

Model Predictive Control of Distributed Energy Resource Aggregators

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S114G: Robust DER Allocation with Data-driven Control and Generative Methods

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Joint work with



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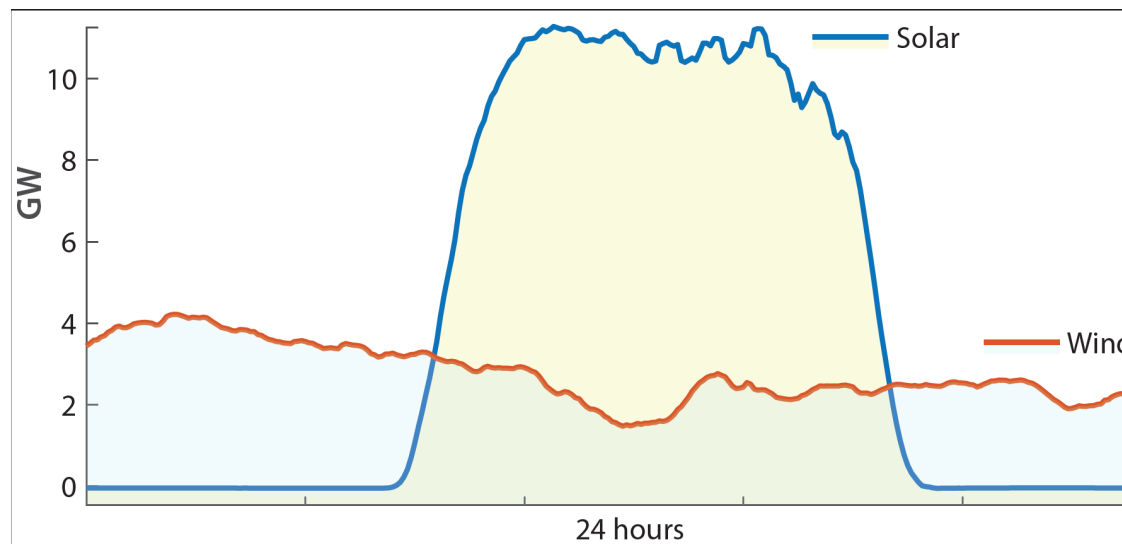


Prof. Oliver Kosut

The Need for Control for DERAs

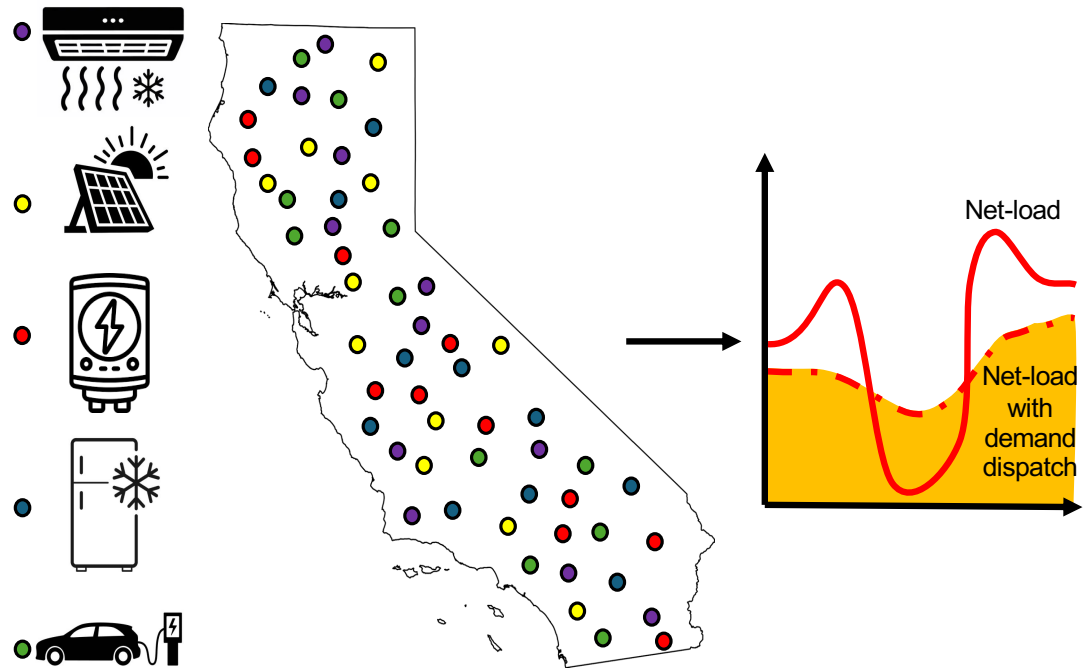


- Power for AI: Driving a massive need for energy
- Renewable penetration introduces volatility
 - Uncertainty in meeting net-demand
- Net-demand ramps and disturbances must be balanced in real-time
- Traditional balancing relies heavily on fossil-fuel generators
 - Costly, inefficient, and environmentally undesirable



Why DER Aggregators (DERAs)?

- Grid operators must continuously maintain supply-demand balance
- Aggregators combine flexible DERs into controllable batteries
 - They are treated as controllable agents that help follow net-demand
- Real-time allocation must account for both short-term dynamics and long-term demand

