

Operation and Configuration of a Storage Portfolio via Convex Optimization

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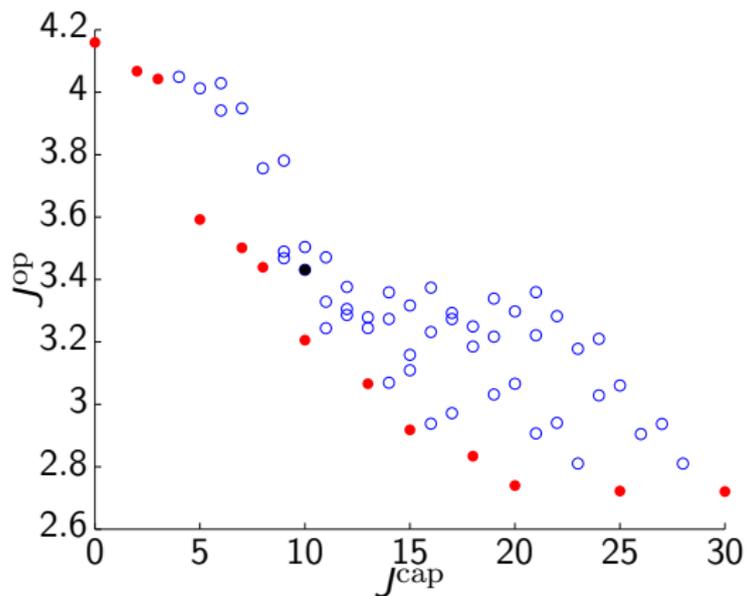
This talk

- ▶ a general framework for operating and configuring a **portfolio** of storage devices
- ▶ find **optimal trade-off** between operation cost (J^{op}) and capital construction cost (J^{cap})

Where we are going

- ▶ assume that J^{cap} is known for all candidate portfolios
- ▶ focus on evaluating J^{op} for each portfolio

The final result



Storage portfolio

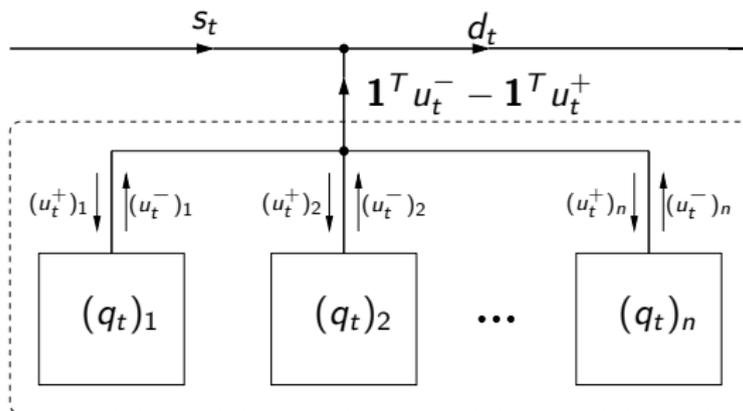
- ▶ portfolio of n different storage devices
- ▶ charge $q \in \mathbf{R}_+^n$, charging/discharging rates $u^+, u^- \in \mathbf{R}_+^n$
- ▶ maximum charge, charging/discharging rates
 $(Q, C, D) \in \mathbf{R}^{3n}$
- ▶ charge leakage, charging/discharging efficiencies
 $(\eta^l, \eta^c, \eta^d) \in (0, 1]^{3n}$
- ▶ exogenous input w
- ▶ discrete time state evolution:

$$q_{t+1} = \eta^l \circ q_t + \eta^c \circ u_t^+ - (1/\eta^d) \circ u_t^- + w_t, \quad t = 0, 1, \dots$$

Storage portfolio

- ▶ pull energy s from source and deliver energy d to destination
- ▶ let $v_t = (d_t, s_t, u_t^+, u_t^-)$
- ▶ power balance:

$$(-1, 1, -\mathbf{1}, \mathbf{1})^T v_t = 0, \quad t = 0, 1, \dots$$



Objective function

- ▶ decomposable objective function

$$\ell_t(\mathbf{v}_t, \mathbf{q}_t) = \phi_t^{\text{sr}}(s_t) + \phi_t^{\text{de}}(d_t) + \phi_t^{\text{ch}}(u_t^+, u_t^-) + \phi_t^{\text{st}}(q_t)$$

- ▶ functions not necessarily known ahead of time
- ▶ encode constraints by setting $\ell_t = +\infty$ if violated
- ▶ $\{\ell_t\}$ encodes all problem uncertainty other than $\{w_t\}$
- ▶ operation cost

$$J^{\text{op}} \equiv \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T \ell_t(\mathbf{v}_t, \mathbf{q}_t)$$

(we assume limit exists)

