Control of distributed electric water heaters for ancillary services provision in the power grid

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Master Thesis Presentation, April 2015

- Thermostatically Controlled Loads (TCLs) controlled as single entity for aggregate power purposes
  - Load Management
- Programmable Communicating Thermostats (PCTs) introduced
  - system operators will have ability to control TCLs by manipulating thermostat set-points

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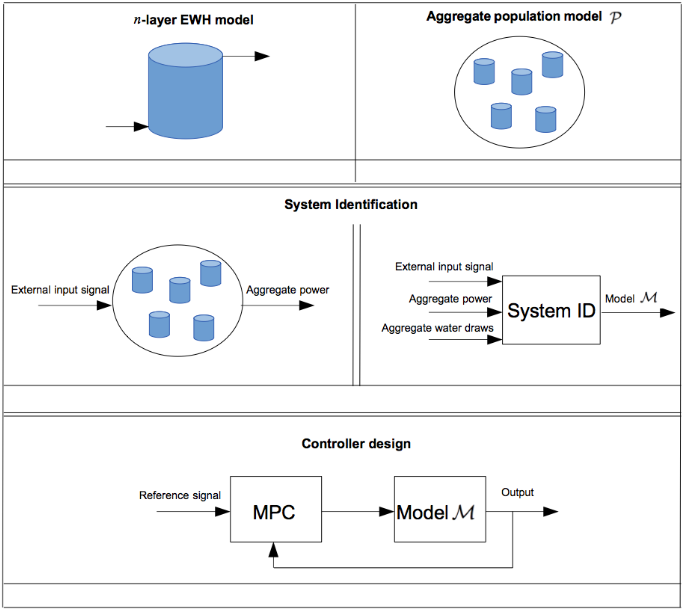

- Model for an **individual** EWH from Vrettos et al. [1]
  - *n*-temperature layers
  - models natural convection and conduction
  - accurate and computationally efficient

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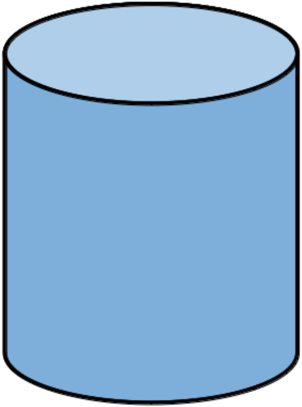
Individual Electric Water Heater model



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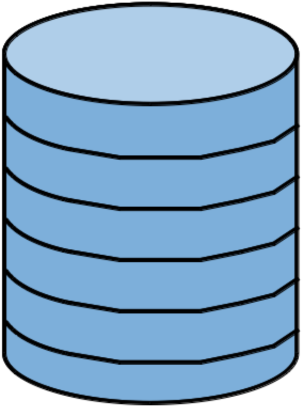

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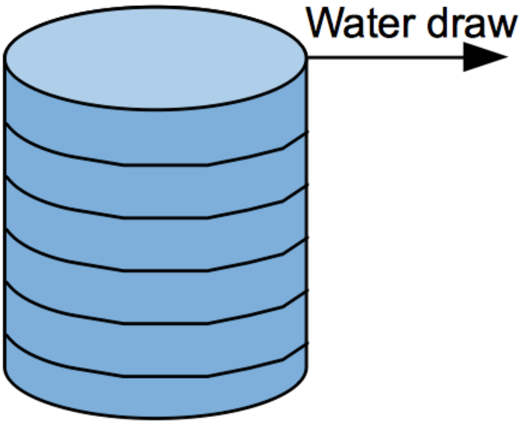
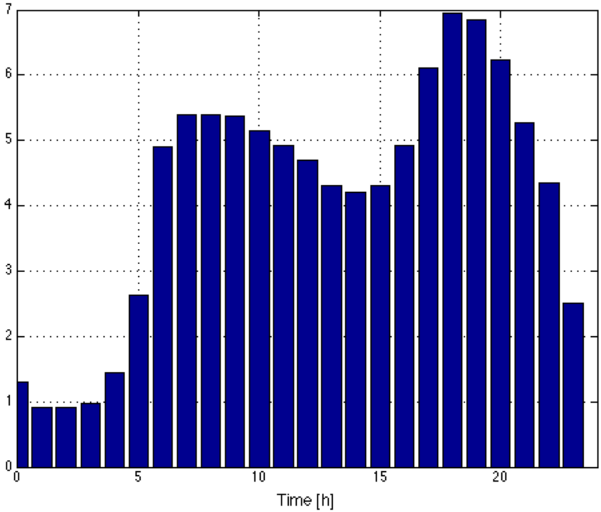


- **Probability of water draw** (in %)



