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

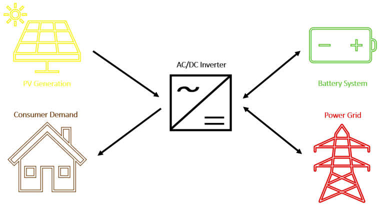


Figure: BESS Diagram

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

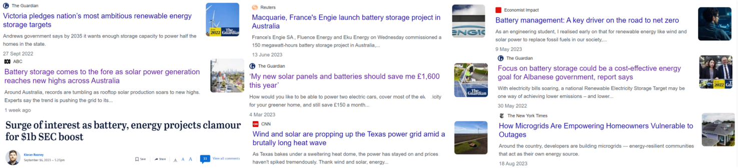


Figure: Some recent news articles showing the prevalence of BESS

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 $T = \{0, \ldots, H-1\}$

Our variable inputs (given for each interval) are:

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

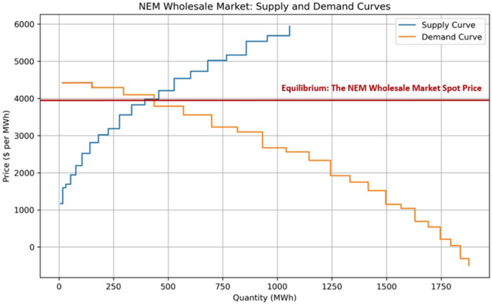


Figure: NEM Pricing Determination Example

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: $C_0, \ldots, C_{H-1} \in [0, P]$ (kWh)
   - Discharging the battery: $D_0, \ldots, D_{H-1} \in [0, P]$, (kWh)
   - Importing energy from grid: $I_0, \ldots, I_{H-1} \in \mathbb{R}^+$ (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: $d_t - g_t = I_t - \frac{C_t}{e} + e \cdot D_t$
   - Updating battery state of charge: $B_t = B_{t-1} + C_t - D_t$

How can we solve this?

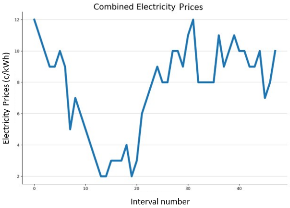
Our problem can be formulated as a linear program (LP)

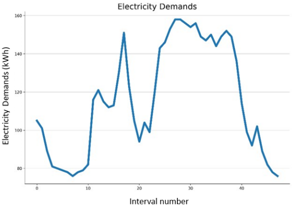
- The objective of our problem is given by $\min \sum_{t \in T} \sum_{i=1,2,3} \boldsymbol{c}_{it}^T \cdot \boldsymbol{x}_{it}$, where $\boldsymbol{c}_t^T = [p_t, 0, 0]$, and $\boldsymbol{x}_t = [I_t, C_t, D_t]^T$ is the decision vector for time t.
- For the constraints, we have:
  1. $\sum_{i=1,2,3} A_i^j \boldsymbol{x}_i \geq \boldsymbol{b}_j, \; \forall j = 1, 2$
  2. $\sum_{k=1}^{t} (\sum_{i=1,2,3} [A^j]_{ik} \boldsymbol{x}_{ik}) \geq (\boldsymbol{b}_j)_t, \; \forall t \in T, j = 3, 4$
  3. $\boldsymbol{x} \in (\mathbb{R}^+)^{|T| \times 3}$
- Where:
  1. $(A^1)_t = [1, -\frac{1}{e}, e]$, $(A^2)_t = [0, -1, -1]$, $(A^3)_t = [0, 1, -1]$, $(A^4)_t = [0, -1, 1]$
  2. $(\boldsymbol{b}_1)_t = [d_t - g_t]$, $(\boldsymbol{b}_2)_t = [-P]$, $(\boldsymbol{b}_3)_t = [-B_{-1}]$, $(\boldsymbol{b}_4)_t = [B_{-1} - c]$

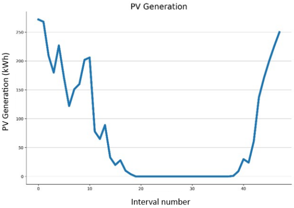
As this LP can be solved (e.g., using Gurobi), we now have a method of optimally scheduling our battery.

