On The Challenges Related To Using Thermostatically Controlled Loads For Demand Response

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Collaborators

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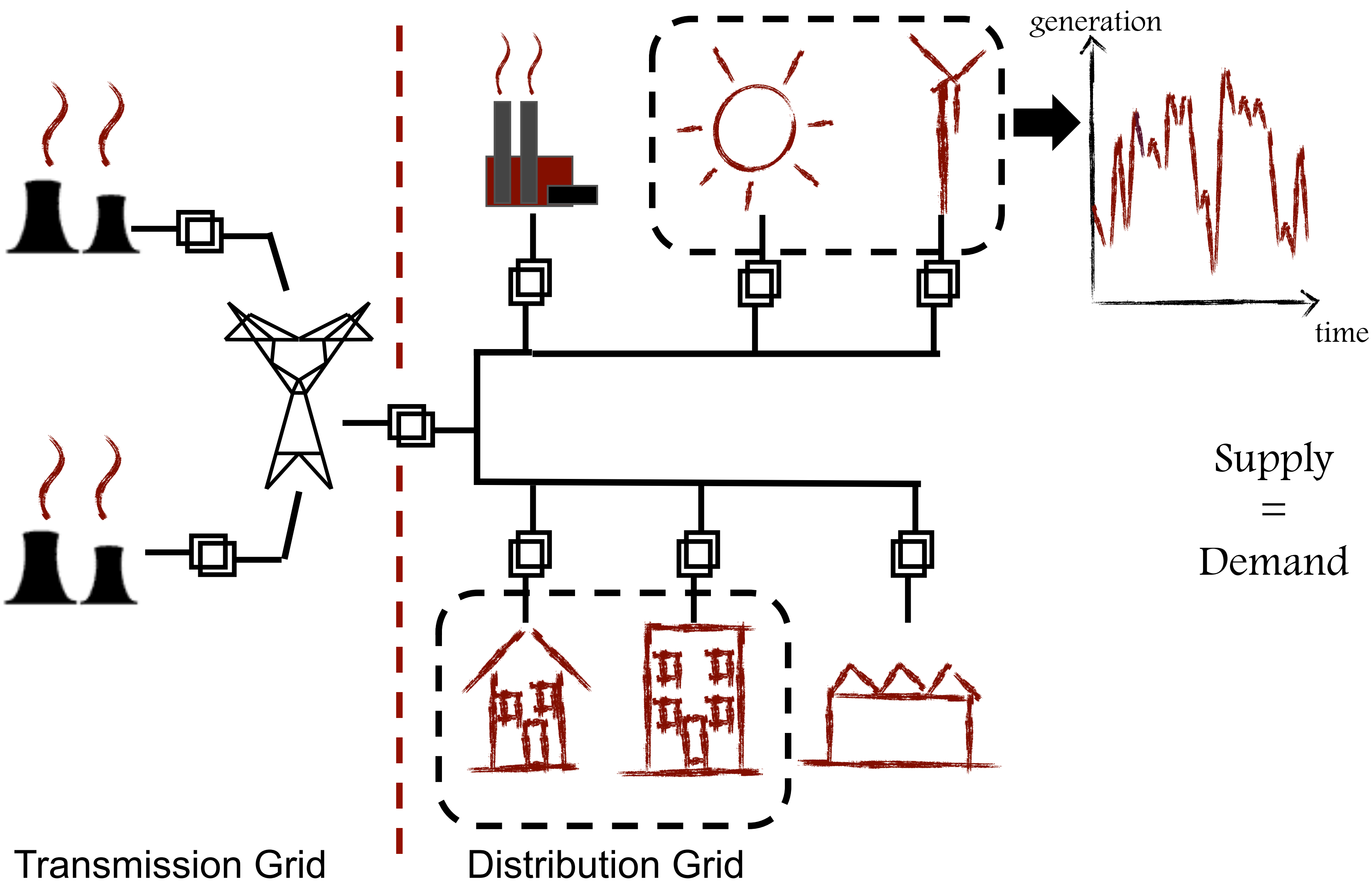
- Soummya Kar (ECE)
- Gabriela Hug (ECE)

Renewable Energy



Supply
=
Demand

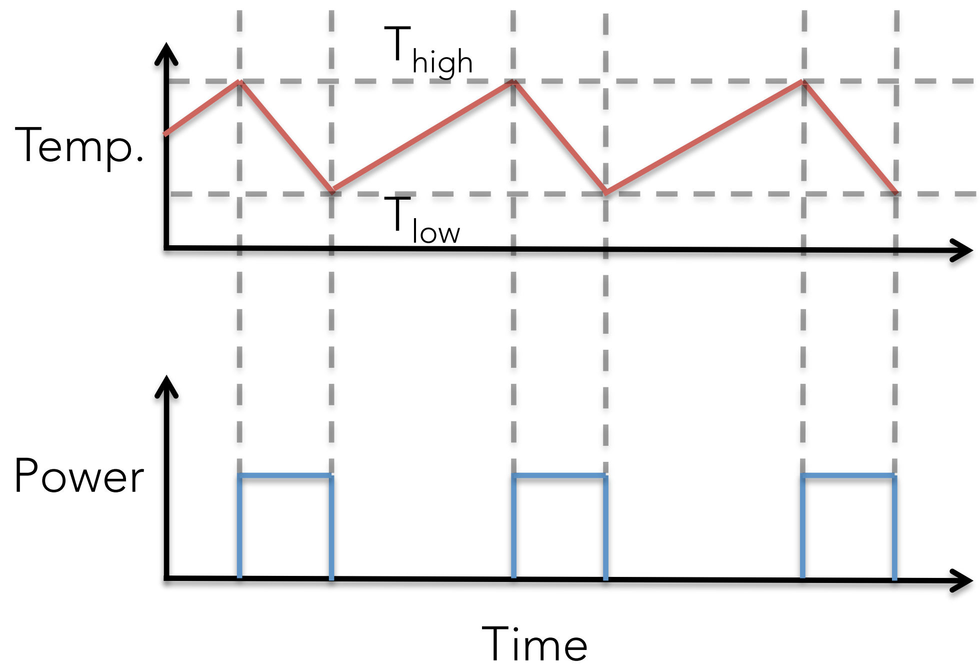
Flexibility and Reliability: Additional Sources