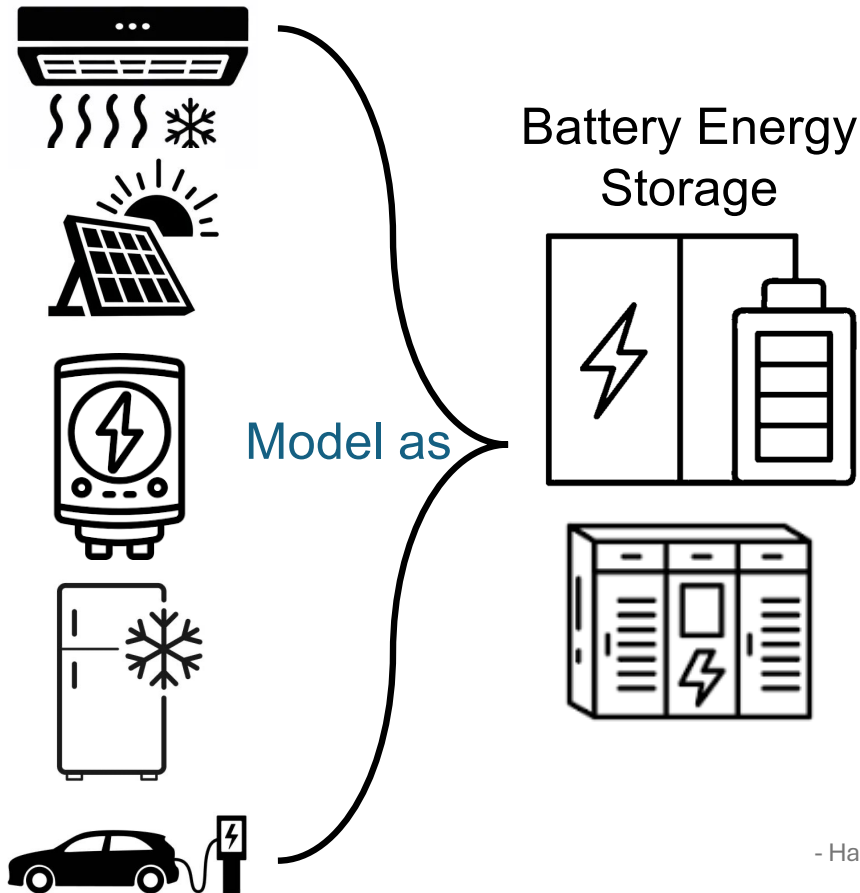


Problem Setup



Modeling Flexible Loads

DERs
Flexible loads



Model:

$$x_i(t+1) = \alpha_i x_i(t) - \beta p_i(t)$$

Constraints:

$$|x_i(t)| \leq C_i,$$

$$-\eta_i^- \leq p_i(t) \leq \eta_i^+$$

x_i : state of charge

β : sampling time constant

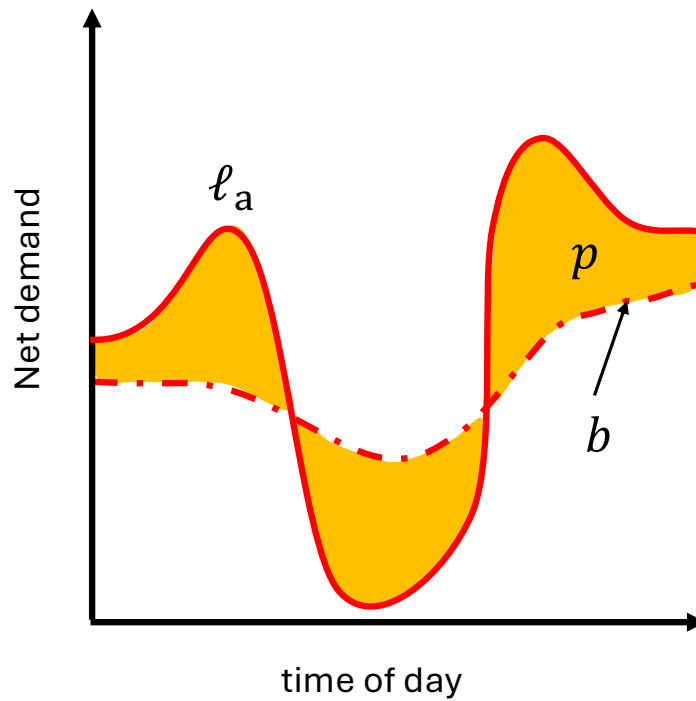
α_i : a leakage parameter

C_i : capacity limits of the state of charge

η_i : power capacity limits

p_i : power output of aggregator i

Grid Objective



ℓ_a : actual net-load

b : bulk generation

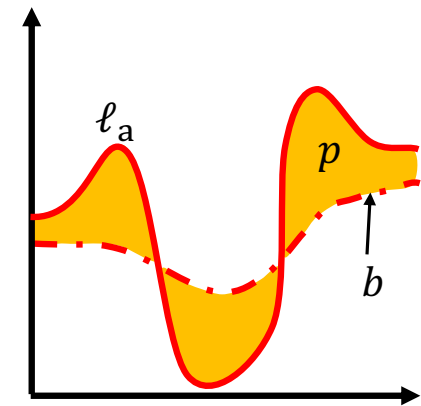
$$p = \sum_{i=1}^M p_i(t)$$

Grid Objective

- Grid objective is to minimize variation in $b(t)$ while matching supply and demand

$$\ell_a(t) = b(t) + \sum_{i=1}^M p_i(t)$$
$$b(t) = \bar{\ell} + \varepsilon(t)$$