Example objective functions

- ▶ $\phi_t^{\text{sr}}(s_t) = p_t s_t$
 - ▶ energy price p_t
 - ▶ with capacitation: $\phi_t^{\text{sr}}(s_t) = \begin{cases} p_t s_t, & 0 \leq s_t \leq S^{\text{max}} \\ \infty, & \text{otherwise} \end{cases}$
- ▶ $\phi_t^{\text{de}}(d_t) = \alpha(r_t - d_t)_+$
 - ▶ energy requests r_t
 - ▶ typically $\alpha \gg p_t$
- ▶ $\phi_t^{\text{ch}}(u_t^+, u_t^-) = \beta(\|u_t^+\|_1 + \|u_t^-\|_1)$
 - ▶ penalize frequent charging/discharging

Control policy

- ▶ $\hat{w}_{\tau|t}, \hat{\ell}_{\tau|t}$: estimates of exogenous input, objective function at time τ , based on information available at time t
- ▶ estimates can be obtained many ways
 - ▶ conditional expectation (if statistical model exists)
 - ▶ historical patterns
 - ▶ analyst predictions
 - ▶ futures market
- ▶ goal: pick v_t to minimize J^{op} and satisfy constraints, based on information available at time t

Control policy

- ▶ we use model predictive control (MPC)
- ▶ at time t , construct estimates $\hat{\ell}_{\tau|t}, \hat{w}_{\tau|t}$ for T steps into the future and solve

$$\begin{aligned} & \text{minimize} && \frac{1}{T} \sum_{\tau=t}^{t+T-1} \hat{\ell}_{\tau|t}(\hat{v}_{\tau}, \hat{q}_{\tau}) \\ & \text{subject to} && \hat{q}_{\tau+1} = \eta^l \circ \hat{q}_{\tau} + \eta^c \circ \hat{u}_{\tau}^+ - (1/\eta^d) \circ \hat{u}_{\tau}^- + \hat{w}_{\tau|t}, \\ & && \hat{d}_{\tau} - \hat{s}_{\tau} + \mathbf{1}^T \hat{u}_{\tau}^+ - \mathbf{1}^T \hat{u}_{\tau}^- = 0, \\ & && 0 \leq \hat{q}_{\tau} \leq Q, \quad 0 \leq \hat{u}_{\tau}^+ \leq C, \\ & && 0 \leq \hat{u}_{\tau}^- \leq D, \quad \tau = t, \dots, t + T - 1 \\ & && \hat{q}_t = q_t, \quad \hat{q}_{t+T} = q_{\text{final}} \end{aligned}$$

- ▶ when $\hat{\ell}_{\tau|t}$ are convex, problem is convex and so easily solved

Numerical example

- ▶ time discretized into 30 minute intervals
- ▶ $T = 48$ (one day prediction horizon)
- ▶ $\ell_t(v_t, q_t) = p_t s_t + \alpha(r_t - d_t)_+$, with capacitated source
- ▶ r_t, p_t are log-normal stochastic process, with diurnal variation
- ▶ $\hat{r}_{\tau|t}, \hat{p}_{\tau|t}$ are conditional expectations

Portfolio configurations

- ▶ 3 types of devices: small (S), medium (M), large (L)

device	Q	C	D	η	η_c	η_d	$J^{\text{cap}}/\text{unit}$
L	5	0.75	0.75	0.98	0.8	0.8	5
M	2	0.5	0.5	0.99	0.9	0.9	3
S	1	0.5	0.5	0.995	1	1	2

- ▶ 64 configurations consisting of all combinations containing 0, 1, 2, or 3 units of each device type

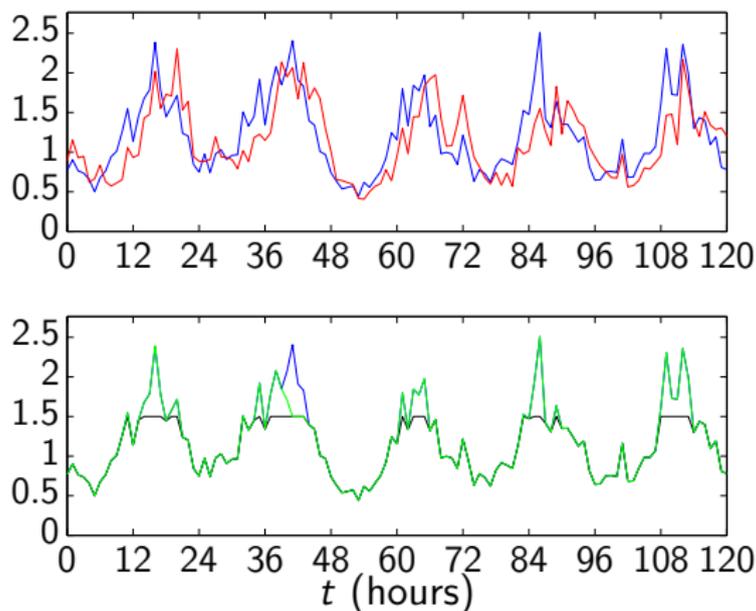
MPC evaluation

- ▶ simulate MPC for each portfolio configuration for 365 days (17520 time periods)
- ▶ solve times on single core of 3.2 Ghz Intel i3
 - ▶ SDPT3: 3.23 s (15 hours total)

