Optimal Control of Battery Storage Under Cycle-Based Degradation

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Need for Storage

Main challenge of renewables:

- They are uncertain and intermittent

Energy Storages

- Act as buffers to smooth out these uncertainties

Focus on electrochemical batteries

- Lithium-ion
- Lead acid
- Flow cell
- etc…

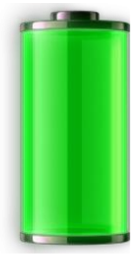
Electrochemical Batteries

- Mature technology
  - Both large and small scale batteries
- Flexible and rapid deployment
  - Geographically unrestricted
  - Small land-use
- Decreasing cost
  - Lithium-ion: 800$/kWh in 2012 to 250$/kWh in 2017

This talk: optimal operation under realistic electrochemical models

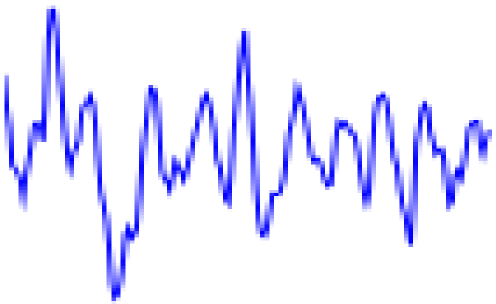
Operation of Batteries

Planning	Scheduling	Operations
Investment	Day-ahead	Real-time



charge

discharge



battery

exogenous signal

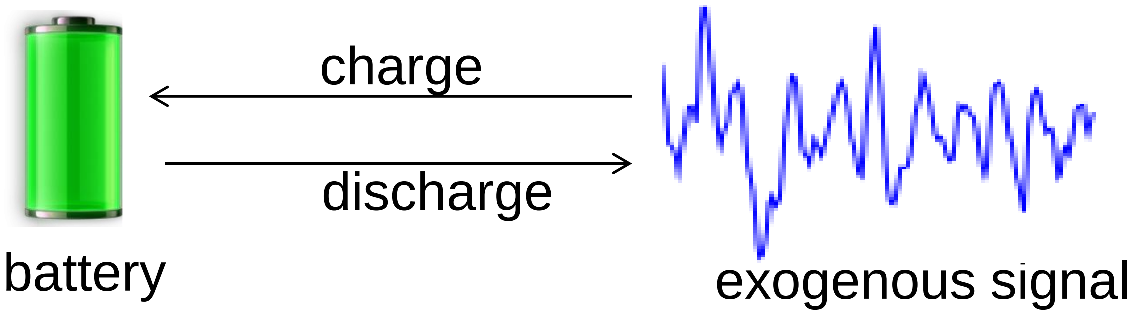
Applications:

- Regulation, price arbitrage, peak shaving,…

Control Problem:

- Determine the real-time charge/discharge power

Real-time Control of Batteries



$$\max\ \text{Utility} - \text{Cost} \longleftarrow \text{degradation of battery}$$

$$P_{\min} \leq P_t \leq P_{\max}$$

$$\left.\begin{array}{l} \displaystyle\sum_{\tau=1}^{t} P_\tau = SoC_t \\ SoC_{\min} \leq SoC_t \leq SoC_{\max} \end{array}\right\} \text{coupling constraints}$$

Hard problem:

- Future is unknown
- Degradation is complicated

Optimal Control of Batteries

Optimal online control of batteries is in a hard problem

- Many negative results in optimal control and online optimization literature

Contribution: under some situations, we show

- Near-optimal online algorithm
- Constant gap to the off-line optimal

Realistic degradation models make the problem easier

Outline

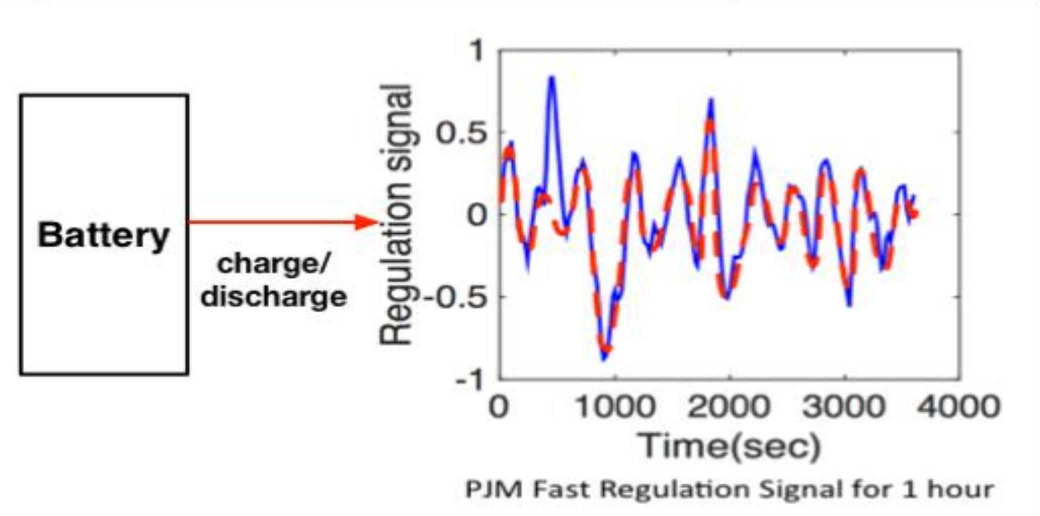
1. Optimization problem for fast regulation

2. Cycle-based degradation cost

1. Threshold algorithm

2. Sketch of the proof

Regulation Problem



- A signal r_t send every 4 seconds, battery power injection P_t tries to follow it

$$\text{profit} = \text{capacity payment} - \underbrace{\sum_{t=1}^{T} |r_t - P_t|}_{\text{focus of real-time control}}$$

