

Evaluation of Control Frameworks for Battery Energy Storage Systems

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What is a “Battery Energy Storage System”?

- It is a system for storing energy in rechargeable batteries for later use
- We refer to BESS in the context of an energy consumer with energy demands, as well as photovoltaic (PV) panels for generating energy
- The consumer can buy energy from the power grid

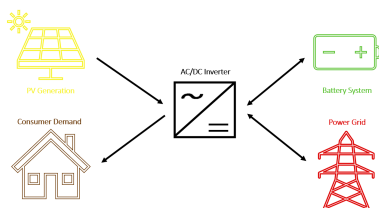


Figure: BESS Diagram

Why should we care about BESS?

- BESS is essential to the renewable energy transition by providing steady and consistent energy supply
- BESS, coupled with a renewable energy source (such as PV panels), can significantly reduce energy costs for consumers, ranging from residential households, to large businesses
- With energy prices across the world soaring (including a 25% increase for Victoria from July), BESS uptake is fast increasing

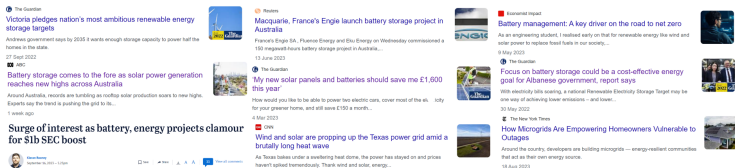


Figure: Some recent news articles showing the prevalence of BESS

What is the BESS Control Problem?

- It typically refers to finding the optimal times to charge and discharge a battery, to minimise the costs of buying energy
- The goal is to create a system that, at any time, can decide whether to charge or discharge a battery (i.e., control our battery) to minimise the costs of energy
- We expect that it would entail charging the battery when prices are low, and discharging it when prices are high
- The precise details are decided by formulating the problem mathematically

What are the inputs to the BESS Control Problem?

Problem defined over H discrete intervals, with time-frame given by $T = \{0, \dots, H - 1\}$

Our variable inputs (given for each interval) are:

- Future energy demands: $d_0, \dots, d_{H-1} \in \mathbb{R}^+$ (kWh)
- Future PV generations: $g_0, \dots, g_{H-1} \in \mathbb{R}^+$ (kWh)
- Future energy prices: $p_0, \dots, p_{H-1} \in [-100, 1500]$ (c/kWh)

Network transmission costs and other miscellaneous charges exist, but we ignore them for this talk

Energy Prices

- We use National Energy Market (NEM) prices, determined for each interval by the energy supply and demand
- NEM participating buyers submit how much energy they want to buy at given prices
- NEM participating generators submit how much energy they want to sell at given prices

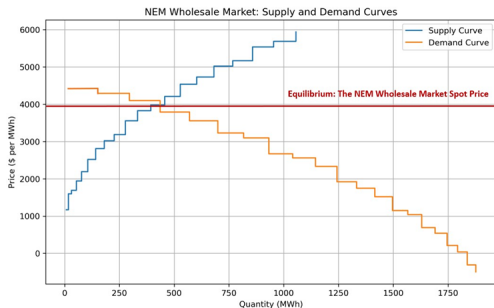


Figure: NEM Pricing Determination Example

What about the battery?

Our static inputs all deal with the battery specifications, they are:

- Battery size (capacity): $c \in \mathbb{R}^+$ (kWh)
- Initial state of charge (SOC): $B_{-1} \in [0, c]$ (kWh)
- Power (max charge/discharge rate): $P \in \mathbb{R}^+$ (in kW)
- Efficiency (how much energy is kept - not lost - when battery is charged or discharged): $e \in (0, 1)$

What are the decision variables, constraints and objective?

