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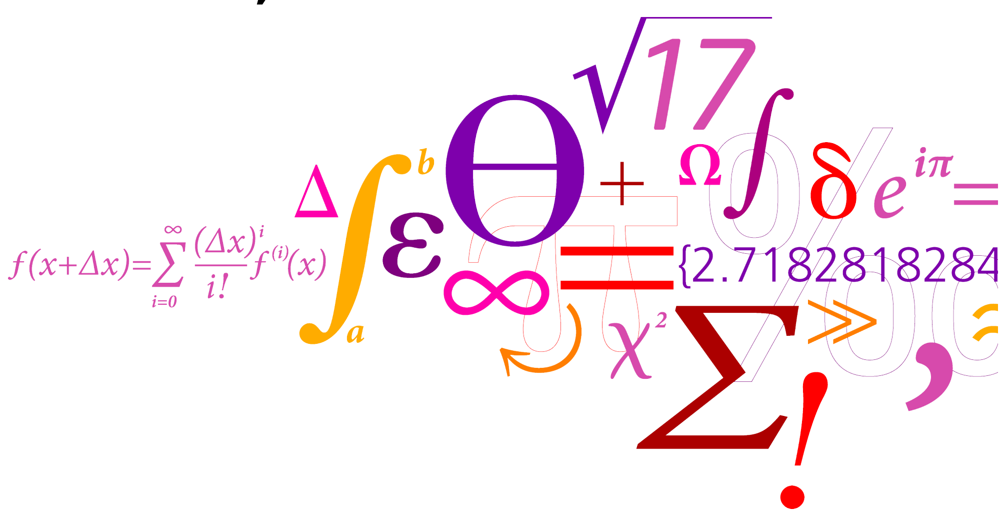
Methods for using online and spatial data for energy systems

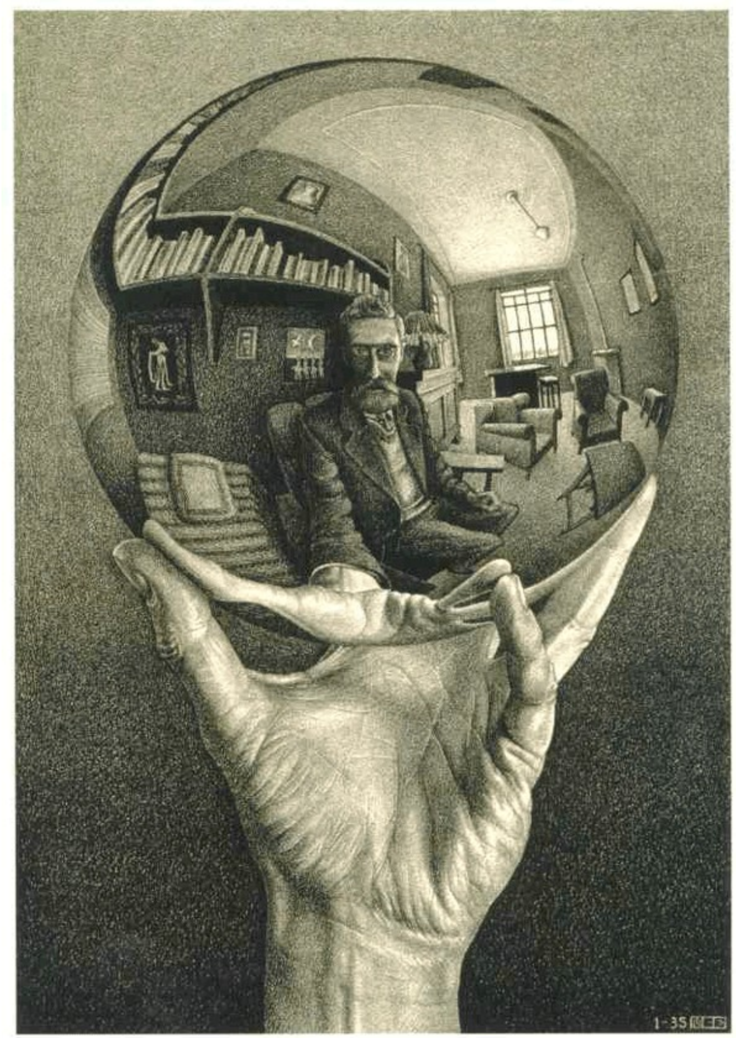
JRC Workshop: Methodologies for energy performance assessment based on location data,
Ispra, September 2016

Henrik Madsen,
www.henrikmadsen.org



DTU Compute
Department of Applied Mathematics and Computer Science

Contents



- A single sensor (smart meter) (UA, ..)
- Several sensors (dyn.)
- Occupancy behavior modeling
- Modeling and operation of DH systems
- Price-based control in smart grids

In all cases location/MET data is used

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Part 1
Simple non-parametric methods

Typically only data from smart meter (and a nearby existing MET station)

Case Study No. 1

Split of total readings into space heating and domestic hot water using data from smart meters

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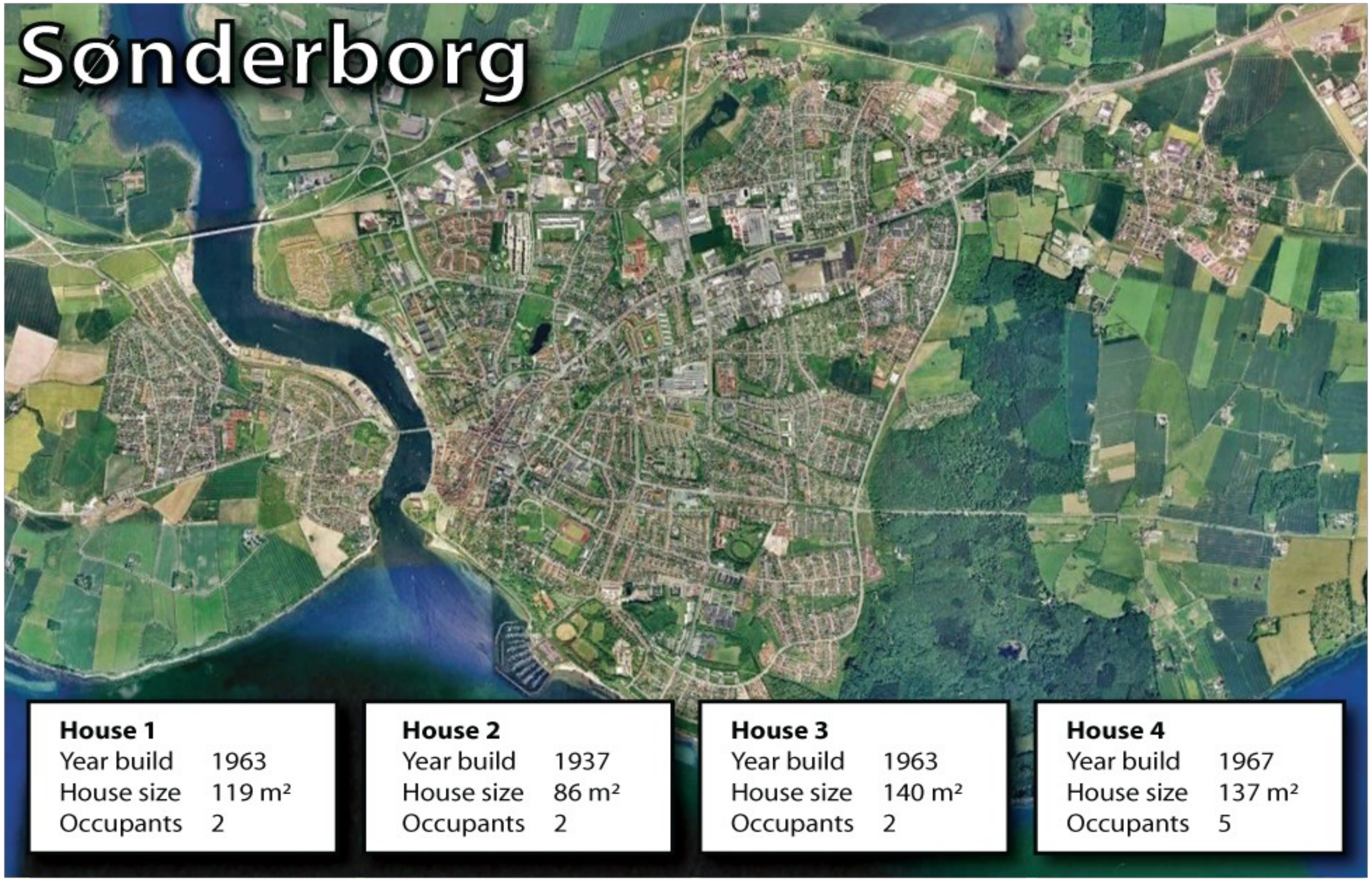
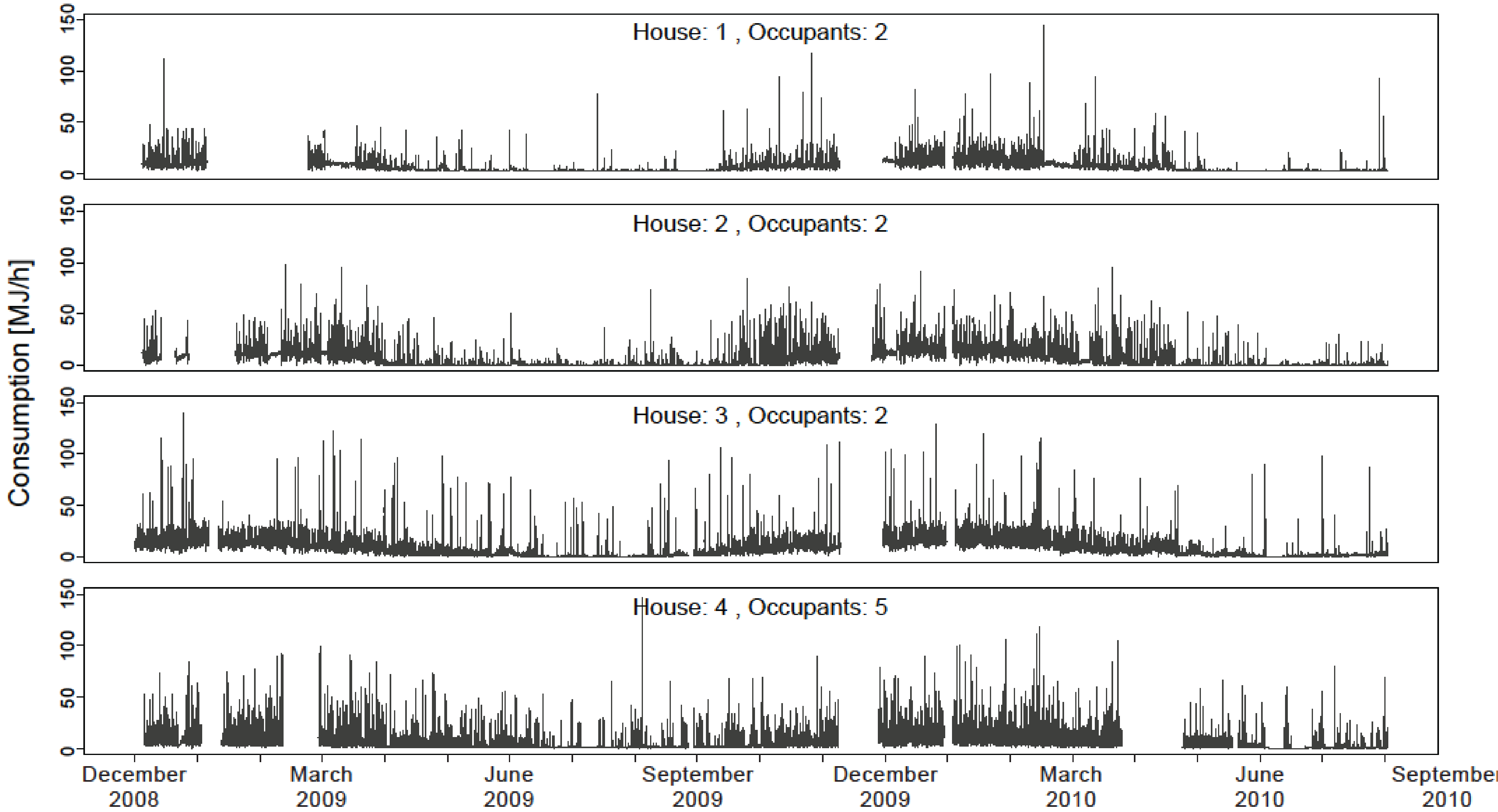
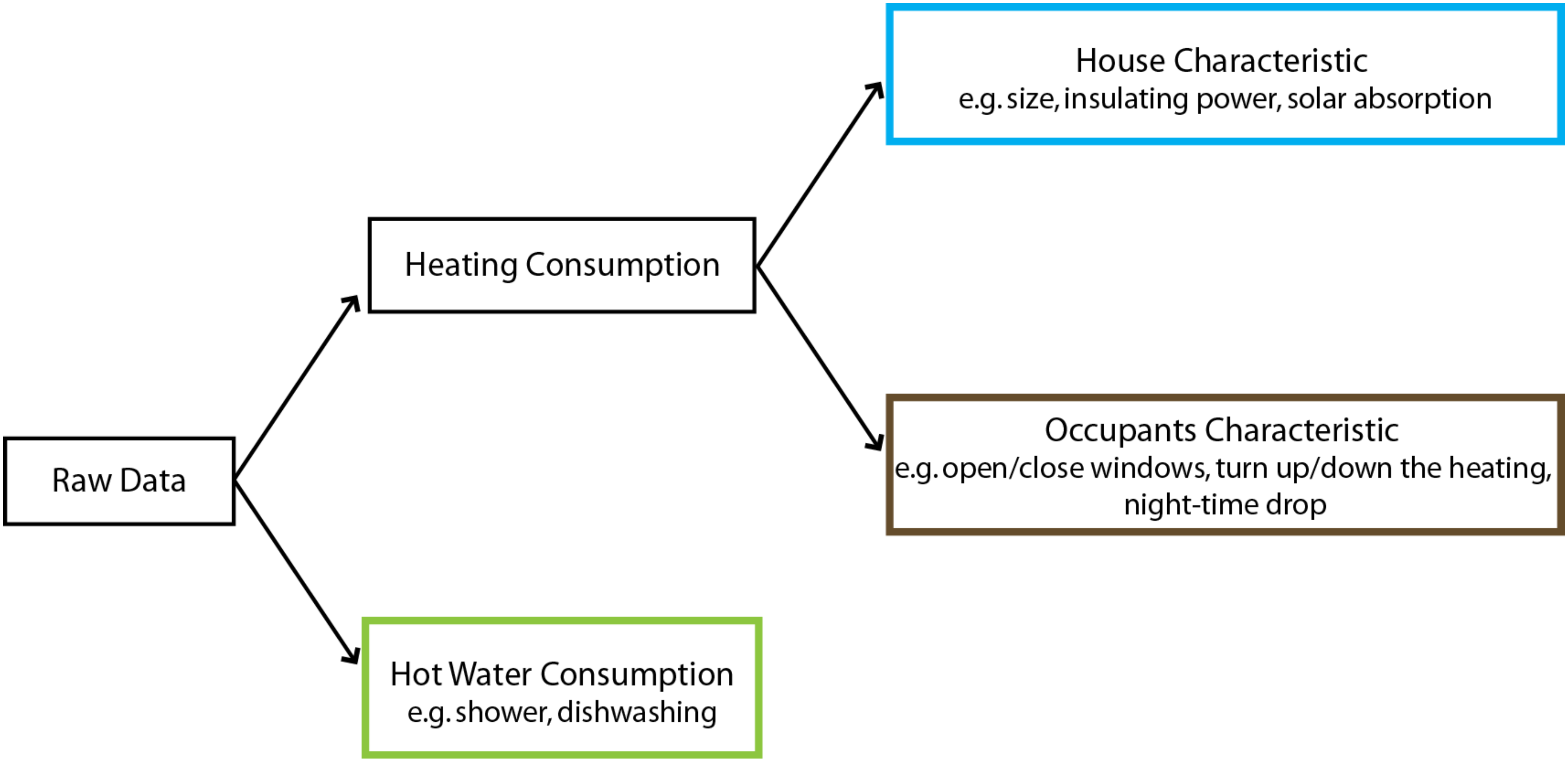
Data

- 10 min averages from a number of houses

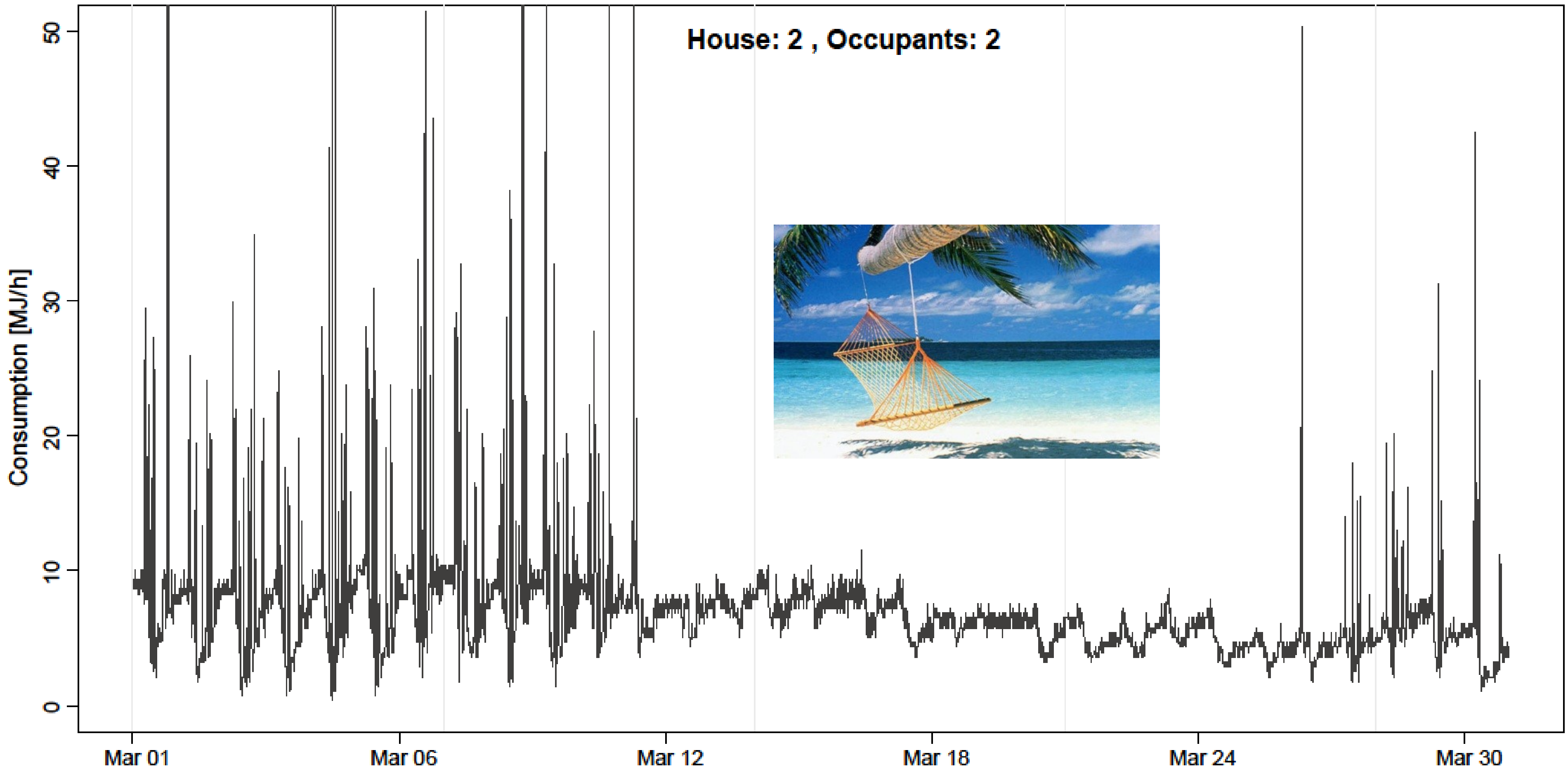



House: 1 , Occupants: 2
House: 2 , Occupants: 2
House: 3 , Occupants: 2
House: 4 , Occupants: 5
Consumption [MJ/h]
0
50
100
150
December 2008
March 2009
June 2009
September 2009
December 2009
March 2010
June 2010
September 2010

Splitting of total meter readings



Holiday period



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Robust Polynomial Kernel

To improve the kernel method

Rewrite the kernel smoother to a Least Square Problem

$$\arg\min_{\theta} \frac{1}{N} \sum_{s=1}^{N} w_s(x) \left(Y_s - \theta\right)^2 \qquad w_s(x) = \frac{k\{x - X_s\}}{\frac{1}{N}\sum_{s=1}^{N} k\{x - X_s\}}$$

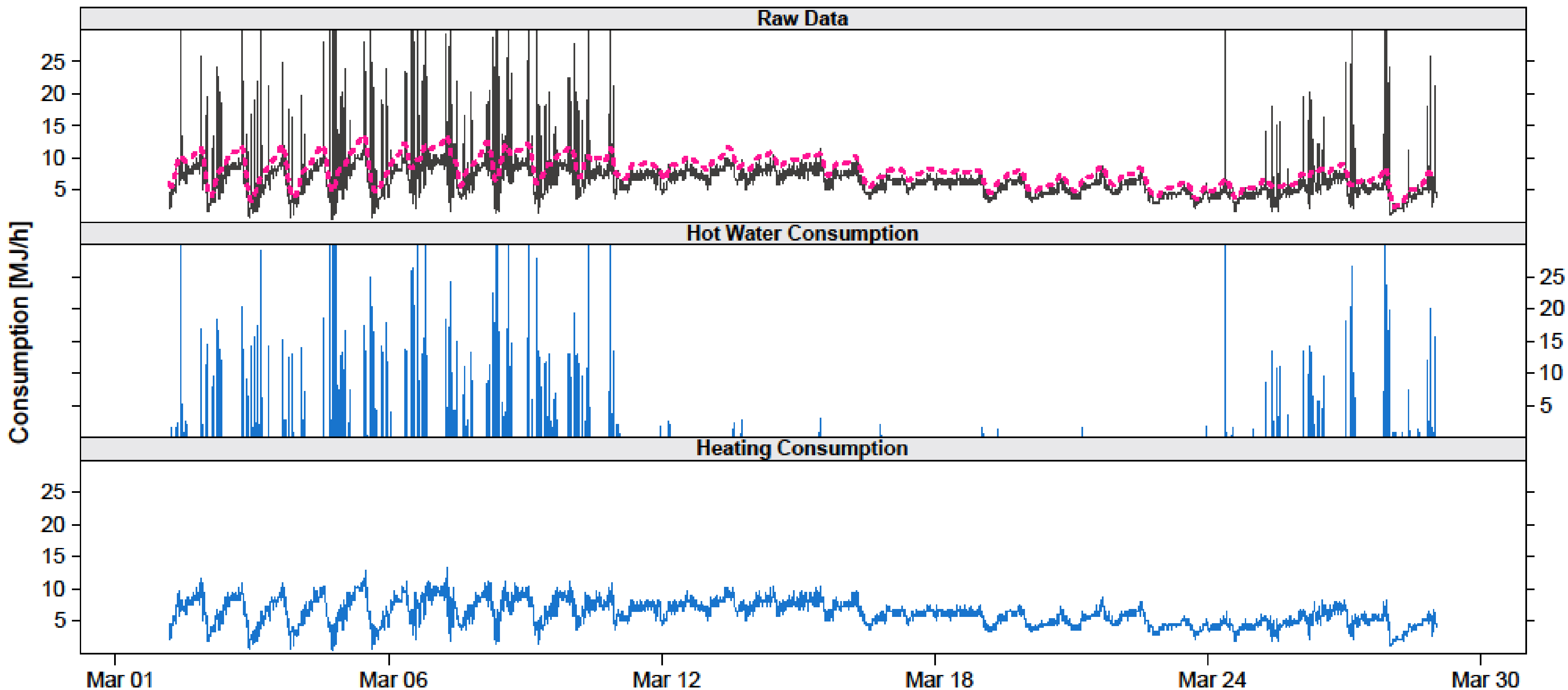
Make the method robust by replacing $(Y_s - \theta)^2$ with

$$\rho_{\text{Huber}}(\varepsilon) = \begin{cases} \frac{1}{2\gamma}\varepsilon^2 & \text{if } |\varepsilon| \le \gamma \\ |\varepsilon| - \frac{1}{2}\gamma & \text{if } |\varepsilon| > \gamma \end{cases} \qquad \varepsilon_s = Y_s - \theta$$