Real-time Optimization Problem

- Optimization problem

$$\min \sum_t |r_t - P_t| + \text{cost}$$

$$P_{\min} \leq P_t \leq P_{\max}$$

$$\sum_{\tau=1}^{t} P_\tau = SoC_t$$

$$SoC_{\min} \leq SoC_t \leq SoC_{\max}$$

- Trade-off between the penalty and the battery operation cost
- The future regulation signals r_t are unknown

Performance Metric

- For a given feasible sequence $P_1, P_2, \ldots, P_T$, define

$$f(\mathbf{P};\mathbf{r}) = \sum_{t=1}^{T} |r_t - P_t| + \text{degradation cost}$$

- Regret

$$\text{regret} = f(\mathbf{P};\mathbf{r}) - \min_{\mathbf{P}} f(\mathbf{P};\mathbf{r})$$

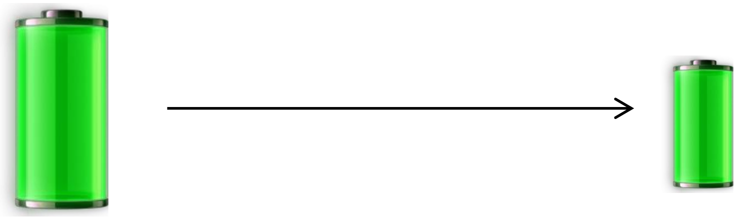
Use only historical information

Full information

- What is the worst case regret?

Battery Degradation

- Batteries degrades with each charging and discharging operation



capacity loss

- For example, Li-ion battery can undergo about 400-1500 cycles before end of life
- The operation cost of batteries

Degradation Cost

- Batteries degrade because of
  - Charging voltage and current (instantaneous)
  - Charging profile
  - Temperature
  - Calendar life
  - Many others…

- There are electrochemical equations to describe these processes

“Reduced” Model

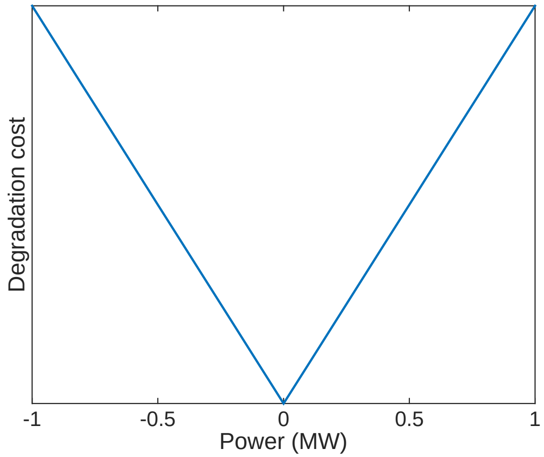
- Reduced order PDEs for Li-ion degradation

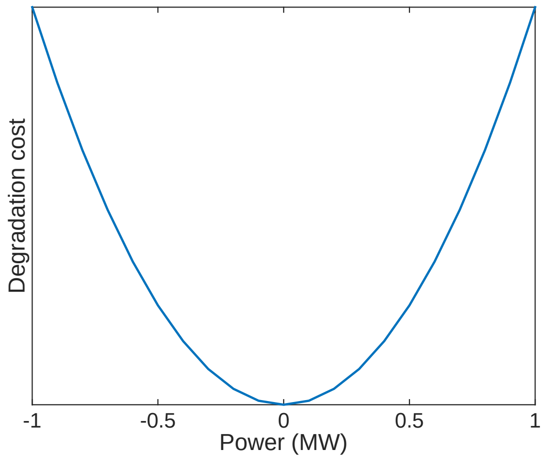
Governing equation	Boundary conditions
Positive	
$\varepsilon_p \frac{\partial c}{\partial t} = \frac{\partial}{\partial x}[D_{\mathrm{eff,p}} \frac{\partial c}{\partial x}] + a_p(1-t_+)j_p$	$\frac{\partial c}{\partial x}\vert_{x=0} = 0$ $-D_{eff,p}\frac{\partial c}{\partial x}\vert_{x=l_p^-} = -D_{eff,s}\frac{\partial c}{\partial x}\vert_{x=l_p^+}$
$-\sigma_{\mathrm{eff,p}}(\frac{\partial \Phi_1}{\partial x}) - \kappa_{\mathrm{eff,p}}(\frac{\partial \Phi_2}{\partial x}) + \frac{2\kappa_{\mathrm{eff,p}}RT}{F}(1-t_+)(\frac{\partial \ln c}{\partial x}) = I$	$\frac{\partial \Phi_2}{\partial x}\vert_{x=0} = 0$ $-\kappa_{\mathrm{eff,p}}\frac{\partial \Phi_2}{\partial x}\vert_{x=1_p^-} = -\kappa_{\mathrm{eff,s}}\frac{\partial \Phi_2}{\partial x}\vert_{x=1_p^+}$