- Demand response systems
  - Price responsive demand
    - Variation in price to encourage customers to reduce/shift consumption
  - Load management and control
    - Loads are automated and controlled directly based on a control signal
    - Tighter control bounds
    - Faster response time
      - provide fast-timescale (seconds to minutes) services

Thermostatically Controlled Loads (TCLs)

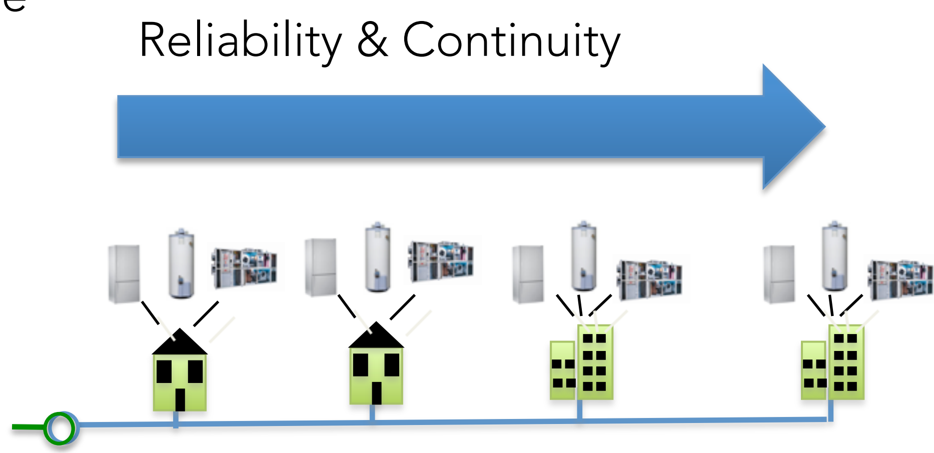
- More than 40% of the electricity consumed in buildings
- Availability in households
- 24/7 available for signals
- Disrupted without any effect on end-user's comfort

Refrigeration example:



Load Aggregation Benefits

- An aggregation of smaller loads provide **more reliable curtailment** than the response of a single or multiple large loads with an equivalent capacity. (Eto et al. 2012)
- Aggregations of small load resources provide **continuous control** with simpler control actuation. (Callaway et al. 2011)
- Individual monitoring systems for small loads are expected to **be less costly** than large load programs.



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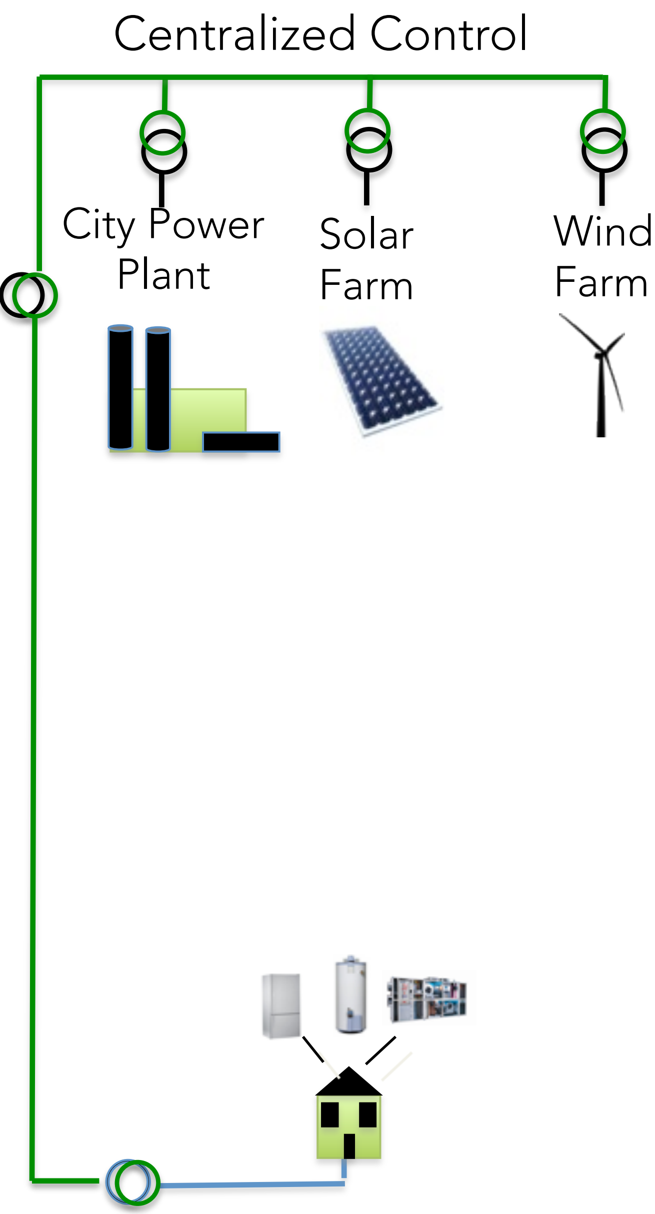
Existing Work