Make the method polynomial by replacing θ with

$$P_s = \theta_0 + \theta_1(X_t - x) + \theta_2(X_t - x)^2$$

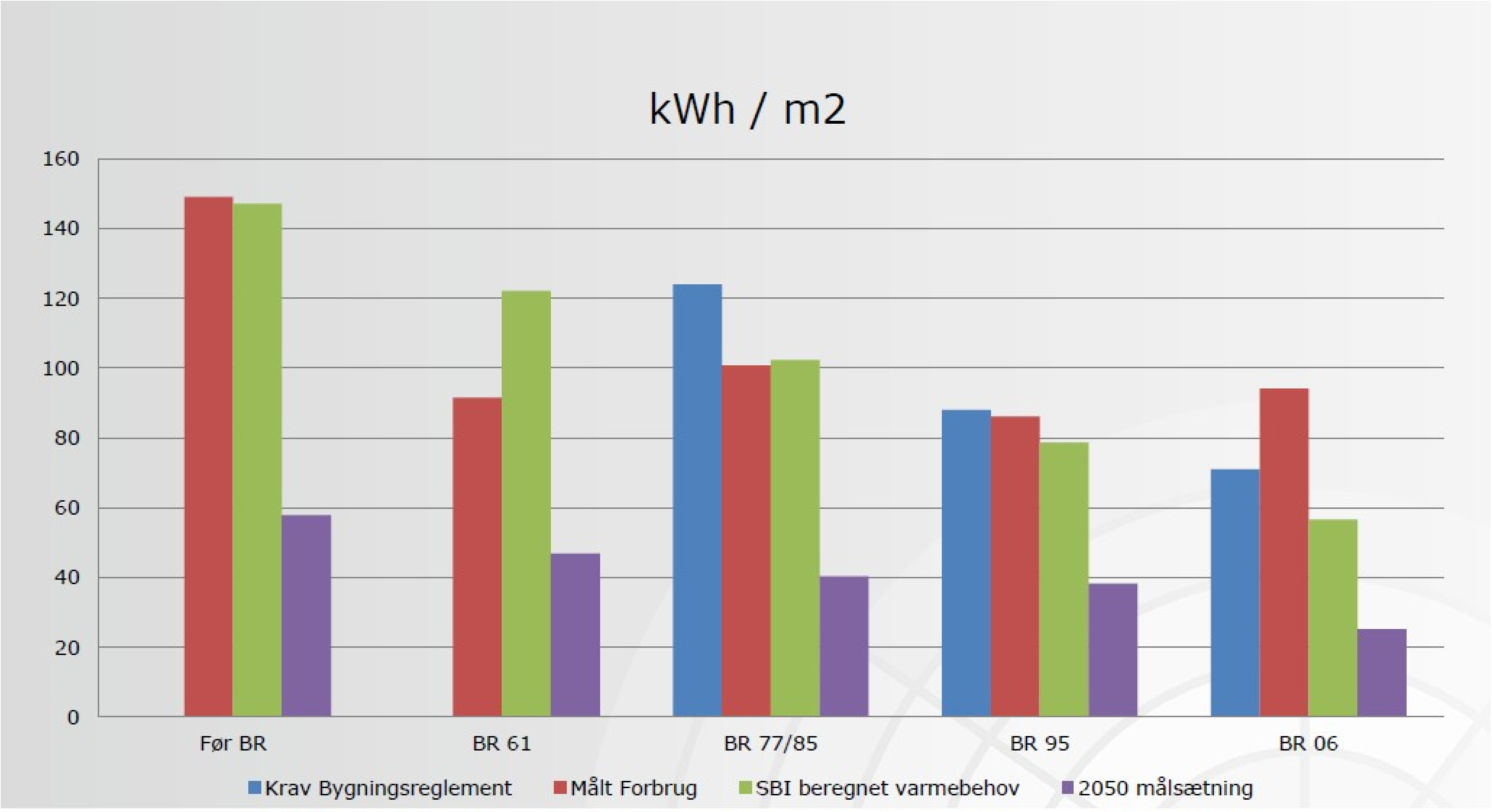
Robust Polynomial Kernel



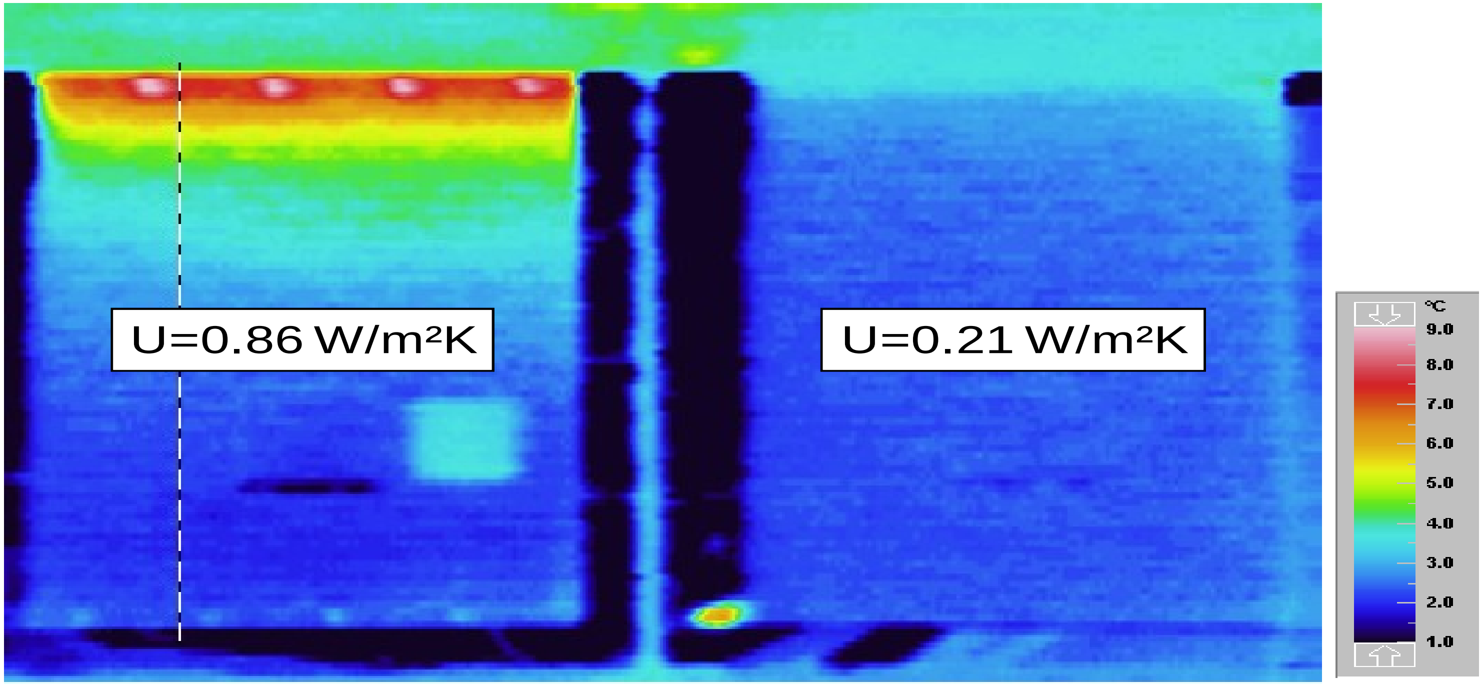
Case Study No. 2

Modelling of Thermal Performance using Smart Meter Data

Energy consumption in DK



Example



Consequence of good or bad workmanship (theoretical value is U=0.16W/m2K)

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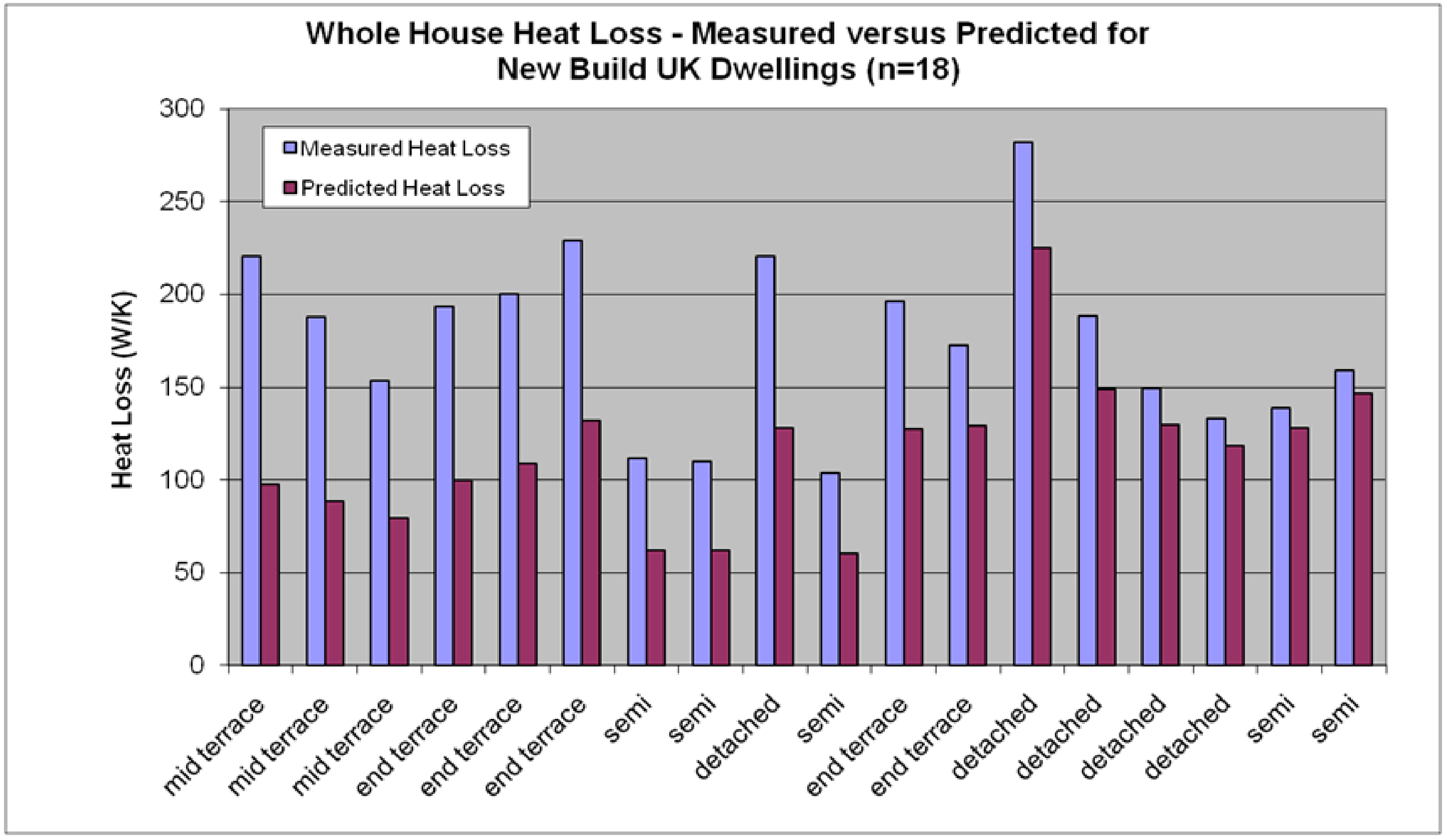
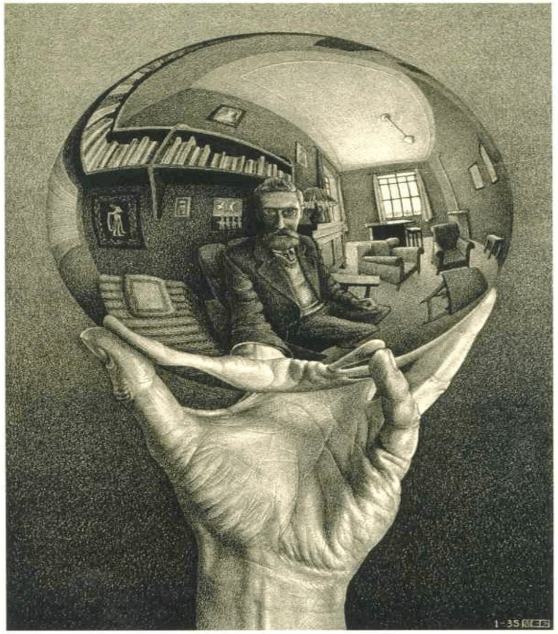
Examples (2)



Measured versus predicted energy consumption for different dwellings

Characterization using Data from Smart Meters



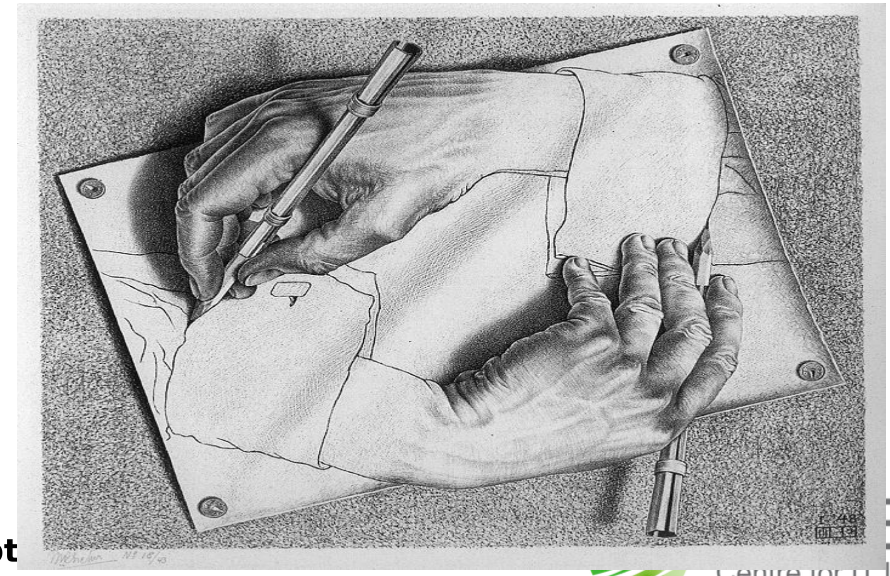
- Energy labelling
- Estimation of UA and gA values
- Estimation of energy signature
- Estimation of dynamic characteristics
- Estimation of time constants

Energy Labelling of Buildings

- Today building experts make judgements of the energy performance of buildings based on drawings and prior knowledge.

- This leads to 'Energy labelling' of the building

- However, it is noticed that two independent experts can predict very different consumptions for the same house.



Simple estimation of UA-values

- Consider the following model (t=day No.) estimated by kernel-smoothing:

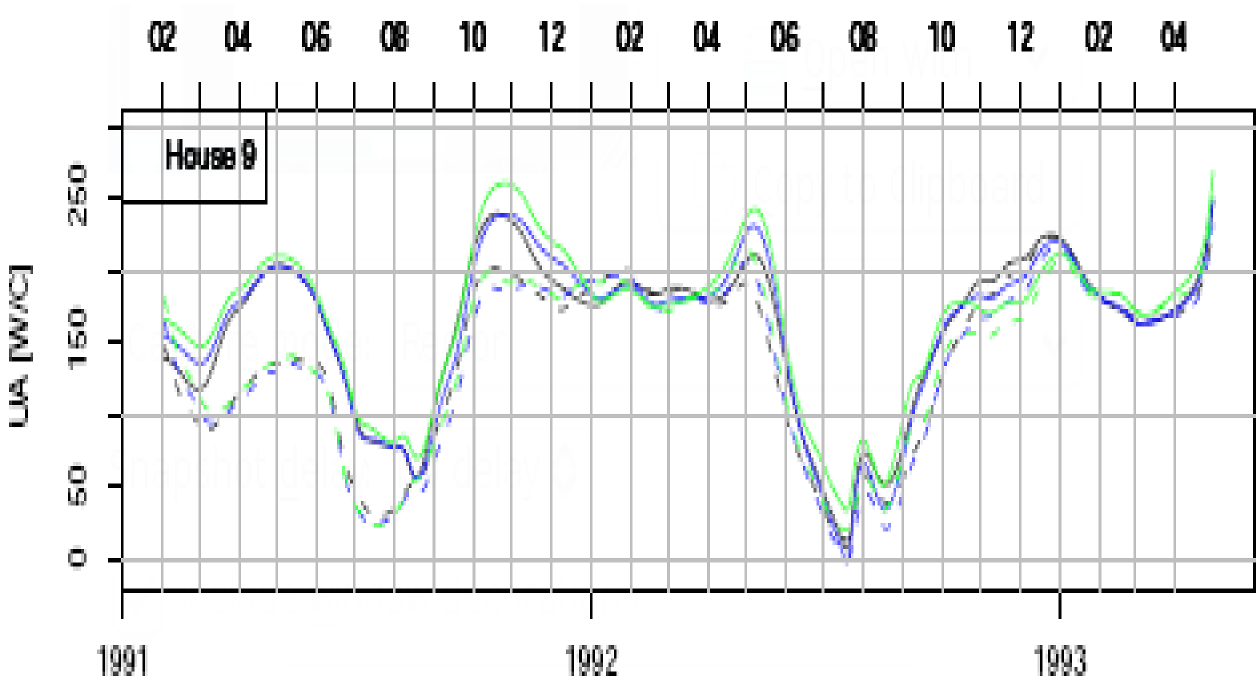
$$Q_t = Q_0(t) + c_0(t)(T_{i,t} - T_{a,t}) + c_1(t)(T_{i,t-1} - T_{a,t-1}) \qquad (1)$$

- The estimated UA-value is

$$\hat{UA}(t) = \hat{c}_o(t) + \hat{c}_1(t) \qquad (2)$$

- With more involved (but similar models) also gA and wA values can be stimated

Estimated UA-values



Results

	UA W/°C	σ_{UA}	gA^{max} W	wA_E^{max} W/°C	wA_S^{max} W/°C	wA_W^{max} W/°C	T_i °C	σ_{T_i}
4218598	211.8	10.4	597.0	11.0	3.3	8.9	23.6	1.1
4381449	228.2	12.6	1012.3	29.8	42.8	39.7	19.4	1.0
4711160	155.4	6.3	518.8	14.5	4.4	9.1	22.5	0.9
4836681	155.3	8.1	591.0	39.5	28.0	21.4	23.5	1.1
4836722	236.0	17.7	1578.3	4.3	3.3	18.9	23.5	1.6
4986050	159.6	10.7	715.7	10.2	7.5	7.2	20.8	1.4
5069878	144.8	10.4	87.6	3.7	1.6	17.3	21.8	1.5
5069913	207.8	9.0	962.5	3.7	8.6	10.6	22.6	0.9
5107720	189.4	15.4	657.7	41.4	29.4	16.5	21.0	1.6
.	.	.	.	.	.	.	.	.

Based on measurements from the heating season **2009/2010** your typical indoor temperature during the heating season has been estimated to **24** ^oC. If this is not correct you can change it here $\boxed{24}$ ^oC.

If your house has been left empty in longer periods with a partly reduced heat supply you have the possibility of specifying the periods in this $\boxed{\text{calendar}}$.

According to BBR the area of your house is **155** m^2 and from **1971**.

Based on BBR information it is assumed that **you do not use any supplementary heat supply**. If this is not correct you can specify the type and frequency of use here:

- Wood burning stove used $\boxed{0}$ times per week in cold periods.
- Solar heating $\boxed{\text{y/n}}$, approximate size of solar panel $\boxed{0} \times \boxed{0}$ meters.

Based on the indoor temperature **24** ^oC, the use of a wood burning stove **0** times per week, and **no** solar heating installed, the response of your house to climate is estimated as:

- The response to outdoor temperature is estimated to **200** $W/^oC$ **which given the size and age of your house is expectable**[a].
- On a windy day the above value is estimated to increase with **60** $W/^oC$ **when the wind blows from easterly directions. This response to wind is relatively high and indicates a problem related to the air sealing on the eastern side of the house.**
- On a sunny day during the heating season the house is estimated to receive **800** W as an average over 24 hours. **This value is quite expectable.**

[a] Many kind of different recommendations can be given here.

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Perspectives for using data from Smart Meters

- Reliable Energy Signature.
- Energy Labelling
- Time Constants (eg for night set-back)
- Proposals for Energy Savings:
  - Replace the windows?
  - Put more insulation on the roof?
  - Is the house too untight?
  - ......
- Optimized Control
- Integration of Solar and Wind Power using DSM