$\frac{\partial}{\partial x}[\sigma_{\mathrm{eff,p}}\frac{\partial \Phi_1}{\partial x}] = a_p F j_p$	$\frac{\partial \Phi_1}{\partial x}\vert_{x=l_p^-} = 0$ $\frac{\partial \Phi_1}{\partial x}\vert_{x=0} = -\frac{I}{\sigma_{eff,p}}$
$\frac{\partial}{\partial t}c_p^{s,ave} = -3\frac{j_p}{R_p}, \frac{D_{s,p}}{R_p}(c_p^{s,surf} - c_p^{s,ave}) = -\frac{j_p}{5}$	
Separator	
$\varepsilon_s \frac{\partial c}{\partial t} = \frac{\partial}{\partial x}\left[D_{\mathrm{eff,s}}\frac{\partial c}{\partial x}\right]$	$c\vert_{x=l_p^-} = c\vert_{x=l_p^+}$ $c\vert_{x=l_p+l_s^-} = c\vert_{x=l_p+l_s^+}$
$-\kappa_{\mathrm{eff,s}}(\frac{\partial \Phi_2}{\partial x}) + \frac{2\kappa_{\mathrm{eff,s}}RT}{F}(1-t_+)(\frac{\partial \ln c}{\partial x}) = I$	$\Phi 2\vert_{x=l_p^-} = \Phi 2\vert_{x=l_p^+}$ $\Phi 2\vert_{x=l_p+l_s^-} = \Phi 2\vert_{x=l_p+l_s^+}$
Negative electrode	
$\varepsilon_n \frac{\partial c}{\partial t} = \frac{\partial}{\partial x}[D_{\mathrm{eff,n}}\frac{\partial c}{\partial x}] + a_n(1-t_+)j_n$	$\frac{\partial c}{\partial x}\vert_{x=l_p+l_s+l_n} = 0$ $-D_{eff,s}\frac{\partial c}{\partial x}\vert_{x=l_p+l_s^-} = -D_{eff,n}\frac{\partial c}{\partial x}\vert_{x=l_p+l_s^+}$
$-\sigma_{\mathrm{eff,n}}(\frac{\partial \Phi_1}{\partial x}) - \kappa_{\mathrm{eff,n}}(\frac{\partial \Phi_2}{\partial x}) + \frac{2\kappa_{\mathrm{eff,n}}RT}{F}(1-t_+)(\frac{\partial \ln c}{\partial x}) = I$	$\Phi 2\vert_{x=1_p+l_s+l_n} = 0$ $-\kappa_{\mathrm{eff,s}}\frac{\partial \Phi_2}{\partial x}\vert_{x=1_p+l_s^-} = -\kappa_{\mathrm{eff,n}}\frac{\partial \Phi_2}{\partial x}\vert_{x=1_p+l_s^+}$
$\frac{\partial}{\partial x}[\sigma_{\mathrm{eff,n}}\frac{\partial}{\partial x}\Phi_1] = a_n F j_n$	$\frac{\partial \Phi_1}{\partial x}\vert_{x=l_p+l_s^-} = 0$ $\frac{\partial \Phi_1}{\partial x}\vert_{x=l_p+l_s+l_n} = -\frac{I}{\sigma_{eff,n}}$
$\frac{\partial}{\partial t}c_n^{s,ave} = -3\frac{j_n}{R_n}, \frac{D_{s,n}}{R_n}(c_n^{s,surf} - c_n^{s,ave}) = -\frac{j_n}{5}$	

