbf{1}_{0<z\leq\lambda_s},$$

where $\alpha \geq 0$: jump magnitude, $\beta \geq 0$: decay rate.



Two realizations of the process with $\lambda_0 = 1$, $\beta = 0.8$, $\alpha = 1$ (curves: arrival rate; dots: arrival times)

Optimal Control of Participating Energy Storage

- **State**: storage level k_t, intensity of shot process λ_t
- **Decision**:
  - ◇ use current versus uncertain future action opportunities
  - ◇ a: amount to be discharged with $a \in \mathcal{A}_t$
- **Objective**:

$$\max_{\pi \in \Pi_t} \mathbb{E} \left[\sum_{i=1}^{N_{T-} - N_{t-}} R_{\tau_{i,t}} \left(x^{\pi}_{\tau_{i-1,t}} - x^{\pi}_{\tau_{i,t}} \right) + R_T \left(x^{\pi}_T \right) \,\middle|\, x^{\pi}_t = k_0 \right]$$

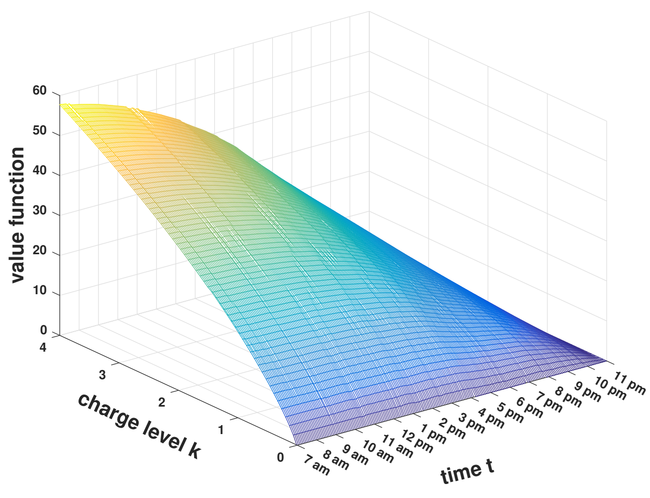
  - ◇ $N_{T-} - N_{t-}$: number of permission arrivals over $[t, T)$
  - ◇ $x^{\pi} = \{x^{\pi}_t\}_{t \in [0,T]}$: storage charge level under the policy π
  - ◇ $\tau_{t,i}$: time of the ith operation permission arriving after t
- Problem constitutes a piecewise deterministic MDP.

Computational Scheme

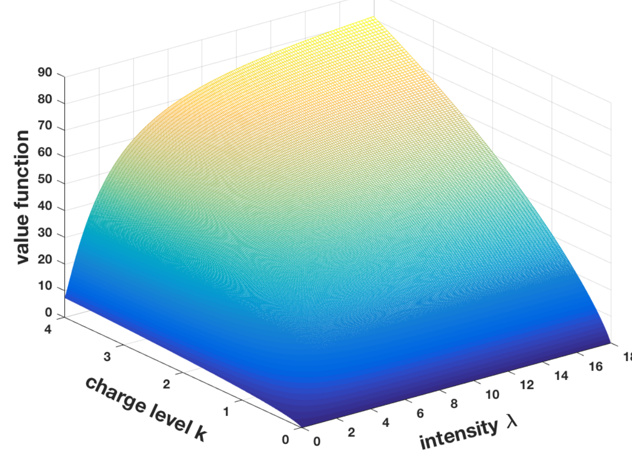
- Value function $V_t(k,\lambda)$ satisfies

$$V_{t-\delta}(k,\lambda_{t-\delta}) = \quad p_{t-\delta}V_t\left(k,\lambda_{t-\delta}e^{-\beta\delta}\right) + (1-p_{t-\delta}) \times \max_{a\in\mathcal{A}_k}\left\{R_t(a) + V_t\left(k-a,\lambda_{t-\delta}e^{-\beta\delta}+\alpha\right)\right\}$$

where $p_{t-\delta} := \exp\left(\frac{-\lambda_{t-\delta}}{\beta}(1-e^{-\beta\delta})\right)$.