- ① Decision variables are made for each interval, they are for:
 - Charging the battery: $C_0, \dots, C_{H-1} \in [0, P]$ (kWh)
 - Discharging the battery: $D_0, \dots, D_{H-1} \in [0, P]$, (kWh)
 - Importing energy from grid: $I_0, \dots, I_{H-1} \in \mathbb{R}^+$ (kW)
 - Decision variables can be simplified to one ‘action’: $a_t := C_t - D_t$
- ② The objective is to minimise costs: $\min \sum_{t \in T} I_t \cdot p_t$
- ③ The (remaining) constraints for each interval $t \in T$ are:
 - Demand Satisfaction: $d_t - g_t = I_t - E_t - \frac{C_t}{e} + e \cdot D_t$
 - Updating battery state of charge: $B_t = B_{t-1} + C_t - D_t$

How can we solve this?

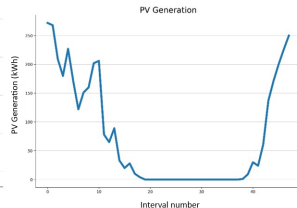
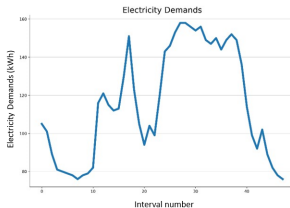
Our problem can be formulated as a linear program (LP)

- The objective of our problem is given by $\min \sum_{t \in T} \mathbf{c}_t^T \cdot \mathbf{x}_t$, where $\mathbf{c}_t^T = [p_t, 0, 0]$, and $\mathbf{x}_t = [I_t, C_t, D_t]^T$.
- For the constraints, we have:
 - ① $A_i \mathbf{x} \geq \mathbf{b}_i, \forall i = 1, \dots, 3$
 - ② $\sum_{k=1}^t ([A_i]_k \mathbf{x}_k) \geq (\mathbf{b}_i)_t, \forall t \in T, i = 4, 5$
 - ③ $\mathbf{x} \in (\mathbb{R}^+)^{|T|}$
- Where:
 - ① $(A_1)_t = [1, -\frac{1}{\epsilon}, \mathbf{e}], (A_2)_t = [0, 1, -1], (A_3)_t = [0, -1, -1],$
 $(A_4)_t = [0, 1, -1], (A_5)_t = [0, -1, 1]$
 - ② $(\mathbf{b}_1)_t = [d_t - g_t], (\mathbf{b}_2)_t = [B_t - B_{t-1}], (\mathbf{b}_3)_t = [-P], (\mathbf{b}_4)_t =$
 $[-B_{-1}], (\mathbf{b}_5)_t = [B_{-1} - c]$

As this LP can be solved (e.g., using Gurobi), we now have a method of optimally scheduling our battery.

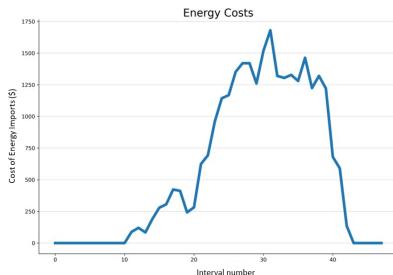
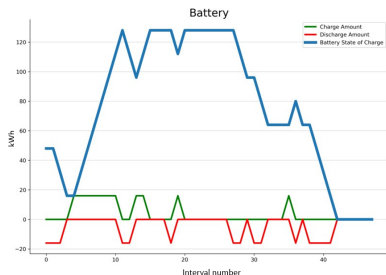
BESS Control problem example

- We have $c = 128$, $P = 32$, $B_{-1} = 64$, $e = 0.999$
- We see the input variables for the electricity prices, demands, and PV generation, respectively



Corresponding optimal actions and costs

- 1 Battery: the the optimal battery state of charge, and charging and discharging actions are shown:
 - Charging: When energy (relatively) cheap, or excess PV generation
 - Discharging: When energy expensive and excess energy demand
- 2 Energy Costs: Costs corresponding to the actions are shown



Have we just solved a billion-dollar problem?

- Unfortunately, we have not...
- Our energy demands (d_t), prices (p_t), and PV generation (g_t) are unknown ahead of time

How can we optimally control our battery now?