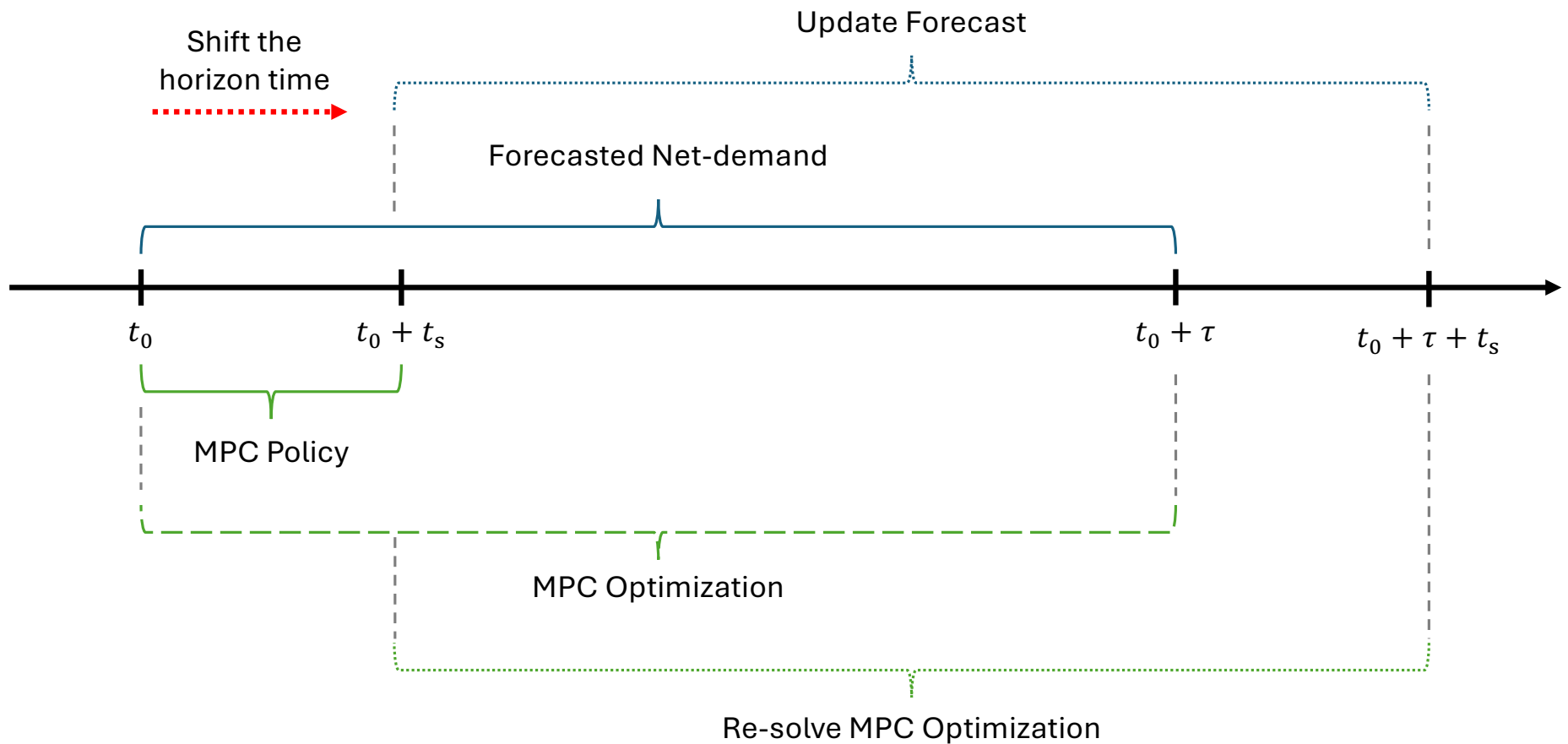
- Actual load is not known in advance
 - We rely on forecast ℓ instead of ℓ_a
 - Optimal control of DERAs requires planning over a horizon time



ℓ_a : actual net-load
 b : bulk generation
 $\bar{\ell}$: constant baseline
 ε : mismatch

Model Predictive Control (MPC) can help achieve this objective

MPC Approach: Horizon Time and Time-shift



MPC Design



MPC Setup



- **Objective:** Minimize cost of supplying forecasted net-load $\ell(t)$
- **Costs:**
 - For each M aggregation state of charge cost:

$$c_x(x) := \sum_{i=1}^M \frac{1}{2} \kappa_i^x x_i^2$$

$$x_i(t+1) = \alpha_i x_i(t) - \beta p_i(t)$$

$$\begin{aligned} -C_i &\leq x_i(t) \leq C_i, \\ -\eta_i^- &\leq p_i(t) \leq \eta_i^+ \end{aligned}$$

- Cost of rapidly changing the output aggregation (ramping cost):

$$c_u(u) := \sum_{i=1}^M \frac{1}{2} \kappa_i^u u_i^2$$

$$u_i(t) := p_i(t+1) - p_i(t)$$

- Load mismatch:

$$c_\varepsilon(\varepsilon(t)) = \frac{1}{2} \kappa^\varepsilon \varepsilon(t)^2$$

$$\varepsilon(t) = \ell(t) - \bar{\ell} - \sum_{i=1}^M p_i(t)$$

$\kappa_i^x, \kappa_i^u, \kappa^\varepsilon$: design cost parameters

Total state cost over all
load classes at a DERA

Total ramping cost

Mismatch penalty

$$\min_{x,p,u,\varepsilon} \sum_{t=t_0}^{t_0+\tau-1} [c_x(x(t)) + c_u(u(t)) + c_\varepsilon(\varepsilon(t))]$$

$$\text{subject to } \ell(t) - \bar{\ell} - \sum_{i=1}^M p_i(t) = \varepsilon(t),$$

$$x_i(t+1) = \alpha_i x_i(t) - \beta p_i(t),$$

$$p_i(t+1) = p_i(t) - u_i(t),$$

$$-C_i \leq x_i(t) \leq C_i,$$

$$-\eta_i^- \leq p_i(t) \leq \eta_i^+$$

$\ell(t)$?

Forecast Models



- We train two types of forecast models:
 - Linear Regression (LR)
 - Long Short-Term Memory (LSTM)
- Features:
 - previous day net demand
 - day of the week
 - time of day
 - holiday binary indicator