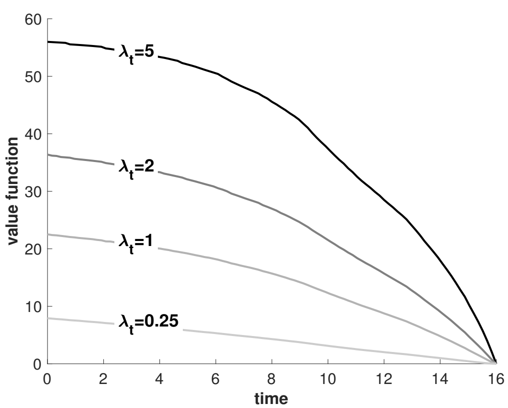
(a) value function at $\lambda_t = 2$



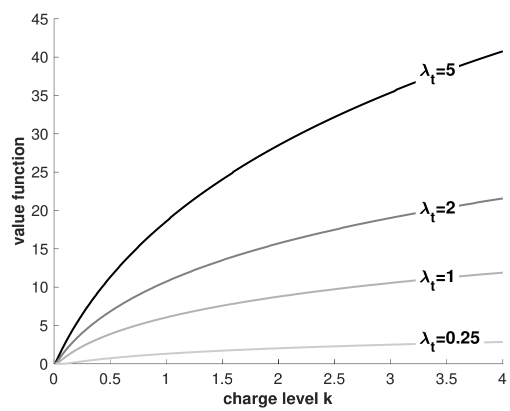
(b) value function at $t = 0$ (7 am)

Structure of the Value Function

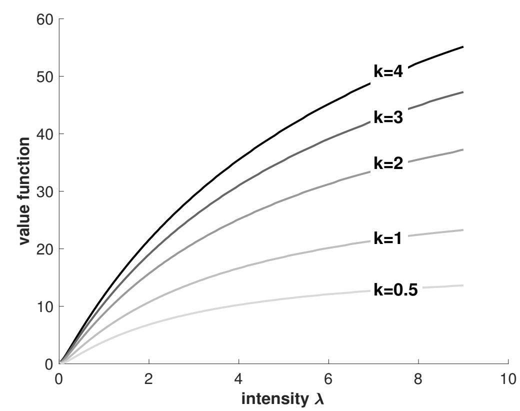
- $V_t(k, \lambda_t)$ is concave and increasing in k.
- $V_t(k, \lambda_t)$ is decreasing and uniformly continuous in t.
- $V_t(k, \lambda_t) \leq \left(1 + \frac{\lambda_t}{(\alpha-\beta)}\left(e^{(\alpha-\beta)(T-t)} - 1\right)\right) \max_{t \in [0,T]} R_t(K)$.
- $\lambda_1 \leq \lambda_2$ implies $V_t(k, \lambda_1) \leq V_t(k, \lambda_2)$, for all k.
- $\beta_1 \geq \beta_2$ and $\alpha_1 \leq \alpha_2$ imply that $V_t^{(1)}(k, \lambda) \leq V_t^{(2)}(k, \lambda)$, for all k, λ.