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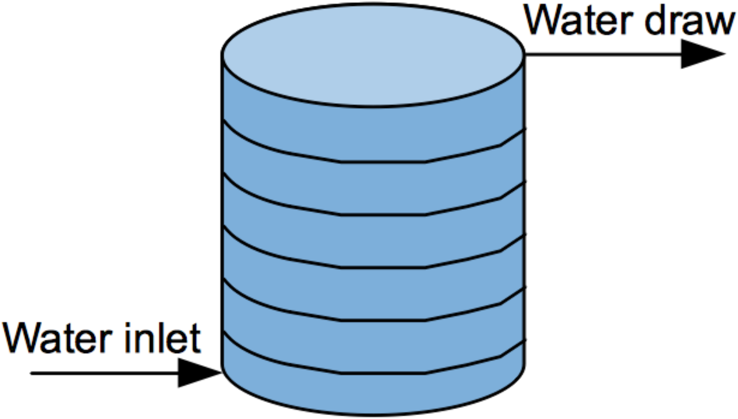

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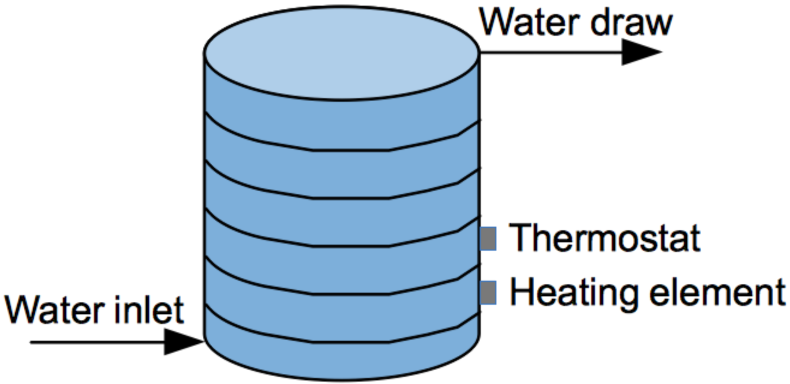

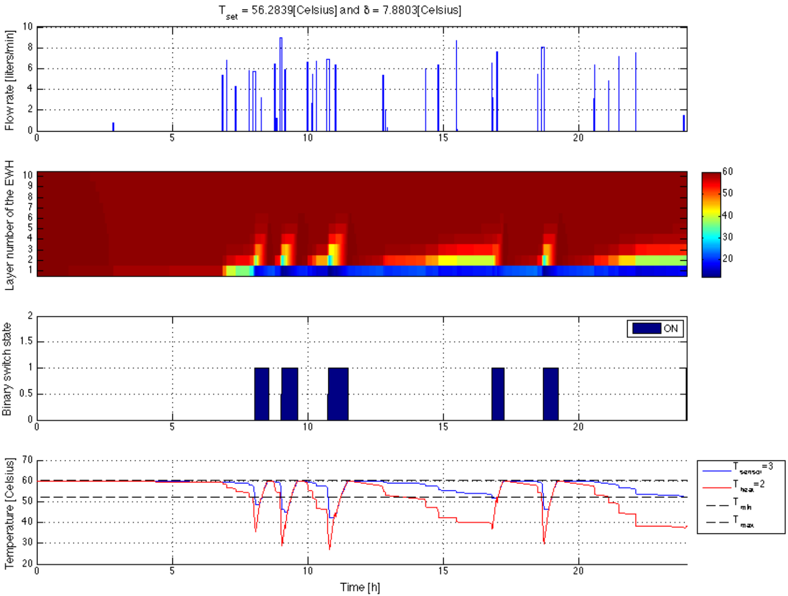
T_set = 56.2839[Celsius] and δ = 7.8803[Celsius]
Flow rate [liters/min]
Layer number of the EWH
Binary switch state
ON
Temperature [Celsius]
T_sensor=3
T_heat=2
T_min
T_max
Time [h]

Parameter selection

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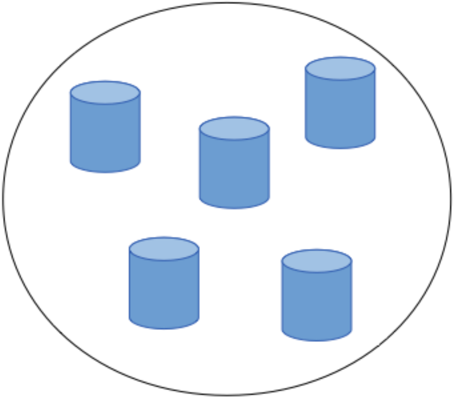

- Population of EWHs with N_{app} loads
- Homogeneous versus **Heterogeneous** population
- Construct population by varying:
  - volume of the tank
  - power consumption
  - deadband and set-point temperatures
  - thermal loss coefficient

