A Privacy-Preserving Framework for Demand Response from Residential Thermal Loads

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Power Distribution and Energy Storage

Link to video presentation: https://youtu.be/GKJcg-LLn_A

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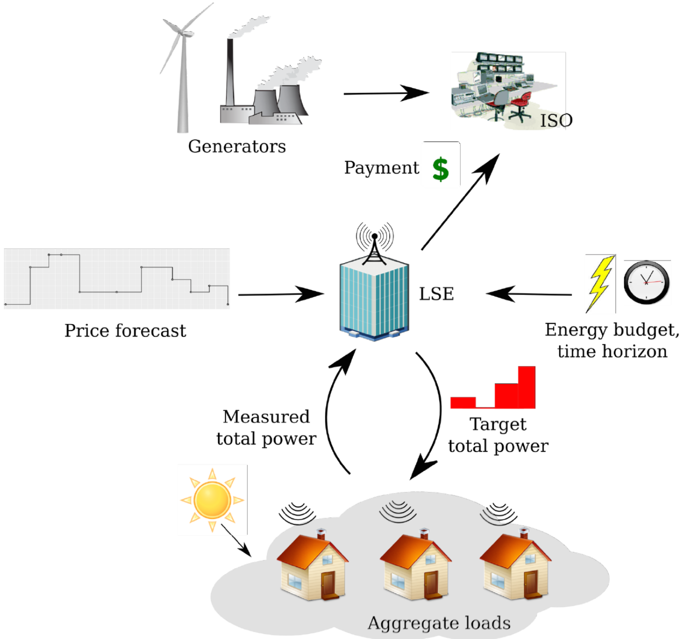
Introduction



Source: Halder, Geng, Kumar and Xie, IEEE Trans. Power Syst., 2016.

- Renewables are introducing new uncertainties into the grid that cannot be handled on the supply side.
- Demand response (shaping energy consumption of consumers) is necessary to mitigate uncertainty introduced by renewables.
- Thermal loads (ACs/heaters) comprise 50% of the energy consumption in homes in the US, and are an attractive option for demand response.
- Aggregators/load serving entities can pool a large number of homes and control their thermal loads to provide demand response services to the grid.

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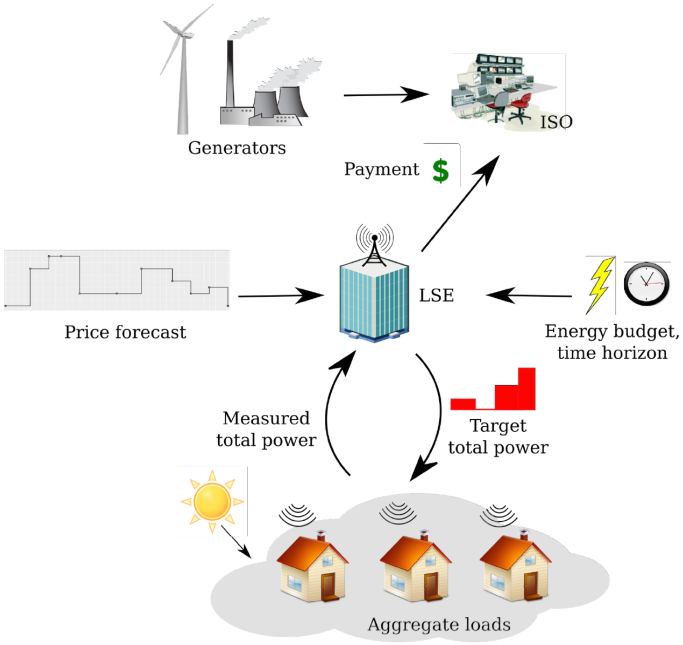
Objective



Source: Halder, Geng, Kumar and Xie, IEEE Trans. Power Syst., 2016.

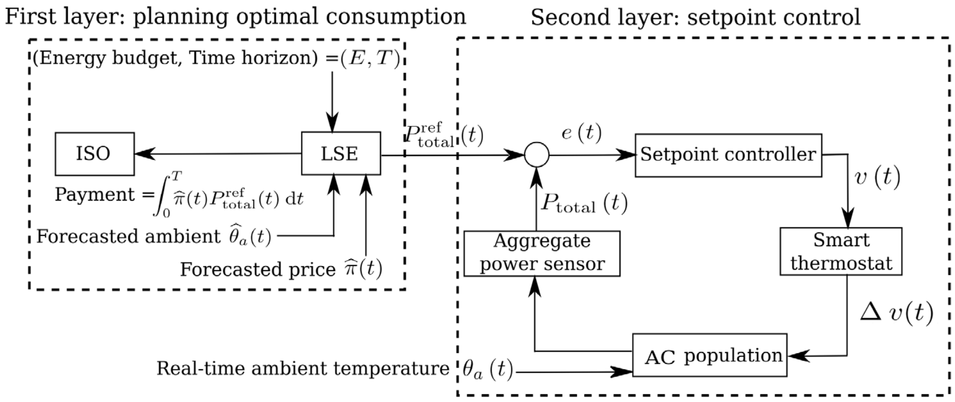
Problem:

Optimizing electricity consumption and electricity costs for a large collection of homes managed by an aggregator/load serving entity by controlling thermal inertial loads.