- Accurate, but hard to use for control

Power-based Approximation

- Degradation is proportional to the power P_t





$$\text{Degradation} \propto |P_t| \qquad \text{Degradation} \propto P_t^2$$

Advantages: simple

Disadvantages: only suits a few kinds of battery within certain SoC ranges

Optimization Problem

$$\min \sum_t |r_t - P_t| + \sum_t P_t^2$$

$$P_{\min} \leq P_t \leq P_{\max}$$

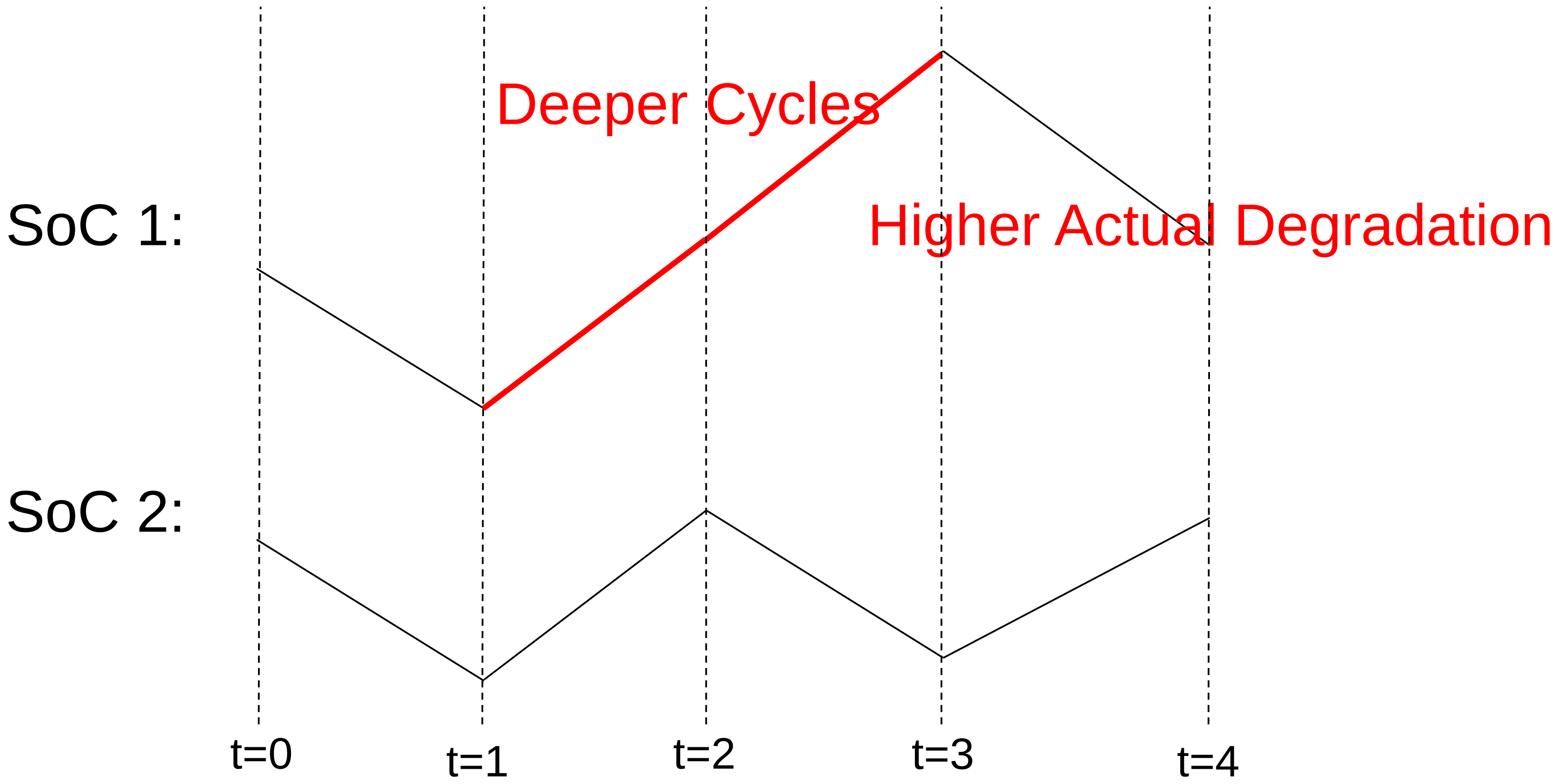
$$\sum_{\tau=1}^{t} P_\tau = SoC_t$$

$$SoC_{\min} \leq SoC_t \leq SoC_{\max}$$

- This is similar to a constrained LQG problem
- Long-standing open problem
- The power-based degradation model is neither accurate nor computational efficient

There is a model that is both more accurate and easier to optimize

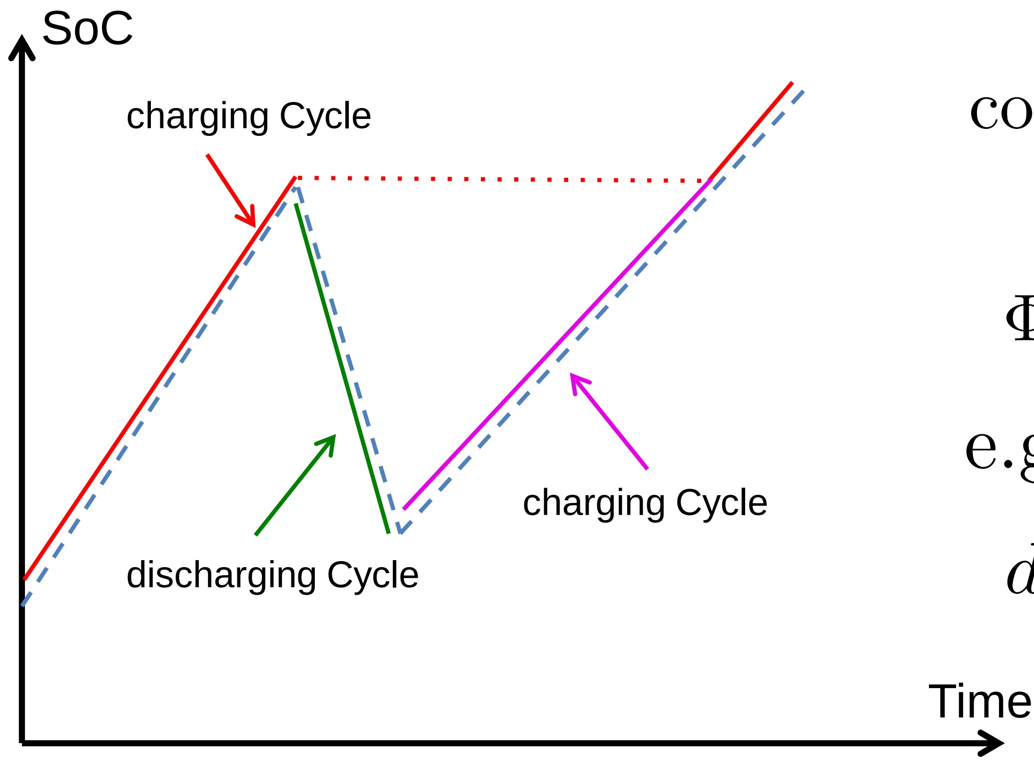
Degradation



Same Power-based degradation

Cycle-based Degradation

- Count cycles instead of power
- A deeper cycle degrades the battery more than many small cycles