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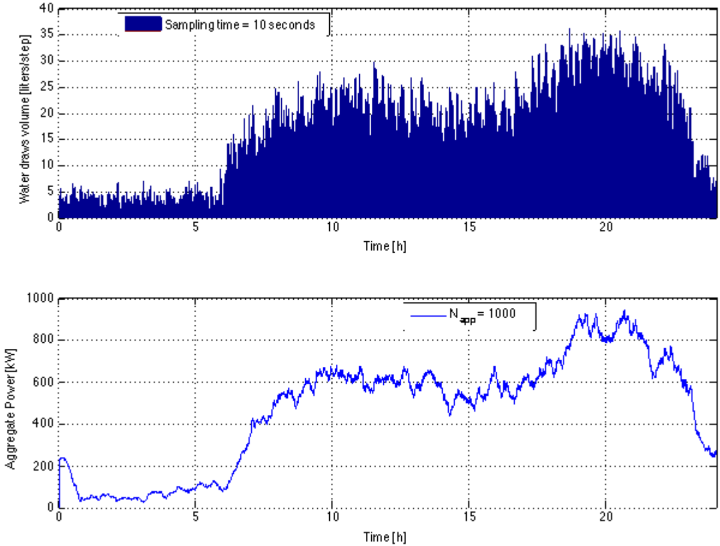
- Simulation for 1 day for population of $N_{\text{app}} = 1000$ EWHs:



- Thermostats automatically switch EWHs ON or OFF
- Look at **autonomous case**
  - no grid operator involved
  - baseline consumption produced

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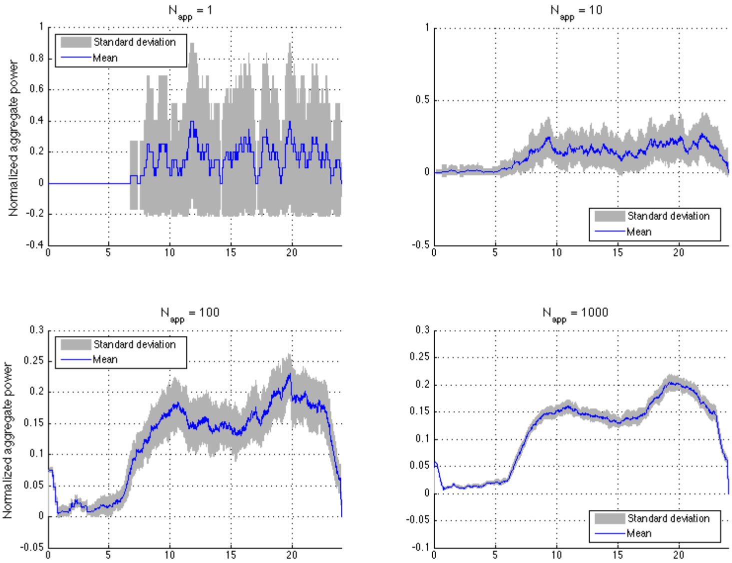
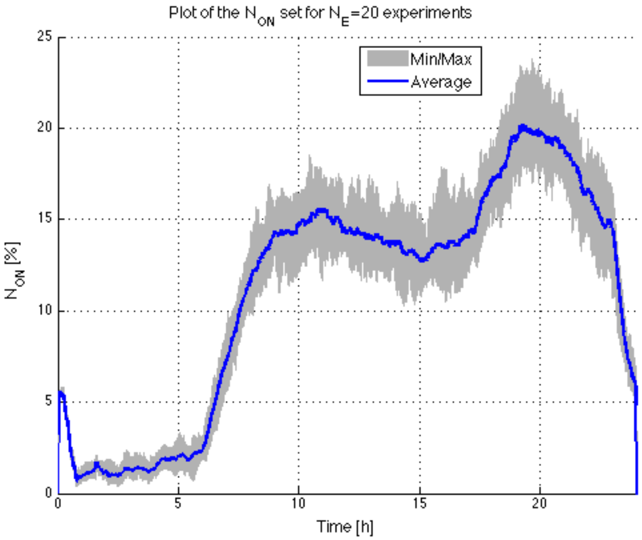
Baseline consumption



Baseline consumption



- From now on take $N_{\text{app}} = 1000$
- Baseline has maximum of 25 % of EWHs in ON state during all day

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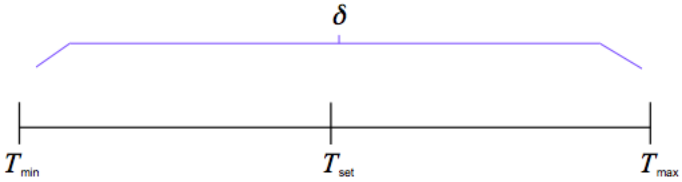
- **All** EWHs *increase* (if $\hat{u} > 0$) or *decrease* (if $\hat{u} < 0$) their temperature set-point by $100 \cdot \hat{u}\,\%$ of their deadband temperature