(a) $k = 2$



(b) $t = 12$



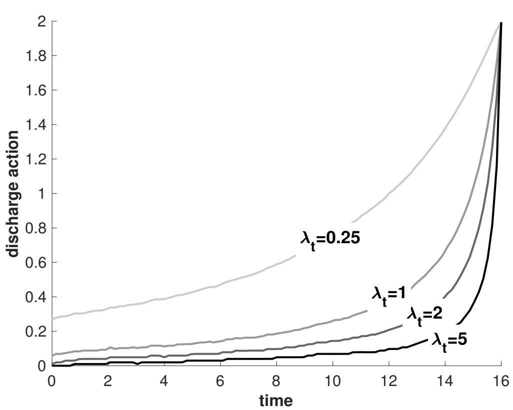
(c) $t = 12$

Structure of the Optimal Policy

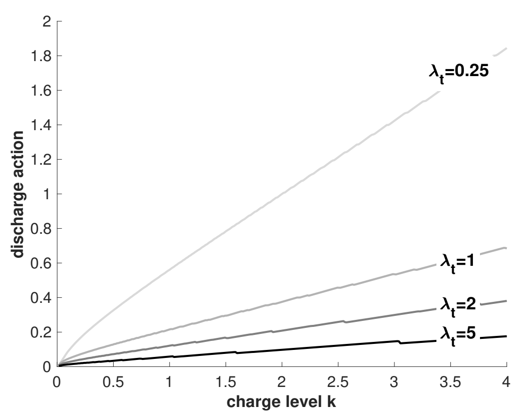
- An optimal discharge action at the permission time t is obtained by

$$a_t(k, \lambda_t) = \arg\max_{a \in \mathcal{A}_k} \; \{R_t(a) + V_t(k - a, \lambda_t)\}$$

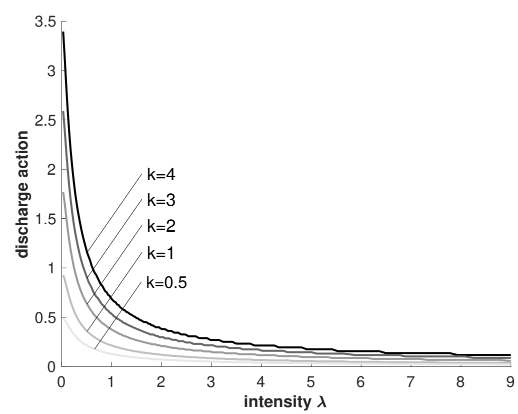
- $t_1 < t_2$ yields $a_{t_1}(k, \lambda) \leq a_{t_2}(k, \lambda)$
- $k_1 \leq k_2$ implies $a_t(k_1, \lambda) \leq a_t(k_2, \lambda)$