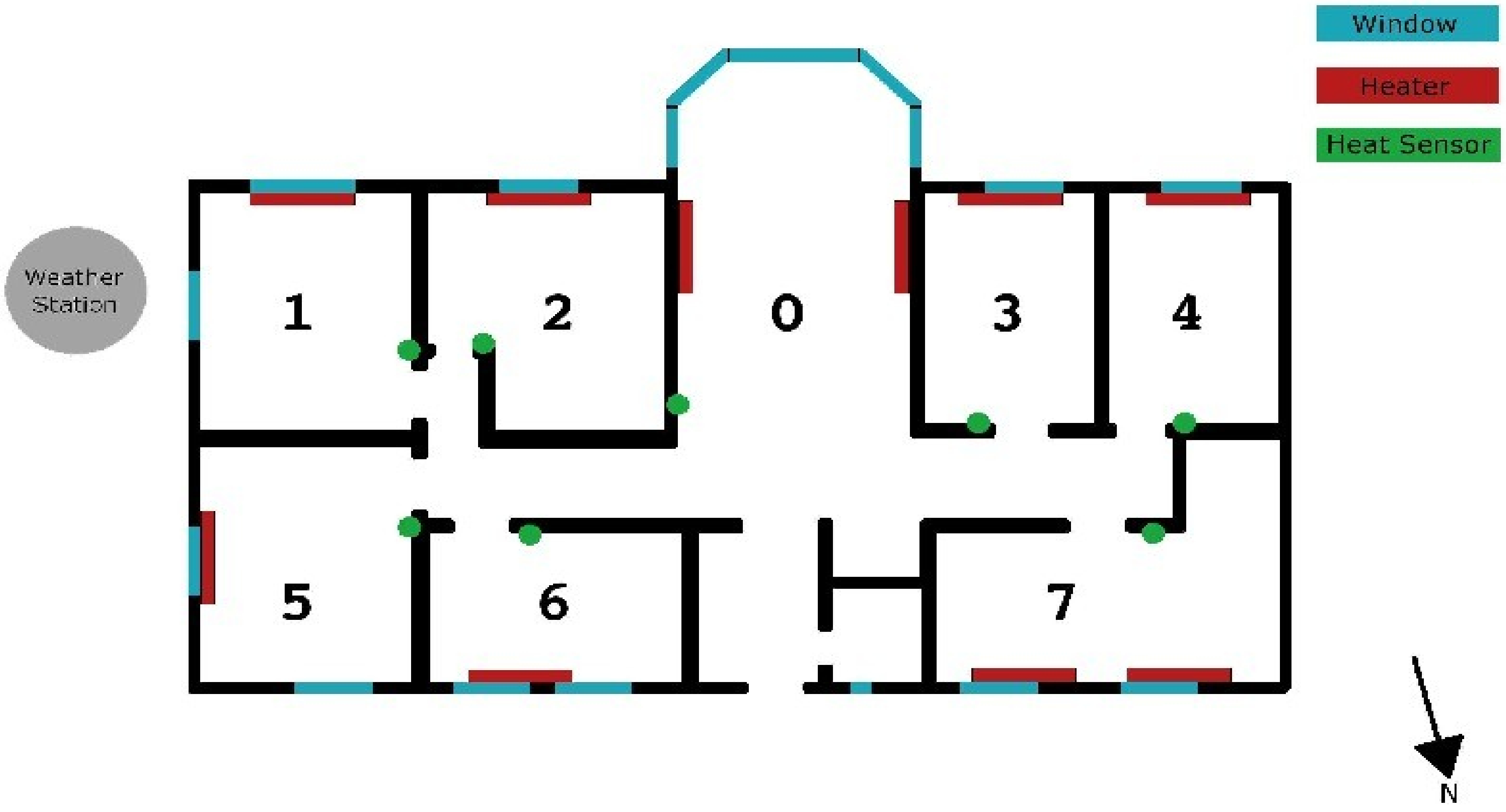
Case study No. 3

Modelling the thermal characteristics of a small office building

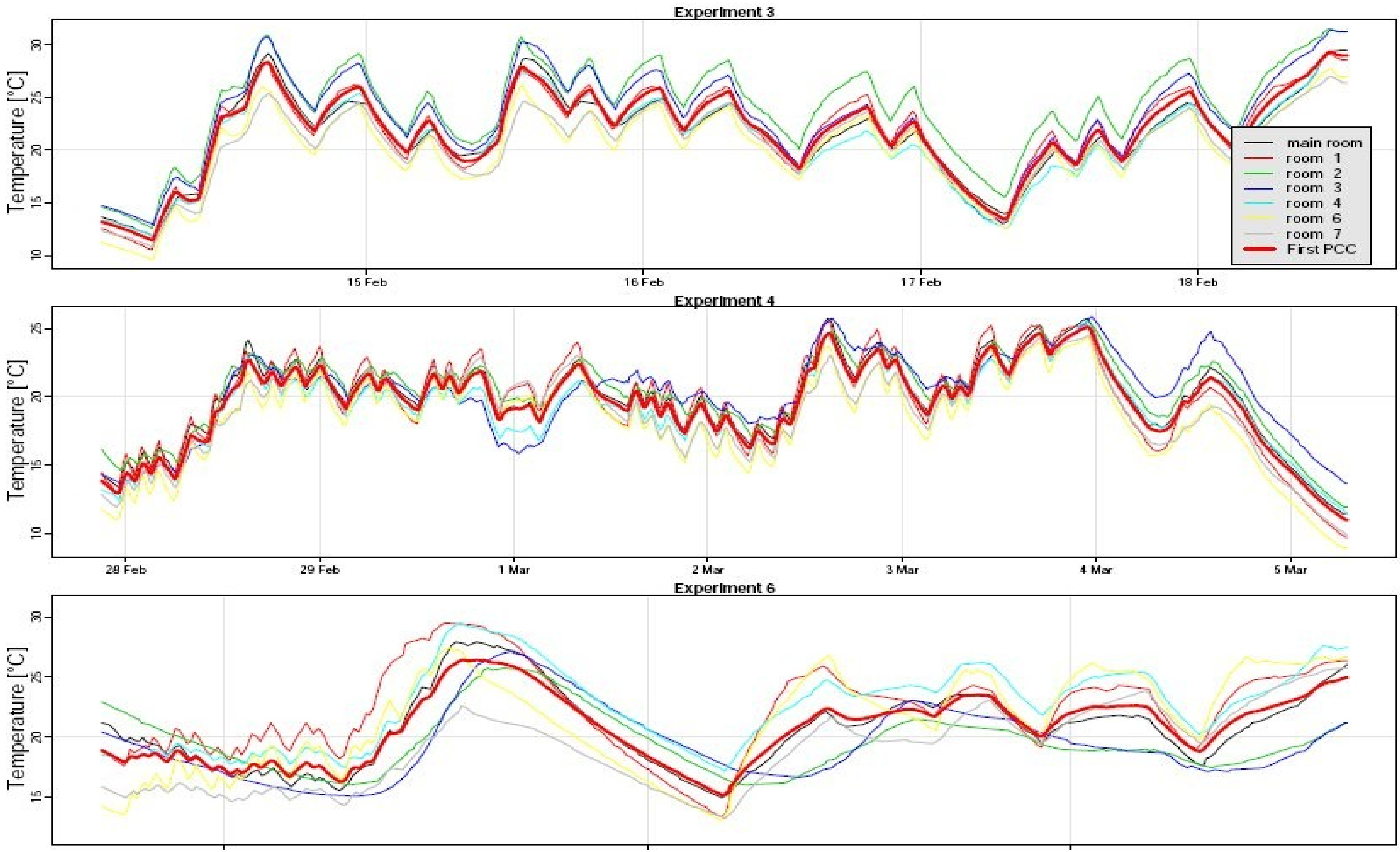
Parametric Models

- A model for the thermal characteristics of a small office building

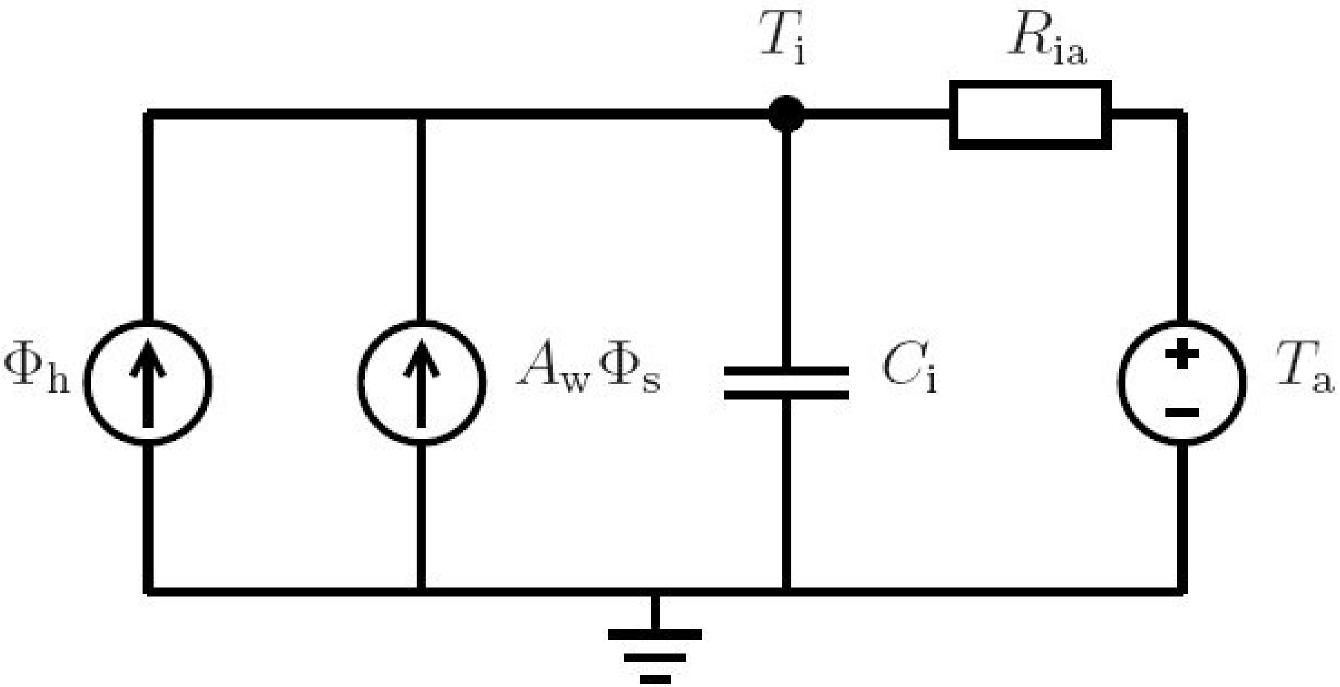
Flexhouse at SYSLAB (DTU Risø)



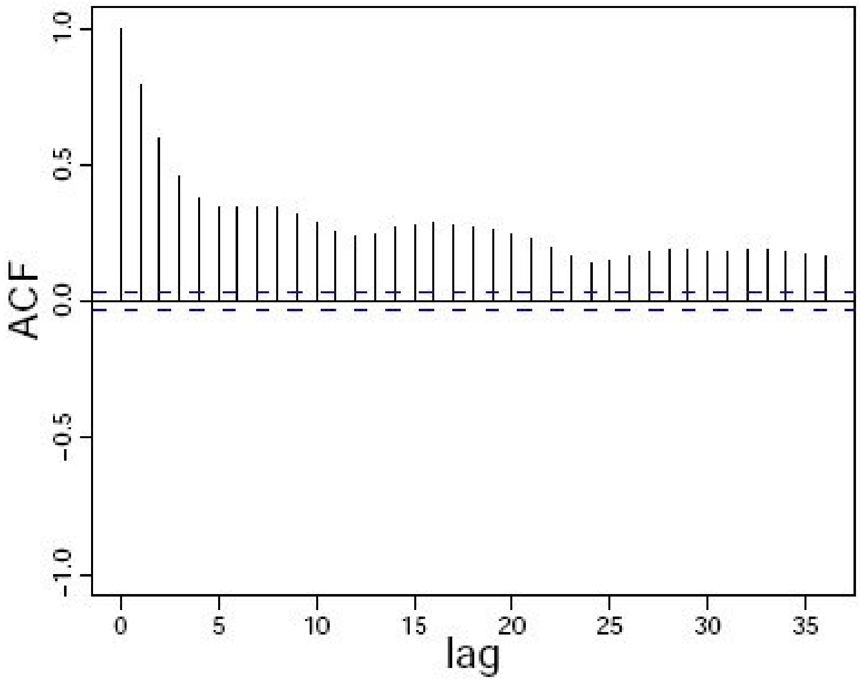
Data and the first principal component

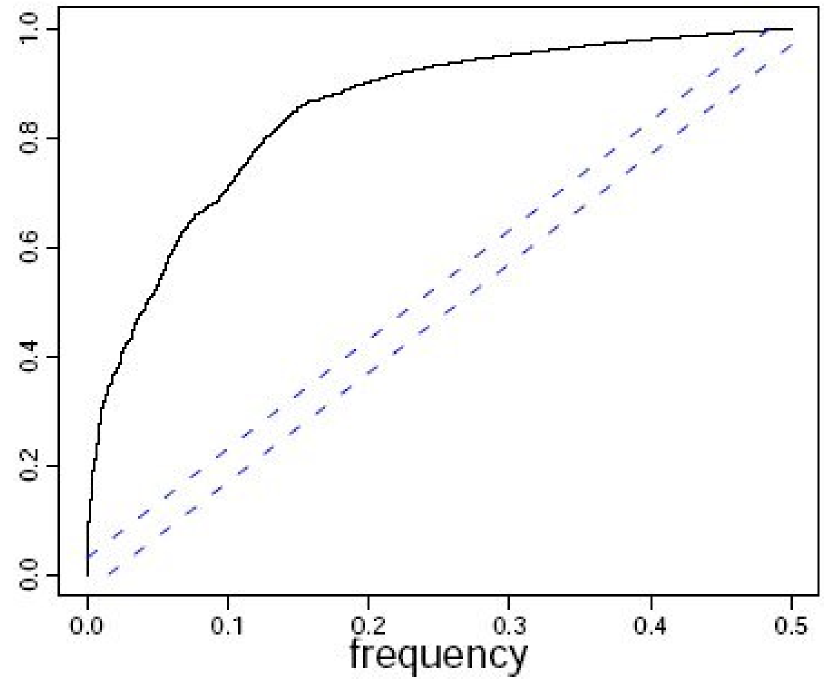


A first order model often used for simulation



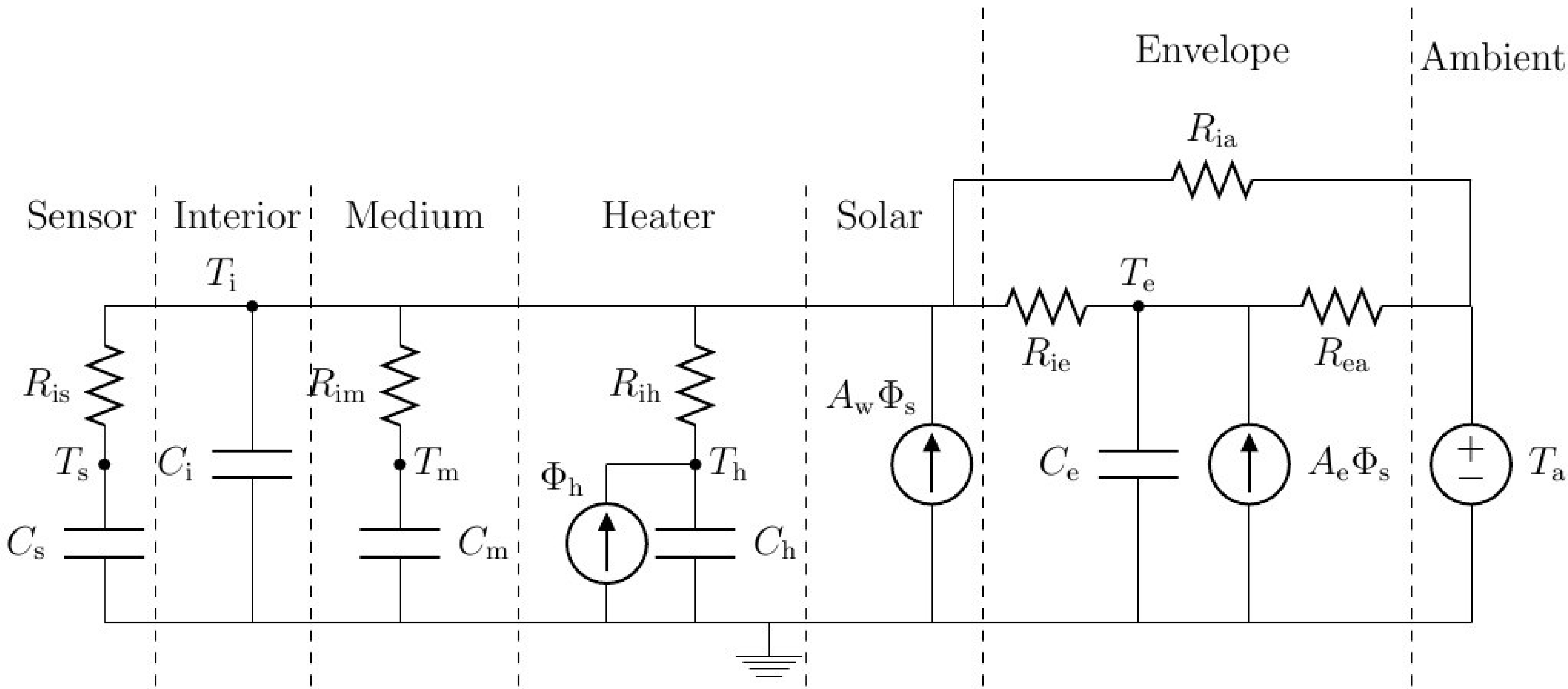
Model evaluation of the first order model



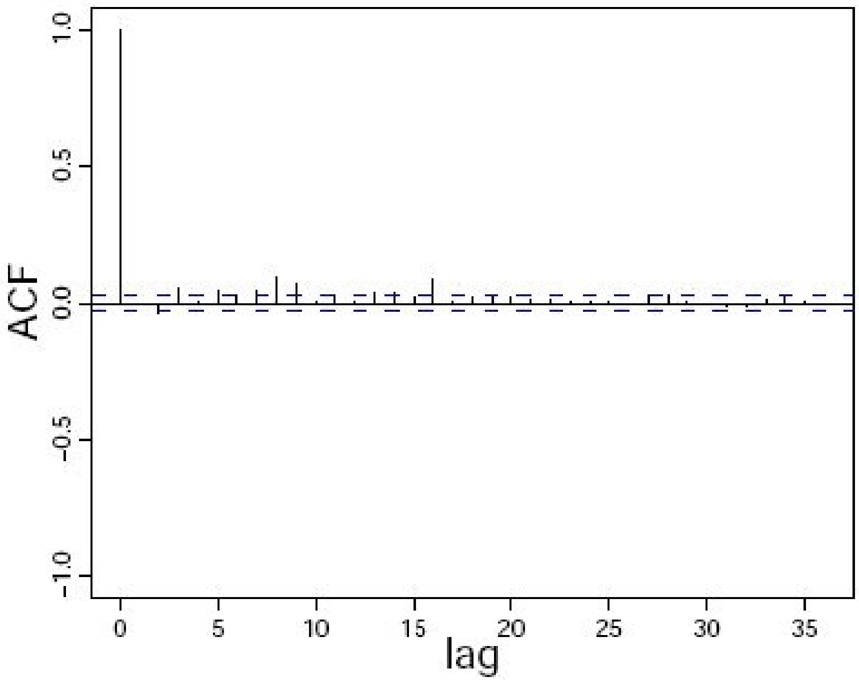


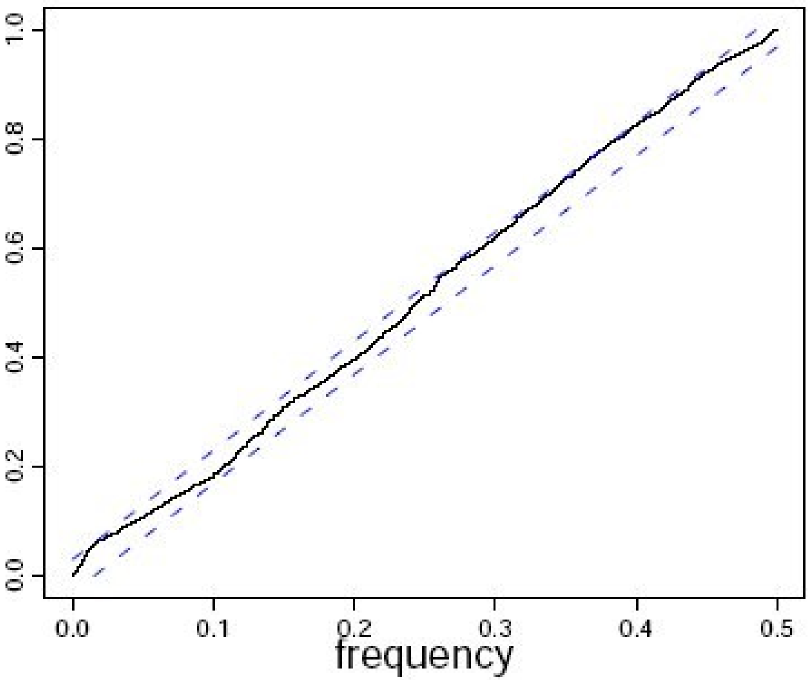
- Model is not adequate since residuals are not white noise

Model found using Grey-box modelling (..... using CTSM-R – http://smart-cities-centre.org/software-solutions/)



Model evaluation – Extended model



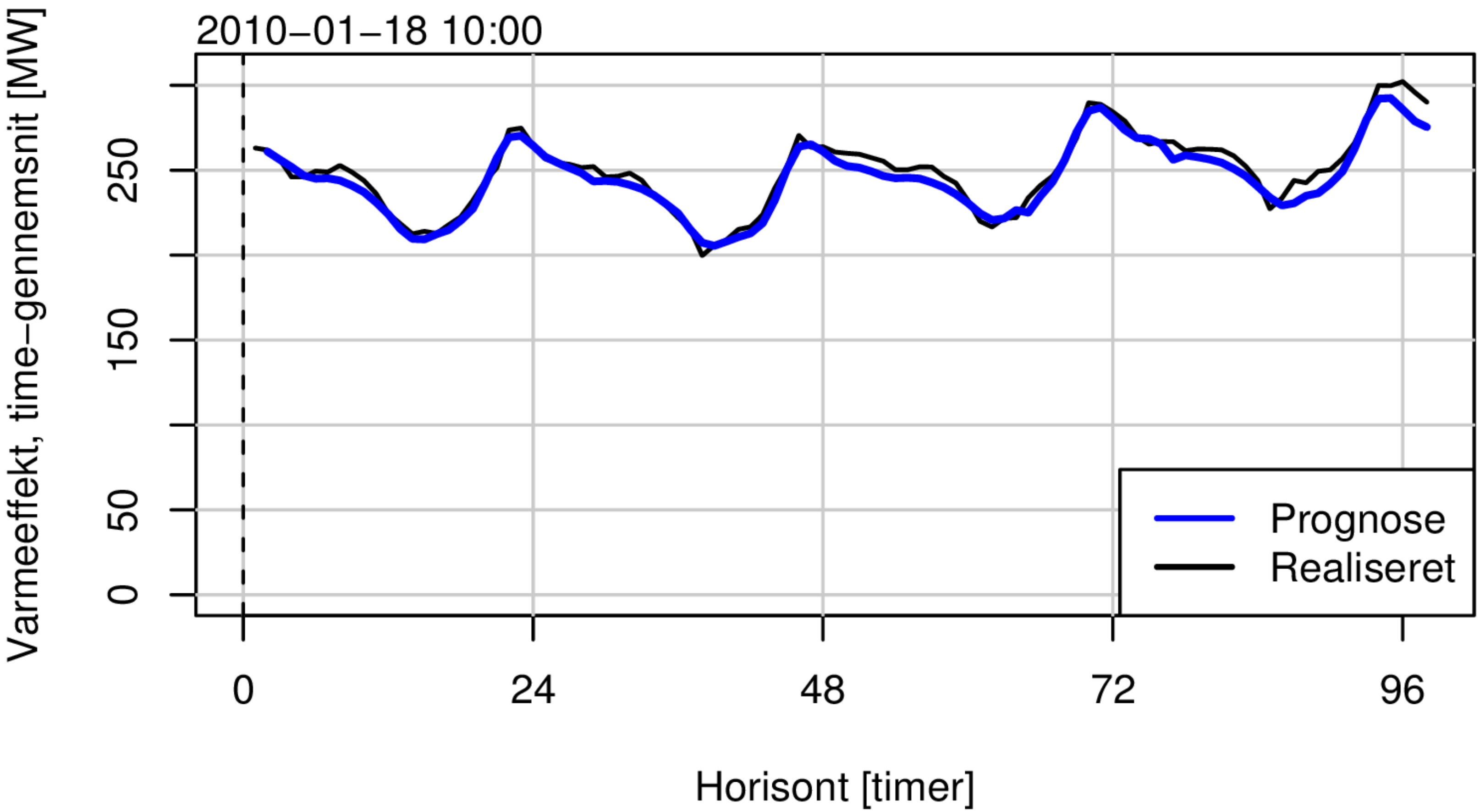


- This model is OK, since residuals are uncorrelated (white noise)

Case study No. 4

Models for DH Systems

Heat Load forecasts – up to 96 h ahead



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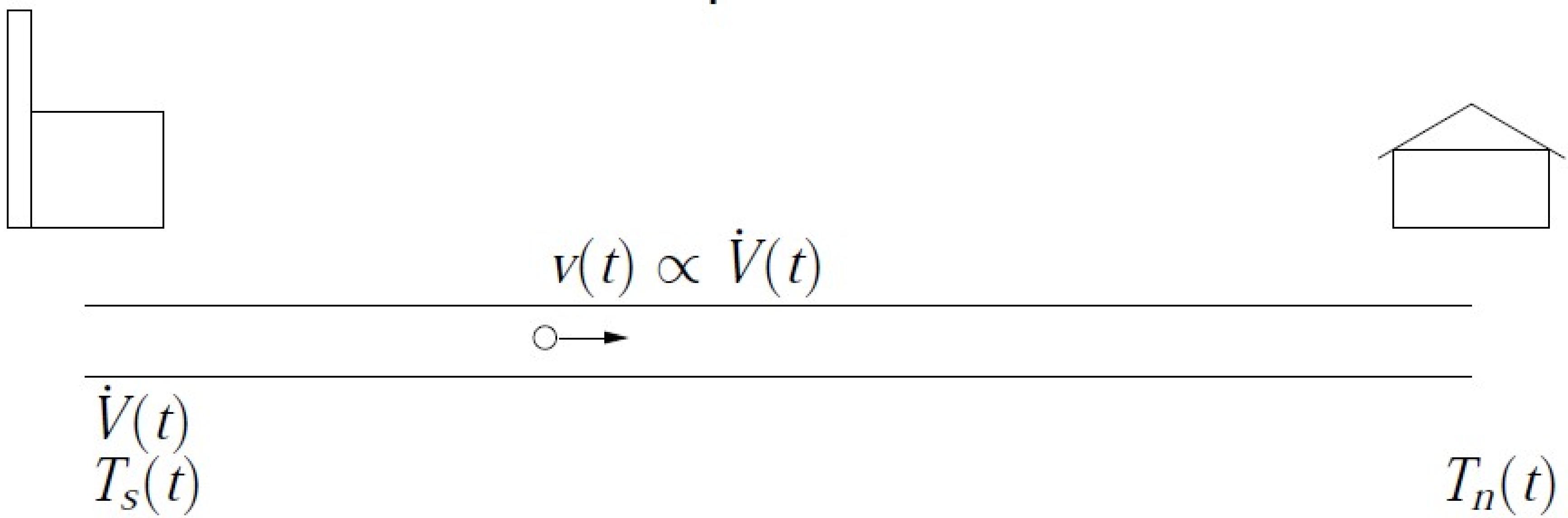
- Simplification -