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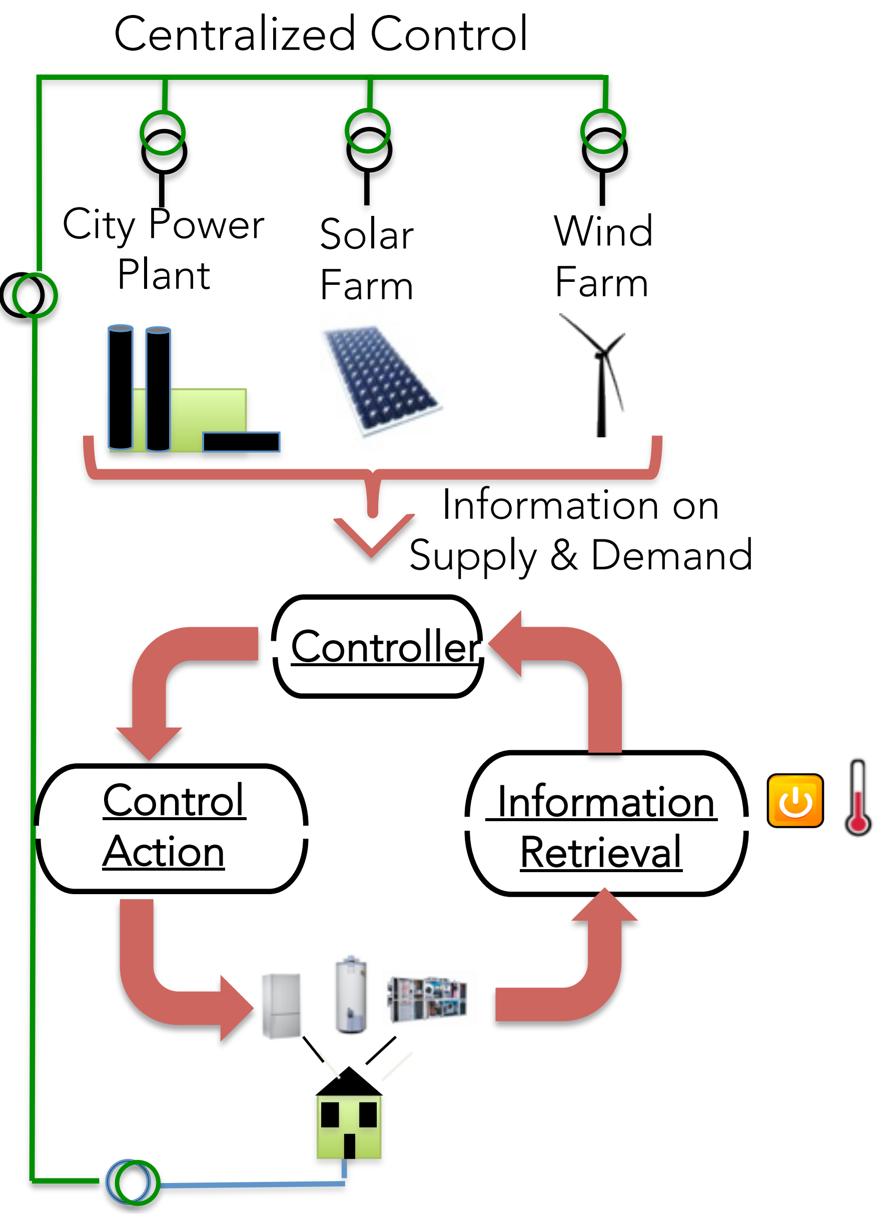

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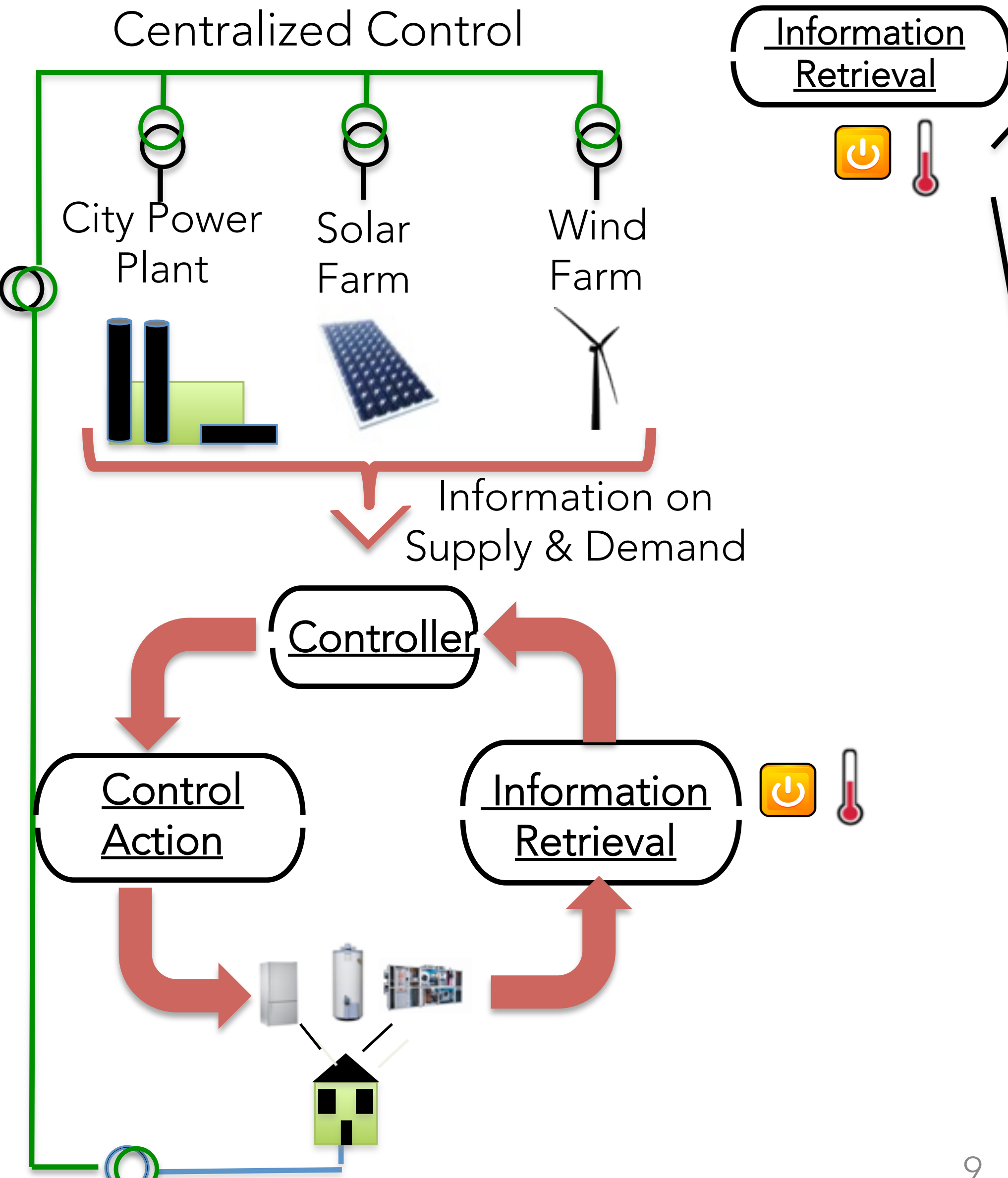
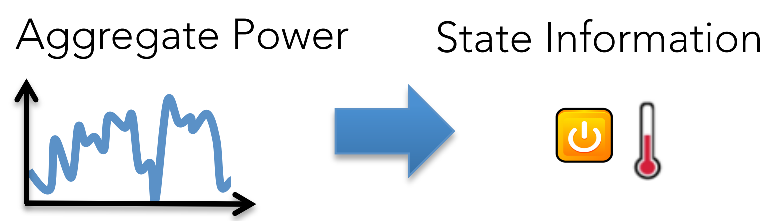
Existing Work