$$\text{cost} = \sum_{i=1}^{N} \Phi(d_i)$$

$$\Phi(\cdot) \text{ cycle stress function}$$

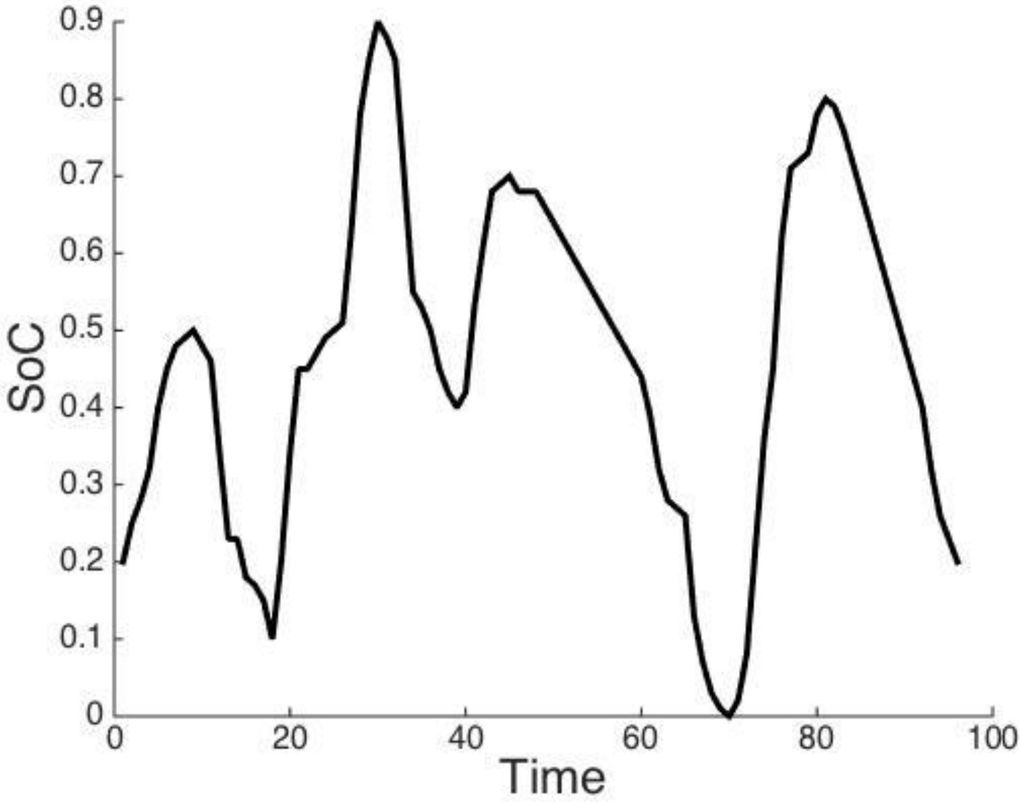
$$\text{e.g. } \Phi(d_i) = a \exp(b \cdot d_i)$$

$$d_1, \ldots, d_N \text{ cycle depth}$$

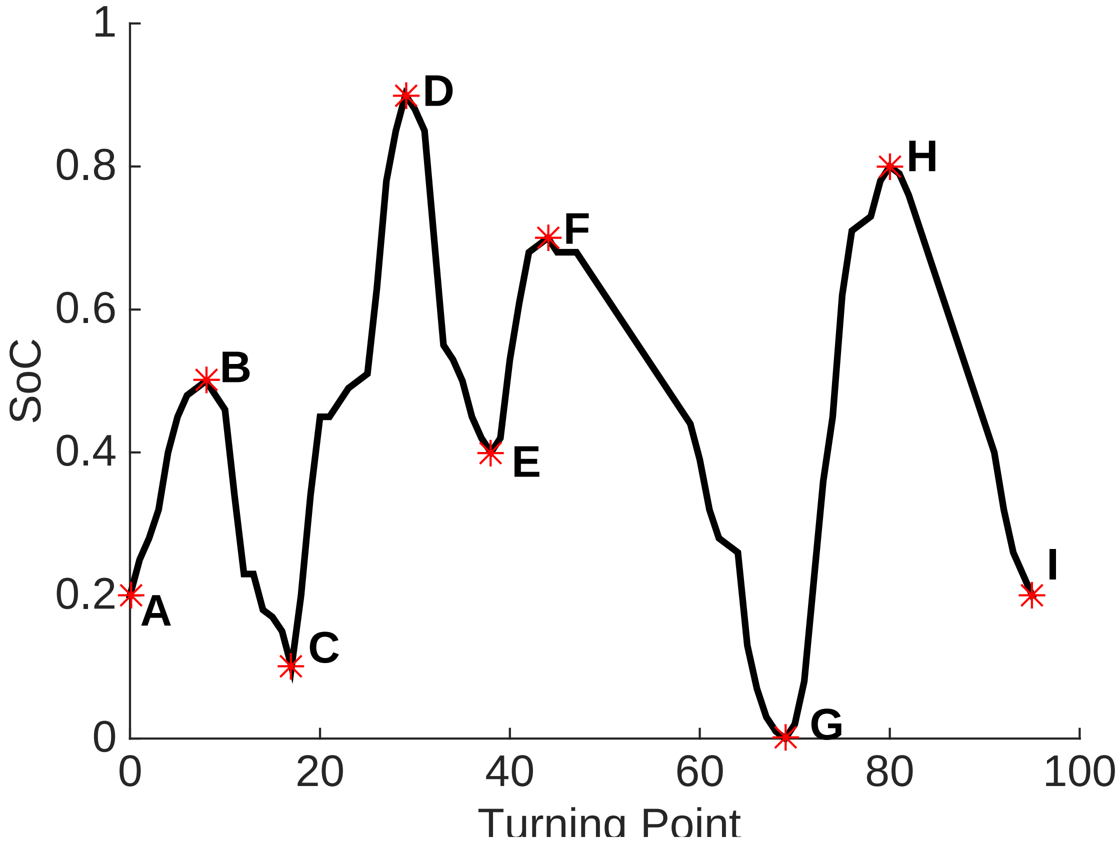
Electrochemically more accurate for power system applications