Temperature set-point variation



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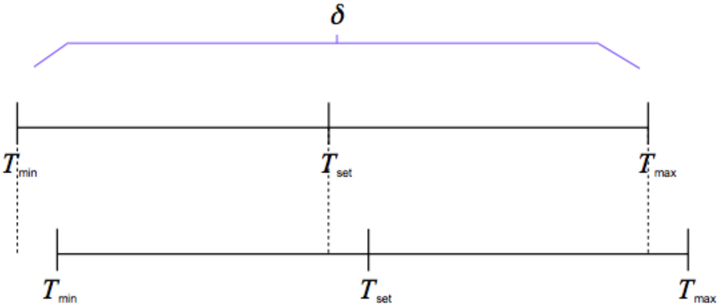
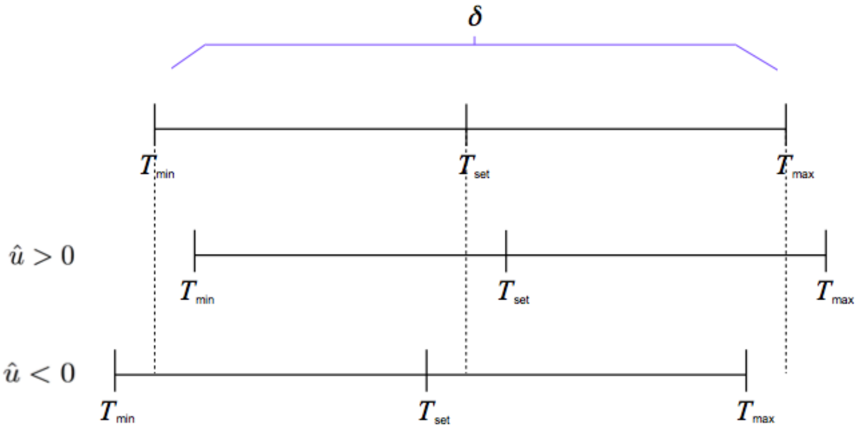


$\hat{u} > 0$

Temperature set-point variation



- Define the signals needed for System Identification
- $\{\hat{u}, \tilde{y}, w^{\text{ave}}\}$

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- Temperature set-point variation $\hat{u}$
- % of deabdand that is added/substracted to the set-point temperature **for all** devices

- Normalized aggregate power deviation $\tilde{y}$:

$$\tilde{y} \doteq \frac{y_{\text{measured}} - y_{\text{baseline}}^{\text{ave}}}{\sum_{\vartheta=1}^{N_{\text{app}}} \frac{P_{\text{el}}^{\vartheta}}{\eta}}$$

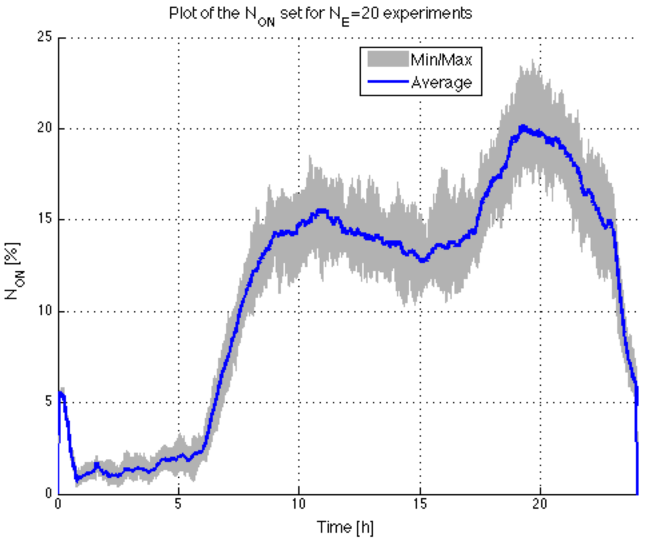
- **Note**: baseline signal $y_{\text{baseline}}^{\text{ave}}$ computed *offline*

- Averaged water draw profile w^{ave}:

$$w^{\text{ave}}(k) = \frac{1}{N_E}\sum_{i=1}^{N_E} w_i(k)$$

- **Note**: this signal is computed *offline*

System properties



- **Linearity**
  - 130 samples with $\hat{u}_1, \hat{u}_2 \sim \mathrm{Unif}\left(0.2, 0.45\right)$, with $\hat{u}_1 > 0, \hat{u}_2 > 0$
  - Evaluate if $\tilde{y}\left(\hat{u}_1 + \hat{u}_2\right) = \tilde{y}\left(\hat{u}_1\right) + \tilde{y}\left(\hat{u}_2\right)$ for linearity

