

SUPSI

Fast sizing methods with realistic performance assumptions for residential electrification

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GARDEN PROJECT Grid Aware Decarbonization of Electricity-driven Neighbourhoods

- Scope: Driving Urban Transition promotes the study and creation of PEDs (positive energy districts)
 - Targets 100 PEDs by 2025 [1], 112 climate neutral cities by 2030 [2]
 - We cannot create them ex-novo, we must RETROFIT
- Scientific questions:
 - What's the best possible technical retrofitting solution (which set of buildings / which intervention), under fixed budget?
 - **Can we develop fast sizing methods for PV/battery systems with good generalization capabilities?**

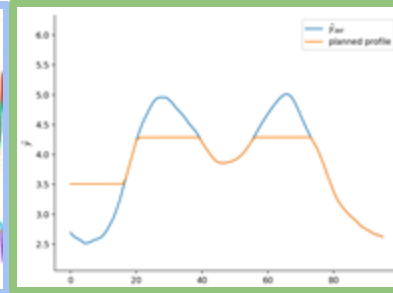
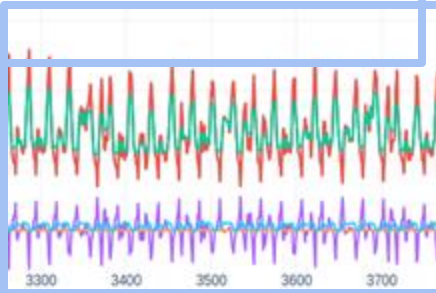


[1] [EU ped implementation plan](#)

[2] [Net Zero Mission Cities](#)

Monolithic problem

$$\begin{aligned}
 & \arg \min_{p_b, E_{batt}, P_{bat}, P_{PV}} LCOE(p, p_b, E_{batt}, P_{bat}, P_{PV}) \\
 & s.t. \quad e_{t+1} = e_t + \eta_{ch} p_b^{ch} - \frac{1}{\eta_{ds}} p_b^{ds} \\
 & \quad p_b^{ch} p_b^{ds} = 0 \\
 & CAPEX_{ann} = crf \left(c_{PV}^{kW} x_{PV} P_{PV}^{peak} + c_{bat}^E E_{bat} + c_{bat}^P P_{bat}^{max} \right) \\
 & OPEX_{energy} = R \sum_t \left(\lambda_t^{imp} \frac{P_t^{imp}}{1000} \Delta t - \lambda_t^{exp} \frac{P_t^{exp}}{1000} \Delta t \right) \\
 & OPEX_{peak} = R \sum_{p \in P} \tau_p P_p^{peak} \\
 & LCOE = CAPEX_{ann} + OPEX_{energy} + OPEX_{peak}
 \end{aligned}$$



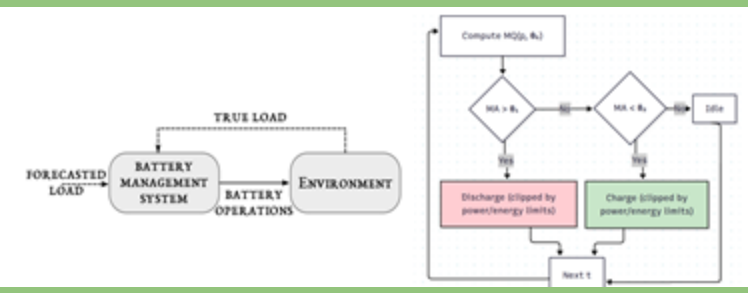
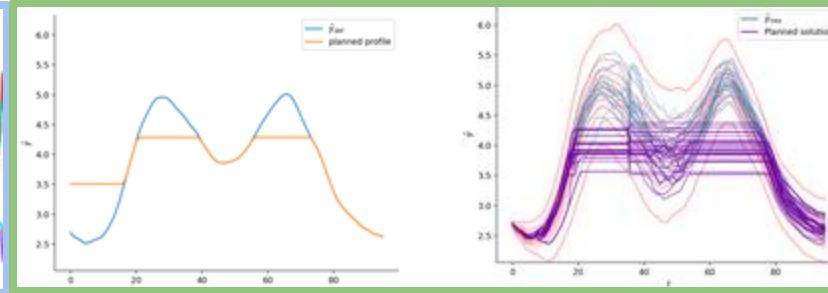
Decomposed problem

SIZING

$$E_{bat}^*, P_{bat}^*, P_{PV}^* = \arg \min_{E_{bat}, P_{bat}, P_{PV}} LCOE(\pi^*(p), E_{bat}, P_{bat}, P_{PV})$$