Privacy Constraints:

- Aggregator has **no access to the state variables** (temperatures or power consumption) **or the thermal models** (building characteristics) of individual homes.
- Aggregator **must guarantee consumer comfort constraints** (temperature differential that the consumer is willing to tolerate).

Current State-of-the-Art: Model-based Scheme



Source: Halder, Geng, Kumar and Xie, IEEE Trans. Power Syst., 2016.

Temperature of home — Ambient Temperature

$$\dot{\theta}_i = -\alpha_i\big(\theta_i(t) - \theta_a(t)\big) - \beta_i P \sigma_i(t),$$ Building thermal model

AC ON/OFF state

$$\sigma_i(t) = \begin{cases} 1, & \theta_i(t) = U_{i0} \\ 0, & \theta_i(t) = L_{i0} \\ \sigma_i(t^-), & otherwise. \end{cases}$$

Upper comfort bound

Lower comfort bound

Power Consumption Optimization:

- Compute ON-OFF schedules for ACs as

$$\underset{\sigma_1,..,\sigma_N \in \{0,1\}^N}{\text{argmin}} \frac{P}{\eta} \int_0^T \hat{\pi}(t) \sum_{i=1}^{N} \sigma_i(t) dt$$

Subject to: Building thermal model, and comfort constraints

- Pre-cool homes to decrease power consumption during peak pricing periods (when demand response is required).

Issues:

- Large-scale integer program ($\sim 2.8 \times 10^6$ variables for N=1000 homes!) – can solve using LP relaxation
- **Not privacy-preserving**: Need thermal parameters of homes (α_i and β_i) – can use joint distributions, but characterizing these quantities is hard, and requires knowledge of the layout/size/characteristics of homes.

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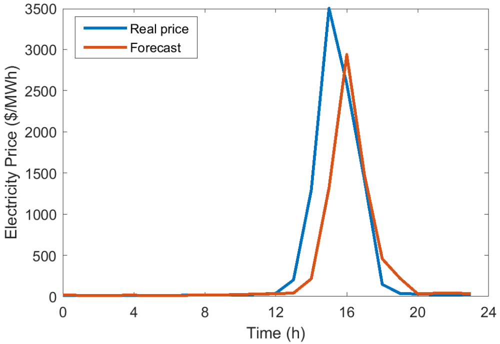
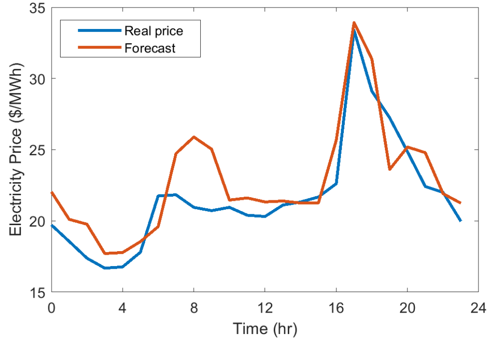
Privacy-Preserving Framework



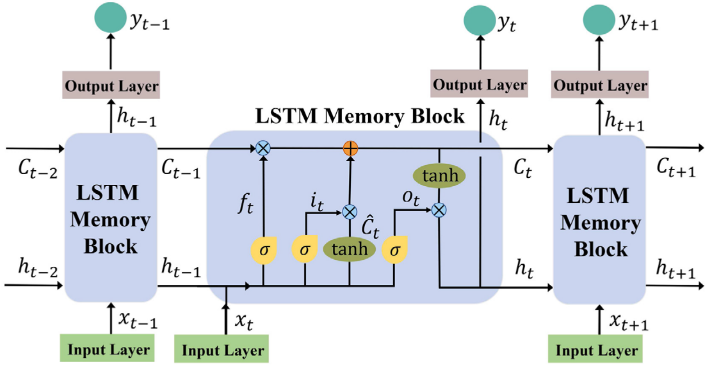
Forecast vs real price, ERCOT, Houston Area, 08/29/2019



Forecast vs real price, ERCOT, Houston Area, 12/31/2019

Step 1: Neural Network based Price Forecasting

Use Long-Short Term Memory (LSTM) neural networks to predict periods of peak electricity pricing



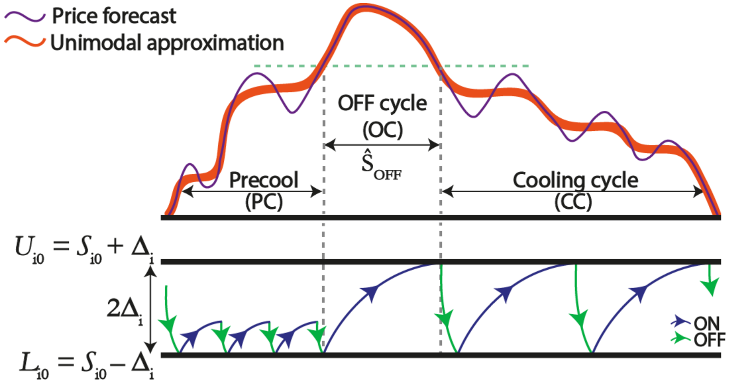
LSTM for hourly electricity price forecasting

Inputs: Historical hourly day-ahead and real-time electricity prices, weather data (temperatures, wind speed, humidity), generation and loads.
Output: Hourly price forecasts.