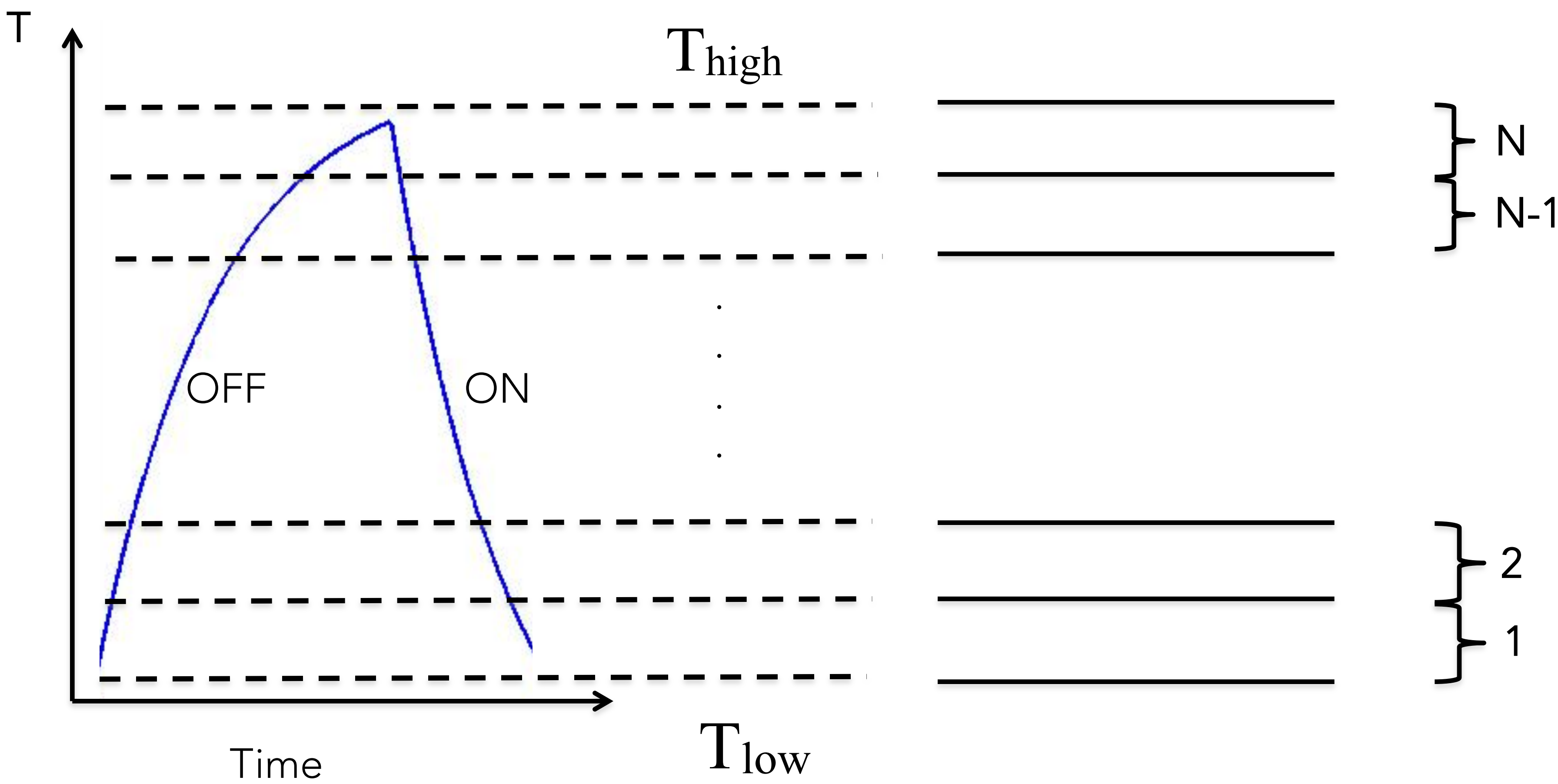


- Real-time state information from appliances.
  (Koch et al. 2011; Kara et al. 2012)
- Kalman filter and Extended Kalman filter for estimation.
  (Mathieu et al. 2012)