In my thesis, I explore three such methods. They are:

- Deterministic model predictive control (MPC)
- Stochastic MPC
- Stochastic dynamic control (SDP)

Today, I will explain deterministic and stochastic MPC

- MPC relies on having explicit forecasts for our random inputs
- SDP models the problem as a Markov chain with associated state values and transition probabilities that depend on state-specific actions

Deterministic MPC

- We model our unknown inputs as random variables (RV), with $X_t = (P_t, D_t, G_t)$, $t \in T$
- We build a forecasting model that outputs the point estimates of these RVs: $[(\hat{p}_0, \hat{d}_0, \hat{g}_0), \dots, (\hat{p}_{H-1}, \hat{d}_{H-1}, \hat{g}_{H-1})]$

For every interval i , we then:

- 1 Generate point forecasts for our RVs:
 $[(\hat{p}_i, \hat{d}_i, \hat{g}_i), \dots, (\hat{p}_{i+H-1}, \hat{d}_{i+H-1}, \hat{g}_{i+H-1})]$
- 2 Solve our previous LP over the H interval horizon by pretending these are deterministic inputs
- 3 Implement the ‘optimal’ action for the first interval
- 4 Continue to the next interval, $i + 1$, with fresh forecasts

Deterministic MPC in action: Input variables

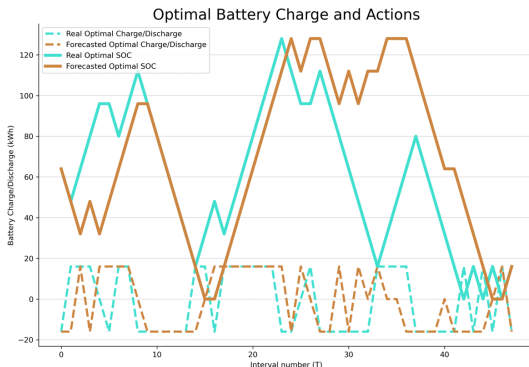
We see the point forecasts (orange), along with real measurements (blue), for energy demands, prices, and PV generation over H an interval horizon



Deterministic MPC in action: Control outputs

We see the optimal battery actions for point forecasts and real measurements

- The first action (the one implemented) is optimal
- The predicted optimal actions differ from the true optimal actions
- Deterministic MPC fails to account for uncertainty



Worked example to show a drawback of deterministic MPC

Assume we have:

- BESS with $H = 2$, $c = 10$, $e = 1$, $B_{-1} = 5$, $P = 10$
- We know $(p_0, d_0, g_0) = (10, 10, 10)$
- (p_1, d_1, g_1) is equally likely to be $(1000, 10, 10)$ or $(1000, 20, 10)$

Then:

- The average of the two forecasts for (p_1, d_1, g_1) is $(1000, 15, 10)$
- If we put this into the LP, the best actions are $a_0 = 0$, $a_1 = -5$, which means $\mathbb{E}(\text{cost}(0, -5)) = 0$
- In reality, these actions mean that
 - ① If $(1000, 10, 10)$: $l_0 = 10 - 10 = 0$; $l_1 = (10 - 10 - 5)^+ = 0$
 - ② If $(1000, 20, 10)$: $l_0 = 10 - 10 = 0$; $l_1 = 20 - 10 - 5 = 5$
- Therefore, $\mathbb{E}(\text{cost}(0, -5)) = \frac{1}{2}5000 = 2500$

By looking at each scenario separately, we can account for uncertainty, we see that $a_0 = 5$, $a_1 = -10$ is optimal, with $\mathbb{E}(\text{cost}(5, -10)) = 50$