BESS Control problem example: Inputs

- 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

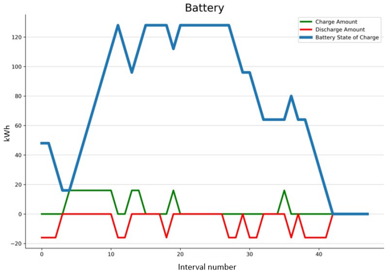


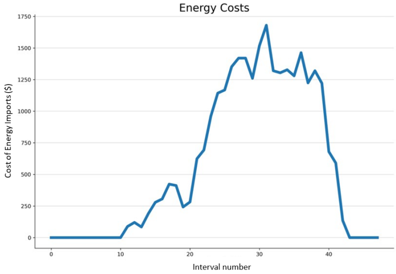




BESS Control problem example: Optimal actions and costs

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: $[(\hat{p_0}, \hat{d_0}, \hat{g_0}), \ldots, (\hat{p_{H-1}}, \hat{d_{H-1}}, \hat{g_{H-1}})]$

For every interval i, we then:

1. Generate point forecasts for our RVs: $[(\hat{p_i}, \hat{d_i}, \hat{g_i}), \ldots, (\hat{p_{i+H-1}}, \hat{d_{i+H-1}}, \hat{g_{i+H-1}})]$
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

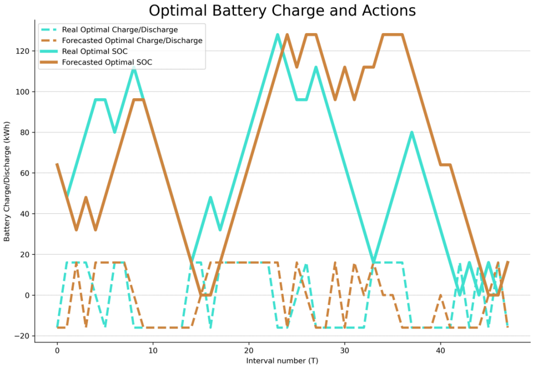
Deterministic MPC in action: Input variables

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 $\mathbb{E}(\hat{cost}(0, -5)) = 0$
- 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, $\mathbb{E}(cost(0, -5)) = \frac{1}{2}5000 = 2500$

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

Incorporating uncertainty: 2-Stage LP

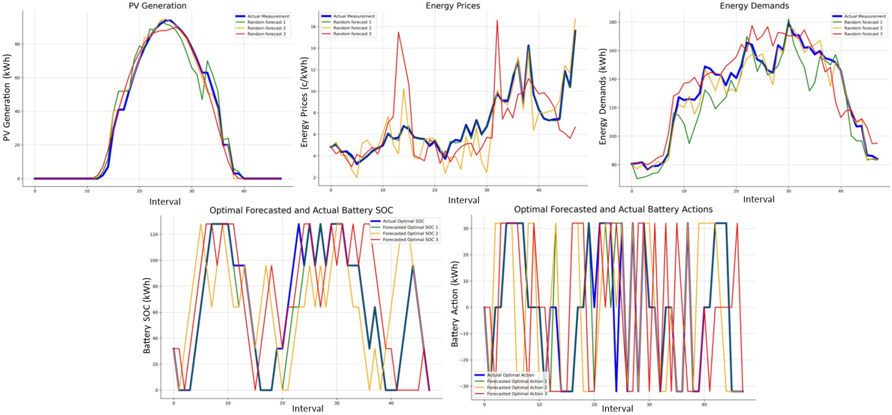
- We want to incorporate the uncertainty inherent to our system
- We generate N random sample paths $\{[(\hat{p}_0^n, \hat{d}_0^n, \hat{g}_0), \ldots (\hat{p}_{H-1}^n, \hat{d}_{H-1}^n, \hat{g}_{H-1}^n)] : n = 1, \ldots, N\}$
- We create N sets of input and decision variables, and constraints
- Our objective becomes: $\min \sum_{n=1,\ldots,N} \frac{1}{N} \sum_{t \in T} \hat{l}_t^n \cdot \hat{p}_t^n$
- 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



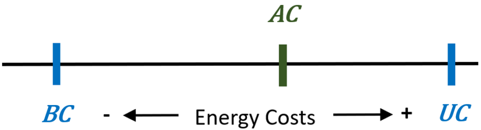
Evaluating the performance of a control framework

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

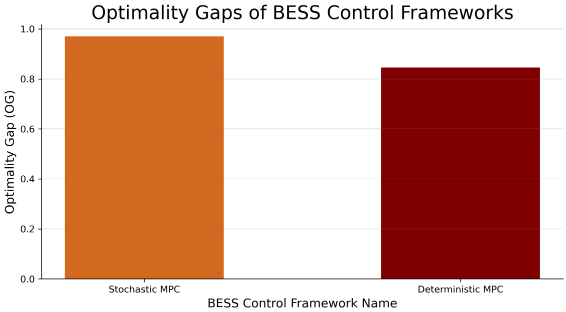
We define the unoptimised system the following way:

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



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.