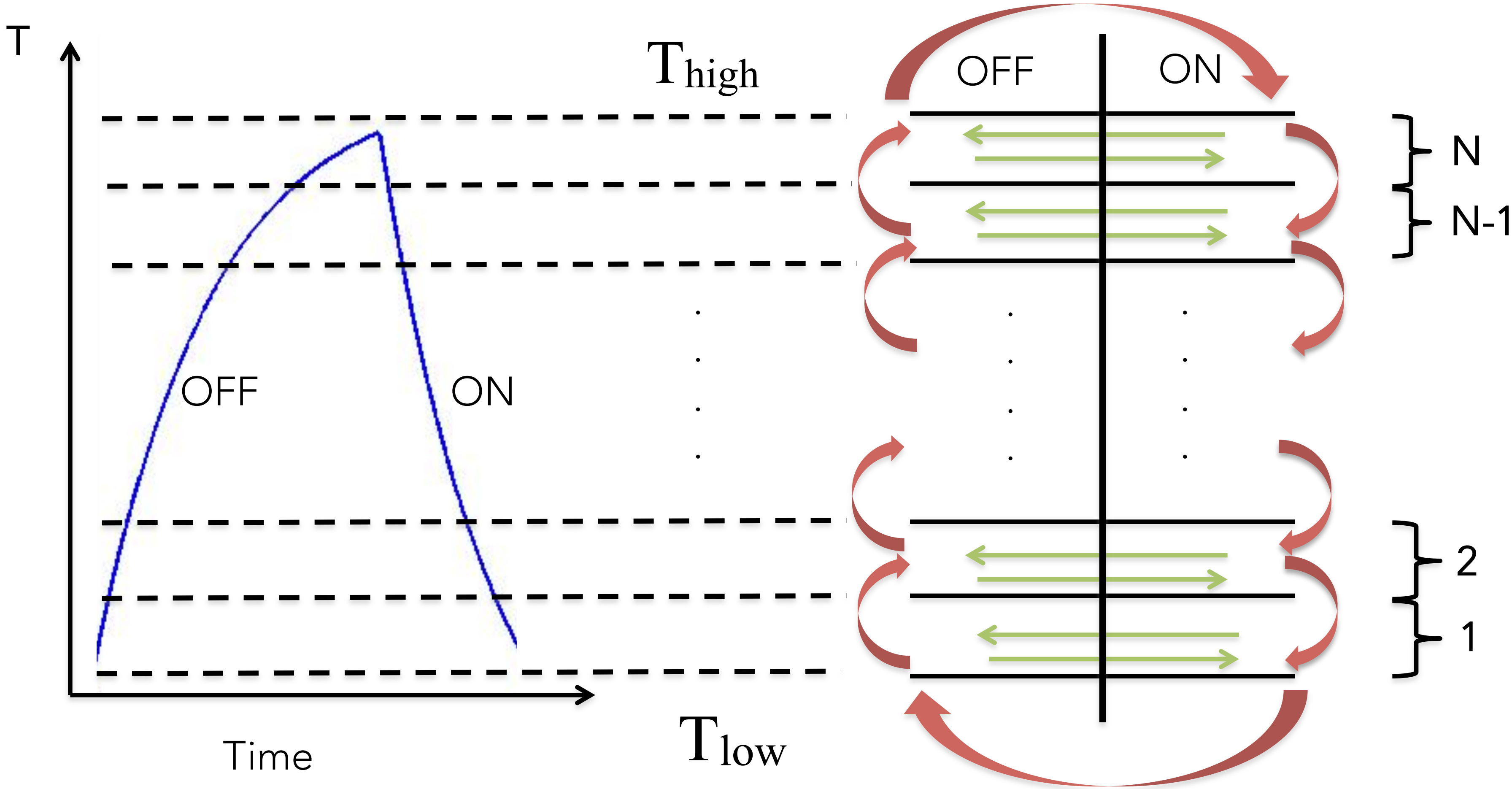


CHALLENGE #1:
STATE ESTIMATION

Population Model



Population Model



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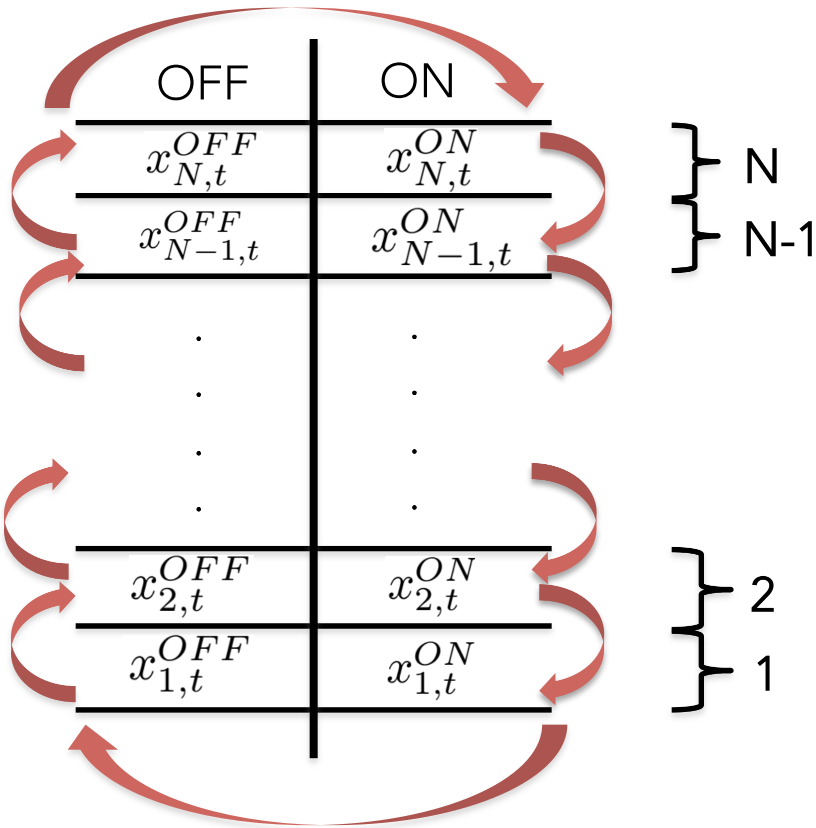
Population Model



- State Vector: Probability of being in a bin

$$X_t = [x^{ON}_{1,t}, \ldots x^{ON}_{N,t}, x^{OFF}_{1,t} \ldots x^{OFF}_{N,t}]$$

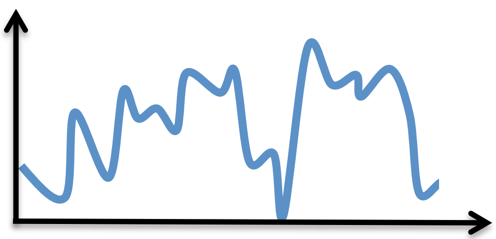
- Control Action: Switching Probabilities

$$d^0_{k,t} = \mathbf{P}\{S_{t+1} = ON | S_t = OFF, I_t = k, controller\}$$
$$d^1_{k,t} = \mathbf{P}\{S_{t+1} = OFF | S_t = ON, I_t = k, controller\}$$