(d) $k = 2$



(e) $t = 12$



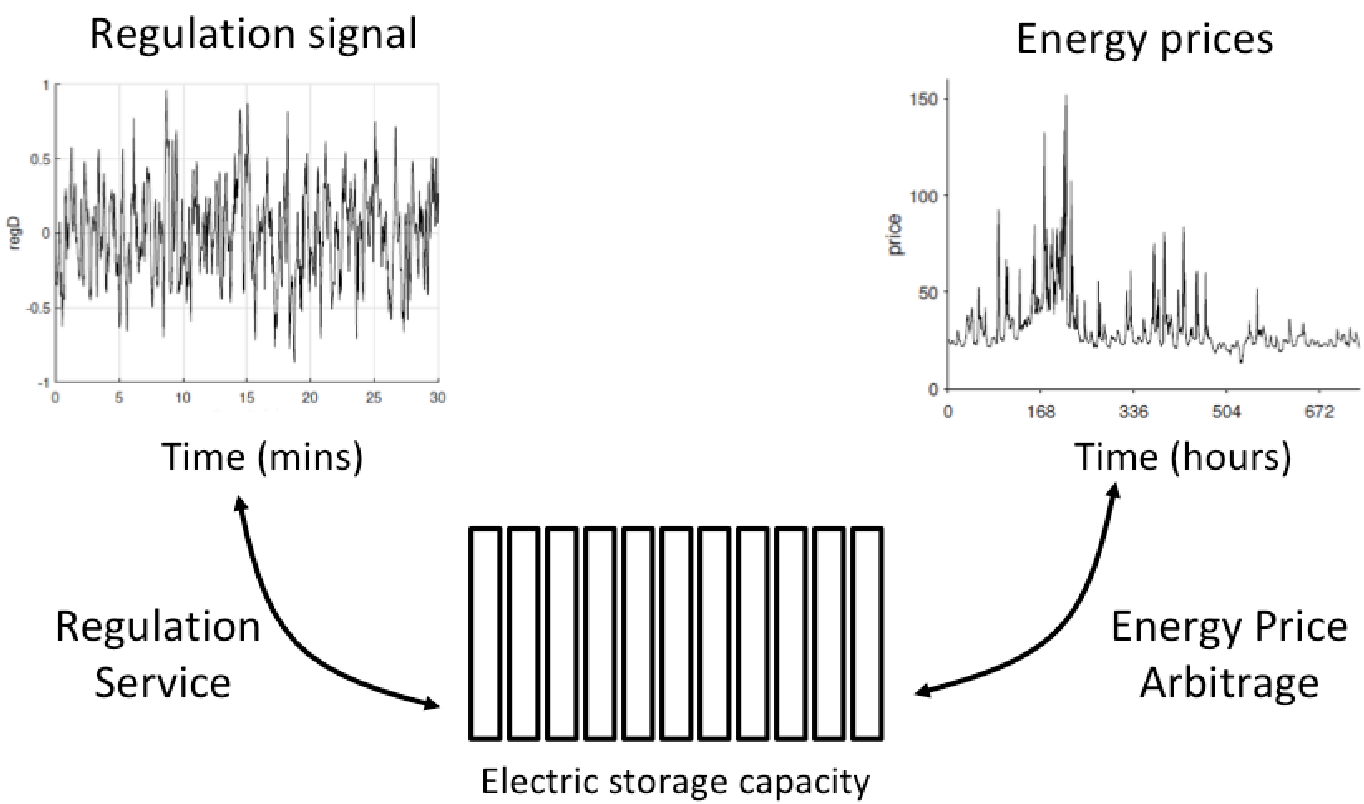
(f) $t = 12$

Challenge of Electric Storage Deployment

- If storage must stand economically by itself, it must get enough revenue from operations.
- Storage resources can provide multiple services simultaneously.
- Two prominent markets:
  - ◇ Energy markets
    Must have large price spreads and enough volatility to compensate for energy losses of charge-discharge
  - ◇ Regulation markets
    Must ask for variations of output within device constraints
    Must pay enough for the use of storage capacity
- The services are coupled physically and differ in their degree of commitment.

Service Stacking

- With service stacking, we try to optimize operations to maximally benefit from the 2 revenue streams



Service Stacking: Stochastic Model

- k_t: Stored energy level for energy arbitrage
- Transactions in the energy market:

  purchase $s = a/\eta^c$ pay $p_m s$ $k_t \leftarrow k_{t-} + a$

  sell $s = a\eta^d$ get $p_m s$ $k_t \leftarrow k_{t-} - a$

- l_t: number of capacity blocks for regulation service
- Service commitments in the regulation market:

  accept block request u receive ρ_m/hour

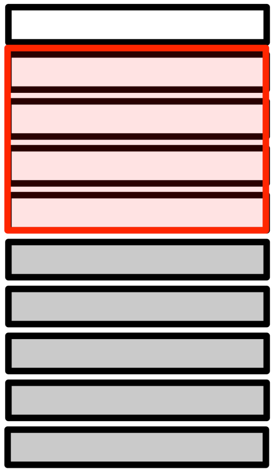
  committed capacity: $l_t \leftarrow l_{t-} + u$

  cannot decommit until block is released

  duration of service is random

  upon release of committed capacity $l_t \leftarrow l_{t-} - u$

- Capacity constraint: $0 \leq k_t + l_t \leq K$



Service Stacking: Stochastic Model

- Opportunities of transactions arrive with intensities:

  λ^c: for buying

  λ^d: for selling

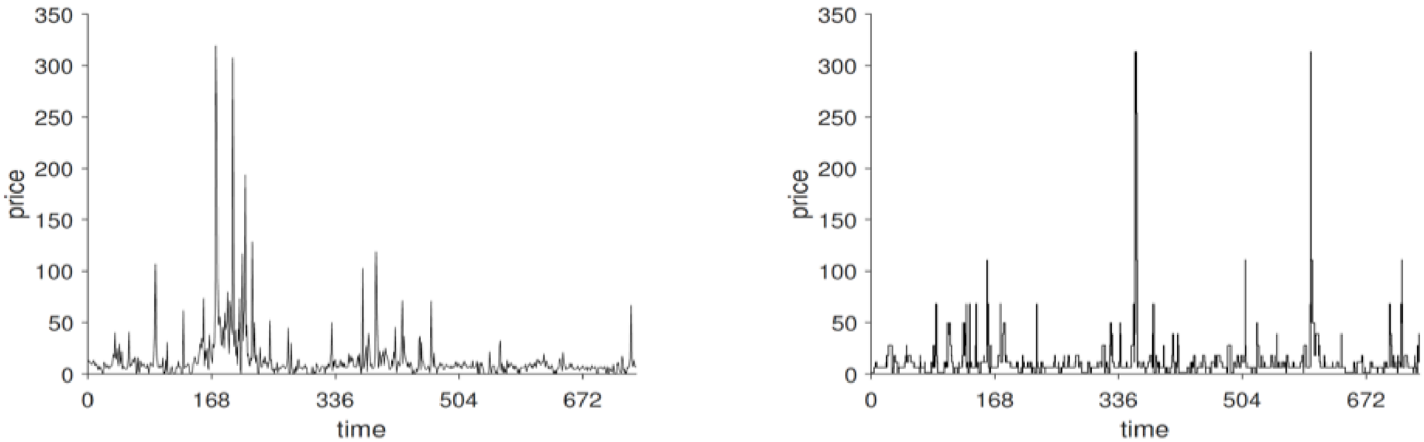
  λ^r: for regulation service

- Finite-state continuous-time background process

$$m_t \sim \text{CT-MDP}(m_0, Q) \quad m_t \in \{1, \cdots, M\}$$

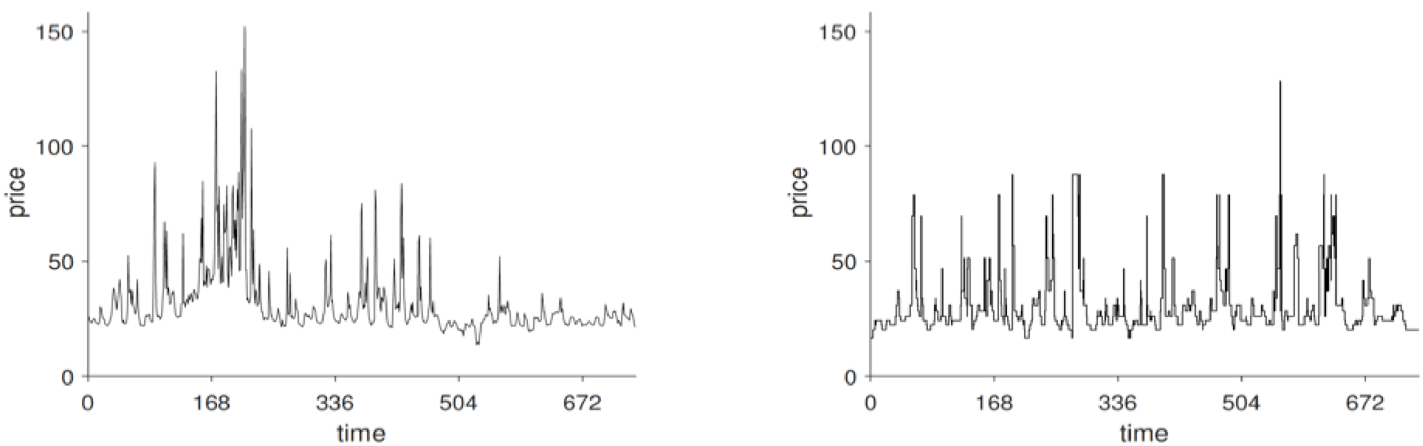
  m: state label, specifies p_m and ρ_m

- PJM data from 2017 is used to fit the price processes ($M = 3756$ states) and calibrate the transition rate matrix Q.
- Objective: to maximize the γ-discounted expected return
- control problem: continuous-time MDP - state: (k, l, m).