Incorporating uncertainty: 2-Stage LP

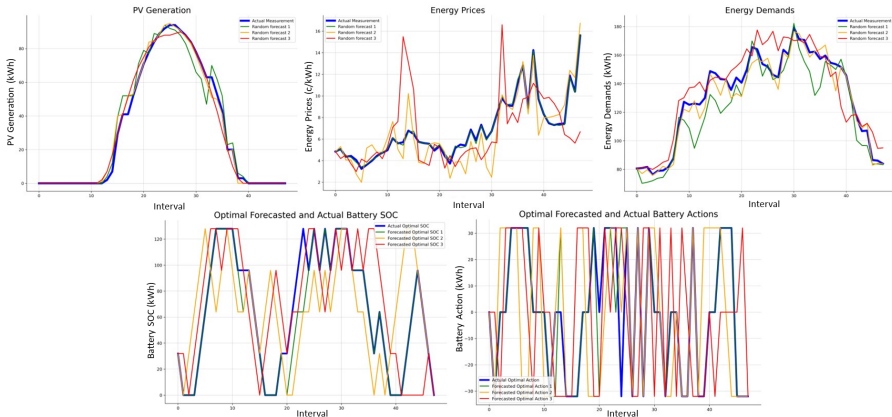
- We want to incorporate the uncertainty inherent to our system
- We generate N random sample paths
 $\{[(\hat{p}_0^n, \hat{d}_0^n, \hat{g}_0), \dots (\hat{p}_{H-1}^n, \hat{d}_{H-1}^n, \hat{g}_{H-1}^n)] : n = 1, \dots, N\}$
- We create N sets of input and decision variables, and constraints
- Our objective becomes: $\min \sum_{n=1, \dots, N} \frac{1}{N} \sum_{t \in T} \hat{l}_t^n \cdot \hat{p}_t^n$
- We force first actions to be equal: $a_0^n = a_0^m \forall 1 \leq n, m \leq N$
- First action considers N different equally likely scenarios

Stochastic MPC

- Our stochastic MPC solves a 2-stage LP as base optimisation model
- Again, only the first action is implemented, then the process is repeated
- The first action now accounts for some uncertainty

Stochastic MPC in action

- Each colour represents a different potential scenario
- We see the optimal predicted actions for each sample path
- Action paths differ, but all are identical for the first interval



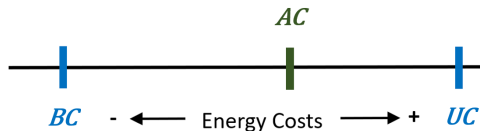
Evaluating the performance of a control framework

We want an optimality gap on savings, we define it as $OG = \frac{UC-AC}{UC-BC}$

- ① Best cost, BC , is the cost for an MPC with real measurements
- ② Algorithm cost, AC , is the cost using the optimisation framework being tested
- ③ Unoptimised cost, UC , is the cost from an unoptimised BESS
 - It is the cost inherent purely due to the BESS
 - It stops the savings inherent to a BESS from being attributed to an optimisation algorithm

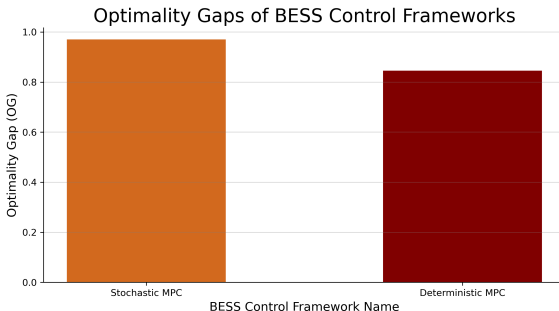
We define the unoptimised system the following way:

- If $g_t \geq d_t$: Use excess PV to charge battery maximally
- Else: Discharge battery maximally (abiding by $I_t \geq 0$)



How do our algorithms perform?

- We evaluate performance using our savings optimality gap
- Based on the data that we test, stochastic MPC outperforms deterministic MPC (as expected)



Conclusion

- Accounting for uncertainty is challenging, but very important
- There are many incentives to optimising BESS control
- Still a lot of work to be done
- To find out about how the forecasting is done, or how SDP is used, feel free to take a look at my thesis
- Don't hesitate to ask any questions that you may have!
- Thank you for listening.