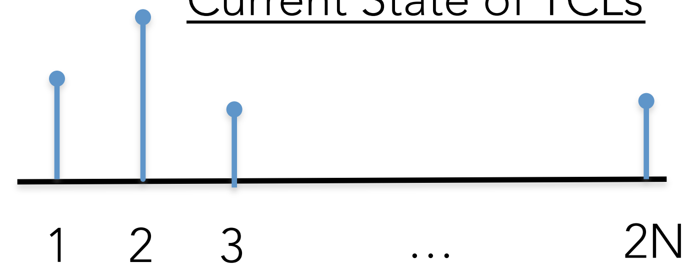
$$D_t = [d^{\xi}_{1,t}, \ldots, d^{\xi}_{N,t}]$$

State Estimation

Aggregate Power

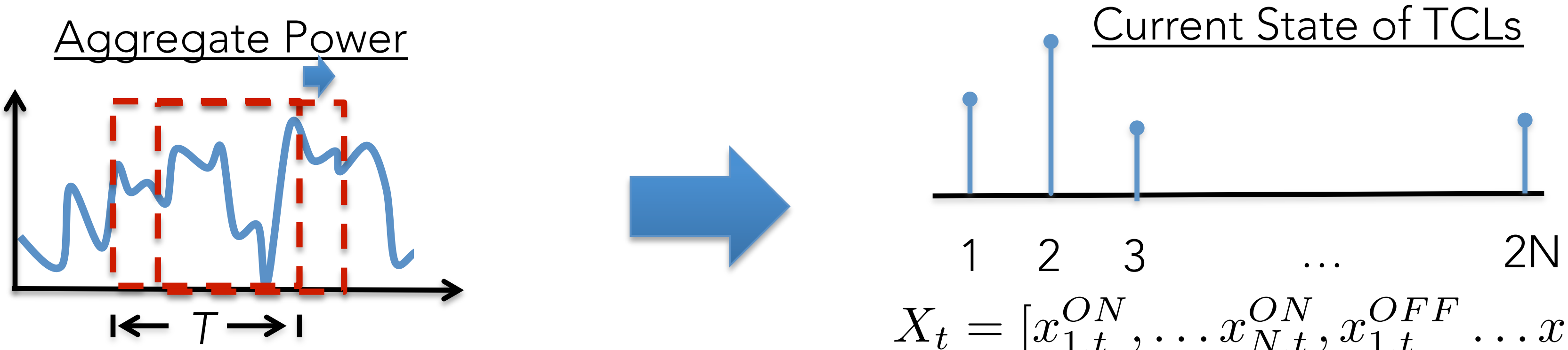


Current State of TCLs



$$X_t = [x_{1,t}^{ON}, \ldots x_{N,t}^{ON}, x_{1,t}^{OFF} \ldots x_{N,t}^{OFF}]$$

State Estimation



$$X_t = [x_{1,t}^{ON}, \ldots x_{N,t}^{ON}, x_{1,t}^{OFF} \ldots x_{N,t}^{OFF}]$$

- Using system dynamics based on Kara et al. 2012

$$X_{t+1} = \mathfrak{T}(D_t, X_t)$$

- Assume C exists such that: $Y_t = CX_t$.

$$\underset{\hat{X}_j}{\text{minimize}} \quad \sum_{t-T+1}^{t} (Y_j - \hat{Y}_j)^2$$

subject to

$$\left.\begin{aligned} &\hat{X}_j = \mathfrak{T}(\hat{X}_{j-1}, D_{j-1}) \\ &\hat{x}_{j,i}^{ON} \geq 0 \\ &\hat{x}_{j,i}^{OFF} \geq 0 \\ &\hat{X}_j \vec{1} = 1 \end{aligned}\right\} \begin{array}{l} j \in [t-T+1, t], \\ i \in [1, N] \end{array}$$

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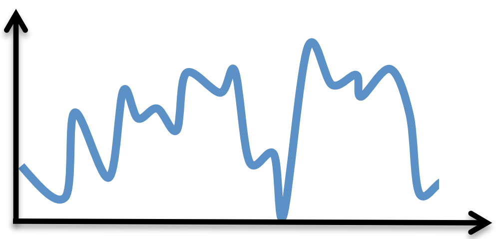
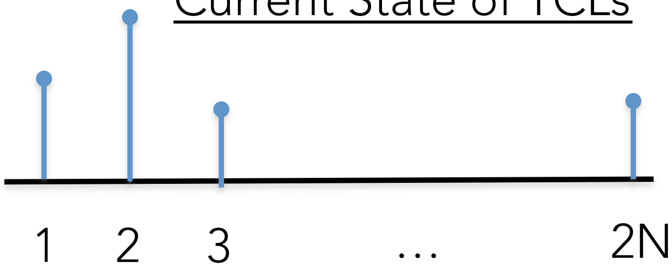
State Estimation





$$X_t = [x_{1,t}^{ON}, \ldots x_{N,t}^{ON}, x_{1,t}^{OFF} \ldots x_{N,t}^{OFF}]$$

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- Using a liner model based on Callaway et al. 2012

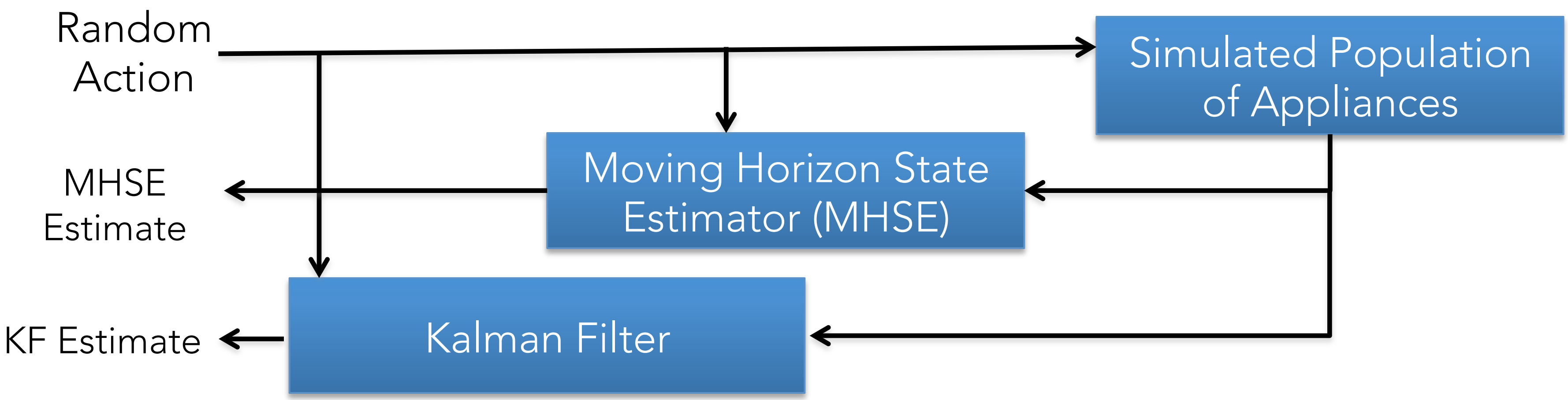
$$X_{t+1} = A_{lin} X_t + Bu_t + B_\omega \omega_t$$