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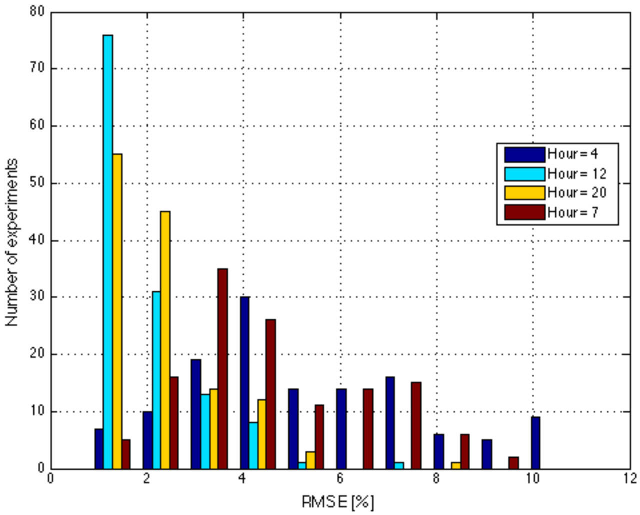
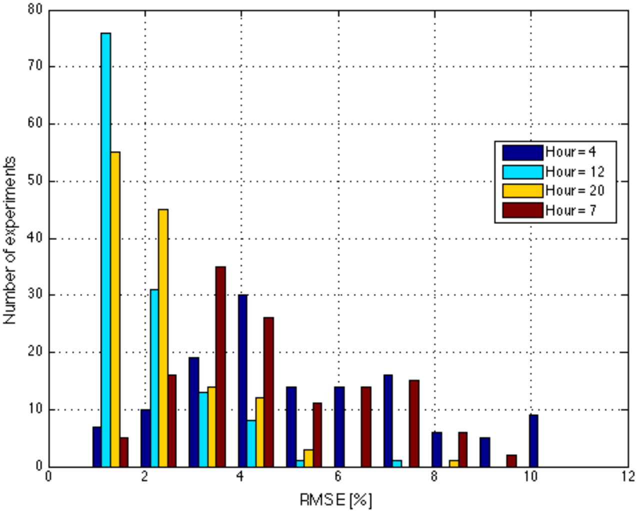


- Hours $\{4, 7\}$ perform much worse than $\{12, 20\}$



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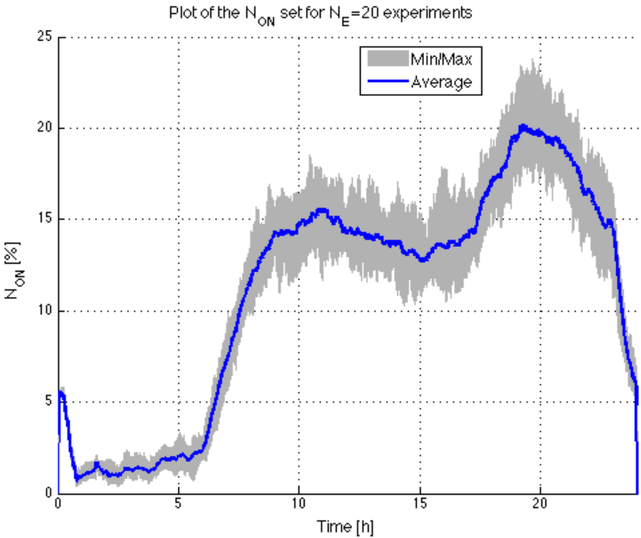
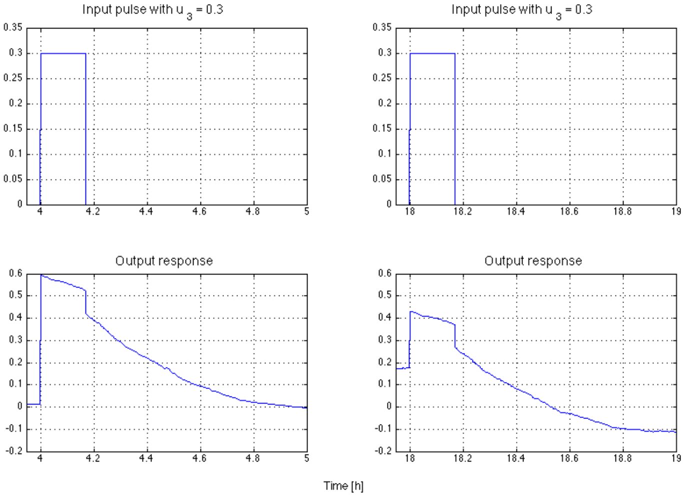


- **Time-invariance** input pulses with $\hat{u} = 0.3$



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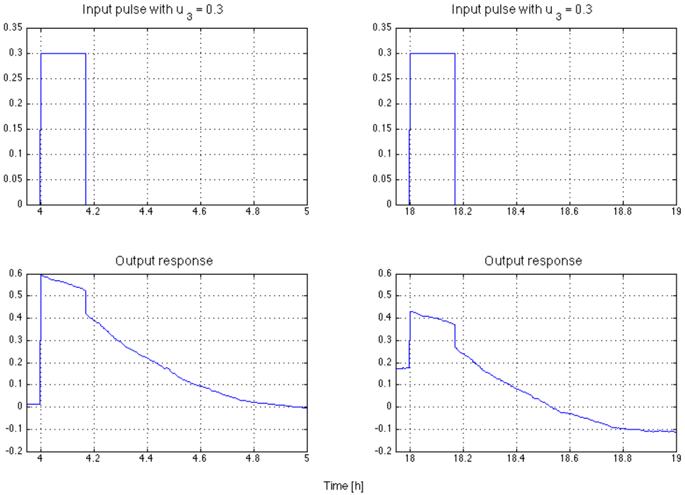