Linear Regression



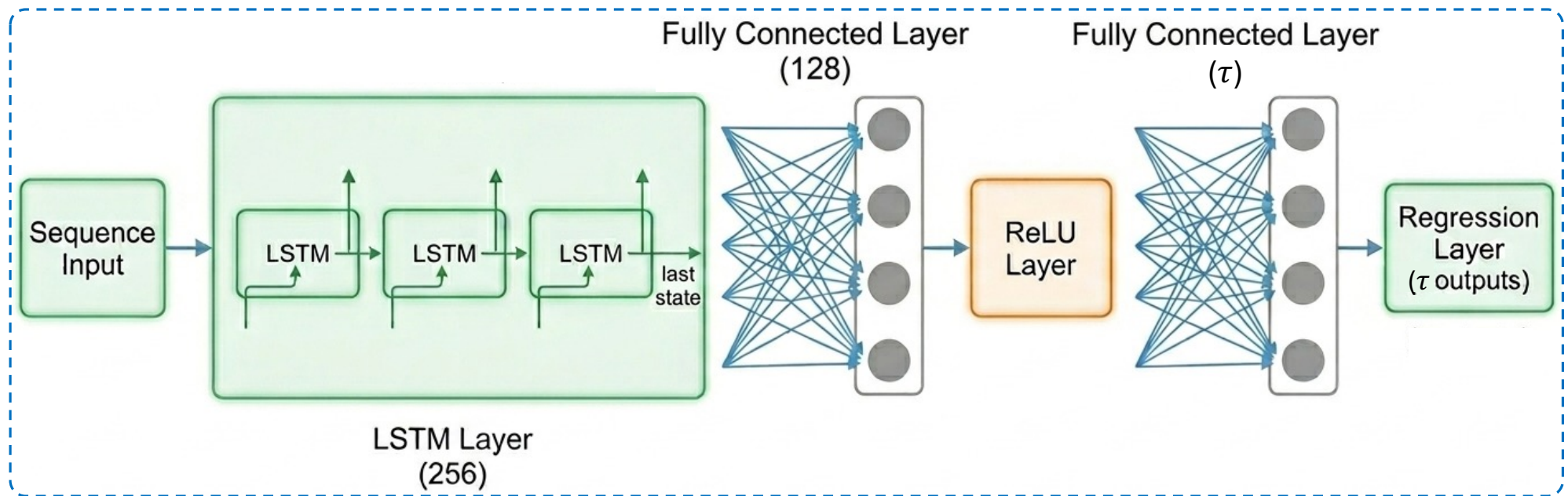
- LR predicts one future point at a time
- A **bank of LR models** is trained for each point in the horizon time with β increments
- Forecast obtained by: $y = x\mathcal{W}$

$$\begin{array}{c}
 \text{Load forecast} \\
 (\tau) \\
 y
 \end{array}
 =
 \begin{array}{c}
 \text{Input features} \\
 (m) \\
 x
 \end{array}
 \times
 \begin{array}{c}
 t_0 \quad \dots \quad t_0 + \tau - 1 \\
 \left[\begin{array}{ccc}
 \omega_{1,1} & \dots & \omega_{1,n} \\
 \vdots & \ddots & \vdots \\
 \omega_{m,1} & \dots & \omega_{m,n}
 \end{array} \right] \\
 \mathcal{W}
 \end{array}
 \begin{array}{l}
 m = (24 \times \frac{60}{\beta}) + 3 \\
 n = \tau \times \frac{60}{\beta}
 \end{array}$$

Linear Regression

Long Short-Term Memory

- A model is trained specifically for each τ
 - The size of last layer changes depending on the forecast horizon time
- A model outputs the net-load for τ window in one shot



Long Short-Term Memory

Related Work



Our Work Vs. Others



Paper	DER control	MPC	Models forecast	Uses forecast	Varies τ	Varies t_s
Espinosa and Almassalkhi, 2020	✓					
Nazir and Almassalkhi, 2022	✓					
Appino et al, 2021	✓					
Benenati et al, 2019	✓	✓				
Y. Shen et al, 2025	✓			✓		
Mathias et al, 2022	✓			✓		
Cammardella et al, 2018	✓	✓		✓		
Yi et al, 2021	✓			✓	✓	
Utkarsh et al, 2022	✓	✓		✓	✓	
Eseye et al, 2022	✓	✓		✓	✓	
Our work	✓	✓	✓	✓	✓	✓