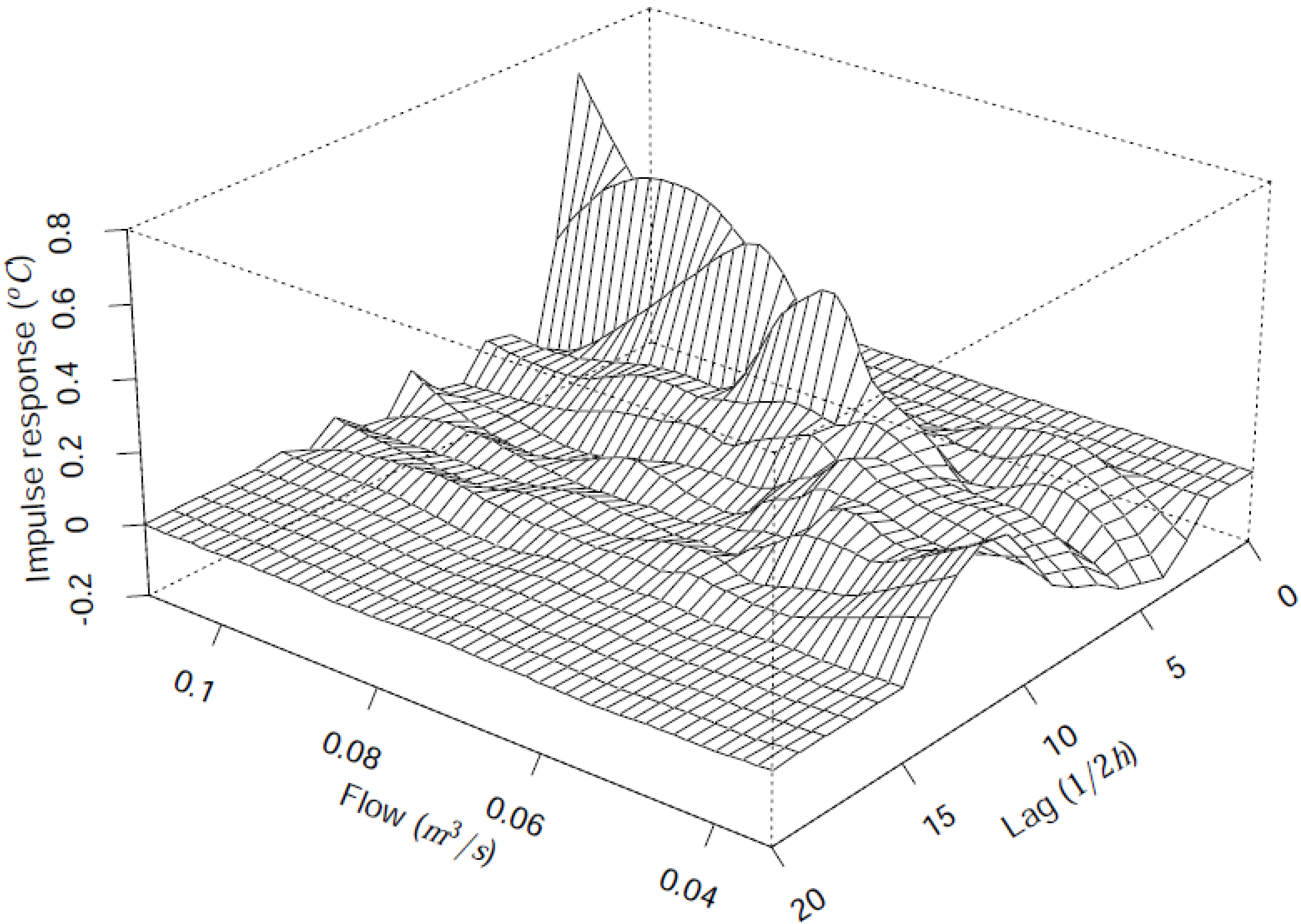
$$\text{Length of pipe} = \int_t^{t+\tau(t)} v(s)\,ds$$

Conditional parametric ARX-model

$$y_t = \sum_{i \in L_y} a_i(x_{t-m}) y_{t-i} + \sum_{i \in L_u} b_i(x_{t-m}) u_{t-i} + e_t,$$

- The **functions** $a_i(x_{t-m})$ and $b_i(x_{t-m})$ must be estimated
- The model may be written as $y_t = \boldsymbol{z}_t^T \boldsymbol{\theta}(\boldsymbol{x}_t) + e_t$

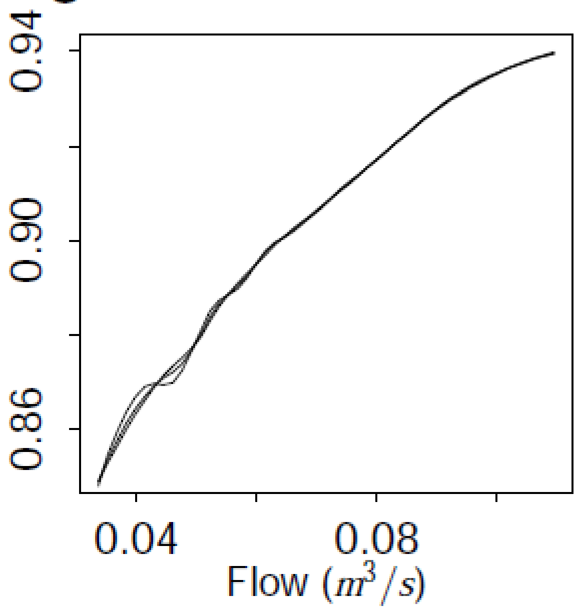
Impulse Response of ARX-model (40%)



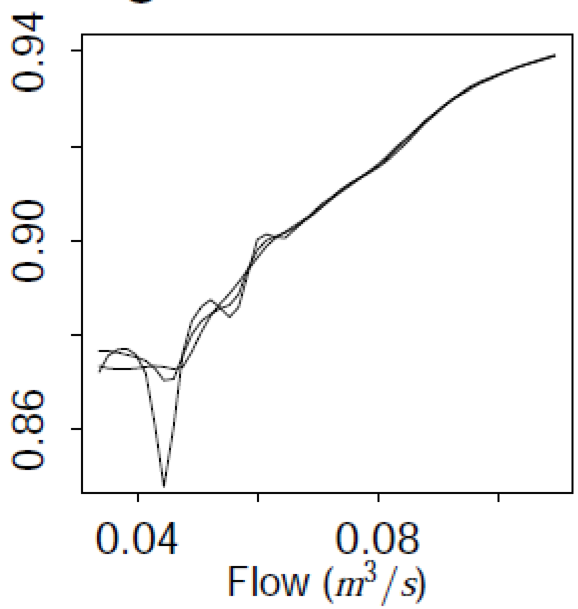
Characteristics

30%, 40%, 50%

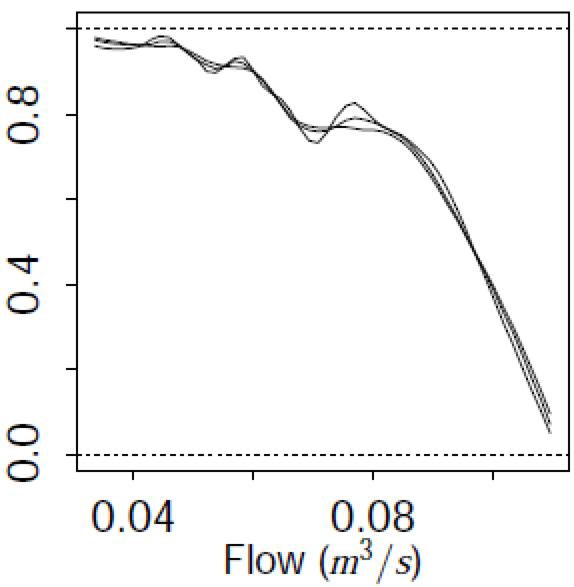
Stationary gain of FIR



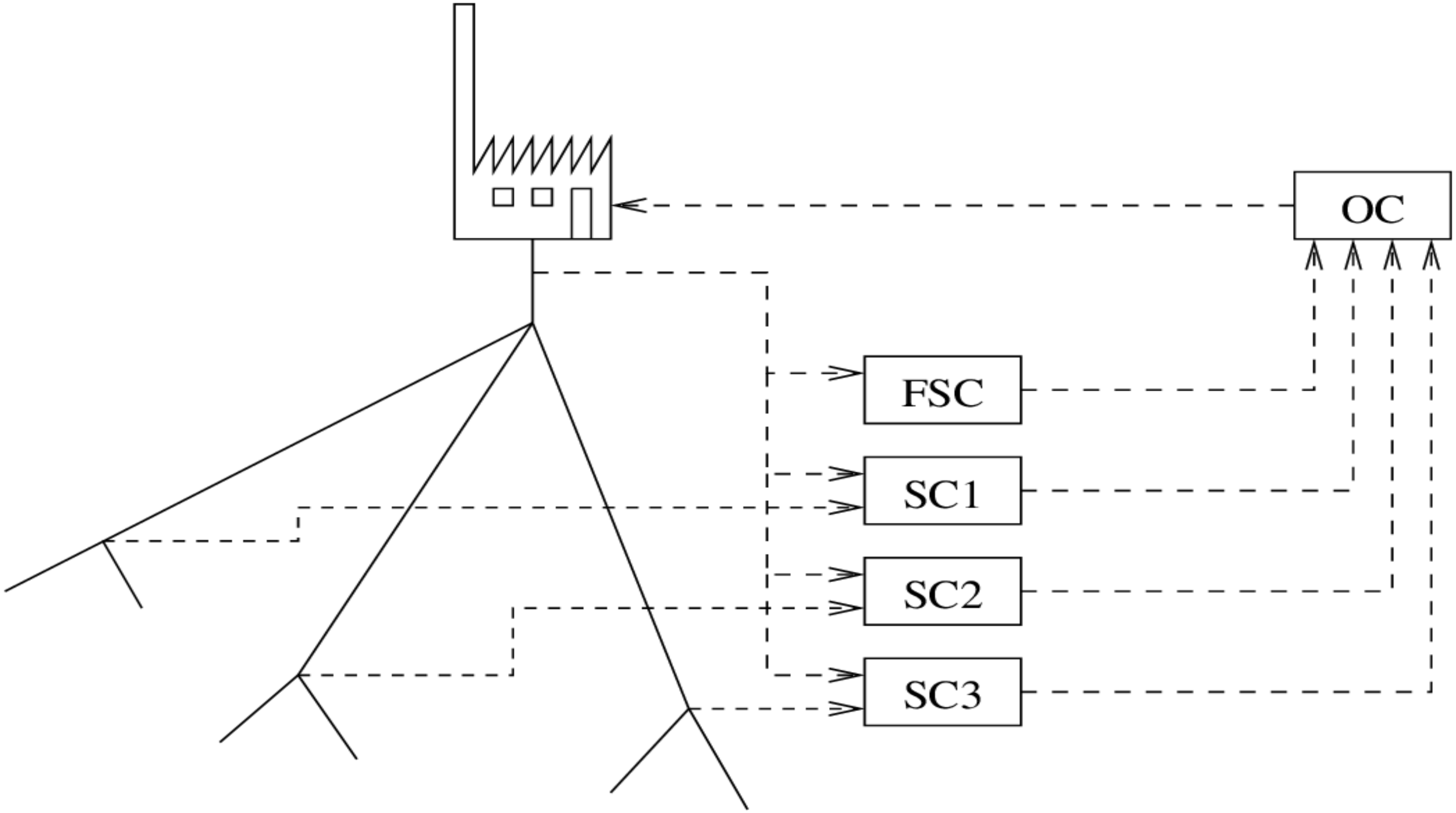
Stationary gain of ARX



Pole of ARX

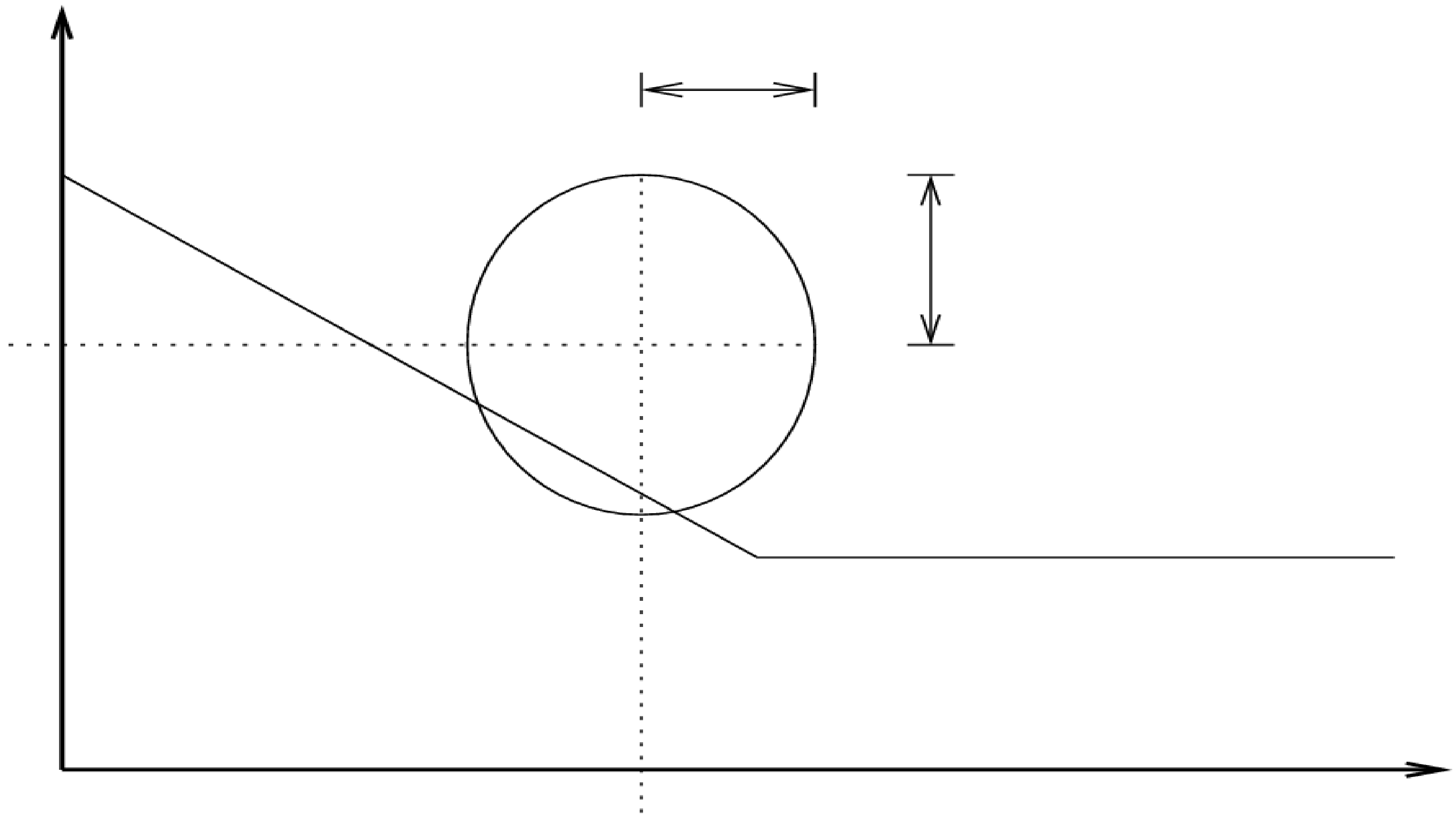


Models and Controllers
(Highly simplified! - In fact 680 km pipes ...)



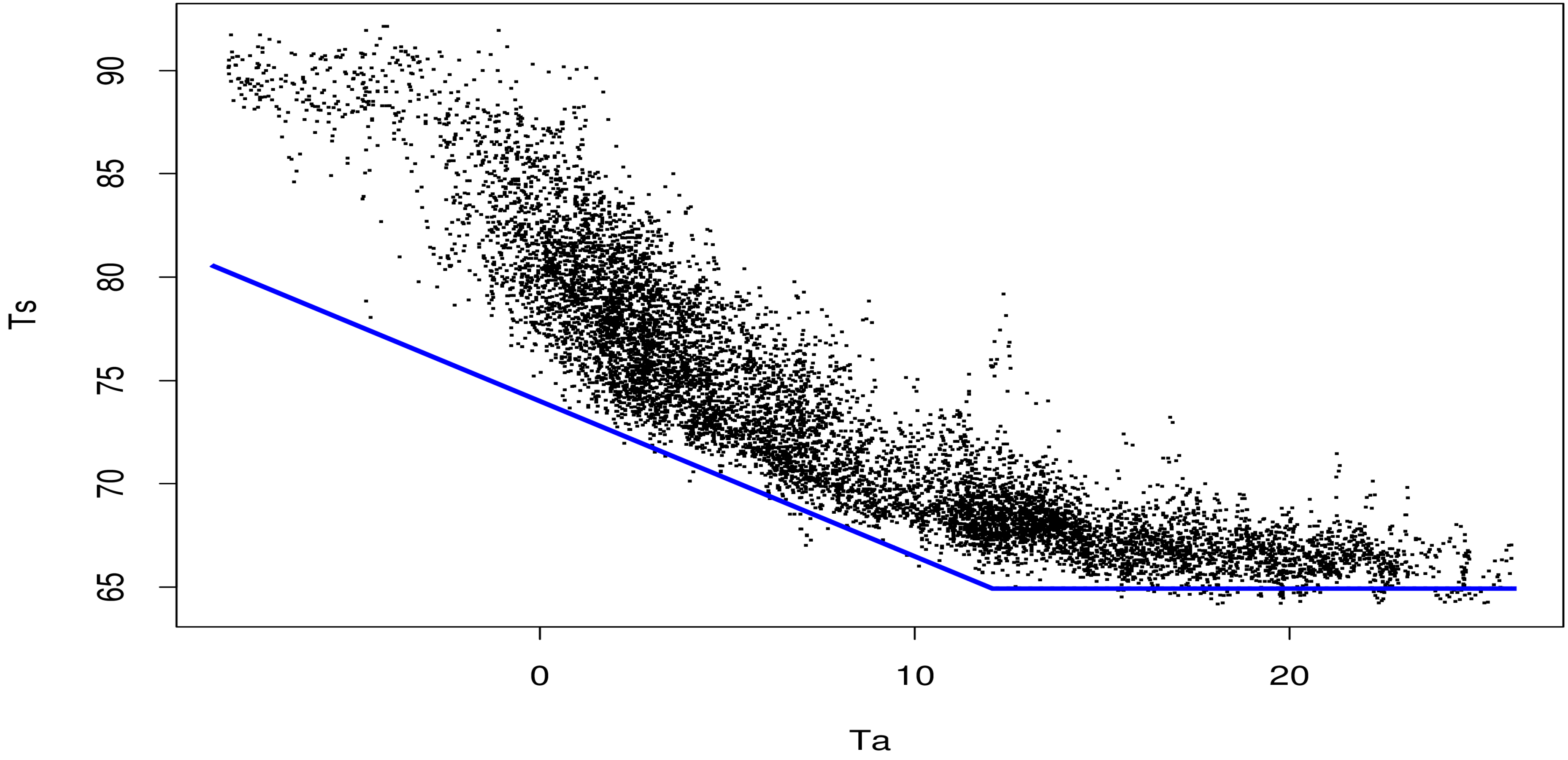
Prob. constraints
Controller set-points

Temp at User

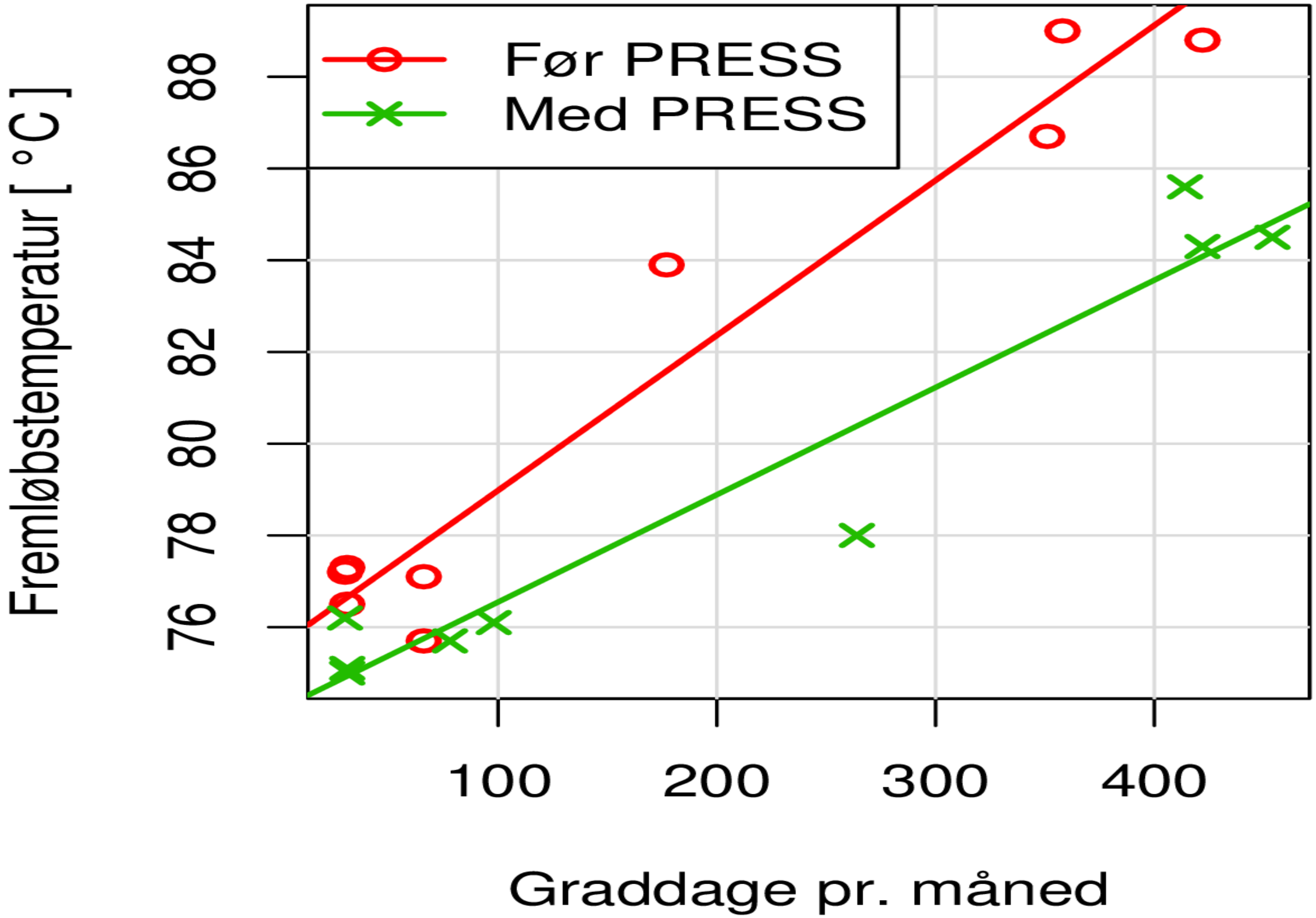


Ambient Air Temp.

Observed User Temp.