$$Y_t = CX_t + v_t$$

- With perfect measurement noise and the process noise given as follows:

$$p(\omega_t) \sim N(0, Q)$$

Case Studies



Case Study I: Understand the effect of changing the time horizon T on estimation performance for MHSE

Case Specific Input	Distribution	Values
Time Horizon, *T*	Constant	10, 20, 30, 40, 50, 60 minutes

Case Study II: Compare the performances of the Kalman Filter and the MHSE under different switching conditions.

Case Specific Input	Distribution	Values
Time Horizon, *T*	Constant	40 minutes
Forcing Parameter, *f*	Constant	12.5, 25, 50, 75, 100%

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Case Studies (Cont'd)

- Simulated 500 TCLs with varying thermal characteristics and white noise on the individual appliance temperature dynamics.

Simulation Input	Distribution	Values
Capacitance	Uniform	[8-12 kWh/°C]
Resistance	Uniform	[1.5-2.5 °C/kW]
Rated Power	Uniform	[10-18 kW]
Temperature Set-point	Constant	20°C
Temperature Deadband Width	Constant	0.5°C
Ambient Temperature	Constant	32°C
Temperature Dynamics Noise	Normal	N(0,0.01)
Simulation Time Step	Constant	1 minutes
Total Estimation Duration	Constant	10 hours

- Estimator specific characteristics:

Kalman Filter	Distribution	Values
Process Noise	Normal	N(0,Q)
Measurement Noise	Constant	0

Case Studies (Cont'd)

- To quantify the information lost whe $\hat{X}_t$ is used to repres X_t:

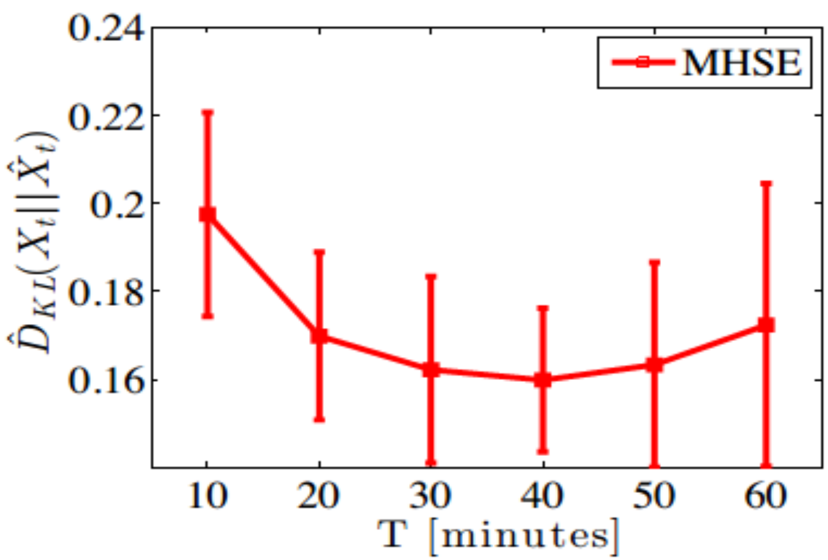
$$D_{KL}(X_t||\hat{X}_t) = \sum_{i}^{2N} \ln\left(\frac{x_{i,t}}{\hat{x}_{i,t}}\right) x_{i,t}$$

- Mean Kullback-Liebler (KL) divergence during the estimation period for each run.

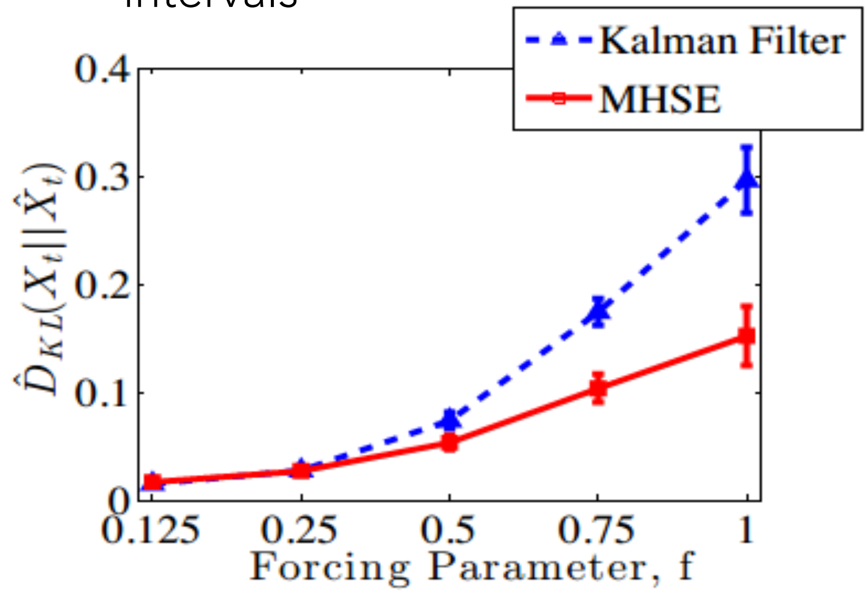
$$\hat{D}_{KL}(X_t||\hat{X}_t) = \frac{\sum_{t=0}^{T_{tot}} D_{KL}(X_t||\hat{X}_t)}{T_{tot}}$$

Results

- Case study I: 10 simulations per estimation horizon
- Showing 95% confidence intervals



- Case study II: 10 simulations per forcing parameter, *f*
- Showing 95% confidence intervals



CHALLENGE #2: DEVIATIONS FROM LINEAR ASSUMPTIONS

Back to the assumptions

- Simulated 500 TCLs with varying thermal characteristics and white noise on the individual appliance temperature dynamics.