Experimental Results



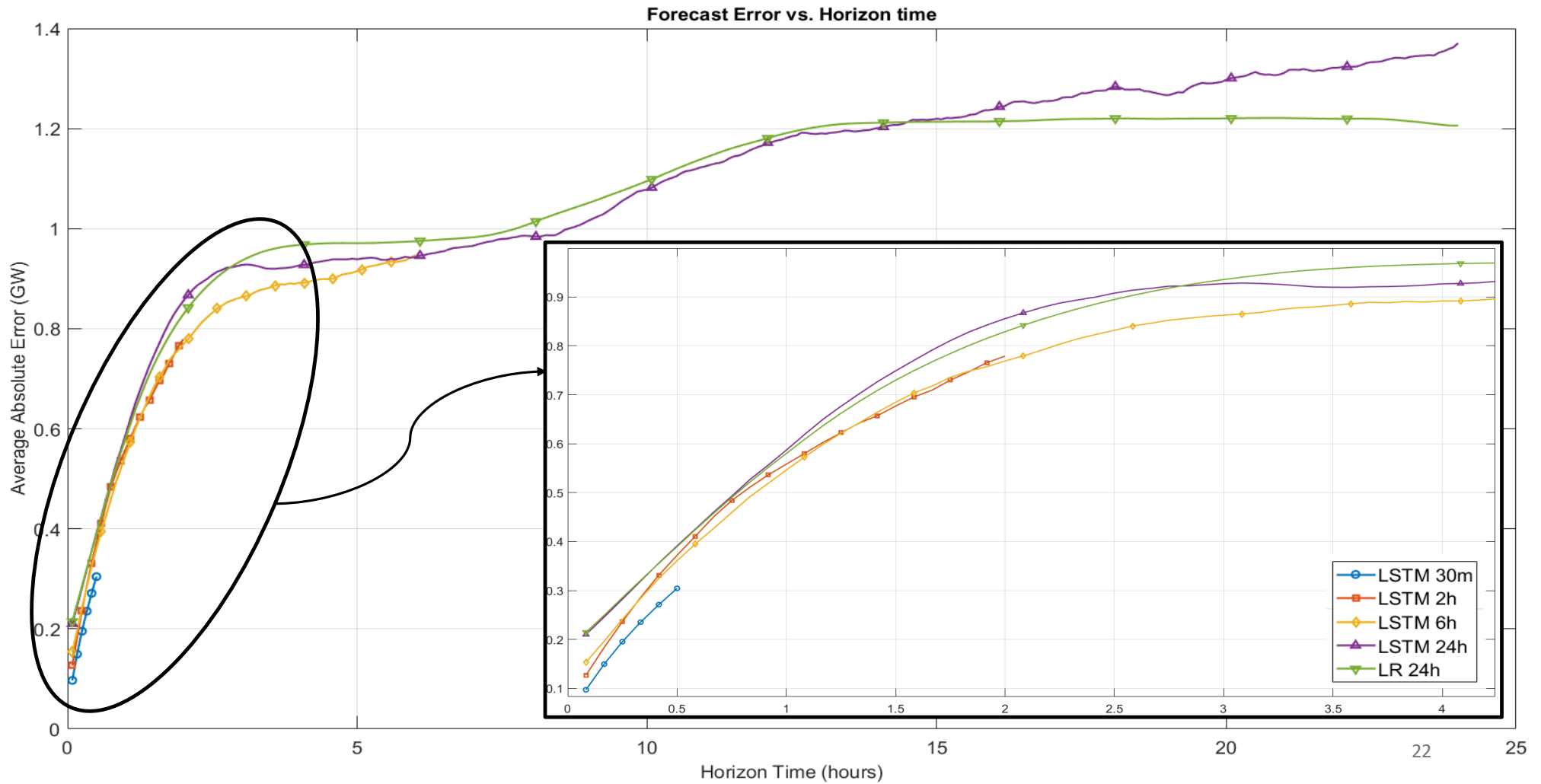
Simulations Setup



- (CAISO) net-load from 2021 to 2025 with 5 minutes sampling rate (β)
 - Three years training set: August 2021 – July 2024
 - One year testing set: August 2024 – July 2025
 - MPC paramters:
 - $\tau \in \{30\text{m}, 1\text{h}, 2\text{h}, 3\text{h}, 6\text{h}, 12\text{h}, 24\text{h}\}$
 - $t_s \in \{15\text{m}, 30\text{m}, 60\text{m}, 90\text{m}, 120\text{m}, 150\text{m}, 180\text{m}\}$
 - DERAs:
 - air conditioners (ACs)
 - electric water heaters (E-WHs)
 - building HVACs (bldgs)
 - refrigerators (RFGs)
 - electric vehicles (EVs)
1. **While** MPC ON **do**:
 2. **Accumulate** previous loads at times $\{t - 24\text{h}, \dots, t_0\}$
 3. **Forecast** the horizon time τ
 4. **Solve** the MPC problem
 5. **Apply** the first t_s trajectories
 6. **Advance** $t_0 \leftarrow t_0 + t_s$

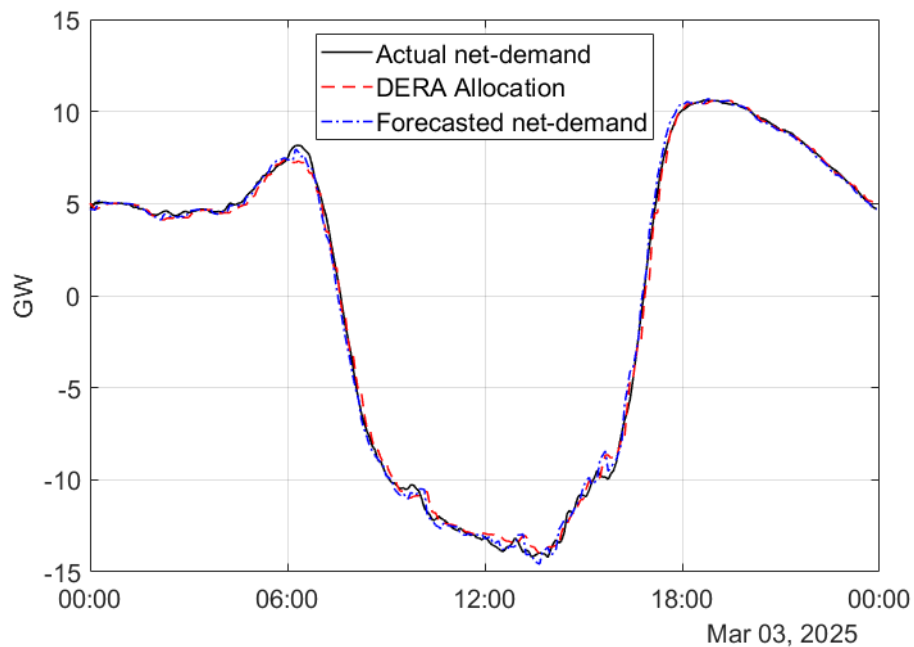
- The forecast models are tested on CAISO data for a year (starting Aug. 02, 2024)
 - Every 5m: forecast next horizon time τ
 - Compute average absolute error for the forecast for each point within τ
- Performance of LR and LSTM models for
$$\tau = \{30\text{m}, 2\text{h}, 6\text{h}, 24\text{h}\}$$