Supply temperature with/without predictive control



Savings
(Reduction of heat loss = 18.3 pct)

	Varmekøb		Elkøb	
	GJ	1000kr	kWh	1000kr
Før PRESS	653,000	30,750	499,000	648
Med PRESS	615,000	28,990	648,000	842
Forskel	37,400	1,760	-149,000	-194

Total besparelse (9 første måneder af normalår): **1,566,000kr**

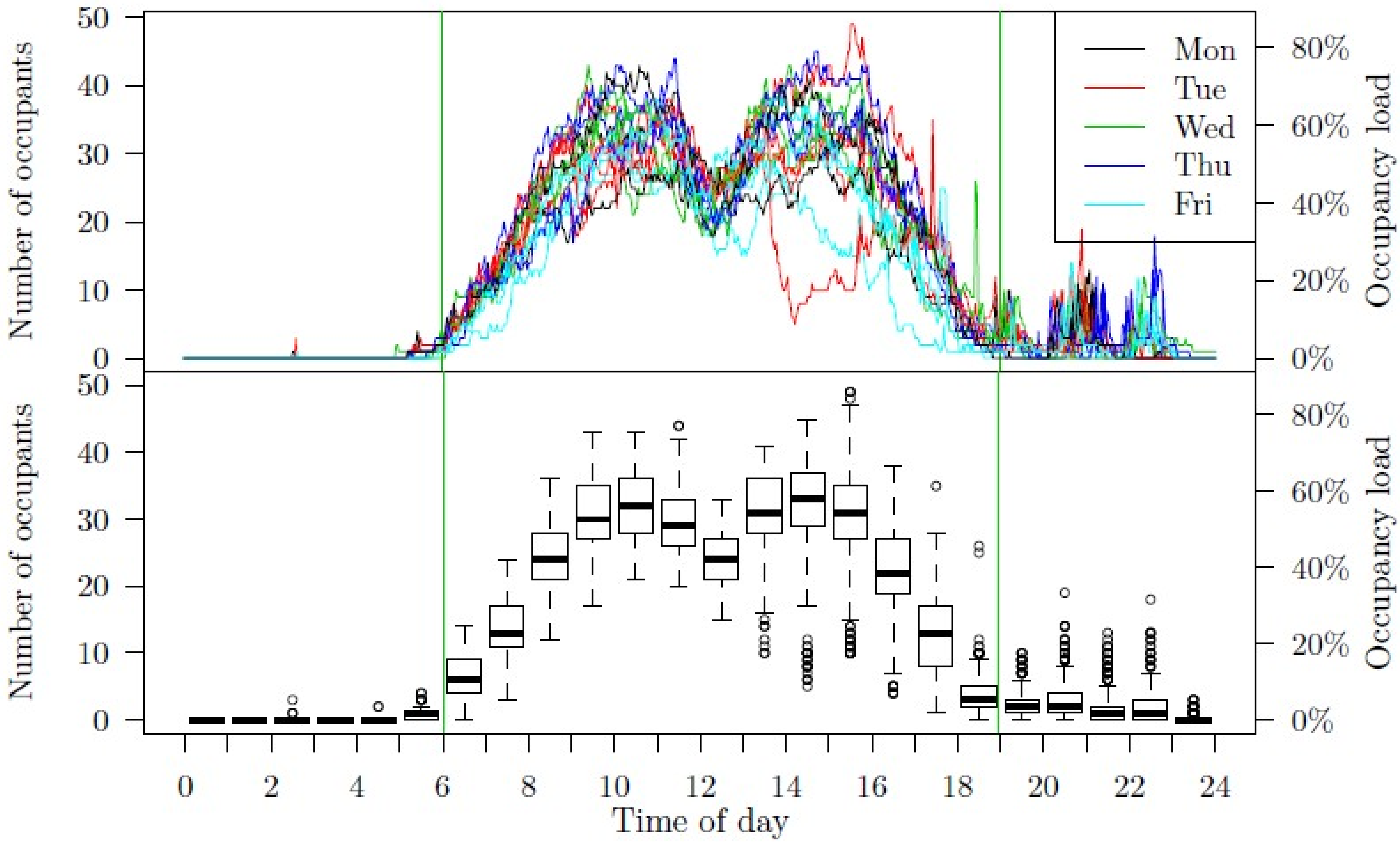
Besparelse for et normalår:

- $12/9 \times$ 1,566,000kr $=$ **2.1 mill.**
- Imidlertid står jan.–sept. (75% af året) kun for ca. 65% af graddagen i er normalår.
- 1,566,000kr$/0.65 =$ **2.4 mill.**

Case study No. 5

Models for Occupance Behavior

Occupant presence (office building in SF)



Markov Chain Models

2.1.1.2. Two-state Markov chains with covariates. Covariates in Markov chains with only the two states, 0 and 1, can be modeled as

$$\operatorname{logit}\left(\mathbb{P}\left(X_{n+1}=0 \,\middle|\, X_n=0\right)\right)=Z_{1,n}\theta_1, \quad \theta_1 Z_{1,n}\in\mathbb{R}^p \tag{4a}$$

$$\operatorname{logit}\left(\mathbb{P}\left(X_{n+1}=1 \,\middle|\, X_n=1\right)\right)=Z_{2,n}\theta_2, \quad \theta_2 Z_{2,n}\in\mathbb{R}^q \tag{4b}$$

where the logistic function denoted logit is defined as

$$\operatorname{logit}:]0,1[\to\mathbb{R}, \quad \operatorname{logit}(x)=\log\left(\frac{x}{1-x}\right) \tag{5}$$

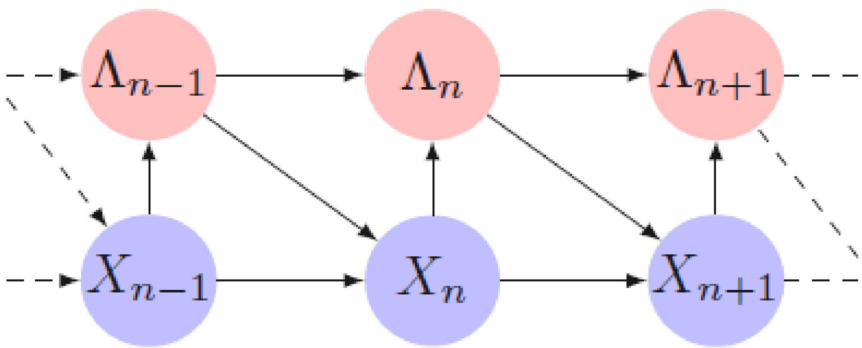
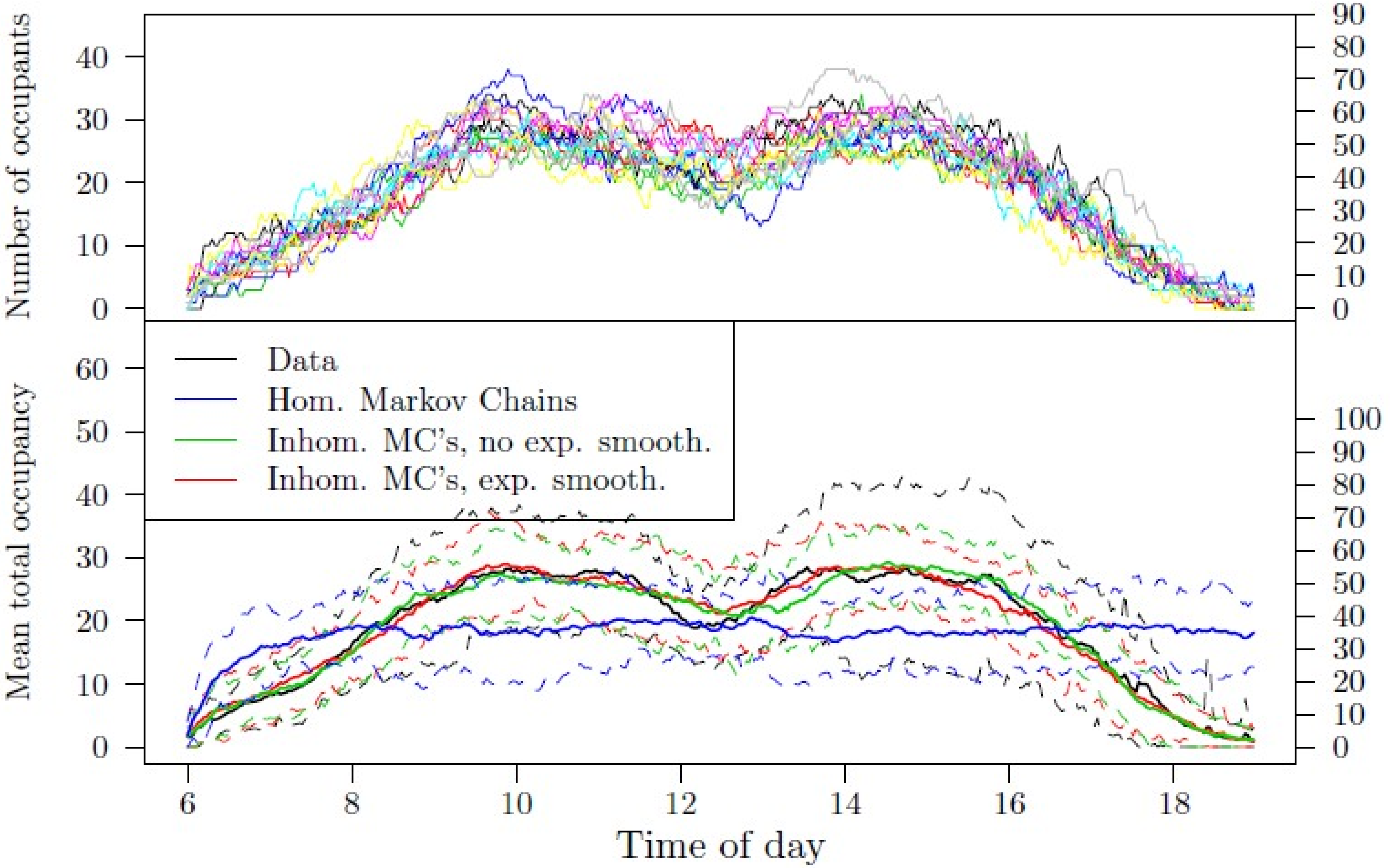
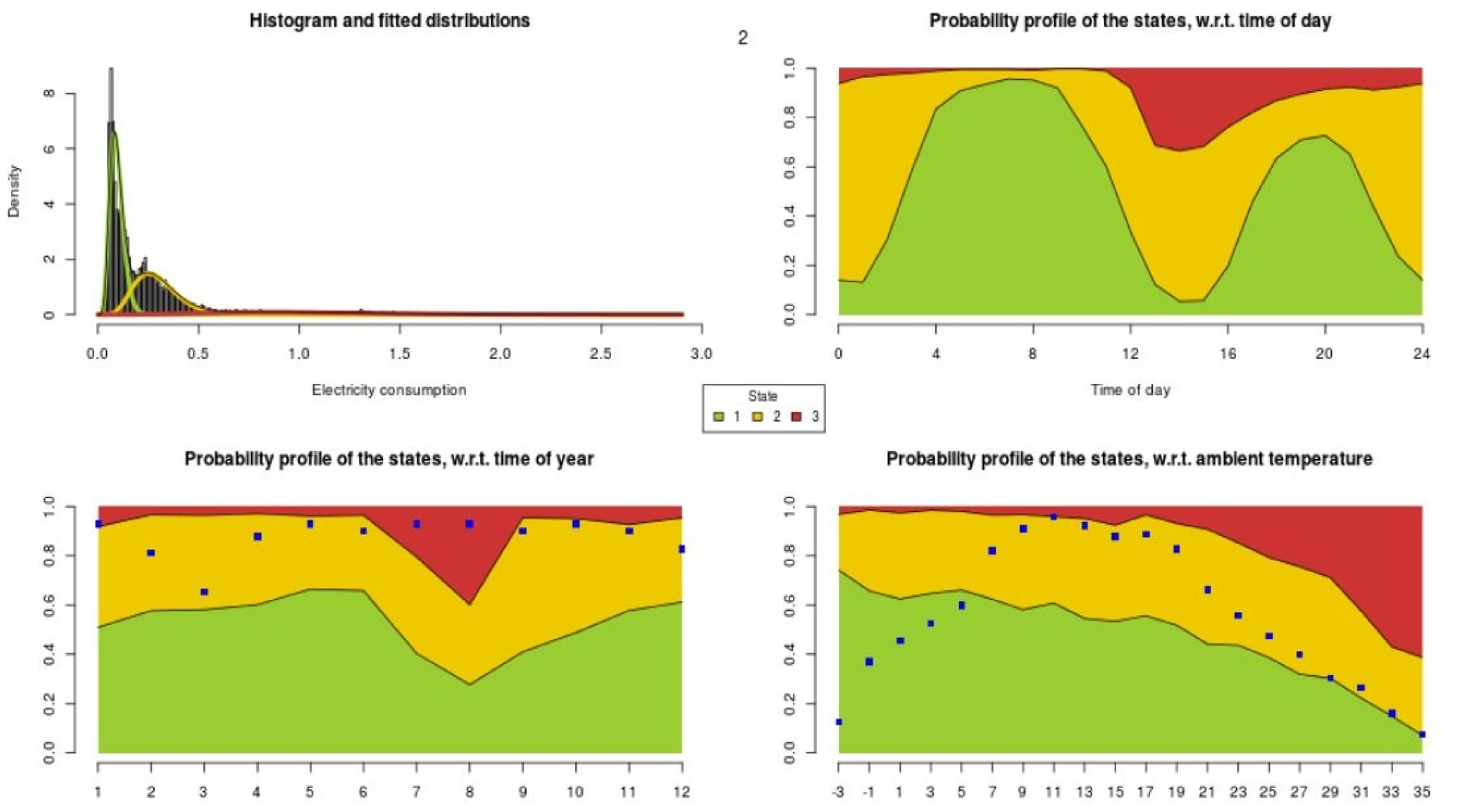


Fig. 3. A Markov chain with exponential smoothing as covariate in the transition probabilities.

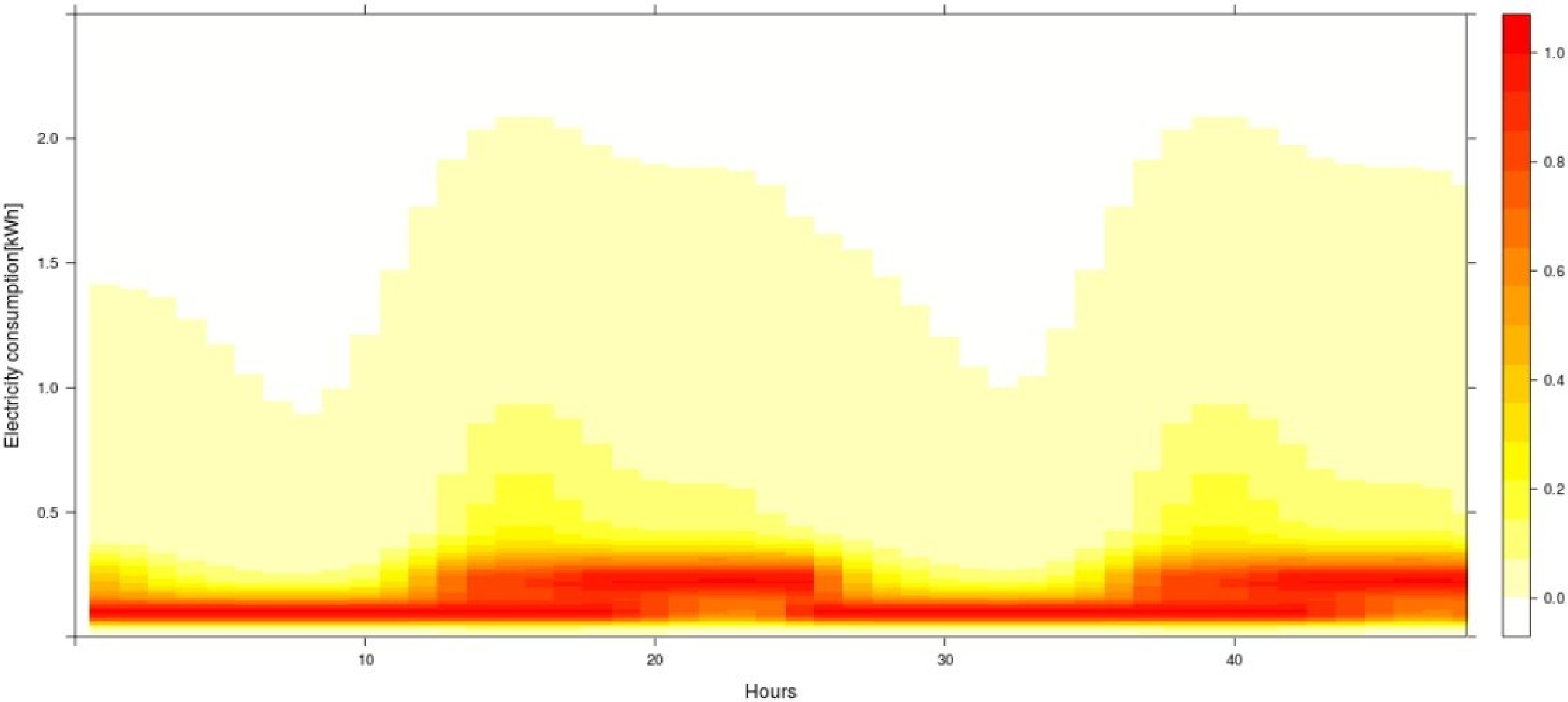
Model simulations



Electricity consumption
(Collaboration with CIMNE and JRC)



Electricity consumption (Data from CIMNE / Barcelona) (Hidden Markov Model)



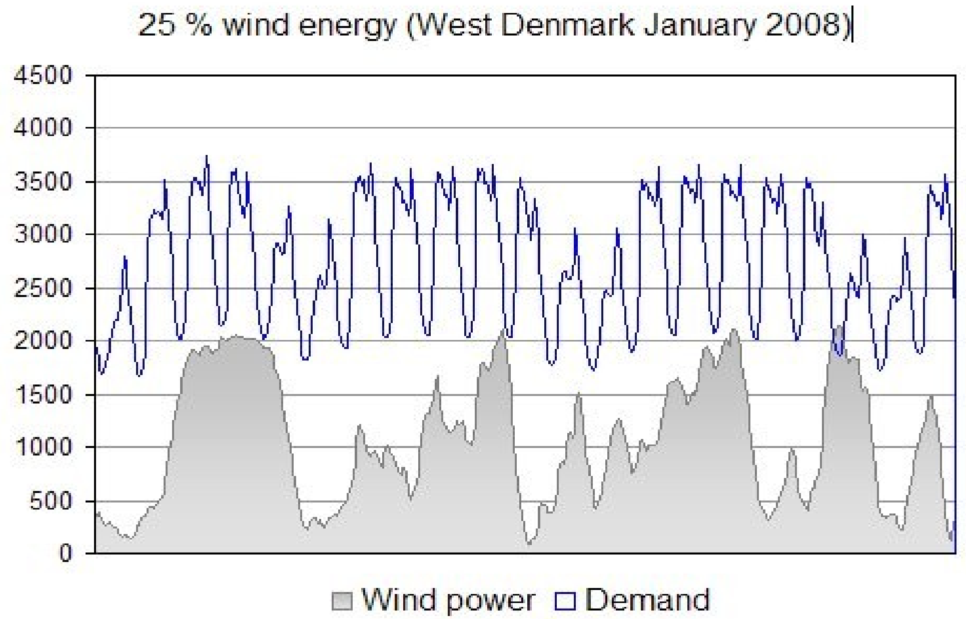
Case study No. 6

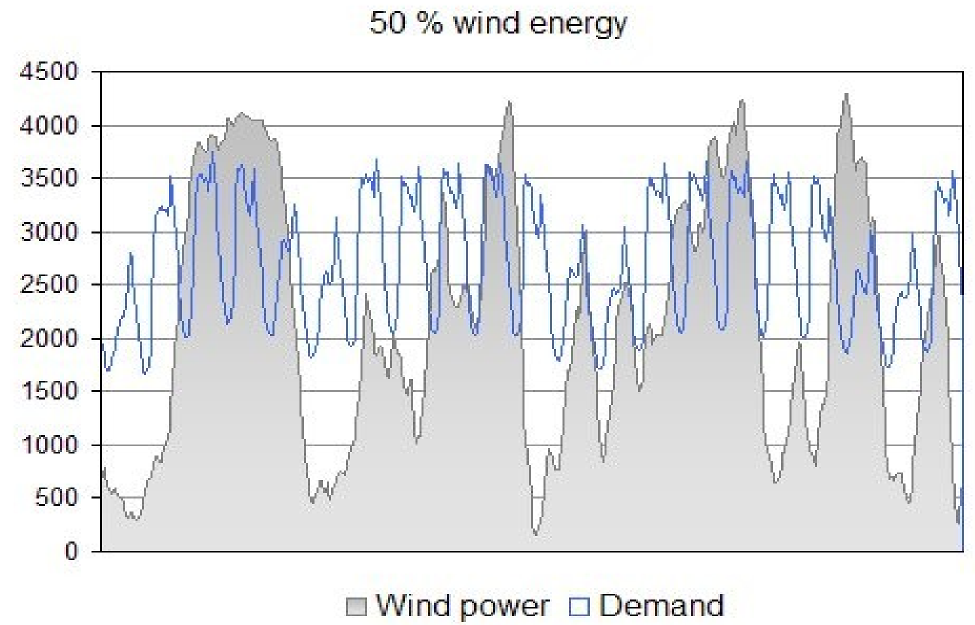
Control of Power Consumption (DSM) using the Thermal Mass of Buildings

Control of Power Consumption

The Danish Wind Power Case

.... balancing of the power system





In 2008 wind power did cover the entire demand of electricity in 200 hours (West DK)

In 2015 approx. 42 pct of electricity load was covered by wind power.

For several days the wind power production was more than 100 pct of the power load.

July 10th, 2015 more than 140 pct of the power load was covered by wind power

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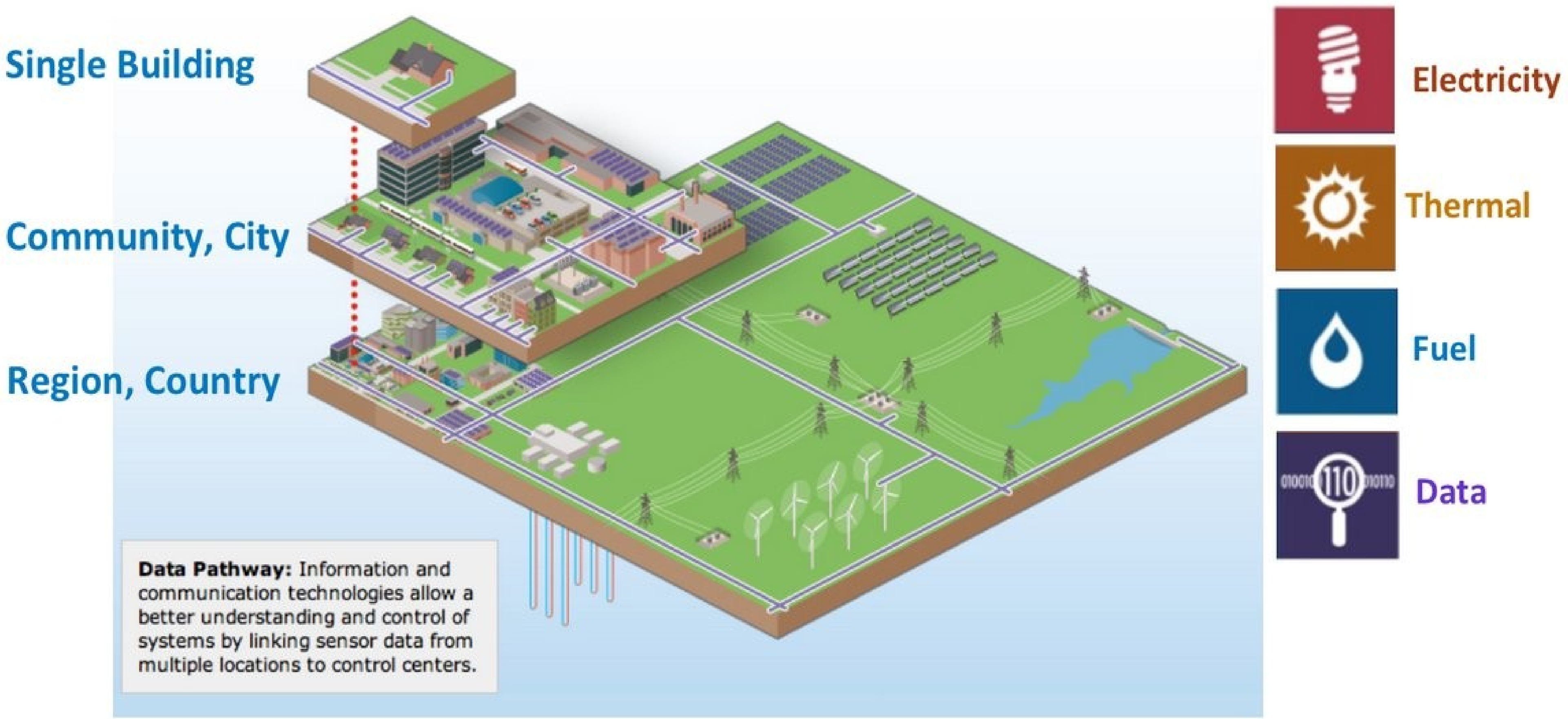
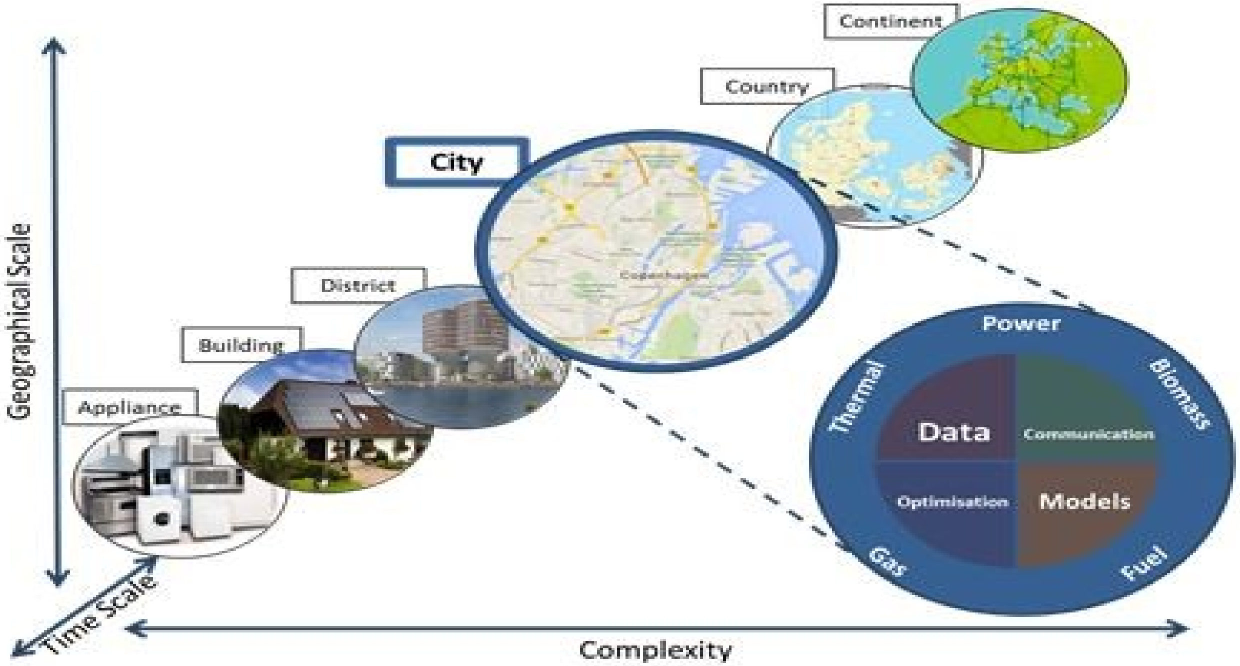
Energy Systems Integration
•in Smart Cities