Rain-Flow Counting

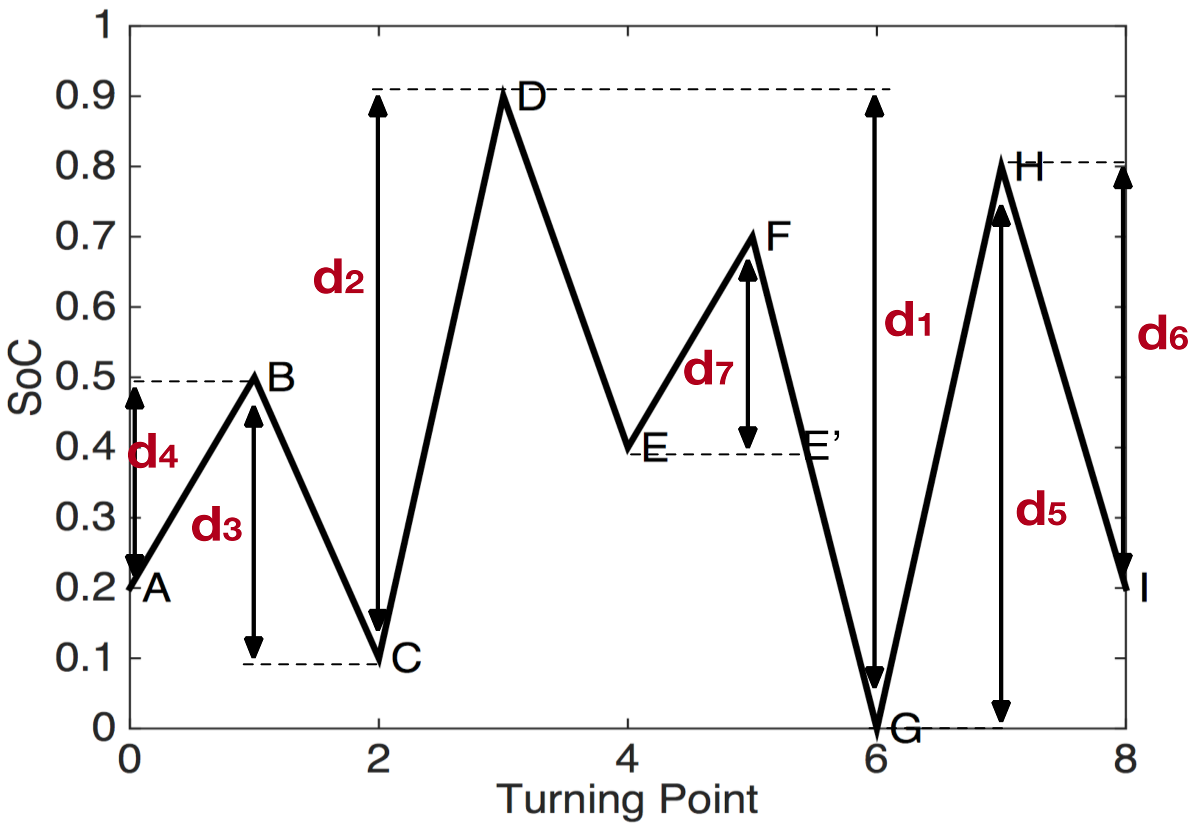
- Counting heterogenous cycles systematically: rain-flow



Rain-Flow Counting



Rain-Flow Counting



Optimization Problems

Power-Based Cost

$$\min \sum_t |r_t - P_t| + \sum_t P_t^2$$

$$P_{\min} \leq P_t \leq P_{\max}$$

$$\sum_{\tau=1}^{t} P_\tau = SoC_t$$

$$SoC_{\min} \leq SoC_t \leq SoC_{\max}$$

Hard

Cycle-Based Cost

$$\min \sum_t |r_t - P_t| + \sum_{i=1}^{N} \Phi(d_i)$$

$$P_{\min} \leq P_t \leq P_{\max}$$

$$\sum_{\tau=1}^{t} P_\tau = SoC_t$$

$$SoC_{\min} \leq SoC_t \leq SoC_{\max}$$

$$d_1, \ldots, d_N = \mathrm{rainflow}(P_1, \ldots, P_T)$$

Easy

Decompose according to cycles

Results

$$\min \sum_{t=1}^{T} |r_t - P_t| + \sum_{i=1}^{N} \Phi(d_i)$$

$$P_{\min} \leq P_t \leq P_{\max}$$

$$\sum_{\tau=1}^{t} P_\tau = SoC_t$$

$$SoC_{\min} \leq SoC_t \leq SoC_{\max}$$

$$d_1, \ldots, d_N = \mathrm{rainflow}(P_1, \ldots, P_T)$$

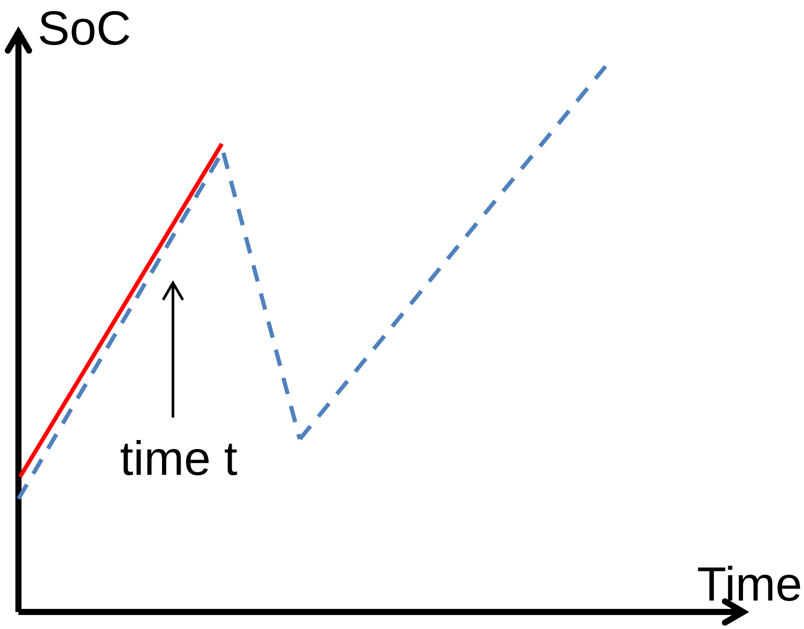
Result:

Worst-case regret is a constant, independent of the time period length *T*

Intuitions

- Suppose we know which cycle we are in
- At time t, solve

$$\min r_t - P_t + \Phi(d_i^{t-1} + P_t)$$
$$P_{\min} \le P_t \le P_{\max}$$
$$SoC_{t-1} + P_t \le SoC_{\max}$$