Forecast Performance

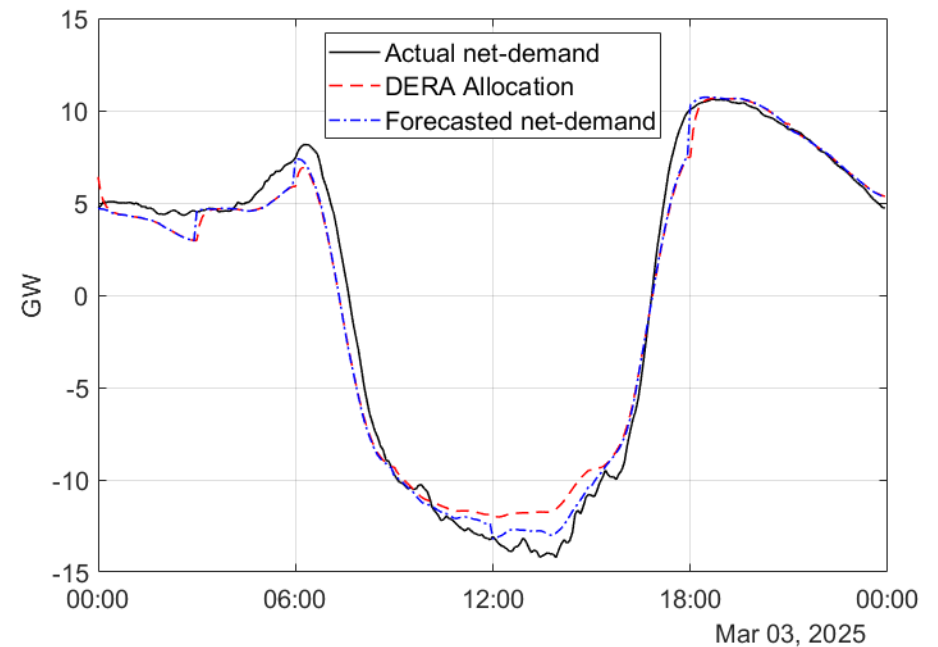


- LR trace captures predictions of every point-wise linear regression model
- Both LR and LSTM show increasing error as horizon time increases
- LSTM performs better overall
- LR becomes better at longer horizon times
 - All LSTM models are trained using the settings for consistency and comparability
 - Different horizon times need different training setups → worse results for LSTM at long horizon times