MPC evaluation

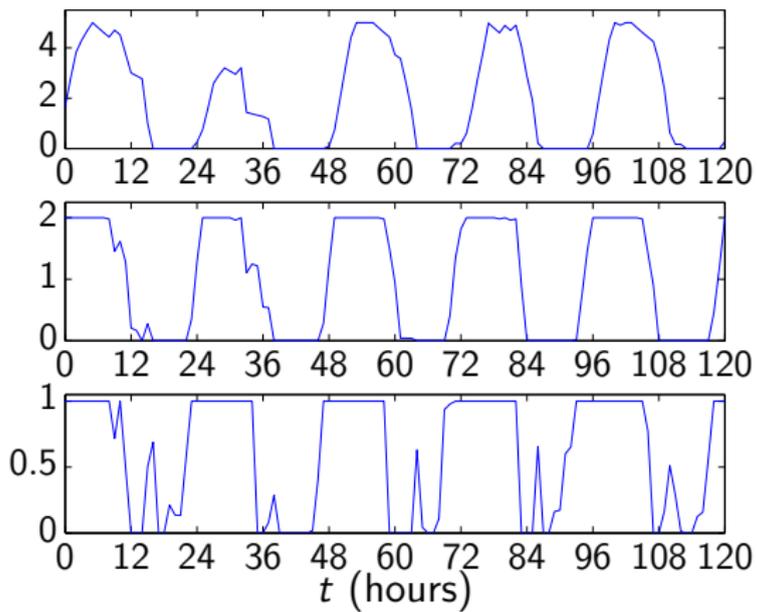
- ▶ simulate MPC for each portfolio configuration for 365 days (17520 time periods)
- ▶ solve times on single core of 3.2 Ghz Intel i3
 - ▶ SDPT3: 3.23 s (15 hours total)
 - ▶ CVXGEN: **6.56 ms** (under 2 minutes total)
- ▶ nearly **500**× speedup

Results



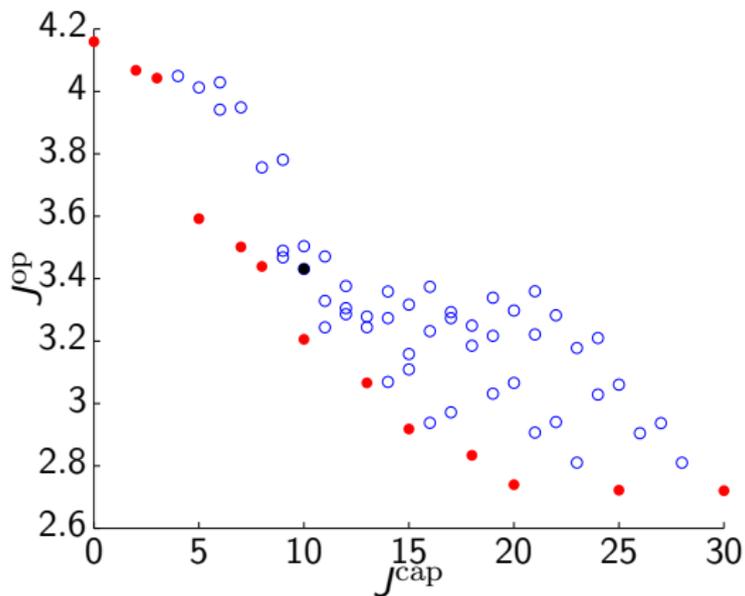
- ▶ top: r_t (blue), p_t (red)
- ▶ bottom: d_t with storage (green), without (black)

Results



- ▶ top: $(q_t)_L$, middle: $(q_t)_M$, bottom: $(q_t)_S$.

Results



- ▶ Pareto optimal portfolios (red)
- ▶ portfolio with one of each type of device (black)

Interpretation

- ▶ at low amounts of storage, well chosen additional devices allow for large decrease in operation cost
- ▶ at high amounts of storage, additional devices have minimal impact on operation cost of well chosen portfolios
- ▶ Pareto optimal portfolios tend to have mixtures of devices

Conclusion

- ▶ a well chosen portfolio of different storage devices can deliver better performance than a single type
- ▶ a storage device must be judged in the application context, with a good control policy
- ▶ while basic operation of a portfolio of storage devices is simple and intuitive, good operation requires optimization
- ▶ super fast solvers make possible substantial simulation-based analysis

Thank you