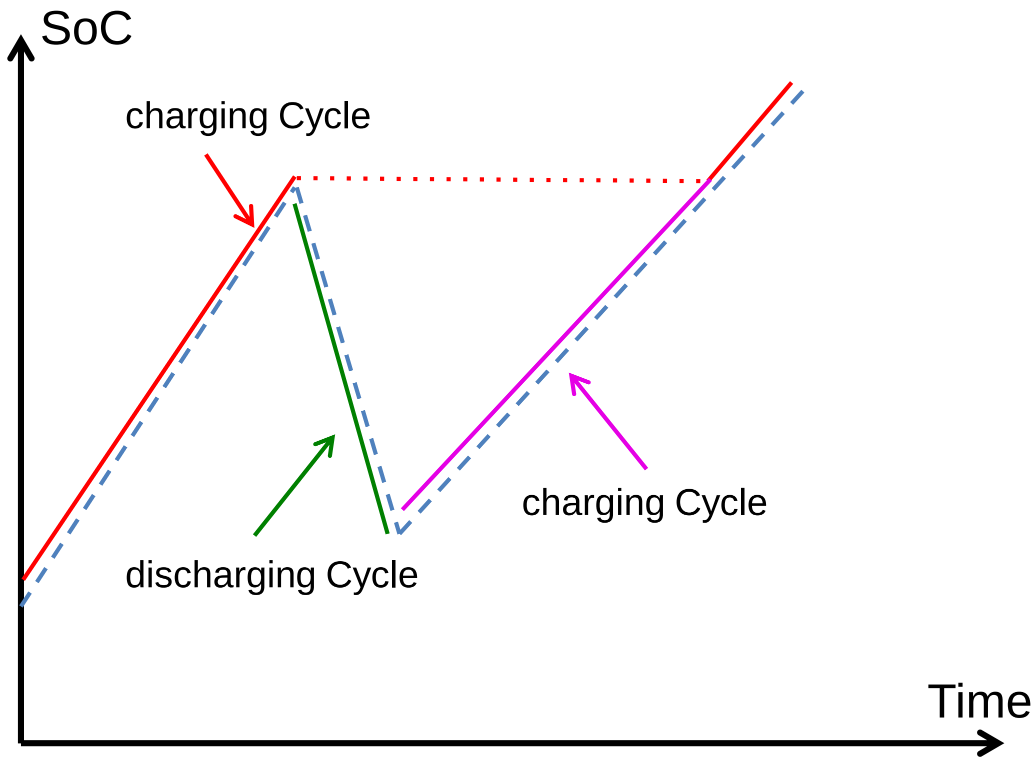
- Optimal solution

$$P_t^* = \max(r_t, \overline{P})$$
$$\text{where } \overline{P} = g(SoC_{\max}, P_{\max}, \Phi)$$

- Future information doesn't matter if each time step is small enough (battery controller operates in milliseconds timescale)

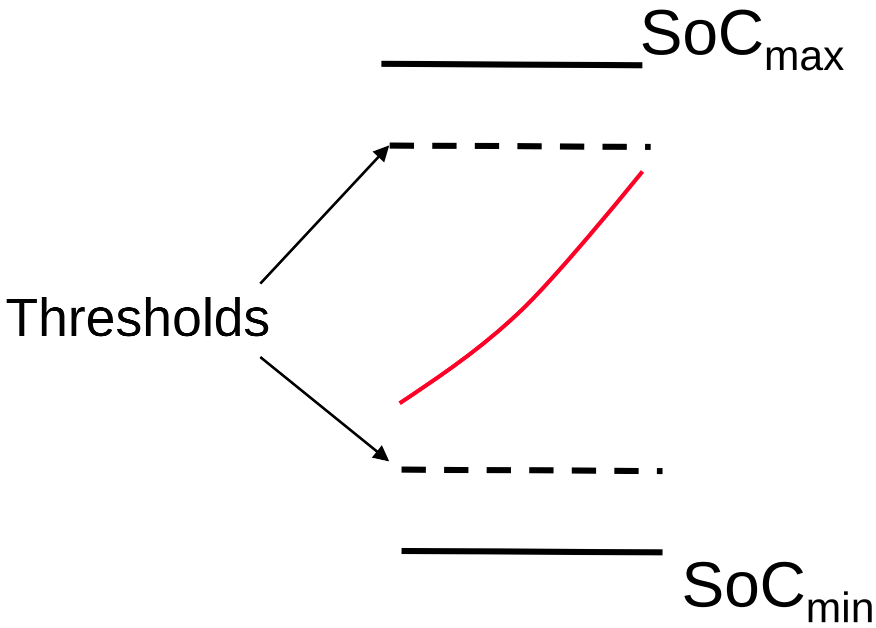
Online Cycle Tracking

- Keep track of which cycle the battery is operating on



Online Algorithm

1. At time t, figure out the cycle currently operating in
2. Look at the historical profile associated with that cycle
3. Apply thresholds