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ARMAX model structure

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$$A(z)\,\tilde{y}(k) = B_1(z)\,\hat{u}(k) + B_2(z)\,w^{\text{ave}}(k) + C(z)\,e(k)$$

- Parameter vector:

$$\theta \doteq \left[a_1, \ldots, a_n, b_1, \ldots, b_m, \bar{b}_1, \ldots, \bar{b}_{\bar{m}}, c_1, \ldots, c_q\right]^T$$

- Predictor:

$$\hat{y}(k|\theta) = \varphi^T(k,\theta) \cdot \theta$$

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- Create *experimental* and *validation* data-sets through simulations

$$\{\tilde{y}, \hat{u}, w^{\mathrm{ave}}\}$$

- Select orders of the ARMAX model

$$[n, m, \bar{m}, q] = [4, 4, 4, 1]$$

- Time dependency $\rightarrow$ hourly models

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- Sample pulse inputs with uniform distribution and get *experimental* and *validation* data-sets

h_{start}	$\hat{u}_+$		$\hat{u}_-$	
	μ fit [%]	σ fit [%]	μ fit [%]	σ fit [%]
4	64.4381	19.7403	26.203	23.8297
7	68.4144	11.238	55.9121	19.4455
12	75.1791	10.1283	60.8689	15.5004
16	74.7440	10.1256	52.4389	22.5337
18	74.1694	9.2298	56.9006	20.6073
20	77.6904	8.1194	60.7367	19.1827
22	73.1659	10.2441	49.4251	27.5658

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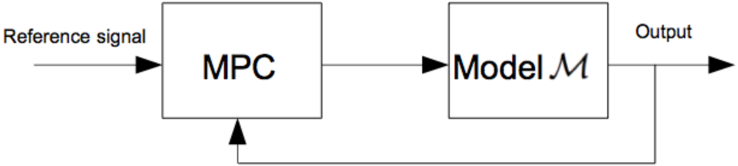
Controller design



- Cost function for **tracking** P^{ref}:

$$x_N^T P x_N + \sum_{k=0}^{N-1} \left\| \tilde{y}(k) - P^{\mathrm{ref}}(k) \right\|_2^2$$

- Sequential Convex Quadratic Program for Model Predictive Controller:
(SCQP for MPC)

$$
\begin{aligned}
\min_{\tilde{z}} \quad & \tilde{z}^T \tilde{Q} \tilde{z} + \tilde{R}^T \tilde{z} + \sum_{k=0}^{N-1} \alpha_k \\
\text{s.t.} \quad & A_{eq} \cdot \tilde{z} = b_{eq} \\
& lb \leq \tilde{z} \leq ub
\end{aligned}
$$

- Use prediction horizon of $N = 30$ steps (5 minutes)

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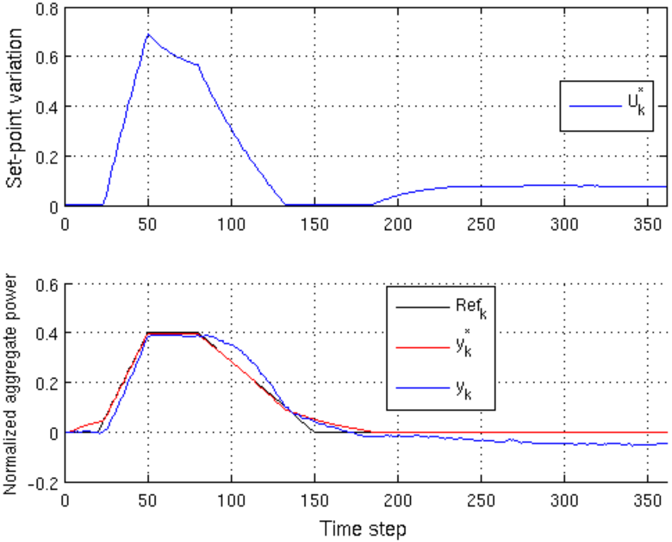
- Model $\mathcal{M}_{16}^{+}$ with $[\hat{u}_{\min}, \hat{u}_{\max}] \doteq [0, 0.95]$