MPC Performance: Linear Regression

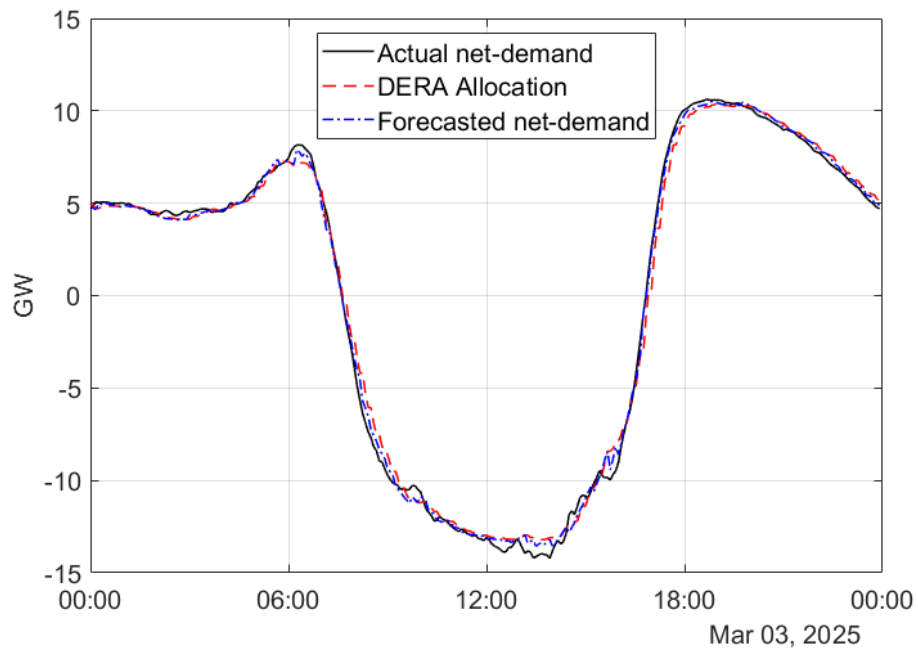


$\tau = 24h$
 $t_s = 15m$

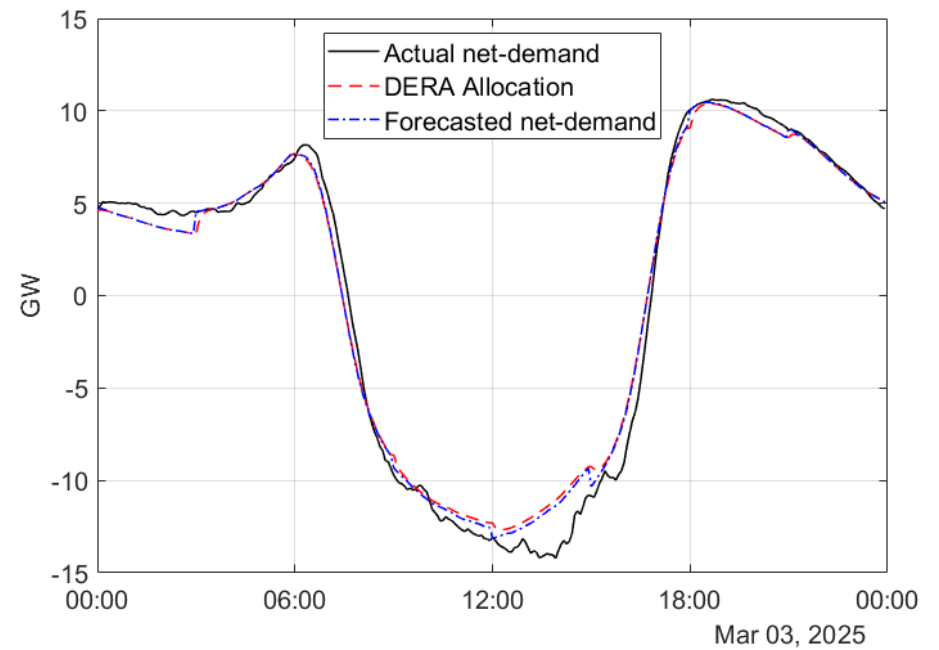


$\tau = 6h$
 $t_s = 180m$

MPC Performance: Long Short-Term Memory



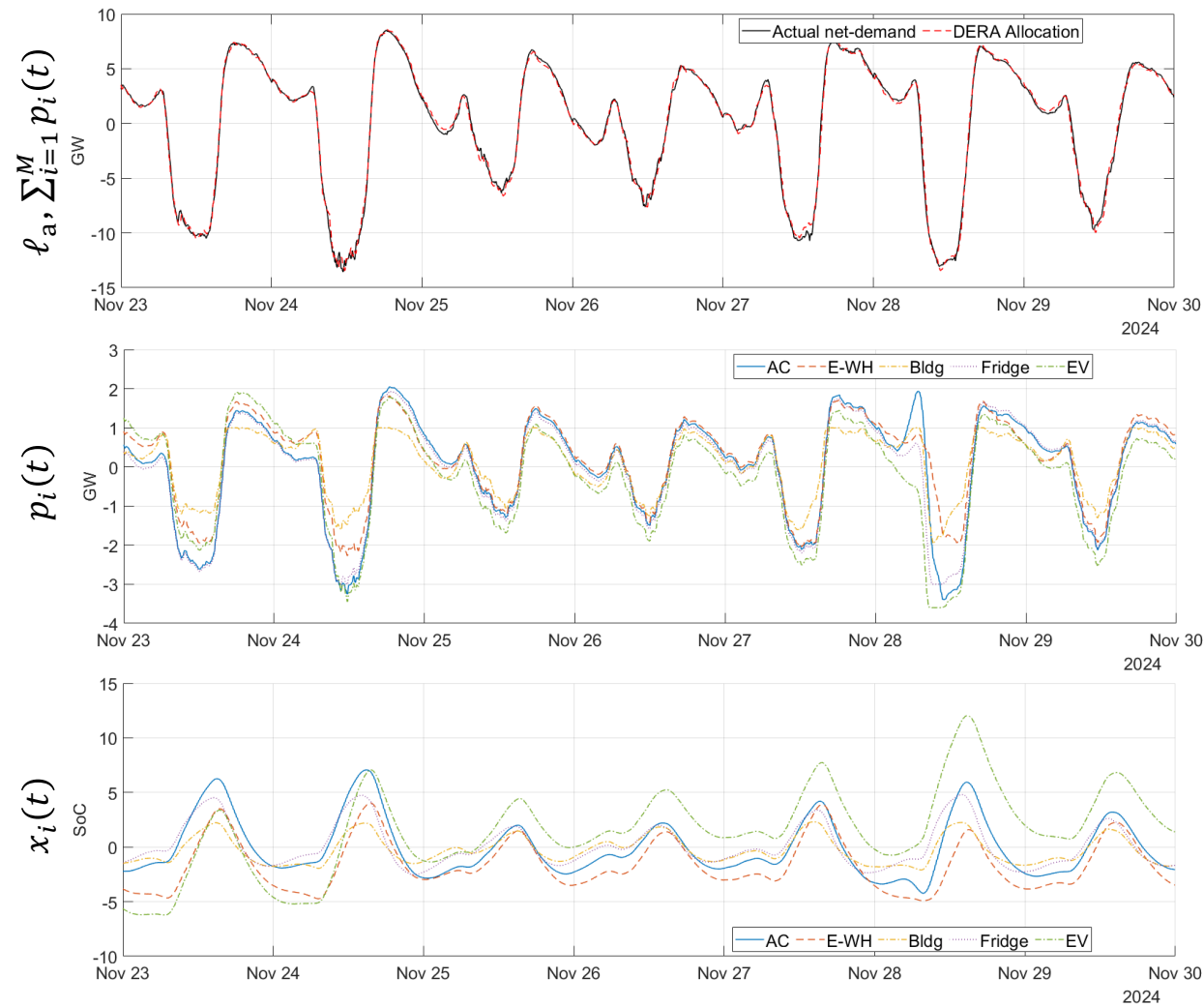
$\tau = 24h$
 $t_s = 15m$



$\tau = 6h$
 $t_s = 180m$

- Long τ with short t_s result in better tracking of net-demand for DERAs
- Short τ with long t_s result worse tracking of net-demand for DERAs
 - MPC plans better for longer horizon times
 - With shorter time shifts, more accurate forecasts and frequent MPC updates results in better tracking

DERA Performance



LR
 $\tau = 24h$
 $t_s = 15m$

- Cumulative DERAs response tightly tracks actual net-demand
 - Capability to provide regulation-type services under fluctuating power demand
- DERs consume (charge) more power during times of low net-demand
- DERs supply (discharge) power as net-demand ramps up

- We calculate the MPC objective over a year period starting August 2nd, 2024

$$\sum_{t=t_0}^{t_0+\tau-1} [c_x(x(t)) + c_u(u(t)) + c_\varepsilon(\varepsilon(t))]$$