Energy system integration (ESI) = the process of optimizing energy systems across multiple pathways and scales

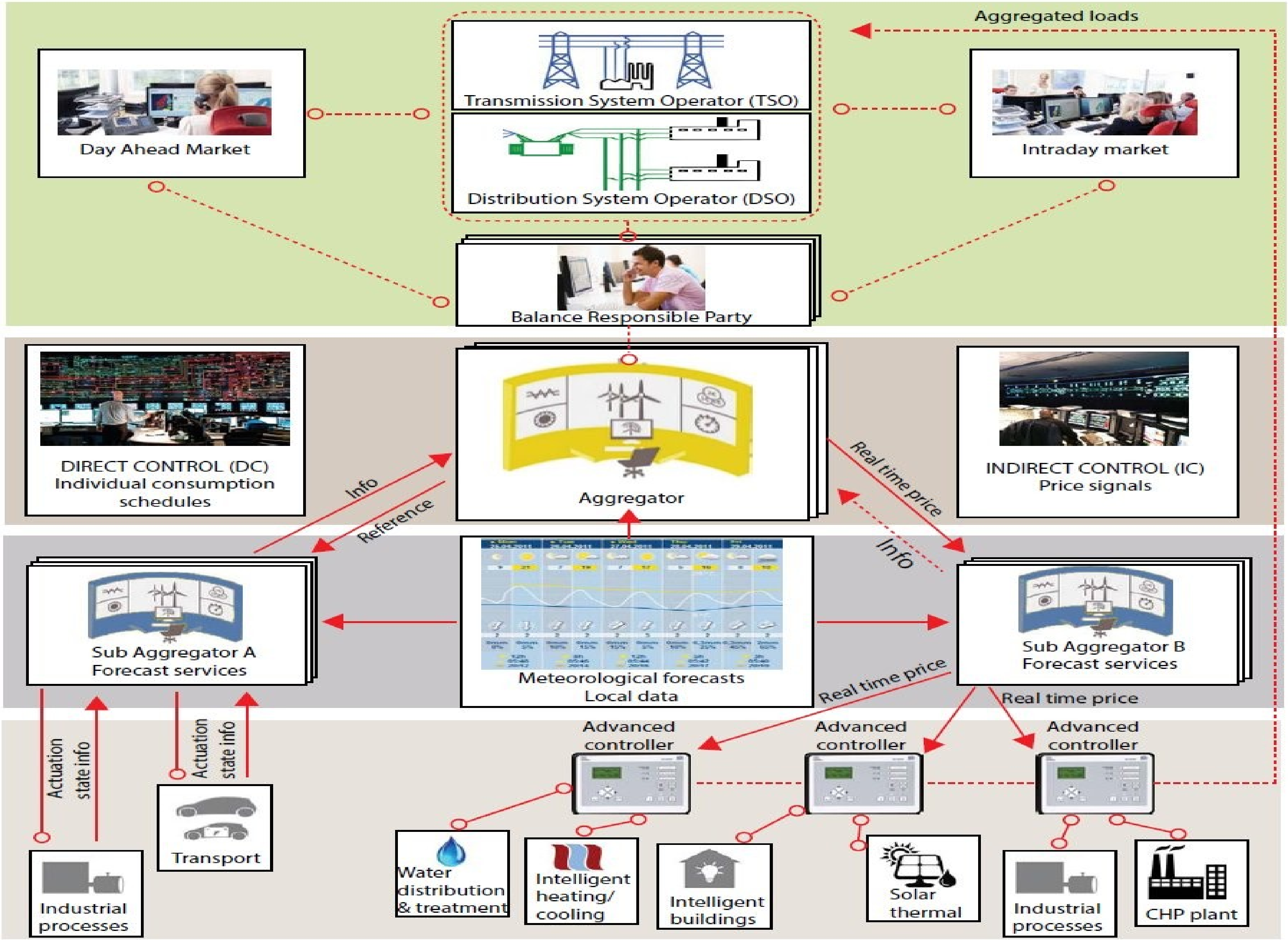


Temporal and Spatial Scales

The ***Smart-Energy Operating-System (SE-OS)*** is used to develop, implement and test of solutions (layers: data, models, optimization, control, communication) for ***operating flexible electrical energy systems*** at **all scales**.



Control and Optimization



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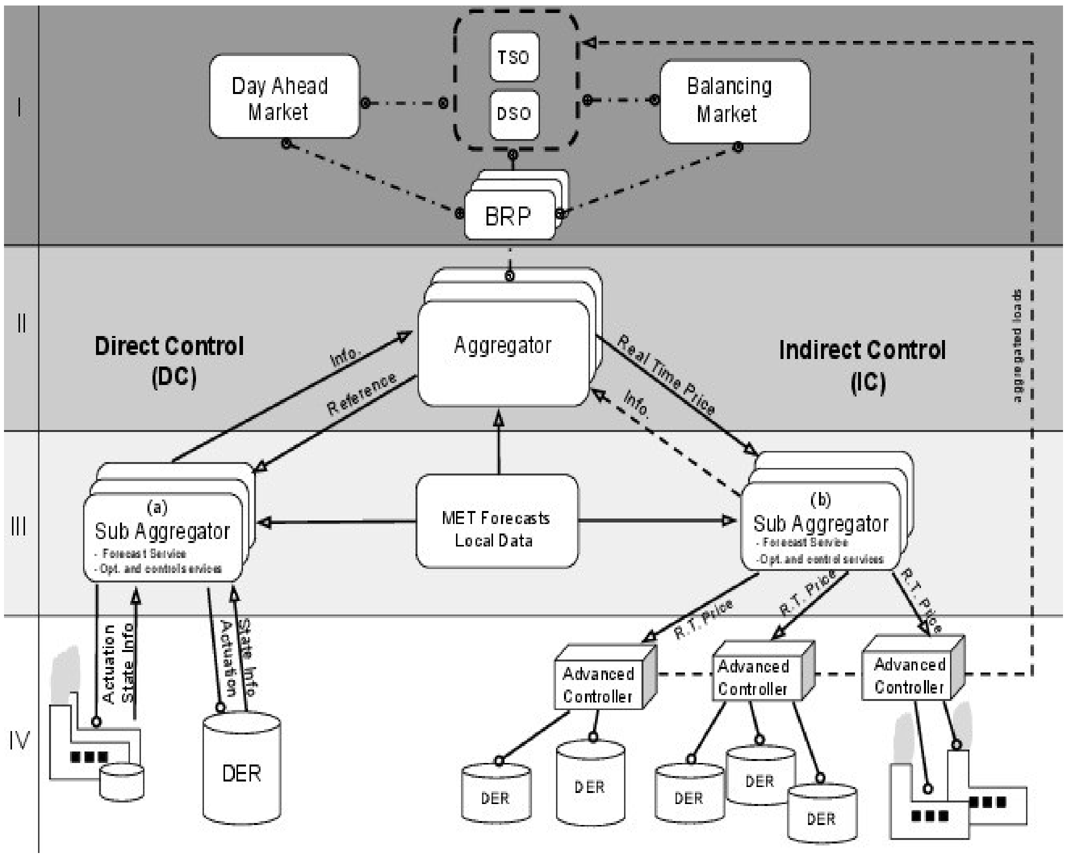
Control and Optimization



In New Wiley Book: Control of Electric Loads in Future Electric Energy Systems, 2015

- **Day Ahead:**

  Stoch. Programming based on eg. Scenarios

  Cost: Related to the market (one or two levels)

- **Direct Control:**

  Actuator: **Power**

  Two-way communication

  Models for DERs are needed

  Constraints for the DERs (calls for state est.)

  Contracts are complicated

- **Indirect Control:**

  Actuator: **Price**

  Cost: E-MPC at **low (DER) level**, One-way communication

  Models for DERs are not needed

  Simple 'contracts'

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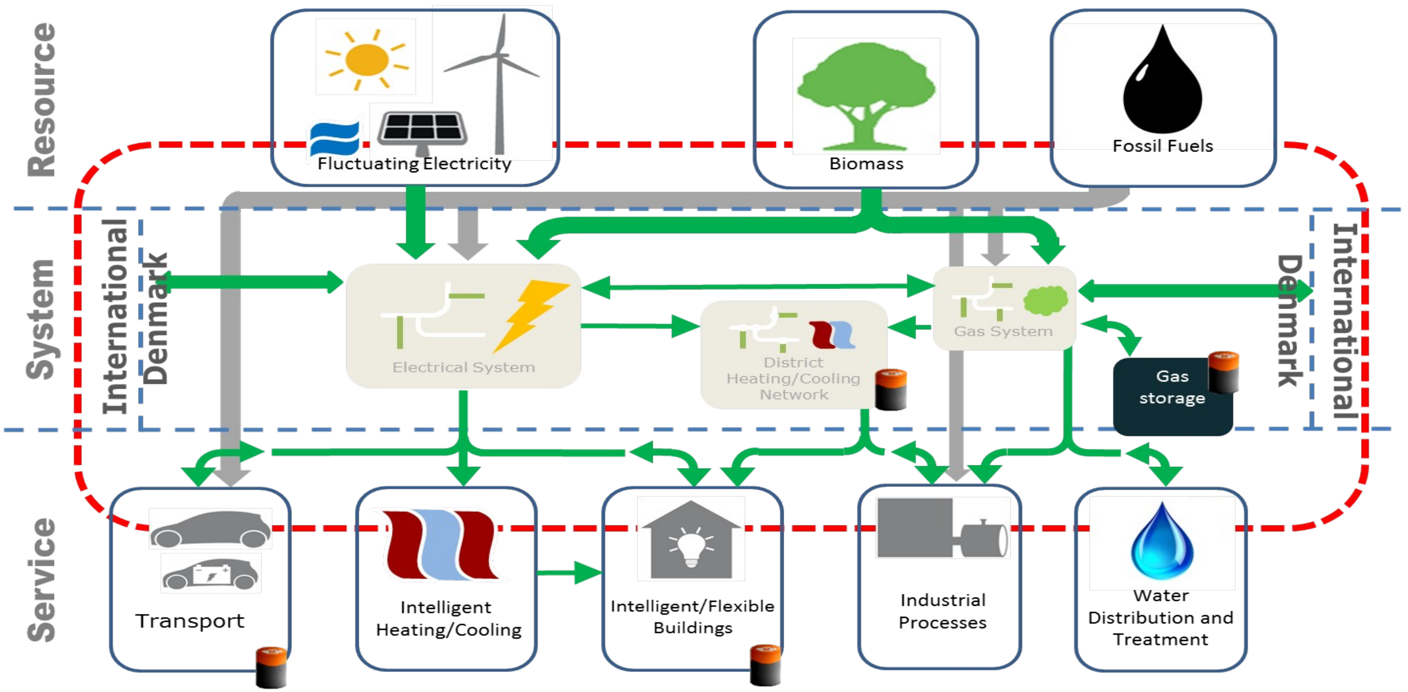
Direct vs Indirect Control

<table>
<tr><th>Level</th><th>Direct Control (DC)</th><th>Indirect Control (IC)</th></tr>
<tr><td>III</td><td rowspan="2">$\min_{x,u} \sum_{k=0}^{N} \sum_{j=1}^{J} \phi_j(x_{j,k}, u_{j,k})$
$\downarrow_{u_1} \cdots \downarrow_{u_J} \quad \uparrow_{x_1} \cdots \uparrow_{x_J}$
s.t. $\quad x_{j,k+1} = f_j(x_{j,k}, u_{j,k}) \quad \forall j \in J$</td><td>$\min_{\hat{z},p} \sum_{k=0}^{N} \phi(\hat{z}_k, p_k)$
s.t. $\quad \hat{z}_{k+1} = f(p_k)$</td></tr>
<tr><td>IV</td><td>$\min_u \sum_{k=0}^{N} \phi_j(p_k, u_k) \quad \forall j \in J$
s.t. $\quad x_{k+1} = f_j(x_k, u_k)$</td></tr>
</table>

Table 1: Comparison between direct (DC) and indirect (IC) control methods. (DC) In direct control the optimization is globally solved at level III. Consequently the optimal control signals u_j are sent to all the J DER units at level IV. (IC) In indirect control the optimization at level III computes the optimal prices p which are sent to the J-units at level IV. Hence the J DERs optimize their own energy consumption taking into account p as the actual price of energy.

Models

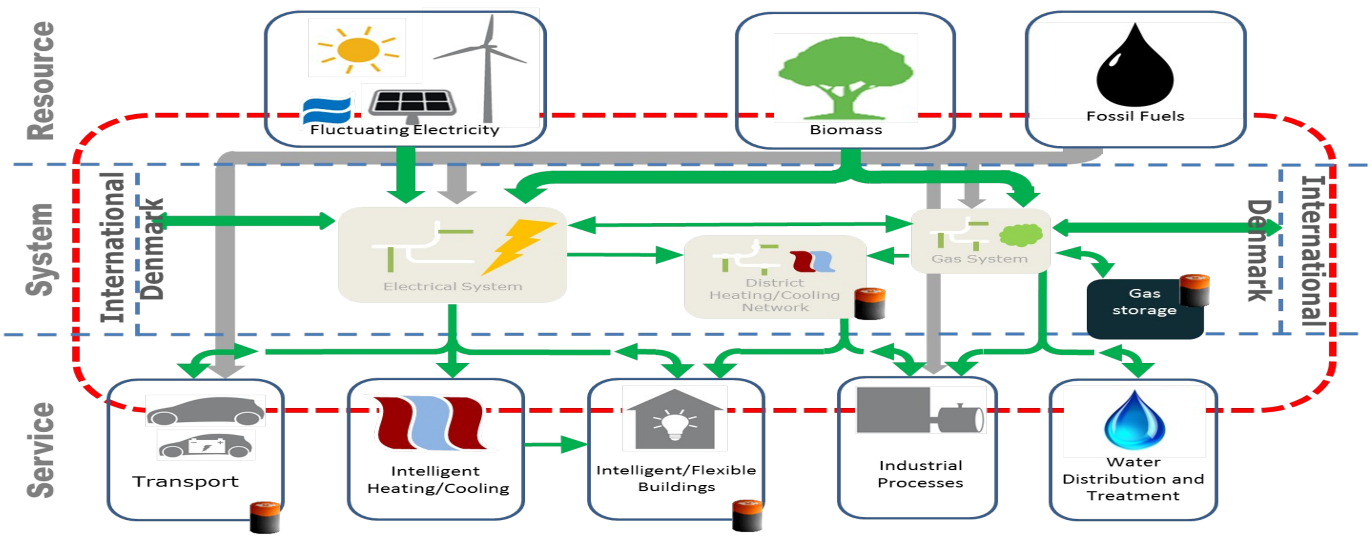
Grey-box modelling are used to establish **models and methods for real-time operation of future electric energy systems**



SE-OS Characteristics

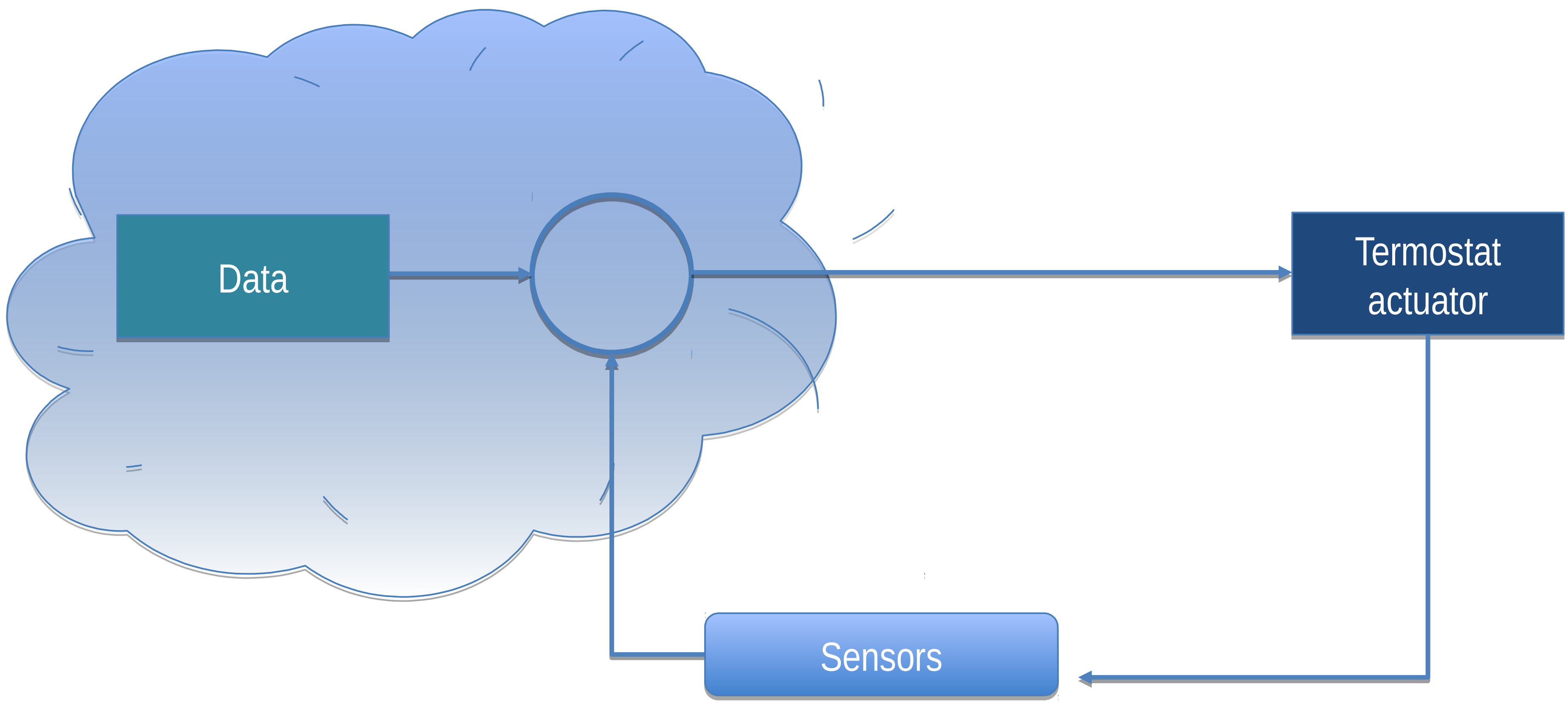
- Bidding – clearing – activation at higher levels
- Control principles at lower levels
- Cloud based solution for forecasting and control
- Facilitates energy systems integration (power, gas, thermal, ...)
- Allow for new players (specialized aggregators)
- Simple setup for the communication
- Simple (or no) contracts
- Rather simple to implement
- Harvest flexibility at all levels in Smart Cities

Virtual Storage solutions in Smart Cities

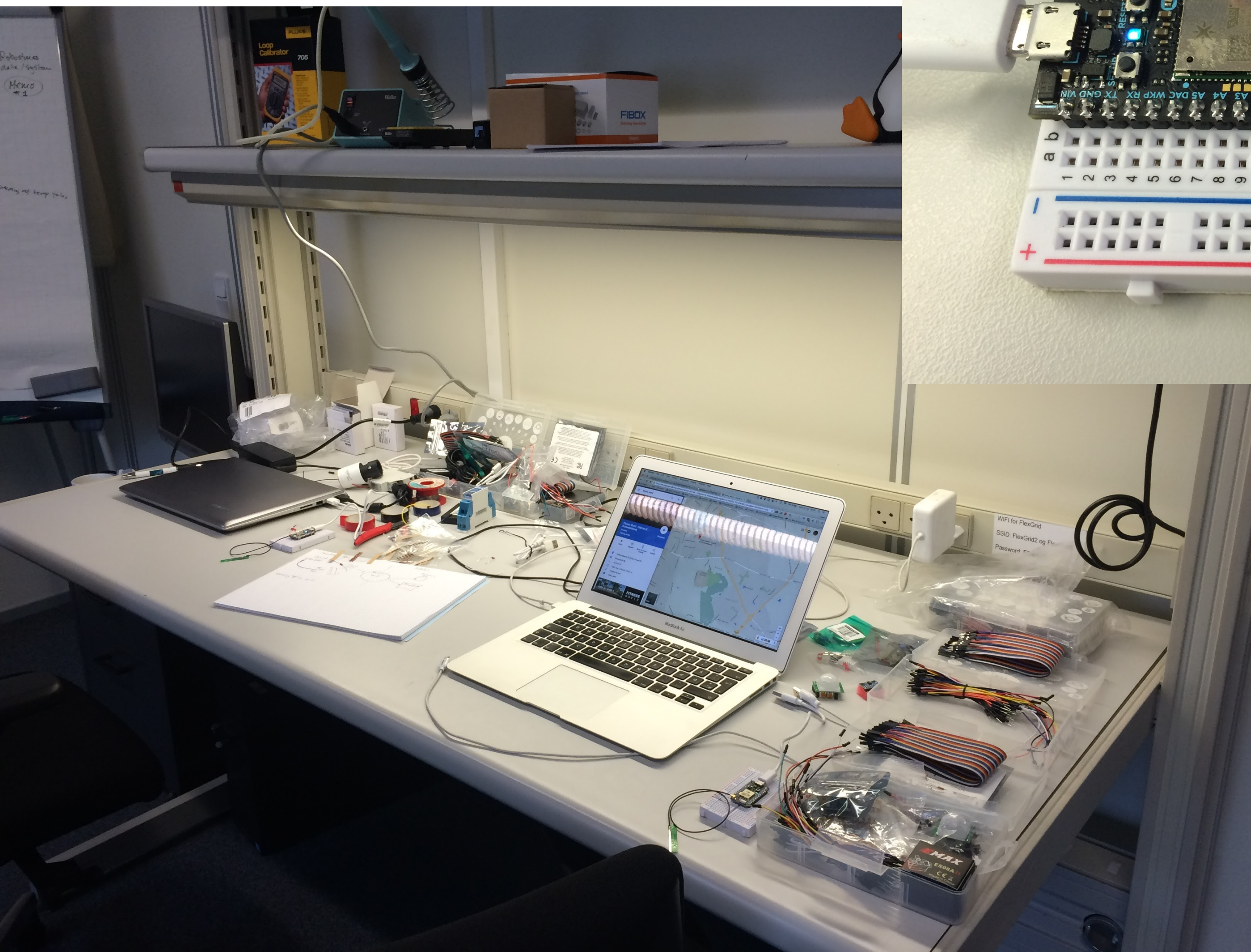


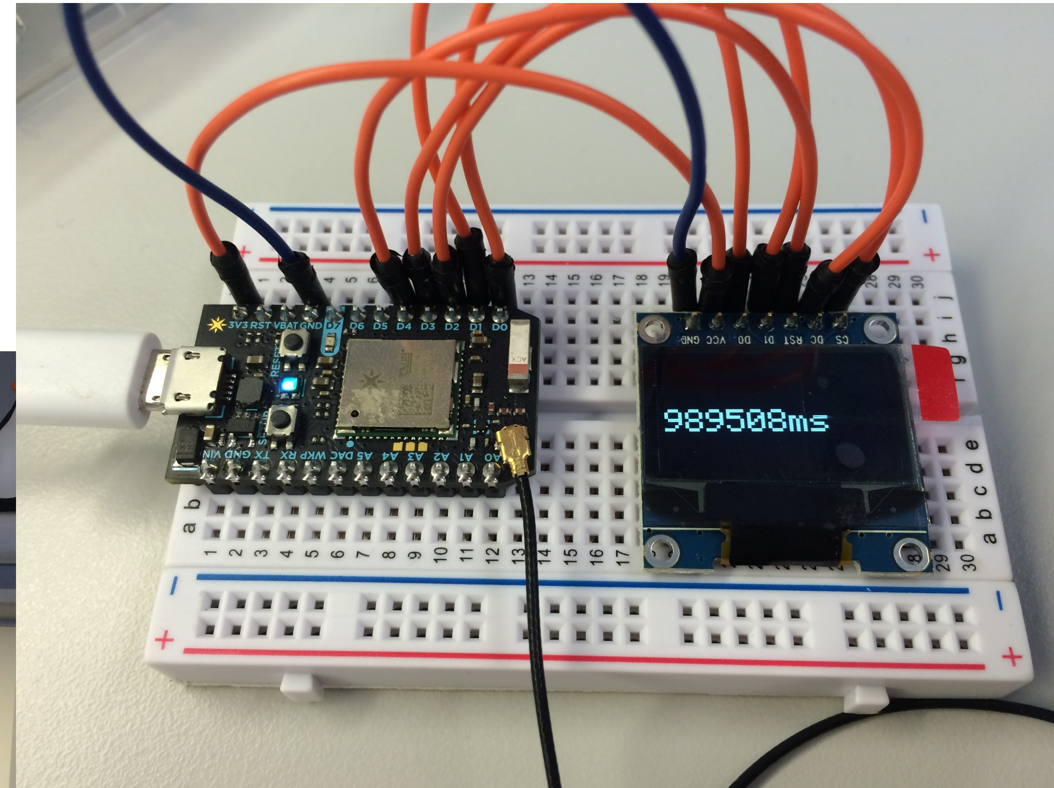
- **Flexibility (or virtual storage) characteristics:**
  - Supermarket refrigeration can provide storage 0.5-2 hours ahead
  - Buildings thermal capacity can provide storage up to, say, 5-10 hours ahead
  - Buildings with local water storage can provide storage up to, say, 2-12 hours ahead
  - District heating/cooling systems can provide storage up to 1-3 days ahead
  - Gas systems can provide seasonal storage

