

SC42110

Dynamic Programming and Stochastic Control

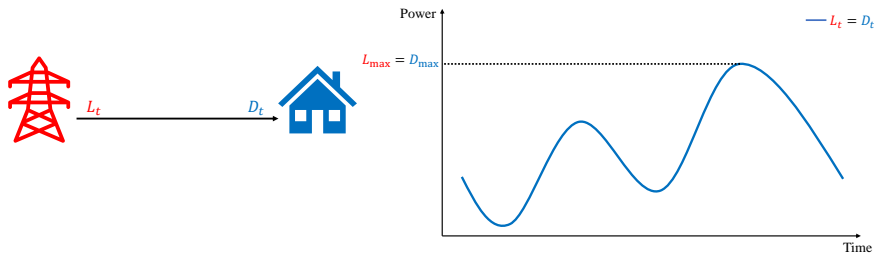
Introduction

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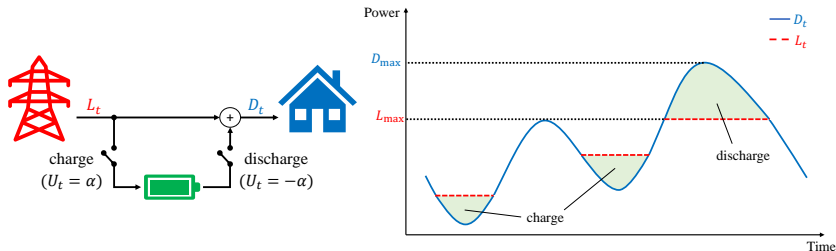
2025

An example: Peak Shaving



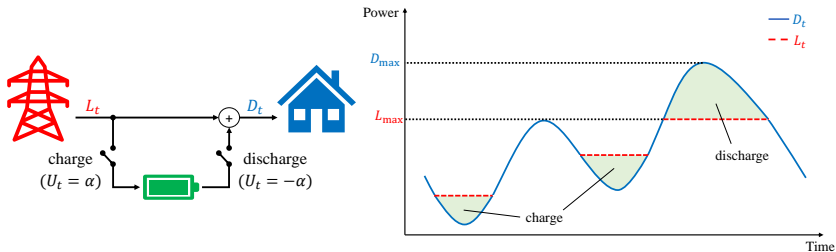
- Consumer's electricity cost: $g_e = \sum_{t=1}^{24} L_t \cdot \phi(t) + \left(\max_{t=1}^{24} L_t \right) \phi_{\text{peak}}$

An example: Peak Shaving



- Consumer's electricity cost: $g_e = \sum_{t=1}^{24} L_t \cdot \phi(t) + (\max_{t=1}^{24} L_t) \phi_{\text{peak}}$.
- Dynamics with battery:
$$\begin{cases} C_{t+1} = \min\{\max\{C_t + U_t, 0\}, C\}, \\ L_{t+1} = (C_{t+1} - C_t) + D_{t+1}, \end{cases}$$
with $U_t \in \mathbb{U} = \{\alpha \text{ (charge)}, -\alpha \text{ (discharge)}, 0 \text{ (idle)}\}$.
- Battery usage cost: $g_b = \sum_{t=0}^{23} |U_t|$.

An example: Peak Shaving

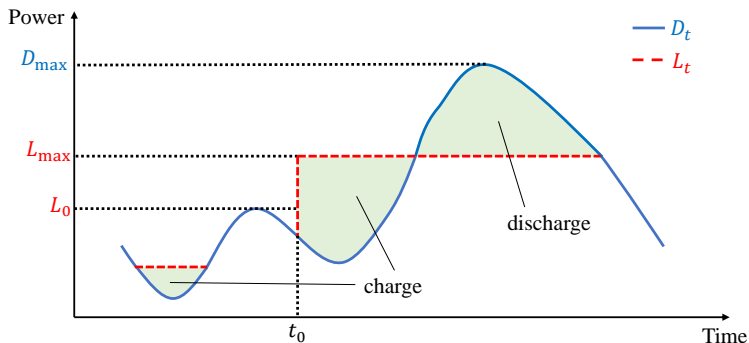


$$\min_{(U_t)_{t=0}^{23}} g_e + g_b$$

An example: Peak Shaving

Sequential decision-making under uncertainty:

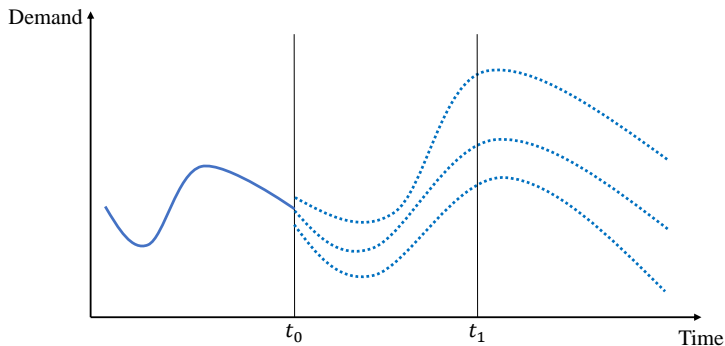
(1) dynamics



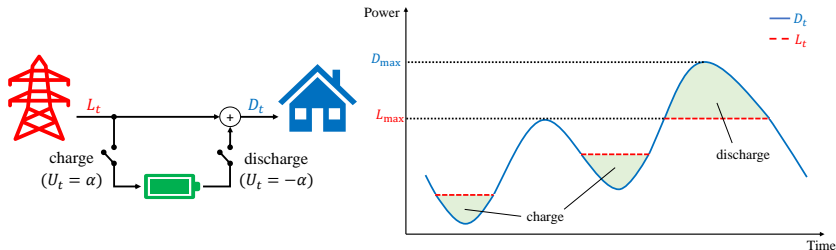
An example: Peak Shaving

Sequential decision-making under uncertainty:

(2) uncertainty



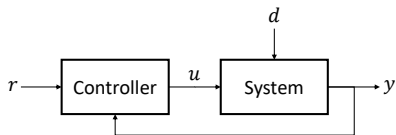
An example: Peak Shaving



$$\min_{\left(U_t = \mu_t(X_t)\right)_{t=0}^{23}} g_e + g_b$$

We have to look for **closed-loop** control laws $\mu_t : \mathbb{X} \rightarrow \mathbb{U}$!

Stochastic control



Preliminaries: Probability

Random variable (r.v.) $X \in \mathbb{X} \subseteq \mathbf{R}$

$\mathbb{P}(A)$: Probability of the event $A \subseteq \mathbb{X}$

- **Discrete** r.v.: Fair die
- **Continuous** r.v.: Uniform $[a, b]$

Preliminaries: Probability

Given discrete r.v.'s $X \in \mathbb{X}$ and $Y \in \mathbb{Y}$ with joint distribution

$$p(x, y) = \mathbb{P}(X = x, Y = y), \quad \forall (x, y) \in \mathbb{X} \times \mathbb{Y}.$$

- Marginalization
- Conditioning
- Independence

Preliminaries: Probability

For discrete r.v.'s $X \in \mathbb{X}$ and $Y \in \mathbb{Y}$:

Lemma (Law of total probability):

$$p_X(x) = \sum_{y \in \mathbb{Y}} p_{X|Y}(x|y) \cdot p_Y(y), \quad \forall x \in \mathbb{X}.$$

Lemma (Bayes' rule):

$$p_{X|Y}(x|y) \cdot p_Y(y) = p_{Y|X}(y|x) \cdot p_X(x), \quad \forall (x, y) \in \mathbb{X} \times \mathbb{Y}.$$

Preliminaries: Probability

Given discrete r.v.'s $X \in \mathbb{X}$ and $Y \in \mathbb{Y}$:

- Expectation
- Variance
- Conditional expectation

Preliminaries: Probability

For two r.v.'s $X \in \mathbb{X}$ and $Y \in \mathbb{Y}$:

Lemma (Linearity of expectation):

$$\mathbb{E}(X + Y) = \mathbb{E}(X) + \mathbb{E}(Y).$$

Lemma (Law of total expectation):

$$\mathbb{E}(X) = \mathbb{E}(\mathbb{E}(X|Y)).$$

Preliminaries: Optimization

Given a function $f : \mathbf{R}^n \rightarrow \mathbf{R}$ and a set $\mathbb{X} \in \mathbf{R}^n$,

minimize $f(x)$ subject to $x \in \mathbb{X}$.

Assuming the minimum is attained and the minimizer is unique:

$$f^* = \min_{x \in \mathbb{X}} f(x) \qquad x^* = \operatorname{argmin}_{x \in \mathbb{X}} f(x)$$

E.g., if $Q \in \mathbf{R}^{n \times n}$ is positive definite,

$$\operatorname{argmin}_{x \in \mathbf{R}^n} \{x^\top Q x + q^\top x\} = -\frac{1}{2} Q^{-1} q.$$

Preliminaries: Mathematical induction

To show a statement \mathcal{S}_k is true for all $k \in [n]$, it suffices to show

- (1) **Base case:** \mathcal{S}_k is true for $k = 1$.
- (2) **Induction step:** if \mathcal{S}_k is true for some $k < n$ (induction hypothesis), then \mathcal{S}_{k+1} is true.

A classic example:

$$\mathcal{S}_k : 1 + 2 + \dots + k = \frac{k(k+1)}{2}, \quad \forall k \in \mathbf{N}.$$