(a) Historical Data (January 2017) (b) One Simulated Sample Path

Regulation Market Price (hourly)



(a) Historical Data (January 2017) (b) One Simulated Sample Path

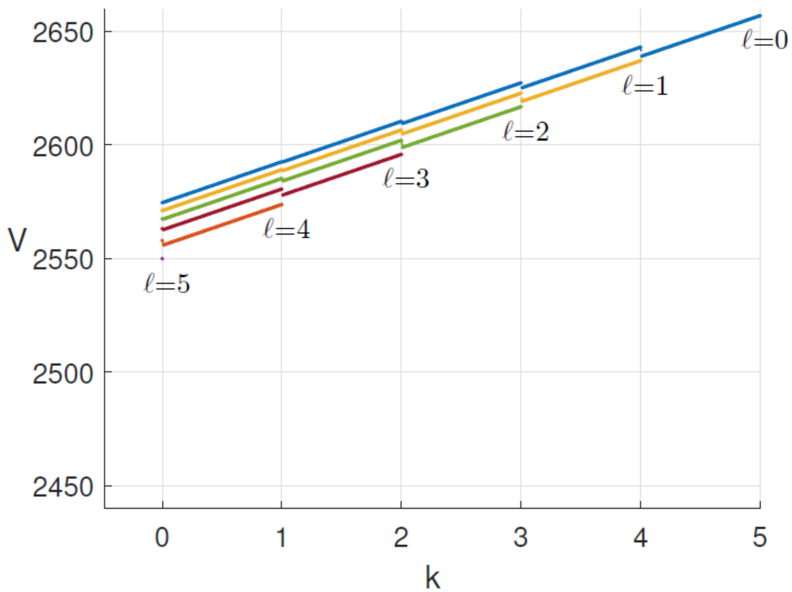
Energy Market Price (hourly)

Properties of the Value Function

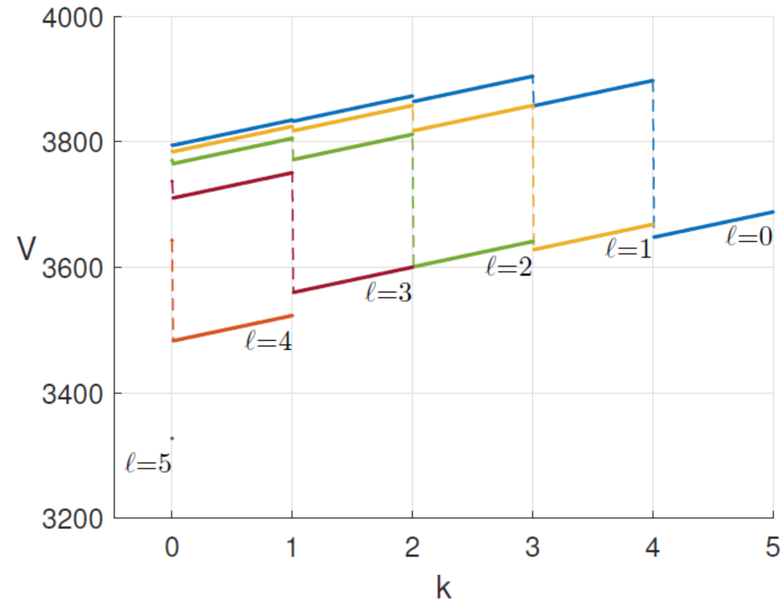
- For each (k, l, m), $V(k, l, m)$ is nondecreasing in λ^c, λ^d, λ^r.
- For each (k, m), $V(k, l, m)$ is nondecreasing in l.
- For each (l, m), $V(k, l, m)$ is not necessarily non-decreasing in k.
- If $\lambda^r = 0$ and $l = 0$ then $V(k, l, m)$ is affine in $k \in [0, K]$, and $a^* \in \{-K, 0, K\}$.
- For each (l, m), $V(k, l, m)$ is piecewise linear in k, left-continuous with right discontinuities at $k \in \{0, 1, \cdots, K-1\} \bigcap \{k \in [0, K], k + l \leq K\}$.
- Directional derivatives $\partial_k^+ V(k, l, m)$ and $\partial_k^- V(k, l, m)$ only depend on m, i.e., is independent of k and l:
  $\partial_k^+ V(k, l, m) := \text{lim}_{\epsilon \to 0^+} [V(k + \epsilon, l, m) - V(k, l, m)]/\epsilon$
  $\partial_k^- V(k, l, m) := \text{lim}_{\epsilon \to 0^+} [V(k, l, m) - V(k - \epsilon, l, m)]/\epsilon$.