SE-OS
Control loop design – **logical drawing**

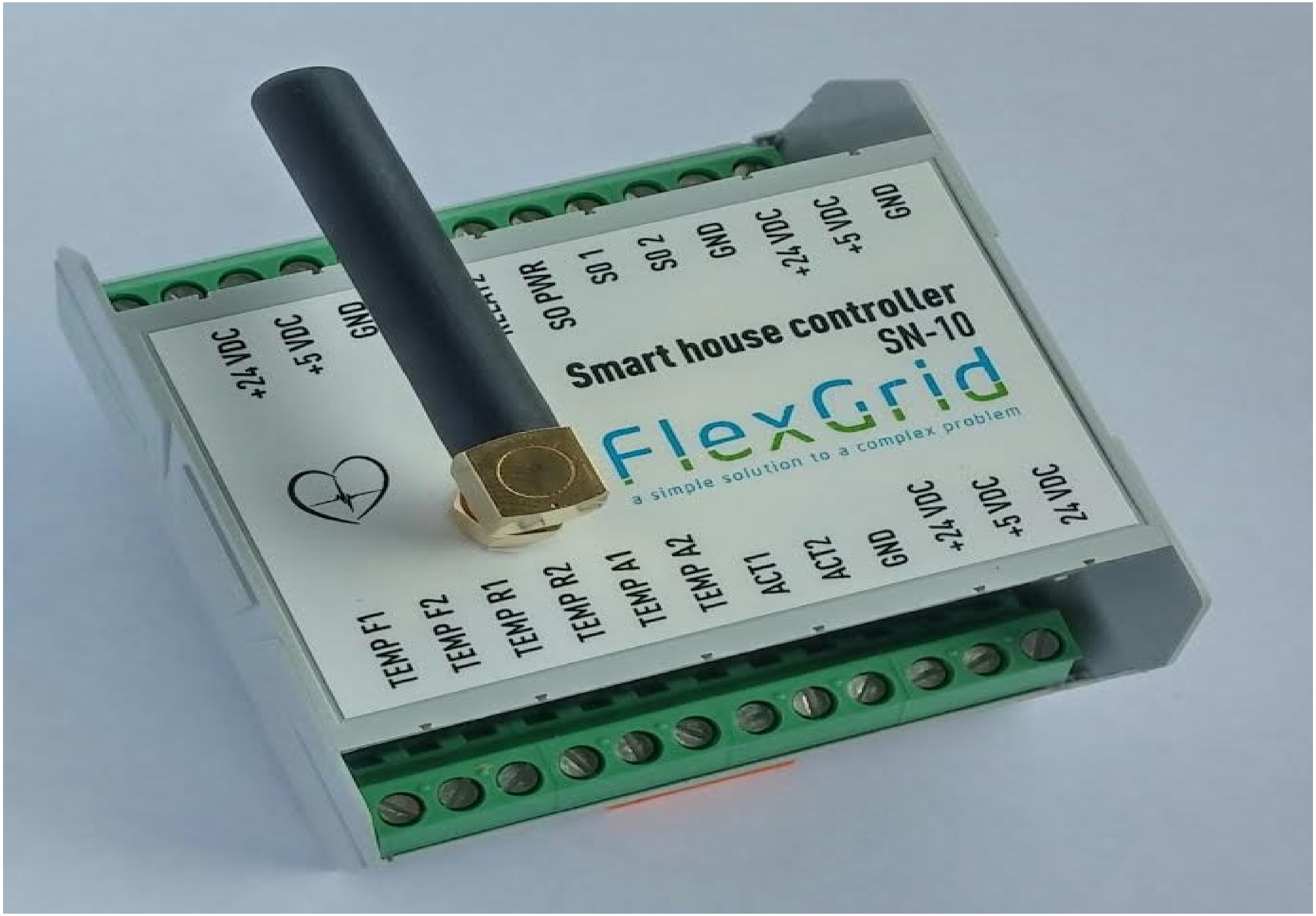


Lab testing ….





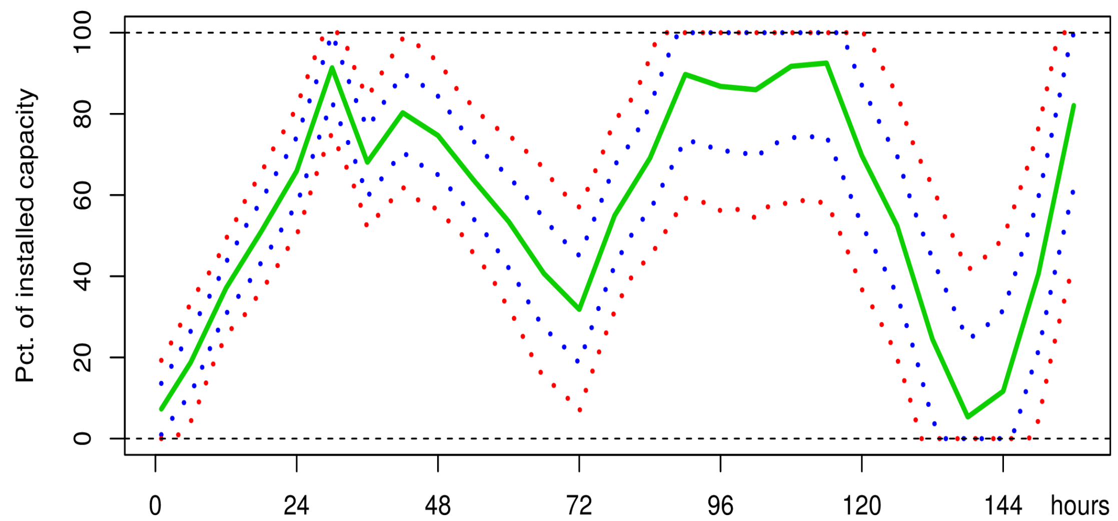
SN-10 Smart House Prototype

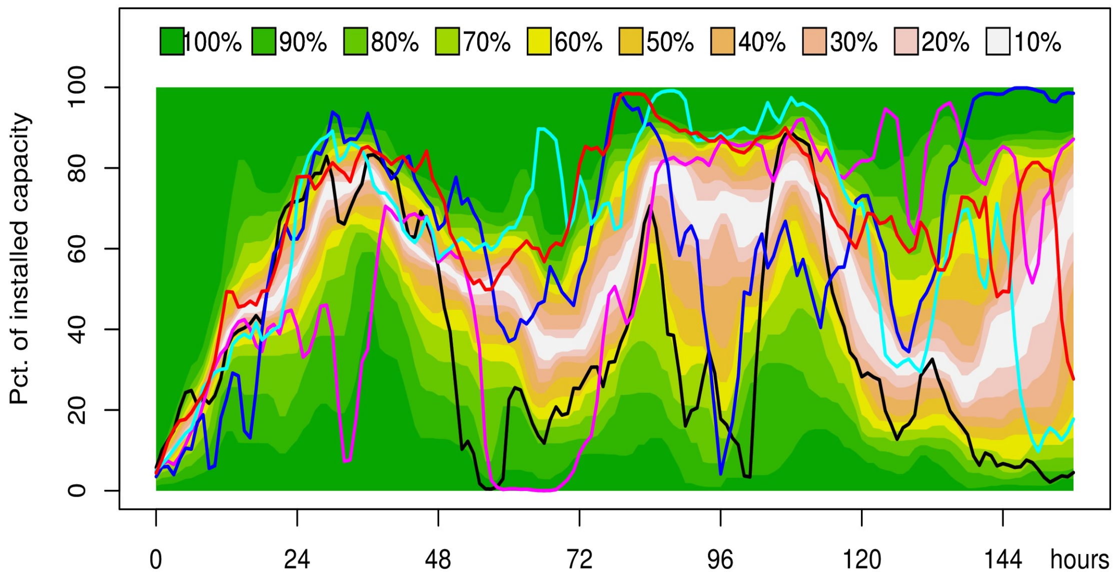


Forecasting is Essential

Tools for Forecasting: (Prob. forecasts)

- Power load
- Heat load
- Gas load
- Prices (power, etc)
- Wind power prod.
- Solar power prod.
- State variables (DER)





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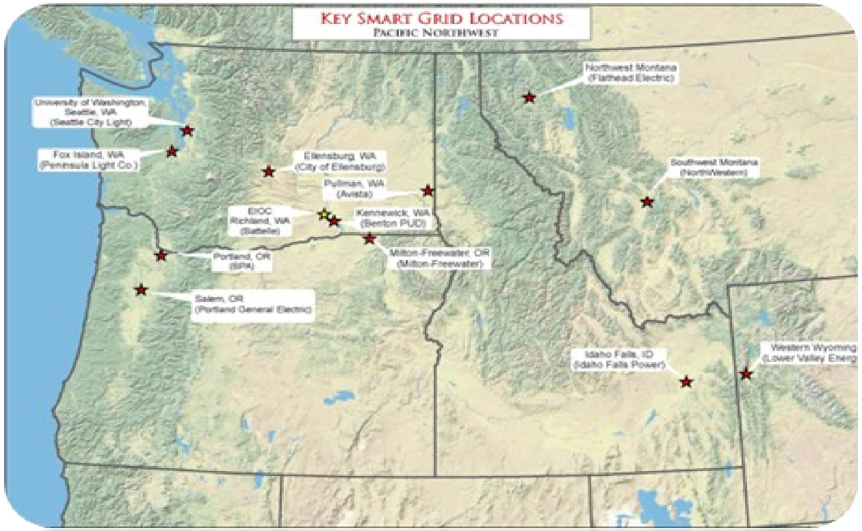
Case study

Control of Power Consumption (DSM) using the Thermal Mass of Buildings

Data from BPA

Olympic Pensinsula project

- 27 houses during one year
- Flexible appliances: HVAC,
  cloth dryers and water boilers
- 5-min prices, 15-min consumption
- Objective: limit max consumption



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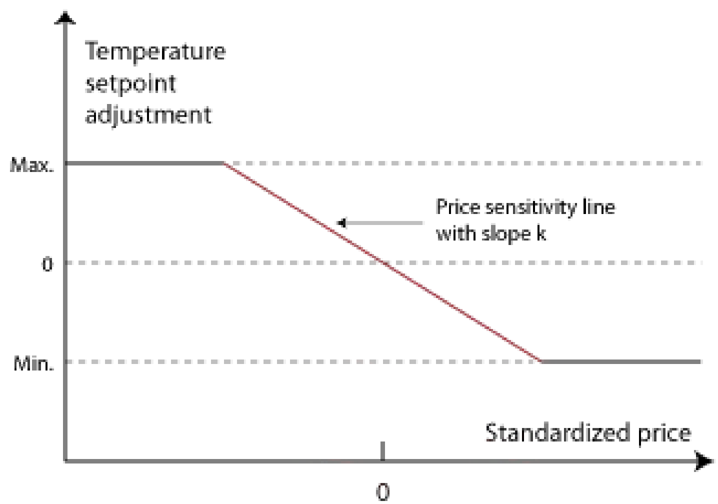
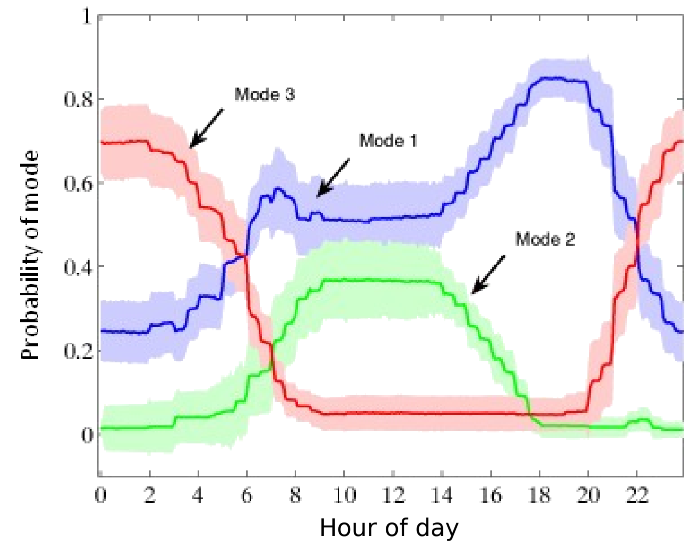
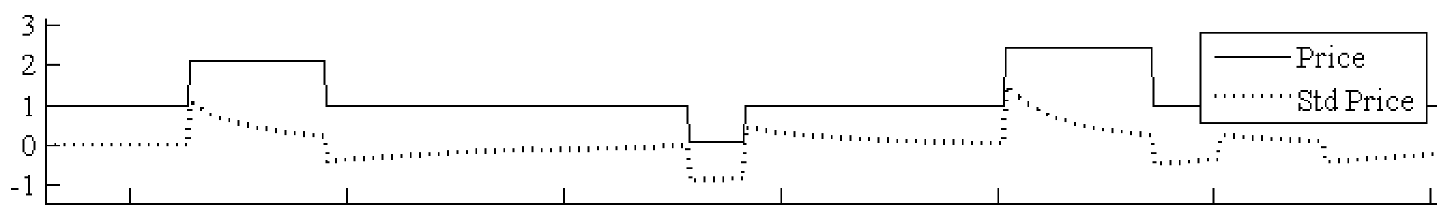
Price responsivity

Flexibility is activated by adjusting the temperature reference (setpoint)







- **Standardized price** is the % of change from a price reference, computed as a mean of past prices with exponentially decaying weights.
- **Occupancy mode** contains a price sensitivity with its related comfort boundaries. 3 different modes of the household are identified (work, home, night).

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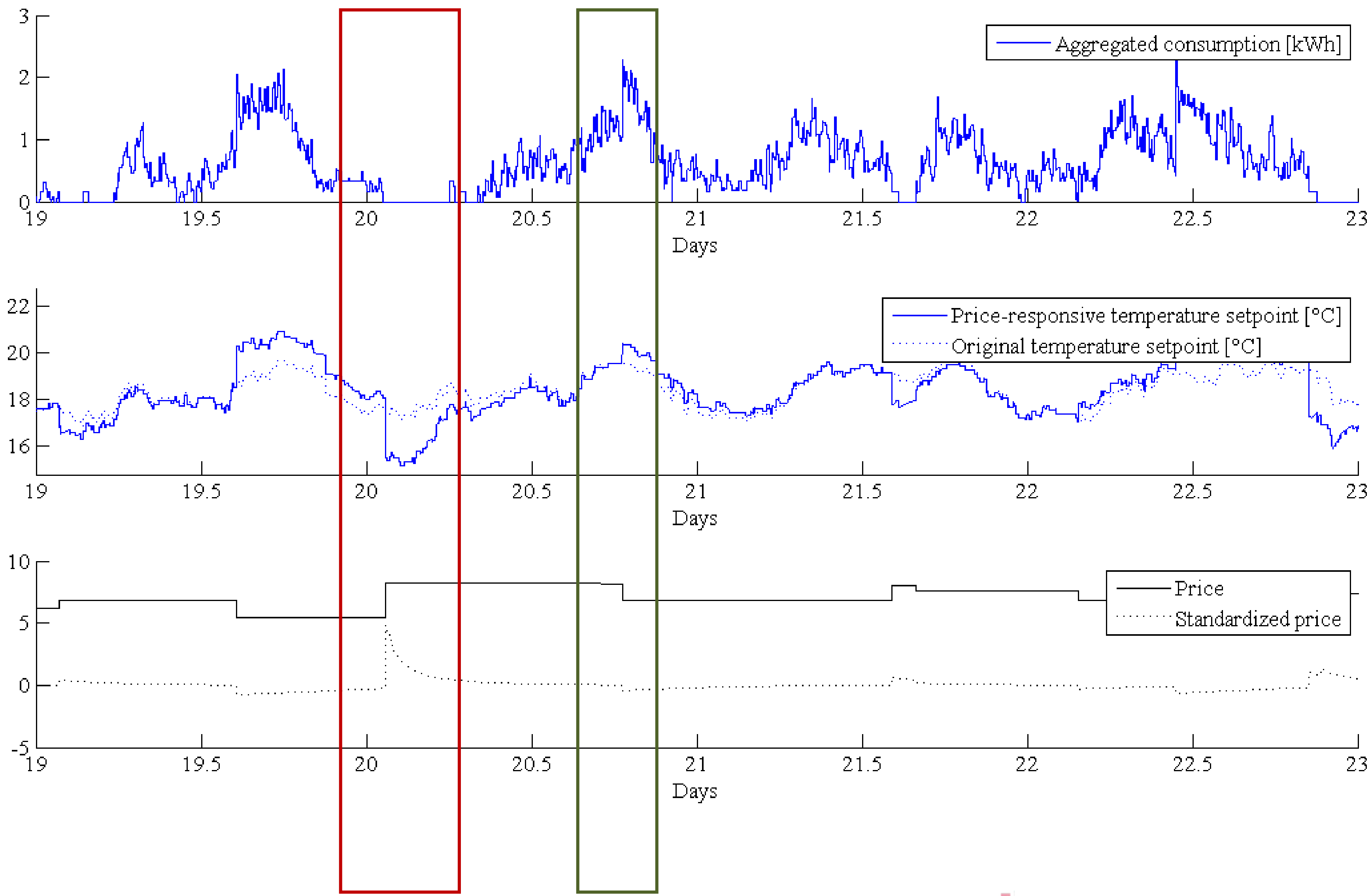
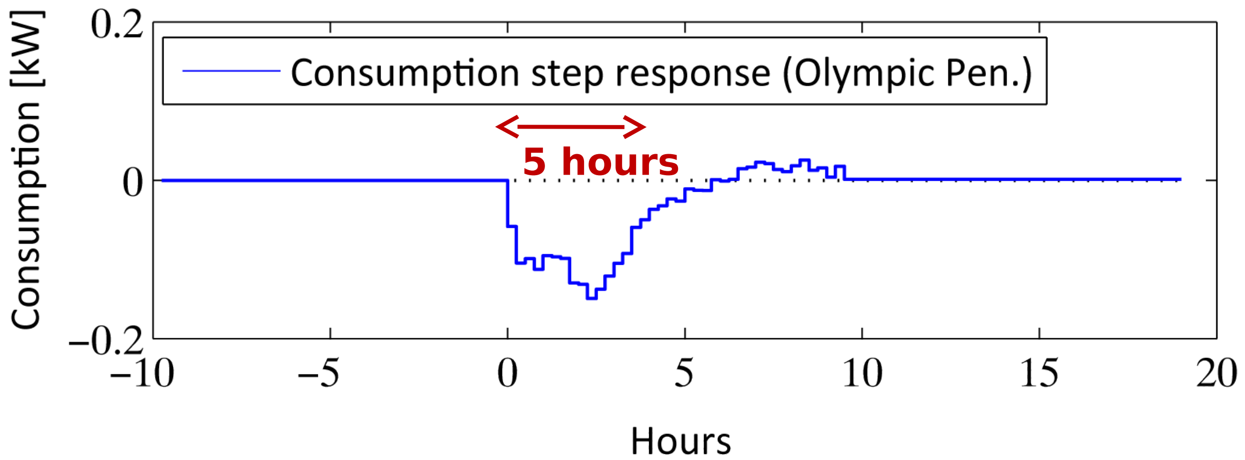
Aggregation (over 20 houses)



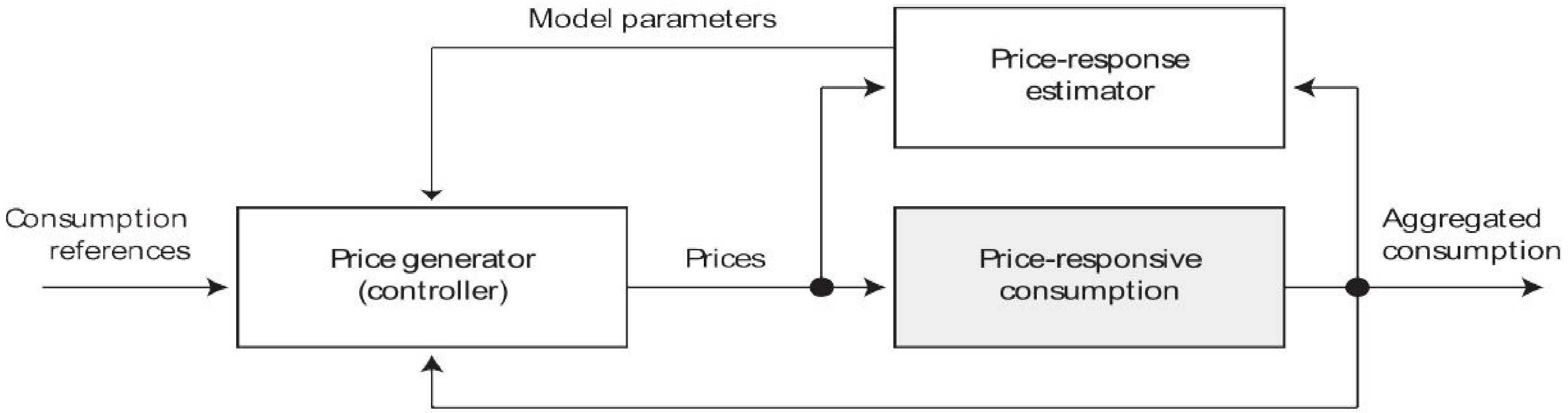
Non-parametric Response on Price Step Change