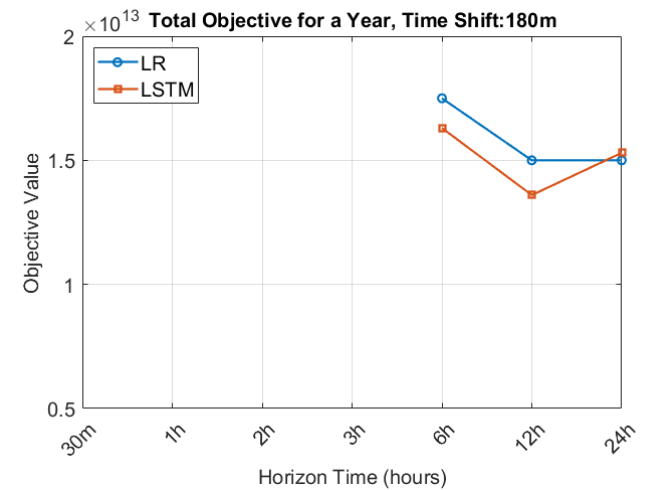
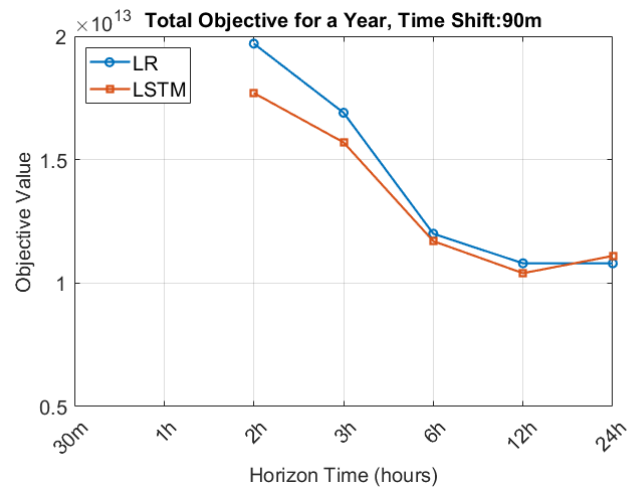
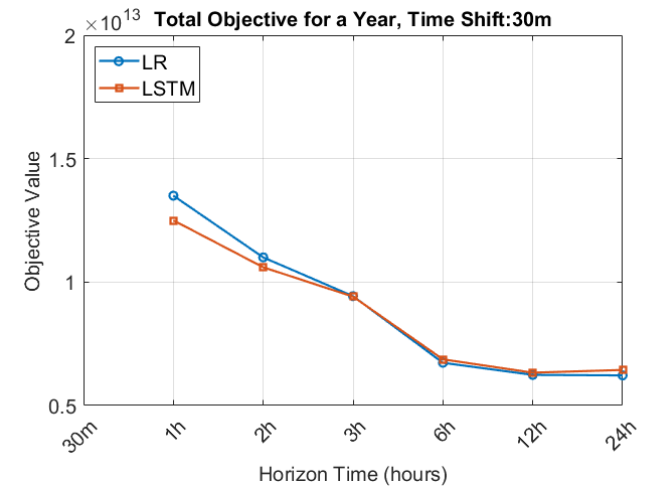
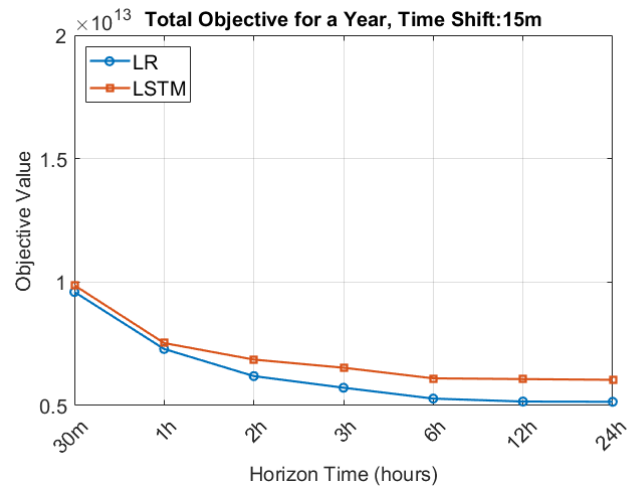
- In the objective, $\ell_a(t)$ is used when calculating $\varepsilon(t)$

$$\varepsilon(t) = \ell_a(t) - \bar{\ell}(t) - \sum_i p_i(t)$$

- The objective for different horizon times for a given time-shift is plotted

Can we evaluating the effect of forecast on MPC performance?

MPC Performance



Concluding Remarks



- Demonstrated effective forecast-coupled MPC for DERA allocation
- The framework respects dynamic and operational constraints
- Close tracking of real net-demand CAISO data
- LSTM is advantageous when long-term planning matters more
- LR is attractive for short-term accuracy with its lower computational burden

Extensions

- Incorporate network-level constraints, e.g., nominal voltages, transfer limits.
- Consider market objectives
- Implement device-level control (disaggregate)

On-going Work: Can We Leverage Reinforcement Learning?

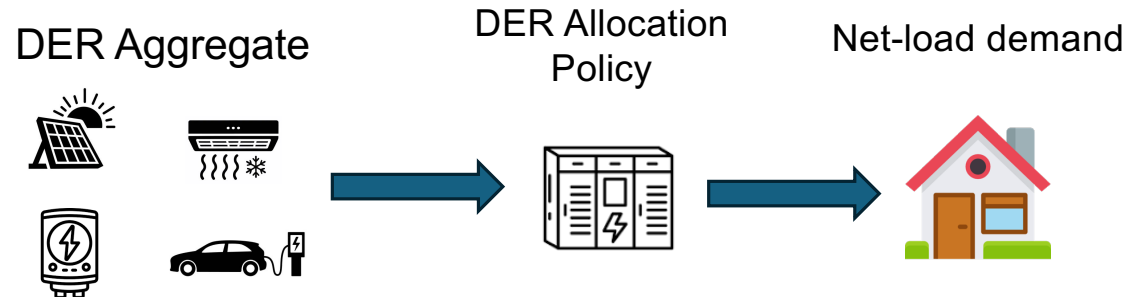


DER aggregate model:

$$x(t+1) = Ax(t) + Bu(t)$$

Net-load demand model:

$$l(t+1) \sim P(l(t+1)|l(t))$$



- DER aggregate is modeled as a deterministic linear dynamical system
- Net-load demand is modeled as a Markov process to capture the stochasticity
- Reinforcement learning framework to learn DER allocation policy from data
 - Enables forecast-free policy learning
 - For case of known system dynamics, simple least-squares value iteration

MPC Work:

- O. Bahwal, O. Kosut and L. Sankar, "Forecast and Model Predictive Control of Distributed Energy Resource Aggregators for Net-Demand Balancing," *in preparation for IEEE Transactions on Smart Grid*.

Reinforcement Learning Work:

- A. Al Makdah, A. Ramanan, S. Zou, O. Kosut and L. Sankar, "Linear Dynamics meets Linear MDPs: Closed-Form Optimal Policies via Reinforcement Learning," *accepted for presentation, IEEE PES GM 2026*.

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