Value Function Computed

- The value function is given by
  $V(k,l,m) = v_{\lceil k \rceil lm} + (w_{1m} - w_{0m})(k - \lceil k \rceil)$ for $k \in [0, K-l]$.
  v_{klm}: value function with the restriction $k \in \{0, 1, \cdots, K\}$
  $w_{k,m}$: value function for $K = 1$ and $\lambda^r = 0$, restricted to $k \in \{0, 1\}$

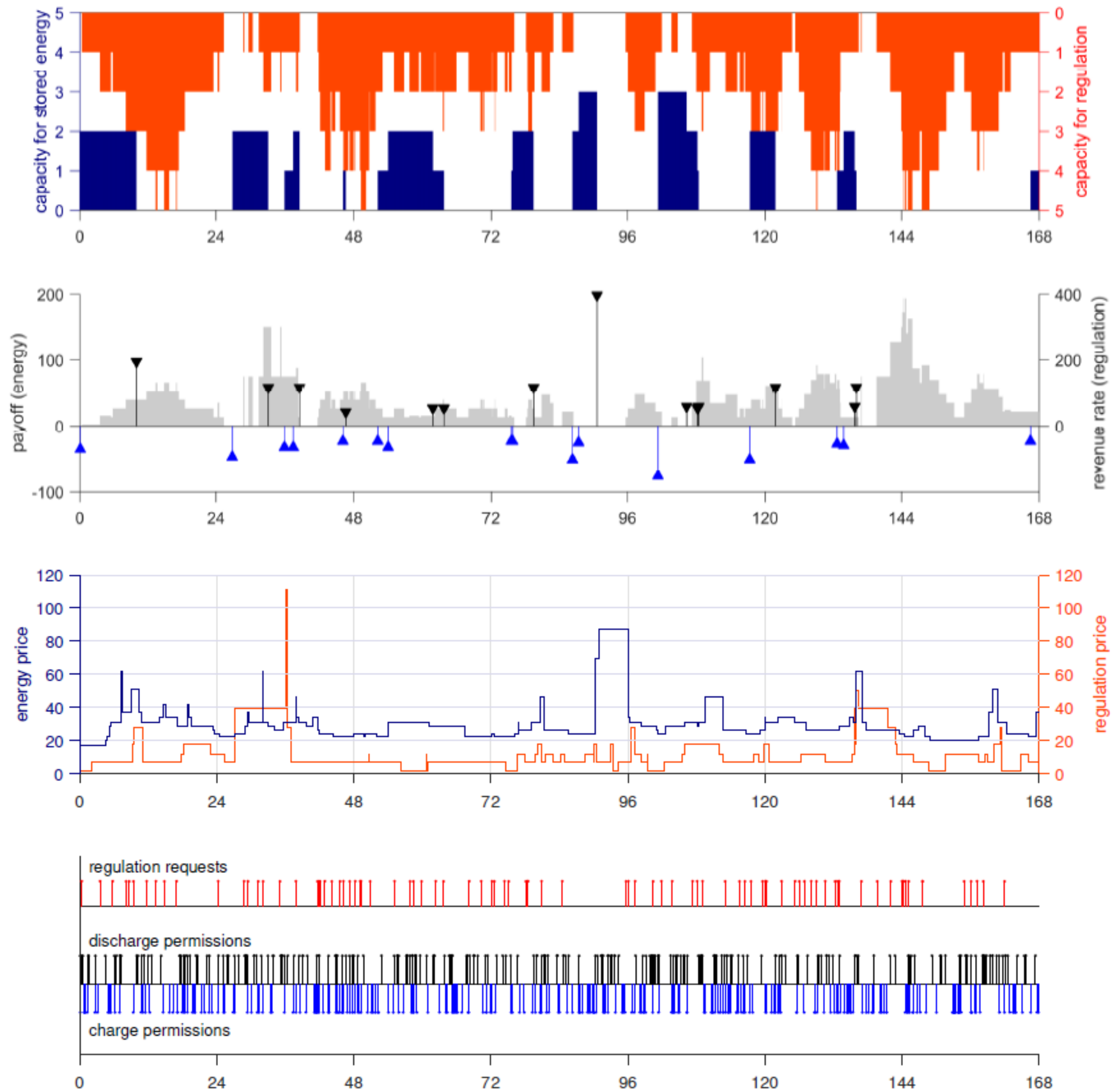


Value function at m=1



Value function at m=3756

Optimal Policy Simulated



Value of Stacking Services

Compare to the value of the best static allocation:

$\max_{x \geq 0,\ y \in \mathbb{N},\ x+y \leq K} V_x^{\text{en}}(k_0, m) + V_y^{\text{reg}}(l_0, m)$

x: capacity allocated to energy

y: capacity allocated to regulation.

Instance			Optimal Static Allocation					With Stacked Services	
p_1^{en}	p_2^{en}	Δ^{en}	x	y	V_x^{en}	V_y^{reg}	V^{static}	V^{dyn}	Improvement
25	30	2.2	0	5	0.0	2535.6	2535.6	2535.6	0.0%
25	50	21.2	1	4	154.7	2396.9	2551.6	2738.2	7.3%
25	70	40.2	2	3	617.5	2126.6	2744.1	3134.8	14.2%
25	90	59.2	2	3	925.6	2126.6	3052.2	3664.3	20.1%

Storage parameters: $K = 5$, $\eta^{\text{c}} = \eta^{\text{d}} = 0.95$. Discount rate: $\gamma = 0.01$.

Market parameters: $\lambda^{\text{c}} = 1.5$, $\lambda^{\text{d}} = 1.5$, $\lambda^{\text{r}} = 0.5$, $\mu = 0.25$, $q_{12}^{\text{en}} = 0.1659$, $q_{21}^{\text{en}} = 0.3095$.

$\Delta^{\text{en}} = p_2^{\text{en}} \eta^d - p_1^{\text{en}} / \eta^c$: efficiency-adjusted energy price spread

Backtesting

- Backtesting of the policies optimized on 2017-data calibrated model

Scenario	Static policy	Dynamic policy	Improvement
Jan-2017	2122.6	2145.8	1.09%
Jan-2018	23606.4	28166.3	19.32%
Feb-2018	2470.7	2325.0	-5.90%
Mar-2018	2906.8	3051.0	4.96%
Apr-2018	3605.6	4117.9	14.21%
May-2018	2845.0	3814.2	34.07%
Jun-2018	6053.1	7452.2	23.11%

Concluding Remarks and Discussion

- The approach allows individual energy storage owners and developers to inject electricity to the grid without participating in the wholesale electricity market, dealing with the bidding process, and bearing the risk of commitments.
- Extension to continuous decisions, but we assume a lead-time L between decision and implementation
- Extension to a midcharge regulation model: the regulation capacity limit is based on midcharge, any number of blocks can be reserved at request time and charged blocks can be reserved.
- Various Payoff Structures

Thank you.

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References:

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