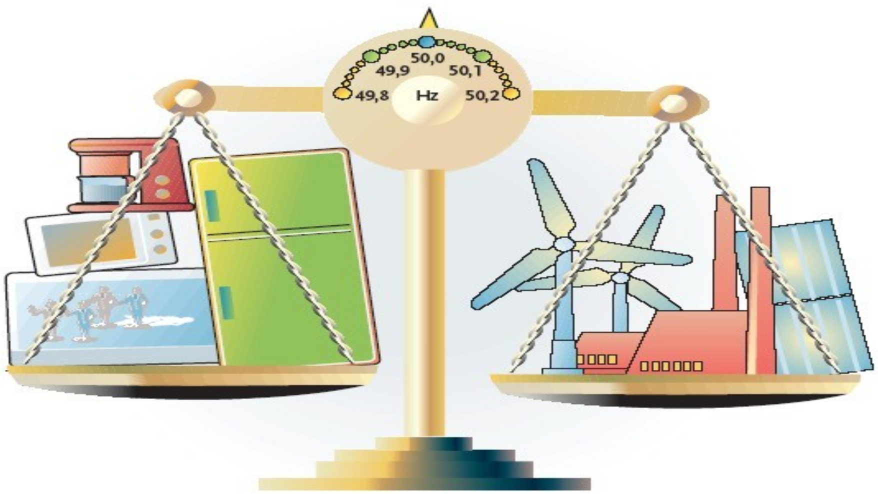
Model inputs: price, minute of day, outside temperature/dewpoint, sun irrandiance

Olympic Peninsula



Control of Energy Consumption

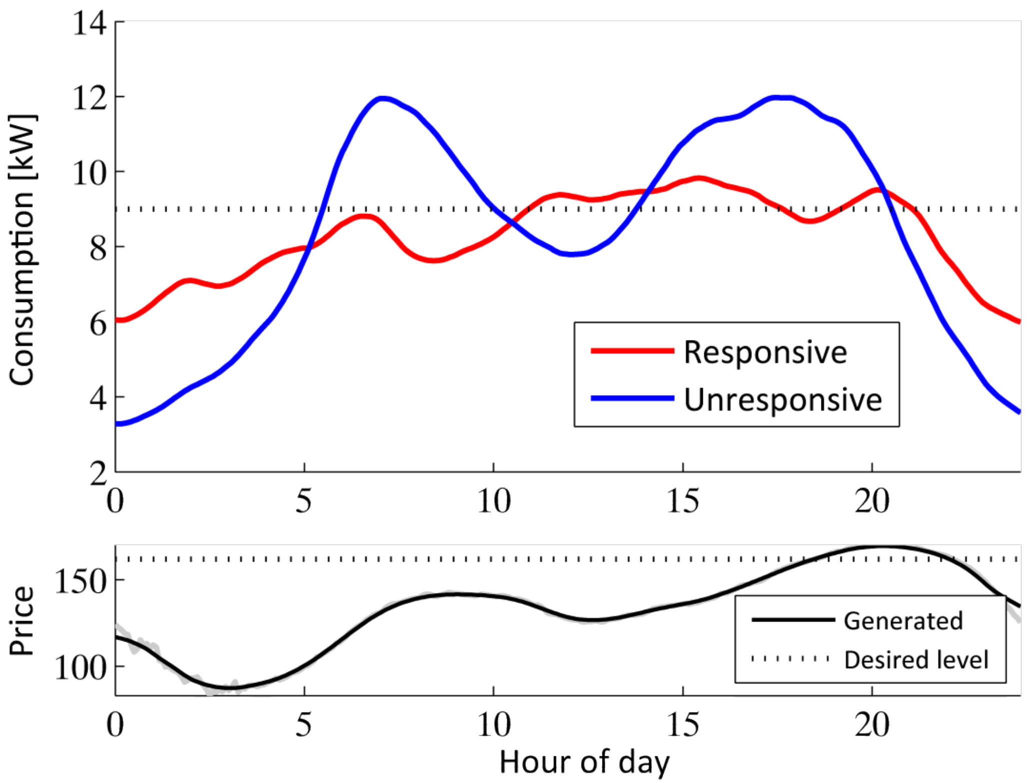




Control performance

With a price penality avoiding its divergence

- Considerable **reduction in peak consumption**
- Mean daily consumption shift



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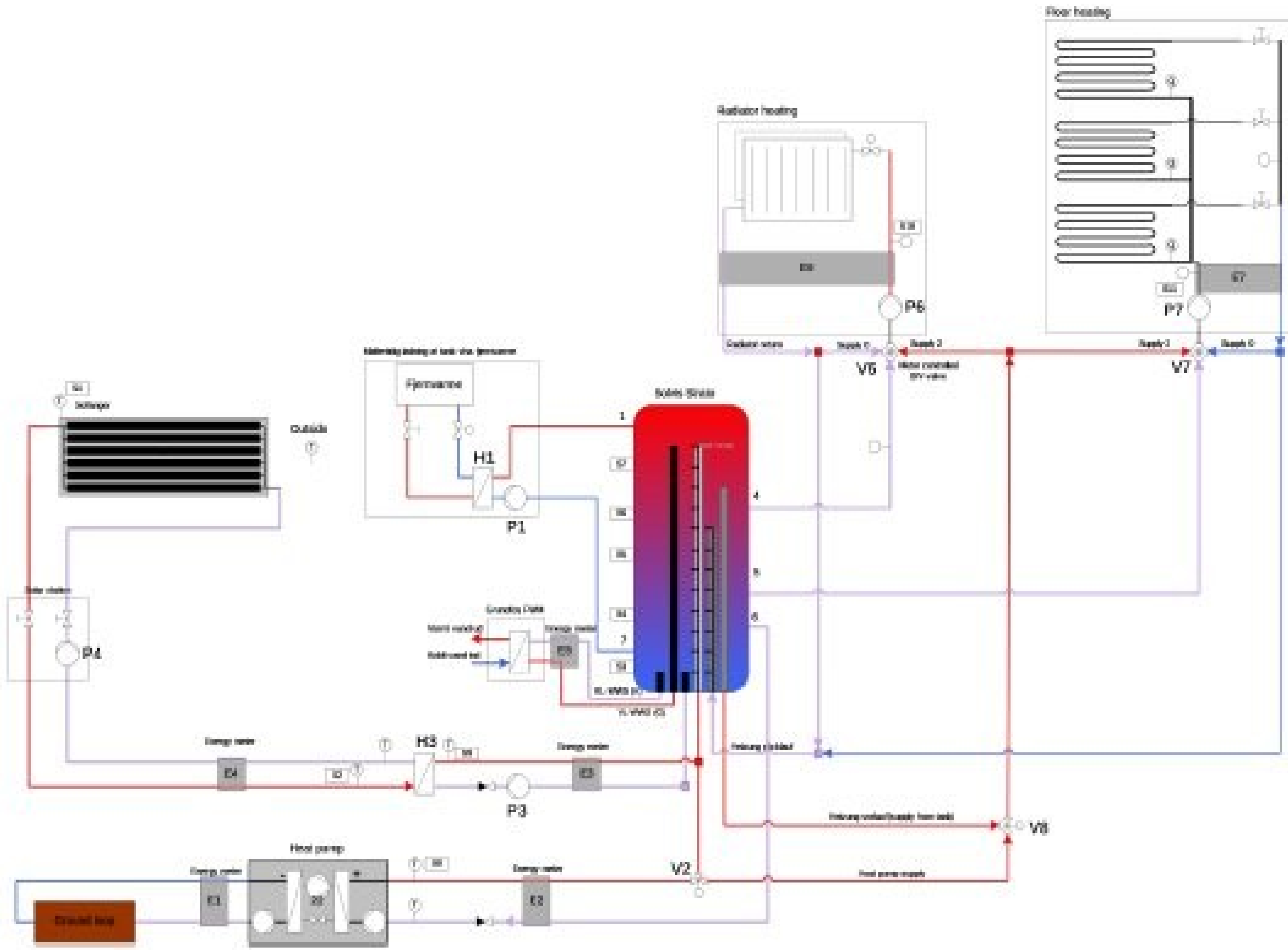
Case study No. 5

Control of Heat Pumps (based on varying prices)

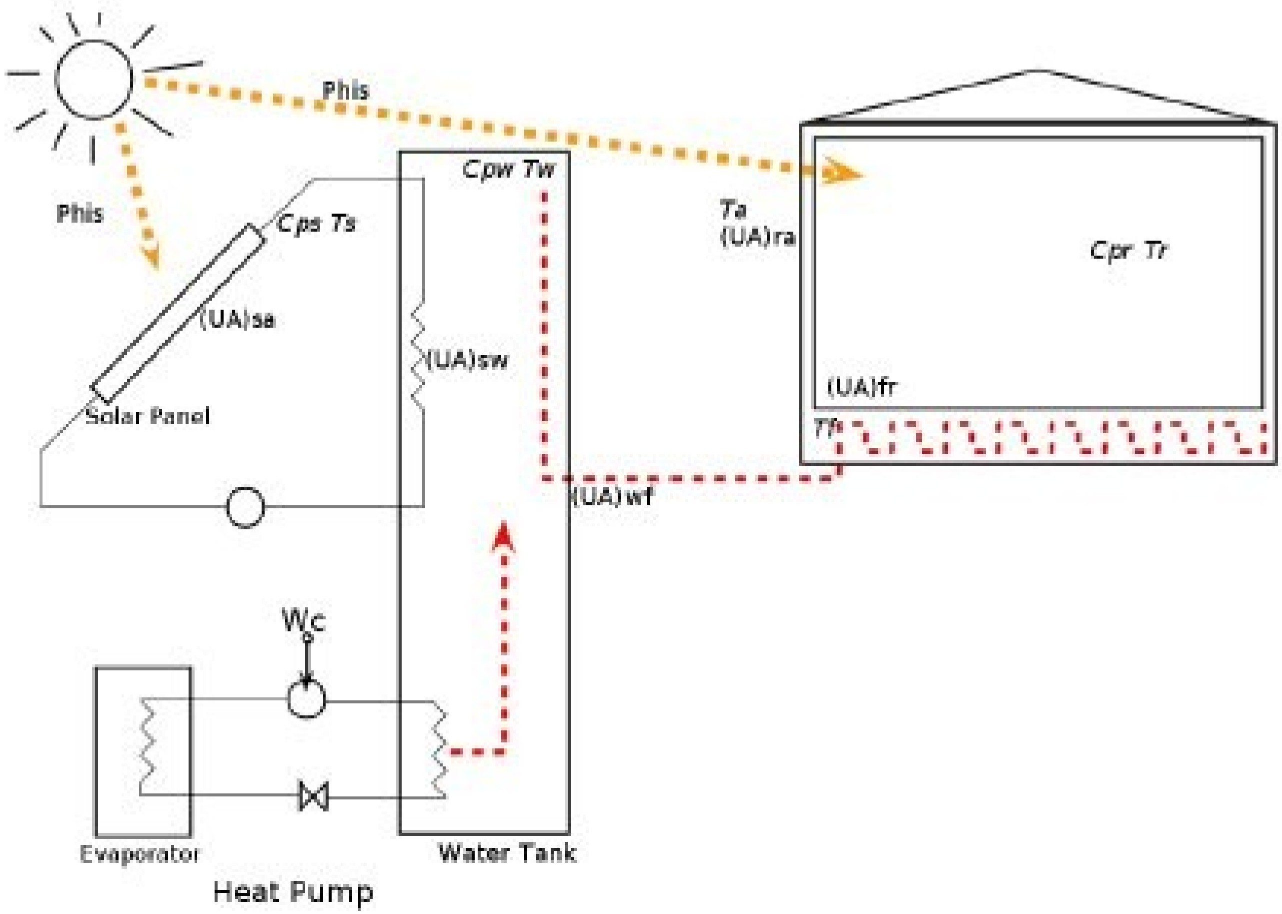
Grundfos Case Study

Schematic of the heating system



Modeling Heat Pump and Solar Collector

Simplified System



Avanced Controller

Economic Model Predictive Control

Formulation

The Economic MPC problem, with the constraints and the model, can be summarized into the following formal formulation:

$$\min_{\{u_k\}_{k=0}^{N-1}} \phi = \sum_{k=0}^{N-1} c' u_k \tag{4a}$$

Subject to

$$x_{k+1} = Ax_k + Bu_k + Ed_k \quad k = 0, 1, \ldots, N-1 \tag{4b}$$

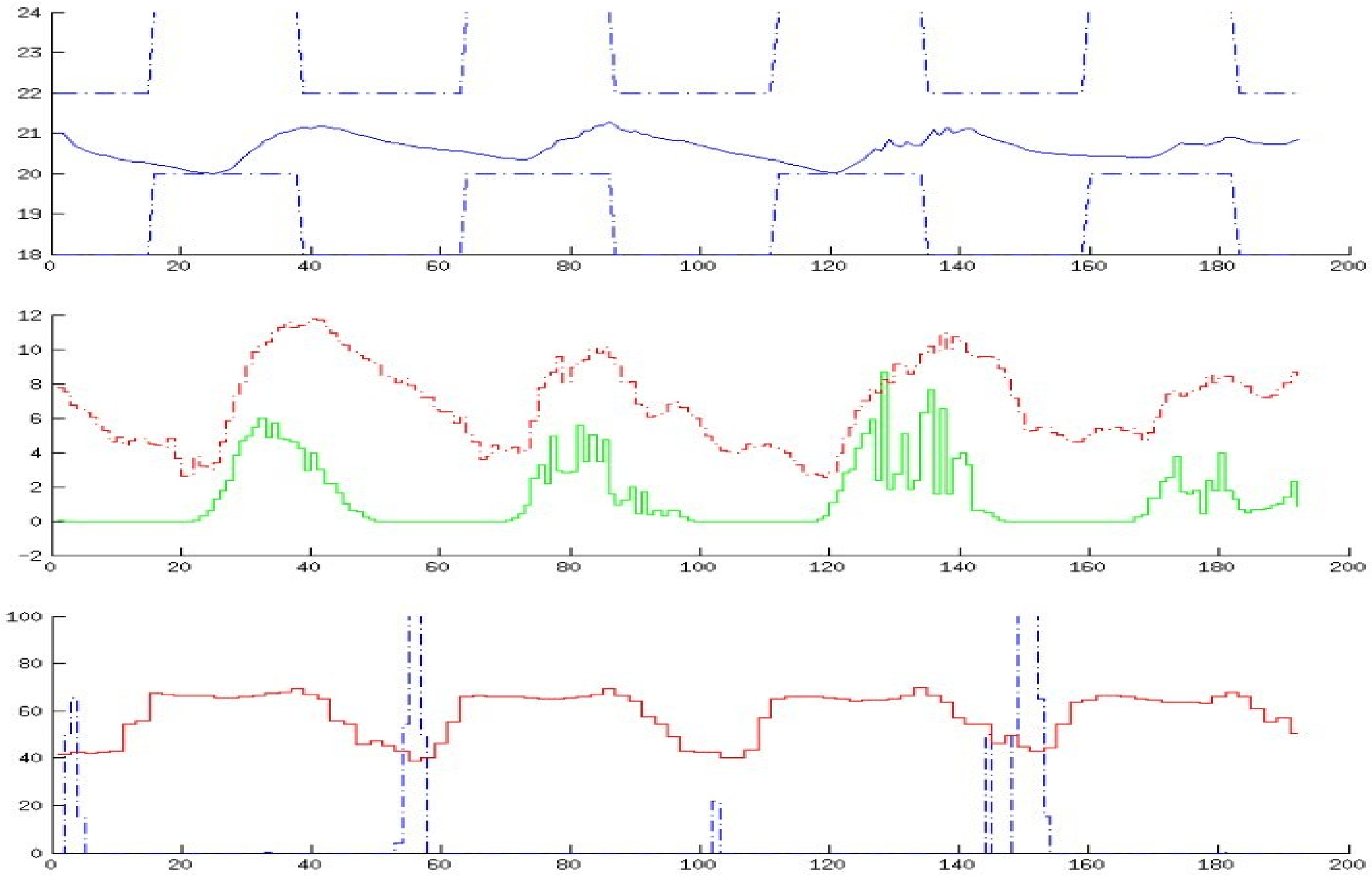
$$y_k = Cx_k \quad k = 1, 2, \ldots, N \tag{4c}$$

$$u_{min} \leq u_k \leq u_{max} \quad k = 0, 1, \ldots, N-1 \tag{4d}$$

$$\Delta u_{min} \leq \Delta u_k \leq \Delta u_{max} \quad k = 0, 1, \ldots, N-1 \tag{4e}$$

$$y_{min} \leq y_k \leq y_{max} \quad k = 0, 1, \ldots, N \tag{4f}$$

EMPC for heat pump with solar collector (savings 35 pct)



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Centre for IT-Intelligent Energy Systems in cities

Demo projects | Software solutions | Work Packages | Partners | Events | Communications | Publications | Vacant positions | Contacts

Software solutions

Software for combined physical and statistical modelling

Continuous Time Stochastic Modelling (CTSM) is a software package for modelling and simulation of combined physical and statistical models. You find a technical description and the software at CTSM.info.

Software for Model Predictive Control

HPMPC is a toolbox for High-Performance implementation of solvers for Model Predictive Control (MPC). It contains routines for fast solution of MPC and MHE (Moving Horizon Estimation) problems on embedded hardware. The software is available at GitHub.

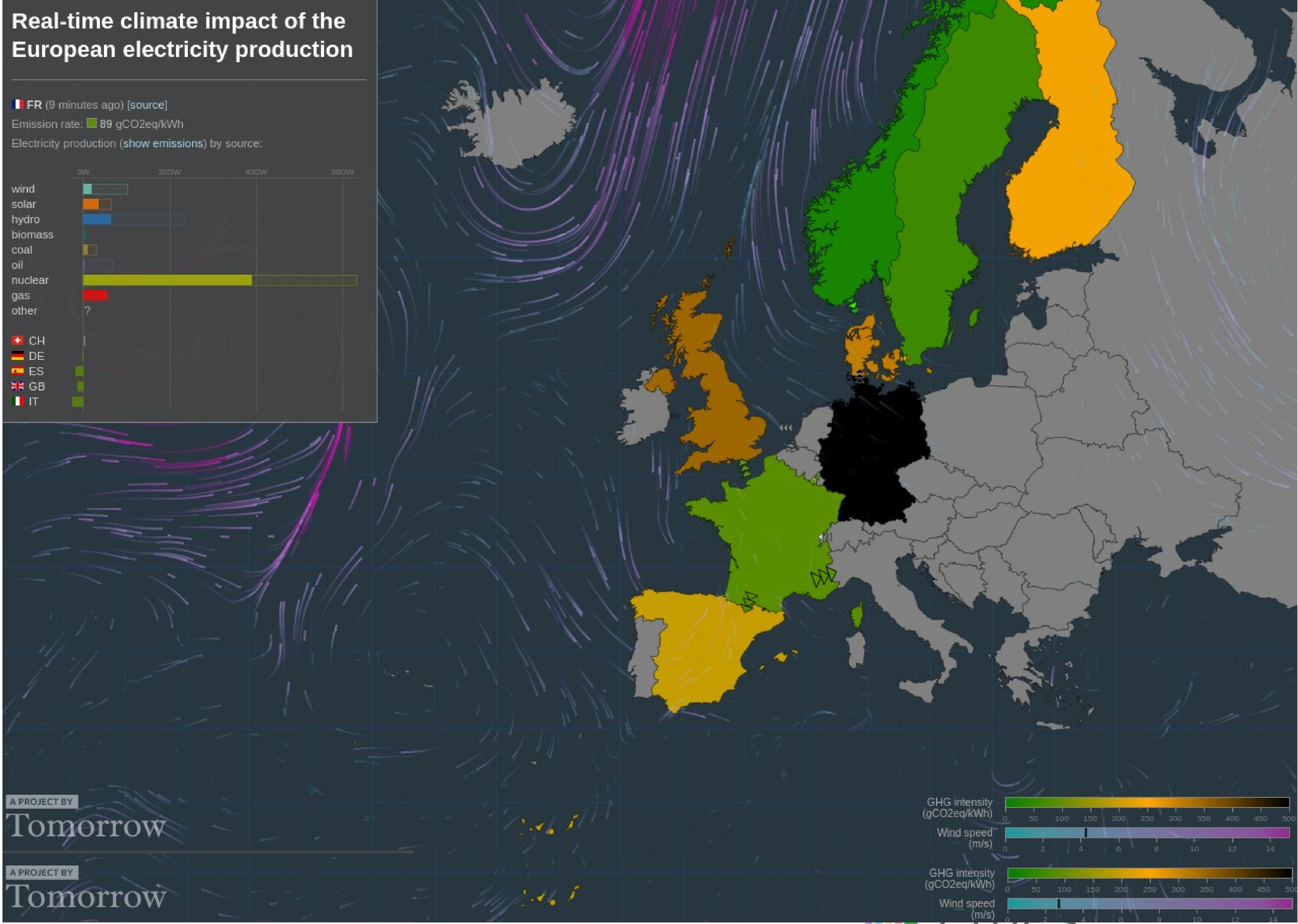
Search ...

Latest news

Ambassador Louise Bang Jespersen visited CITIES, October 29th 2015

CITIES Korean International Workshop – KIER, Daejeon, Korea, October 22nd 2015

Workshop on Mathematical Sciences Collaboration in Energy Systems Integration – DTU,


Real-time climate impact of the European electricity production
FR (9 minutes ago) [source]
Emission rate: 89 gCO2eq/kWh
Electricity production (show emissions) by source:
0W
20GW
40GW
60GW
wind
solar
hydro
biomass
coal
oil
nuclear
gas
other
?
CH
DE
ES
GB
IT
A PROJECT BY
Tomorrow
GHG intensity (gCO2eq/kWh)
0 50 100 150 200 250 300 350 400 450 500
Wind speed (m/s)
0 2 4 6 8 10 12 14
A PROJECT BY
Tomorrow
GHG intensity (gCO2eq/kWh)
0 50 100 150 200 250 300 350 400 450 500
Wind speed (m/s)

Real-time electricity data sources

- Denmark: energinet.dk
- Finland: energinet.dk
- France: RTE
- Germany: Agora Energiewende
- Great Britain: ELEXON
- Norway: energinet.dk
- Spain: REE
- Sweden: energinet.dk

Production capacity data sources

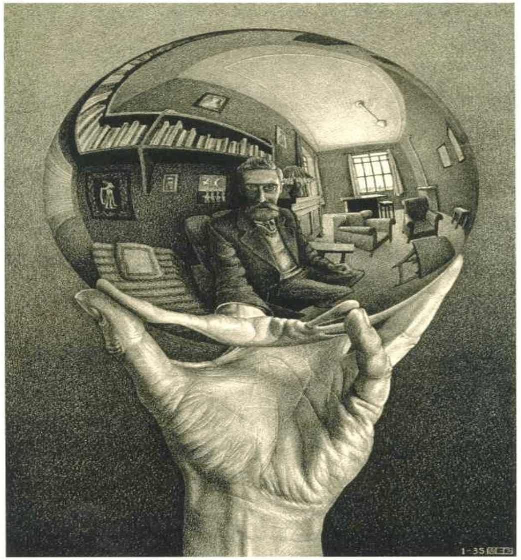
- Denmark
  - Solar: wikipedia.org
  - Wind: wikipedia.org
- Finland
  - Hydro: worldenergy.org
  - Nuclear: iaea.org
  - Wind: EWEA
- France
  - Solar: wikipedia.org
  - Wind: EWEA
  - Other: RTE
- Germany: Fraunhofer ISE
- Great Britain
  - Gas: energy-uk.org.uk
  - Hydro: wikipedia.org
  - Nuclear: wikipedia.org
  - Solar: wikipedia.org

Discussion

- IT-Intelligent Energy Systems Integration in Smart Societies can provide virtual storage solutions (so maybe we should put less focus on electrical storage solutions)
- District heating (or cooling) systems can provide flexibility on the essential time scale (up to a few days)
- Gas systems can provide seasonal virtual storage solutions
- Smart Cities are just smart elements of a Smart Society
- We see a large potential in Demand Response. Automatic solutions, price based control, and end-user focus are important
- We see large problems with the tax and tariff structures in many countries (eg. Denmark).
- Markets and pricing principles need to be reconsidered; we see an advantage of having a physical link to the mechanism (eg. nodal pricing, capacity markets)

Some of the other Demo-Projects in CITIES

- Control of WWTP (with ED, Kruger, ..)
- Supermarket cooling (with Danfoss, ..)
- Summerhouses (with DC, ..)
- Green Houses
- CHP
- Industrial production
- EVs (optimal charging)
- ....



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For more information ...

- See for instance

  www.henrikmadsen.org

  www.smart-cities-centre.org

- ...or contact
  - Henrik Madsen (DTU Compute)

    hmad@dtu.dk

- Acknowledgement CITIES (DSF 1305-00027B)

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