Optimality

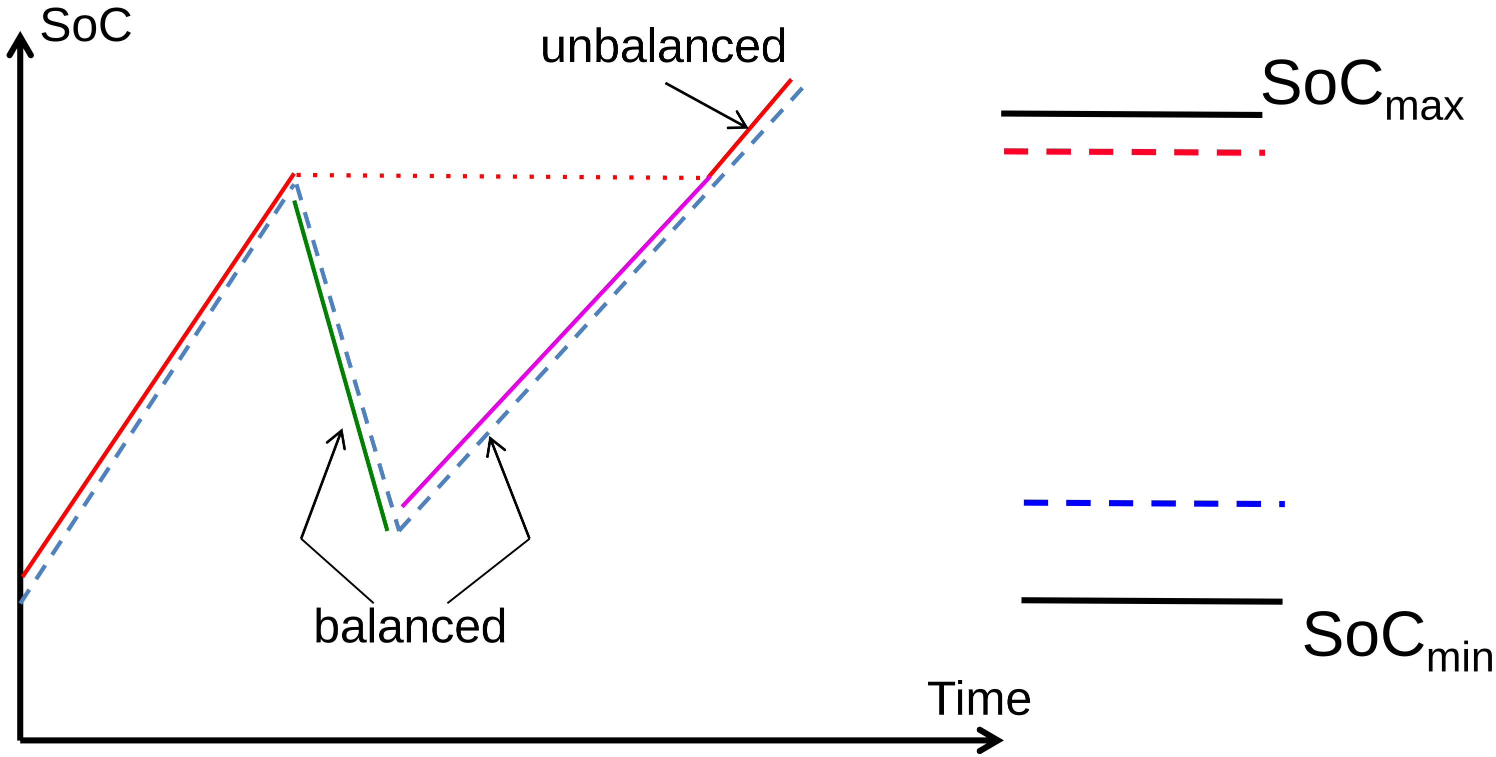
Important facts

1. Historical traces are monotonic in each cycle
2. Cycles decouple
3. Full information problem is convex

Online threshold policy is off-line optimal (zero regret) if the charge/discharge have the same efficiency

Inefficiencies

- Some batteries have different charge/discharge efficiencies
- Need to balance charge/discharge amount



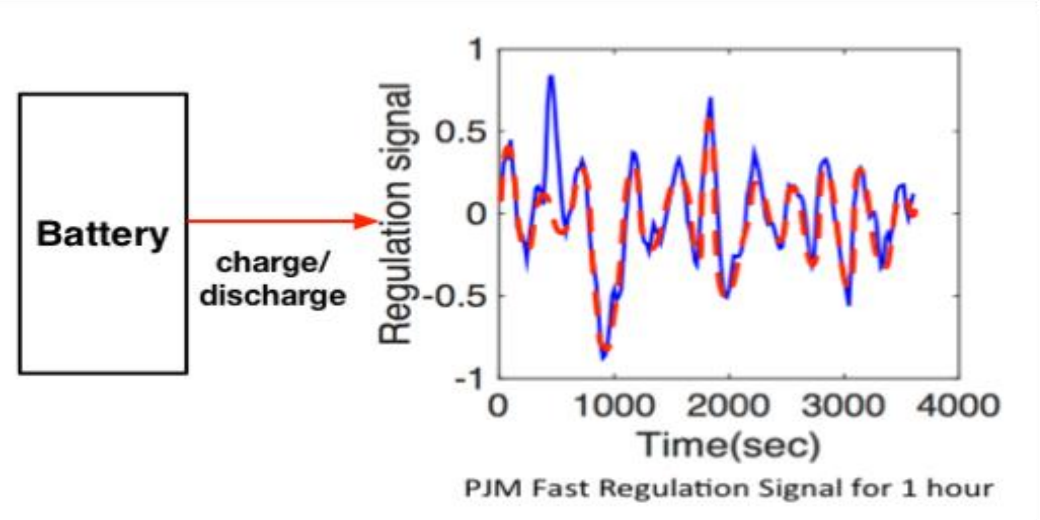
Inefficiencies

- Some batteries have different charge/discharge efficiencies
- Need to balance charge/discharge amount

One charge or discharge cycle maybe unbalanced

- Creates a gap between online and offline
- But there is at most one such cycle over an entire time period: constant gap

Simulation Setup



- PJM market signal, 1MW capacity bid
- Battery degradation cost calculated as amortized capital cost
- Empiric data used to find degradation functions

Simulation Results

Annual Cost (k$)	Rainflow cycle-based	Power-based
Total utility	176	137.9
Regulation payment	338.9	438
Modeled battery deg.	162.9	207.2
Actual battery deg.	175	300.2
Life expectancy (month)	22.1	12

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Conclusion

- Considered online control of battery systems
- Realistic degradation models actually make the problem easier
- Near-optimal online control