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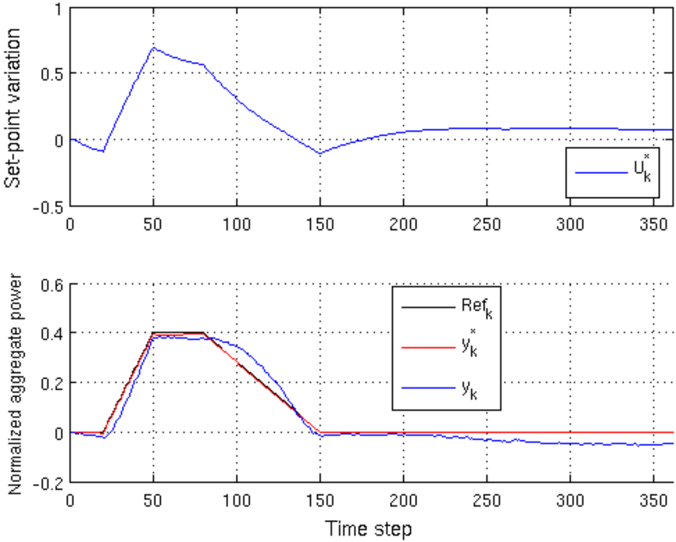

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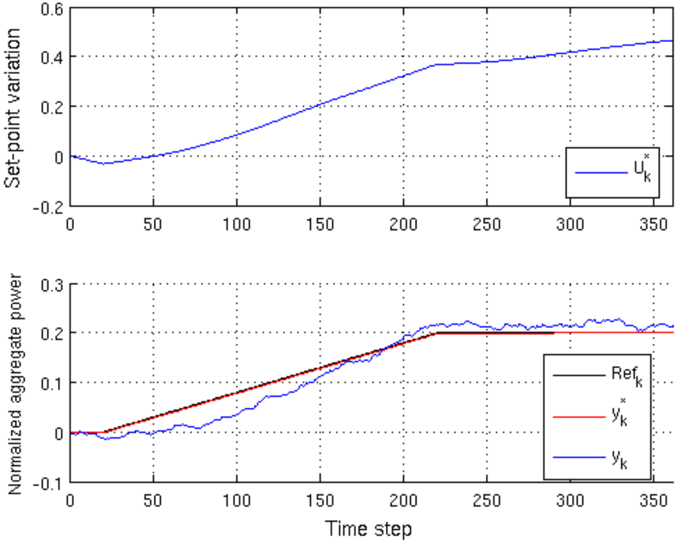

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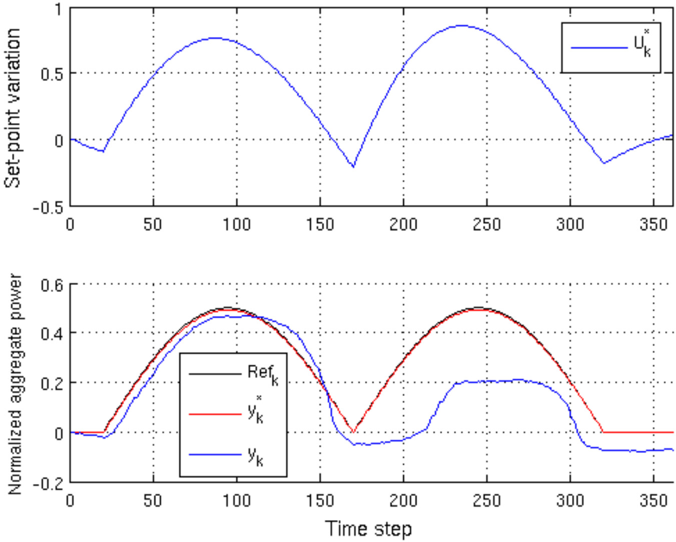

