Optimal Control for Battery Storage Using Nonlinear Models

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Outline

1. Introduction
2. Optimal charging control using linear and nonlinear models
3. Case study
4. Conclusion and future work
Introduction

Background

Grid applications:
- Energy arbitrage
- Balancing service
- Capacity value
- Distribution system upgrade deferral
- Outage mitigation

Customer-side applications:
- Energy charge reduction
- Demand charge reduction
Optimal control is desired in order to best utilize the limited power and energy capacity of BSS.

Look-ahead optimization is required to capture interdependent operation over time.

Fixed power rating and constant round-trip or one-way efficiencies are used in existing optimal scheduling methods:

- Inaccurate economic assessment results
- Infeasible operating schedule
Optimal scheduling with linear battery model

\[ \begin{align*}
\mathbf{P}_1 : & \quad \max_{p_k, p_k^{\text{batt}}, s_k, \Delta s_k} \quad \sum_{k=1}^{K} \lambda_k p_k \\
\text{subject to:} & \quad -p^-_{\text{max}} \leq p_k \leq p^+_{\text{max}}, \quad \forall k = 1, \ldots, K \\
\text{Charging/discharging limit:} & \quad \left\{ \begin{array}{ll}
p_k/\eta^+ & \text{if } p_k \geq 0 \\
p_k \eta^- & \text{if } p_k < 0
\end{array} \right. , \quad \forall k = 1, \ldots, K \\
\text{Rate change of energy in batt.:} & \quad p_k^{\text{batt}} = \\
\text{SOC change:} & \quad \Delta s_k = p_k^{\text{batt}} \Delta T/E_{\text{max}}, \quad \forall k = 1, \ldots, K \\
\text{Dynamics of SOC:} & \quad s_k = s_{k-1} - \Delta s_k, \quad \forall k = 1, \ldots, K \\
\text{SOC limits:} & \quad s^L_k \leq s_k \leq s^U_k, \quad \forall k = 1, \ldots, K
\end{align*} \]
Limitations with existing linear battery model

- \([-p_{\text{min}}, p_{\text{max}}]\): incapable to model varying charging/discharging range
- \(E_{\text{max}}\): inaccurate to represent energy capacity
- \(\eta^+, \eta^+\): difficult to estimate overall efficiency and inaccurate to capture actual losses
Varying power capability and SOC change rate

1 MW/3.2 MWh vanadium redox BSS
Varying power capability and SOC change rate (cont.)

1 MW/3.2 MWh vanadium redox BSS
Optimal scheduling with nonlinear battery model

\[ \mathbf{P}_2 : \max_{p_k, s_k, \Delta s_k} \sum_{k=1}^{K} \lambda_k p_k \]

subject to:

Charging/discharging limit:
\[ p_k \in \mathcal{P}_{s_k}, \quad \forall k = 1, \cdots, K \]

SOC change:
\[ \Delta s_k = f(p_k, s_k), \quad \forall k = 1, \cdots, K \]

Dynamics of SOC:
\[ s_k = s_{k-1} - \Delta s_k, \quad \forall k = 1, \cdots, K \]

SOC limits:
\[ \underline{S}_k \leq s_k \leq \overline{S}_k, \quad \forall k = 1, \cdots, K \]
Assumptions and inputs

- BSS: 1 MW/3.2 MWh vanadium redox BSS at Turner substation in Pullman in Washington State.
- Applications: energy arbitrage and energy imbalance reduction
- Price: The Mid-Columbia prices from 2011 to 2015
Economic performance comparison results

2 MW/6.4 MWh
Varying round-trip efficiency

\[ \eta(s) = \frac{r_{\text{ch}}(s)}{r_{\text{disch}}(s)} \]
BSS power and SOC

![Price ($/MWh)](image)

![Power (MW)](image)

![SOC](image)

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Conclusion and future work

Conclusion:

- Nonlinear BSS model better captures varying charging/discharging power capability and efficiencies.
- Optimal scheduling without accurate nonlinear BSS model could result in significant errors in benefits assessment, and even infeasible operation.

Future work:

- Apply the proposed method with nonlinear model for other grid and/or customer-side applications.
Thank you! Questions?

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