Sivaranjani S., P. R. Kumar, and Le Xie, "A Privacy Preserving Model-Free Optimization and Control Framework for Demand Response from Residential Thermal Loads", IEEE Conference on Decision and Control (CDC), 2020 (Invited).

Privacy-Preserving Framework

Step 2: Model-free Optimization



Key Idea:

Average duty cycle $(\hat{S}_{OFF})$
$\approx$ peak price period

Step 3: Private control implementation

Private Dynamics :

$$\dot{\theta}_i = -\alpha_i(\theta_i(t) - \theta_a(t)) - \beta_i P \sigma_i(t),$$

Binary Control Signal:

(broadcast to all homes by the aggregator and privately implemented at each home)

$$c(t) = \begin{cases} 1, & \theta_i(t) = U_{i0} \text{ OR } t \in PC \text{ OR } t \in CC \\ 0, & \theta_i(t) = L_{i0} \text{ OR } t \in \hat{S}_{OFF} \end{cases}$$

Note: Dynamics need not even be known to the home.

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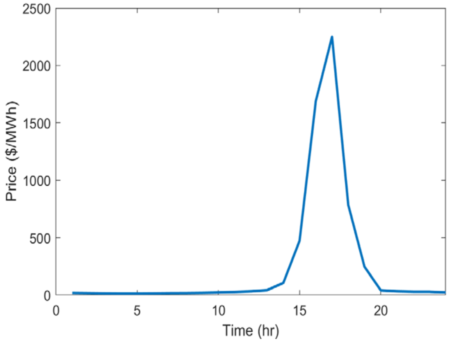
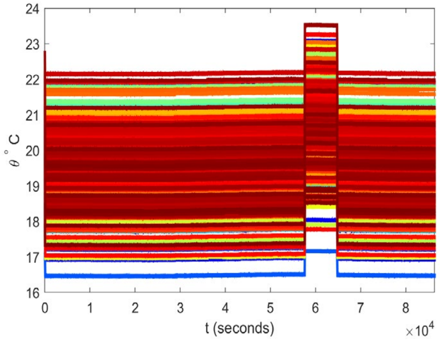
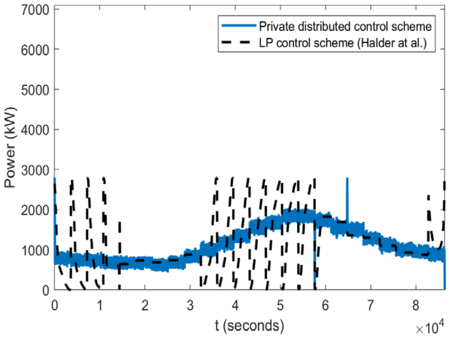
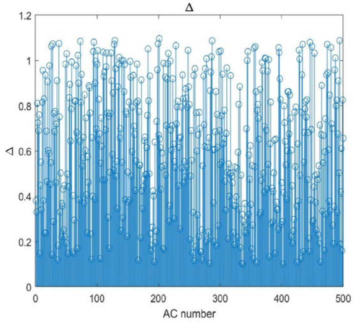
Case Study: Houston (N=500 homes)

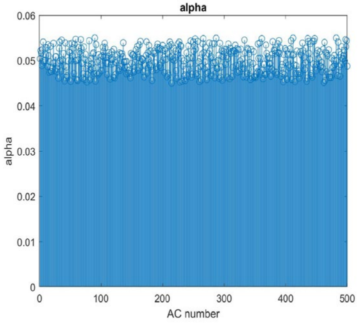


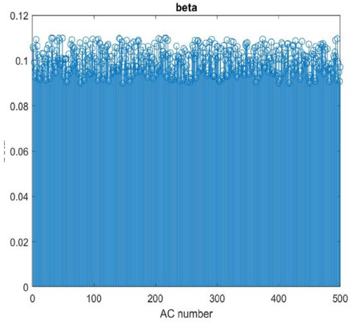




Can achieve significant reduction in power consumption and electricity costs for consumers, while maintaining complete privacy.







Average uncontrolled power = 25.68 MW

Average Power (Model-based scheme – Halder et. al., IEEE Trans. Power Syst., 2017) = 22.4 MW, Savings= $3787

Average Power (Privacy-preserving scheme) = 23 MW, Savings= $3597

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Conclusions and Future Work

- Framework for privacy-preserving demand response from residential thermal loads based on electricity price forecasting.
- Demand response framework will help promote renewable integration by mitigating uncertainties in grids with high penetration of renewables.
- Framework will also decrease energy costs for consumers in a non-intrusive and privacy-preserving manner.
- **Future work:** commercial/pilot-scale realization in collaboration with aggregators/industry partners in the Houston area.