- **Conclusions**
  - Linearity and controllability can be assumed only for **certain hours** of the day
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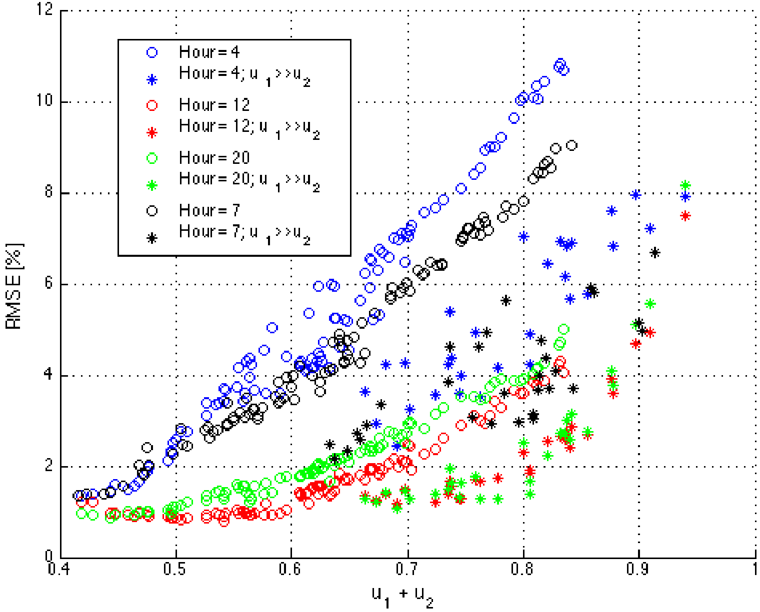
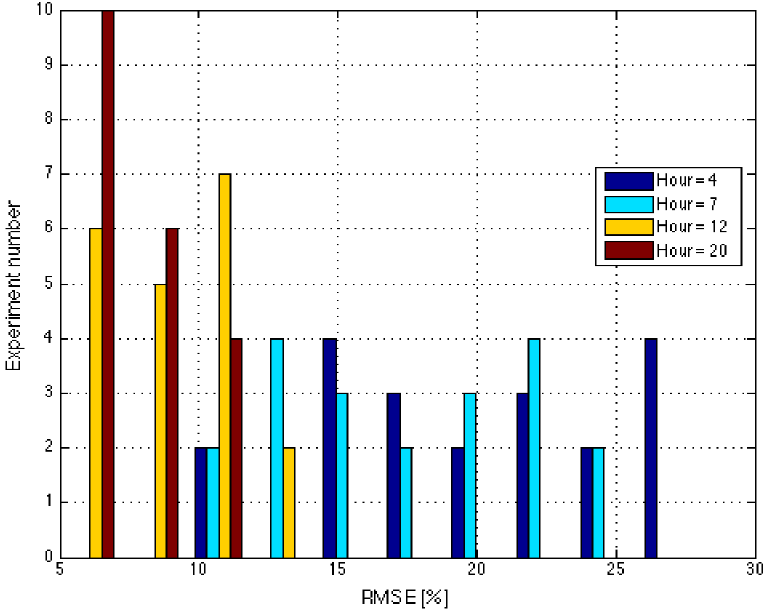
E. Vrettos, S. Koch, and G. Andersson.
Load frequency control by aggre- gations of thermally stratified electric water heaters.
IEEE PES Innovative Smart Grid Technologies Conference Europe, pp. 1–8, 2012.

- **Extra slides**


Hour = 4
Hour = 4; u 1 >> u 2
Hour = 12
Hour = 12; u 1 >> u 2
Hour = 20
Hour = 20; u 1 >> u 2
Hour = 7
Hour = 7; u 1 >> u 2
RMSE [%]
u 1 + u 2
0
2
4
6
8
10
12
0.4
0.5
0.6
0.7
0.8
0.9
1

- **Experiment 2**
  - Sample $\hat{u}_1, \hat{u}_2$, with $\hat{u}_2 = -\hat{u}_1$
  - Evaluate if $\tilde{y}\left(\hat{u}_1 + \hat{u}_2\right) = \tilde{y}\left(\hat{u}_1\right) + \tilde{y}\left(\hat{u}_2\right)$ for additivity

Previous Work



- Hours $\{4, 7\}$ are much worse than $\{12, 20\}$
- Lower RMSE if $\hat{u}_1 \gg \hat{u}_2$
- If $\hat{u}_1 + \hat{u}_2 = 0$, then do not expect $\tilde{y}(\hat{u}_1 + \hat{u}_2) \neq 0$
  - because of baseline signal levels

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- Without signal w^{ave}:

$h_{\mathbf{start}}$	$\hat{u}_+$		$\hat{u}_-$	
	μ fit [%]	σ fit [%]	μ fit [%]	σ fit [%]
4	53.6127	18.9433	26.9027	23.3065
7	62.9294	14.5207	54.9051	16.7200
12	72.7326	10.1333	58.8198	13.5585
16	74.2262	9.5457	51.4375	23.1314
18	74.4609	8.8512	54.1234	17.9858
20	66.4757	9.0371	58.4155	18.0240
22	73.6999	8.9560	-18.4136	24.0030

Table : Fit of the models ARMAX to the validation data

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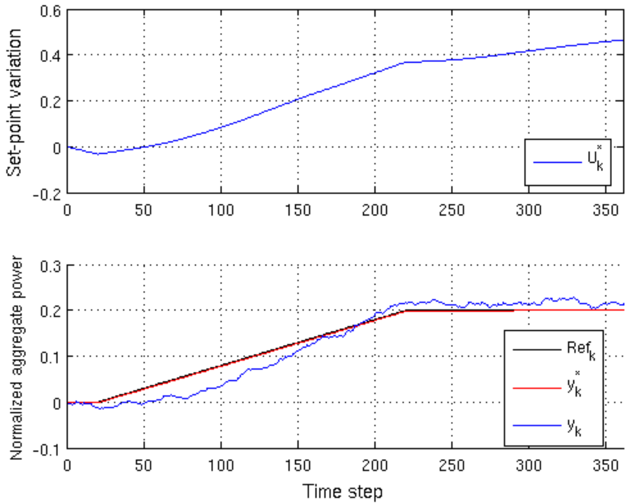

- Model $\mathcal{M}_{20}^{+}$ with $[\hat{u}_{\min}, \hat{u}_{\max}] \doteq [-0.95, 0.95]$