Simulation Input	Distribution	Values
Capacitance	Uniform	[8-12 kWh/°C]
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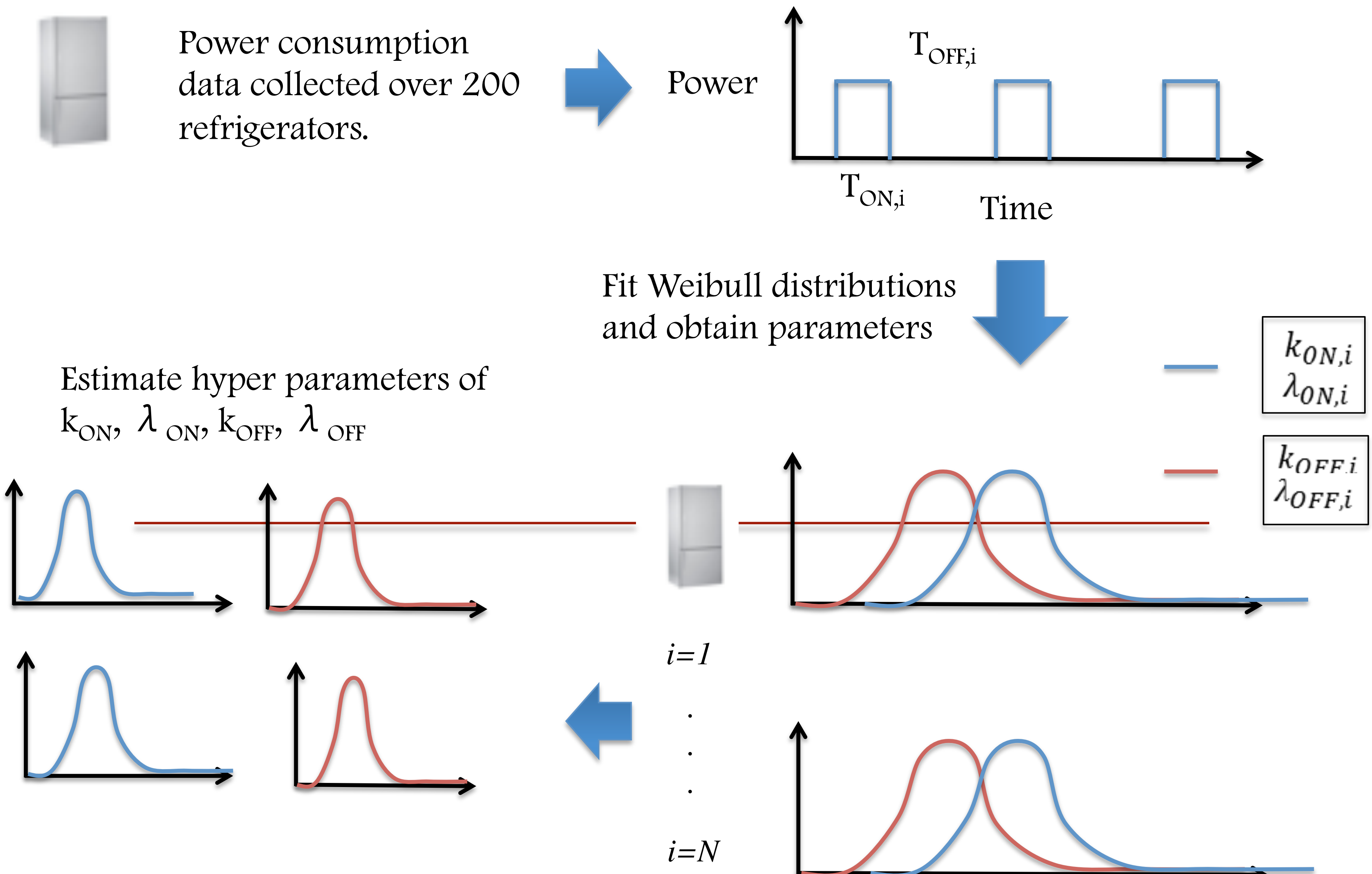
- Estimator specific characteristics:

Kalman Filter	Distribution	Values
Process Noise	Normal	N(0,Q)
Measurement Noise	Constant	0


Power consumption data collected over 200 refrigerators.
Power
$T_{OFF,i}$
$T_{ON,i}$
Time
Fit Weibull distributions and obtain parameters
$k_{ON,i}$
$\lambda_{ON,i}$
$k_{OFF,i}$
$\lambda_{OFF,i}$
Estimate hyper parameters of k_{ON}, λ_{ON}, k_{OFF}, λ_{OFF}
i=1
.
.
.
i=N

Parameter	Distribution	Range
Thermal Resistance, R_i(°C/kW)	Uniform	80~100
Thermal Capacitance, C_i(kWh/°C)	Uniform	0.4~0.8
Rated Power, $P_{rated,i}$ (kW)	Uniform	0.2~1.0
Ambient Temperature, $\Theta_{i,a}$ (°C)	Constant	20
Thermostatic dead-band, δ_i (°C)	Uniform	1~2
Temperature set point, $\Theta_{i,set}$ (°C)	Uniform	1.7~3.3

$$\hat{c}_{v,R} = s_R/\bar{R} \qquad \hat{c}_{v,R} = s_C/\bar{C}$$

Population	$\bar{R}$ (°C/kW)	$\bar{C}$ (kWh/°C)	s_R (°C/kW)	s_C (kWh/°C)	$\hat{c}_{v,R}$	$\hat{c}_{v,C}$
P1	419.41	0.07	9205.7	0.07	**21**	**1**
P2	90.00	0.60	175.76	0.12	**0.06**	**0.19**

References

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Acknowledgments

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The End

QUESTIONS?

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INFERLab

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