OPERATION

$$\pi^*(p) = \begin{cases} \arg \min_{p_b} OPEX(\hat{p}, p_b) & \text{MPC} \\ \arg \min_{p_{b, tree}} OPEX(\hat{p}_{tree}, p_b) & \text{SMPC} \\ \arg \min_{\theta} \mathbb{E}_{sim} OPEX(p, p_b = f(\theta)) & \text{RL} \end{cases}$$



	Deterministic, perfect forecast	Deterministic MPC (lookahead)	Stochastic (lookahead)	RL	Tunable RBC
Optimistic	+++ , lower bound	++	+	+	+
CPU time	- 1-2 s full year opt	+ 0.06s per horizon	++ 1.2s per horizon	+++	low 6e-3s full year, 0.8s full year opt
Complexity	low (one shot sizing + operation)	medium (forecast + optimize)	high (tree based forecast / policy)	high (NN based)	low, interpretable policy

The idea

- Use a parametric (tunable) rule based controller [1], eg

for t in $1..T$:

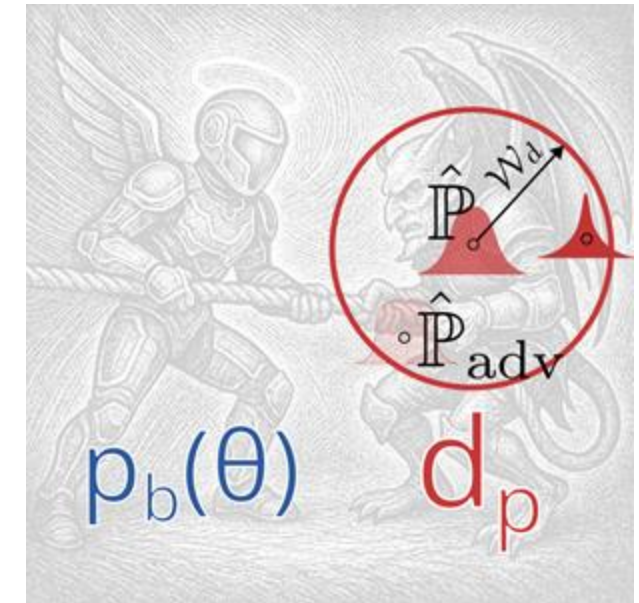
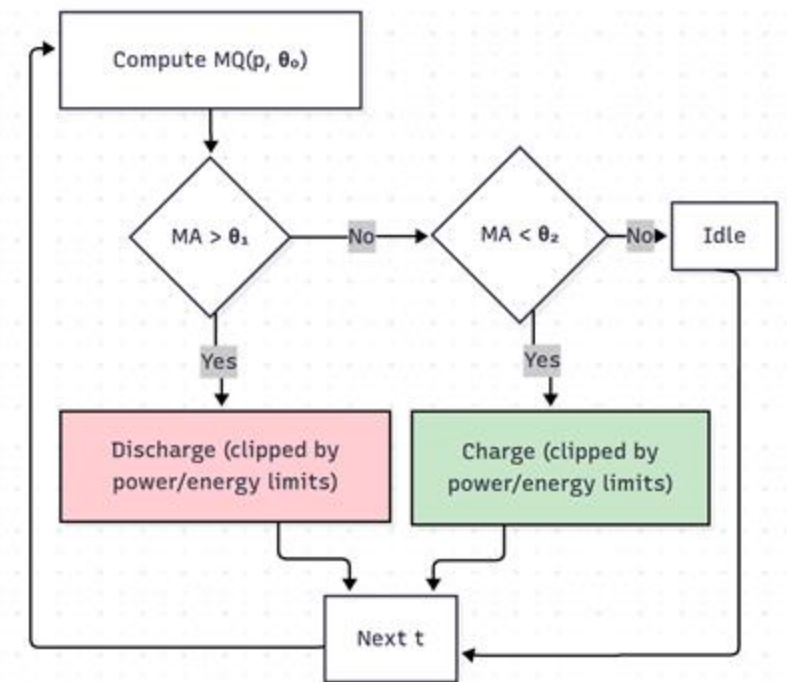
if $MQ(p, \theta_0) > \theta_1$:

discharge within operative lims

if $MQ(p, \theta_0) < \theta_2$:

charge within operative lims

- Tune the parameters θ on a Training Set and test it on hold out dataset
- Since simulating it is so fast, we can
 - Retrieve the loss landscape for inspection
 - Perturb the problem with adversarial noise to make it even more robust. This process is loosely connected with distributionally robust optimization [2].



Takeaways:

- Rule based controllers can be made robust via parametrization and stochastic tuning
- We can apply this technique to FAST simulators
 - e.g. thermodynamics of buildings via RC equivalent $\rightarrow$ HP sizing
- The controller is interpretable (very few parameters) and easily embeddable

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